FINAL PROJECT SUBMISSION

Please fill out:

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- Student pace: full time
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- Blog post URL: https://github.com/SamuelMathenge/PHASE-2-PROJECT.git

BUSINESS UNDERSTANDING

The movie market is one of the industries which have been there for a long time, it is mostly used for entertainment and educational purposes. The main source of income for movie studios is from the sales of a movie,both locally and globally. The company wishes to venture into this industry by setting up a studio. To do this there are alot of considerations, the main one being viewer satisfaction and that is by being considerate of the genre,movie runtime among others that would satisfy the users experience. The movie Industry is growing and to get a share of the market you need to have a large number of audience. This is what the analysis is all about, getting Customer Insights which will help me make recommendations which are data driven. To understand the movie industry well I put into consideration three question.

- Does the movie runtime have any influence on the movie rating?
- At this point I want to explore the likelihood of a movie getting a higher rating maybe because the runtime is not too long or the vice versa.
- Does the popularity of a studio determine the income of the studio in question?
- In the industry there are both popular and not so popular studio, I want to look into them and try to find out if the most popular studios attract higher incomws.
- What is the effect of movie budgeting to it's sales?
- Some movies have a very high production budget while others have a lower budget. In my analysis I want to find out the outcomes of both instances, where the movie budgeting is low and where the movie budgeting is high.

DATA UNDERSTANDING

The data being used is from various movie rating sites. For this analysis I have used three datasets.

- One of the datasets,bom movie dataset represents various studios,their domestic income and the years. It's source is https://www.boxofficemojo.com/.
- The other dataset the IMDB dataset from https://www.imdb.com/ and contains columns such as movie ratings, runtime and genre which are essential for the analysis.
- The third dataset is TN MOVIE which has been sourced from https://www.themoviedb.org/ and it contains mostly columns which help in quantifying the gross generated by various movies and the years.

```
#importing all the required libraries
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
import sqlite3

#accessing the datasets
bom_movie = pd.read_csv('bom.movie_gross.csv')
tn_movie = pd.read_csv('tn.movie_budgets.csv')


#Accessing the databse using sql queries
#creating a connection
connection = sqlite3.connect('im.db')

#accessing the available tables in our database
tables = pd.read_sql_query("SELECT name FROM sqlite_master WHERE
type='table';",connection)
```

Viewing the first 5 rows of the BOM MOVIE DATASET

```
bom_movie.head(5)
```

```
                                          title studio  domestic_gross
\
0                                Toy Story 3     BV     415000000.0
```

```
1                    Alice in Wonderland (2010)     BV     334200000.0

2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0

3                                     Inception     WB     292600000.0

4                            Shrek Forever After   P/DW     238700000.0


  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
```

Viewing the first 5 rows of the TN MOVIE DATASET

```
tn_movie.head(5)
```

```
   id  release_date                                          movie  \
0   1  Dec 18, 2009                                         Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                   Dark Phoenix
3   4   May 1, 2015                    Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

Since IMDB is a database we explore some of the Tables in the database

```
tables
```

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

Choosing the tables to use, in my case I have choosen movie_basics, movie_akas and movie_ratings

```
#Quering  all the rows from the movie_basics table
df2 = pd.read_sql_query("SELECT * FROM movie_basics",connection)
df2.head(5)
```

```
    movie_id                     primary_title
original_title  \
0  tt0063540                         Sunghursh
Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek
Din
2  tt0069049       The Other Side of the Wind  The Other Side of the
Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada
Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela
Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy
```

```
#Quering  all the rows from the movie_akas table
df3 = pd.read_sql_query("SELECT * FROM movie_akas",connection)
df3.head(5)
```

```
    movie_id  ordering                                  title region
\
0  tt0369610        10                              Джурасик свят     BG

1  tt0369610        11                          Jurashikku warudo     JP

2  tt0369610        12  Jurassic World: O Mundo dos Dinossauros     BR

3  tt0369610        13                  O Mundo dos Dinossauros     BR

4  tt0369610        14                            Jurassic World     FR


  language        types   attributes  is_original_title
0       bg         None         None                0.0
1     None  imdbDisplay         None                0.0
2     None  imdbDisplay         None                0.0
3     None         None  short title                0.0
4     None  imdbDisplay         None                0.0
```

```
#Quering  all the rows from the movie_akas table
df4 = pd.read_sql_query("SELECT * FROM movie_ratings",connection)
df4.head(5)
```

```
     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
```

Used an inner loop to connect the three tables because am concerned with the rows which contain matching entrie for a better analysis.

```
#used inner to only include entries that are in all tables
df5 = pd.read_sql_query("""
    SELECT *
    FROM
        movie_basics AS mb
    INNER JOIN
        movie_akas AS ma ON ma.movie_id=mb.movie_id
    INNER JOIN
        movie_ratings AS mr ON mb.movie_id=mr.movie_id

    """,connection)
imdb = df5
```

Viewing the dataset after the join

```
imdb.head(5)
```

```
    movie_id primary_title original_title  start_year  runtime_minutes
\
0  tt0063540     Sunghursh      Sunghursh        2013            175.0

1  tt0063540     Sunghursh      Sunghursh        2013            175.0

2  tt0063540     Sunghursh      Sunghursh        2013            175.0

3  tt0063540     Sunghursh      Sunghursh        2013            175.0

4  tt0063540     Sunghursh      Sunghursh        2013            175.0


                genres   movie_id  ordering      title region language
\
0  Action,Crime,Drama  tt0063540         1  Sangharsh     IN       hi

1  Action,Crime,Drama  tt0063540         2  Sunghursh   None     None
```

```
2  Action,Crime,Drama  tt0063540         3  Sunghursh     IN     None

3  Action,Crime,Drama  tt0063540         4  Sunghursh     IN       hi

4  Action,Crime,Drama  tt0063540         5  Sungharsh     IN       hi


       types                    attributes  is_original_title   movie_id
\
0      None  alternative transliteration                0.0  tt0063540

1  original                          None                1.0  tt0063540

2      None                          None                0.0  tt0063540

3      None  alternative transliteration                0.0  tt0063540

4      None          alternative spelling                0.0  tt0063540


   averagerating  numvotes
0            7.0        77
1            7.0        77
2            7.0        77
3            7.0        77
4            7.0        77
```

FUNCTION TO CHECK THE ATTRIBUTES OF ALL THREE TABLES AT ONCE

```
#function to check for common attributes for the three datasets
#here we define two parameters where df is for the dataset name and
name is for the description
def dataset_description(df, dataset_name):
    print(f"{dataset_name}")
    print("Dataset Shape:", df.shape)
    print("Dataset Columns:", df.columns)
    print("Dataset Datatypes", df.dtypes)

    print("Dataset Basic Statistics", df.describe())
    print("Dataset missing value", df.isnull().sum())


#Calling on the function for each of our available dataset
dataset_description(bom_movie, 'BOM DATASET')
dataset_description(imdb, 'IMDB MOVIES')
dataset_description(tn_movie, 'TN MOVIES')

BOM DATASET
Dataset Shape: (3387, 5)
Dataset Columns: Index(['title', 'studio', 'domestic_gross',
```

```
'foreign_gross', 'year'], dtype='object')
Dataset Datatypes title              object
studio              object
domestic_gross     float64
foreign_gross       object
year                 int64
dtype: object
Dataset Basic Statistics        domestic_gross         year
count    3.359000e+03  3387.000000
mean     2.874585e+07  2013.958075
std      6.698250e+07     2.478141
min      1.000000e+02  2010.000000
25%      1.200000e+05  2012.000000
50%      1.400000e+06  2014.000000
75%      2.790000e+07  2016.000000
max      9.367000e+08  2018.000000
Dataset missing value title                 0
studio                5
domestic_gross       28
foreign_gross      1350
year                  0
dtype: int64
IMDB MOVIES
Dataset Shape: (261806, 17)
Dataset Columns: Index(['movie_id', 'primary_title', 'original_title',
'start_year',
       'runtime_minutes', 'genres', 'movie_id', 'ordering', 'title',
'region',
       'language', 'types', 'attributes', 'is_original_title',
'movie_id',
       'averagerating', 'numvotes'],
      dtype='object')
Dataset Datatypes movie_id              object
primary_title         object
original_title        object
start_year             int64
runtime_minutes      float64
genres                object
movie_id              object
ordering               int64
title                 object
region                object
language              object
types                 object
attributes            object
is_original_title    float64
movie_id              object
averagerating        float64
numvotes               int64
```

```
dtype: object
Dataset Basic Statistics           start_year  runtime_minutes
ordering  is_original_title  \
count  261806.000000    250553.000000  261806.000000
261806.000000
mean     2014.107736       100.106121       6.094788
0.140925
std         2.570717       208.231112       7.214429
0.347945
min      2010.000000         3.000000       1.000000
0.000000
25%      2012.000000        87.000000       1.000000
0.000000
50%      2014.000000        96.000000       3.000000
0.000000
75%      2016.000000       110.000000       7.000000
0.000000
max      2019.000000     51420.000000      61.000000
1.000000

       averagerating      numvotes
count  261806.000000  2.618060e+05
mean        6.272423  2.878090e+04
std         1.257559  9.473448e+04
min         1.000000  5.000000e+00
25%         5.600000  6.200000e+01
50%         6.400000  6.170000e+02
75%         7.100000  7.505500e+03
max        10.000000  1.841066e+06
Dataset missing value movie_id                  0
primary_title             0
original_title            0
start_year                0
runtime_minutes       11253
genres                 1185
movie_id                  0
ordering                  0
title                     0
region                43465
language             224726
types                108538
attributes           248882
is_original_title         0
movie_id                  0
averagerating             0
numvotes                  0
dtype: int64
TN MOVIES
Dataset Shape: (5782, 6)
```

```
Dataset Columns: Index(['id', 'release_date', 'movie',
'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
Dataset Datatypes id                    int64
release_date         object
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
Dataset Basic Statistics                 id
count  5782.000000
mean     50.372363
std      28.821076
min       1.000000
25%      25.000000
50%      50.000000
75%      75.000000
max     100.000000
Dataset missing value id                  0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

```
#Function to check for duplicates in all datasets
def duplicates_check(df, dataset_name):
    print(f"The number of duplicates in {dataset_name} is
",df.duplicated().value_counts())

duplicates_check(bom_movie, 'BOM DATASET')
duplicates_check(imdb, 'TN MOVIES')
duplicates_check(tn_movie, 'TN MOVIES')
```

```
The number of duplicates in BOM DATASET is  False    3387
Name: count, dtype: int64
The number of duplicates in TN MOVIES is  False    261806
Name: count, dtype: int64
The number of duplicates in TN MOVIES is  False    5782
Name: count, dtype: int64
```

DATA PREPARATION

BOM MOVIE DATASET

```
#selecting the relevant columns from the BOM dataset
bom_movie = bom_movie[[
    #'title',
    'studio',
    'domestic_gross',
    #'foreign_gross',
    'year'
]]
#dropping all rows with missing  values
bom_movie[bom_movie[['studio','domestic_gross']].isna().any(axis=1)]
bom_movie.dropna(subset=['studio','domestic_gross'],inplace=True)
```

From the attributes for BOM dataset I noticed that the foreign gross column contained many missing values, about 50% and since I have another dataset that has a similar column I decided to drop the column in the BOM dataset as it won't affect my analysis.

```
#Dropping all the rows with missing data
bom_movie.isnull().sum()
```

```
studio            0
domestic_gross    0
year              0
dtype: int64
```

TN MOVIE DATASET

The tn movie dataset does not have missing values, however the production_budget, domestic_gross and worldwide_gross columns were of type object. This means that we can't do any numeric calculation on this columns so the first step is to convert this rows into a numeric type.

```
#Function for converting the object columns to numerical for purposes
of calculations
def to_numeric(df,column_name):
    #getting rid of the dollar sign
    df[column_name] = df[column_name].str.replace('$','',regex =
False)
    #getting rid of the comma
    df[column_name] = df[column_name].str.replace(',','',regex =
False)
    #converting into numeric
    df[column_name] = pd.to_numeric(df[column_name])

#calling the convert function
to_numeric(tn_movie,'production_budget')
to_numeric(tn_movie,'domestic_gross')
to_numeric(tn_movie,'worldwide_gross')
```

```
#Viewing the first 5 rows after the conversion
tn_movie.head(5)
```

```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                  Dark Phoenix
3   4   May 1, 2015                    Avengers: Age of Ultron
4   5  Dec 15, 2017           Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
```

IMDB MOVIE DATASET

Dropping the columns I don't need for my analysis and retaining the columns which are significant for the analysis. Dropping the rows which also contain missing values. For this analysis it was earsier to drop the rows as it wouldn't affect the analysis.

```
imdb = imdb[['movie_id',
             'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres',
             #'movie_id',
             'ordering', 'title', 'region',
       #'language', 'types', 'attributes',
             #'is_original_title',
             #'movie_id',
       'averagerating', 'numvotes']]
imdb[imdb[['region','runtime_minutes','genres']].isna().any(axis=1)]
imdb.dropna(subset=['region','runtime_minutes','genres'],inplace=True)
```

```
C:\Users\sam\AppData\Local\Temp\ipykernel_4564\455507930.py:11:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy

imdb.dropna(subset=['region','runtime_minutes','genres'],inplace=True)

imdb.isnull().sum()

movie_id           0
movie_id           0
movie_id           0
```

```
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
ordering           0
title              0
region             0
averagerating      0
numvotes           0
dtype: int64
```

SAVING THE CLEANED DATASETS TO LOCAL STORAGE

```
imdb.to_csv('C:\\Users\\sam\\Desktop\\clean_IMDB.csv', index=False)
tn_movie.to_csv('C:\\Users\\sam\\Desktop\\clean_TN_MOVIE.csv',
index=False)
bom_movie.to_csv('C:\\Users\\sam\\Desktop\\clean_BOM_MOVIE.csv',
index=False)
```

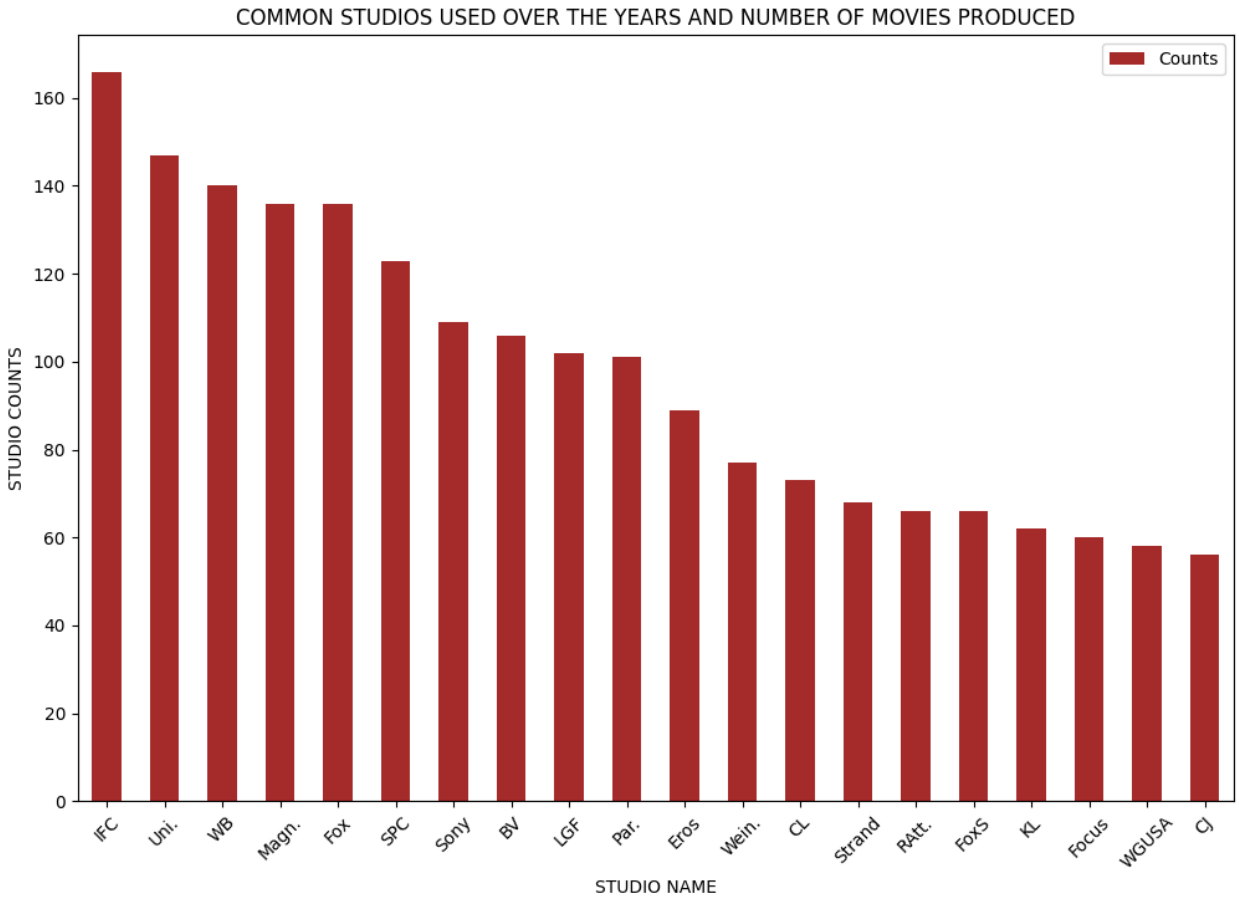
DATA ANALYSIS AND VISUALIZATIONS

BAR GRAPH

This bar graph helps us identify the most common studios based on the number of movies they have produced. The visualization doesn't really answer any question apart from showing the common studiios but in the next visualization , we try to find out if this common studio appear in the top earning studios.

```
#Grouping  the most common studios
common_studios = bom_movie['studio'].value_counts().reset_index()
common_studios.columns = ['studio', 'Counts']
#plotting the bar graph
#top ten most common studios
plt.figure(figsize=(12,8))
common_studios.head(20).plot(kind='bar', x='studio', y='Counts',
figsize=(12,8), legend=True,color='brown')
plt.title('COMMON STUDIOS USED OVER THE YEARS AND NUMBER OF MOVIES
PRODUCED')
plt.xlabel('STUDIO NAME')
plt.ylabel('STUDIO COUNTS')

plt.xticks(rotation=45)
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```

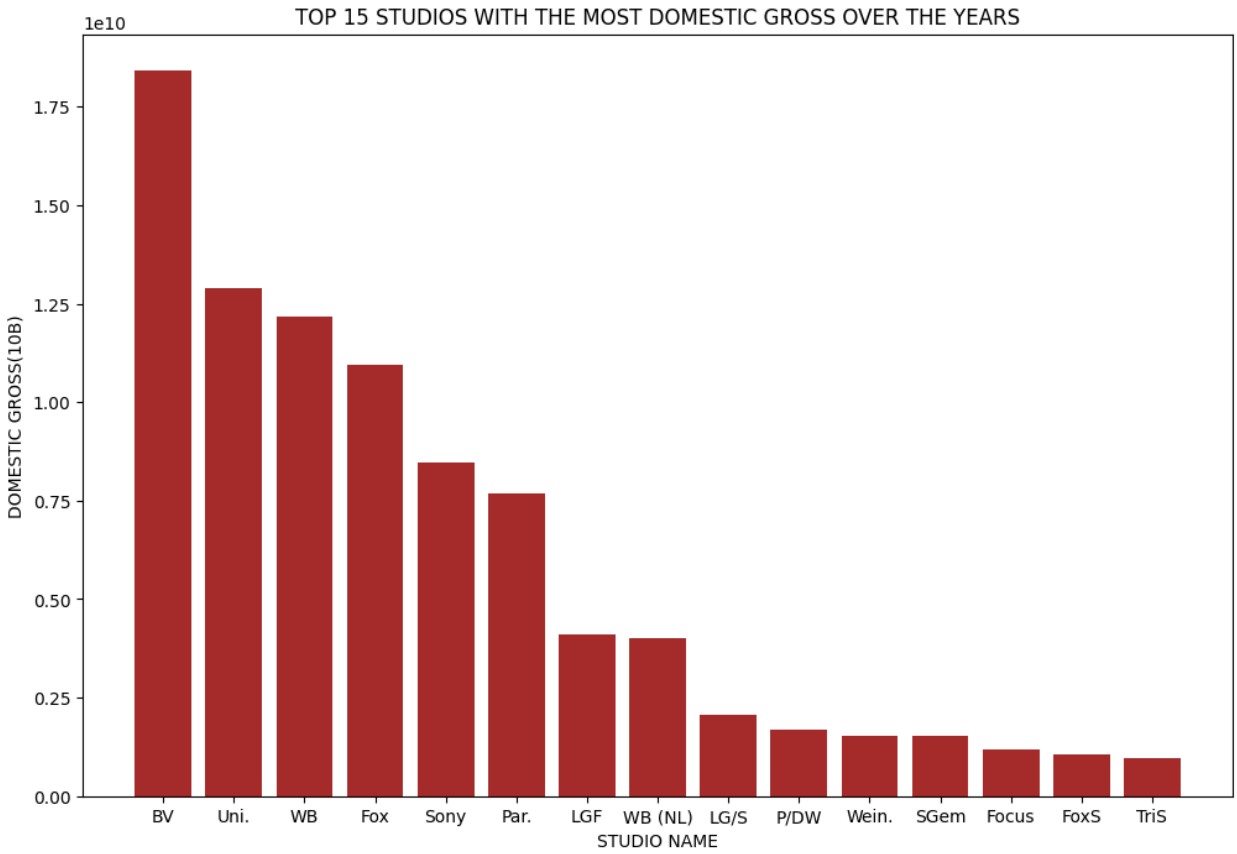


BAR GRAPH FOR TOP EARNING STUDIOS FROM THE DOMESTIC GROSS

First I grouped by studio so that all the gross from a particular movie studio is added together. I then sort the values so the studios with highest gross start. Refering back to my previous visualization it's evident that popular studios have the highest domestic gross.

```
#grouping by studio name and getting the total gross
Income_per_studio = bom_movie.groupby('studio')
['domestic_gross'].sum().reset_index()
#sorting from highest
Income_per_studio = Income_per_studio.sort_values(by='domestic_gross',
ascending=False).head(15)
#Plotting the bar graph
plt.figure(figsize=(12,8))
plt.bar(Income_per_studio['studio'],
Income_per_studio['domestic_gross'],color='brown')

plt.title('TOP 15 STUDIOS WITH THE MOST DOMESTIC GROSS OVER THE
YEARS')
plt.xlabel('STUDIO NAME')
plt.ylabel('DOMESTIC GROSS(10B)')
```

```
plt.show()
```

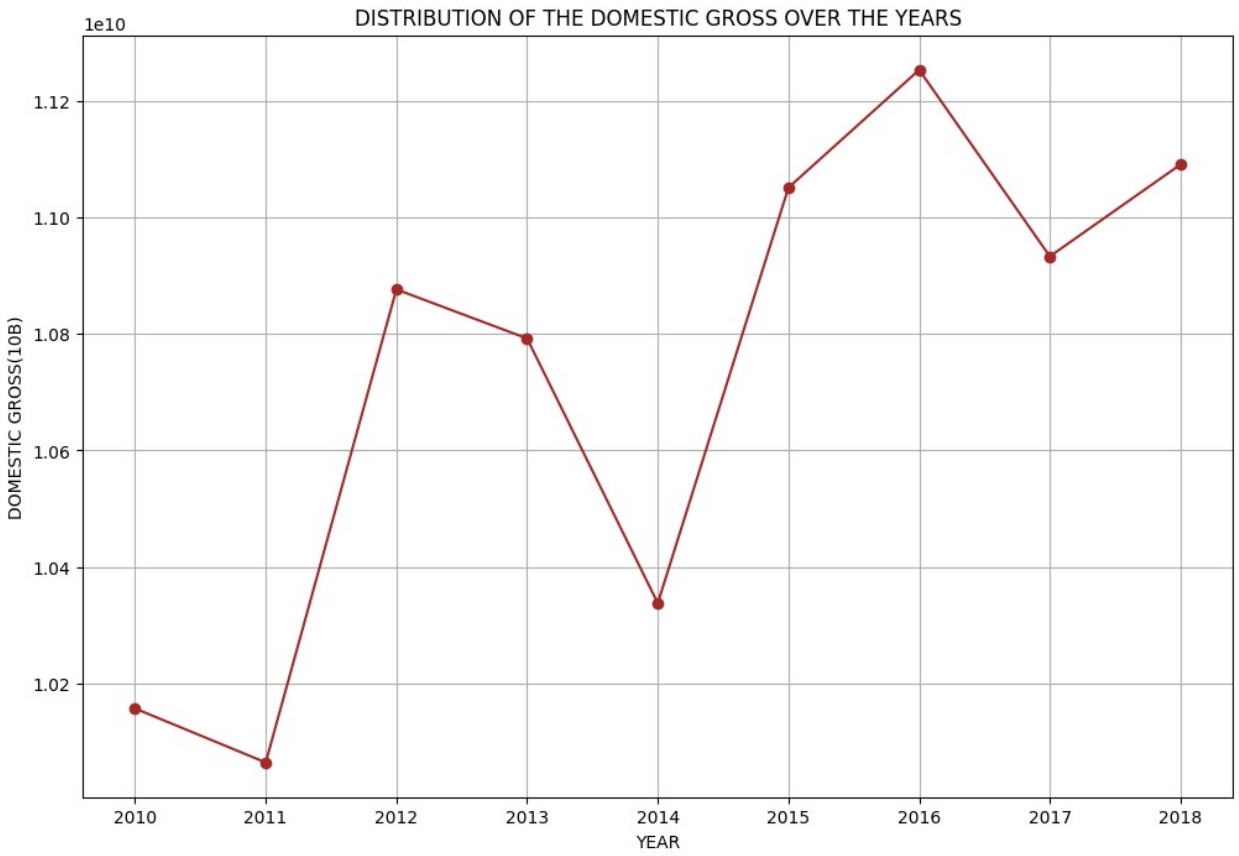


LINE PLOT FOR THE DISTRIBUTION OF GROSS OVER THE YEARS

The analytical significance of the plot is that it helps us understand the trend of the income over the years. It helps us evaluate whether the gross has been increasing over the years or not.

```
#grouping the gross by year and adding all the gross of that
particular year
Income_per_year = bom_movie.groupby('year')
['domestic_gross'].sum().reset_index()

#Plotting
plt.figure(figsize=(12,8))
plt.plot(Income_per_year['year'], Income_per_year['domestic_gross'],
marker='o',color='brown')


plt.title('DISTRIBUTION OF THE DOMESTIC GROSS OVER THE YEARS')
plt.xlabel('YEAR')
plt.ylabel('DOMESTIC GROSS(10B)')
```

```
plt.grid(True)
plt.show()
```



TN MOVIE

TN MOVIE dataset has a column release_date which has a format that limits us from plotting well. First we convert it to datetime and create a new column in the dataset to hold the converted year.

```
#converting release time to date time by year
tn_movie['release_date'] = pd.to_datetime(tn_movie['release_date'])

#creating a new column to hold the years
tn_movie['Year'] = tn_movie['release_date'].dt.year
```

The dataset also contains data from as far back as 1915 so the best thing would be to bin the years.

```
#binning the years
tn_movie['Year'] = pd.cut(tn_movie['Year'],

bins=[1915,1930,1945,1960,1975,1990,2005,2020],
```

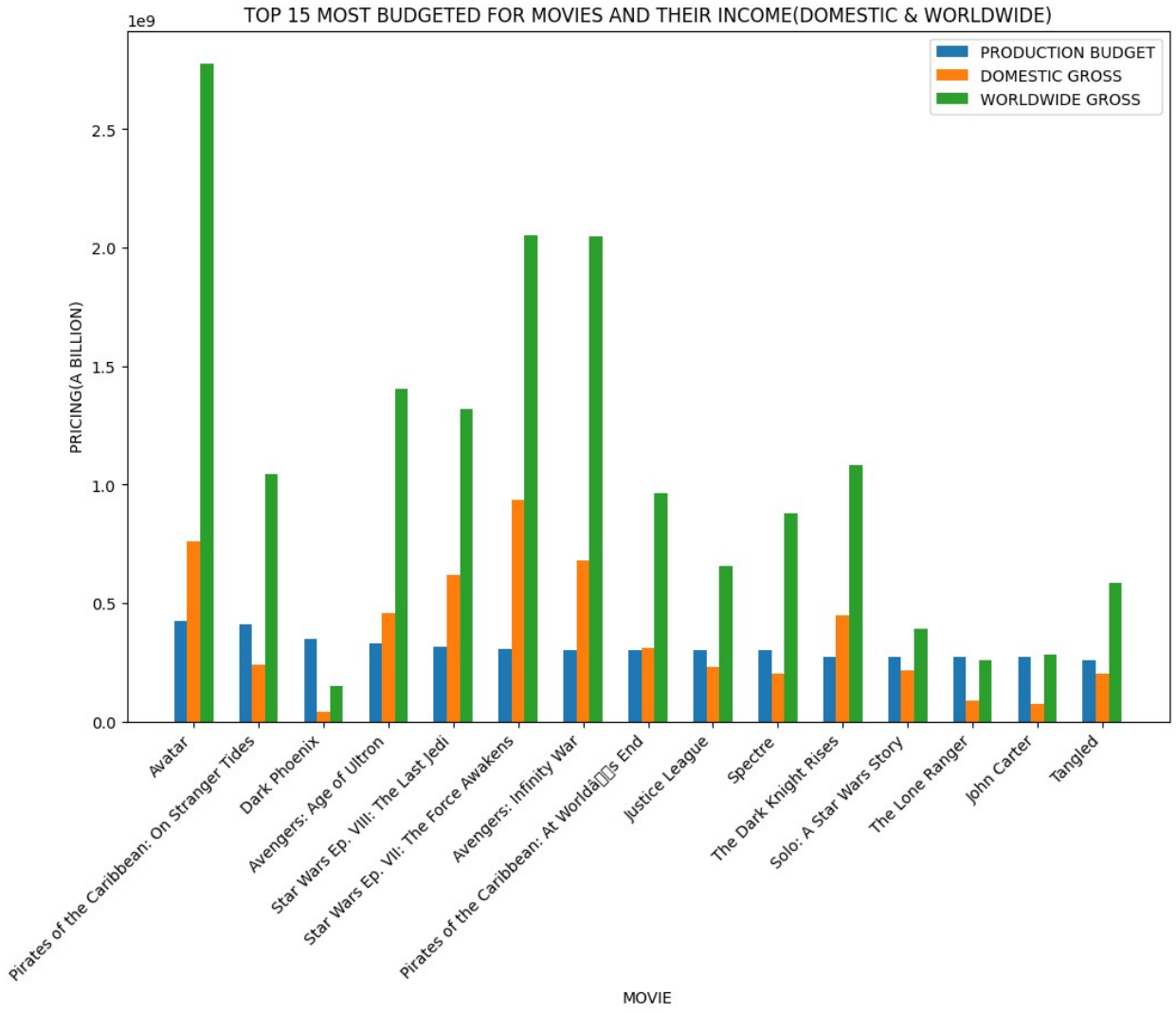
```
                            labels = ['1915-1930','1930-1945','1945-
1960','1960-1975','1975-1990','1990-2005','2005-2020'])
```

GROUPED BAR GRAPH FRO HIGH BUDGETED MOVIES AND THEIR INCOMES

The idea of using a grouped bar graph is so that I could get a more clear comparison. The first bar being the production budget followed by domestic and worldwide gross. With this grouped bar graph I took the top 15 most budget for movies.

```
#Sorting movies by the most budgeted for and taking the first 15
top_budgeted_movies = tn_movie.sort_values(by = 'production_budget',
ascending = False)
top_budgeted_movies = top_budgeted_movies.head(15)
plt.figure(figsize=(12,8))
w = 0.2

#Setting the number of bins for each bar graph
bar1 = np.arange(len(top_budgeted_movies['movie']))
bar2 = [i+w for i in bar1]
bar3 = [i+w for i in bar2]

#plotting the bar graphs
plt.bar(bar1,top_budgeted_movies['production_budget'],w,label="PRODUCT
ION BUDGET")
plt.bar(bar2,top_budgeted_movies['domestic_gross'],w,label="DOMESTIC
GROSS")
plt.bar(bar3,top_budgeted_movies['worldwide_gross'],w,label="WORLDWIDE
GROSS")

plt.xlabel('MOVIE')
plt.ylabel('PRICING(A BILLION)')
plt.title('TOP 15 MOST BUDGETED FOR MOVIES AND THEIR INCOME(DOMESTIC &
WORLDWIDE)')
plt.legend()
plt.xticks(bar1+w,top_budgeted_movies['movie'],rotation=45,
ha='right')
plt.show()
```

```
C:\Users\sam\AppData\Local\Programs\Python\Python313\Lib\site-
packages\IPython\core\pylabtools.py:170: UserWarning: Glyph 128 (\x80)
missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
C:\Users\sam\AppData\Local\Programs\Python\Python313\Lib\site-
packages\IPython\core\pylabtools.py:170: UserWarning: Glyph 153 (\x99)
missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```

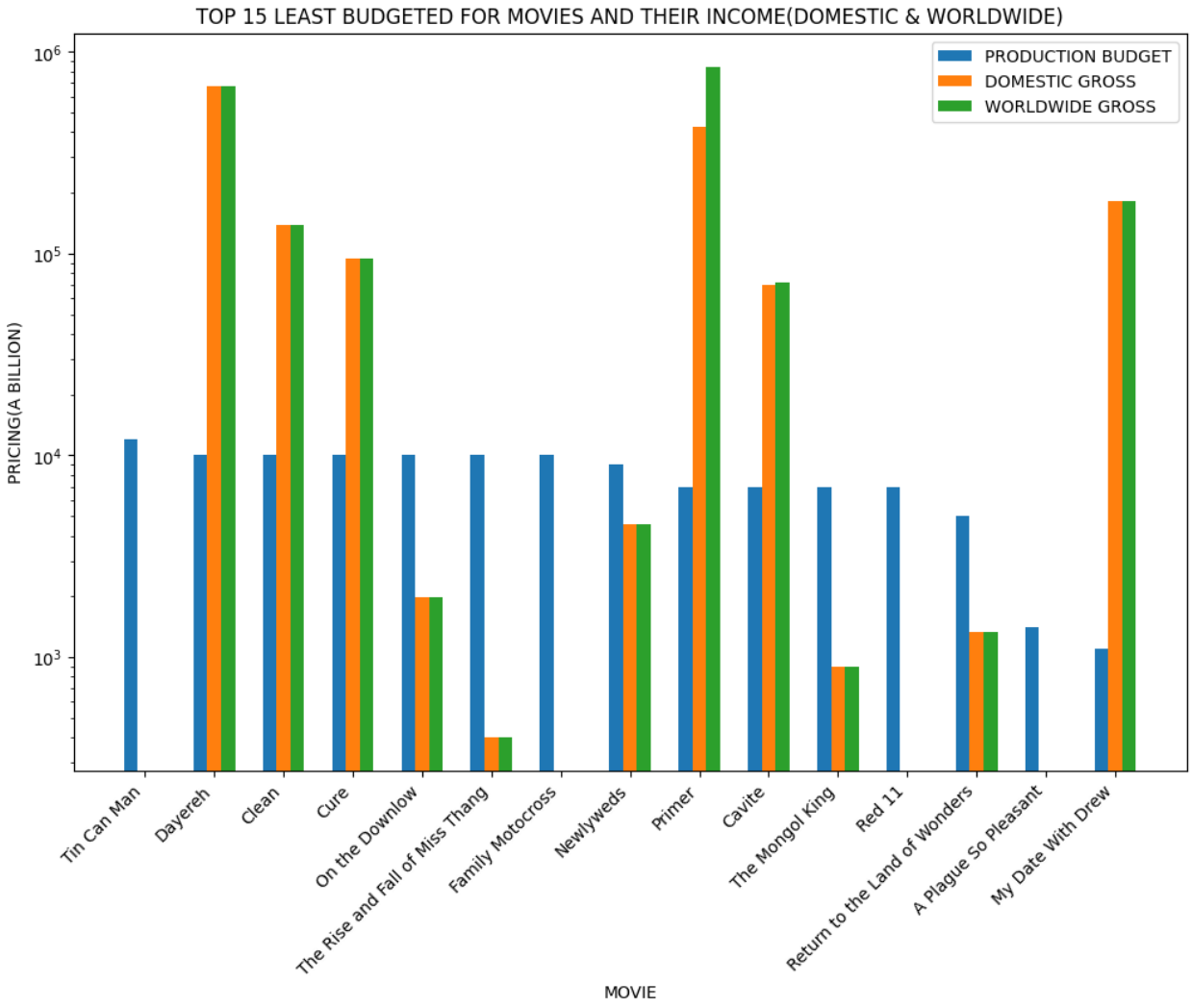


GROUPED BAR GRAPH FOR LOW BUDGETED MOVIES AND THEIR INCOMES

With this grouped bar graph for low budgeted movies I decided to use latest data so I used data from 2000 to date.

```
#converting to years
tn_movie['release_date'] = pd.to_datetime(tn_movie['release_date'])
tn_movie['INDIVIDUAL_YEAR'] = tn_movie['release_date'].dt.year

#sorting from the lowest to highest and choosing from year 2000
least_budgeted_movies = tn_movie.sort_values(by = 'production_budget',
ascending = False)
least_budgeted_movies =
least_budgeted_movies[least_budgeted_movies['INDIVIDUAL_YEAR']>2000].t
ail(15)

#plotting
plt.figure(figsize=(12,8))
```

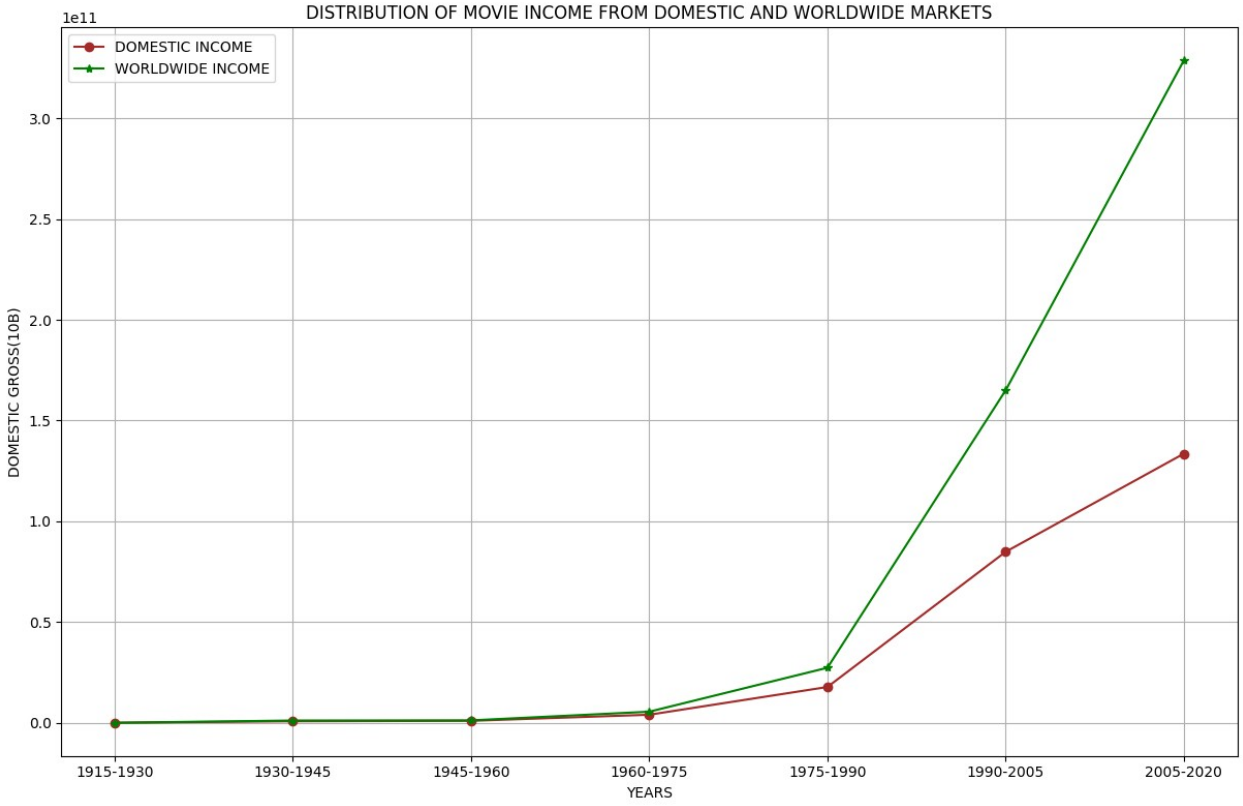
```
w = 0.2

first_bar = np.arange(len(least_budgeted_movies['production_budget']))
second_bar = [x+w for x in first_bar]
third_bar = [x+w for x in second_bar]

plt.bar(first_bar,least_budgeted_movies['production_budget'],w,label="
PRODUCTION BUDGET",log=True)
plt.bar(second_bar,least_budgeted_movies['domestic_gross'],w,label="DO
MESTIC GROSS",log=True)
plt.bar(third_bar,least_budgeted_movies['worldwide_gross'],w,label="WO
RLDWIDE GROSS",log=True)

plt.xlabel('MOVIE')
plt.ylabel('PRICING(A BILLION)')
plt.title('TOP 15 LEAST BUDGETED FOR MOVIES AND THEIR INCOME(DOMESTIC
& WORLDWIDE)')
plt.legend()
plt.xticks(bar1+w,least_budgeted_movies['movie'],rotation=45,
ha='right')
plt.show()
```



PLOT FOR COMPARING THE INCOMES OF MOVIES IN DOMESTIC AND WORLWODE MARKETS

```
#grouping by the binned years and gettings both domestic and worldwide
gross for the binned years
performing_years_domestic = tn_movie.groupby('Year',observed=False)
['domestic_gross'].sum().reset_index()
performing_years_worldwide = tn_movie.groupby('Year',observed=False)
['worldwide_gross'].sum().reset_index()

#plotting
plt.figure(figsize=(12,8))
plt.plot(performing_years_domestic['Year'],
performing_years_domestic['domestic_gross'],
marker='o',color='brown',label= "DOMESTIC INCOME")
plt.plot(performing_years_worldwide['Year'],
performing_years_worldwide['worldwide_gross'],
marker='*',color='green',label= "WORLDWIDE INCOME")
```

```
plt.title('DISTRIBUTION OF MOVIE INCOME FROM DOMESTIC AND WORLDWIDE
MARKETS')
plt.xlabel('YEARS')
plt.tight_layout()
plt.legend()
plt.ylabel('DOMESTIC GROSS(10B)')
plt.grid(True)
plt.show()
```



IMDB DATASET

A look at the first 5 rows and the last 5 rows of the imdb dataset and something is quite clear. Some movie_id appear several times, this is not an error from the inner join rather the results are because in the movie_akas table each movie id was linked to different alias(nicknames) used in different regions and also a column ordering which differentiates the movies. Though the table is significant I can't use it as it is as i.e if I decide to get the average rating of all movies the result would be biased as some movies appear many times yet the rating is the same only difference is the movie nicknames.

```
imdb.head()
```

```
    movie_id   movie_id   movie_id                    primary_title  \
0  tt0063540  tt0063540  tt0063540                        Sunghursh
2  tt0063540  tt0063540  tt0063540                        Sunghursh
3  tt0063540  tt0063540  tt0063540                        Sunghursh
```

```
4  tt0063540  tt0063540  tt0063540                        Sunghursh
5  tt0066787  tt0066787  tt0066787  One Day Before the Rainy Season

    original_title  start_year  runtime_minutes              genres
ordering  \
0        Sunghursh        2013            175.0  Action,Crime,Drama
1
2        Sunghursh        2013            175.0  Action,Crime,Drama
3
3        Sunghursh        2013            175.0  Action,Crime,Drama
4
4        Sunghursh        2013            175.0  Action,Crime,Drama
5
5  Ashad Ka Ek Din        2019            114.0     Biography,Drama
1

                             title region  averagerating  numvotes
0                        Sangharsh     IN            7.0        77
2                        Sunghursh     IN            7.0        77
3                        Sunghursh     IN            7.0        77
4                        Sungharsh     IN            7.0        77
5  One Day Before the Rainy Season    XWW            7.2        43
```

DROPPING THE DUPLICATES ROWS USING THE MOVIE ID

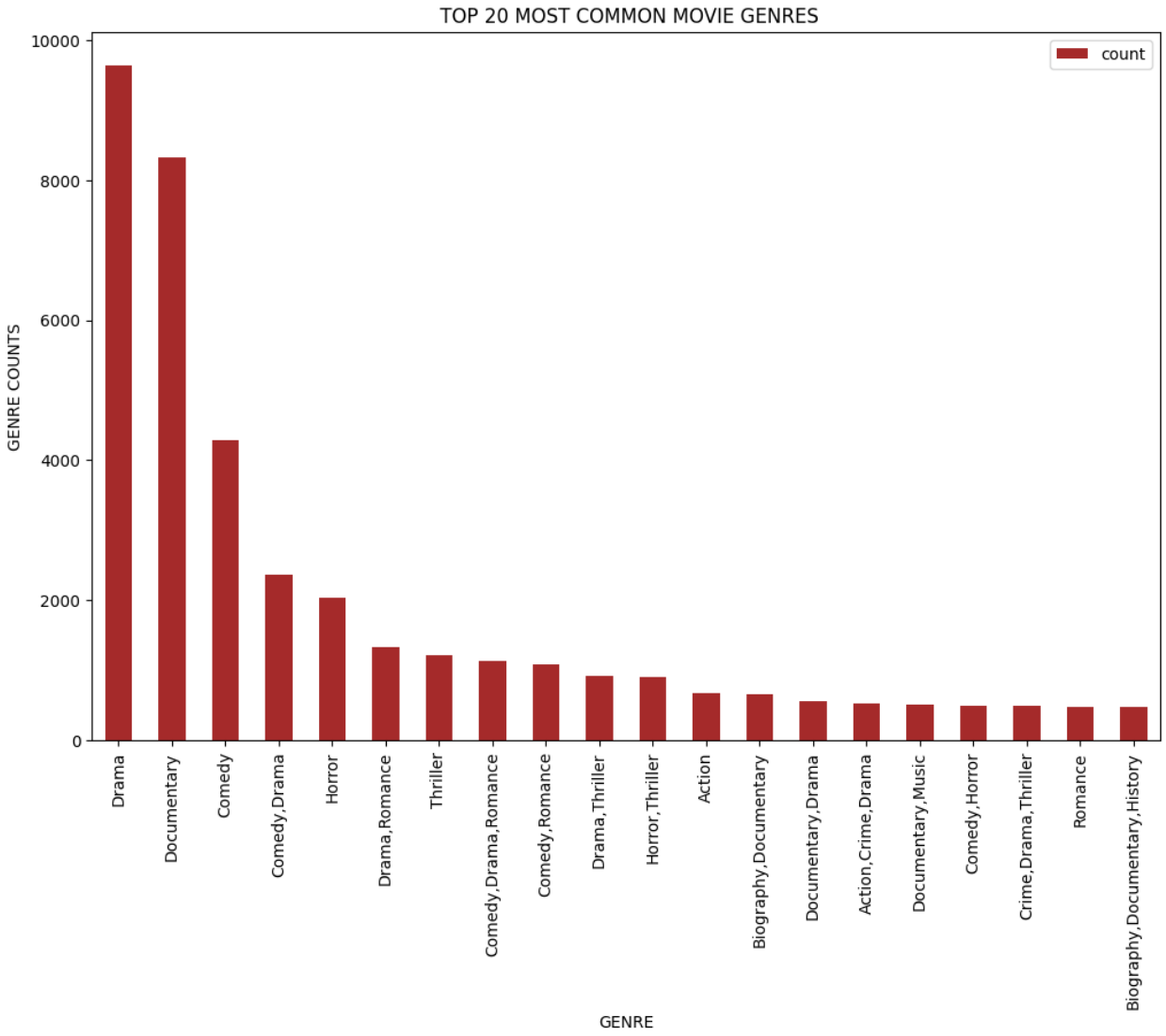
```
imdb = imdb.drop_duplicates(subset=['movie_id'])
imdb

         movie_id   movie_id   movie_id
primary_title  \
0       tt0063540  tt0063540  tt0063540
Sunghursh
5       tt0066787  tt0066787  tt0066787  One Day Before the Rainy
Season
9       tt0069049  tt0069049  tt0069049       The Other Side of the
Wind
26      tt0100275  tt0100275  tt0100275         The Wandering Soap
Opera
31      tt0137204  tt0137204  tt0137204                 Joe Finds
Grace
...           ...        ...        ...                              .
..
261792  tt9899860  tt9899860  tt9899860   Watching This Movie Is a
Crime
261796  tt9899880  tt9899880  tt9899880
Columbus
261797  tt9903952  tt9903952  tt9903952      BADMEN with a good
behavior
261801  tt9905462  tt9905462  tt9905462
```

```
Pengalila
261804  tt9911774  tt9911774  tt9911774        Padmavyuhathile
Abhimanyu

                     original_title  start_year  runtime_minutes  \
0                          Sunghursh        2013            175.0
5                    Ashad Ka Ek Din        2019            114.0
9        The Other Side of the Wind         2018            122.0
26            La Telenovela Errante         2017             80.0
31                  Joe Finds Grace         2017             83.0
...                             ...          ...              ...
261792       Didan in film jorm ast         2019            100.0
261796                      Columbus        2018             85.0
261797  BADMEN with a good behavior         2018             87.0
261801                     Pengalila        2019            111.0
261804    Padmavyuhathile Abhimanyu         2019            130.0

                             genres  ordering
title  \
0                Action,Crime,Drama         1
Sangharsh
5                    Biography,Drama         1  One Day Before the Rainy
Season
9                             Drama          1            O Outro Lado
do Vento
26             Comedy,Drama,Fantasy          2         The Wandering
Soap Opera
31      Adventure,Animation,Comedy          1                  Joe
Finds Grace
...                              ...       ...
...
261792               Drama,Thriller          1   Watching This Movie Is
a Crime
261796                       Comedy          2
Colombos
261797                Comedy,Horror          1      BADMEN with a good
behavior
261801                        Drama          2
Sisterleaf
261804                        Drama          2       Pathmavyuhathile
Abhimanyu

       region  averagerating  numvotes
0          IN            7.0        77
5         XWW            7.2        43
9          BR            6.9      4517
26        XWW            6.5       119
31         CA            8.1       263
...       ...            ...       ...
261792    XWW            8.1         7
```

```
261796     IR            5.8          5
261797     DE            9.2          5
261801     IN            8.4        600
261804     IN            8.4        365

[62374 rows x 13 columns]
```

BAR GRAPH TO SHOW THE MOST COMMON GENRES

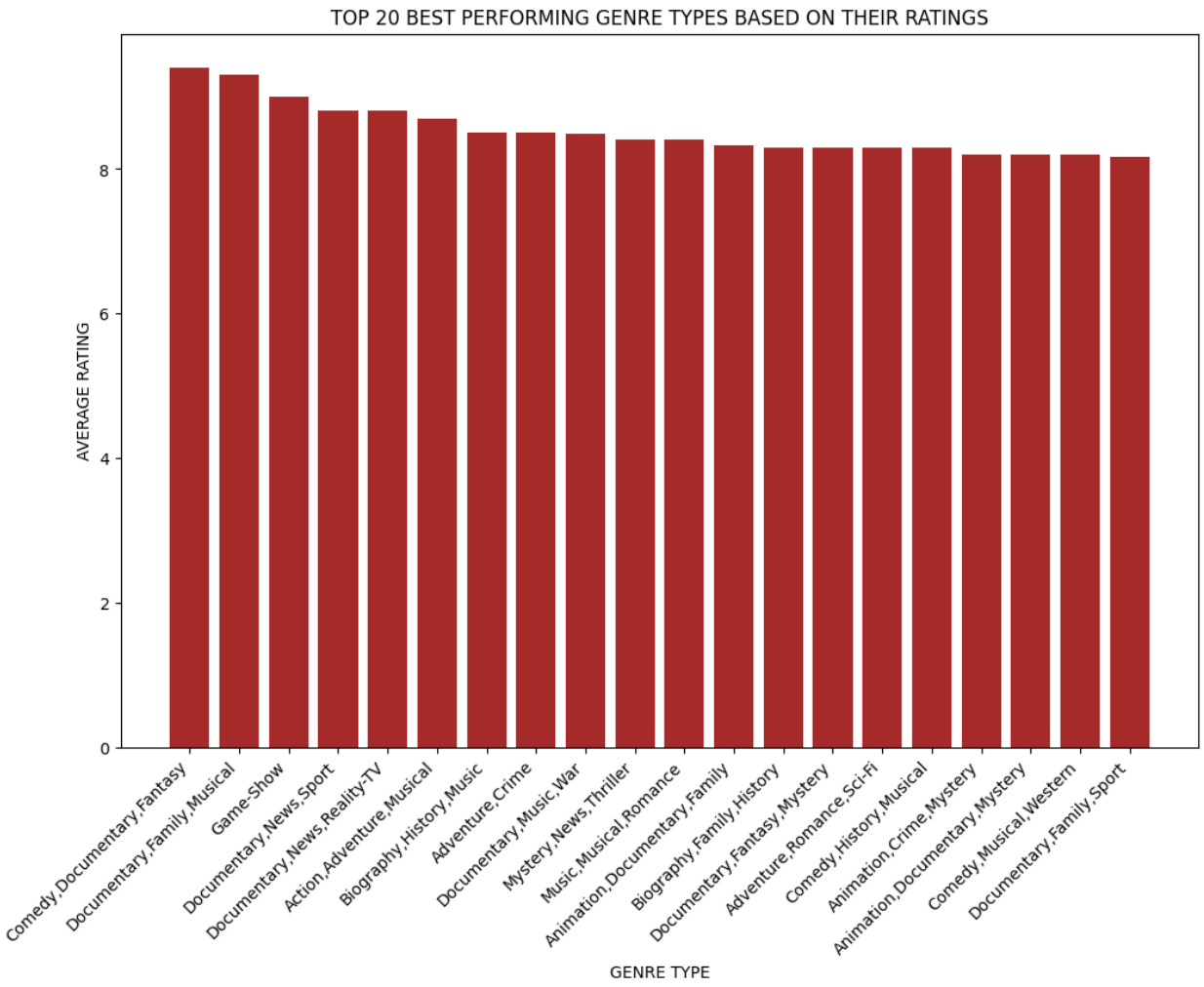
```
#getting the values counts of the most common genres
common_genres = imdb['genres'].value_counts().head(20)
common_genres.columns = ['genres', 'Counts']
#plotting
plt.figure(figsize=(12,8))
common_genres.plot(kind='bar', x='genres', y='Counts', figsize=(12,8),
legend=True,color='brown')
plt.title(' TOP 20 MOST COMMON MOVIE GENRES')
plt.xlabel('GENRE')
plt.ylabel('GENRE COUNTS')


plt.show()
```



Bar graph showing the best performing type of genres.

```
#Highest_rating1 = imdb.sort_values(by = 'averagerating', ascending =
False)
Highest_rating2 = imdb.groupby('genres')
['averagerating'].mean().reset_index()
Highest_rating2 = Highest_rating2.sort_values(by =
'averagerating',ascending = False).head(20)

plt.figure(figsize=(12,8))
plt.bar(Highest_rating2['genres'],
Highest_rating2['averagerating'],color='brown')

plt.title('TOP 20 BEST PERFORMING GENRE TYPES BASED ON THEIR RATINGS')
plt.xlabel('GENRE TYPE')
plt.ylabel('AVERAGE RATING')
```

```
plt.xticks(rotation = 45, ha='right')

plt.show()
```

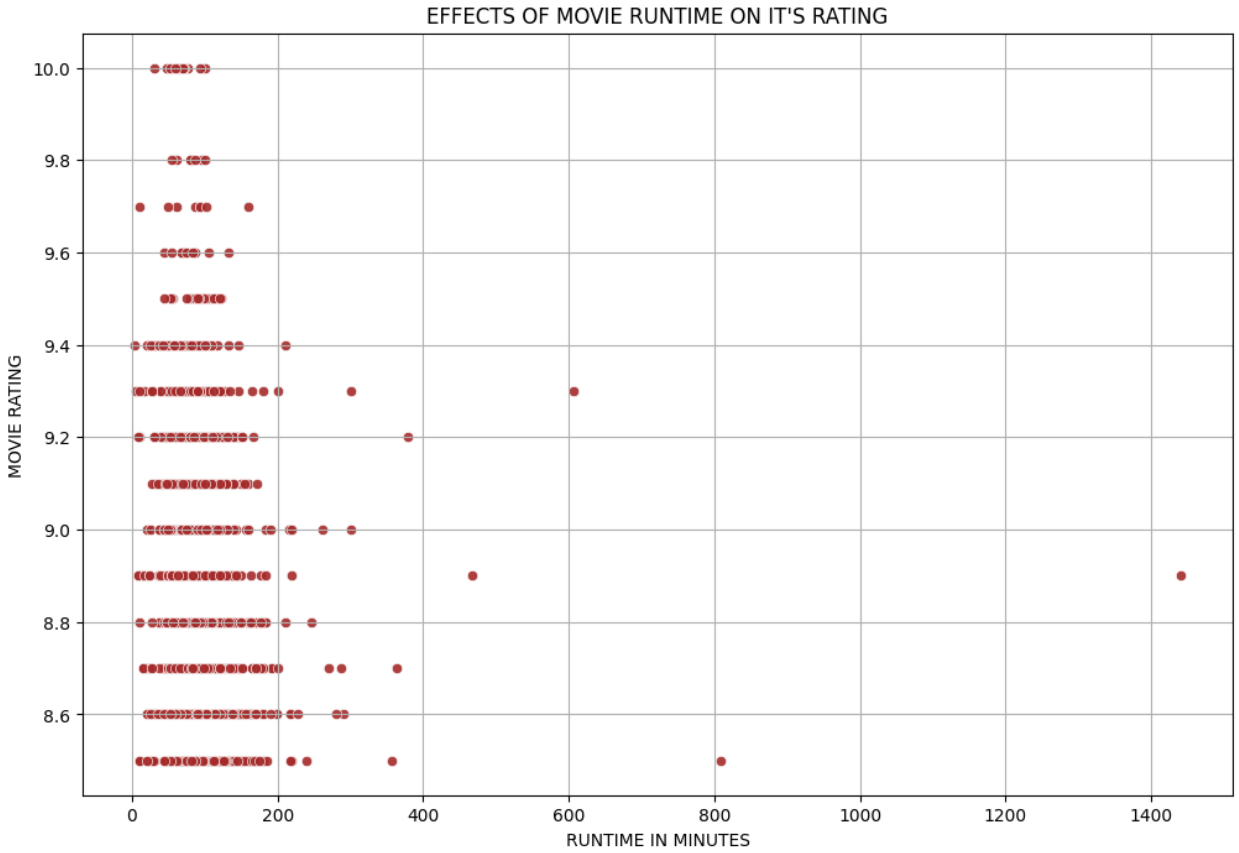


SCATTER PLOT OF RUNTIME AGAINST THE RATING

The scatter plot aims at finding out if the ratings of the movies is in any way connected to the rating of the movie. In the scatter plot below I used the highest rated movies (Top 3000) to try and find out if it has any effect.

```
#sorting values by the highest rated
Highest_rating = imdb.sort_values(by = 'averagerating', ascending =
False).head(3000)

#plottting
plt.figure(figsize=(12,8))
sns.scatterplot(data=Highest_rating, x='runtime_minutes',
y='averagerating', alpha=0.9,color= 'brown')
```

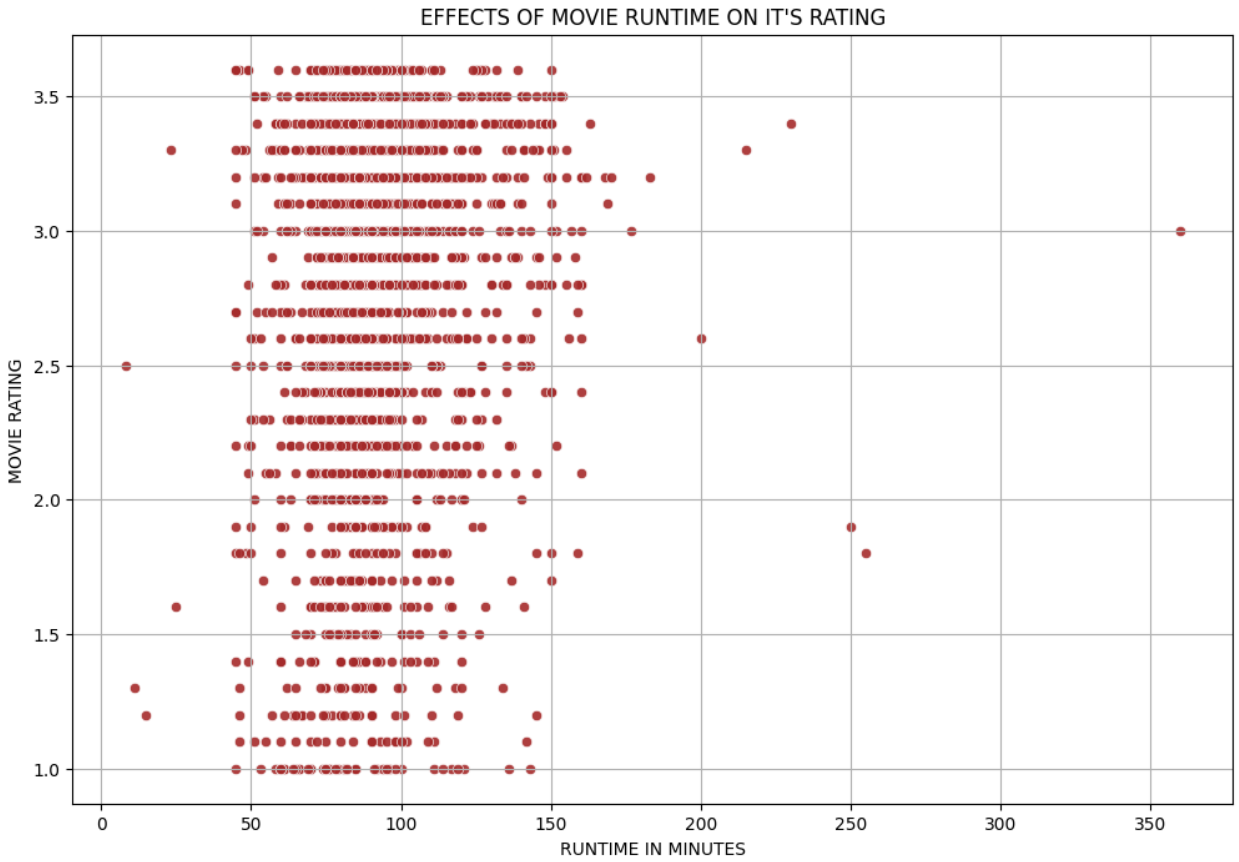
```
plt.title("EFFECTS OF MOVIE RUNTIME ON IT'S RATING")
plt.xlabel("RUNTIME IN MINUTES")
plt.ylabel("MOVIE RATING")
plt.grid(True)

plt.show()
```



SCATTER PLOT OF RUNTIME AGAINST THE RATING

In the scatter plot below I used the lowest rated movies to try and find out if it has any effect.

```
Lowest_rating = imdb.sort_values(by = 'averagerating').head(3000)
plt.figure(figsize=(12,8))
sns.scatterplot(data=Lowest_rating, x='runtime_minutes',
y='averagerating', alpha=0.9,color='brown')

plt.title("EFFECTS OF MOVIE RUNTIME ON IT'S RATING")
plt.xlabel("RUNTIME IN MINUTES")
plt.ylabel("MOVIE RATING")
plt.grid(True)

plt.show()
```



RECOMMENDATIONS

Film types with a lower runtime going upto 150 minutes have a lower average rating. This means that they don't meet user preferences, my recommendatiion is to produce film types with upto 200 minutes of runtime. When considering the film type genre type should be put into consideration hence through my findings the company should focus on the genre's with a good average rating. Some of this genres include

- Adventure,Biography,Documentary
- Adventure,Comedy
- Adventure,Documentary
- Animation,Documentary,Family
- Biography
- Biography,Documentary,Drama

The type of films the company should highly consider are those that have a global influence as the global market generates more gross.