Group 9: Box Office Movies Analysis

text

Project Overview

This project uses exploratory data analysis to uncover factors driving movie profitability and box office success, providing data-driven insights for a new movie studio's strategy. By examining historical data on production budgets, release timing, genres ,and revenues, we aim to inform decisions on film types, optimal budget allocations, and release schedules, guiding the studio in creating high-performing content.

Business Problem

As major companies invest in original video content, our company has decided to establish a new movie studio to enter the competitive film industry. However, with limited experience in movie production, the company lacks insights into what drives box office success. Our goal is to explore which types of films perform best at the box office, using factors like release timing, production budgets, and profit margins to inform strategic decisions. The insights generated from this an analysis will support the new movie studio's head in deciding what type of films to create and how to allocate resources effectively for maximum profitability.

Importing Libraries

```
# import libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import scipy.stats as stats
from scipy.stats import pearsonr
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

Objectives

1. To identify audience preferences across genres.
2. To explore seasonal trends in movie releases.
3. To determine the profitability of movies based on revenue and profit margins.
4. To determine the change of movie revenue over time.

Objective 1 : Audiences Preferrences

Question : Which genre had highest ratings?

Analysis of the popular movie genres in Box Office

To analyze the popularity of movie genres in the box office, we need to examine trends over time, considering factors like genre performance, audience preferences, and overall box office revenue.

Dataset

For this analysis we will look at the movie ratings dataset for of our analysis.

```
rating_df = pd.read_csv("./DataSets/rt.movie_info.tsv",sep ='\t')
```

Data Cleaning

```
rating_df.head()

   id                                           synopsis rating  \
0   1  This gritty, fast-paced, and innovative police...      R
1   3  New York City, not-too-distant-future: Eric Pa...      R
2   5  Illeana Douglas delivers a superb performance ...      R
3   6  Michael Douglas runs afoul of a treacherous su...      R
4   7                                                NaN     NR

                                 genre          director  \
0  Action and Adventure|Classics|Drama  William Friedkin
1     Drama|Science Fiction and Fantasy  David Cronenberg
2     Drama|Musical and Performing Arts    Allison Anders
3            Drama|Mystery and Suspense    Barry Levinson
4                         Drama|Romance    Rodney Bennett

                            writer  theater_date      dvd_date
currency  \
0                   Ernest Tidyman   Oct 9, 1971  Sep 25, 2001
NaN
1     David Cronenberg|Don DeLillo  Aug 17, 2012   Jan 1, 2013
$
2                   Allison Anders  Sep 13, 1996  Apr 18, 2000
NaN
3  Paul Attanasio|Michael Crichton   Dec 9, 1994  Aug 27, 1997
NaN
4                     Giles Cooper           NaN           NaN
NaN

  box_office      runtime             studio
0        NaN  104 minutes                NaN
```

```
1    600,000  108 minutes  Entertainment One
2        NaN  116 minutes                NaN
3        NaN  128 minutes                NaN
4        NaN  200 minutes                NaN
```

```
#Checking for duplicates;There are no duplicates in my dataset
duplicated =rating_df.duplicated().sum()
duplicated
```

```
0
```

```
#Check for missing values
missing =rating_df.isnull().sum()
missing
```

```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime           30
studio          1066
dtype: int64
```

```
#Fill the NA values in synopsis with No synopsis available
rating_df['synopsis'].fillna("No synopsis available", inplace=True)
#   In rating null =mode
mode_rating = rating_df['rating'].mode()[0]
rating_df['rating'].fillna(mode_rating, inplace=True)
#Replace missing genre with unknown
rating_df['genre'].fillna("Unknown", inplace=True)
#Replace writing with unknown
rating_df['writer'].fillna("Unknown", inplace=True)
#Drop rows with missing theatre date
rating_df.dropna(subset=['theater_date'], inplace=True)
#Fill na directors as Unknown
rating_df['director'].fillna("Unknown", inplace=True)


#Dropping bot currency and box office columns
rating_df.drop(columns=['currency', 'box_office'], inplace=True)
#Dropping the nulls in runtime colmnn
rating_df.dropna(subset=['runtime'], inplace=True)
#Checking if we have any null values
rating_df.isnull().sum()
```

```
id                  0
synopsis            0
rating              0
genre               0
director            0
writer              0
theater_date        0
dvd_date            0
runtime             0
studio            734
dtype: int64
```

Data types

```
rating_df.dtypes
```

```
id                 int64
synopsis          object
rating            object
genre             object
director          object
writer            object
theater_date      object
dvd_date          object
runtime           object
studio            object
dtype: object
```

```
#Converting Data type
#ID to Integer
rating_df['id'] = rating_df['id'].astype(int)
#Date to datetime
rating_df['theater_date'] = pd.to_datetime(rating_df['theater_date'],
errors='coerce')
rating_df['dvd_date'] = pd.to_datetime(rating_df['dvd_date'],
errors='coerce')
#Remove text in runtime and converting the data to int
rating_df['runtime'] = rating_df['runtime'].str.replace(' minutes',
'').astype(int)
```

```
rating_df.head()
```

```
   id                                           synopsis rating  \
0   1  This gritty, fast-paced, and innovative police...      R
1   3  New York City, not-too-distant-future: Eric Pa...      R
2   5  Illeana Douglas delivers a superb performance ...      R
3   6  Michael Douglas runs afoul of a treacherous su...      R
5   8  The year is 1942. As the Allies unite overseas...     PG

                                 genre         director  \
```

```
0  Action and Adventure|Classics|Drama  William Friedkin
1    Drama|Science Fiction and Fantasy  David Cronenberg
2    Drama|Musical and Performing Arts    Allison Anders
3             Drama|Mystery and Suspense    Barry Levinson
5                  Drama|Kids and Family       Jay Russell

                            writer theater_date   dvd_date  runtime  \
0                   Ernest Tidyman   1971-10-09 2001-09-25      104
1     David Cronenberg|Don DeLillo   2012-08-17 2013-01-01      108
2                   Allison Anders   1996-09-13 2000-04-18      116
3  Paul Attanasio|Michael Crichton   1994-12-09 1997-08-27      128
5                  Gail Gilchriest   2000-03-03 2000-07-11       95

                  studio
0                    NaN
1      Entertainment One
2                    NaN
3                    NaN
5  Warner Bros. Pictures
```

```
#Assighn the rating to numerical values
rating_df["rating"].unique()
```

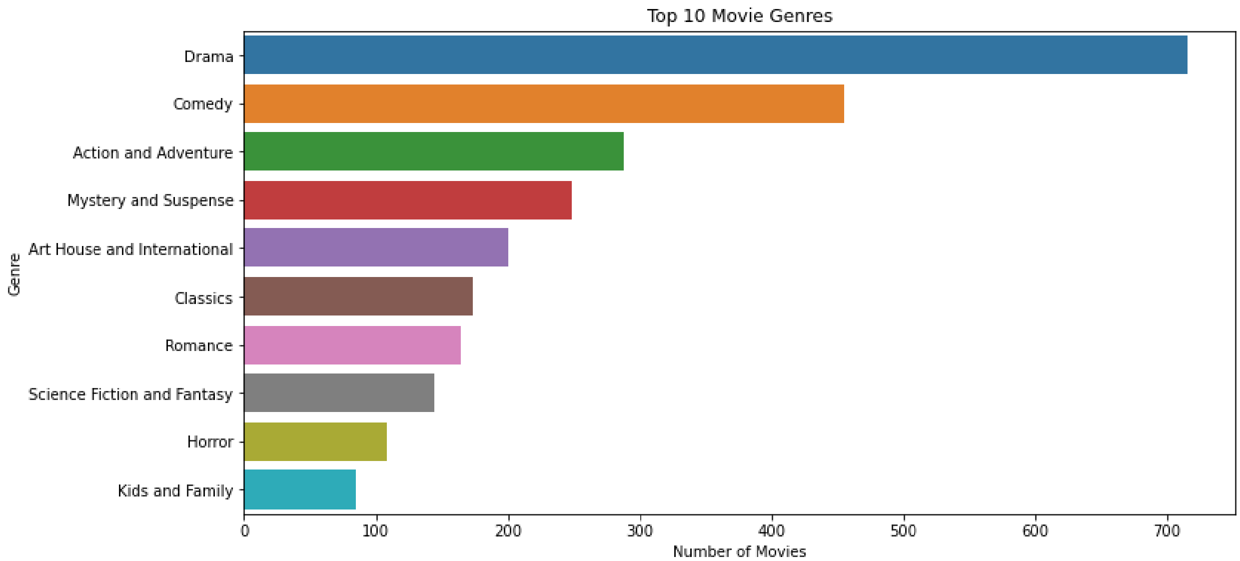
```
array(['R', 'PG', 'PG-13', 'NR', 'G', 'NC17'], dtype=object)
```

```
#Mapping
rating_mapping = {'R': 1, 'PG': 2, 'PG-13': 3, 'NR': 4, 'G': 5,
'NC17': 6}
rating_df['numeric_rating'] = rating_df['rating'].map(rating_mapping)
```

Data Visualization

Top 10 most popular Movies Genre

```
#An Histogram presentation of Genre and the number of movie counts
rating_df['genre'] = rating_df['genre'].fillna('').apply(lambda x:
x.split('|'))
genre_counts = rating_df.explode('genre')
['genre'].value_counts().head(10)
plt.figure(figsize=(12, 6))
sns.barplot(x=genre_counts.values, y=genre_counts.index)
plt.title('Top 10 Movie Genres')
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.show()
```



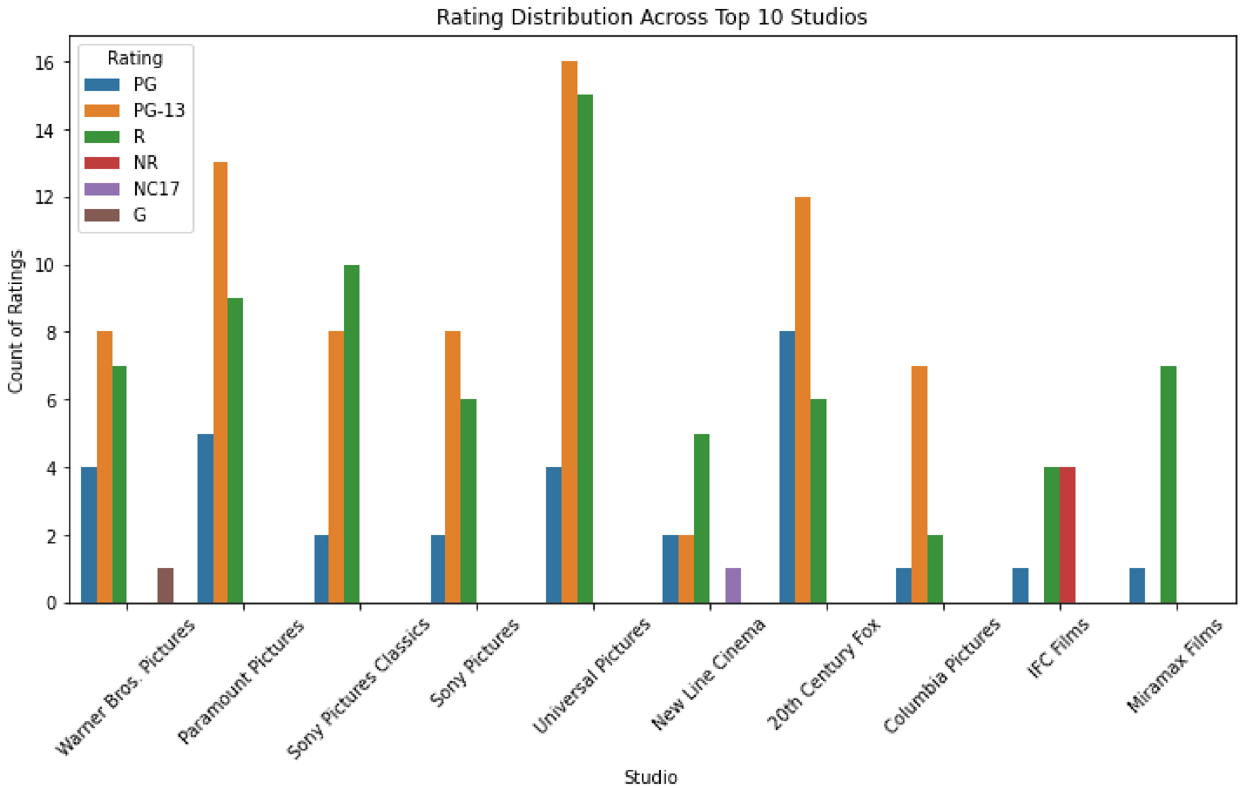
Interpretation

-The bar plot shows that the Drama Gernre has a a lot of movies produced followed by the comedy genre

A ratings vs top 10 studio plot

This is a plot to show the studio and how the ratings are spread across the top 10 studios

```
studio_rating_counts = rating_df.groupby(['studio', 'numeric_rating'])

# Plotting the data
top_studios = rating_df['studio'].value_counts().nlargest(10).index
top_studio_data = rating_df[rating_df['studio'].isin(top_studios)]
plt.figure(figsize=(12, 6))
sns.countplot(data=top_studio_data, x='studio', hue='rating')
plt.title("Rating Distribution Across Top 10 Studios")
plt.xlabel("Studio")
plt.ylabel("Count of Ratings")
plt.xticks(rotation=45)
plt.legend(title='Rating')
plt.show()
```



Observation

The independent Studios have the highest number of movies produced

Checking for normality

We want to check if our ratings follow a normal distribution.We will use the Shapiro-wilk Test

```
# Shapiro-Wilk Test
from scipy.stats import shapiro
ratings = (rating_df['numeric_rating'])
stat, p_value = shapiro(ratings)
alpha =0.05
if p_value > alpha :
    print ("The p-value is greater than 0.05, hence we fail to reject the null hypothesis since we do not have enough evidence."
            "we can conclude that the ratings does not significantly deviate from a normal distribution.")
else:
    print("The p-value is less than 0.05 , hence we reject the null hypothesis at 0.05 level of significance and "
          "conclude that the ratings significantly deviates from the normal distribution")
```

```
The p-value is less than 0.05 , hence we reject the null hypothesis at
0.05 level of significance and conclude that the ratings significantly
deviates from the normal distribution
```

Our Rating data does not have a normal distribution

Objective 2 : Movie Realease Month Variation

Question 2.1 : How movie release dates vary by month and determine peak release times e.g school holidays, Christmas, Valentines

```
# Load the budget dataset
budget = pd.read_csv("DataSets/tn.movie_budgets.csv")
budget.head()
```

```
   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
```

```
# Remove dollar signs and commas from budget and revenue columns and
convert them to numeric
currency_columns = ['production_budget', 'domestic_gross',
'worldwide_gross']
for col in currency_columns:
    budget[col] = budget[col].replace('[\$,]', '',
regex=True).astype(float)
budget.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   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
```

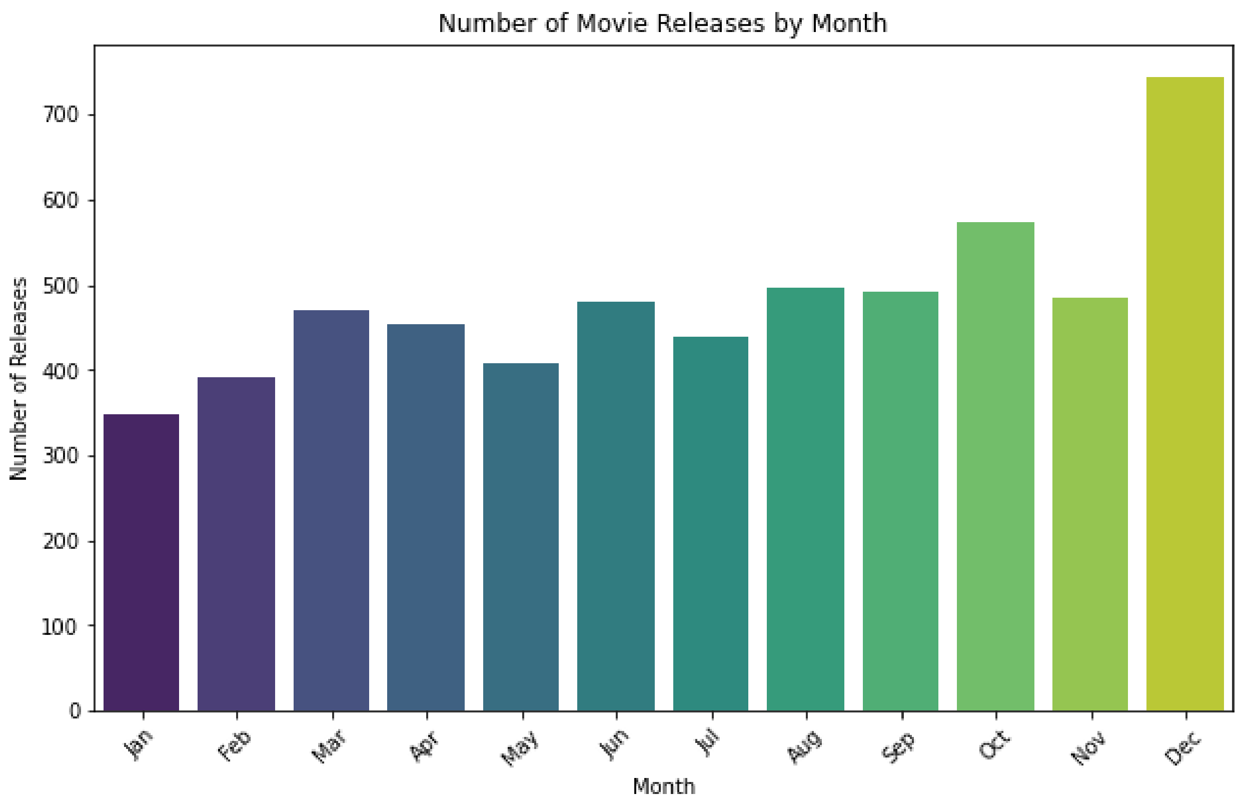
```
dtypes: float64(3), int64(1), object(2)
memory usage: 271.2+ KB

# Convert release_date to datetime and extract month and year for
analysis
budget['release_date'] = pd.to_datetime(budget['release_date'],
errors='coerce')
budget['release_month'] = budget['release_date'].dt.month
budget['release_year'] = budget['release_date'].dt.year
budget.head()

   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2   3   2019-06-07                                 Dark Phoenix
3   4   2015-05-01                      Avengers: Age of Ultron
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
release_month  \
0        425000000.0     760507625.0     2.776345e+09             12

1        410600000.0     241063875.0     1.045664e+09              5

2        350000000.0      42762350.0     1.497624e+08              6

3        330600000.0     459005868.0     1.403014e+09              5

4        317000000.0     620181382.0     1.316722e+09             12


   release_year
0          2009
1          2011
2          2019
3          2015
4          2017
```

Aggregating Monthly Data

Grouping by release_month to calculate the count of movies released and the average budget, domestic gross, and worldwide gross.

```
# Aggregate data by month to analyze release trends and financials
monthly_data =budget.groupby('release_month').agg(
    release_count=('id', 'size'),  # Count of movies released
    avg_budget=('production_budget', 'mean'),  # Average production
budget
    avg_domestic_gross=('domestic_gross', 'mean'),  # Average domestic
revenue
```

```
    avg_worldwide_gross=('worldwide_gross', 'mean')  # Average
worldwide revenue
).reset_index()

# Plot the number of releases per month
plt.figure(figsize=(10, 6))
sns.barplot(data=monthly_data,x='release_month',
y='release_count',palette= 'viridis')
plt.title('Number of Movie Releases by Month')
plt.xlabel('Month')
plt.ylabel('Number of Releases')
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May',
'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], rotation=45)
plt.show()
```

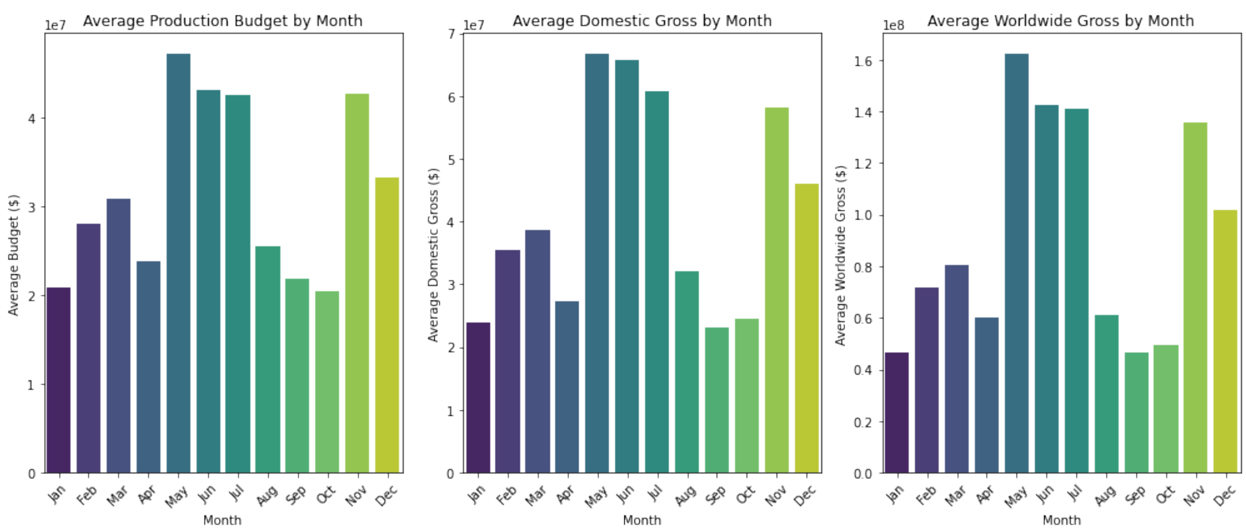


Analyzing Revenue by Month

We can further plot the average box office revenue for movies released each month to see if there is a correlation between release timing and financial success.

```
fig, axs = plt.subplots(1, 3, figsize=(14, 6))

# Average Budget by Month
sns.barplot(data=monthly_data, x='release_month', y='avg_budget',
```

```
palette='viridis', ax=axs[0])
axs[0].set_title('Average Production Budget by Month')
axs[0].set_xlabel('Month')
axs[0].set_ylabel('Average Budget ($)')
axs[0].set_xticks(range(0, 12))
axs[0].set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'],rotation=45)

# Average Domestic Gross by Month
sns.barplot(data=monthly_data, x='release_month',
y='avg_domestic_gross', palette='viridis', ax=axs[1])
axs[1].set_title('Average Domestic Gross by Month')
axs[1].set_xlabel('Month')
axs[1].set_ylabel('Average Domestic Gross ($)')
axs[1].set_xticks(range(0, 12))
axs[1].set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'],rotation=45)

# Average Worldwide Gross by Month
sns.barplot(data=monthly_data, x='release_month',
y='avg_worldwide_gross', palette='viridis', ax=axs[2])
axs[2].set_title('Average Worldwide Gross by Month')
axs[2].set_xlabel('Month')
axs[2].set_ylabel('Average Worldwide Gross ($)')
axs[2].set_xticks(ticks=range(0,12))
axs[2].set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'],rotation=45)

plt.tight_layout();
```



Observation

- Revenue Trends: December, July, and May exhibit higher average worldwide and domestic revenues, suggesting that films released in these months tend to perform well financially. This trend likely reflects the appeal of holiday and summer periods, when audiences have more leisure time to visit theaters.

- Average Production Budget: December has high average production budgets, likely associated with blockbuster releases targeting the holiday season. May through July also see relatively high budgets, aligning with summer releases that often aim for large audiences.

Statistical Analysis

Testing for Monthly Release Distribution Uniformity

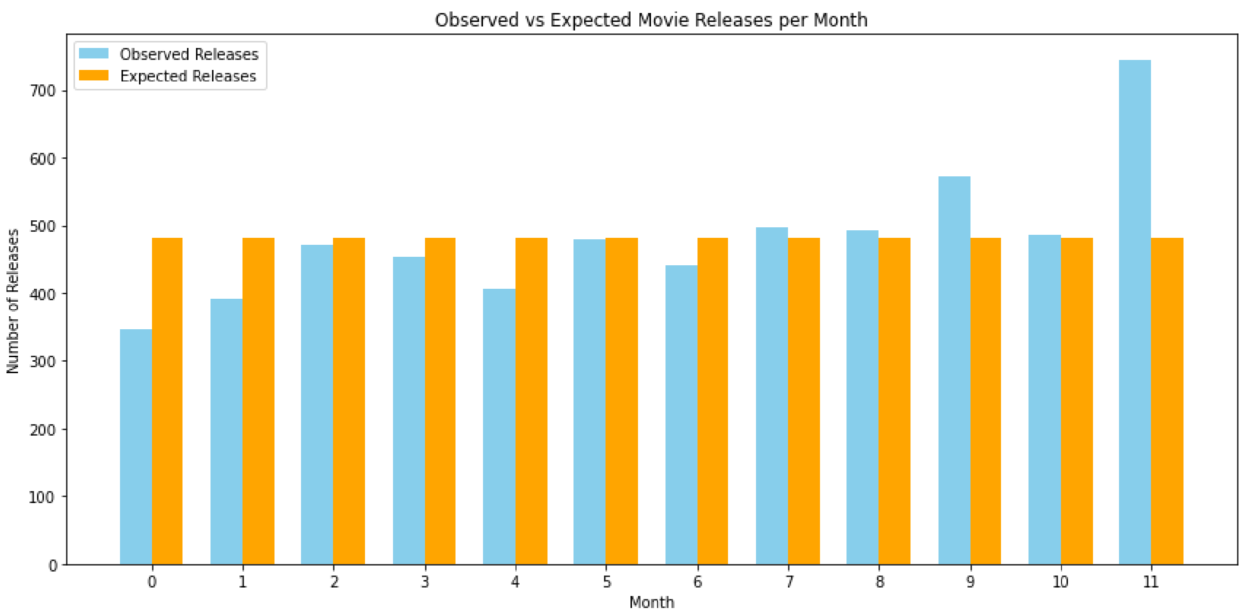
To determine if movies are uniformly released throughout the year, we can use a chi-square test. This test will help us see if the observed distribution of movie releases across months significantly deviates from a uniform distribution.

```
#Calculating Chi-square statistic
from scipy.stats import chisquare

# Perform chi-square test on the frequency of releases per month
observed_releases = monthly_data['release_count'].values
expected_releases = [monthly_data['release_count'].mean()] * 12  # 
Expected value for uniform distribution

chi_stat, p_value = chisquare(observed_releases, expected_releases)
print(f"Chi-square Statistic: {chi_stat}, P-value: {p_value}")

if p_value < 0.05:
    print("The distribution of movie releases across months is 
significantly different from uniform.")
else:
    print("The distribution of movie releases across months is not 
significantly different from uniform.")
```

```
Chi-square Statistic: 233.34555517122104, P-value: 8.493608319019405e-
44
The distribution of movie releases across months is significantly 
different from uniform.
```

```
#Visual representation of the chi-square results
months = monthly_data['release_count'].index
bar_width = 0.35
x = np.arange(len(months))

# Create figure and axis
plt.figure(figsize=(12, 6))

# Plot observed releases as bars
plt.bar(x - bar_width/2, observed_releases, width=bar_width, 
label='Observed Releases', color='skyblue')
```

```
# Plot expected releases as bars
plt.bar(x + bar_width/2, expected_releases, width=bar_width,
label='Expected Releases', color='orange')

# Add labels, title, and legend
plt.xlabel("Month")
plt.ylabel("Number of Releases")
plt.title("Observed vs Expected Movie Releases per Month")
plt.xticks(x, months)  # Set x-axis labels to month names
plt.legend()

# Show the plot
plt.tight_layout()
plt.show()
```



Observation

- The bar chart is comparing observed and expected monthly movie releases revealing noticeable deviations from a uniform distribution. Specifically, January shows significantly fewer releases than expected, while December has substantially more, suggesting seasonal trends. Smaller but consistent deviations are also visible in months like February, July, and August.
- The chi-square test yields a chi-square statistic of 233.35 and a p-value of 8.49e-44, which is far below the 0.05 significance threshold. This result confirms that the observed distribution of movie releases across months is statistically significantly different from a uniform (even) distribution.

Recommendation

1.Focus on releasing big-budget movies in December and summer months (May to July) to leverage peak moviegoing times.

2.Allocate larger budgets to films slated for release in these high-performance months, aiming for broad audience appeal and potential blockbuster status.

Question 2.1 : Analysis of movie profitability across the release months.

```
# Calculate Total gross
budget['total_gross'] = budget['worldwide_gross'] +
budget['domestic_gross']
# Calculate profit
budget['profit'] = (budget['total_gross'] -
budget['production_budget'])

budget.head()
```

```
   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2   3   2019-06-07                                 Dark Phoenix
3   4   2015-05-01                      Avengers: Age of Ultron
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
release_month  \
0        425000000.0     760507625.0     2.776345e+09             12

1        410600000.0     241063875.0     1.045664e+09              5

2        350000000.0      42762350.0     1.497624e+08              6

3        330600000.0     459005868.0     1.403014e+09              5

4        317000000.0     620181382.0     1.316722e+09             12


   release_year   total_gross        profit
0          2009  3.536853e+09  3.111853e+09
1          2011  1.286728e+09  8.761278e+08
2          2019  1.925247e+08 -1.574753e+08
3          2015  1.862020e+09  1.531420e+09
4          2017  1.936903e+09  1.619903e+09
```

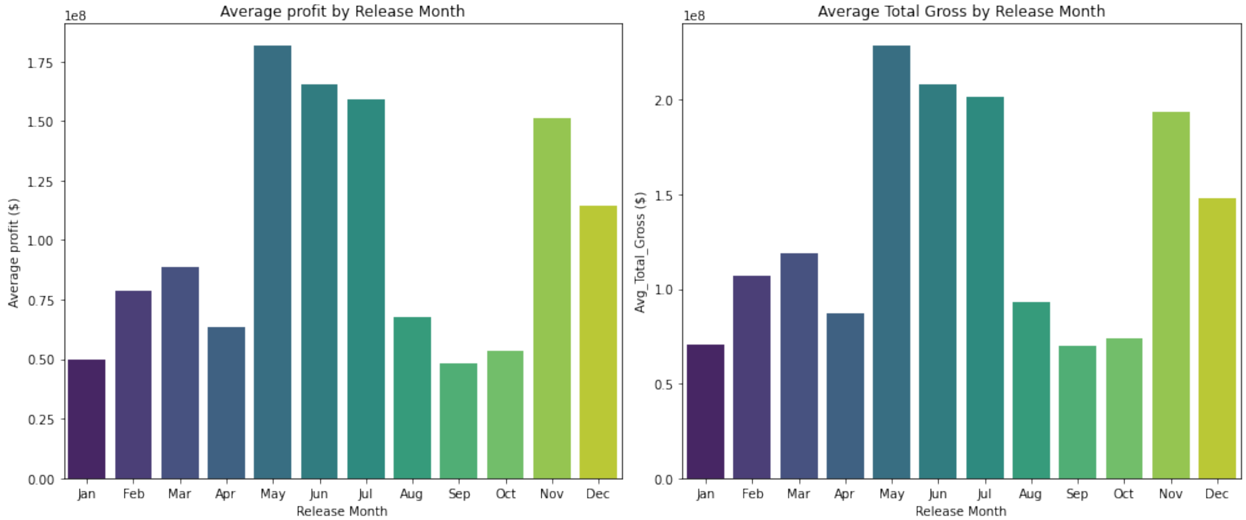
```
# Calculate average profit and total_gross by month
monthly_seasonality = budget.groupby('release_month').agg(
    avg_total_gross=('total_gross', 'mean'),
```

```
    avg_profit=('profit', 'mean')
).sort_values(by='avg_profit', ascending=False).reset_index()
```

Visualizations

The visuals showing Average Profit and Average Total Gross

```
fig, axs = plt.subplots(1, 2, figsize=(14,6))

# Average Profit by Month
sns.barplot(data=monthly_seasonality,
x=monthly_seasonality['release_month'],
y=monthly_seasonality['avg_profit'], palette='viridis', ax=axs[0])
axs[0].set_title("Average profit by Release Month")
axs[0].set_xlabel("Release Month")
axs[0].set_ylabel("Average profit ($)")
axs[0].set_xticks(range(12))
axs[0].set_xticklabels([
    'Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',
'Oct', 'Nov', 'Dec'
])

# Average Total Gross by Month
sns.barplot(data=monthly_seasonality,
x=monthly_seasonality['release_month'],
y=monthly_seasonality['avg_total_gross'], palette='viridis',
ax=axs[1])
axs[1].set_title("Average Total Gross by Release Month")
axs[1].set_xlabel("Release Month")
axs[1].set_ylabel("Avg_Total_Gross ($)")
axs[1].set_xticks(range(0,12))
axs[1].set_xticklabels([
    'Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',
'Oct', 'Nov', 'Dec'
])

plt.tight_layout()
plt.show()
```

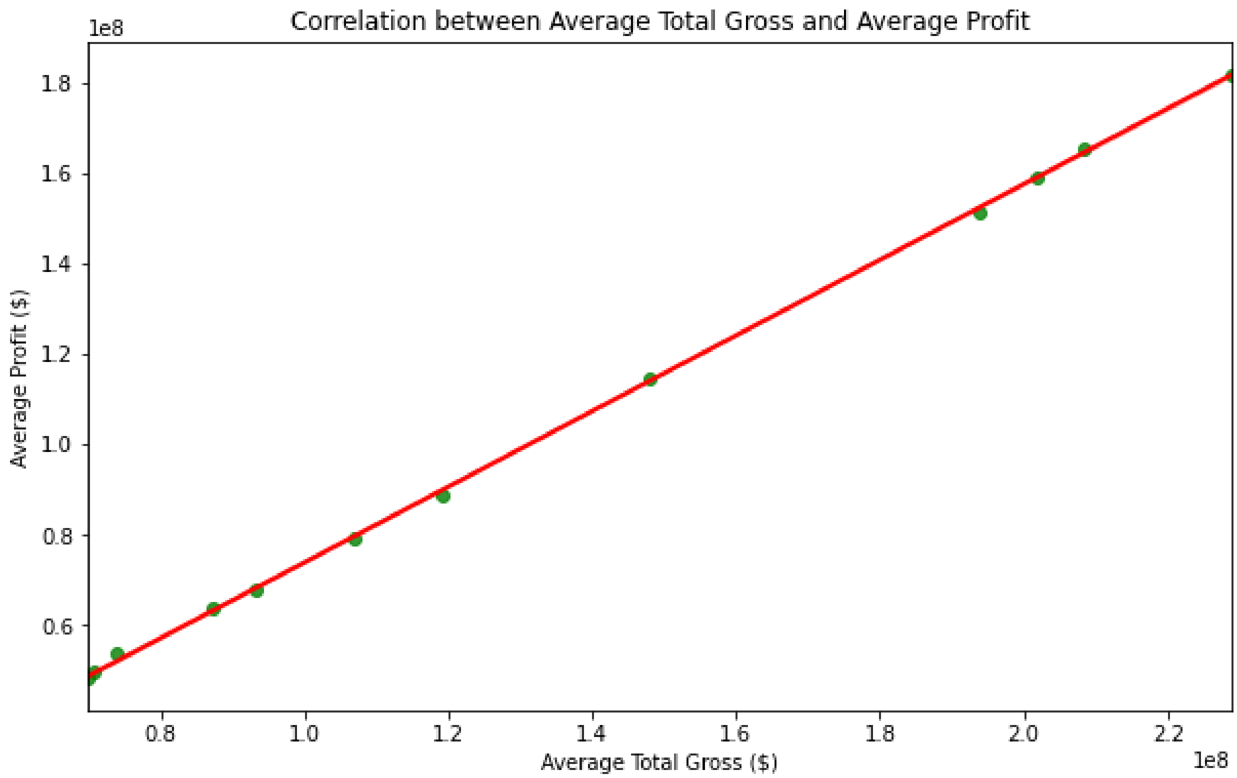


Observations

1. From the Barchat, it is clear that Most profitable months to release are during May, June, July, November and December. This is particularly because these are times of the year are both summer and Holiday Seasons where many people have alot of time to watch movies. The Least Profitable months being Jan and September.

Statistical Analysis

```
# Scatter plot with regression line

plt.figure(figsize=(10, 6))

sns.regplot(data=monthly_seasonality, x="avg_total_gross",
y="avg_profit", marker="o", color="green", line_kws={"color": "red"})
plt.title("Correlation between Average Total Gross and Average
Profit")
plt.xlabel("Average Total Gross ($)")
plt.ylabel("Average Profit ($)")

plt.show()
```



Observation

- Positive trend of the scatter plot, indicates that as the avg_total_gross increases, the avg_profit also tends to increase.

- The regression line indicates a strong positive linear relationship, where higher total gross amounts are generally associated with higher profits.

```
#Pearson Correlation and p-value Analysis

#Null_Hypothesis = There is no linear relationship
#Alternative_Hypothesis = There exits a linear relationship

#Calculate pearson correlation and p-value
correlation, p_value =
pearsonr(monthly_seasonality['avg_total_gross'],
monthly_seasonality['avg_profit'])

correlation, p_value
```

```
(0.9998499405185896, 5.990445879349743e-19)
```

Observations

- With Correlation coefeficient(r) = 0.9998, this is very close to +1, indicating a positive linear relationship between avg_total_gross and avg_profit. This means that as avg_total gross increases, avg_profit consistently increases at a proportional rate.

- p_value = 5.99*10e-19, which is way below the common significance thresholds of 0.05 or 0.01. This means there exits a statistical significance allowing us to reject the null hypothesis that there is no linear relationship between avg_total_gross and avg_profit

Summary and Recommendations

1. The studio should consider focusing on high-grossing months (May, June, July,November and December) as these months could yield the greatest profits due to their strong correlation

Objective 3 : Revenue Changes Over Time

Question How has the average box office revenue changed over time to identify trends that could impact movie production and marketing strategies?

For this objective, we have to match both income and movies datasets together to have one datafame for our analysis.

```
# Load the revenues dataset
income = pd.read_csv("./DataSets/bom.movie_gross.csv")
income.head()

                                          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

# load the movies dataset
movies = pd.read_csv("./DataSets/tmdb.movies.csv")
movies.head()
```

```
   Unnamed: 0             genre_ids     id original_language  \
0           0      [12, 14, 10751]  12444                en
1           1  [14, 12, 16, 10751]  10191                en
2           2        [12, 28, 878]  10138                en
3           3      [16, 35, 10751]    862                en
4           4        [28, 878, 12]  27205                en

                            original_title  popularity
release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-
19
1                       How to Train Your Dragon      28.734   2010-03-
26
2                                     Iron Man 2      28.515   2010-05-
07
3                                      Toy Story      28.005   1995-11-
22
4                                      Inception      27.920   2010-07-
16

                                         title  vote_average
vote_count
0  Harry Potter and the Deathly Hallows: Part 1           7.7
10788
1                       How to Train Your Dragon           7.7
7610
2                                     Iron Man 2           6.8
12368
3                                      Toy Story           7.9
10174
4                                      Inception           8.3
22186
```

```
# merge the movies and revenue datasets to serve objective 5
# preview the first 5 rows
income_movies_merged = pd.merge(movies, income, on='title',
how='inner')
income_movies_merged.head()
```

```
   Unnamed: 0             genre_ids     id original_language  \
0           1  [14, 12, 16, 10751]  10191                en
1           2        [12, 28, 878]  10138                en
2           4        [28, 878, 12]  27205                en
3           7      [16, 10751, 35]  10193                en
4           8      [16, 10751, 35]  20352                en

             original_title  popularity release_date  \
0  How to Train Your Dragon      28.734   2010-03-26
1                Iron Man 2      28.515   2010-05-07
2                 Inception      27.920   2010-07-16
```

```
3                Toy Story 3      24.445   2010-06-17
4              Despicable Me      23.673   2010-07-09

                           title  vote_average  vote_count studio
domestic_gross  \
0  How to Train Your Dragon            7.7        7610   P/DW
217600000.0
1                Iron Man 2            6.8       12368   Par.
312400000.0
2                 Inception            8.3       22186     WB
292600000.0
3               Toy Story 3            7.7        8340     BV
415000000.0
4             Despicable Me            7.2       10057   Uni.
251500000.0

  foreign_gross  year
0     277300000  2010
1     311500000  2010
2     535700000  2010
3     652000000  2010
4     291600000  2010
```

Now we have our merged dataset "income_movies_merged" we will proceed with preview, cleaning, analysis, interpretation and finally conclusion and recommendation

Data Inspection

```
#  check overview
income_movies_merged.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2703 entries, 0 to 2702
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         2703 non-null   int64
 1   genre_ids          2703 non-null   object
 2   id                 2703 non-null   int64
 3   original_language  2703 non-null   object
 4   original_title     2703 non-null   object
 5   popularity         2703 non-null   float64
 6   release_date       2703 non-null   object
 7   title              2703 non-null   object
 8   vote_average       2703 non-null   float64
 9   vote_count         2703 non-null   int64
 10  studio             2702 non-null   object
 11  domestic_gross     2682 non-null   float64
 12  foreign_gross      1723 non-null   object
 13  year               2703 non-null   int64
```

```
dtypes: float64(3), int64(4), object(7)
memory usage: 316.8+ KB
```

```
# check the shape
income_movies_merged.shape
```

```
(2703, 14)
```

```
# check for statistical description
income_movies_merged.describe()
```

```
         Unnamed: 0             id   popularity  vote_average
vote_count  \
count   2703.000000    2703.000000  2703.000000   2703.000000
2703.000000
mean   11686.778024  213291.491306    10.002752      6.418572
1358.194599
std     7459.175381  139706.978070     7.294182      0.916424
2408.885097
min        1.000000    1771.000000     0.600000      0.000000
1.000000
25%     5289.000000   76493.500000     5.881000      5.900000
78.000000
50%    11319.000000  209249.000000     8.627000      6.500000
393.000000
75%    17675.000000  334521.500000    12.698500      7.000000
1440.000000
max    26506.000000  574534.000000    80.773000     10.000000
22186.000000

       domestic_gross         year
count    2.682000e+03  2703.000000
mean     3.629150e+07  2014.044395
std      7.734897e+07     2.440458
min      1.000000e+02  2010.000000
25%      2.000000e+05  2012.000000
50%      3.800000e+06  2014.000000
75%      3.882500e+07  2016.000000
max      9.367000e+08  2018.000000
```

Data Cleaning and Processing

```
# check for null values
income_movies_merged.isnull().sum()
```

```
Unnamed: 0              0
genre_ids               0
id                      0
original_language       0
```

```
original_title         0
popularity             0
release_date           0
title                  0
vote_average           0
vote_count             0
studio                 1
domestic_gross        21
foreign_gross        980
year                   0
dtype: int64
```

Data type conversion

The 'foreign_gross' column is in the form of an object instead of numeric and we must convert to a float.

```
# convert object to foat
income_movies_merged['foreign_gross'] =
income_movies_merged['foreign_gross'].replace({',': ''},
regex=True).astype(float)
```

Remove null values

From our observation, We have three columns wih null values which we should drop for us to achieve our objctive.

```
# drop null values
df = income_movies_merged.dropna()

# check the shape after dropping the null values
df.shape

(1701, 14)
```

Drop unnecessary columns

We have to drop columns which are not important to our study

```
# drop columns
df_1 = df.drop(columns=["vote_count", "id", "original_language",
"original_title","popularity", "genre_ids"])

# preview the remaining columns
df_1.columns

Index(['Unnamed: 0', 'release_date', 'title', 'vote_average',
'studio',
```

```
       'domestic_gross', 'foreign_gross', 'year'],
      dtype='object')


clean_data = df_1.drop(df.columns[0], axis=1)
clean_data.head()

  release_date                        title  vote_average studio
domestic_gross  \
0   2010-03-26  How to Train Your Dragon           7.7   P/DW
217600000.0
1   2010-05-07                  Iron Man 2           6.8   Par.
312400000.0
2   2010-07-16                   Inception           8.3     WB
292600000.0
3   2010-06-17                 Toy Story 3           7.7     BV
415000000.0
4   2010-07-09               Despicable Me           7.2   Uni.
251500000.0

   foreign_gross  year
0    277300000.0  2010
1    311500000.0  2010
2    535700000.0  2010
3    652000000.0  2010
4    291600000.0  2010
```

Aggregate Revenues

We will create one column for total revenues from both regions

```
# add one column of total revenues
clean_data["Total_Revenue"]=clean_data["domestic_gross"] +
clean_data["foreign_gross"]

# save the cleaned data
clean_data.to_csv('./DataSets/Movie_Revenue.csv', index=False)
```

2. Data Analysis

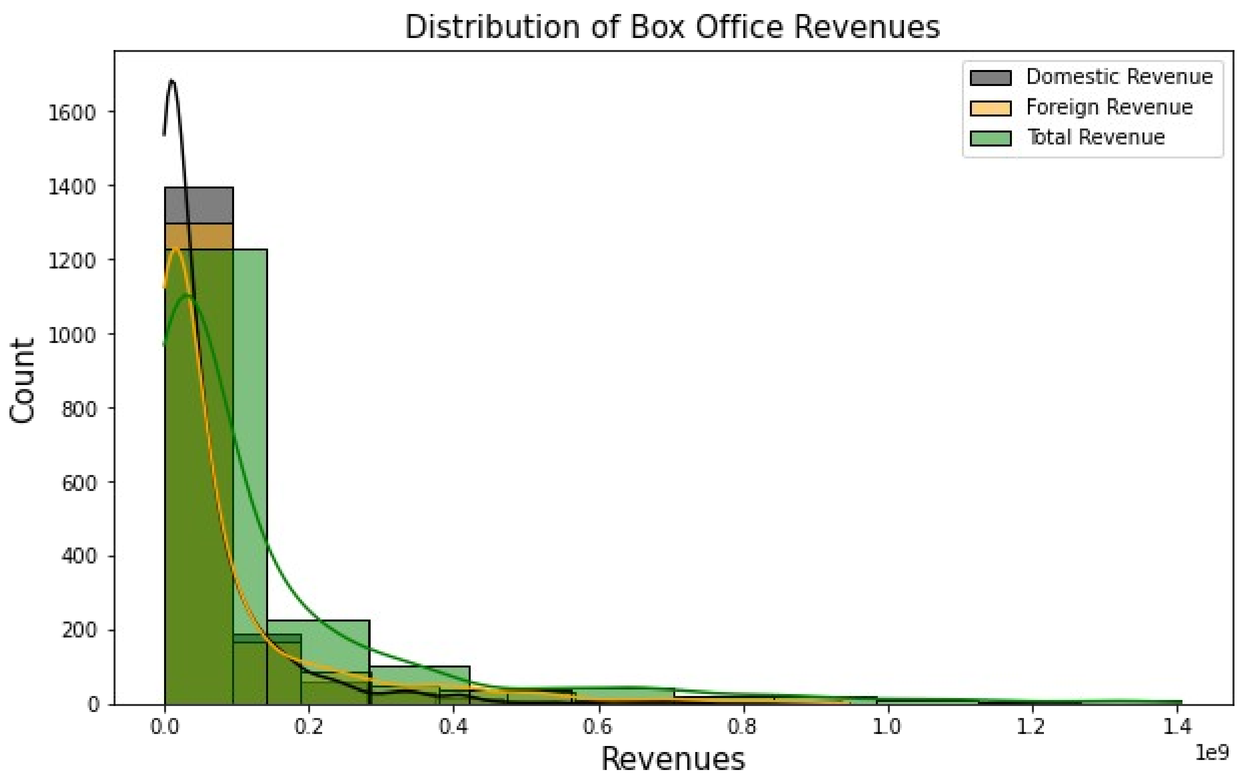
```
# reload cleaned data
df_clean = pd.read_csv("./DataSets/Movie_Revenue.csv")
df_clean.head()

  release_date                        title  vote_average studio
domestic_gross  \
0   2010-03-26  How to Train Your Dragon           7.7   P/DW
217600000.0
```

```
1   2010-05-07                        Iron Man 2            6.8   Par.
312400000.0
2   2010-07-16                         Inception            8.3     WB
292600000.0
3   2010-06-17                       Toy Story 3            7.7     BV
415000000.0
4   2010-07-09                     Despicable Me            7.2   Uni.
251500000.0

   foreign_gross  year  Total_Revenue
0    277300000.0  2010   4.949000e+08
1    311500000.0  2010   6.239000e+08
2    535700000.0  2010   8.283000e+08
3    652000000.0  2010   1.067000e+09
4    291600000.0  2010   5.431000e+08
```

2.1 Univariate Analysis of Revenues

Here we analyze the distribution of domestic, foreign and total revenues.

```
# use kde plot to visualize the istribution of revenue
plt.figure(figsize=(10, 6))

sns.histplot(df_clean['domestic_gross'], kde=True,
color='black',bins=10, label='Domestic Revenue')
sns.histplot(df_clean['foreign_gross'], kde=True, color='orange',bins
= 10, label='Foreign Revenue')
sns.histplot(df_clean['Total_Revenue'], kde=True, color='g',bins=10,
label='Total Revenue')
plt.legend()
plt.title('Distribution of Box Office Revenues', fontsize =15)
plt.xlabel("Revenues", fontsize=15)
plt.ylabel("Count", fontsize =15)
plt.show()
```



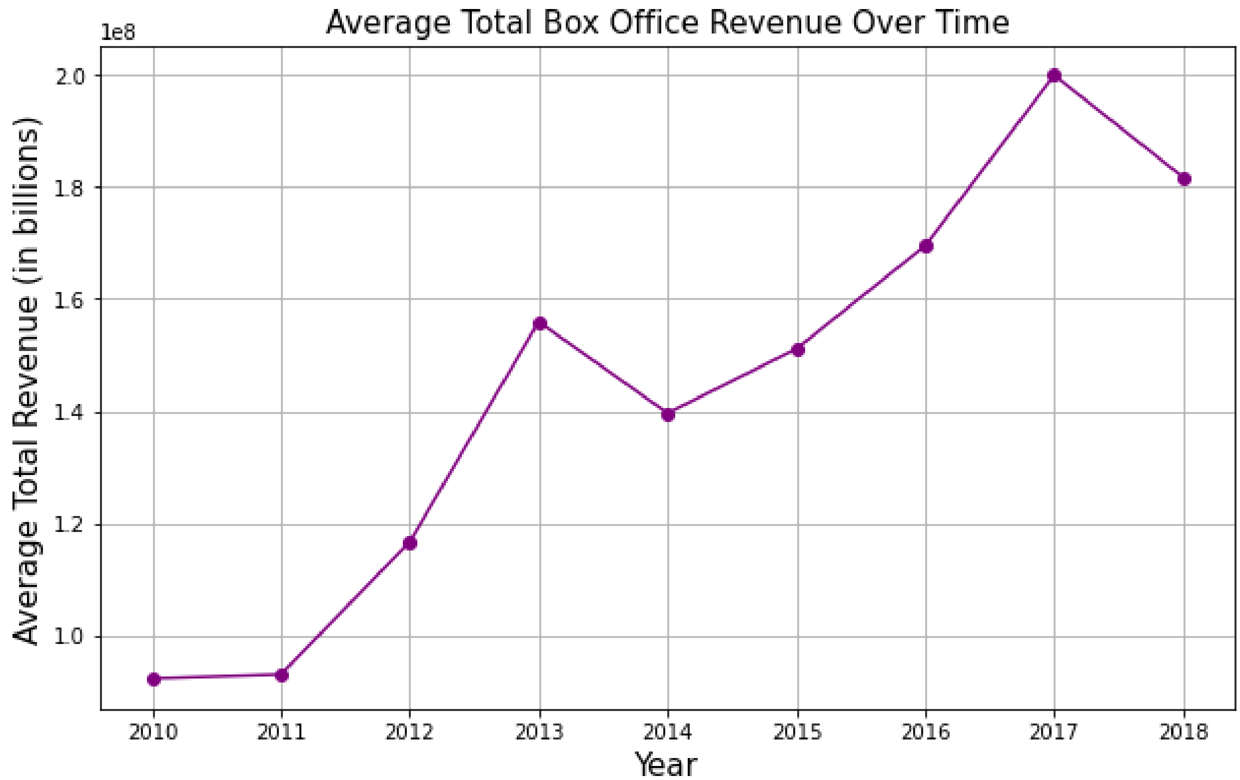
Interpretation

From the graph we can note that majority of that data is clusterd and dense torwards the left. This means that majority of the data points are close to zero.

2.1.1 Bivariate analysis of Revenues

We will plot to see how domestic, foreign and total revenes have changed over years. This will help us understand understand trends over time.

```
# plot a line graph of average revenues againast time

plt.figure(figsize=(10,6))
avg_revenue_by_year = df_clean.groupby('year')['Total_Revenue'].mean()
# data grouped by year and average calculated

avg_revenue_by_year.plot(kind='line', marker='o', color='purple')
plt.title('Average Total Box Office Revenue Over Time', fontsize = 15)
plt.xlabel('Year', fontsize=15)
plt.ylabel('Average Total Revenue (in billions)', fontsize=15)
plt.grid(True)
plt.show()
```



Interpretation

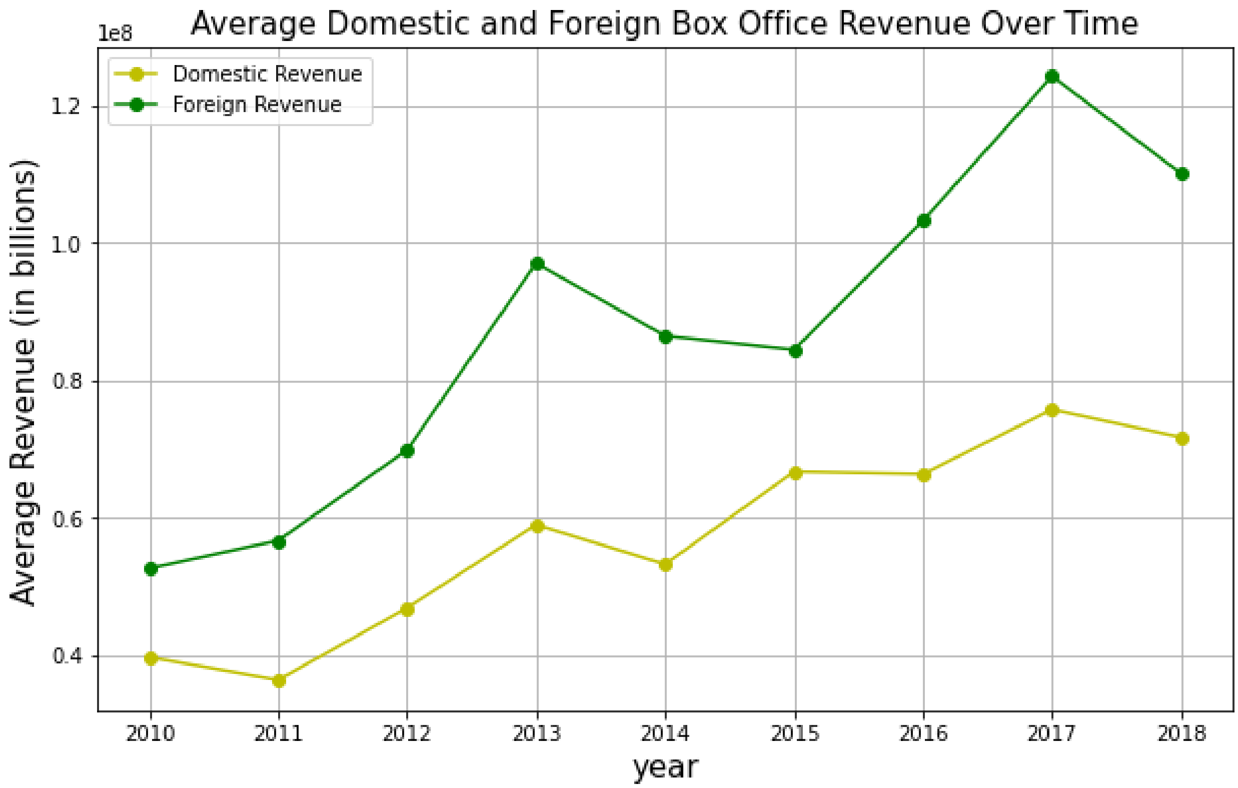
The line graph shows an upward increase on average revenue. The revenue for the year between 2010 and 2011 showed constance in revenues, however there was a steady increase between the years 2011 and 2013. Again, there was a sharp decline between 2013 and 2014. Stability was again realized between 2014 and 2017. The year 2018 saw revenue decline again.

Domestic vs Foreign revenues

It is also important for us to look at domestic and foreign revenues separately to spot trends in each region.

```
# calculate and visalize the average revenues for each region
avg_domestic = df_clean.groupby('year')['domestic_gross'].mean()
avg_foreign = df_clean.groupby('year')['foreign_gross'].mean()

plt.figure(figsize=(10,6))
plt.plot(avg_domestic.index, avg_domestic.values,marker='o',
label='Domestic Revenue', color='y')
plt.plot(avg_foreign.index, avg_foreign.values,marker='o',
label='Foreign Revenue', color='green')
plt.title('Average Domestic and Foreign Box Office Revenue Over Time',
fontsize=15)
plt.xlabel('year', fontsize=15)
plt.ylabel('Average Revenue (in billions)', fontsize=15)
```

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



Interpretation

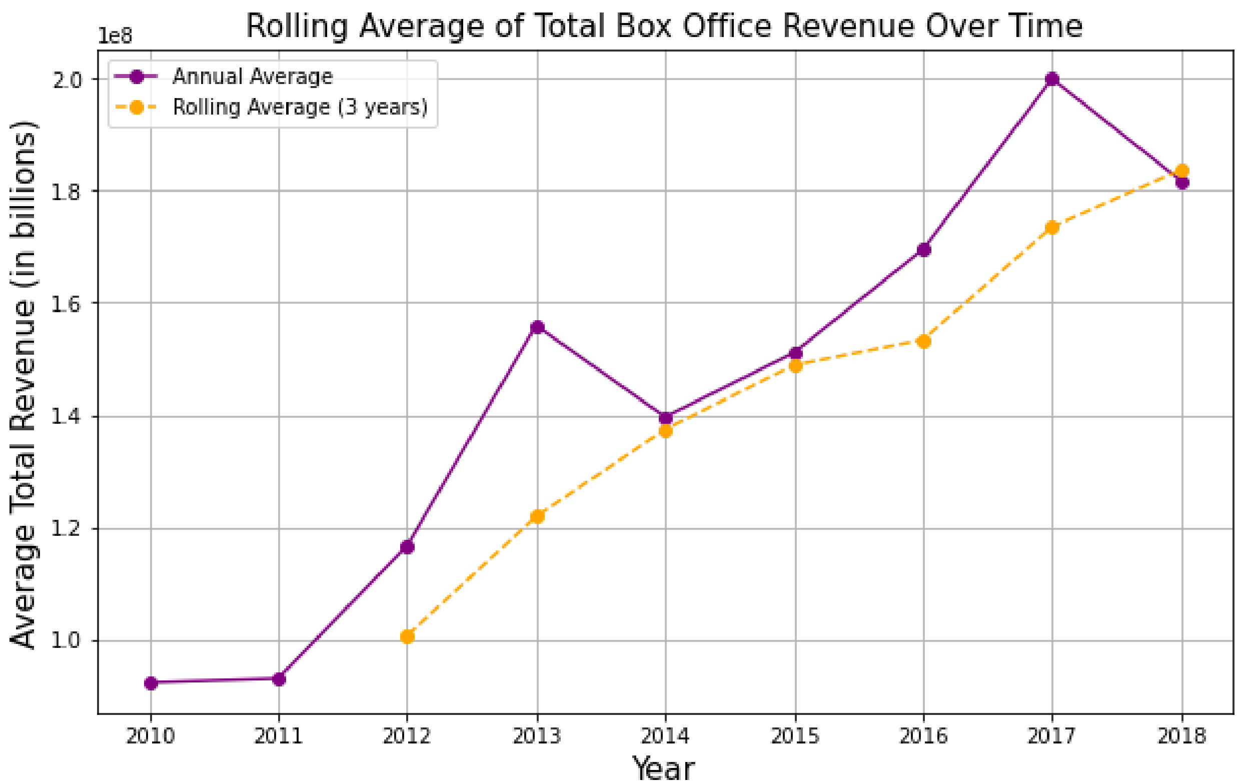
Both graphs shows an upward trend, meaning that over time, revenue in both the domestic and foreign revenue is generally increasing. This suggests growth in both markets, and this is a positive sign for the movie industry. On average, revenues are rising, however the pattern implies some volatilities.

Trend analysis: Rolling averge

we wil apply a rolling average to smooth out year-to-year volatility and reveal longer-term trends in box office revenue.

```
# 3-year rolling average
avg_revenue_rolling = avg_revenue_by_year.rolling(window=3).mean()

plt.figure(figsize=(10,6))
avg_revenue_by_year.plot(label='Annual Average',marker='o',
color='purple')
avg_revenue_rolling.plot(label='Rolling Average (3 years)',marker='o',
color='orange', linestyle='--')
plt.title('Rolling Average of Total Box Office Revenue Over
```

```
Time',fontsize=15)
plt.xlabel('Year', fontsize=15)
plt.ylabel('Average Total Revenue (in billions)', fontsize=15)
plt.legend()
plt.grid(True)
plt.show()
```



Interpretation

The rolling graph show an upward trend in the rolling average suggesting sustained growth in revenue. The stability of the rolling indicates that although there are volatile events, there is an overall growth in revenue.

Statistical Testing and Anaysis

Before we embark on any hypothesis testing, we will start by examining the descriptive statistics (mean, median, standard deviation, range) for the different revenue types and years.

```
# check the description
df_clean[['domestic_gross', 'foreign_gross',
'Total_Revenue']].describe()
```

	domestic_gross	foreign_gross	Total_Revenue
count	1.701000e+03	1.701000e+03	1.701000e+03
mean	5.597406e+07	8.460974e+07	1.405838e+08

```
std      9.139882e+07   1.437055e+08   2.209891e+08
min      7.000000e+02   6.000000e+02   4.900000e+03
25%      2.500000e+06   5.200000e+06   1.196000e+07
50%      2.510000e+07   2.460000e+07   5.470000e+07
75%      6.600000e+07   8.950000e+07   1.592000e+08
max      9.367000e+08   9.464000e+08   1.405400e+09
```

Hypthesis Testing

Two_Sample t-test

We will perform a t-test to compare the means of the revenues in the two regions. Our level of significance is 0.05.

Null Hypothesis: The mean revenues for the two groups are the same.

Alternative Hypothesis: The mean revenes for the two groups are different.

```
# Calculate T-test between Domestic and Foreign Revenue
t_stat, p_value = stats.ttest_ind(df_clean['domestic_gross'],
df_clean['foreign_gross'])

print("T-statistic:", t_stat)
print("P-value:", p_value)
# use if statement
if p_value <= 0.05:
    print("Null Hypothesis is rejected")
if p_value > 0.05:
    print("Fail to reject the null hypothesis")
```

```
T-statistic: -6.934628358439761
P-value: 4.85384078108989e-12
Null Hypothesis is rejected
```

Interpretation

From our output we can clearly see that p_value is less than our level of significance and therefore we reject the null hypothesis. This means that there is a significant variability between the means of revenues for the two regions.

Correlation

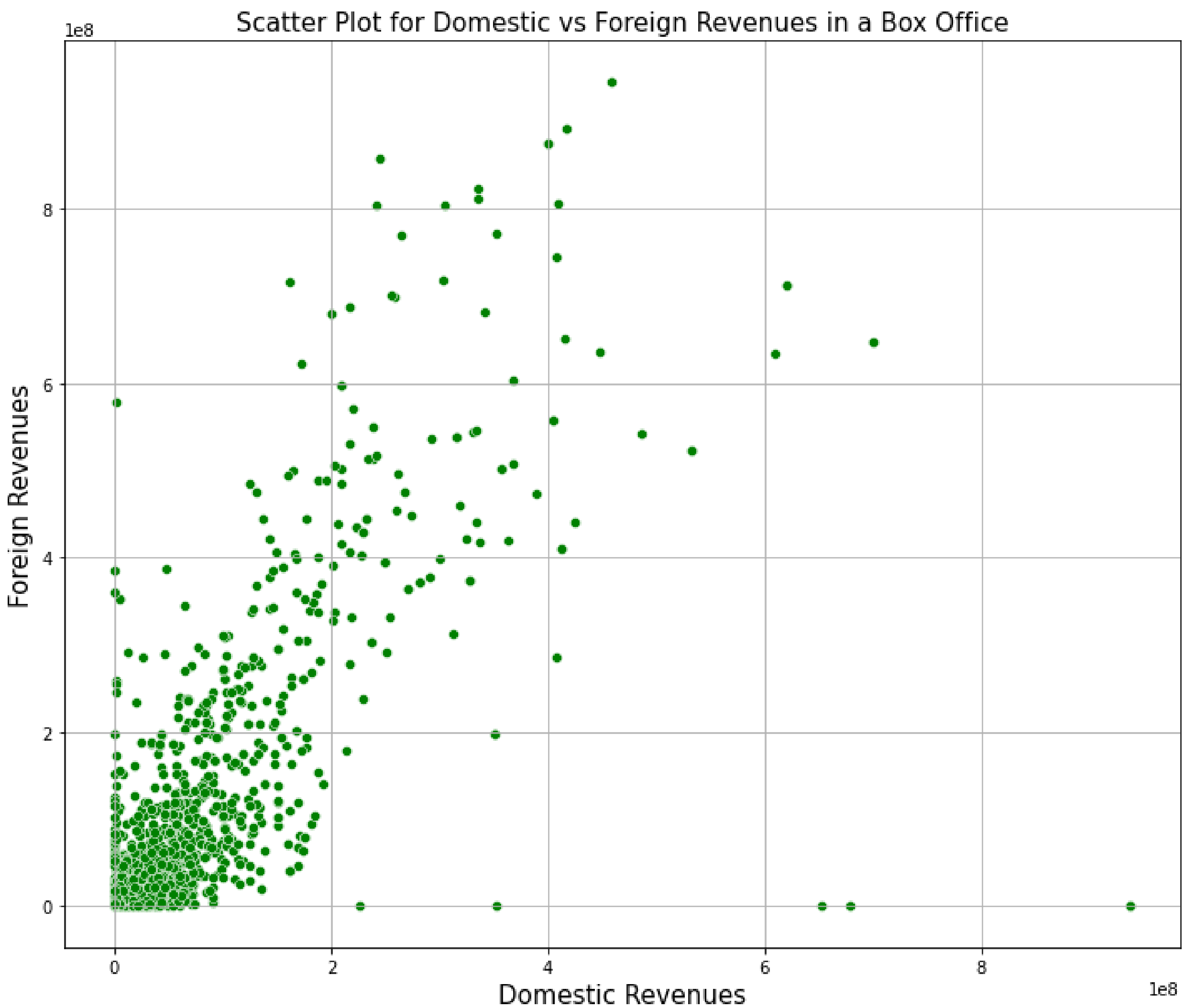
A correlaion analysis between domestic and foreign revenues is neccessary to understand the strength and directon of their linear relatioships. Values range from -1 (perfect negative correlation) to 1 (perfect positive correlation).

```
# calculate the correlation
corr = df_clean["domestic_gross"].corr (df_clean["foreign_gross"])
print(corr)
# use if statement to print out the result and its strength
```

```python
if corr > 0.7:
    print("There is a strong positive correlation")
elif corr > 0.5:
    print("Moderate positive correlation")
elif corr > 0:
    print("Weak positive correlation")
elif corr == 0:
    print("No correlation")
elif corr > -0.5:
    print("Weak negative correlation")
elif corr > -0.8:
    print("Moderate negative correlation")
else:
    print("Strong negative correlation")
```

```
0.7549260607466057
There is a strong positive correlation
```

```python
# scatter plot for this correlation
plt.figure(figsize=(12,10))
sns.scatterplot(df_clean["domestic_gross"], df_clean["foreign_gross"],
color='g')
plt.title("Scatter Plot for Domestic vs Foreign Revenues in a Box
Office", fontsize=15)
plt.xlabel("Domestic Revenues", fontsize = 15)
plt.ylabel("Foreign Revenues", fontsize=15)
plt.grid(True)
plt.show()
```



Interpretation

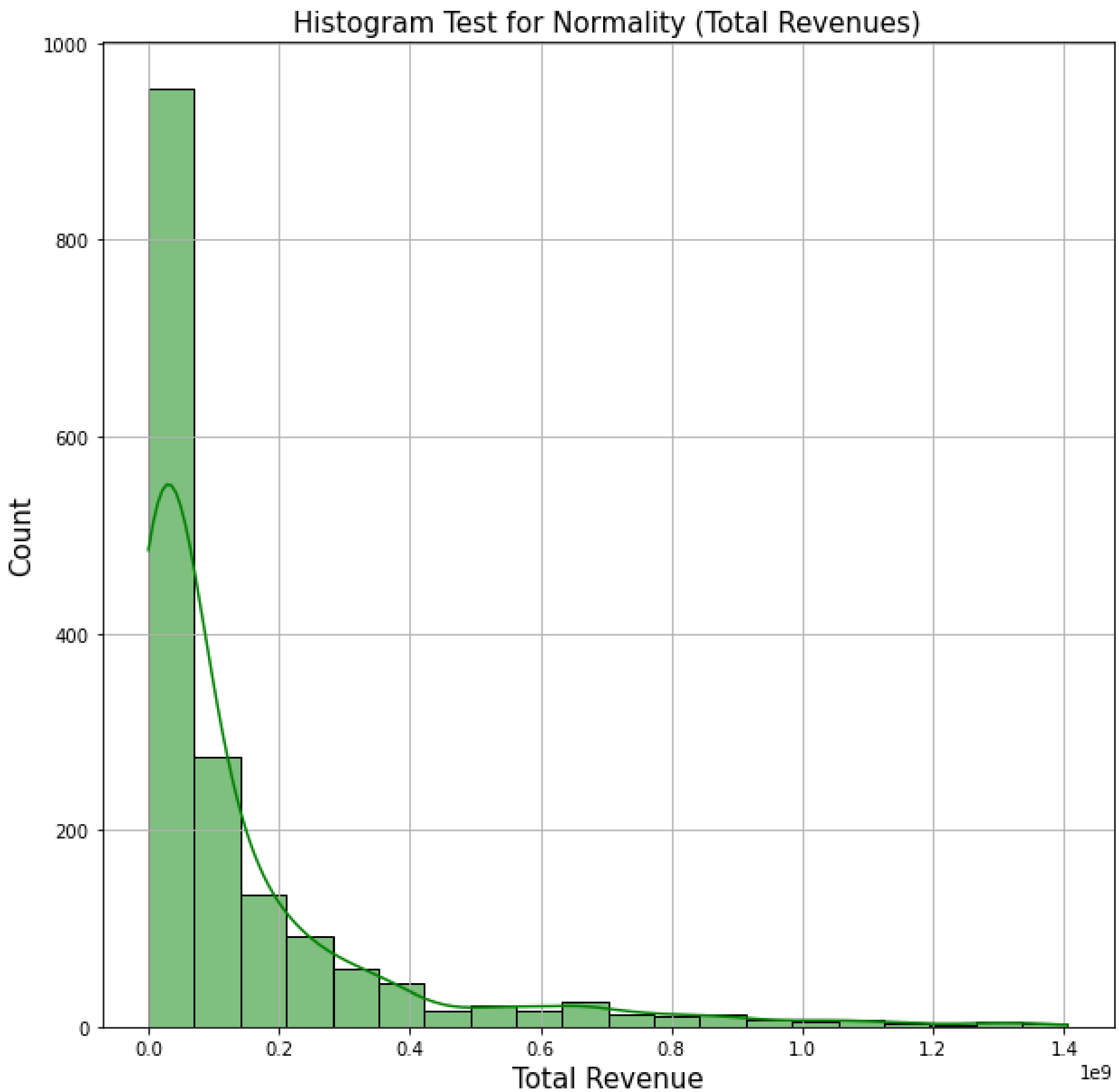
A strong correlation of 0.7 confirms to us that indeed there is a strong relatonship between the revenues in the two regions. This means that if one revenue changes, the other tend to change in a predictable and consistent manner. From the scatter plot we can see the linearity of the data of an upward trend. It indicates that as domestic revenue increase, the foreign revenue tends to increase as well. However, this does not produce a perfect line since there is variability in the data points along the trend.

Normality Test

We will check to see the normality and distribution of our numerical data columns. In this case we will use the total revenue column.

```
# use histogram plus kde plot
plt.figure(figsize=(10, 10))
sns.histplot(df_clean["Total_Revenue"], kde=True, bins =20,
```

```
color='g');
plt.title("Histogram Test for Normality (Total Revenues)",
fontsize=15)
plt.xlabel("Total Revenue", fontsize = 15)
plt.ylabel("Count", fontsize=15)
plt.grid(True)
plt.show()
```



Observation

From our observation, the revenue concentration is on the left, indicating that for the majority of observations, movie revenues remains at low or minimal levels. This suggests that the revenue is predominantly associated with smaller values, with relatively few instances where higher values occur. This is a perfect case of right-skewed data distribution.

Summary and Conclusion

The analysis of movie revenues reveals an overall upward trend in revenue generation over time, indicating growth in the industry and increasing box office performance. This upward trend suggests that audiences are generally spending more on movies, possibly driven by factors such as increased ticket prices, expanded distribution channels, or more frequent high-rate releases.

However, the revenue data also shows periodic volatility. These fluctuations indicate that while the industry is growing, individual movie performances can vary significantly. Such volatility might stem from seasonal variations, differences in marketing success, shifts in consumer preferences, or the impact of blockbuster releases that temporarily elevate revenue figures.