EXPLORATORY DATA ANALYSIS FOR A NEW MOTION PICTURE STUDIO

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Introduction

Exploratory Data Analysis (EDA) is important for emerging studios into the ever-changing landscape of the entertainment business when it comes to what works at the boxoffice. This project performs exploratory data analysis on historical film data, looking for patterns that tie to the financial results of the film. Popular Genre, Release Timing, Budget Allocation, and Consumer Reception analysis will help to obtain actionable insights for a nascent movie studio's content planning. The studio can make data-informed production decisions according to the market and future pattern which align so that the

Project Overview

Business Problem

Your company now sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of your company's new movie studio can use to help decide what type of films to create.

Business Understanding

The company is venturing into the interesting global of filmmaking with the release of a new movie studio. However, getting into the film industry with out prior revel in comes with its demanding situations. To ensure the studio starts strong, our role as data analysts is to dive deep into the dynamics of the film industry. By knowledge what drives container office achievement, we are able to offer actionable insights to assist form the studio's content advent and manufacturing strategies.

To do this, we'll discover key questions about the enterprise:

1. How many movies are released each year/month?
2. Which genre is most successful at the box office?
3. Which production budget range yield the most profitable movies?

Data Understanding

For the exploratory analysis, we will make use of data collected from the following sources:

Box Office(https://www.boxofficemojo.com/ (https://www.boxofficemojo.com/))

IMDB(https://www.imdb.com/ (https://www.imdb.com/))

Rotten Tomatoes(https://www.rottentomatoes.com/ (https://www.rottentomatoes.com/))

TheMovieDB(https://www.themoviedb.org/ (https://www.themoviedb.org/))

The Numbers (https://www.the-numbers.com/ (https://www.the-numbers.com/))

Data Cleaning and Preparation

In [94]:

```
#Import the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sqlite3
import seaborn as sns
%matplotlib inline
```

IMDB database

Creating a connection where we will be able to view and analyze what is in the database

In [95]:
```
#Loading imdb database
conn = sqlite3.connect('zippedData/im.db')

movie_basics = pd.read_sql_query("SELECT * FROM movie_basics", conn)
movie_ratings = pd.read_sql_query("SELECT * FROM movie_ratings", conn)
```

In [96]:
```
# Check for missing values in each DataFrame
print("Movie Basics Missing Values:\n", movie_basics.isnull().sum())
print("\nMovie Ratings Missing Values:\n", movie_ratings.isnull().sum())
```

```
Movie Basics Missing Values:
 movie_id              0
primary_title         0
original_title       21
start_year            0
runtime_minutes    31739
genres              5408
dtype: int64

Movie Ratings Missing Values:
 movie_id        0
averagerating    0
numvotes         0
dtype: int64
```

In [97]:
```
# Drop rows with missing 'genres' in movie_basics
movie_basics.dropna(subset=['genres'], inplace=True)
movie_ratings.dropna(inplace=True)
```

In [98]:
```
#Fill the missing values in runtime_minutes with its mode
mode_runtime = movie_basics['runtime_minutes'].mode()[0]
movie_basics['runtime_minutes'].fillna(mode_runtime, inplace=True)
```

In [99]:
```
#Convert runtime_minutes into numeric data type
movie_basics['runtime_minutes'] = pd.to_numeric(movie_basics['runtime_minutes']
```

In [100]:
```
# Use inner join to keep only matching rows
movie_data = pd.merge(movie_basics, movie_ratings, on='movie_id', how='inner')
movie_data
```

Out[100]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genre
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dram
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dram
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dram
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	90.0	Comedy,Dram
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantas
...	...	...	...	...	...	.

Here we will be able to see which genre has the most shows produced and also we will check the top 10 rate movies and from which genre they are from.

In [101]:
```
# Analyze genre distribution
genre_counts = movie_basics['genres'].str.split(',', expand=True).stack().value
print("\nGenre Counts:\n", genre_counts)
```

```

Genre Counts:
 Documentary    51640
Drama          49883
Comedy         25312
Thriller       11883
Horror         10805
Action         10335
Romance         9372
Biography       8722
Crime           6753
Adventure       6465
Family          6227
History         6225
Mystery         4659
Music           4314
Fantasy         3516
Sci-Fi          3365
Animation       2799
Sport           2234
News            1551
Musical         1430
War             1405
Western          467
Reality-TV        98
Talk-Show         50
Adult             25
Short             11
Game-Show          4
dtype: int64
```

In [102]:
```
top_rated_movies= pd.read_sql('''
            SELECT primary_title, genres, averagerating, numvotes
            FROM movie_basics
            JOIN movie_ratings
            USING(movie_id)
            ORDER BY averagerating DESC
            ''', conn).head(10)

top_rated_movies
```

Out[102]:

	primary_title	genres	averagerating	numvotes
0	Exteriores: Mulheres Brasileiras na Diplomacia	Documentary	10.0	5
1	The Dark Knight: The Ballad of the N Word	Comedy,Drama	10.0	5
2	Freeing Bernie Baran	Crime,Documentary	10.0	5
3	Hercule contre Hermès	Documentary	10.0	5
4	I Was Born Yesterday!	Documentary	10.0	6
5	Dog Days in the Heartland	Drama	10.0	5
6	Revolution Food	Documentary	10.0	8
7	Fly High: Story of the Disc Dog	Documentary	10.0	7
8	All Around Us	Documentary	10.0	6
9	The Paternal Bond: Barbary Macaques	Documentary	10.0	5

From the output above we can see that Documentaries are dominating the top 10 movies table. This shows that people enjoy watching documentaries more.

In [103]:
```
# Acquire writers name from writer and persons table

writers_query = """
SELECT writers.movie_id, persons.primary_name AS writers_names
FROM writers
JOIN persons ON writers.person_id = persons.person_id;
"""

writers_df = pd.read_sql(writers_query, conn)
writers_df
```

Out[103]:

	movie_id	writers_names
0	tt0285252	Tony Vitale
1	tt0438973	Steve Conrad
2	tt0438973	Sean Sorensen
3	tt0462036	Bill Haley
4	tt0835418	Peter Gaulke
...	...	...
255866	tt8999892	Bradley T. Castle
255867	tt8999974	Daysi Burbano
255868	tt9001390	Bernard Lessa
255869	tt9004986	Fredrik Horn Akselsen
255870	tt9010172	Vibol S. Sungkriem

In [104]:

```
conn.close()
```

A. Loading Data

At this section we will load all the datasets from various trusted sources; clean to make it make sense then do some exploration for the next section after this which will be data analysis.

1. Movie Info tsv file

In [105]:

```python
movie_info_df = pd.read_csv('./zippedData/rt.movie_info.tsv', sep='\t')
print(movie_info_df.shape)
print(movie_info_df.info())
movie_info_df.head()
```

```
(1560, 12)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            1560 non-null   int64 
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
None
```

Out[105]:

	id	synopsis	rating	genre	director	writer	theater_date	dvc
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	S
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	A
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	A
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	

2. Reviews tsv file

In [106]:

```
reviews_df = pd.read_csv('./zippedData/rt.reviews.tsv', sep='\t', header=0, enc
print(reviews_df.shape)
print(reviews_df.info())
reviews_df.head()
```

```
(54432, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          54432 non-null  int64 
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64 
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
None
```

Out[106]:

id	review	rating	fresh	critic	top_critic	publisher	date

In [107]:

```
reviews_df["rating"]
```

Out[107]:

```
0          3/5
1          NaN
2          NaN
3          NaN
4          NaN
         ...
54427      NaN
54428      1/5
54429      2/5
54430    2.5/5
54431      3/5
Name: rating, Length: 54432, dtype: object
```

In [108]:

```
#Filling in the missing values

#filling missing reviews with "No review available" to distinguish them from ac
reviews_df['review'].fillna("No review available", inplace=True)

#Extract valid numeric ratings in the form "x/y"
numeric_ratings = reviews_df['rating'].str.extract(r'(\d+(\.\d+)?)/\d+').astype

#Assign numeric values back to `rating` and fill missing values with the median
reviews_df['rating'] = numeric_ratings[0]
reviews_df['rating'].fillna(reviews_df['rating'].median(), inplace=True)
```

In [109]:
```
reviews_df["rating"]
```

Out[109]:
```
0        3.0
1        3.0
2        3.0
3        3.0
4        3.0
        ...
54427    3.0
54428    1.0
54429    2.0
54430    2.5
54431    3.0
Name: rating, Length: 54432, dtype: float64
```

3. Movie Budgets tsv file

In [110]:
```
movie_budget_df = pd.read_csv('./zippedData/tn.movie_budgets.csv')
print(movie_budget_df.shape)
print(movie_budget_df.info())
movie_budget_df.head()
```

```
 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
None
```

Out[110]:

	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	$330,600,000	$459,005,868	$1,403,013,963

In [111]:
```
movie_budget_df.describe(include = 'all')
```

Out[111]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
count	5782.000000	5782	5782	5782	5782	5782
unique	NaN	2418	5698	509	5164	5356
top	NaN	Dec 31, 2014	King Kong	$20,000,000	$0	$0
freq	NaN	24	3	231	548	367
mean	50.372363	NaN	NaN	NaN	NaN	NaN
std	28.821076	NaN	NaN	NaN	NaN	NaN
min	1.000000	NaN	NaN	NaN	NaN	NaN
25%	25.000000	NaN	NaN	NaN	NaN	NaN
50%	50.000000	NaN	NaN	NaN	NaN	NaN
75%	75.000000	NaN	NaN	NaN	NaN	NaN
max	100.000000	NaN	NaN	NaN	NaN	NaN

In [ ]:
```
#removing the '$' sign, comas and changing the datatype changing the datatype
#to float
movie_budget_df['domestic_gross']=movie_budget_df['domestic_gross'].str.replace
```

In [114]:
```
movie_budget_df['worldwide_gross']=movie_budget_df['worldwide_gross'].str.repla
```

In [115]:
```
movie_budget_df['production_budget']=movie_budget_df['production_budget'].str.r
```

In [163]:
```
# Changed the type of release_date column from object to datetime and added
#seperate columns called "release year" and "release month"
movie_budget_df['release_date'] = pd.to_datetime(movie_budget_df['release_date'
                                        format='%b %d, %Y', errors='coerce')
movie_budget_df['release_year'] = movie_budget_df['release_date'].dt.year
movie_budget_df['release_month'] = movie_budget_df['release_date'].dt.month

# Create a new column that adds up thedomestic and worldwide gross earnings
movie_budget_df['Total_Earnings'] = movie_budget_df['domestic_gross'] + movie_b

# checking for new columns
movie_budget_df.head()
```

Out[163]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross	release_yea
0	1	2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	2009
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011
2	3	2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017

In [116]:
```
#movie_budget_df['Total_Earnings']=movie_budget_df['Total_Earnings'].str.replac
```

In [164]:
```
movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   title              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
 6   release_year       5782 non-null   int64
 7   release_month      5782 non-null   int64
 8   Total_Earnings     5782 non-null   float64
 9   net_income         5782 non-null   float64
 10  PB_ranges          5782 non-null   object
 11  profitable         5782 non-null   object
dtypes: datetime64[ns](1), float64(5), int64(3), object(3)
memory usage: 542.2+ KB
```

4. TMBD csv file

In [118]:
```
df_popularity = pd.read_csv('./zippedData/tmdb.movies.csv')
print(df_popularity.shape)
print(df_popularity.info())
df_popularity.head()
```

```
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
None
```

Out[118]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26

5. Movie Gross csv file

In [119]:
```
movie_gross_df = pd.read_csv('./zippedData/bom.movie_gross.csv')
print(movie_gross_df.shape)
print(movie_gross_df.info())
movie_gross_df.head()
```

```
(3387, 5)
<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
None
```

Out[119]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010

Data Analysis

B. Merging Datasets

In this section we will merge the datasets that can be connected together by a similer id or field that they both share. This will help in Exloratory Data Analysis(EDA) where we will be able to come up with comprehensive findings.

We are going to merge **review_df** and **movie_info_df** on the id column since they share a common column and are from the same source. Rotten Tomatoes

1. review and movie_info

In [120]:

```
# Using the merge() function in pandas to merge the two datasets on a common co

review_movieinfo_df = pd.merge(reviews_df, movie_info_df, on='id', how='inner')

review_movieinfo_df.head(10)
```

Out[120]:

	id	review	rating_x	fresh	critic	top_critic	publisher	date	synopsis
0	3	A distinctly gallows take on contemporary fina...	3.0	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	New York City, not-too-distant-future: Eric Pa...
1	3	It's an allegory in search of a meaning that n...	3.0	rotten	Annalee Newitz	0	io9.com	May 23, 2018	New York City, not-too-distant-future: Eric Pa...
2	3	... life lived in a bubble in financial dealin...	3.0	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018	New York City, not-too-distant-future:

2. movie_basics and movie_ratings

In [121]:

```
# Merge movie_basics and movie_ratings on 'movie_id'
#Both share primary and foreign keys
imdb_data = pd.merge(movie_basics, movie_ratings, on='movie_id', how='left')
imdb_data
```

Out[121]:

	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	90.0	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
140731	tt9916428	The Secret of China	The Secret of China	2019	90.0	Adventure,History,War
140732	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
140733	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	90.0	Documentary
140734	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	90.0	Comedy
140735	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	90.0	Documentary

140736 rows × 8 columns

3. imdb_data and df_popularity

In [122]:

```
# Merge 'imdb_data' and 'df_popularity' DataFrames on the 'original_title' colu
imdb_tmdb = pd.merge(imdb_data, df_popularity, on='original_title', how = 'inne
imdb_tmdb
```

Out[122]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
1	tt0112502	Bigfoot	Bigfoot	2017	90.0	Horror,Thriller
2	tt4503112	Bigfoot	Bigfoot	2018	90.0	Action,Horror
3	tt9181914	Bigfoot	Bigfoot	2018	86.0	Animation,Family
4	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy
...	...	...	...	...	...	...
20774	tt9678886	Vacancy	Vacancy	2018	81.0	Documentary
20775	tt9777830	John Leguizamo's Latin History for Morons	John Leguizamo's Latin History for Morons	2018	90.0	Comedy
20776	tt9814730	The Flare	The Flare	2017	63.0	Sport
20777	tt9862978	Terra	Terra	2018	60.0	Documentary
20778	tt9869514	Wake Up Call	Wake Up Call	2017	90.0	Action

20779 rows × 17 columns

In [123]:

```python
# get average rating from averagerating and vote_average columns
imdb_tmdb['avg_rating'] = (imdb_tmdb['averagerating'] + imdb_tmdb['vote_average
imdb_tmdb
```

3	tt9181914	Bigfoot	Bigfoot	2018	86.0	Animation,Fan
4	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Come
...	...	...	...	...	...	
20774	tt9678886	Vacancy	Vacancy	2018	81.0	Document
20775	tt9777830	John Leguizamo's Latin History for Morons	John Leguizamo's Latin History for Morons	2018	90.0	Come
20776	tt9814730	The Flare	The Flare	2017	63.0	Sp
20777	tt9862978	Terra	Terra	2018	60.0	Document
20778	tt9869514	Wake Up Call	Wake Up Call	2017	90.0	Act

20779 rows × 18 columns

In [124]:

```
#Getting the release year from release date column
imdb_tmdb['release_year'] = pd.to_datetime(imdb_tmdb['release_date'], format="%
    errors='coerce').dt.year
imdb_tmdb['release_month'] = pd.to_datetime(imdb_tmdb['release_date'], format="
    errors='coerce').dt.month

imdb_tmdb
```

Out[124]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
1	tt0112502	Bigfoot	Bigfoot	2017	90.0	Horror,Thriller
2	tt4503112	Bigfoot	Bigfoot	2018	90.0	Action,Horror
3	tt9181914	Bigfoot	Bigfoot	2018	86.0	Animation,Family
4	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy
...	...	...	...	...	...	...
20774	tt9678886	Vacancy	Vacancy	2018	81.0	Documentary
20775	tt9777830	John Leguizamo's Latin History for Morons	John Leguizamo's Latin History for Morons	2018	90.0	Comedy
20776	tt9814730	The Flare	The Flare	2017	63.0	Sport
20777	tt9862978	Terra	Terra	2018	60.0	Documentary
20778	tt9869514	Wake Up Call	Wake Up Call	2017	90.0	Action

20779 rows × 20 columns

4. movie_budget_df and movie_gross_df

In [125]:

```
# Rename 'movie' in movie_budget_df to 'title'
movie_budget_df.rename(columns={'movie':'title'}, inplace = True)
# Merge 'movie_budget_df' and 'movie_gross_df' DataFrames on the 'title' column
merged_data_df = pd.merge(movie_budget_df,movie_gross_df, on= 'title', how = 'l
merged_data_df
```

Out[125]:

	id	release_date	title	production_budget	domestic_gross_x	worldwide_gross	releas
0	1	2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	
2	3	2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	
...	...	...	...	...	...	...	
5777	78	2018-12-31	Red 11	7000.0	0.0	0.000000e+00	
5778	79	1999-04-02	Following	6000.0	48482.0	2.404950e+05	
5779	80	2005-07-13	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03	
5780	81	2015-09-29	A Plague So Pleasant	1400.0	0.0	0.000000e+00	
5781	82	2005-08-05	My Date With Drew	1100.0	181041.0	1.810410e+05	

5782 rows × 13 columns

In [126]:
```
#Calculate sum of missing values
merged_data_df.isna().sum()
```

Out[126]:
```
id                     0
release_date           0
title                  0
production_budget      0
domestic_gross_x       0
worldwide_gross        0
release_year           0
release_month          0
Total_Earnings         0
studio              4536
domestic_gross_y    4537
foreign_gross       4696
year                4535
dtype: int64
```

In [127]:
```
#Remove rows with missing values from the merged datasets
merged_data_df.dropna(inplace=True)
```

In [128]:
```
merged_data_df.duplicated().sum()
```

Out[128]:
```
0
```

5. movie_gross_df and imdb_data

In [129]:

```
# Merge imdb output to the movie_gross_df
merged_data = pd.merge(movie_gross_df, imdb_data, left_on='title', right_on='pr
merged_data
```

Out[129]:

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	origin
0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010	NaN	NaN	
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010	NaN	NaN	
3	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	In
4	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Forev
...	...	...	...	...	...	...	...	
4102	The Quake	Magn.	6200.0	NaN	2018	tt6523720	The Quake	S
4103	Edward II (2018 re-release)	FM	4800.0	NaN	2018	NaN	NaN	
4104	El Pacto	Sony	2500.0	NaN	2018	NaN	NaN	
4105	The Swan	Synergetic	2400.0	NaN	2018	NaN	NaN	
4106	An Actor Prepares	Grav.	1700.0	NaN	2018	tt5718046	An Actor Prepares	A Pr

4107 rows × 13 columns

In [130]:

```
# Check missing values in merged data
print(merged_data.isna().sum())
```

```
title                 0
studio                5
domestic_gross       35
foreign_gross      1618
year                  0
movie_id            781
primary_title       781
original_title      781
start_year          781
runtime_minutes     781
genres              781
averagerating      1087
numvotes           1087
dtype: int64
```

In [131]:

```
#Handle Missing values in key columns

# filling missing studio values with 'Unknown'
merged_data['studio'].fillna('Unknown', inplace=True)

# filling missing domestic gross and foreign gross with '0'
merged_data['domestic_gross'].fillna(0, inplace=True)
merged_data['foreign_gross'].fillna(0, inplace=True)

# finding median runtime and replacing missing runtimes
median_runtime = merged_data['runtime_minutes'].median()
merged_data['runtime_minutes'].fillna(median_runtime, inplace=True)

# filling missing genres with 'Unknown'
merged_data['genres'].fillna('Unknown', inplace=True)

# finding mean rating and replace to missing average ratings
mean_rating = merged_data['averagerating'].mean()
merged_data['averagerating'].fillna(mean_rating, inplace=True)

# dropping rows that do not have movie id
merged_data.dropna(subset=['movie_id'], inplace=True)

# check if there are further missing values
merged_data.isna().sum()
```

```
title                0
studio               0
domestic_gross       0
foreign_gross        0
year                 0
movie_id             0
primary_title        0
original_title       0
start_year           0
runtime_minutes      0
genres               0
averagerating        0
numvotes           306
dtype: int64
```

In [132]:

```
# Standardize genre column
def clean_and_explode(df, genre_column):
    df[genre_column] = df[genre_column].str.split(',')
    df = df.explode(genre_column).reset_index(drop=True)
    return df

merged_data = clean_and_explode(merged_data, 'genres')

merged_data['averagerating'] = merged_data['averagerating'].fillna(merged_data[

merged_data.head()
```

Out[132]:

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	original_title	s
0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	
1	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	
2	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	
3	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Inception	
4	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Inception	

In [133]:

```
# Ensuring that revenue data is captured as int or float for analysis
merged_data['domestic_gross'] = pd.to_numeric(merged_data['domestic_gross'], er
merged_data['foreign_gross'] = pd.to_numeric(merged_data['foreign_gross'], erro
```

In [134]:

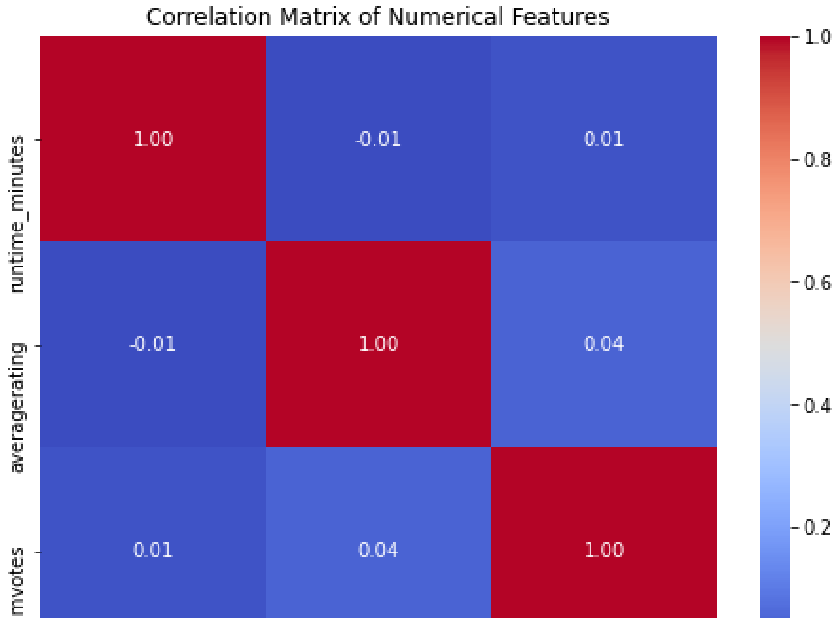
```
# Aggregated Domestic and Foreign Revenue by Genre
genre_revenue = merged_data.groupby('genres')[['domestic_gross', 'foreign_gross
    'domestic_gross': ['sum', 'mean'],
    'foreign_gross': ['sum', 'mean'],
    'averagerating': 'mean'
}).reset_index()

# rename main columns for easier identity
genre_revenue.columns = ['genre', 'total_domestic_gross', 'average_domestic_gro

# Sort by total domestic gross revenue
genre_revenue = genre_revenue.sort_values(by='total_domestic_gross', ascending=

print(genre_revenue)
```

```
4        4.639226e+10        4.807488e+07        6.256148
7        4.262900e+10        2.272335e+07        6.580984
17       2.368079e+10        1.703654e+08        6.451325
19       2.182380e+10        4.556117e+07        6.188146
2        2.587052e+10        1.647804e+08        6.692310
5        1.012734e+10        2.596755e+07        6.479150
9        1.861195e+10        1.051523e+08        6.250903
16       9.261870e+09        1.917571e+07        6.339292
11       9.251392e+09        3.544594e+07        5.746856
3        7.633332e+09        2.494553e+07        6.938005
8        8.359439e+09        6.480185e+07        6.246531
6        6.099421e+09        1.826174e+07        7.025342
14       7.247272e+09        3.279308e+07        6.286514
10       3.742451e+09        2.511712e+07        6.842021
18       2.318602e+09        4.067724e+07        6.839196
12       2.191535e+09        2.236260e+07        6.738278
13       7.411853e+08        3.900975e+07        6.324134
21       7.018230e+08        3.190105e+07        6.557207
20       5.830160e+08        1.100030e+07        6.789002
15       4.800000e+07        8.000000e+06        6.886181
```

Collinearity Check using heatmap

In [135]:

```
numerical_features = ['runtime_minutes', 'averagerating', 'numvotes']
correlation_matrix = movie_data[numerical_features].corr()

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



Explanation:

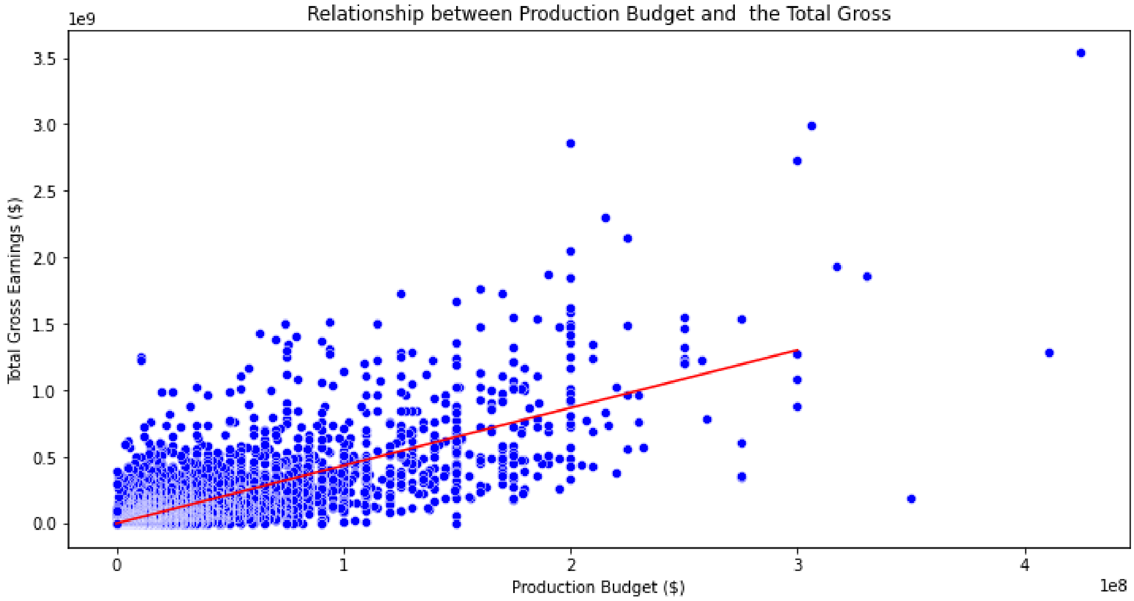
The perfect correlation between each variable and itself is represented by the diagonal values in this correlation heatmap being all 1.00. The correlations between runtime_minutes, averagerating, and numvotes are extremely weak, ranging between -0.01 and 0.04 when we look at the off-diagonal values. This shows that these numerical features are not significantly correlated with one another, indicating that there is no significant collinearity between them. Also, there is no need to worry about multicollinearity or redundancy when using each of these features separately in a model.

A simple linear regression Model

In [165]:

```
#Importing from sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Assigning the X and Y variables
X = movie_budget_df['production_budget'].values.reshape(-1, 1)
y = movie_budget_df['Total_Earnings'].values

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random

# Creating the linear regression model
model = LinearRegression()

# Training the model
model.fit(X_train, y_train)

# Making predictions
y_pred = model.predict(X_test)

# Plotting the data and the regression line
fig, ax = plt.subplots(figsize=(12,6))
sns.scatterplot(x=movie_budget_df['production_budget'], y=movie_budget_df['Tota
sns.lineplot(x=X_test.flatten(), y=y_pred, color='red', ax=ax)

# Customizing the plot
ax.set_title('Relationship between Production Budget and  the Total Gross')
ax.set_xlabel('Production Budget ($)')
ax.set_ylabel('Total Gross Earnings ($)')

# Evaluating the model by finding the mse and the r2 scores
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')
plt.show()
```

```
Mean Squared Error: 2.4964034400804492e+16
R^2 Score: 0.5355997835611248
```



Interpreting the model:

The Coefficient of Determination with the value of 0.5355997835611248 suggestthat the model explains about 54% of tha variance which indicates moderate levels of explanatory power.

In this case, the MSE is quite large (2.4964034400804492e+16). Since the values are squared, this large number suggests that there are significant differences between the actual and predicted values.

This suggests a weak positive covariance

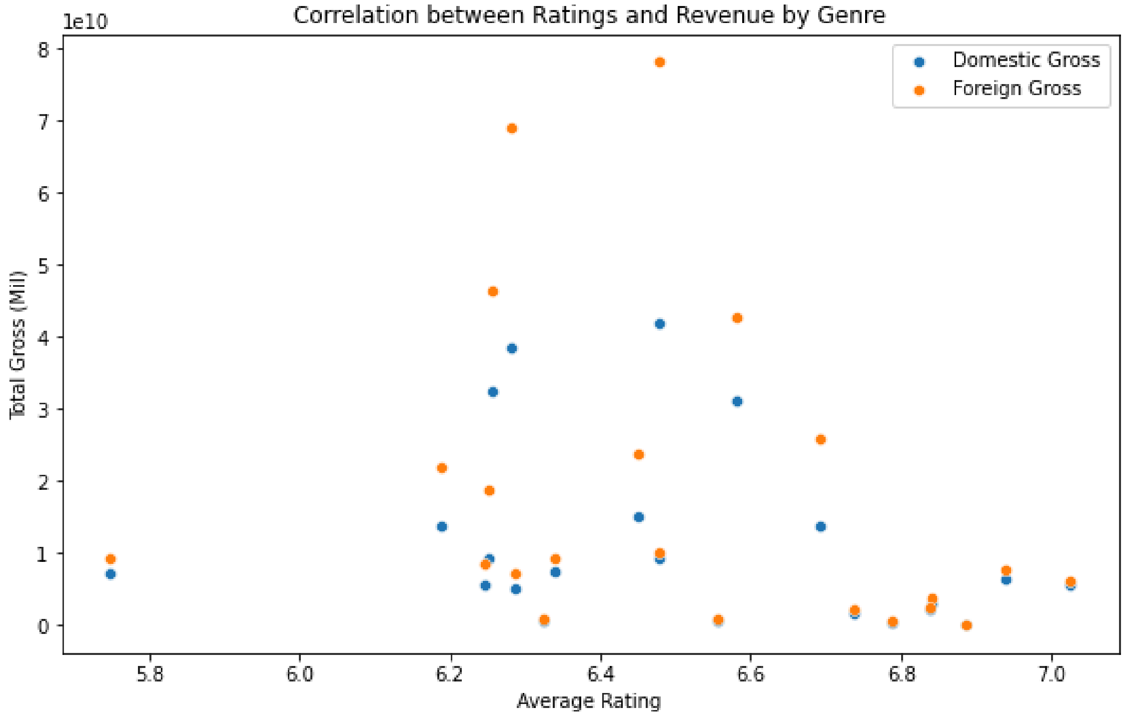
The model has a moderate fit, as indicated by the R² score. While it explains a significant portion of the variance,further investigation may be needed but we've already established a positive linear relationship

Visualizations

1. Correlation between ratings and revenue by genre

In [137]:

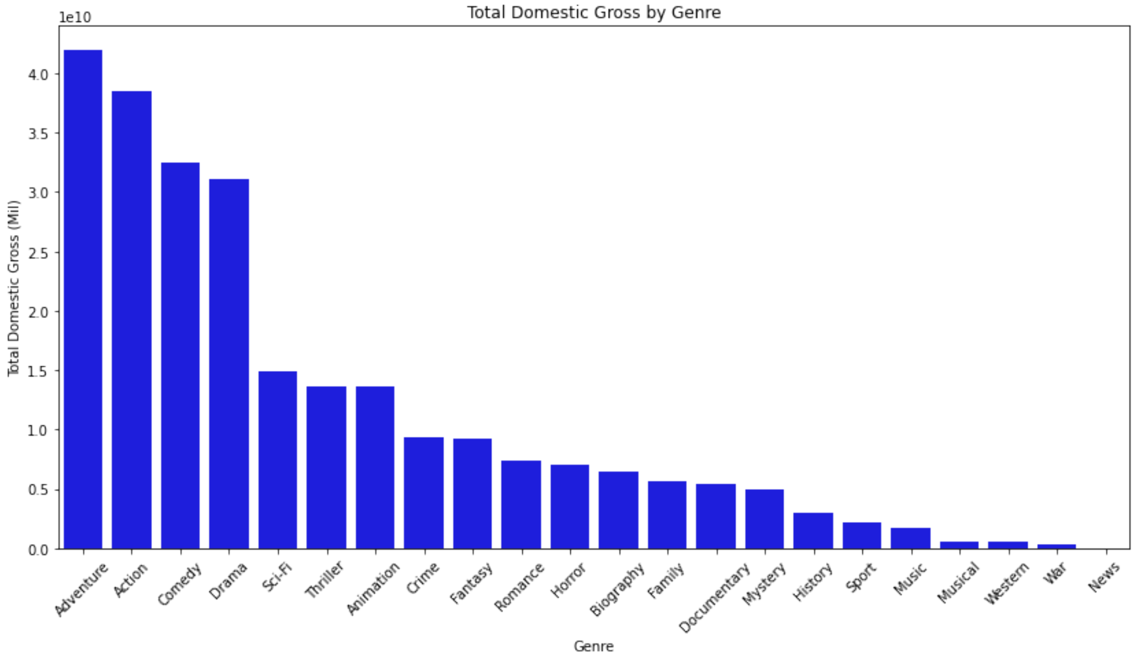
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='average_rating', y='total_domestic_gross', data=genre_revenu
sns.scatterplot(x='average_rating', y='total_foreign_gross', data=genre_revenue
plt.title('Correlation between Ratings and Revenue by Genre')
plt.xlabel('Average Rating')
plt.ylabel('Total Gross (Mil)')
plt.legend()
plt.show()
```



2. Genre income from the domestic market

In [138]:

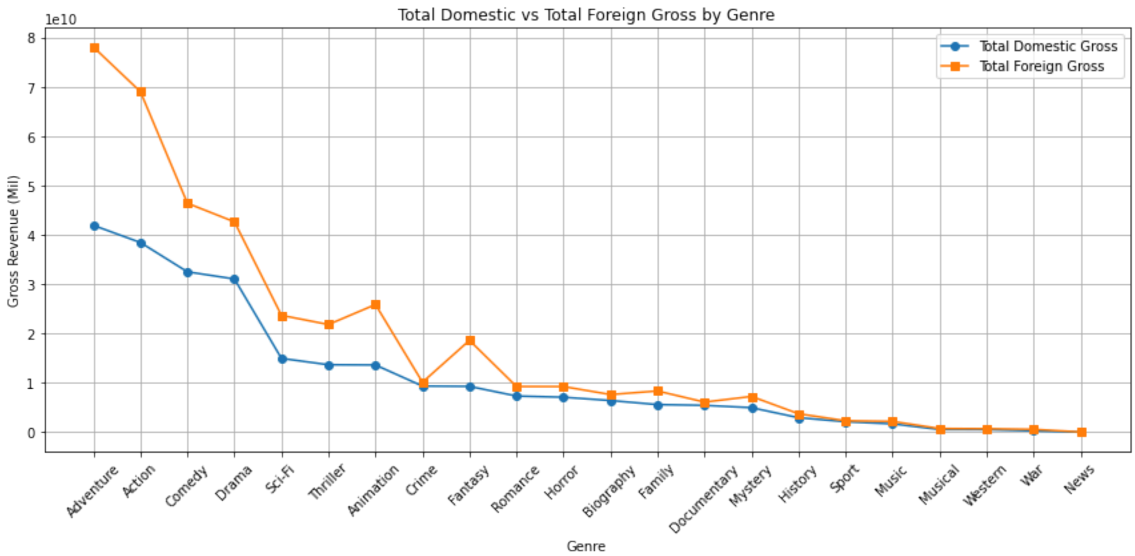
```
plt.figure(figsize=(14, 7))
sns.barplot(x='genre', y='total_domestic_gross', data=genre_revenue, color="blu
plt.title('Total Domestic Gross by Genre')
plt.xlabel('Genre')
plt.ylabel('Total Domestic Gross (Mil)')
plt.xticks(rotation=45)
plt.show()
```



3. Comparison of revenue generated in the domestic and foreign markets

In [139]:

```
plt.figure(figsize=(12, 6))
plt.plot(genre_revenue['genre'], genre_revenue['total_domestic_gross'], marker=
plt.plot(genre_revenue['genre'], genre_revenue['total_foreign_gross'], marker='
plt.title('Total Domestic vs Total Foreign Gross by Genre')
plt.xlabel('Genre')
plt.ylabel('Gross Revenue (Mil)')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Business Questions

Question 1

How many movies are released each year?

In [140]:
```
# getting the overall data
df_popularity.head()
```

Out[140]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows Part 1
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception

In [141]:
```
#dropping unnecessary columns
df_popularity= df_popularity.drop(df_popularity.columns[0], axis=1)
```

In [142]:
```
# Checked for null values
df_popularity.isna().sum()
```

Out[142]:
```
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

In [143]:
```
# checking for duplicates
dupl=df_popularity[df_popularity.duplicated()]
dupl
```

Out[143]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vo
2473	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
2477	[16, 35, 10751]	863	en	Toy Story 2	22.698	1999-11-24	Toy Story 2	
2536	[12, 28, 878]	20526	en	TRON: Legacy	13.459	2010-12-10	TRON: Legacy	
2673	[18, 10749]	46705	en	Blue Valentine	8.994	2010-12-29	Blue Valentine	
2717	[35, 18, 14, 27, 9648]	45649	en	Rubber	8.319	2010-09-01	Rubber	
...	...	...	...	...	...	...	...	
26481	[35, 18]	270805	en	Summer League	0.600	2013-03-18	Summer League	
26485	[27, 53]	453259	en	Devils in the Darkness	0.600	2013-05-15	Devils in the Darkness	
26504	[27, 35, 27]	534282	en	Head	0.600	2015-03-28	Head	
26510	[99]	495045	en	Fail State	0.600	2018-10-19	Fail State	
26511	[99]	492837	en	Making Filmmakers	0.600	2018-04-07	Making Filmmakers	

1020 rows × 9 columns

In [144]:
```
# Dropping the duplicated rows
df_popularity = df_popularity[~df_popularity.duplicated(subset=['id'], keep='fi
```

In [145]:
```
df_popularity.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25497 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          25497 non-null  object 
 1   id                 25497 non-null  int64  
 2   original_language  25497 non-null  object 
 3   original_title     25497 non-null  object 
 4   popularity         25497 non-null  float64
 5   release_date       25497 non-null  object 
 6   title              25497 non-null  object 
 7   vote_average       25497 non-null  float64
 8   vote_count         25497 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 1.9+ MB
```

In [146]:
```
# Converting the columns type to datetime
df_popularity['release_date'] = pd.to_datetime(df_popularity['release_date'],
                                               format='%Y-%m-%d', errors='coerce')
df_popularity['release_date'].dtype
```

Out[146]:
```
dtype('<M8[ns]')
```

In [147]:
```
# Checking if there are any null values emerged due to an error.
df_popularity['release_date'].isnull().sum()
```

Out[147]:
```
0
```

In [148]:
```
# Created new columns of year and month.
df_popularity['release_year'] = df_popularity['release_date'].dt.year
df_popularity['release_month'] = df_popularity['release_date'].dt.month

df_popularity.head()
```

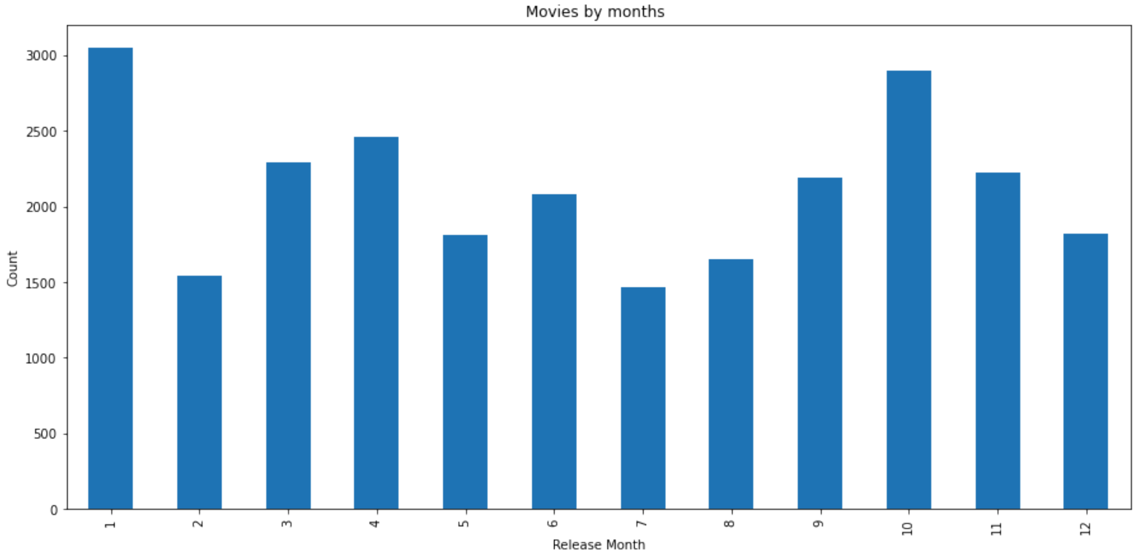
Out[148]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_aver
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [149]:
```
#It is clear the number of movies increased each year from 2009.
df_popularity['release_year'].value_counts()[:15]
```

Out[149]:
```
2015    3066
2013    3066
2014    3052
2016    2970
2017    2921
2011    2645
2012    2615
2018    2496
2010    2393
2019      63
2009      39
2008      13
2004      10
2005       9
2006       9
Name: release_year, dtype: int64
```

In [150]:
```
# Showing distribution of movies by months

fig, ax = plt.subplots(figsize=(15,7))
df_popularity.groupby('release_month')['id'].count().plot.bar()
ax.set_xlabel('Release Month')
ax.set_ylabel('Count')
ax.set_title('Movies by months ')
plt.show()
```



1.1 Findings:

According to the visualizations above we can see that the number of movies released increased after 2009 where we see the highrst number of movies released was in 2013, 2014 and 2015 and then the number went down. We can also see that the month in which many movies are released is in January followed by October.

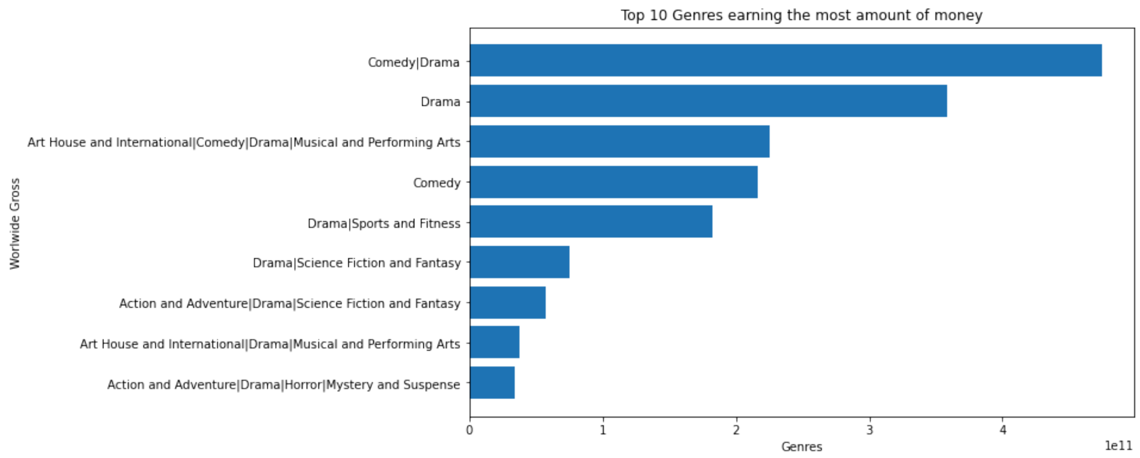
Question 2

Which genre is the most successful in movie box?

In [151]:
```
#Merging two merged datasets to answer the business question
merged_data = pd.merge(merged_data_df,review_movieinfo_df, on = 'id')

#Checking missing values
merged_data.isna().sum()

#Dropping missing values
merged_data.dropna(inplace=True)

#Checking for duplicates
merged_data.drop_duplicates(inplace=True)

genre_success = merged_data.groupby('genre')['worldwide_gross'].sum().reset
sorted_genre_Success = genre_success.sort_values(by = 'worldwide_gross', as
first_ten = sorted_genre_Success.tail(10)
```

In [152]:
```
# Save the top ten genres data to an Excel file
first_ten.to_excel('top_ten_genres.xlsx', index=False)
```

In [153]:
```
# Plotting a horizontal bar chart to show the top 10 genres by worldwide gross

plt.figure(figsize=(10, 6))
plt.barh(first_ten['genre'], first_ten['worldwide_gross'])
plt.xlabel('Genres')
plt.ylabel('Worlwide Gross')
plt.title('Top 10 Genres earning the most amount of money')
plt.show()
```



2.1 Findings

According to the data, the most popular genre at the box office is commedy|drama, which is followed by drama. This indicates that viewers enjoy movies that are funny and evoke feelings presented by the drama genre.

Concentrating on genres like "Comedy|Drama" and "Drama" could be a lucrative approach to filmmaking. Also, diversity in genres, such as combining comedy and musicals or drama and science fiction, also offers substantial financial potential.

Question 3

Which production budget ranges yield the most profitable movies?

Does a higher production budget lead to more profitable movies than those with lower production budgets?

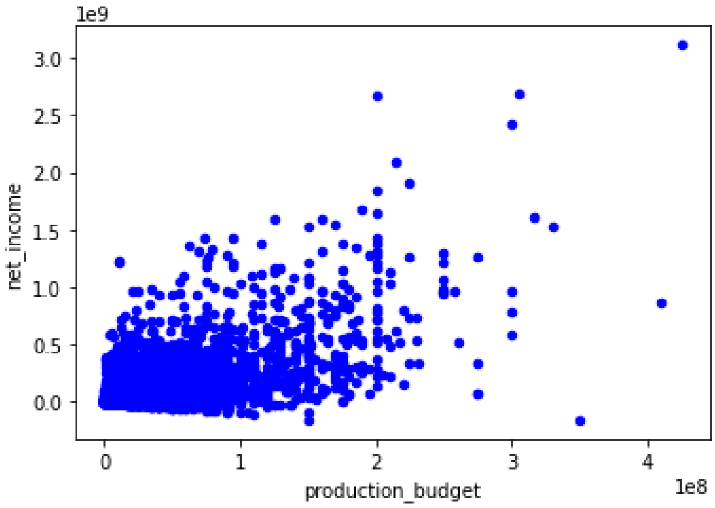
In [154]:
```
#computing the net income
movie_budget_df['net_income']=(movie_budget_df['domestic_gross']+
            movie_budget_df['worldwide_gross'])- movie_budget_df['production '
```

In [155]:
```
# checking for min and max and outliers
movie_budget_df['net_income'].describe()
```

Out[155]:
```
count    5.782000e+03
mean     1.017730e+08
std      2.108880e+08
min     -1.574753e+08
25%     -3.098222e+05
50%      2.499538e+07
75%      1.111648e+08
max      3.111853e+09
Name: net_income, dtype: float64
```

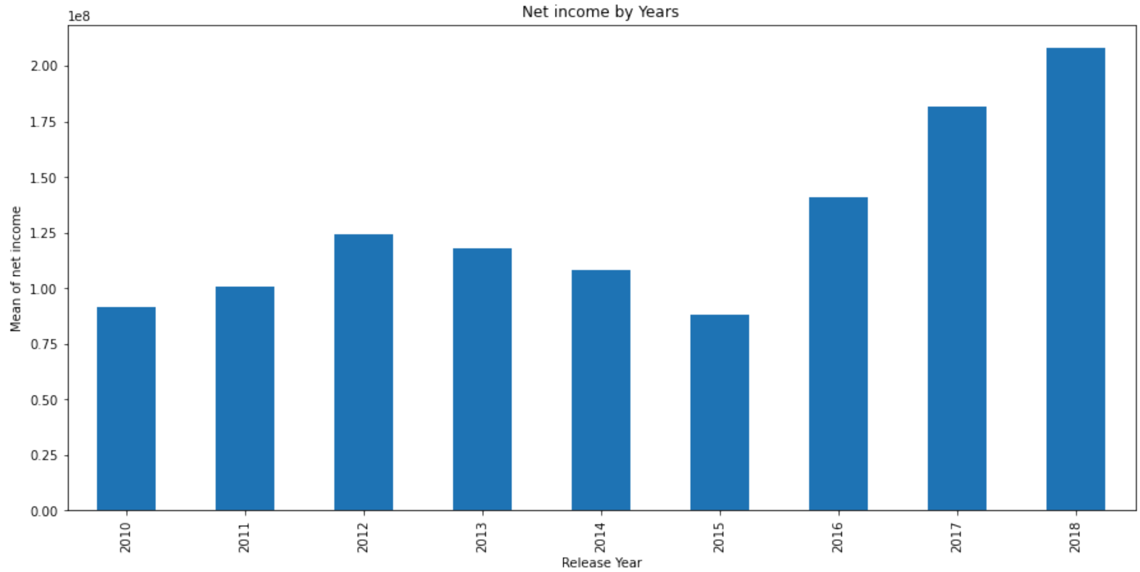
In [156]:
```
#making scatter plot which shows positive connection between production budget
movie_budget_df.plot.scatter(x='production_budget',
                      c='Blue',
                      y='net_income',)
```

Out[156]: <AxesSubplot:xlabel='production_budget', ylabel='net_income'>



In [157]:

```
# showing the change of net income over the years considering the mean to get b
#We can see starting from 2016 net income is increasing
fig, ax = plt.subplots(figsize=(15,7))
movie_budget_df[(movie_budget_df["release_year"] >= 2010) &
           (movie_budget_df["release_year"] <2019)].groupby('release_year')['ne
ax.set_ylabel('Mean of net income')
ax.set_xlabel('Release Year')
ax.set_title('Net income by Years')
plt.show()
```



In [158]:

```
#defining a function for different ranges
def product_budg_range(production_budget):
    if production_budget < 5000000:
        return "< $5M"
    elif 5000000 <= production_budget <= 10000000:
        return "$5-10M"
    elif 10000000 <= production_budget <= 20000000:
        return "$10-20M"
    elif 2000000 <= production_budget <= 30000000:
        return "$20-30M"
    elif 3000000 <= production_budget <= 40000000:
        return "$30-40M"
    elif 40000000 <= production_budget <= 50000000:
        return "$40-50M"
    elif 50000000 < production_budget <= 60000000:
        return "$50-60M"
    elif 60000000 < production_budget <= 70000000:
        return "$60-70M"
    elif 70000000 <= production_budget <= 80000000:
        return "$70-80M"
    elif 80000000 < production_budget <= 90000000:
        return "$80-90M"
    elif 90000000 < production_budget <= 1000000000:
        return "$90-100M"

    else:
        return "> $100M"
```

In [159]:

```
#creating a new column to connect each movie with it's production budget range.

movie_budget_df['PB_ranges'] = movie_budget_df['production_budget'].apply(produ
movie_budget_df.head()
```

Out[159]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross	release_yeaı
0	1	2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	2009
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011
2	3	2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017

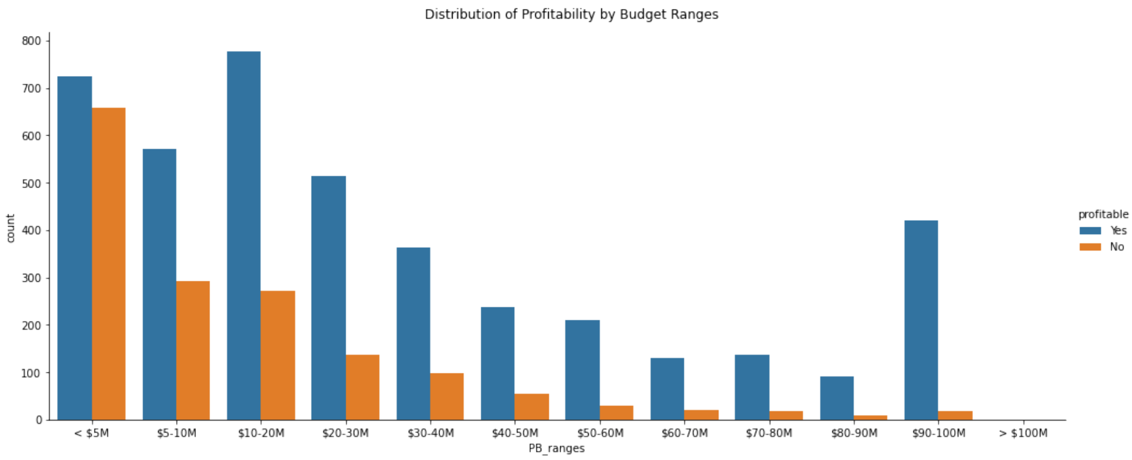
In [160]:

```
#adding a column that tells us whether or not a movie was profitable

movie_budget_df['profitable'] = movie_budget_df['net_income'].apply(lambda x: "
movie_budget_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   title              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
 6   release_year       5782 non-null   int64
 7   release_month      5782 non-null   int64
 8   Total_Earnings     5782 non-null   float64
 9   net_income         5782 non-null   float64
 10  PB_ranges          5782 non-null   object
 11  profitable         5782 non-null   object
dtypes: datetime64[ns](1), float64(5), int64(3), object(3)
memory usage: 542.2+ KB
```

In [169]:
```
# showing the results where we can see which range is more profitable
order = ["< $5M", "$5-10M", "$10-20M", "$20-30M",
         "$30-40M", "$40-50M", "$50-60M", "$60-70M",
         "$70-80M", "$80-90M", "$90-100M", "> $100M"]

catplot = sns.catplot(x='PB_ranges',
                      data=movie_budget_df,
                      kind="count", hue='profitable',
                      height=5.5, aspect=2.5, order=order)

catplot.fig.suptitle("Distribution of Profitability by Budget Ranges", y=1.03)
```

Out[169]:
```
Text(0.5, 1.03, 'Distribution of Profitability by Budget Ranges')
```



3.1 Findings:

The scatter plot indicates that net income and production budget are positively correlated. Although returns vary greatly, bigger production budgets typically result in higher net revenues. Some expensive films don't make a lot of money, proving that money isn't the only factor that determines success.

From 2010 to 2018, the mean net income of films increased steadily, as shown by the bar chart (second image). The biggest increase is seen beginning in 2016, suggesting that the movie business has become more profitable over time.

As shown in the third chart,films with smaller budgets (less than 5 million) make less money. However, the frequency of lucrative films climbs with the production budget, particularly in the 10M–20M and 90M–100M categories. This trend implies that films with medium to high budgets have a higher chance of making money.

Business Recommendations

1. Invest in the highly rated genres

The business should expand into genres where success is closely correlated with higher ratings. T' genres of commedy|drama, drama, and drama|sport and fitness show that favorable reviews greaı increase their revenue.

2. Target global market

The company should consider investing in the global audience. Our analysis indicates that almost every genre does well in the foreign market compared to the domestic market.

3. Ensure a balanced budget to maximize ROI.

In [ ]:

```

```