Phase One Project

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MICROSOFT'S NEW MOVIE STUDIO ANALYSIS

1. Business Understanding

a) Introduction

Movies have been a captivating form of entertainment for decades, transporting audiences into different worlds and evoking a range of emotions. The diverse landscape of film genres offers something for everyone, catering to individual preferences and tastes. From heart-pounding action blockbusters to thought-provoking dramas, and from light-hearted comedies to spine-chilling thrillers, each genre brings its own unique appeal and storytelling style.

Understanding the significance of genres in the film industry is crucial for filmmakers, studios, and audiences alike. Genres provide a framework for categorizing films based on their thematic elements, narrative structures, and intended emotional impact. They offer a roadmap for creative expression, allowing filmmakers to tap into established conventions while also pushing boundaries and introducing fresh perspectives.

In a rapidly evolving entertainment landscape, Microsoft has recognized the growing trend of major corporations venturing into original video content creation. Eager to join the excitement, Microsoft has made the decision to establish its own movie studio.

b) Problem Statement

Microsoft, being relatively unfamiliar with the intricacies of the film industry, it requires a detailed examination of the current landscape to make informed decisions regarding the types of films to produce.

Main Objective

To explore the types of films that have been performing exceptionally well at the box office and extract actionable insights that can guide the decision-making process for Microsoft's new movie studio.

Specific objectives

- To find out what movie type 'Genre" are currently most successful.
- To find out what budget amount tends to achieve the highest box office gross.
- To find out when is the most lucrative time of year to release a movie.

c) Experimental Design

- Data Collection
- Read and check the data
- Cleaning the data
- Exploratory Data Analysis
- Conclusions and Recommendations

d) Data Understanding

The data was collected from various locations, the different files have different formats. Some are CSV or TSV files that can be opened using spreadsheet software or pd.read_csv, while the data from IMDB is located in a SQLite database.

The data includes different information concerning the movies ranging from the title, genres, average-rating, e.t.c

Analyzing dataset will determine what contributes to the "success" of a movie. In this analysis, I will define analysis in financial terms basing the success of a movie on the amount of money it earns in comparison to the budget.

2. Importing Libaries

In [2]:
```
#importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import csv
import sqlite3
from pandasql import sqldf
import calendar
```

3. Reading and Checking the Data

In [3]:
```
#Loading the tn.movie_budgets data
tn_movie_budgets = pd.read_csv(r'C:\Users\hp\Desktop\Project_1\tn.movie_budgets
tn_movie_budgets.head()
```

Out[3]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [4]:
```
movie_principals = pd.read_csv(r'C:\Users\hp\Desktop\Project_1\title.principals
movie_principals.head(10)
```

Out[4]:

	tconst	ordering	nconst	category	job	characters
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]
1	tt0111414	2	nm0398271	director	NaN	NaN
2	tt0111414	3	nm3739909	producer	producer	NaN
3	tt0323808	10	nm0059247	editor	NaN	NaN
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]
5	tt0323808	2	nm2694680	actor	NaN	["Steve Thomson"]
6	tt0323808	3	nm0574615	actor	NaN	["Sir Lachlan Morrison"]
7	tt0323808	4	nm0502652	actress	NaN	["Lady Delia Morrison"]
8	tt0323808	5	nm0362736	director	NaN	NaN
9	tt0323808	6	nm0811056	producer	producer	NaN

In [5]:
```
movie_crew = pd.read_csv(r'C:\Users\hp\Desktop\Project_1\title.crew.csv')
movie_crew.head(10)
```

Out[5]:

	tconst	directors	writers
0	tt0285252	nm0899854	nm0899854
1	tt0438973	NaN	nm0175726,nm1802864
2	tt0462036	nm1940585	nm1940585
3	tt0835418	nm0151540	nm0310087,nm0841532
4	tt0878654	nm0089502,nm2291498,nm2292011	nm0284943
5	tt0879859	nm2416460	NaN
6	tt0996958	nm2286991	nm2286991,nm2651190
7	tt0999913	nm0527109	nm0527109,nm0329051,nm0001603,nm0930684
8	tt10003792	nm10539228	nm10539228
9	tt10005130	nm10540239	nm5482263,nm10540239

In [6]:
```
# Loading the title.basics.csv
movie_basics = pd.read_csv(r'C:\Users\hp\Desktop\Project_1\title.basics.csv')
movie_basics.head(10)
```

Out[6]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	Comedy
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thriller
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,History
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	Biography

In [7]:
```
#loading the title.ratings.csv
movie_ratings = pd.read_csv(r'C:\Users\hp\Desktop\Project_1\title.ratings.csv'
movie_ratings.head(10)
```

Out[7]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
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

4. Data Wrangling

In [10]:
```
# joining the movie_basics and movie_crew
imdb_movies = movie_basics.set_index("tconst").join(movie_crew.set_index("tcon
                                                   how="inner")
imdb_movies = imdb_movies.reset_index().rename(columns={"index": "tconst"})
imdb_movies.rename(columns={'tconst': 'movie_id'}, inplace=True)
imdb_movies.head()
```

Out[10]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	nm07

In [17]:
```
#joining the imdb_movies and tn_movie_budgets.
movies = imdb_movies.set_index('primary_title').join(tn_movie_budgets.set_inde
                                                    how="inner")
movies.head()
```

Out[17]:

	movie_id	original_title	start_year	runtime_minutes	genres	director
#Horror	tt3526286	#Horror	2015	101.0	Crime,Drama,Horror	nm083696
10 Cloverfield Lane	tt1179933	10 Cloverfield Lane	2016	103.0	Drama,Horror,Mystery	nm087046
10 Days in a Madhouse	tt3453052	10 Days in a Madhouse	2015	111.0	Drama	nm038572
12 Rounds	tt3517850	12 Rounds	2017	NaN	Action,Drama,Romance	nm121797
12 Strong	tt1413492	12 Strong	2018	130.0	Action,Drama,History	nm335042

In [18]:
```
#Updating the index name of the "movies" DataFrame to "movie"
movies.index.name = "movie"
movies.reset_index(inplace=True)
movies.head()
```

Out[18]:

	movie	movie_id	original_title	start_year	runtime_minutes	genres	direct
0	#Horror	tt3526286	#Horror	2015	101.0	Crime,Drama,Horror	nm0836
1	10 Cloverfield Lane	tt1179933	10 Cloverfield Lane	2016	103.0	Drama,Horror,Mystery	nm0870
2	10 Days in a Madhouse	tt3453052	10 Days in a Madhouse	2015	111.0	Drama	nm0385
3	12 Rounds	tt3517850	12 Rounds	2017	NaN	Action,Drama,Romance	nm1217
4	12 Strong	tt1413492	12 Strong	2018	130.0	Action,Drama,History	nm3350

In [19]:
```
#Checking to see a summary of our data.
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3815 entries, 0 to 3814
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              3815 non-null   object 
 1   movie_id           3815 non-null   object 
 2   original_title     3814 non-null   object 
 3   start_year         3815 non-null   int64  
 4   runtime_minutes    3328 non-null   float64
 5   genres             3743 non-null   object 
 6   directors          3727 non-null   object 
 7   writers            3351 non-null   object 
 8   id                 3815 non-null   int64  
 9   release_date       3815 non-null   object 
 10  production_budget  3815 non-null   object 
 11  domestic_gross     3815 non-null   object 
 12  worldwide_gross    3815 non-null   object 
dtypes: float64(1), int64(2), object(10)
memory usage: 387.6+ KB
```

Oservations made from our data that needs to be fixed includes;

- production budget, domestic_gross and worldwide_gross are of type objects but we need to change them to type integer for mathematical operations.
- The release date is an object wich we want it as dates.
- In genres, writers, directors, runtime_minutes, and original_title there are missing values. In this scenario, it would be best to drop them as it would be a challenge to replace them as they are categorical.

In [20]:
```
#Dropping some columns
cols_to_remove = ["original_title", "start_year", "runtime_minutes", "id"]
movies = movies.drop(cols_to_remove, axis=1)
```

In [21]:
```
#Removeing any rows containing missing values (NaN) from the DataFrame
movies.dropna(inplace=True)
```

In [22]:
```
#converting the values in columns 6 and
#onwards of the DataFrame to integers.
#applymap() function with a lambda function
#removes commas and dollar signs from the values.

movies[movies.columns[6:]] = movies[movies.columns[6:]].applymap(lambda x: int
movies.head()
```

Out[22]:

	movie	movie_id	genres	directors	writers	rele
0	#Horror	tt3526286	Crime,Drama,Horror	nm0836964	nm0836964	Nov
1	10 Cloverfield Lane	tt1179933	Drama,Horror,Mystery	nm0870469	nm1061091,nm1173295,nm3227090	Ma
2	10 Days in a Madhouse	tt3453052	Drama	nm0385725	nm0385725	Nov
3	12 Rounds	tt3517850	Action,Drama,Romance	nm1217972	nm1217972	Mar
4	12 Strong	tt1413492	Action,Drama,History	nm3350420	nm0848217,nm0185976,nm3066678	Jar

In [23]:
```
#Converting release_date to datetime format.
movies["release_date"] = pd.to_datetime(movies["release_date"])
movies.head()
```

Out[23]:

	movie	movie_id	genres	directors	writers	rele
0	#Horror	tt3526286	Crime,Drama,Horror	nm0836964	nm0836964	2(
1	10 Cloverfield Lane	tt1179933	Drama,Horror,Mystery	nm0870469	nm1061091,nm1173295,nm3227090	2(
2	10 Days in a Madhouse	tt3453052	Drama	nm0385725	nm0385725	2
3	12 Rounds	tt3517850	Action,Drama,Romance	nm1217972	nm1217972	2(
4	12 Strong	tt1413492	Action,Drama,History	nm3350420	nm0848217,nm0185976,nm3066678	2(

In [24]:
```
#Checking for duplicates in our dataset
set(list(movies.duplicated(subset="movie_id")))
```

Out[24]: {False, True}

In [25]:
```
#Dropping duplicates
movies.drop_duplicates(subset="movie_id", inplace=True)
```

In [26]:
```
#checking the number of rows left after dropping the duplicated rows
len(movies)
```

Out[26]: 3145

Data Analysis and Visualization

A successful movie will be determined on condition that its worldwide gross is at least double its production budget.

In [27]:
```
#find the movies where the worldwide gross is at least double the production bu
success_movies = movies.loc[movies['worldwide_gross'] >= 2 * movies['productio
success_movies.head(10)
```

Out[27]:

	movie	movie_id	genres	directors	
1	10 Cloverfield Lane	tt1179933	Drama,Horror,Mystery	nm0870469	nı
4	12 Strong	tt1413492	Action,Drama,History	nm3350420	nı
5	12 Years a Slave	tt2024544	Biography,Drama,History	nm2588606	
6	127 Hours	tt1542344	Adventure,Biography,Drama	nm0000965	nı
10	2 Guns	tt1272878	Action,Comedy,Crime	nm0466349	
11	21	tt5097012	Horror	nm7641690	
12	21 Jump Street	tt1232829	Action,Comedy,Crime	nm0588087,nm0520488	nm0045209,nı
13	22 Jump Street	tt2294449	Action,Comedy,Crime	nm0588087,nm0520488	nm0045209,nm1706767,
24	300: Rise of an Empire	tt1253863	Action,Fantasy,War	nm1729171	nı
27	42	tt0453562	Biography,Drama,Sport	nm0001338	

Calculating the income ratio(worldwide_gross/production_budget) for each movie and adding it as a new column "income_ratio" to the Dataframe.

Then we oder our data by the most successful in terms of income ratio.

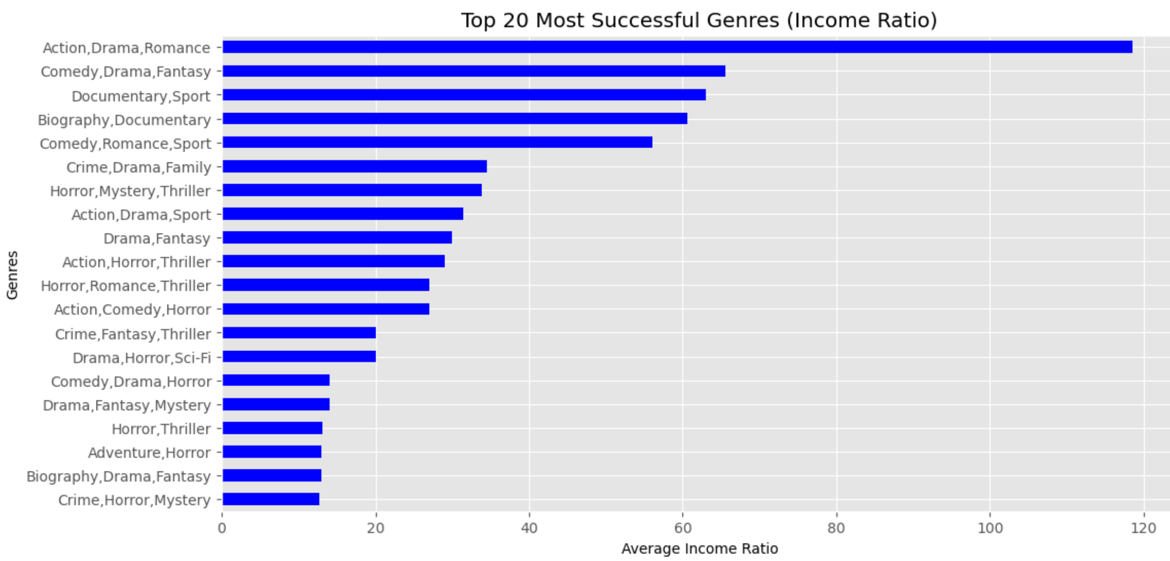
In [57]:
```
#Dividing the worldwide gross of each movie by its production
#budget and rounding the result to the nearest whole number.

success_movies["income_ratio"] = round(success_movies.worldwide_gross / succes

#sorting the success_movies dataframe in descending order based on the "income_
success_movies = success_movies.sort_values("income_ratio", ascending=False)
success_movies.head()
```

Out[57]:

	movie	movie_id	genres	directors	
2882	The Gallows	tt2309260	Horror,Mystery,Thriller	nm4000389,nm3951039	nm3951039,nm4
287	Bambi	tt2668120	Biography,Documentary	nm0509852	nm0
2296	Rocky	tt9430578	Action,Drama,Romance	nm9645626	nm3358805,nm7633074,nm9
2478	Snow White and the Seven Dwarfs	tt9691476	Comedy,Drama,Fantasy	nm10441208	nm10
2812	The Devil Inside	tt1560985	Horror	nm0068587	nm0068587,nm1

Visualization of the top 20 most succesful genres in terms of income ratio

In [29]:
```
# Grouping and calculating average income ratio for each genre
genres_income_ratio = success_movies.groupby("genres")["income_ratio"].mean()

# Sorting genres by average income ratio in descending order
sorted_genres = genres_income_ratio.sort_values(ascending=True)

# Selecting the top 20 genres
top_20_genres = sorted_genres.tail(20)

# Set the plot style to "ggplot"
plt.style.use("ggplot")

# Plotting the top 20 genres and their average income ratios
plt.figure(figsize=(12, 6))
top_20_genres.plot(kind="barh", color= 'blue')
plt.title("Top 20 Most Successful Genres (Income Ratio)")
plt.xlabel("Average Income Ratio")
plt.ylabel("Genres")
plt.show()
```



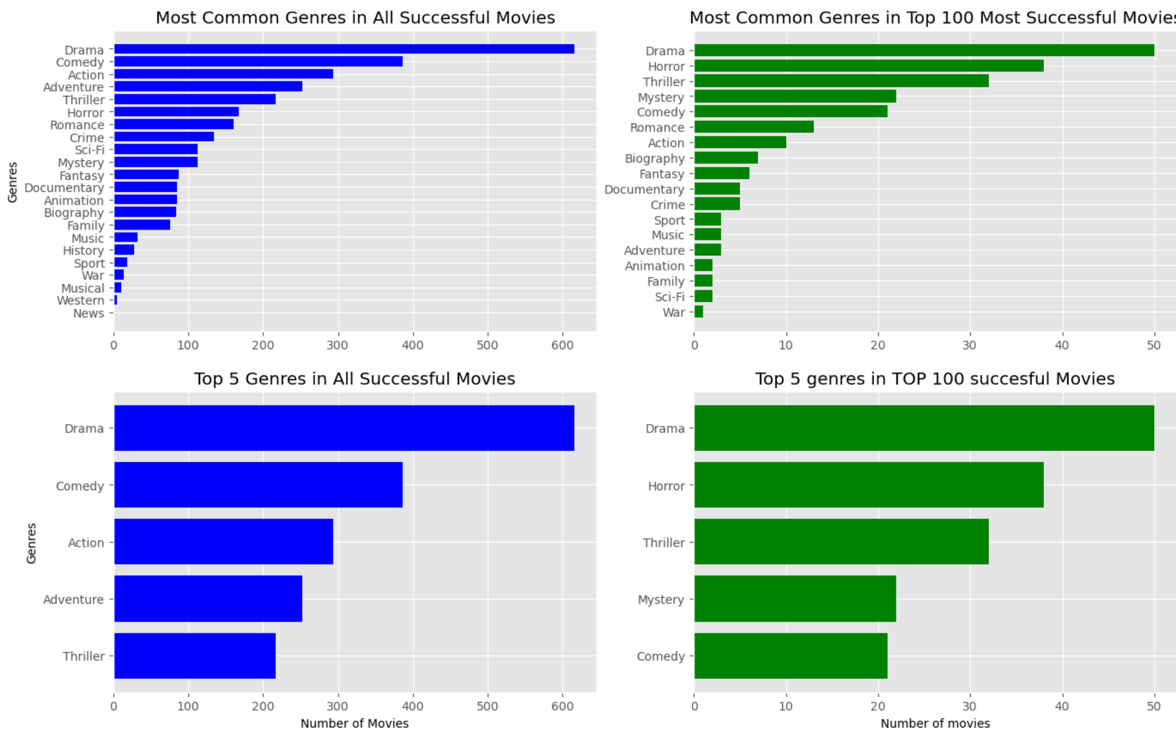
- From the above plot we can observe that the combination of Action, Drama and Romance genres had the highest average income ratio.

Finding out the genres which are common in the successful movies.

In [30]:
```
# Counting the occurrence of each genre in the "success_movies"
top_genres = []
for genre in list(success_movies.genres):
    top_genres.extend(genre.split(","))

top_genres = pd.Series(top_genres).value_counts().sort_values()

#Secting the top five genres.
top_5_generes = top_genres[-5:]
```

In [31]:
```
#Finding the Most common genres in the TOP 100 most successful movies.
genres = list(success_movies.genres)[:100]
#Selecting the top 100 movies based on a success metric income_ratio
income_ratio = list(success_movies.income_ratio.astype(int))[:100]

top_100_genres = []
for gen in genres:
    top_100_genres.extend(gen.split(","))
top_100_genres = pd.Series(top_100_genres).value_counts().sort_values()

#top five common generes from 100 most successful movies.
top_5_gs = top_100_genres[-5:]
```

In [32]:
```
# plotting most common genres in Top 100 and in all succesful movies
fig, ([ax1,ax2],[ax3,ax4]) = plt.subplots(figsize=(16,10), ncols=2, nrows=2)

ax1.barh(top_genres.index, top_genres.values, color = 'blue')
ax2.barh(top_100_genres.index, top_100_genres.values, color = 'green')
ax3.barh(top_5_generes.index, top_5_generes.values, color = 'blue')
ax4.barh(top_5_gs.index, top_5_gs.values, color = 'green')

ax1.set(ylabel = "Genres",
          title = "Most Common Genres in All Successful Movies")
ax2.set(title = "Most Common Genres in Top 100 Most Successful Movies")

ax3.set(xlabel = "Number of Movies", ylabel = "Genres",
          title = "Top 5 Genres in All Successful Movies")
ax4.set(xlabel = "Number of movies",
          title = "Top 5 genres in TOP 100 succesful Movies");
```



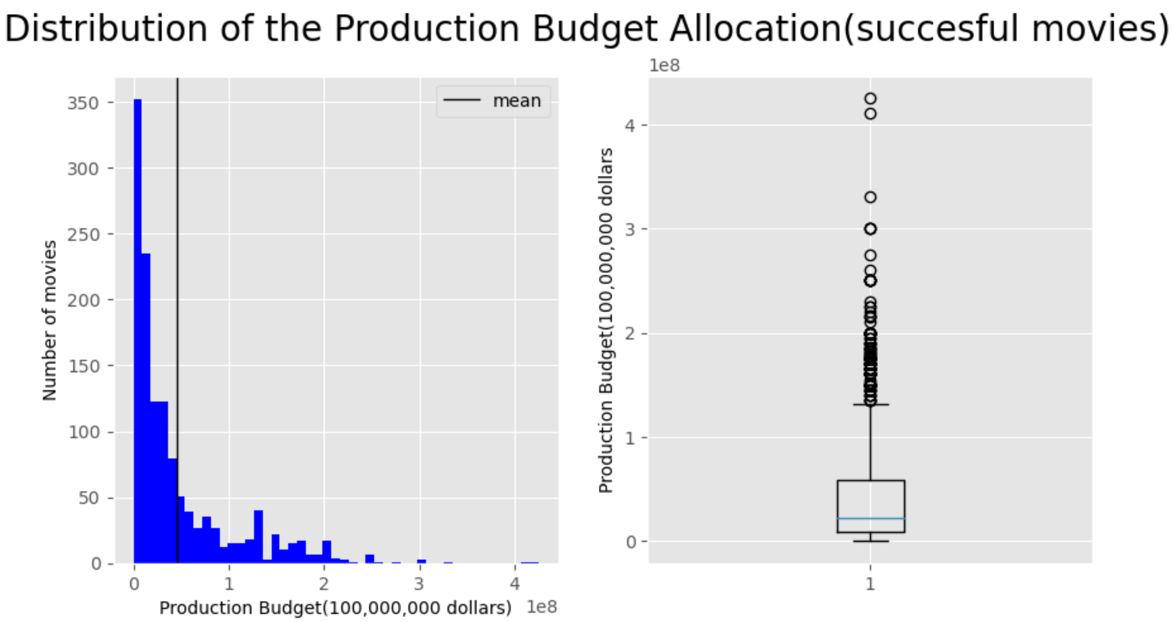
- We can observe that Drama movies are the most common in successful movies.

Now, finding if the production budget a movie have an effect on the income ratio and also finding out the average production budget in successful movies.

In [33]:
```
#Calculating the mean, median, standard deviation
print("mean: ", success_movies.production_budget.mean())
print("median: ", success_movies.production_budget.median())
print("standard dev: ", success_movies.production_budget.std())
```

```
mean:  45881831.76394194
median:  22000000.0
standard dev:  57263963.10221424
```

In [34]:
```
# Set the plot style to "ggplot"
plt.style.use("ggplot")

# Plotting the distribution of production_budget
fig, ax = plt.subplots(figsize = (10,5), ncols=2)

ax[0].hist(success_movies.production_budget, bins="auto", color= "blue")
ax[1].boxplot(success_movies.production_budget)

ax[0].axvline(success_movies.production_budget.mean(), c = "black", linewidth=
ax[0].set(xlabel = "Production Budget(100,000,000 dollars)", ylabel = "Number
ax[0].legend(["mean"])
ax[1].set(ylabel = "Production Budget(100,000,000 dollars")



fig.suptitle("Distribution of the Production Budget Allocation(succesful movie
```



- From the above we can observe that most movies were successful even when their production budget was below the mean of the production budgets.
- From the median we can see that $22,000,000 is a good production budget for a movie.

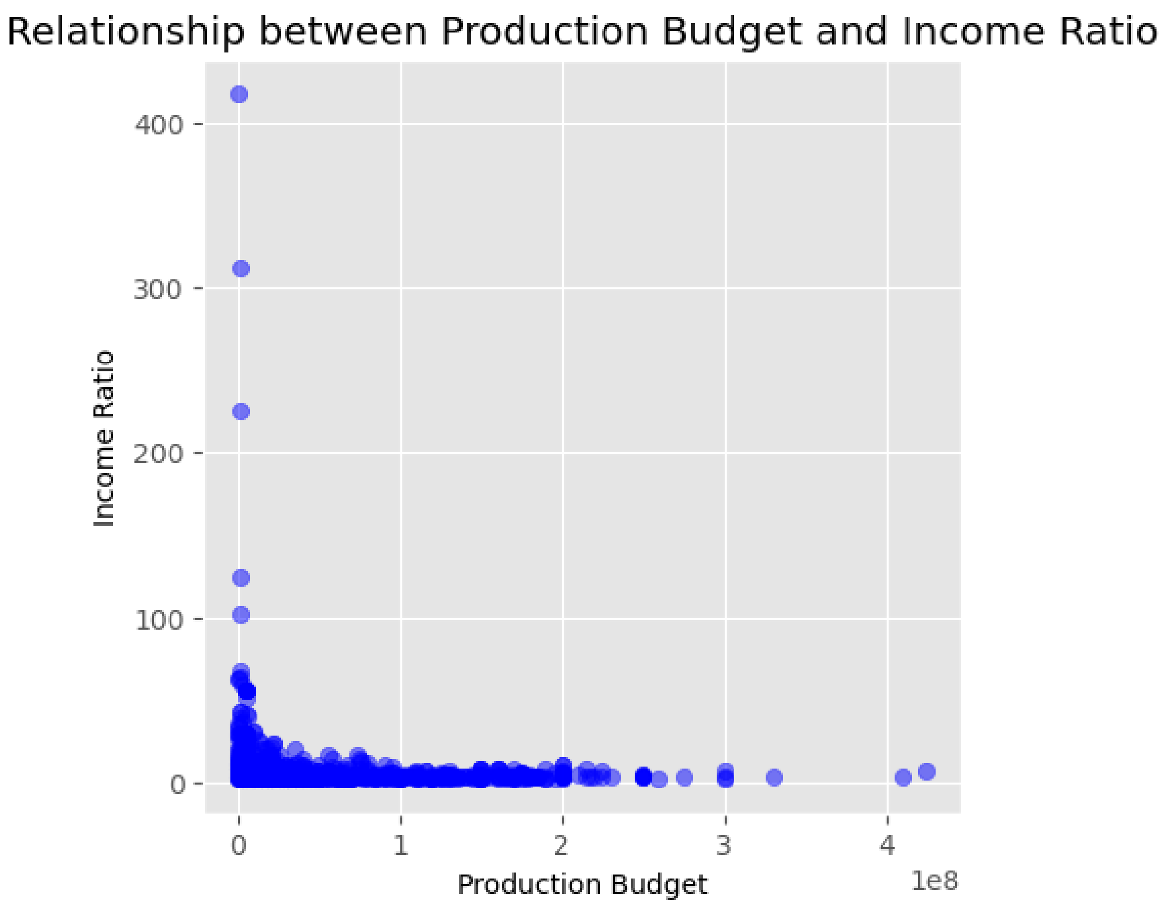
Finding if there's a correlation between production budget and the income ratio.

In [35]:
```
# Calculate the correlation coefficient
correlation = np.corrcoef(success_movies.production_budget, success_movies.inc

# Print the correlation coefficient
print("Correlation coefficient between production budget and income ratio:", c
```

```
Correlation coefficient between production budget and income ratio: -0.127796
02090121223
```

Plotting a scatter plot display the relationship between the production budget and the income ratio in successful movies.

In [36]:
```
# Set the plot style to "ggplot"
plt.style.use("ggplot")

# Plotting the scatter plot
plt.figure(figsize=(5, 5))
plt.scatter(success_movies.production_budget, success_movies.income_ratio, col
plt.title("Relationship between Production Budget and Income Ratio")
plt.xlabel("Production Budget")
plt.ylabel("Income Ratio")
plt.show()
```



- Correlation coefficient between production budget and income ratio is -0.12779602090121223.
- This means that there's a light inverse relation between production budget and income ratio. That is, more production budget results to low income ratio.

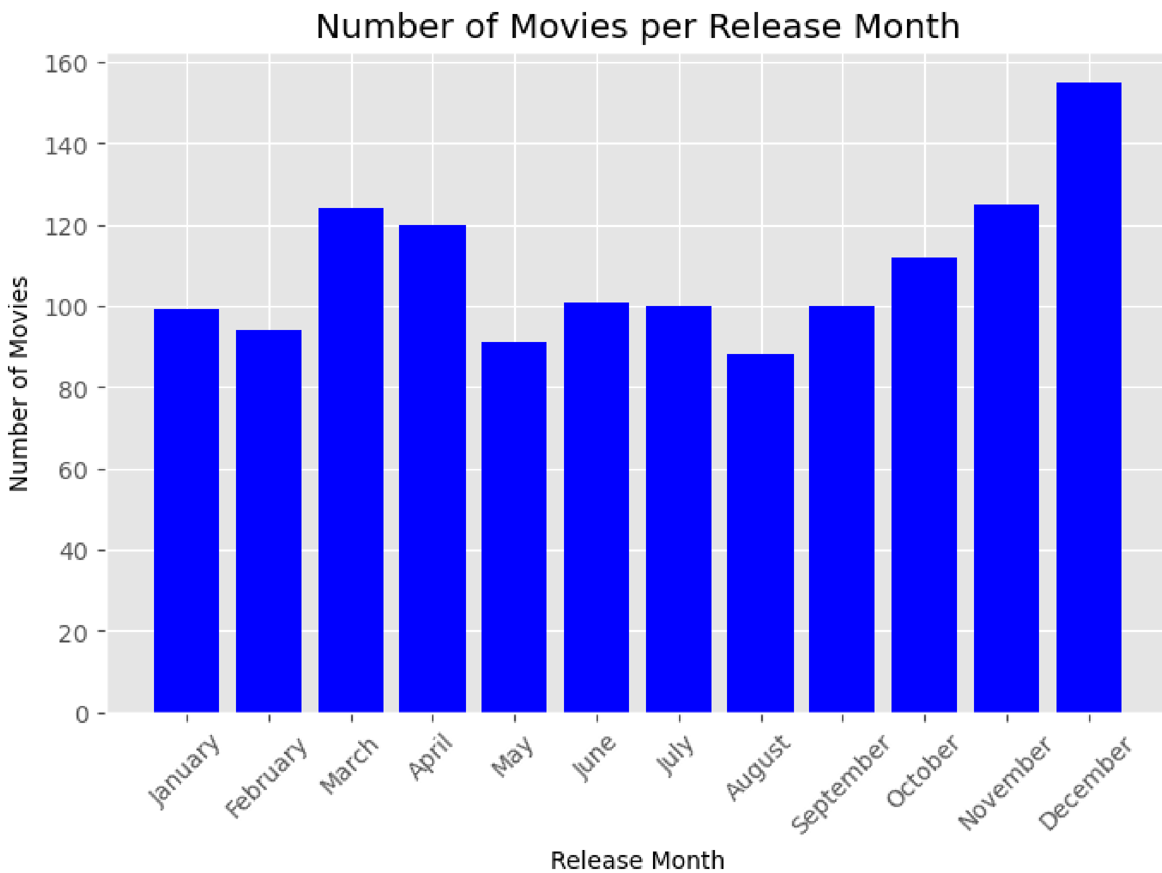
Finding when is the most lucrative time of year to release a movie.

In [41]:
```
# Define the 'pysqldf' function
pysqldf = lambda q: sqldf(q, globals())
#A dataframe to display the count of movies in each month.
# Calculate the number of movies in each month
months_count = pysqldf("""
                        SELECT COUNT(*) movie_count,
                               strftime("%m", release_date) release_month
                        FROM success_movies
                        GROUP BY release_month
                        ORDER BY release_month ASC
                        """)

# Convert month numbers to month names
months_count['release_month'] = months_count['release_month'].apply(lambda x: 

# Print the result
print(months_count)
```

```
    movie_count release_month
0            99       January
1            94      February
2           124         March
3           120         April
4            91           May
5           101          June
6           100          July
7            88        August
8           100     September
9           112       October
10          125      November
11          155      December
```

Plotting the number of movies released in each month.

In [42]:
```
# Set the plot style to "ggplot"
plt.style.use("ggplot")

# Plotting the number of movies per release month
plt.figure(figsize=(8, 5))
plt.bar(months_count['release_month'], months_count['movie_count'], color='blu
plt.title("Number of Movies per Release Month")
plt.xlabel("Release Month")
plt.ylabel("Number of Movies")
plt.xticks(rotation=45)
plt.show()
```



- From the above, we can see that movie release months were fairly evenly distributed throughout the year, with the most releases in December and the least in August.

Calculating the average income ratio by release month.

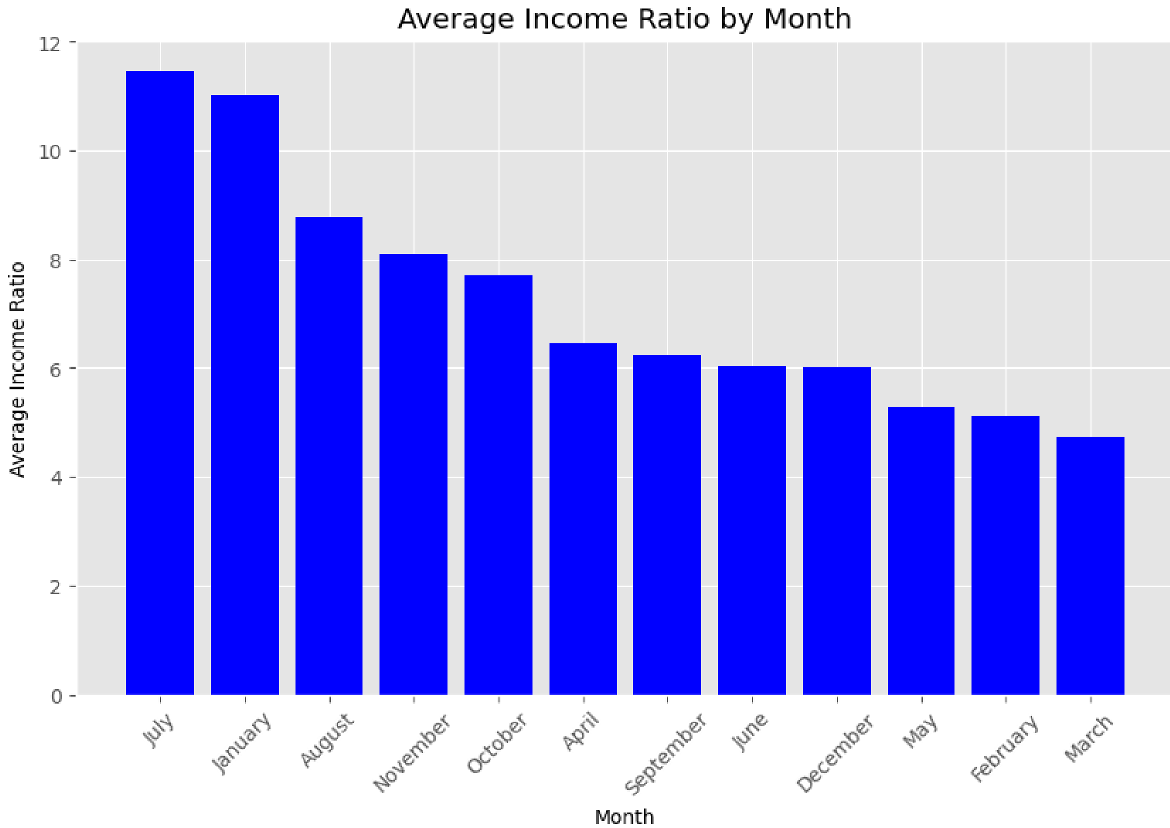
In [43]:
```
# Extracting the month from the release_date column
success_movies['release_months'] = pd.to_datetime(success_movies['release_date

# Calculating the average income ratio by release month
months_income = success_movies.groupby('release_months')['income_ratio'].mean(

# Sorting the results in descending order of average income ratio
months_income = months_income.sort_values('income_ratio', ascending=False)

# Converting the numeric months to month names
months_income['release_months'] = months_income['release_months'].apply(lambda

# Displaying the top records
months_income
```

Out[43]:

	release_months	income_ratio
6	July	11.470000
0	January	11.020202
7	August	8.784091
10	November	8.088000
9	October	7.705357
3	April	6.441667
8	September	6.240000
5	June	6.029703
11	December	6.012903
4	May	5.285714
1	February	5.117021
2	March	4.741935

Plotting a bargraph to visualize the months and their respective income ratio.

In [44]:
```
# Set the plot style to "ggplot"
plt.style.use("ggplot")

# Plotting the bar graph
plt.figure(figsize=(10, 6))
plt.bar(months_income['release_months'], months_income['income_ratio'], color=
plt.title("Average Income Ratio by Month")
plt.xlabel("Month")
plt.ylabel("Average Income Ratio")
plt.xticks(rotation=45)
plt.show()
```



- Considering the income ratio, we can oberseve that the best months to produce a movie is on July, January and August.

Additional Attributes.

Finding the top five most successful indivudual movies, their respective genres and the crew behind the movie.

In [50]:
```
# Selecting the top five most successful movies
top_five_movies = success_movies.nlargest(5, 'income_ratio')

# Extracting genres and directors of the top five movies
genres_directors = top_five_movies[['genres', 'directors','writers']]

# Displaying the result
print(genres_directors)
```

```
                      genres            directors  \
2882  Horror,Mystery,Thriller  nm4000389,nm3951039
287     Biography,Documentary            nm0509852
2296     Action,Drama,Romance            nm9645626
2478     Comedy,Drama,Fantasy           nm10441208
2812                   Horror            nm0068587

                           writers
2882           nm3951039,nm4000389
287                      nm0509852
2296  nm3358805,nm7633074,nm9645626
2478                    nm10441208
2812           nm0068587,nm1834343
```

- From the above dataframe, we can see the genres of top five most successful movies and their respetive principals.

Conclusion

From the above analysis, we can conclude that:

- The combination of Action, Drama and Romance genres had the highest average income ratio.
- Drama movies are the most common genres in successful movies.
- Production budget for a movie can be around $22,000,000.
- Movie release months were fairly distributed throught the year and the best three months to releae a moving considering the income ratio is on July, January and August.

Recommendations

- I would recommend that Microsoft release movies with three genres which include **Drama, Comedy and Thriller**
- Overall, the genre combination: **(Action, Drama, Romance)** topped with being the highest in terms of income ratio and it's worth taking note of.
- Production budget should be 22 to 24 million dollars.
- Release month should be July, January, or August and directed by a top-grossing director with a history of proven successful **Drama, Comedy, or Thriller** movies, such as **nm4000389, nm3951039**, **nm10441208**, or **nm9645626**.