MOVIE ANALYSIS FOR MICROSOFT CORPORATION

Final Project Submission

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OVERVIEW

This project was aimed at helping Microsoft break into the movie industry by obtaining much needed insight into what makes for a great movie. I looked into a wide variety of films produced over the years to see what makes some perform better than others.

From my analysis, the following were the greatest determiners of a movie's success:

- Genre: Different genres appeal to different audiences and certain genres tend to perform better at the box office than others. Genres such as action, adventure, drama and comedies tend to have a wider appeal and thus generate more box office revenue.
- Release Timing: The time of year a movie is released directly impacts its box office performance. Movies released during peak seasons or strategically timed to coincide with holidays or special events tend to perform better.
- Budget: The effectiveness of a movie's production, marketing and promotional campaigns significantly influence its box office success. A larger budget enables the best production methods and teams and wider promotion tours for a movie leading to higher ticket sales.

BUSINESS UNDERSTANDING

Microsoft is a multinational technology company headquatered in Redmond, Washington,USA. They are well known for their software products and services and are now looking to dive into the movie making scene and compete against industry heavy hitters. Microsoft have decided to create a new movie studio but they lack proper insight as to what makes great movies,GREAT! The goal is to analyse some of the most successful box office movies and advice the head of Microsoft's new movie studio on what they need inorder to produce successful films.

DATA UNDERSTANDING

The following were the sources of data I chose for this project:

- ImDb movie database - This is an internet movie database accessible via SQLite3 that contains two tables relevant to my analysis. The first table is the movie basics table that contains the following data: movie id, original and primary movie title, start year, genre, runtime in minutes. The second table is called movie rating and it contains the following data: movie id, average rating and number of votes a movie has garnered.
- Box office mojo (BOM) - BOM is a popular box office data website that analyzes and tracks performance of films in theatres. This dataset contains movie name, domestic and foreign gross, year of production and the studio that produced the movie.
- The Numbers - This website conducts financial analysis of films and tracks box office revenue. This particular dataset contains data on movie production budgets, domestic and worldwide gross revenues and movie release dates.

I began by importing the modules I would require for the entirety of this project.

In [1]:
```
# importing the necessary modules to carry out the project
import pandas as pd
# configuring pandas to display floating point numbers
# to 2 decimal places
pd.options.display.float_format = '{:.2f}'.format
import sqlite3
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

International Movie Database (IMDB)

Then I started assessing the data contained in the movie basics table in the imdb database using SQLite3.

In [2]:
```
# declaring the path to the database
database_path = r'/Users/claire/Desktop/DS-FT08/Project files/im.db'
# connecting to the database
conn = sqlite3.connect(database_path)
# querying the database to view the movie basics table
q = '''
SELECT *
FROM movie_basics;
'''
movie_basics_df = pd.read_sql(q, conn)
# closing the database connection
conn.close()
# previewing the dataframe
movie_basics_df.head()
```

Out[2]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy

In [3]:
```
# assessing information about the dataframe
movie_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

I could see I had some missing values in the original_title column, the start_year column, runtime_minutes and genres column. My major focus was on the genres, runtime minutes and start year column so I went ahead to see what they contained.

In [4]:
```
# assessing the value counts of the top 10 genres
movie_basics_df['genres'].value_counts().head(10)
```

Out[4]:
```
Documentary                 32185
Drama                       21486
Comedy                       9177
Horror                       4372
Comedy,Drama                 3519
Thriller                     3046
Action                       2219
Biography,Documentary        2115
Drama,Romance                2079
Comedy,Drama,Romance         1558
Name: genres, dtype: int64
```

In [5]:
```
# getting descriptive statistics of the runtime minutes column
movie_basics_df['runtime_minutes'].describe()
```

Out[5]:
```
count   114405.00
mean        86.19
std        166.36
min          1.00
25%         70.00
50%         87.00
75%         99.00
max      51420.00
Name: runtime_minutes, dtype: float64
```

Now to view the contents of the movie ratings dataframe.

In [6]:
```
# declaring the path to the database
database_path = r'/Users/claire/Desktop/DS-FT08/Project files/im.db'
# connecting to the database
conn = sqlite3.connect(database_path)
# querying the database to view the movie ratings table
q = '''
SELECT *
FROM movie_ratings;
'''
movie_ratings_df = pd.read_sql(q, conn)
# closing the database connection
conn.close()
# previewing the dataframe
movie_ratings_df.head()
```

Out[6]:

	movie_id	averagerating	numvotes
0	tt10356526	8.30	31
1	tt10384606	8.90	559
2	tt1042974	6.40	20
3	tt1043726	4.20	50352
4	tt1060240	6.50	21

In [7]:
```
# assessing information about the dataframe
movie_ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   movie_id       73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

Luckily there were no missing values so I went on to get descriptive statistics of the average rating column and the numvotes column to get a feel of the data.

In [8]:
```
# getting descriptive statistics of average movie ratings
movie_ratings_df['averagerating'].describe()
```

Out[8]:
```
count   73856.00
mean        6.33
std         1.47
min         1.00
25%         5.50
50%         6.50
75%         7.40
max        10.00
Name: averagerating, dtype: float64
```

In [9]:
```
# getting descriptive statistics of numvotes
movie_ratings_df['numvotes'].describe()
```

Out[9]:
```
count     73856.00
mean       3523.66
std       30294.02
min           5.00
25%          14.00
50%          49.00
75%         282.00
max     1841066.00
Name: numvotes, dtype: float64
```

Merging

I saw that the numvotes column contained some outliers which I would have to deal with along the way. At this point I thought it best to merge the two tables from the imdb database in order to assign the average ratings to specific movies.

In [10]:
```
# merging the movie basics dataframe and the movie ratings dataframe t
# link movie titles and genres and their respective rating
imdb_merged_df = pd.merge(movie_basics_df, movie_ratings_df, how = 'ou
# previewing the top 5 results
imdb_merged_df.head()
```

Out[10]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	av
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crime,Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy	

In [11]:
```
# assessing dataframe info
imdb_merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 146144 entries, 0 to 146143
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
 6   averagerating    73856 non-null   float64
 7   numvotes         73856 non-null   float64
dtypes: float64(3), int64(1), object(4)
memory usage: 10.0+ MB
```

Cleaning

I decided to deal with duplicate values with the same primary title, genre and start year so as to make the data less murky.

In [12]:
```
# looking for duplicate values in relation to the primary title, start
imdb_merged_df.loc[imdb_merged_df.duplicated(subset = ['primary_title'
```

Out[12]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
948	tt10064536	Untitled Disney Marvel Film	Untitled Disney Marvel Film	2022	nan	
949	tt10064558	Untitled Marvel Film	Untitled Marvel Film	2021	nan	
1478	tt10127292	Plushtubers: The Apocalypse	Plushtubers: The Apocalypse	2019	nan	Act
2231	tt10224422	Olanda	Olanda	2019	154.00	
2286	tt10230042	Rok Sako To Rok Lo	Rok Sako To Rok Lo	2018	nan	
...	...	...	...	...	...	
145222	tt9786006	Waiting for the Carnival	Waiting for the Carnival	2019	76.00	
145459	tt9819724	The Tale of Two Deaf Travellers	The Tale of Two Deaf Travellers	2018	5.00	Adventure,Biography,
145559	tt9838402	Furie	Furie	2019	nan	
145903	tt9883728	Congo, My Precious	Congo, My Precious	2017	nan	
145937	tt9889072	The Promise	The Promise	2017	nan	

355 rows × 8 columns

In [13]:
```
# confirming duplicates have same start year, primary titles and genre
imdb_merged_df.loc[imdb_merged_df['primary_title'] == 'Olanda']
```

Out[13]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	average
2001	tt10195890	Olanda	Olanda	2019	154.00	Documentary	
2231	tt10224422	Olanda	Olanda	2019	154.00	Documentary	

In [14]:
```
# confirming duplicates have same start year, primary titles and genre
imdb_merged_df.loc[imdb_merged_df['primary_title'] == 'Furie']
```

Out[14]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averageratin
142723	tt9412268	Furie	Hai Phuong	2019	98.00	Action	6.7
145559	tt9838402	Furie	Furie	2019	nan	Action	na

Since the main aim was to retain only entries with genre values, I decided to drop duplicates with null values.

In [15]:
```
# dropping duplicate values
imdb_merged_df.drop_duplicates(subset=['primary_title', 'start_year',
```

In [16]:
```
# checking on the status of the remaining columns
imdb_merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 145789 entries, 0 to 146143
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         145789 non-null  object 
 1   primary_title    145789 non-null  object 
 2   original_title   145768 non-null  object 
 3   start_year       145789 non-null  int64  
 4   runtime_minutes  114145 non-null  float64
 5   genres           140398 non-null  object 
 6   averagerating    73771 non-null   float64
 7   numvotes         73771 non-null   float64
dtypes: float64(3), int64(1), object(4)
memory usage: 10.0+ MB
```

Now was the time to get rid of unwanted columns to zero in on the target data. I opted to drop the numvotes,start_year,original_title, movie_id columns and runtime_minutes as they would not be relevant to my analysis.

In [17]:
```
# declaring columns to drop in a list
to_drop = ['numvotes', 'start_year', 'original_title', 'movie_id', 'ru
# dropping listed columns
imdb_merged_df.drop(columns = to_drop, axis=1, inplace=True)
```

In [18]:
```
# previewing dataframe columns
imdb_merged_df.columns
```

Out[18]:
```
Index(['primary_title', 'genres', 'averagerating'], dtype='object')
```

In [19]:
```
# renaming the averagerating column to rating
imdb_merged_df = imdb_merged_df.rename(columns = {'averagerating': 'ra
# previewing first 5 results
imdb_merged_df.head()
```

Out[19]:

	title	genres	rating
0	Sunghursh	Action,Crime,Drama	7.00
1	One Day Before the Rainy Season	Biography,Drama	7.20
2	The Other Side of the Wind	Drama	6.90
3	Sabse Bada Sukh	Comedy,Drama	6.10
4	The Wandering Soap Opera	Comedy,Drama,Fantasy	6.50

The next step was to eliminate null values in the rating and genres columns as these would affect the analysis.

In [20]:
```
# checking for null values in order to remove them
imdb_merged_df.isna().sum()
```

Out[20]:
```
title          0
genres      5391
rating     72018
dtype: int64
```

In [21]:
```
# dropping rows containing null values
imdb_merged_df.dropna(subset=['genres', 'rating'], inplace=True)
```

In [22]:
```
# confirming our data is now free of null values
imdb_merged_df.isna().sum()
```

Out[22]:
```
title     0
genres    0
rating    0
dtype: int64
```

In [23]:
```
#final check of the dataframe columns to confirm no missing values
imdb_merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 72967 entries, 0 to 146134
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   title   72967 non-null  object 
 1   genres  72967 non-null  object 
 2   rating  72967 non-null  float64
dtypes: float64(1), object(2)
memory usage: 2.2+ MB
```

In [24]:
```
#saving the dataframe in current directory as a csv file
#imdb_merged_df.to_csv('./imdb_merged_df.csv')
```

Box Office Mojo (BOM)

I decided to look into the Box Office Mojo (bom) movie gross dataset to see what additional insights I would gain.

In [25]:
```
# declaring the file path
file_path = r'/Users/claire/Desktop/DS-FT08/Project files/bom.movie_gr
# reading the csv file into a dataframe
bom_movie_gross_df = pd.read_csv(file_path)
# displaying first five results
bom_movie_gross_df.head()
```

Out[25]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.00	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.00	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.00	664300000	2010
3	Inception	WB	292600000.00	535700000	2010
4	Shrek Forever After	P/DW	238700000.00	513900000	2010

In [26]:
```
# getting information about the dataframe
bom_movie_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [27]:
```
# investigating the years the data spans
bom_movie_gross_df['year'].value_counts()
```

Out[27]:
```
2015    450
2016    436
2012    400
2011    399
2014    395
2013    350
2010    328
2017    321
2018    308
Name: year, dtype: int64
```

In [28]:
```
# getting descriptive statistics of the domestic gross column
bom_movie_gross_df['domestic_gross'].describe()
```

Out[28]:
```
count        3359.00
mean     28745845.07
std      66982498.24
min           100.00
25%        120000.00
50%       1400000.00
75%      27900000.00
max     936700000.00
Name: domestic_gross, dtype: float64
```

In [29]:
```
# getting descriptive statistics of the foreign gross column
bom_movie_gross_df['foreign_gross'].describe()
```

Out[29]:
```
count        2037
unique       1204
top       1200000
freq           23
Name: foreign_gross, dtype: object
```

Cleaning

Upon realizing that data in the foreign gross column was of the type object, I got to changing its format to float64 after stripping any unneccesary commas present in some of the values.

In [30]:
```
# converting data type from object to float64
bom_movie_gross_df['foreign_gross'] = bom_movie_gross_df['foreign_gros
```

In [31]:
```
# confirming data type has changed to float64
bom_movie_gross_df.dtypes
```

Out[31]:
```
title              object
studio             object
domestic_gross    float64
foreign_gross     float64
year                int64
dtype: object
```

In [32]:
```
# getting descriptive statistics of the foreign gross column
bom_movie_gross_df['foreign_gross'].describe()
```

Out[32]:
```
count        2037.00
mean     74872810.15
std     137410600.84
min           600.00
25%       3700000.00
50%      18700000.00
75%      74900000.00
max     960500000.00
Name: foreign_gross, dtype: float64
```

I decided to do away with the studio column and rename the year column to release_year

In [33]:
```
# dropping the studio column
bom_movie_gross_df.drop('studio' ,axis=1, inplace=True)
# previewing first five results of the dataframe
bom_movie_gross_df.head()
```

Out[33]:

	title	domestic_gross	foreign_gross	year
0	Toy Story 3	415000000.00	652000000.00	2010
1	Alice in Wonderland (2010)	334200000.00	691300000.00	2010
2	Harry Potter and the Deathly Hallows Part 1	296000000.00	664300000.00	2010
3	Inception	292600000.00	535700000.00	2010
4	Shrek Forever After	238700000.00	513900000.00	2010

In [34]:
```
# renaming the year column to release_year
bom_movie_gross_df = bom_movie_gross_df.rename(columns = {'year': 'rel
# previewing column names
bom_movie_gross_df.columns
```

Out[34]:
```
Index(['title', 'domestic_gross', 'foreign_gross', 'release_year'],
dtype='object')
```

In [35]:
```
#picking only films produced after 2015
bom_movie_gross_df = bom_movie_gross_df[(bom_movie_gross_df['release_y
```

In [36]:
```
# previewing first 5 results
bom_movie_gross_df.head()
```

Out[36]:

	title	domestic_gross	foreign_gross	release_year
1872	Star Wars: The Force Awakens	936700000.00	1131.60	2015
1873	Jurassic World	652300000.00	1019.40	2015
1874	Furious 7	353000000.00	1163.00	2015
1875	Avengers: Age of Ultron	459000000.00	946400000.00	2015
1876	Minions	336000000.00	823400000.00	2015

In [37]:
```
#saving the dataframe in current directory as a csv file
# bom_movie_gross_df.to_csv('./bom_movie_gross_df.csv')
```

The Numbers dataset

This dataset contained data on the production budget of different movies and how much they grossed domestically and worldwide after the release date. Below is how I went about exploring and cleaning the data.

In [38]:
```
# declaring the file path
file_path = r'/Users/claire/Desktop/DS-FT08/Project files/tn.movie_buc
# reading the csv file into a dataframe
movie_budgets_df = pd.read_csv(file_path)
# displaying first five results
movie_budgets_df.head()
```

Out[38]:

	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 [39]:
```
# assessing the number of rows and columns in the dataframe
movie_budgets_df.shape
```

Out[39]:
```
(5782, 6)
```

In [40]:
```
movie_budgets_df.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   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Cleaning

I was glad to see that the dataset was not missing any values so I decided to dive right into cleaning up the data by configuring the release dates to datetime format and stripping the $ signs and commas from the budget and gross income figures and lastly converting them from objects to integers.

In [41]:
```
# stripping dollar signs and commas from the production budget column 
movie_budgets_df['production_budget'] = movie_budgets_df['production_b
# stripping dollar signs and commas from the domestic gross column and
movie_budgets_df['domestic_gross'] = movie_budgets_df['domestic_gross'
# stripping dollar signs and commas from the worldwide gross column ar
movie_budgets_df['worldwide_gross'] = movie_budgets_df['worldwide_gros
# previewing the dataframe
movie_budgets_df
```

Out[41]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000	0	0
5778	79	Apr 2, 1999	Following	6000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041

5782 rows × 6 columns

I created a new column for gross_profit to see the return on investment in relation to a movie's production budget

In [42]:
```
# creating a new column for gross profit made
movie_budgets_df['gross_profit'] = (movie_budgets_df['worldwide_gross'
# previewing results
movie_budgets_df
```

Out[42]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	gros
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	2351
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-200
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999
...	...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	7000	0	0	
5778	79	Apr 2, 1999	Following	6000	48482	240495	
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338	
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0	
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041	

5782 rows × 7 columns

In [43]:
```
# converting release date to datetime format
movie_budgets_df['release_date'] = pd.to_datetime(movie_budgets_df['re
# creating new column for the release month
movie_budgets_df['release_month'] = movie_budgets_df['release_date'].c
# creating new column for release years
movie_budgets_df['release_year'] = movie_budgets_df['release_date'].dt
# creating new column for release day
movie_budgets_df['release_day'] = movie_budgets_df['release_date'].dt.
# renaming the movie column to title
movie_budgets_df = movie_budgets_df.rename(columns = {'movie': 'title'
# dropping the id column
movie_budgets_df.drop(columns='id', inplace=True)
# previewing dataframe
movie_budgets_df
```

Out[43]:

	release_date	title	production_budget	domestic_gross	worldwide_gross	gross_pro
0	2009-12-18	Avatar	425000000	760507625	2776345279	23513452
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	6350638
2	2019-06-07	Dark Phoenix	350000000	42762350	149762350	-2002376
3	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	10724139
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	9997217
...	...	...	...	...	...	
5777	2018-12-31	Red 11	7000	0	0	-70
5778	1999-04-02	Following	6000	48482	240495	2344
5779	2005-07-13	Return to the Land of Wonders	5000	1338	1338	-36
5780	2015-09-29	A Plague So Pleasant	1400	0	0	-14
5781	2005-08-05	My Date With Drew	1100	181041	181041	1799

5782 rows × 9 columns

In [44]:
```
# filtering only films produced after 2015
movie_budgets_df = movie_budgets_df[(movie_budgets_df['release_year']>
# previewing the first 10 results
movie_budgets_df.head(10)
```

Out[44]:

	release_date	title	production_budget	domestic_gross	worldwide_gross	gross_profit
2	2019-06-07	Dark Phoenix	350000000	42762350	149762350	-200237650
3	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999721747
5	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	1747311220
6	2018-04-27	Avengers: Infinity War	300000000	678815482	2048134200	1748134200
8	2017-11-17	Justice League	300000000	229024295	655945209	355945209
9	2015-11-06	Spectre	300000000	200074175	879620923	579620923
11	2018-05-25	Solo: A Star Wars Story	275000000	213767512	393151347	118151347
16	2016-05-06	Captain America: Civil War	250000000	408084349	1140069413	890069413
17	2016-03-25	Batman v Superman: Dawn of Justice	250000000	330360194	867500281	617500281

In [45]:
```
# checking the final number of rows and columns in the dataframe
movie_budgets_df.shape
```

Out[45]:
```
(938, 9)
```

In [46]:
```
# cofirming there are no null values in the dataframe
movie_budgets_df.isna().sum()
```

Out[46]:
```
release_date         0
title                0
production_budget    0
domestic_gross       0
worldwide_gross      0
gross_profit         0
release_month        0
release_year         0
release_day          0
dtype: int64
```

In [47]:
```
#saving the dataframe in current directory as a csv file
#movie_budgets_df.to_csv('./movie_budgets_df.csv')
```

Merging

Now was the time to merge the three datframes systematically inorder to bring together all the different columns with values that would enable us to derive insights for Microsoft. The first step was to merge the dataframes containing financial data of the different movies. I went with a right join inorder to include all rows from the movie_budgets dataframe and matching rows from the box office mojo dataframe in order to fill in any missing values and kind of get the best of both worlds.

In [48]:
```
# merging the bom_movie_gross dataframe with the movie_budgets datafra
bom_moviebudgets_df = pd.merge(bom_movie_gross_df, movie_budgets_df, h
# creating a new column for foreign gross values
bom_moviebudgets_df['foreign_gross'] = (bom_moviebudgets_df['worldwide
# previewing the top 10 results
bom_moviebudgets_df.head(10)
```

Out[48]:

	title	domestic_gross	foreign_gross	release_year	release_date	production_budget	w
0	Dark Phoenix	42762350	107000000	2019	2019-06-07	350000000	
1	Avengers: Age of Ultron	459005868	944008095	2015	2015-05-01	330600000	
2	Star Wars Ep. VIII: The Last Jedi	620181382	696540365	2017	2017-12-15	317000000	
3	Star Wars Ep. VII: The Force Awakens	936662225	1116648995	2015	2015-12-18	306000000	
4	Avengers: Infinity War	678815482	1369318718	2018	2018-04-27	300000000	
5	Justice League	229024295	426920914	2017	2017-11-17	300000000	
6	Spectre	200074175	679546748	2015	2015-11-06	300000000	
7	Solo: A Star Wars Story	213767512	179383835	2018	2018-05-25	275000000	
8	Captain America: Civil War	408084349	731985064	2016	2016-05-06	250000000	
9	Batman v Superman: Dawn of Justice	330360194	537140087	2016	2016-03-25	250000000	

In [49]:
```
# sorting the dataframe by gross profit in descending order
bom_moviebudgets_df_sorted = bom_moviebudgets_df.sort_values(by= 'gros
bom_moviebudgets_df_sorted.head(10)
```

Out[49]:

	title	domestic_gross	foreign_gross	release_year	release_date	production_budget
4	Avengers: Infinity War	678815482	1369318718	2018	2018-04-27	300000000
3	Star Wars Ep. VII: The Force Awakens	936662225	1116648995	2015	2015-12-18	306000000
13	Jurassic World	652270625	996584239	2015	2015-06-12	215000000
21	Furious 7	353007020	1165715774	2015	2015-04-03	190000000
14	Black Panther	700059566	648198658	2018	2018-02-16	200000000
44	Jurassic World: Fallen Kingdom	417719760	888053039	2018	2018-06-22	170000000
52	Beauty and the Beast	504014165	755185541	2017	2017-03-17	160000000
155	Minions	336045770	824290403	2015	2015-07-10	74000000
1	Avengers: Age of Ultron	459005868	944008095	2015	2015-05-01	330600000
15	Incredibles 2	608581744	633938967	2018	2018-06-15	200000000

In [50]:
```
# previewing number of rows and columns in the merged dataset.
bom_moviebudgets_df_sorted.shape
```

Out[50]:
```
(938, 10)
```

In [51]:
```
# checking for any null values
bom_moviebudgets_df_sorted.isna().sum()
```

Out[51]:
```
title                0
domestic_gross       0
foreign_gross        0
release_year         0
release_date         0
production_budget    0
worldwide_gross      0
gross_profit         0
release_month        0
release_day          0
dtype: int64
```

In [52]:
```
#saving the dataframe in current directory as a csv file
#bom_moviebudgets_df_sorted.to_csv('./bom_moviebudgets_df_sorted.csv')
```

Lastly I performed an inner join/ merge on the imdb_merged dataframe and the earlier merged box office mojo and movie_budgets dataframes to link the movie release details and financials to their respective genres.

In [53]:
```
# merging the imdb_merged dataframe to the bom_moviebudgets dataframe
imdb_bom_moviebudgets_df = pd.merge(imdb_merged_df, bom_moviebudgets_d
# previewing merged dataframe
imdb_bom_moviebudgets_df.head()
```

Out[53]:

	title	genres	rating	domestic_gross	foreign_gross	release_year	relea
0	Jurassic World	Action,Adventure,Sci-Fi	7.00	652270625	996584239	2015	201
1	Alita: Battle Angel	Action,Adventure,Sci-Fi	7.50	85710210	317265826	2019	201
2	Before We Go	Comedy,Drama,Romance	6.80	37151	446787	2015	201
3	Before We Go	Documentary,Drama,News	7.00	37151	446787	2015	201
4	The History of Love	Drama,Romance,War	6.30	0	476624	2016	201

In [54]:
```
# sorting the values in desecnding order by worldwide gross
imdb_bom_moviebudgets_df_sorted = imdb_bom_moviebudgets_df.sort_values
# previewing sorted dataframe
imdb_bom_moviebudgets_df_sorted.head()
```

Out[54]:

	title	genres	rating	domestic_gross	foreign_gross	release_year	releas
788	Avengers: Infinity War	Action,Adventure,Sci-Fi	8.50	678815482	1369318718	2018	201
0	Jurassic World	Action,Adventure,Sci-Fi	7.00	652270625	996584239	2015	201
577	Furious 7	Action,Crime,Thriller	7.20	353007020	1165715774	2015	201
475	Avengers: Age of Ultron	Action,Adventure,Sci-Fi	7.30	459005868	944008095	2015	201
255	Black Panther	Action,Adventure,Sci-Fi	7.30	700059566	648198658	2018	201

In [55]:
```
# previewing number of rows and columns in the dataframe
imdb_bom_moviebudgets_df_sorted.shape
```

Out[55]:
```
(994, 12)
```

In [56]:
```
# checking for any null values in the dataframe
imdb_bom_moviebudgets_df_sorted.isna().sum()
```

Out[56]:
```
title                0
genres               0
rating               0
domestic_gross       0
foreign_gross        0
release_year         0
release_date         0
production_budget    0
worldwide_gross      0
gross_profit         0
release_month        0
release_day          0
dtype: int64
```

In [57]:
```
#saving the dataframe in current directory as a csv file
#imdb_bom_moviebudgets_df_sorted.to_csv('./imdb_bom_moviebudgets_df_sc
```

DATA ANALYSIS

The focus of my analysis would be on three key factors that I concluded were directly related to a movie's success as I went about cleaning and normalizing the data. These three factors were movie genre, the release time(month and day of the week) and the production budget.

Genre

I decided to plot a histogram showing which genres were most popular.

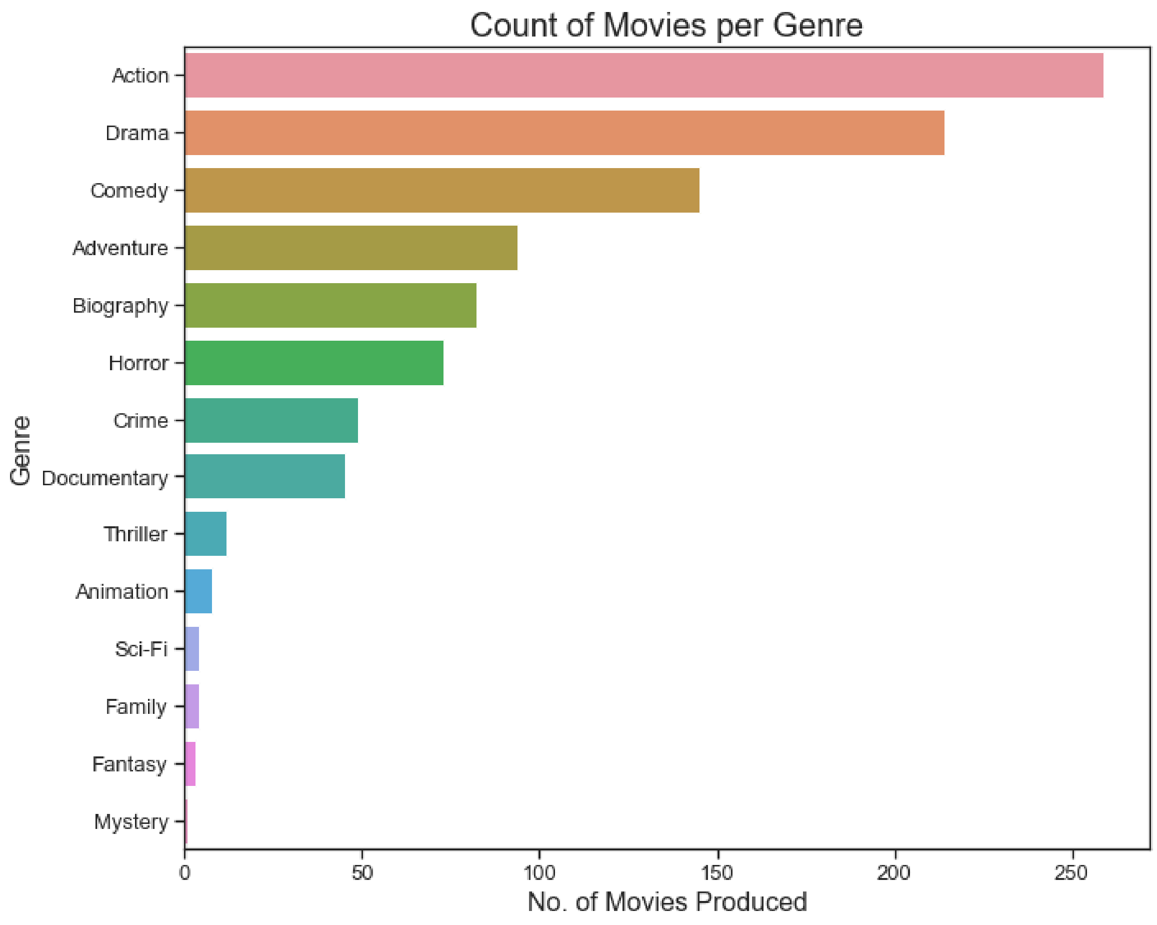
I knew I would have a difficult time trying to visualize all the different genres seeing as some movies had more than two genres associated with them. I decided to define a function that would aggregate the genres into different categories of genres in the film industry.

In [58]:
```
# defining the function
def count_movie_genres(genres_column):
    '''
    This function accepts a column of genres as its input and loops
    through it extracting the first element from a list of strings
    separated by commas. It assumes the first element is the main movi
    genre and confirms its presence in the movie_genres list. It then
    over all the elements increasing their count value by 1 whenever t
    genre is encountered
    '''
# Initializing main movie categories
    movie_genres = ['Action', 'Adventure', 'Animation', 'Biography', '
                    'Family', 'Fantasy', 'History', 'Horror', 'Music',
                    'Thriller', 'War']
# starting count per genre at 0
    genre_count = {genre: 0 for genre in movie_genres}
# looping over all elements in the column and incrementing genres and
    for genres in genres_column:
        movie_genre = genres.split(',')[0]
        if movie_genre in movie_genres:
            genre_count[movie_genre] += 1
# expected output
    return genre_count
# calling the function on the dataset
genre_count = count_movie_genres(imdb_bom_moviebudgets_df['genres'])
# converting dictionary into dataframe
genres_df = pd.DataFrame(list(genre_count.items()), columns=['genre',
# sorting the genres in descending order according to count
genres_df_sorted = genres_df.sort_values(by='count', ascending=False)
# previewing the dataframe
genres_df_sorted.head()
```

Out[58]:

	genre	count
0	Action	259
7	Drama	214
4	Comedy	145
1	Adventure	94
3	Biography	82

In [59]:
```python
# setting size of the figure
plt.figure(figsize=(10,8))
# setting seaborn theme and plotting bar plot
sns.set_theme(style='ticks', palette='deep')
sns.barplot(x='count', y='genre', data=genres_df_sorted.head(14))
# setting x-axis and y-axis labels
plt.xlabel('No. of Movies Produced', fontsize=16)
plt.ylabel('Genre', fontsize=16)
# setting plot title
plt.title('Count of Movies per Genre', fontsize=20)
# setting x-axis and y-axis ticks fontsize
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving the figure
#plt.savefig('./fig1.png');
```



Action movies were the most produced genre according to the dataset. Other popular genres were drama, comedy and adventure movies. Next was to assess which genres had the best return on investment in terms of gross profits. Gross profit was determined by the difference between worldwide gross income and production budget.

First step was to extract the first genre listed in every row of the genres column inorder to group production budgets and gross profits accordingly.

In [60]:
```
# applying a lambda function to the genres column to retrieve the firs
imdb_bom_moviebudgets_df['genres'] = imdb_bom_moviebudgets_df['genres'
# previewing genres column
imdb_bom_moviebudgets_df['genres'].value_counts()
```

Out[60]:
```
Action         259
Drama          214
Comedy         145
Adventure       94
Biography       82
Horror          73
Crime           49
Documentary     45
Thriller        12
Animation        8
Family           4
Sci-Fi           4
Fantasy          3
Mystery          1
Romance          1
Name: genres, dtype: int64
```

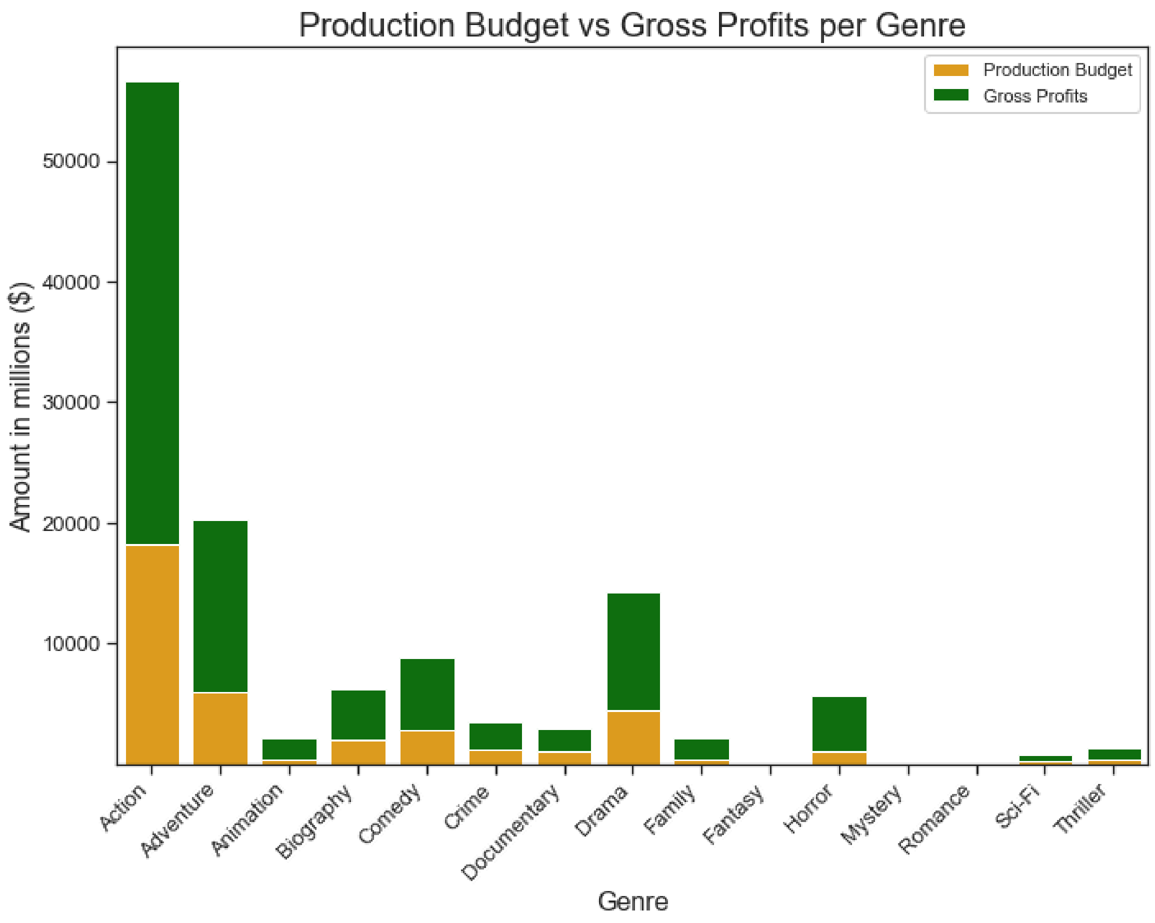
Next step was to convert values in the production budget, gross profits, worldwide, foreign and domestic gross to millions using a lambda function.

In [61]:
```
# defining the lambda function
lambda_function = lambda x: x / 1000000
# applying lambda function to production budget, gross profits,
# worldwide, foreign and domestic gross and creating new columns for v
imdb_bom_moviebudgets_df['gross_profits_mil'] = imdb_bom_moviebudgets_
imdb_bom_moviebudgets_df['production_budget_mil'] = imdb_bom_moviebudg
imdb_bom_moviebudgets_df['world_gross_mil'] = imdb_bom_moviebudgets_df
imdb_bom_moviebudgets_df['dom_gross_mil'] = imdb_bom_moviebudgets_df['
imdb_bom_moviebudgets_df['foreign_gross_mil'] = imdb_bom_moviebudgets_
# previewing changes
imdb_bom_moviebudgets_df.head()
```

Out[61]:

	title	genres	rating	domestic_gross	foreign_gross	release_year	release_date	pr
0	Jurassic World	Action	7.00	652270625	996584239	2015	2015-06-12	
1	Alita: Battle Angel	Action	7.50	85710210	317265826	2019	2019-02-14	
2	Before We Go	Comedy	6.80	37151	446787	2015	2015-09-04	
3	Before We Go	Documentary	7.00	37151	446787	2015	2015-09-04	
4	The History of Love	Drama	6.30	0	476624	2016	2016-11-18	

In [62]:
```
# grouping by genre and summing up production budgets and gross profit
grouped_df = imdb_bom_moviebudgets_df.groupby('genres')[['production_b
# setting seaborn style
sns.set_theme(style='ticks')
# seting size of the figure
plt.figure(figsize=(10, 8))
# plotting stacked bar plot
sns.barplot(data=grouped_df, x='genres', y='production_budget_mil', la
sns.barplot(data=grouped_df, x='genres', y='gross_profits_mil', label=
            bottom=grouped_df['production_budget_mil'])
# setting x-axis and y-axis labels
plt.xlabel('Genre', fontsize=16)
plt.ylabel('Amount in millions ($)', fontsize=16)
# setting plot title
plt.title('Production Budget vs Gross Profits per Genre', fontsize=20)
# setting x-axis and y-axis ticks fontsize
plt.xticks(fontsize=13, rotation=45, ha='right')
plt.yticks(fontsize=13)
# setting legend
plt.legend()
# adjusting layout
plt.tight_layout()
# saving the figure
#plt.savefig('./fig2.png');
```

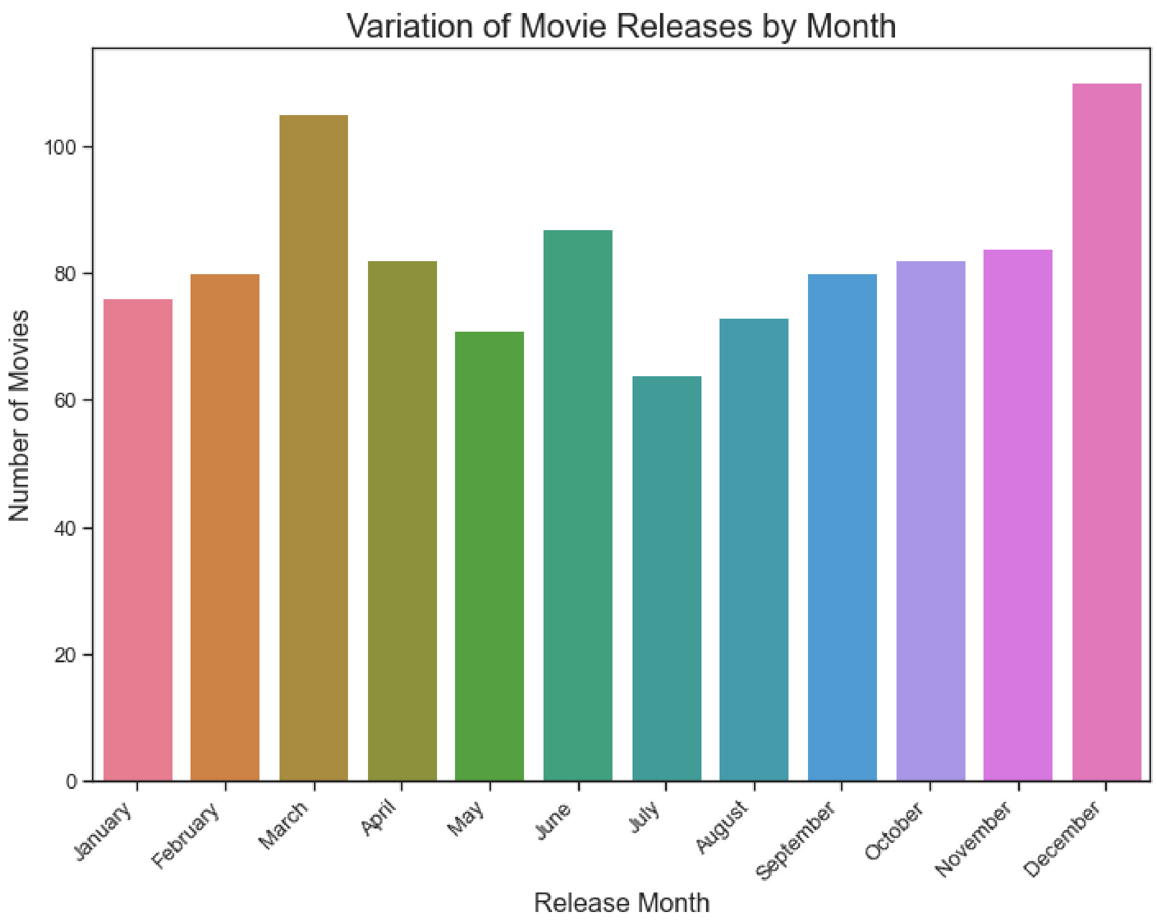


Action movies continued to stand out by raking in the highest gross profits compared to production budget. This is even though action movies had significantly higher production budget. Adventure films seemed to have almost the same production budget as dramas but they posted higher gross profits than dramas. Microsoft would do well to consider those three genres in order to see a sizeable return on their investment.

Release day and month

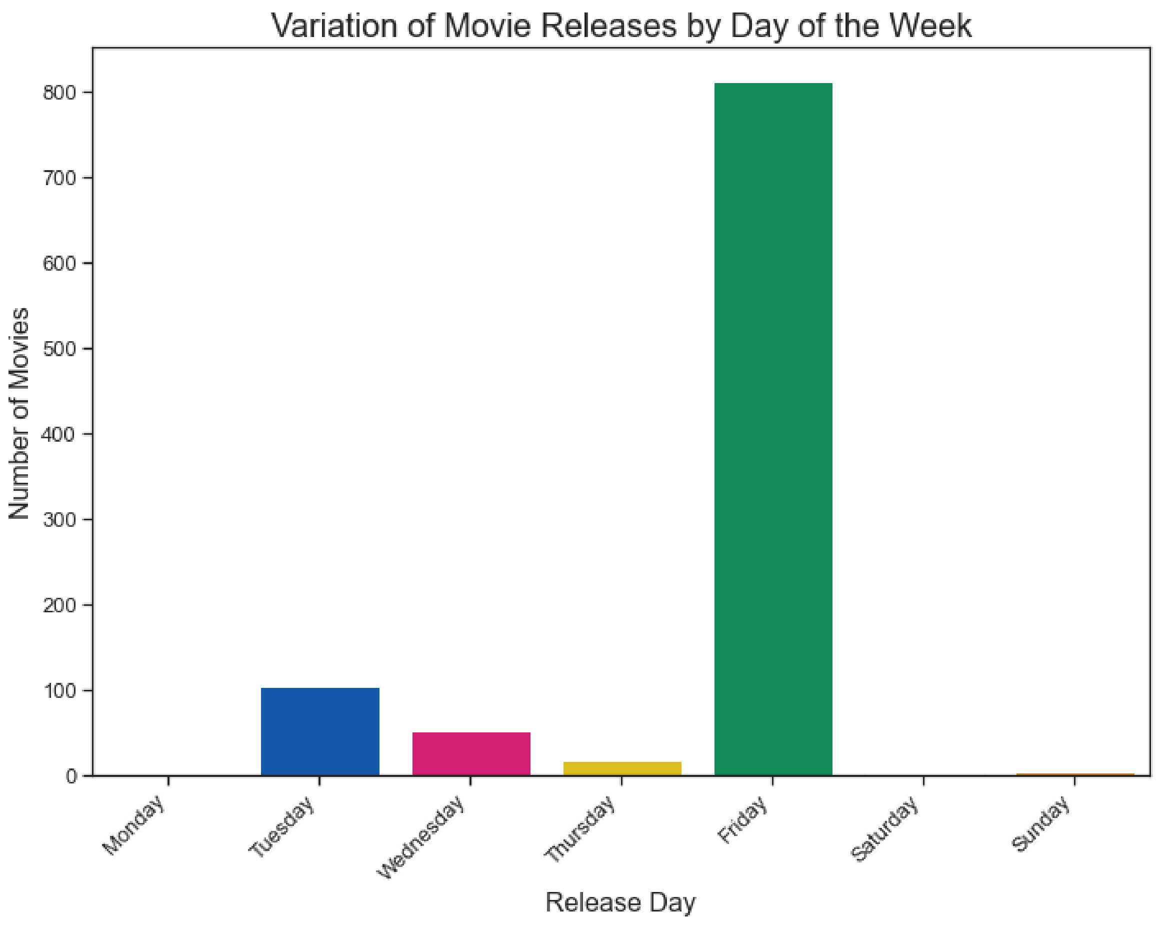
Next I looked at how release timings affect the success of a film. I wanted to see how the release month and day of the week impacted how a movie would perform.

In [63]:
```
# getting value counts of release_month column
months = imdb_bom_moviebudgets_df['release_month'].value_counts().rese
# declaring month columns
months.columns = ['Month', 'Number of Movies']
# setting seaborn theme
sns.set_theme(style='ticks')
# setting size of the figure
plt.figure(figsize=(10, 8))
# plotting bar plot of variation of movie releases by month
sns.barplot(data=months, x='Month', y='Number of Movies', palette='hus
           order = ['January', 'February', 'March', 'April', 'May', 'J
                'July', 'August', 'September', 'October', 'November', '
# setting plot title
plt.title('Variation of Movie Releases by Month', fontsize=20)
# setting x-axis and y-axis labels
plt.xlabel('Release Month', fontsize=16)
plt.ylabel('Number of Movies', fontsize=16)
# setting xticks format to prevent overlapping
plt.xticks(fontsize=13, rotation=45, ha='right')
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving the figure
#plt.savefig('./fig3.png');
```



Most releases occured in March and December with the lowest release months being July, January and May.

In [64]:
```
# getting value counts of release_day column
days = imdb_bom_moviebudgets_df['release_day'].value_counts().reset_ir
# declaring columns
days.columns = ['Day', 'Number of Movies']
# setting seaborn theme
sns.set_theme(style='ticks')
# settting size of the figure
plt.figure(figsize=(10, 8))
# plotting bar plot of variation of movie releases by day of the week
sns.barplot(data=days, x='Day', y='Number of Movies', palette='prism',
            order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Fri
# setting plot title
plt.title('Variation of Movie Releases by Day of the Week', fontsize=2
# setting x-axis and y-axis labels
plt.xlabel('Release Day', fontsize=16)
plt.ylabel('Number of Movies', fontsize=16)
# setting xticks format to avoid overlapping
plt.xticks(fontsize=13,rotation=45, ha='right')
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout();
# saving the figure
#plt.savefig('./fig4.png');
```



Its no surprise that most movies are released on friday because studios aim to take advantage of the weekend box office. This gurantees a larger audience as majority of people have free time from friday evenings all through the weekend to watch new releases.

Budget

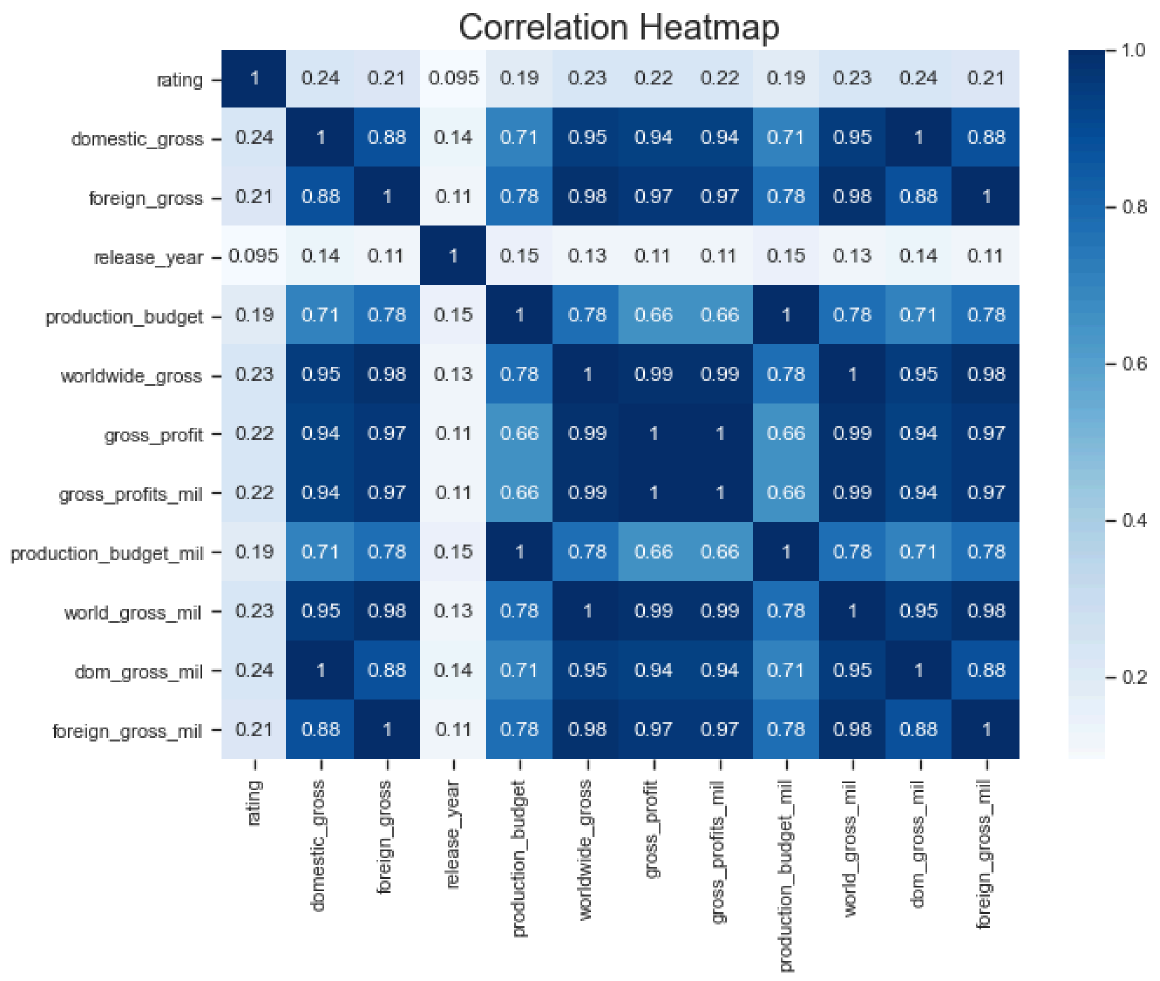
Next I wanted to establish the relationship between production budget and how much a movie grossed domestically and worldwide. I decided to begin by creating a correlation heatmap to explore the correlation of financial variables within the dataset.

In [65]:
```
# gettting the correlation matrix
corr_matrix = imdb_bom_moviebudgets_df.corr()
# previewing coorrlation matrix
corr_matrix
```

Out[65]:

	rating	domestic_gross	foreign_gross	release_year	production_budget
rating	1.00	0.24	0.21	0.09	0.19
domestic_gross	0.24	1.00	0.88	0.14	0.71
foreign_gross	0.21	0.88	1.00	0.11	0.78
release_year	0.09	0.14	0.11	1.00	0.15
production_budget	0.19	0.71	0.78	0.15	1.00
worldwide_gross	0.23	0.95	0.98	0.13	0.78
gross_profit	0.22	0.94	0.97	0.11	0.66
gross_profits_mil	0.22	0.94	0.97	0.11	0.66
production_budget_mil	0.19	0.71	0.78	0.15	1.00
world_gross_mil	0.23	0.95	0.98	0.13	0.78
dom_gross_mil	0.24	1.00	0.88	0.14	0.71
foreign_gross_mil	0.21	0.88	1.00	0.11	0.78

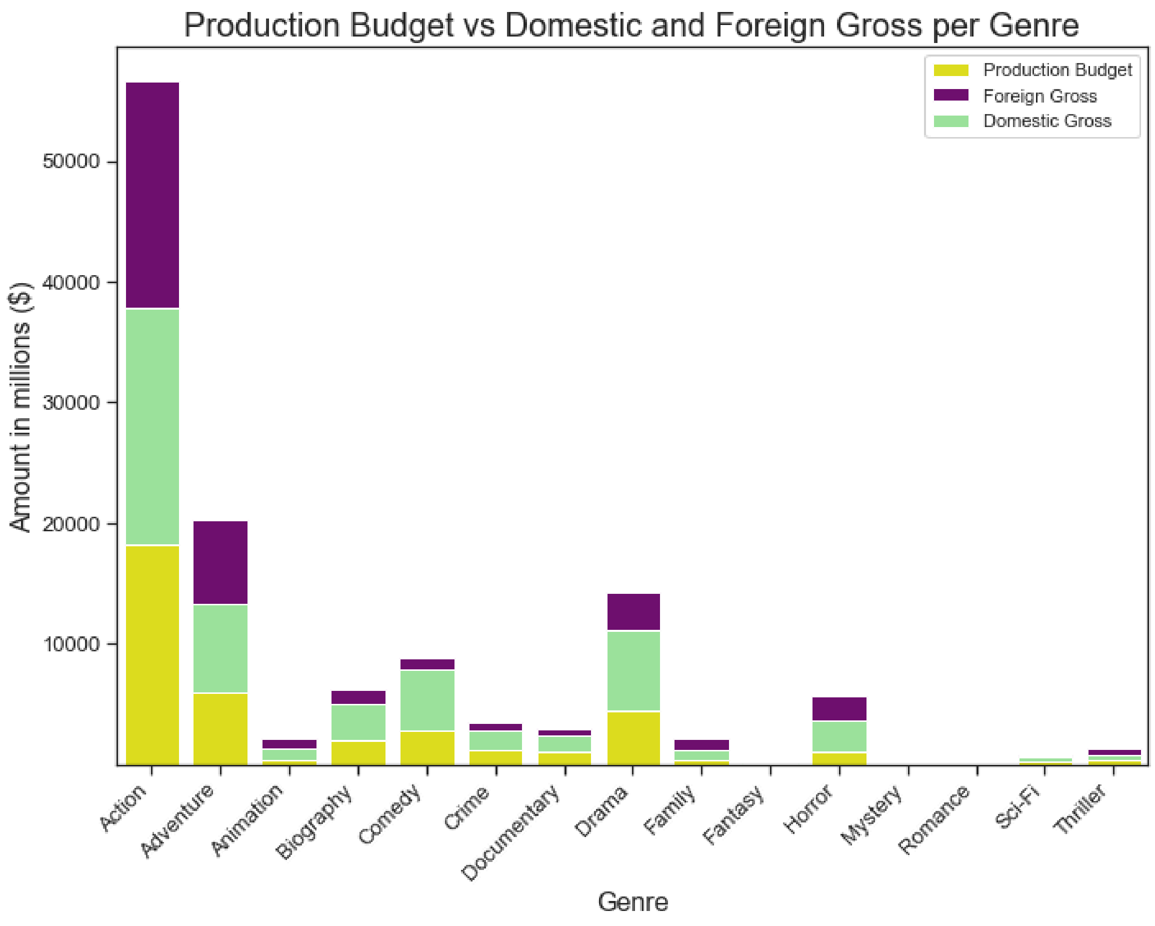
In [66]:
```
# setting size of the figure
plt.figure(figsize=(10,8))
# plotting correlation matrix heatmap and displaying correlation coeffi
sns.heatmap(corr_matrix, cmap='Blues', annot=True)
# setting plot title
plt.title('Correlation Heatmap', fontsize=20)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig5.png');
```



	rating	domestic_gross	foreign_gross	release_year	production_budget	worldwide_gross	gross_profit	gross_profits_mil	production_budget_mil	world_gross_mil	dom_gross_mil	foreign_gross_mil
rating	1	0.24	0.21	0.095	0.19	0.23	0.22	0.22	0.19	0.23	0.24	0.21
domestic_gross	0.24	1	0.88	0.14	0.71	0.95	0.94	0.94	0.71	0.95	1	0.88
foreign_gross	0.21	0.88	1	0.11	0.78	0.98	0.97	0.97	0.78	0.98	0.88	1
release_year	0.095	0.14	0.11	1	0.15	0.13	0.11	0.11	0.15	0.13	0.14	0.11
production_budget	0.19	0.71	0.78	0.15	1	0.78	0.66	0.66	1	0.78	0.71	0.78
worldwide_gross	0.23	0.95	0.98	0.13	0.78	1	0.99	0.99	0.78	1	0.95	0.98
gross_profit	0.22	0.94	0.97	0.11	0.66	0.99	1	1	0.66	0.99	0.94	0.97
gross_profits_mil	0.22	0.94	0.97	0.11	0.66	0.99	1	1	0.66	0.99	0.94	0.97
production_budget_mil	0.19	0.71	0.78	0.15	1	0.78	0.66	0.66	1	0.78	0.71	0.78
world_gross_mil	0.23	0.95	0.98	0.13	0.78	1	0.99	0.99	0.78	1	0.95	0.98
dom_gross_mil	0.24	1	0.88	0.14	0.71	0.95	0.94	0.94	0.71	0.95	1	0.88
foreign_gross_mil	0.21	0.88	1	0.11	0.78	0.98	0.97	0.97	0.78	0.98	0.88	1

The heatmap showed a somewhat strong positive correlations between production budget and foreign and domestic gross. Gross profit had a strong positive correlation with domestic and foreign gross unsurprisingly. I decided to plot a stacked bar chart to see how foreign, domestic and worldwide gross varied per genre.

In [67]:
```
# grouping genres by sum of production budget, foreign and domestic gr
grouped_df_2 = imdb_bom_moviebudgets_df.groupby('genres')[['productior
# setting seaborn theme
sns.set_theme(style='ticks')
# setting size of the figure
plt.figure(figsize=(10, 8))
# plotting stacked bar plot
sns.barplot(data=grouped_df_2, x='genres', y='production_budget_mil',
sns.barplot(data=grouped_df_2, x='genres', y='foreign_gross_mil', labe
            bottom=grouped_df_2['dom_gross_mil'])
sns.barplot(data=grouped_df_2, x='genres', y='dom_gross_mil', label='D
            bottom=grouped_df_2['production_budget_mil'])
# setting x-axis and y_axis labels
plt.xlabel('Genre', fontsize=16)
plt.ylabel('Amount in millions ($)', fontsize=16)
# setting plot title
plt.title('Production Budget vs Domestic and Foreign Gross per Genre',
# setting xticks and yticks format
plt.xticks(fontsize=13, rotation=45, ha='right')
plt.yticks(fontsize=13)
# setting plot legend
plt.legend()
# adjusting layout
plt.tight_layout()
# saving the figure
#plt.savefig('./fig6.png');
```

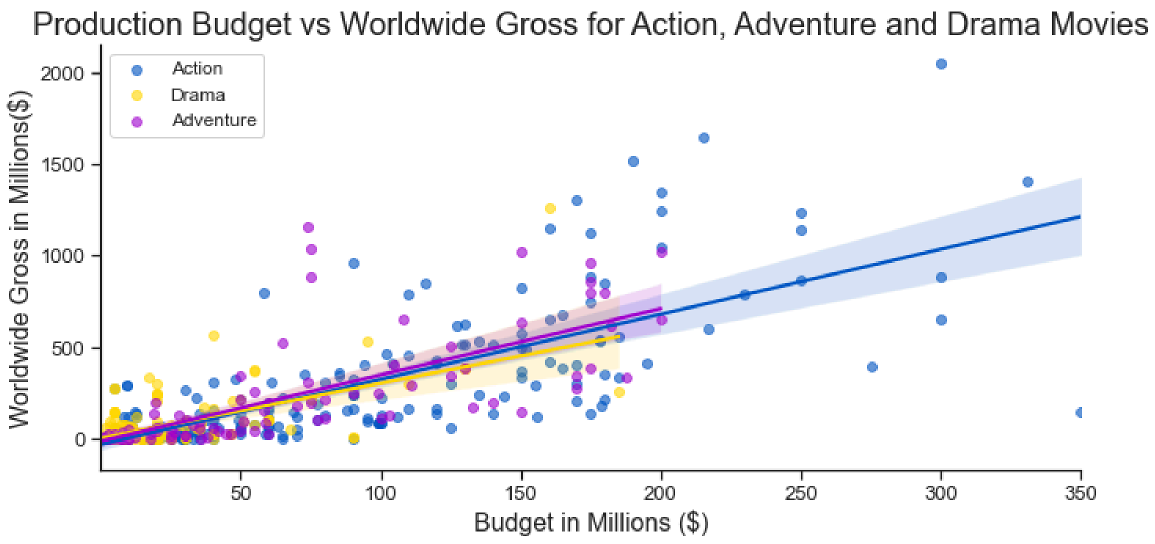


From the stacked bar chart I inferred that action movies being the most produced genre had highest production budgets and in turn made more money in both domestic and foreign markets. Sci-Fi movies, thrillers,family and animation, romance and fantasy movies were generally not produced as frequently as drama, adventure and comedy hence their values

Next I decided to see how changes in production budget affected the worldwide gross of the top 3 genres as per their production budget to gross income ratios depicted above.

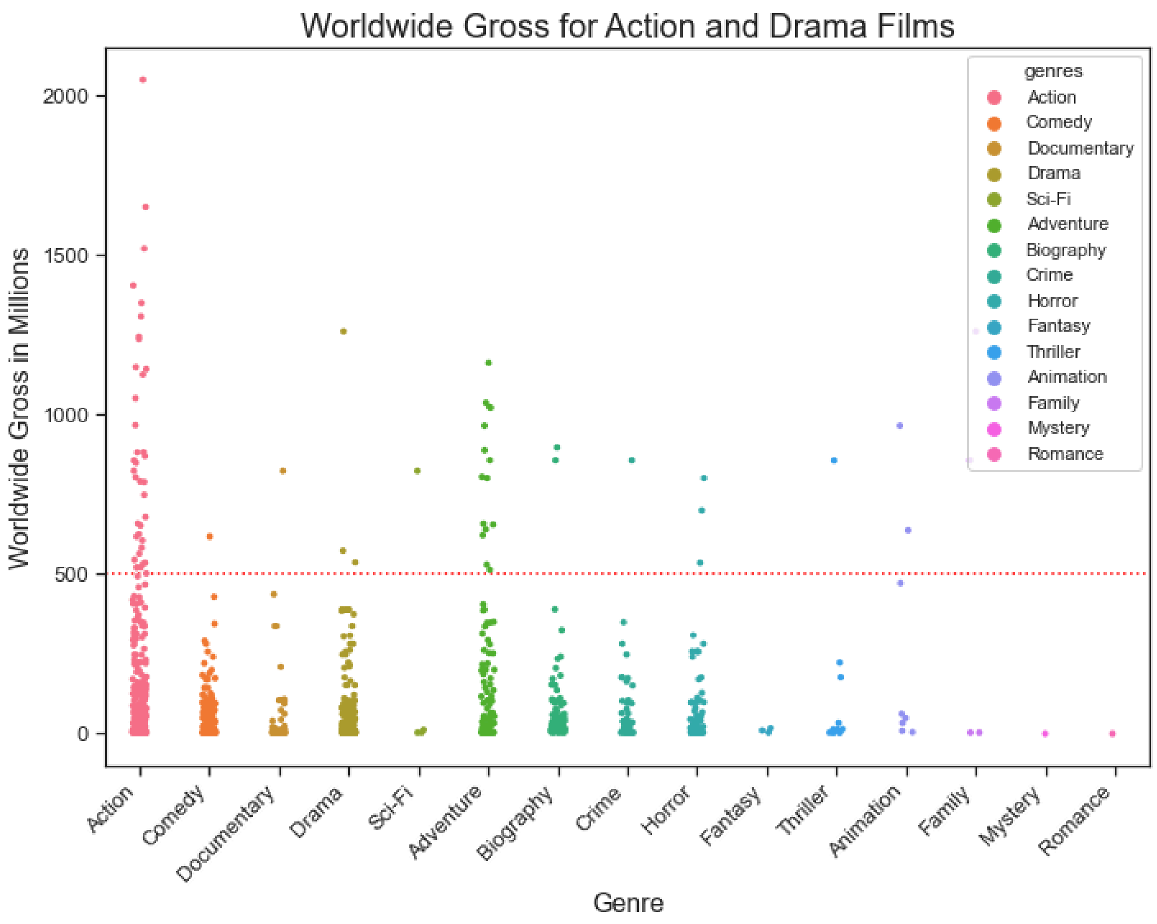
In [68]:
```
# setting size of the figure
plt.figure(figsize=(10,8))
# setting seaborn style
sns.set_style('ticks')
# plotting linear model plot
sns.lmplot(x='production_budget_mil', y='world_gross_mil',
           data=imdb_bom_moviebudgets_df.loc[(imdb_bom_moviebudgets_df
                                             (imdb_bom_moviebudgets_df
                                             (imdb_bom_moviebudgets_df
                                             legend=False, hue='genres
                                             scatter_kws={'alpha': 0.6
# setting x-axis and y-axis labels
plt.xlabel('Budget in Millions ($)', fontsize=16)
plt.ylabel('Worldwide Gross in Millions($)', fontsize=16)
# setting plot title
plt.title('Production Budget vs Worldwide Gross for Action, Adventure
# setting xticks and yticks format
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
# setting legend
plt.legend(loc=2, fontsize=12)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig7.png');
```

```
<Figure size 720x576 with 0 Axes>
```



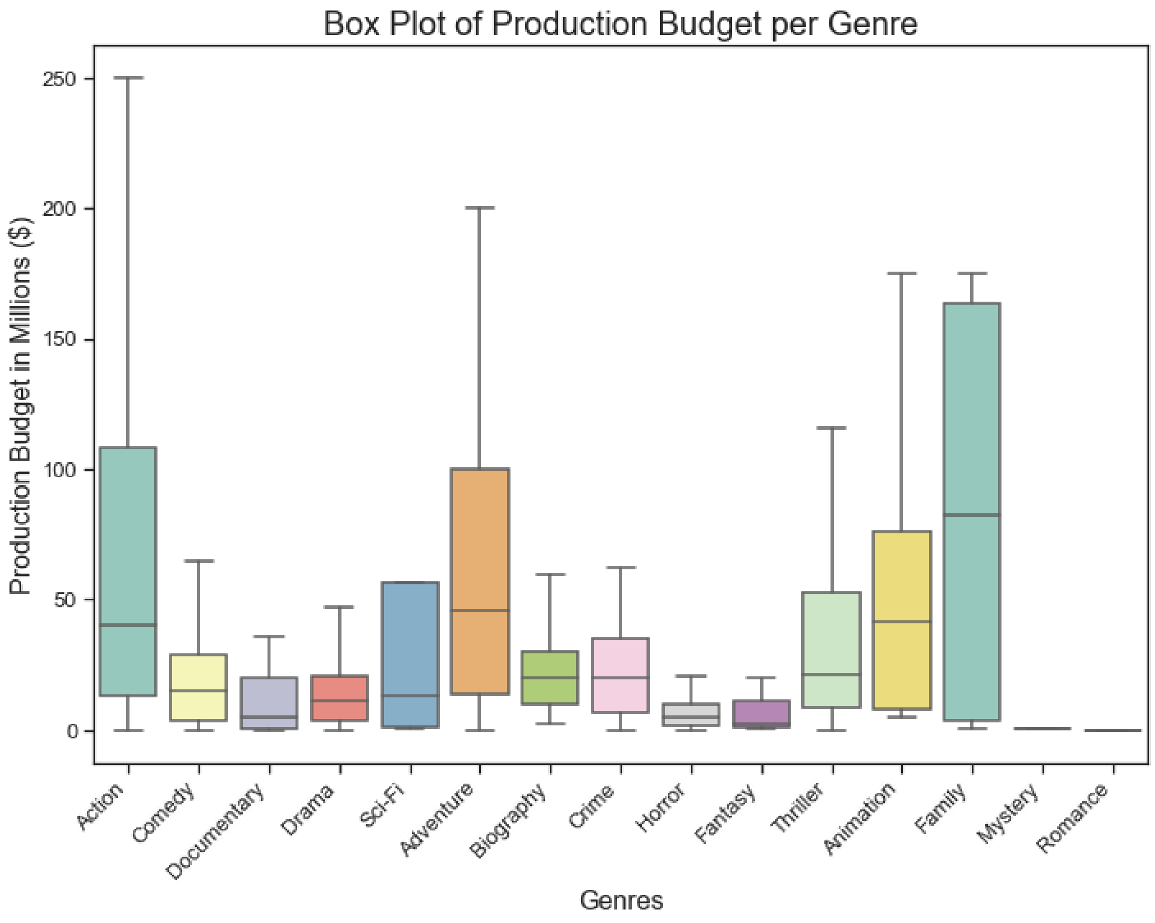
From this regression plot I inferred that lower production budgets translated to lower worldwide gross earnings in most cases. The outliers in the plot mostly represent films that performed exceptionally well or poorly relative to their production budgets. Overall, the general trend was that the higher the production budget, the higher the worldwide gross and the higher the potential return on investment. Vice versa is also true.

```
In [69]: # setting size of the figure
         plt.figure(figsize=(10, 8))
         # setting seaborn style
         sns.set_style('ticks')
         # plotting strip plot
         sns.stripplot( x='genres', y="world_gross_mil", data=imdb_bom_moviebuc
                       hue='genres', s=4, palette='husl')
         # seting x-axis and y-axis labels
         plt.xlabel('Genre', fontsize=16)
         plt.ylabel('Worldwide Gross in Millions', fontsize=16)
         # setting plot title
         plt.title('Worldwide Gross for Action and Drama Films', fontsize=20)
         # setting horizontal line on y=500
         plt.axhline(y=500, c='red', ls=':')
         # setting xticks and yticks format
         plt.xticks(rotation=45, ha='right', fontsize=13)
         plt.yticks(fontsize=13)
         # adjusting layout
         plt.tight_layout()
         # saving figure
         #plt.savefig('./fig8.png');
```



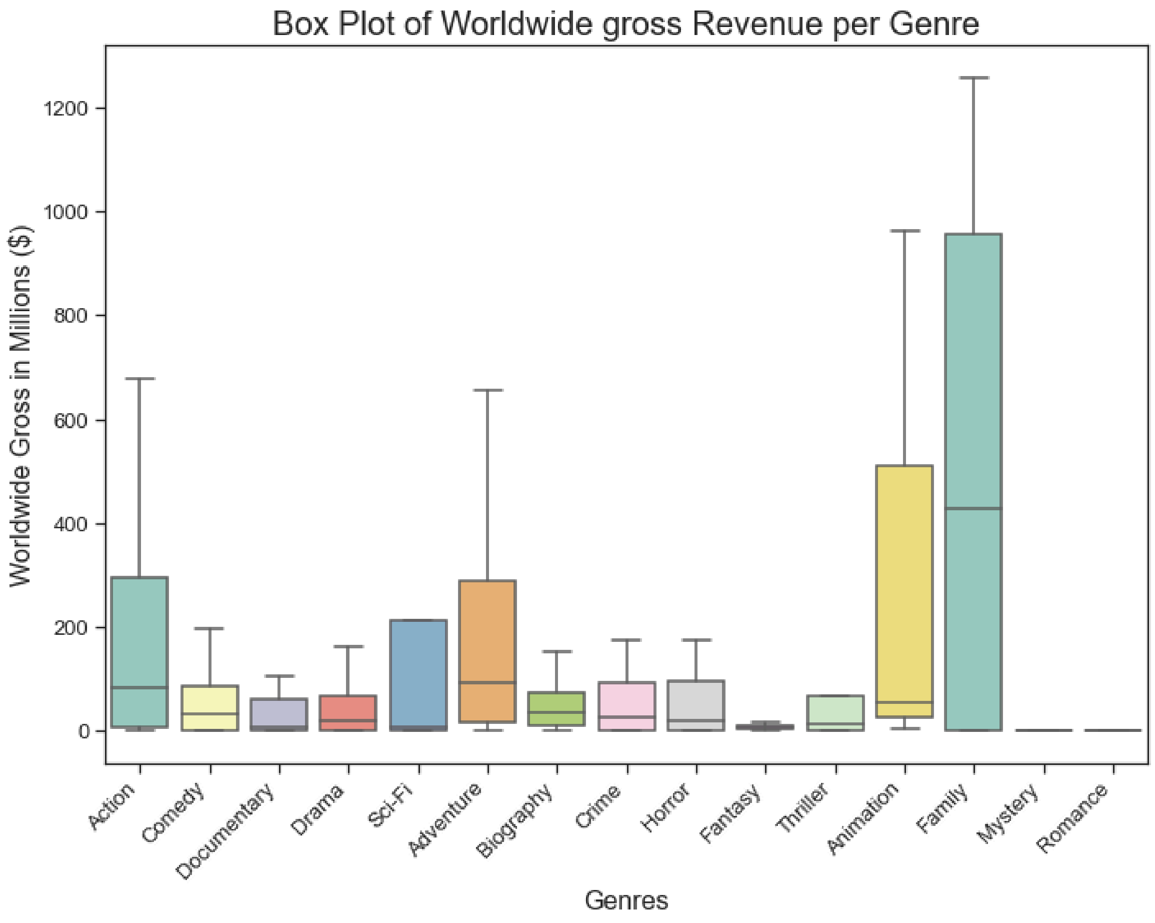
Action and adventure films show alot of promise in terms of how much they gross worldwide so next was to find out the median production budget and worldwide gross of all the genres.

In [70]:
```
# setting size of the figure
plt.figure(figsize=(10, 8))
# setting seaborn style
sns.set_style('ticks')
# ploting boxplot
sns.boxplot(x='genres', y='production_budget_mil', data=imdb_bom_movie
# setting x-axis and y-axis labels
plt.xlabel('Genres', fontsize=16)
plt.ylabel('Production Budget in Millions ($)', fontsize=16)
# setting plot title
plt.title('Box Plot of Production Budget per Genre', fontsize=20)
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right', fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig9.png');
```



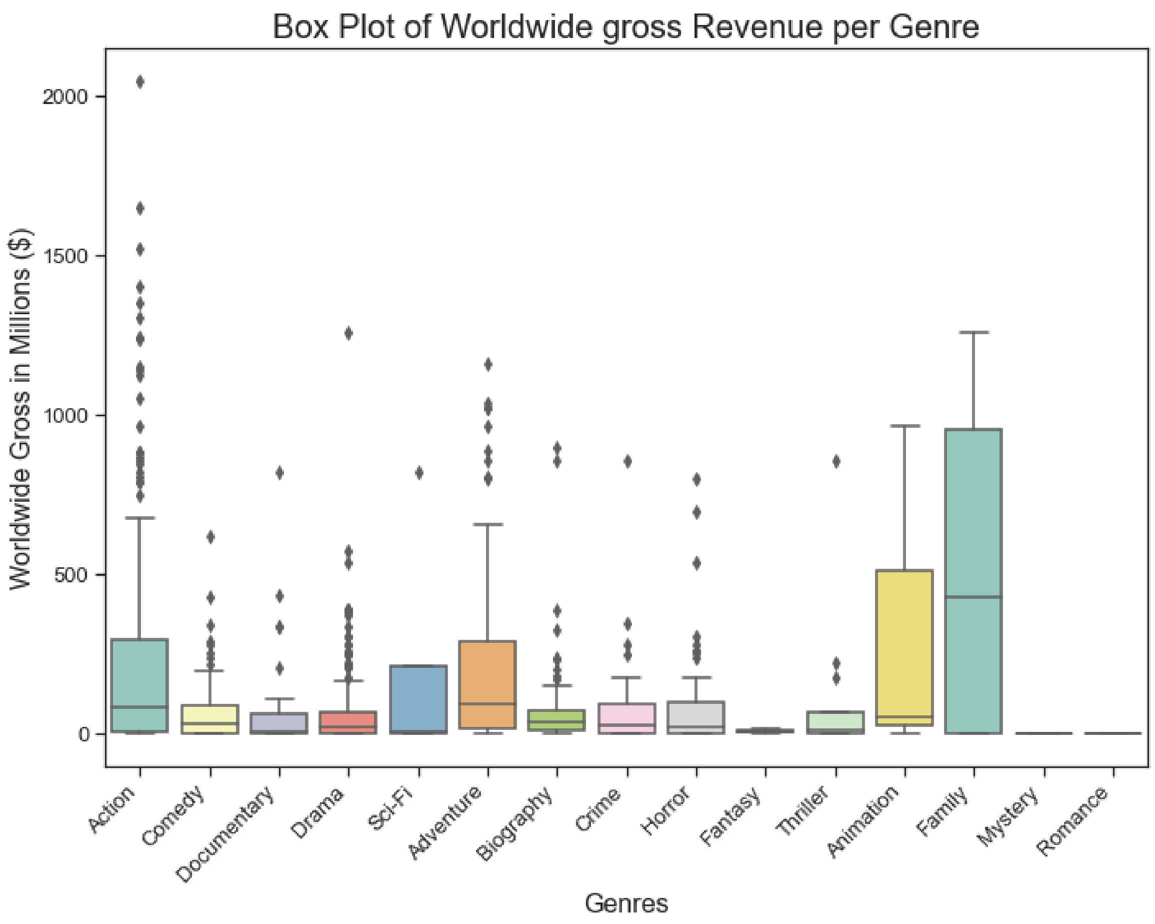
The median production budget of family movies appeared to be the highest followed by animation, action and adventure movies. The boxplot also showed that the family genre had the highest interquartile range meaning that there was a large variance in family movie production budgets from the mean of the dataset and that they had relatively high median budgets. Action movies and adventure movies also depicted high interquartile ranges but significantly lower production budget median values as compared to family type movies.

In [71]:
```
# setting size of the figure
plt.figure(figsize=(10, 8))
# setting seaborn style
sns.set_style=('ticks')
# ploting boxplot
sns.boxplot(x='genres', y='world_gross_mil', data=imdb_bom_moviebudget
# setting x-axis and y-axis labels
plt.xlabel('Genres', fontsize=16)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=16)
# setting plot title
plt.title('Box Plot of Worldwide gross Revenue per Genre', fontsize=2(
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right', fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig10.png');
```



From this plot we can conclude that family movies appear very promising in terms of worldwide gross as they also present a high median value in comparison to the other genres. Action and adventure films follow closely but I suspected that the values were being affected by outliers so I proceeded to visualize the box plot with outliers.

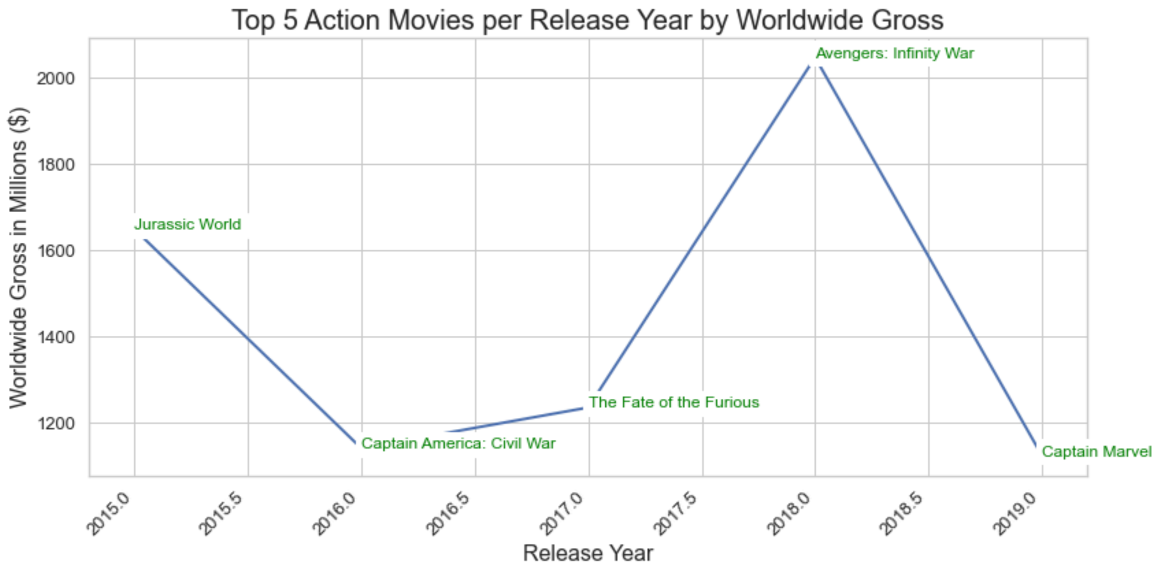
In [72]:
```
# setting size of the figure
plt.figure(figsize=(10, 8))
# setting seaborn style
sns.set_style=('ticks')
# ploting boxplot
sns.boxplot(x='genres', y='world_gross_mil', data=imdb_bom_moviebudget
# setting x-axis and y-axis labels
plt.xlabel('Genres', fontsize=16)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=16)
# setting plot title
plt.title('Box Plot of Worldwide gross Revenue per Genre', fontsize=2(
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right', fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig11.png');
```



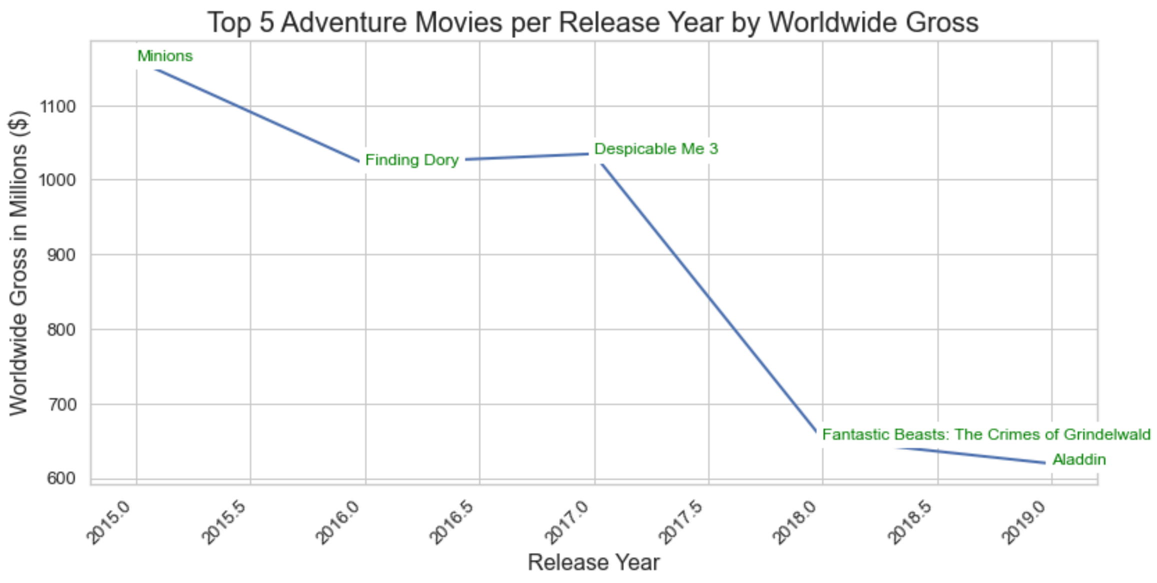
My guess was right. The action and adventure genres did possess a number of outliers and so did all the other genres except for family, animation and fantasy. The family genre continued to look very promising as a genre to invest in terms of median worldwide gross but more research was required in order to make the best informed decision.

The final step was to look at the top grossing movies worldwide per year in the action, adventure and drama categories. This would guide decisions about what actors, directors, producers, crew, agents and PR teams to engage in order to create a winning film.

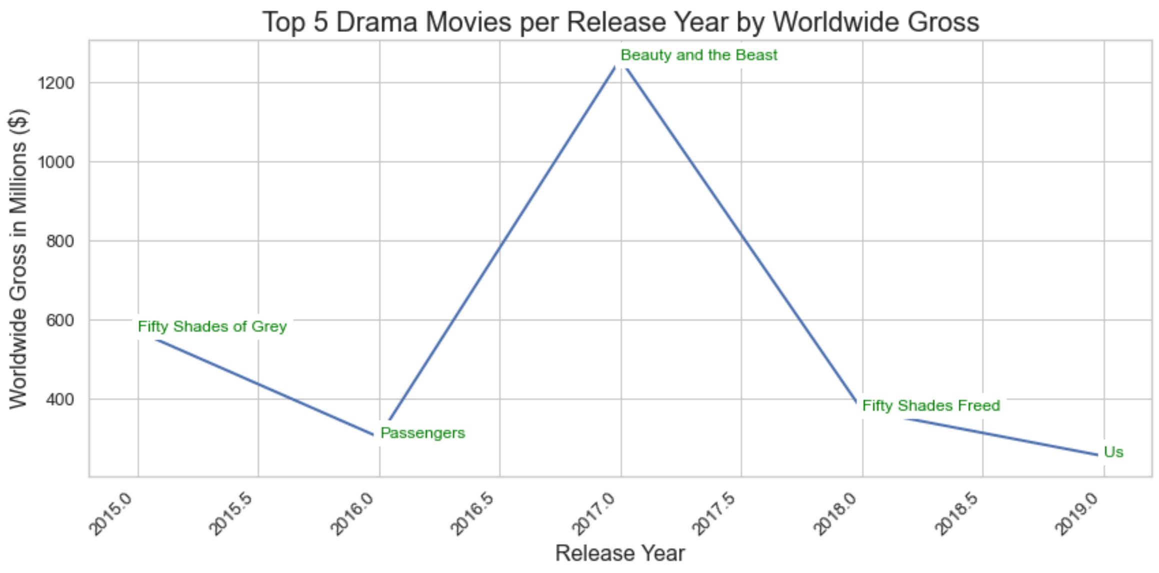
In [73]:
```
# creating new dataframe of action movies
action_movies_df = imdb_bom_moviebudgets_df[imdb_bom_moviebudgets_df['
# grouping by release year and getting sum of worldwide gross
action_grouped_df = action_movies_df.groupby('release_year')['world_gr
# sorting data to identify top 10 action movies per year
top_action_movies= (action_movies_df.sort_values(by='world_gross_mil',
                    .groupby('release_year').head(1))
# setting size of the figure
plt.figure(figsize=(12, 6))
# setting seaborn style
sns.set(style='whitegrid')
# plotting line plot
sns.lineplot(data=action_grouped_df, x='release_year', y='world_gross_
# iterating through each row of top action movies annoting top action
for i , row in top_action_movies.iterrows():
    plt.text(row['release_year'], row['world_gross_mil'], row['title']
             horizontalalignment='left', fontsize=12, color='green',).
# setting x-axis and y-axis labels
plt.xlabel('Release Year', fontsize=16)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=16)
# setting plot title
plt.title('Top 5 Action Movies per Release Year by Worldwide Gross', f
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right',fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig12.png');
```



In [74]:
```
# creating new dataframe of action movies
adventure_movies_df = imdb_bom_moviebudgets_df[imdb_bom_moviebudgets_d
# grouping by release year and getting sum of worldwide gross
adv_grouped_df = adventure_movies_df.groupby('release_year')['world_gr
# sorting data to identify top 10 action movies per year
top_adventure_movies= (adventure_movies_df.sort_values(by='world_gross
                    .groupby('release_year').head(1))
# setting size of the figure
plt.figure(figsize=(12, 6))
# setting seaborn style
sns.set(style='whitegrid')
# plotting line plot
sns.lineplot(data=adv_grouped_df, x='release_year', y='world_gross_mil
# iterating through each row of top action movies annoting top action
for i , row in top_adventure_movies.iterrows():
    plt.text(row['release_year'], row['world_gross_mil'], row['title']
             horizontalalignment='left', fontsize=12, color='green',).
# setting x-axis and y-axis labels
plt.xlabel('Release Year', fontsize=16)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=16)
# setting plot title
plt.title('Top 5 Adventure Movies per Release Year by Worldwide Gross'
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right',fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig13.png');
```



In [75]:
```
# creating new dataframe of action movies
drama_movies_df = imdb_bom_moviebudgets_df[imdb_bom_moviebudgets_df['g
# grouping by release year and getting sum of worldwide gross
drama_grouped_df = drama_movies_df.groupby('release_year')['world_gros
# sorting data to identify top 10 action movies per year
top_drama_movies= (drama_movies_df.sort_values(by='world_gross_mil', a
                    .groupby('release_year').head(1))
# setting size of the figure
plt.figure(figsize=(12, 6))
# setting seaborn style
sns.set(style='whitegrid')
# plotting line plot
sns.lineplot(data=drama_grouped_df, x='release_year', y='world_gross_m
# iterating through each row of top action movies annoting top action 
for i , row in top_drama_movies.iterrows():
    plt.text(row['release_year'], row['world_gross_mil'], row['title']
             horizontalalignment='left', fontsize=12, color='green',).
# setting x-axis and y-axis labels
plt.xlabel('Release Year', fontsize=16)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=16)
# setting plot title
plt.title('Top 5 Drama Movies per Release Year by Worldwide Gross', fo
# setting xticks and yticks format
plt.xticks(rotation=45, ha='right',fontsize=13)
plt.yticks(fontsize=13)
# adjusting layout
plt.tight_layout()
# saving figure
#plt.savefig('./fig14.png');
```



CONCLUSIONS

Microsoft stands a great chance at breaking into the movie industry by taking into consideration these three factors:

- Genre - The top 5 most produced genres in the movie industry are acttion, drama, comedy, adventure and biographies. These depict genres that have been tried and tested as being popular with a wide variety of masses. If microsoft focuses its attention on these genres they are guaranteed to successfully attract audiences the world over and break into the movie scene in an earth-shattering way.

- Release day - Microsoft should aim to release their movies on fridays for maximum success. Friday being the end of the week makes it the most ideal period for moviegoers to visit theatres and watch new movie releases. Many movie studios strategically choose Fridays for releases to maximize box office earnings. This is because movies have more time to attract larger audiences and generate higher revenue. By creating buzz in the days before the day of release, a movie is guaranteed great success.
- Release month - The period between March to June is very popular with movie releases and according to research, many critically acclaimed films that win at the Oscars are released in March and April. This can be a contributing factor to Microsoft's success. May to August also witnesses a rise in movie releases as movie studios count on the summer months to take advantage of the larger audience and school vacations. Summer break also means that families have more opportunities to go out for entertainment. Family films have a better opportunity when released from late November to December as this is the period of holidays such as Thanksgiving, Christmas, and New Year. The festive spirit means that families have a higher likelihood of going to movies together thus making it a good time for family-oriented films.
- Budget - My analysis has shown that the more money that is put into producing a film, the more money there stands to be made in terms of domestic and foreign revenue. Less investment into producing a film will mean that production quality will be compromised. A higher budget will enable a movie studio to enlist top-tier actors, invest in high-quality special effects and CGI, create elaborate sets and producee captivating cinematography for its audience. This will have the domino effect of attracting more viewers. A larger budget will also enable effective marketing and promotional campaigns creating buzz and generating anticipation among audiences leading to higher ticket sales across multiple theaters both domestically and internationally.

RECOMMENDATIONS

I would recommend that Microsoft do the following:

- Produce an action film preferably a superhero movie seeing as three of the five top grossing action films worldwide between 2015 and 2019 are superhero movies. They should aim for a production budget of between 150 to 300 million dollars and aim to release the movie between March and June. This is the best time period for a demographic that enjoys superhero action films. Microsoft should also enlist a top-grossing superhero movie director for their premier film. As worlwide gross income numbers are to go by, they should work with the Russo brothers (Anthony and Joseph Russo) who are the directors of the movie Avengers: Infinity War.
- Microsoft should also aim to produce an adventure movie going by budget to worldwide gross income ratio. The top three adventure movies between 2015 and 2019 are animation comedy adventure films that appeal to younger and older audiences. This movie should be released between May and July during school summer breaks guaranteeing a massive audience of kids and parents alike. The production budget should be set around the median which is between 70 to 100 million dollars. Microsoft should also aim to enlist top animation producers such as Pierre Coffin who has directed both Minions and Despicable Me, Kyle Balda from Minions or Andrew Stanton from Finding Dory.
- Microsoft can also produce a romantic drama going by 3 of the top 5 drama movies in the 2015 to 2019 time period. Two of these are the Fifty Shades franchise so Microsooft can enlist top directors proficient in the genre. Some of them are James Foley from Fifty

Shades Freed and Morten TTyldum from the movie Passengers. The production budget should be between 50 and 100 million dollars.

NEXT STEPS

- Invest in the best producers, screenwriters, actors and cinematographers per genre in the recommendations.
- Get the best suited sound, design, costumes and art crew for each movie.
- Invest in the highest quality sound, music, visual and special effects software and hardware in the market to ensure the best quality of production.
- Enlist the best PR and marketing firms to boost advertising, marketing and distribution of their upcoming films.
- Research on the feasibility and viability of producing a family film.

REFERENCES

Image by upklyak on Freepik (https://www.freepik.com/free-vector/film-crew-movie-production-studio-staff_29314759.htm#fromView=search&page=1&position=8&uuid=1c379553-fabc-44ff-a8ab-f4c3d5519362)