Business Understanding

The objective of this project is to analyze historical movie data to generate actionable insights for a new movie studio venture. Specifically, the analysis aims to identify the key factors that contribute to the commercial success of movies, focusing on profitability, audience reception, and production efficiency. This will help the studio make data-driven decisions regarding budget allocation, genre selection, and release strategies to maximize return on investment (ROI) and minimize financial risks.

Key Business Questions:

- Which genres consistently generate the highest revenue?
- How do budgets correlate with worldwide gross?
- What are the most profitable release windows for movies?
- Which studios have the highest profit margins?
- Does the original language of a movie influence its global performance?
- Can I use movie attributes to predict revenue?

Dataframes for Analysis

Based on the analysis goals, the following datasets will be most useful for deriving insights:

1. **Box Office Mojo Data**

- **Key Variables**: `title` , `studio` , `domestic_gross` , `foreign_gross` , `year`
- **Usage**: Analyze box office performance, studio performance, and trends in domestic vs. international earnings.

2. **The Numbers Data**

- **Key Variables**: `movie` , `production_budget` , `domestic_gross` , `worldwide_gross` , `release_date`
- **Usage**: Analyze the correlation between production budgets and box office revenues to assess profitability.

3. **Rotten Tomatoes Movie Info Data**

- **Key Variables**: `rating` , `genre` , `director` , `runtime` , `box_office`
- **Usage**: Analyze how different factors like genre, director, and runtime impact box office performance.

4. **TheMovieDB Data**

- **Key Variables**: `title` , `popularity` , `vote_average` , `vote_count` , `release_date`
- **Usage**: Investigate how popularity, audience ratings, and vote counts correlate with box office success.

Movie Data ERD

5. **im.db.zip**

- Zipped SQLite database (you will need to unzip then query using SQLite)
- `movie_basics` and `movie_ratings` tables are most relevant

Data preparation

In [1]:
```
# Import libraries
# Data manipulation and analysis
import pandas as pd  # pandas is used for handling and processing data in DataFrame
import numpy as np  # numpy is useful for numerical computations and handling array
import gzip  # gzip is for handling compressed files

# Data visualization
import matplotlib.pyplot as plt  # matplotlib is used for creating static, interact
import seaborn as sns  # seaborn provides a high-level interface for drawing attrac

# Database interaction
import sqlite3  # sqlite3 is used to connect to SQLite databases
import nbconvert  # nbconvert is used to convert Jupyter Notebooks into various for
```

```python
import os
import re

# Set visualization style
sns.set_theme(style="whitegrid")
```

1. Box Office Mojo Data

In [2]:
```python
# Define the path to your raw zipped data
file_path = 'C:/Users/USER/Desktop/Movie-Project/data/raw/zippedData/bom.movie_gros

# Load the gzipped CSV directly
bom_gross = pd.read_csv(file_path, compression='gzip')

# Display the first few rows of the data
display(bom_gross.head())
bom_gross.dtypes
```

	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
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

Out[2]:
```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
```

2. The Numbers Data

In [3]:
```python
# Load The Numbers (movie budgets) dataset
tn_budgets = pd.read_csv('C:/Users/USER/Desktop/Movie-Project/data/raw/zippedData/t
print("The Numbers Data:")
display(tn_budgets.head())  # Display the first few rows
print(tn_budgets.info())  # Get an overview of the dataset
```

```
The Numbers Data:
```

	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

```
<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
None
```

3. **Rotten Tomatoes Movie Info Data**

In [4]:

```
# Load Rotten Tomatoes Reviews dataset
rt_reviews = pd.read_csv('C:/Users/USER/Desktop/Movie-Project/data/raw/zippedData/r
print("Rotten Tomatoes Reviews Data:")
display(rt_reviews.head(), "\n")  # Display the first few rows
print(rt_reviews.info())  # Get an overview of the dataset
```

```
Rotten Tomatoes Reviews Data:
```

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

```
'\n'
<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
```

4. **TheMovieDB Data**

In [5]:
```
# Load Rotten Tomatoes Movie Info dataset
rt_info = pd.read_csv('C:/Users/USER/Desktop/Movie-Project/data/raw/zippedData/rt.m
print("Rotten Tomatoes Movie Info Data:")
display(rt_info.head())  # Display the first few rows
print(rt_info.info())  # Get an overview of the dataset
```

```
Rotten Tomatoes Movie Info Data:
```

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	curr
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	
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	Jan 1, 2013	
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997	
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN	

```
<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
```

5. **tmdb.movies**

In [6]:
```
# Load TMDB dataset
```

```
tmdb_movies = pd.read_csv('C:/Users/USER/Desktop/Movie-Project/data/raw/zippedData/
print("TheMovieDB Data:")
print(tmdb_movies.info())  # Get an overview of the dataset
display(tmdb_movies.head(), "\n")  # Display the first few rows
```

```
TheMovieDB Data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 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
```

	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
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16

```
'\n'
```

6.im.db.zip

- Zipped SQLite database

In [7]:
```
# Path to the SQL database file
```

```
db_path = 'C:/Users/USER/Desktop/dsc-phase-2-project-v3-main/unzipped/im.db'

# Connecting to the database
conn = sqlite3.connect(db_path)

# Load tables from the database
movie_basics = pd.read_sql_query("SELECT * FROM movie_basics", conn)
movie_ratings = pd.read_sql_query("SELECT * FROM movie_ratings", conn)
```

In [8]:

```
display(movie_basics.head())  # Display the first few rows
print(movie_basics.info())  # Get an overview of the dataset
```

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

```
<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
None
```

In [9]:

```
display(movie_ratings.head())  # Display the first few rows
print(movie_ratings.info())  # Get an overview of the dataset
```

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

```
<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
None
```

Since I have all the data loaded I shall proceed to cleaning it throughly.

Data Cleaning

1.1 **Box Office Mojo Data**

In [10]:
```
# Convert 'foreign_gross' to numeric by removing non-numeric characters
bom_gross['foreign_gross'] = bom_gross['foreign_gross'].replace('[^0-9]', '', regex


# Convert 'year' column to integer type, handling non-convertible values
bom_gross['year'] = pd.to_numeric(bom_gross['year'], errors='coerce').astype('Int64

#Remove special characters and multiple spaces to standardize title
bom_gross['title'] = (
    bom_gross['title']
    .str.lower()
    .str.strip()
    .str.replace(r'[^\w\s]', '', regex=True)
    .str.replace(r'\s+', ' ', regex=True)
)


# Drop duplicate rows
bom_gross = bom_gross.drop_duplicates()

# Remove all rows with any NaN values
bom_gross.dropna(inplace=True)

# Display the first few rows of the data
display(bom_gross.head())

# Check for missing values
print(bom_gross.isnull().sum())

# Display dataset info
bom_gross.info()

# Save the DataFrame to a CSV file
bom_gross.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/bom_gro
print("Dataset information saved as 'bom_gross_info.csv'.")
```

	title	studio	domestic_gross	foreign_gross	year
0	toy story 3	BV	415000000.0	652000000.0	2010
1	alice in wonderland 2010	BV	334200000.0	691300000.0	2010
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010
3	inception	WB	292600000.0	535700000.0	2010
4	shrek forever after	P/DW	238700000.0	513900000.0	2010

```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           2007 non-null   object
 1   studio          2007 non-null   object
 2   domestic_gross  2007 non-null   float64
 3   foreign_gross   2007 non-null   float64
 4   year            2007 non-null   Int64
dtypes: Int64(1), float64(2), object(2)
memory usage: 96.0+ KB
Dataset information saved as 'bom_gross_info.csv'.
```

1.2. **The Numbers Data**

In [11]:

```python
# Remove '$' and ',' from financial columns and convert them to numeric
for col in ['production_budget', 'domestic_gross', 'worldwide_gross']:
    tn_budgets[col] = tn_budgets[col].replace(r'[\$,]', '', regex=True).astype(floa

# Convert 'release_date' to datetime
tn_budgets['release_date'] = pd.to_datetime(tn_budgets['release_date'], errors='coe

#Extracting year from release_date
tn_budgets['year'] = tn_budgets['release_date'].dt.year

#Remove special characters and multiple spaces to standardize 'movie'
tn_budgets['movie'] = (
    tn_budgets['movie']
    .str.lower()
    .str.strip()
    .str.replace(r'[^\w\s]', '', regex=True)
    .str.replace(r'\s+', ' ', regex=True)
)


# Display the first few rows of the data
display(tn_budgets.head())

# Check for missing values
print(tn_budgets.isnull().sum())

# Display dataset info
tn_budgets.info()

# Save the DataFrame to a CSV file
tn_budgets.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/tn_bud
print("Dataset saved as 'tn_budgets.csv'.")
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year
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

```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
year                 0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
 6   year               5782 non-null   int64
dtypes: datetime64[ns](1), float64(3), int64(2), object(1)
memory usage: 316.3+ KB
Dataset saved as 'tn_budgets.csv'.
```

1.3. **TMDB Dataset**

In [12]:
```
# Drop the unnecessary 'Unnamed: 0' & 'genre_ids'columns
tmdb_movies.drop(columns=['Unnamed: 0','genre_ids'], inplace=True)


# Convert 'release_date' to datetime
tmdb_movies['release_date'] = pd.to_datetime(tmdb_movies['release_date'], errors='c
```

```
#Remove special characters and multiple spaces to standardize
tmdb_movies['title'] = (
    tmdb_movies['title']
    .str.lower()
    .str.strip()
    .str.replace(r'[^\w\s]', '', regex=True)
    .str.replace(r'\s+', ' ', regex=True)
)


# Display the first few rows
display(tmdb_movies.head())

# Check for missing values
print(tmdb_movies.isnull().sum())

# Display dataset info
tmdb_movies.info()

# Save the DataFrame to a CSV file
tmdb_movies.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/tmdb_
print("Dataset saved as 'tmdb_movies.csv'.")
```

	id	original_language	original_title	popularity	release_date	title	vote_average
0	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	harry potter and the deathly hallows part 1	7.7
1	10191	en	How to Train Your Dragon	28.734	2010-03-26	how to train your dragon	7.7
2	10138	en	Iron Man 2	28.515	2010-05-07	iron man 2	6.8
3	862	en	Toy Story	28.005	1995-11-22	toy story	7.9
4	27205	en	Inception	27.920	2010-07-16	inception	8.3

```
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   id                 26517 non-null  int64         
 1   original_language  26517 non-null  object        
 2   original_title     26517 non-null  object        
 3   popularity         26517 non-null  float64       
 4   release_date       26517 non-null  datetime64[ns]
 5   title              26517 non-null  object        
 6   vote_average       26517 non-null  float64       
 7   vote_count         26517 non-null  int64         
dtypes: datetime64[ns](1), float64(2), int64(2), object(3)
memory usage: 1.6+ MB
Dataset saved as 'tmdb_movies.csv'.
```

1.4. **Rotten Tomatoes Reviews Data**

In [13]:
```python
# Drop rows where `review` or `rating` is missing
rt_reviews.dropna(subset=['review', 'rating', 'critic'], inplace=True)


# Convert `date` column to datetime
rt_reviews['date'] = pd.to_datetime(rt_reviews['date'], errors='coerce')

# Convert Data Types
# Parse `rating` to extract numeric scores (e.g., '3/5' -> 3.0)
def parse_rating(rating):
    try:
        return float(rating.split('/')[0]) if '/' in rating else None
    except:
        return None

rt_reviews['rating'] = rt_reviews['rating'].apply(parse_rating)

# Drop rows with missing  `rating_score`
rt_reviews.dropna(subset=['rating'], inplace=True)

# Remove Duplicates
rt_reviews.drop_duplicates(inplace=True)

# Rename Columns to snake_case
rt_reviews.rename(columns={
    'review': 'review_text',
    'rating': 'rating_score',
```

```
    'fresh': 'is_fresh',
    'critic': 'critic_name',
    'top_critic': 'is_top_critic',
    'publisher': 'publisher_name',
    'date': 'review_date'
}, inplace=True)

print("Rotten Tomatoes Reviews Data:")
print(rt_reviews.info())  # Get an overview of the dataset
display(rt_reviews.head())  # Display the first few rows

# Save the DataFrame to a CSV file
rt_reviews.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/rt_rev
print("Dataset saved as 'rt_reviews.csv'.")
```

```
Rotten Tomatoes Reviews Data:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 27745 entries, 0 to 54424
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              27745 non-null  int64
 1   review_text     27745 non-null  object
 2   rating_score    27745 non-null  float64
 3   is_fresh        27745 non-null  object
 4   critic_name     27745 non-null  object
 5   is_top_critic   27745 non-null  int64
 6   publisher_name  27587 non-null  object
 7   review_date     27745 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(1), int64(2), object(4)
memory usage: 1.9+ MB
None
```

	id	review_text	rating_score	is_fresh	critic_name	is_top_critic	publisher_name	reviev
0	3	A distinctly gallows take on contemporary fina...	3.0	fresh	PJ Nabarro	0	Patrick Nabarro	2018
7	3	Cronenberg is not a director to be daunted by ...	2.0	rotten	Matt Kelemen	0	Las Vegas CityLife	2013
12	3	Robert Pattinson works mighty hard to make Cos...	2.0	rotten	Christian Toto	0	Big Hollywood	2013
14	3	For those who like their Cronenberg thick and ...	3.0	fresh	Marty Mapes	0	Movie Habit	2012
15	3	For better or worse - often both - Cosmopolis ...	3.0	fresh	Adam Ross	0	The Aristocrat	2012

```
Dataset saved as 'rt_reviews.csv'.
```

1.5. **Rotten Tomatoes Movie Info Data**

In [14]:
```
# Convert to datetime and coerce invalid dates to NaT
rt_info['theater_date'] = pd.to_datetime(rt_info['theater_date'], errors='coerce')
rt_info['dvd_date'] = pd.to_datetime(rt_info['dvd_date'], errors='coerce')

# Clean 'runtime' to extract numerical values
rt_info['runtime'] = rt_info['runtime'].str.extract(r'(\d+)').astype(float)  # Use


# Clean 'box_office' to extract numerical values
rt_info['box_office'] = rt_info['box_office'].replace(r'[\$,]', '', regex=True).ast

# Drop all rows with any NaN values
rt_info.dropna(inplace=True)

# Display the cleaned dataset
print("After dropping all rows with NaN values:")
print(rt_info.info())
display(rt_info.head())

# Save the DataFrame to a CSV file
rt_reviews.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/rt_inf
print("Dataset saved as 'rt_info.csv'.")
```

```
After dropping all rows with NaN values:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 235 entries, 1 to 1545
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            235 non-null    int64
 1   synopsis      235 non-null    object
 2   rating        235 non-null    object
 3   genre         235 non-null    object
 4   director      235 non-null    object
 5   writer        235 non-null    object
 6   theater_date  235 non-null    datetime64[ns]
 7   dvd_date      235 non-null    datetime64[ns]
 8   currency      235 non-null    object
 9   box_office    235 non-null    float64
 10  runtime       235 non-null    float64
 11  studio        235 non-null    object
dtypes: datetime64[ns](2), float64(2), int64(1), object(7)
memory usage: 23.9+ KB
None
```

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	2012-08-17	2013-01-01
6	10	Some cast and crew from NBC's highly acclaimed...	PG-13	Comedy	Jake Kasdan	Mike White	2002-01-11	2002-06-18
7	13	Stewart Kane, an Irishman living in the Austra...	R	Drama	Ray Lawrence	Raymond Carver|Beatrix Christian	2006-04-27	2007-10-02
15	22	Two-time Academy Award Winner Kevin Spacey giv...	R	Comedy|Drama|Mystery and Suspense	George Hickenlooper	Norman Snider	2010-12-17	2011-04-05
18	25	From ancient Japan's most enduring tale, the e...	PG-13	Action and Adventure|Drama|Science Fiction and...	Carl Erik Rinsch	Chris Morgan|Hossein Amini	2013-12-25	2014-04-01

```
Dataset saved as 'rt_info.csv'.
```

1.6.**im.db.zip**

- Zipped SQLite database

a. **movie_basics**

In [15]:
```
# Display the first few rows
display(movie_basics.head())
movie_basics.info()
```

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

```
<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
```

In [16]:

```
# Drop rows where 'runtime_minutes' or 'genres' columns have missing values
movie_basics.dropna(subset=['runtime_minutes', 'genres'], inplace=True)

# Drop any remaining rows with missing values in any column
movie_basics.dropna(inplace=True)

# Normalize 'primary_title' and 'original_title' columns: lowercase, remove punctua
string_columns = ['primary_title', 'original_title']
for col in string_columns:
    movie_basics[col] = (
        movie_basics[col]
        .str.lower()  # Convert to lowercase
        .str.strip()  # Remove leading/trailing spaces
        .str.replace(r'[^\w\s]', '', regex=True)  # Remove punctuation
        .str.replace(r'\s+', ' ', regex=True)  # Replace multiple spaces with a sin
    )

# Display the first few rows to inspect changes
print("\nPreview of cleaned movie_basics dataset:")
display(movie_basics.head())

# Display information about the cleaned dataframe
print("\nInformation about cleaned movie_basics dataset:")
```

```
movie_basics.info()

# Save the DataFrame to a CSV file
rt_reviews.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/movie_
print("Dataset saved as 'movie_basics.csv'.")
```

```
Preview of cleaned movie_basics dataset:
```

	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
4	tt0100275	the wandering soap opera	la telenovela errante	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	a thin life	a thin life	2018	75.0	Comedy

```
Information about cleaned movie_basics dataset:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 112232 entries, 0 to 146139
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         112232 non-null  object 
 1   primary_title    112232 non-null  object 
 2   original_title   112232 non-null  object 
 3   start_year       112232 non-null  int64  
 4   runtime_minutes  112232 non-null  float64
 5   genres           112232 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.0+ MB
Dataset saved as 'movie_basics.csv'.
```

b. **movie_ratings**

In [17]:
```
# Display the first few rows of the movie_ratings dataframe
display(movie_ratings.head())

# Display detailed information about the dataframe
movie_ratings.info()

# Observed that there are no missing values in any column of the dataframe.
print(f'The movie_ratings dataframe is already clean with no missing values.')

# Save the DataFrame to a CSV file
rt_reviews.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/movie_
print("Dataset saved as 'movie_ratings.csv'.")
```

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

```
<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
The movie_ratings dataframe is already clean with no missing values.
Dataset saved as 'movie_ratings.csv'.
```

3. Data Preparation

3.1. **Merging Datasets**

In [18]:
```
# Prepare `bom_gross` and `tn_budgets` for merging
tn_budgets['year'] = tn_budgets['release_date'].dt.year  # Extract year from releas

# Clean the 'title' field in bom_gross
bom_gross['title'] = (
    bom_gross['title']
    .str.lower()  # Convert to lowercase
    .str.strip()  # Remove leading and trailing whitespace
    .str.replace(r'[^\w\s]', '', regex=True)  # Remove special characters
    .str.replace(r'\s+', ' ', regex=True)  # Replace multiple spaces with a single
)

# Clean the 'title' field in tn_budgets
tn_budgets['movie'] = (
    tn_budgets['movie']
    .str.lower()  # Convert to lowercase
    .str.strip()  # Remove leading and trailing whitespace
    .str.replace(r'[^\w\s]', '', regex=True)  # Remove special characters
    .str.replace(r'\s+', ' ', regex=True)  # Replace multiple spaces with a single
)
#Check Overlap Between bom_gross and tmdb_movies:
matched_titles = bom_gross['title'].isin(tmdb_movies['title']).sum()
print(f"Number of matched titles between bom_gross and tmdb_movies: {matched_titles
```

```
Number of matched titles between bom_gross and tmdb_movies: 1560
```

In [19]:
```
#Check Overlap Between bom_gross and tmdb_movies:
matched_titles = movie_basics['original_title'].isin(tmdb_movies['original_title'])
print(f"Number of matched titles between bom_gross and tmdb_movies: {matched_titles
```

```
Number of matched titles between bom_gross and tmdb_movies: 67
```

In [20]:
```
#Check Overlap Between tn_budgets and tmdb_movies:
matched_titles = tn_budgets['movie'].isin(tmdb_movies['title']).sum()
print(f"Number of matched titles between tn_budgets and tmdb_movies: {matched_title
```

```
Number of matched titles between tn_budgets and tmdb_movies: 2051
```

In [21]:
```
#Check for duplicates in title_normalized:

display("Duplicates in bom_gross:", bom_gross[bom_gross['title'].duplicated()])
display("Duplicates in tn_budgets:", tn_budgets[tn_budgets['movie'].duplicated()])
display("Duplicates in tmdb_movies:", tmdb_movies[tmdb_movies['title'].duplicated()
```

```
'Duplicates in bom_gross:'
```

title	studio	domestic_gross	foreign_gross	year

```
'Duplicates in tn_budgets:'
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	yea
273	74	1998-05-19	godzilla	125000000.0	136314294.0	376000000.0	1998
408	9	2018-11-21	robin hood	99000000.0	30824628.0	84747441.0	2018
484	85	2005-07-08	fantastic four	87500000.0	154696080.0	333132750.0	2005
543	44	1999-05-07	the mummy	80000000.0	155385488.0	416385488.0	1999
707	8	1997-06-13	hercules	70000000.0	99112101.0	250700000.0	1997
...	...	...	...	...	...	...	..
5668	69	1942-11-16	cat people	134000.0	4000000.0	8000000.0	1942
5676	77	1968-10-01	night of the living dead	114000.0	12087064.0	30087064.0	1968
5677	78	1915-02-08	the birth of a nation	110000.0	10000000.0	11000000.0	1915
5699	100	1972-08-30	the last house on the left	87000.0	3100000.0	3100000.0	1972
5718	19	2008-02-22	the signal	50000.0	251150.0	406299.0	2008

84 rows × 7 columns

```
'Duplicates in tmdb_movies:'
```

	id	original_language	original_title	popularity	release_date	title	vote_a
781	51462	en	Brotherhood	2.235	2010-01-03	brotherhood	
1037	44369	tl	Boy	1.504	2009-06-01	boy	
1230	371702	en	All That Glitters	1.241	2010-09-25	all that glitters	
1354	155711	en	After-Life	0.994	2010-01-01	afterlife	
1501	36410	en	Zero	0.840	2010-02-06	zero	
...	...	...	...	...	...	...	
26495	556601	en	Recursion	0.600	2018-08-28	recursion	
26504	534282	en	Head	0.600	2015-03-28	head	
26506	561861	en	Eden	0.600	2018-11-25	eden	
26510	495045	en	Fail State	0.600	2018-10-19	fail state	
26511	492837	en	Making Filmmakers	0.600	2018-04-07	making filmmakers	

1880 rows × 8 columns

In [22]:
```
#Remove duplicates:
tn_budgets.drop_duplicates(subset='movie', inplace=True)
tmdb_movies.drop_duplicates(subset='title', inplace=True)
```

In [23]:
```
#Check for duplicates in title_normalized:

display("Duplicates in bom_gross:", bom_gross[bom_gross['title'].duplicated()])
display("Duplicates in tn_budgets:", tn_budgets[tn_budgets['movie'].duplicated()])
display("Duplicates in tmdb_movies:", tmdb_movies[tmdb_movies['title'].duplicated()
```

'Duplicates in bom_gross:'

title	studio	domestic_gross	foreign_gross	year

'Duplicates in tn_budgets:'

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year

'Duplicates in tmdb_movies:'

id	original_language	original_title	popularity	release_date	title	vote_average	vote_cour

Join bom_gross and tmdb_movies

In [24]:
```
#Join bom_gross and tmdb_movies
bom_tmdb_merged = pd.merge(bom_gross, tmdb_movies, on='title', how='inner', suffixe
print(f"bom_tmdb_merged shape: {bom_tmdb_merged.shape}")

# Check for missing values
```

```
missing_values = bom_tmdb_merged.isna().sum()
print("\nMissing values in bom_tmdb_merged:")
print(missing_values)

# Preview merged data
print("\nPreview of merged dataset:")
display(bom_tmdb_merged.head())
```

```
bom_tmdb_merged shape: (1560, 12)

Missing values in bom_tmdb_merged:
title                0
studio               0
domestic_gross       0
foreign_gross        0
year                 0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
vote_average         0
vote_count           0
dtype: int64

Preview of merged dataset:
```

	title	studio	domestic_gross	foreign_gross	year	id	original_language	original_
0	toy story 3	BV	415000000.0	652000000.0	2010	10193	en	Toy Stc
1	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	12444	en	Harry Pc anc Dea Hallows:
2	inception	WB	292600000.0	535700000.0	2010	27205	en	Incep
3	shrek forever after	P/DW	238700000.0	513900000.0	2010	10192	en	S Forever /
4	the twilight saga eclipse	Sum.	300500000.0	398000000.0	2010	24021	en	The Twi Saga: Ec

'movie' from tn_budgets and 'title' from tmdb_movies

In [25]:
```
# Merge using 'movie' from tn_budgets and 'title' from tmdb_movies
budgets_tmdb_merged = pd.merge(
    tn_budgets, tmdb_movies,
    left_on='movie', right_on='title',
```

```
    how='inner', suffixes=('_budget', '_tmdb')
)

# Print shape of the merged dataframe
print(f"budgets_tmdb_merged shape: {budgets_tmdb_merged.shape}")
```

```
budgets_tmdb_merged shape: (1998, 15)
```

In [26]:
```
# Check for missing values in the merged dataset
missing_values = budgets_tmdb_merged.isna().sum()
print("\nMissing values in budgets_tmdb_merged:")
print(missing_values)

#Preview merged dataset
print("\nPreview of merged dataset:")
display(budgets_tmdb_merged.head())
```

```
Missing values in budgets_tmdb_merged:
id_budget             0
release_date_budget   0
movie                 0
production_budget     0
domestic_gross        0
worldwide_gross       0
year                  0
id_tmdb               0
original_language     0
original_title        0
popularity            0
release_date_tmdb     0
title                 0
vote_average          0
vote_count            0
dtype: int64

Preview of merged dataset:
```

	id_budget	release_date_budget	movie	production_budget	domestic_gross	worldwide
0	1	2009-12-18	avatar	425000000.0	760507625.0	2.77634
1	2	2011-05-20	pirates of the caribbean on stranger tides	410600000.0	241063875.0	1.04566
2	4	2015-05-01	avengers age of ultron	330600000.0	459005868.0	1.40301
3	7	2018-04-27	avengers infinity war	300000000.0	678815482.0	2.04813
4	9	2017-11-17	justice league	300000000.0	229024295.0	6.55945

In [27]:
```
# Combine all three datasets
final_merged = pd.merge(
    bom_tmdb_merged, budgets_tmdb_merged,
    on='title',
    how='inner',
```

```
    suffixes=('_bom_tmdb', '_budget_tmdb')
)
print(f"final_merged shape: {final_merged.shape}")
```

```
final_merged shape: (1082, 26)
```

In [28]:

```
#Check for missing values
print("\nMissing values in final_merged:")
print(final_merged.isna().sum())

# Preview the final merged dataset
display(final_merged.head())
```

```
Missing values in final_merged:
title                            0
studio                           0
domestic_gross_bom_tmdb          0
foreign_gross                    0
year_bom_tmdb                    0
id                               0
original_language_bom_tmdb       0
original_title_bom_tmdb          0
popularity_bom_tmdb              0
release_date                     0
vote_average_bom_tmdb            0
vote_count_bom_tmdb              0
id_budget                        0
release_date_budget              0
movie                            0
production_budget                0
domestic_gross_budget_tmdb       0
worldwide_gross                  0
year_budget_tmdb                 0
id_tmdb                          0
original_language_budget_tmdb    0
original_title_budget_tmdb       0
popularity_budget_tmdb           0
release_date_tmdb                0
vote_average_budget_tmdb         0
vote_count_budget_tmdb           0
dtype: int64
```

	title	studio	domestic_gross_bom_tmdb	foreign_gross	year_bom_tmdb	id	origi
0	toy story 3	BV	415000000.0	652000000.0	2010	10193	
1	inception	WB	292600000.0	535700000.0	2010	27205	
2	shrek forever after	P/DW	238700000.0	513900000.0	2010	10192	
3	the twilight saga eclipse	Sum.	300500000.0	398000000.0	2010	24021	
4	iron man 2	Par.	312400000.0	311500000.0	2010	10138	

5 rows × 26 columns

In [29]:

```
# Remove unnecessary or duplicate columns
columns_to_drop = [
    'id', 'id_budget', 'id_tmdb', 'release_date_tmdb', 'year_budget_tmdb','domestic
    'original_language_budget_tmdb', 'original_title_bom_tmdb', 'vote_count_budget_
    'release_date_budget', 'original_title_budget_tmdb'
]

final_merged_cleaned = final_merged.drop(columns=columns_to_drop)

# Rename columns for consistency and clarity
final_merged_cleaned.rename(columns={
    'release_date': 'release_date',
    'year_bom_tmdb': 'year',
    'vote_count_bom_tmdb':    'vote_count',
    'vote_average_budget_tmdb': 'vote_average',
    'domestic_gross_budget_tmdb': 'domestic_gross',
    'original_language_bom_tmdb': 'original_language',
    'popularity_bom_tmdb':'popularity'
}, inplace=True)

# Display the cleaned dataframe information
print("Cleaned final_merged DataFrame Info:")
final_merged_cleaned.info()

# Preview the cleaned dataframe
display(final_merged_cleaned.head())
```

```
Cleaned final_merged DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1082 entries, 0 to 1081
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              1082 non-null   object
 1   studio             1082 non-null   object
 2   foreign_gross      1082 non-null   float64
 3   year               1082 non-null   Int64
 4   original_language  1082 non-null   object
 5   popularity         1082 non-null   float64
 6   release_date       1082 non-null   datetime64[ns]
 7   vote_count         1082 non-null   int64
 8   movie              1082 non-null   object
 9   production_budget  1082 non-null   float64
 10  domestic_gross     1082 non-null   float64
 11  worldwide_gross    1082 non-null   float64
 12  vote_average       1082 non-null   float64
dtypes: Int64(1), datetime64[ns](1), float64(6), int64(1), object(4)
memory usage: 119.4+ KB
```

	title	studio	foreign_gross	year	original_language	popularity	release_date	vote_c
0	toy story 3	BV	652000000.0	2010	en	24.445	2010-06-17	ξ
1	inception	WB	535700000.0	2010	en	27.920	2010-07-16	2:
2	shrek forever after	P/DW	513900000.0	2010	en	15.041	2010-05-16	:
3	the twilight saga eclipse	Sum.	398000000.0	2010	en	20.340	2010-06-23	‹
4	iron man 2	Par.	311500000.0	2010	en	28.515	2010-05-07	1:

In [30]:
```
# Save the DataFrame to a CSV file
final_merged_cleaned.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/proces
print("Dataset saved as 'final_merged_cleaned.csv'.")
```

```
Dataset saved as 'final_merged_cleaned.csv'.
```

In [31]:
```
#Check Overlap Between movie_basic and movie_ratings:
matched_titles = movie_basics['movie_id'].isin(movie_ratings['movie_id']).sum()
print(f"Number of matched movie_id between movie_basics and movie_ratings: {matched
```

```
Number of matched movie_id between movie_basics and movie_ratings: 65720
```

In [32]:
```
# Merge `movie_basics` and `movie_ratings` on `movie_id`
db_data = pd.merge(movie_basics, movie_ratings, on='movie_id', how='inner')

# Display the merged DataFrame information
```

```
print("Merged db_data DataFrame Info:")
db_data.info()

# Display the first few rows of the merged DataFrame
display(db_data.head())
```

```
Merged db_data DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 65720 entries, 0 to 65719
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         65720 non-null  object
 1   primary_title    65720 non-null  object
 2   original_title   65720 non-null  object
 3   start_year       65720 non-null  int64
 4   runtime_minutes  65720 non-null  float64
 5   genres           65720 non-null  object
 6   averagerating    65720 non-null  float64
 7   numvotes         65720 non-null  int64
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	g
0	tt0063540	sunghursh	sunghursh	2013	175.0	Action,Crime,D
1	tt0066787	one day before the rainy season	ashad ka ek din	2019	114.0	Biography,D
2	tt0069049	the other side of the wind	the other side of the wind	2018	122.0	D
3	tt0100275	the wandering soap opera	la telenovela errante	2017	80.0	Comedy,Drama,Fa
4	tt0137204	joe finds grace	joe finds grace	2017	83.0	Adventure,Animation,Co

In [33]:
```
# Create a normalized version of the title for merging (without changing original t
db_data['primary_title'] = (
    db_data['primary_title']
    .str.lower()
    .str.strip()
    .str.replace(r'[^\w\s]', '', regex=True)  # Remove special characters
    .str.replace(r'\s+', ' ', regex=True)  # Replace multiple spaces with a single
)
```

In [34]:
```
#Check Overlap Between bom_gross and tmdb_movies:
matched_titles = final_merged_cleaned['title'].isin(db_data['primary_title']).sum()
print(f"Number of matched movie_id between movie_basics and movie_ratings: {matched
```

```
Number of matched movie_id between movie_basics and movie_ratings: 1062
```

In [35]:
```
# Standardize titles for merging
final_merged_cleaned['title'] = final_merged_cleaned['title'].str.lower().str.strip

# Merge datasets on titles
merged_data = pd.merge(
    final_merged_cleaned,
    db_data,
    left_on='title',
    right_on='primary_title',
    how='inner'
)
```

In [36]:
```
display(merged_data.head())
```

	title	studio	foreign_gross	year	original_language	popularity	release_date	vote_c
0	toy story 3	BV	652000000.0	2010	en	24.445	2010-06-17	ɛ
1	inception	WB	535700000.0	2010	en	27.920	2010-07-16	2:
2	shrek forever after	P/DW	513900000.0	2010	en	15.041	2010-05-16	:
3	the twilight saga eclipse	Sum.	398000000.0	2010	en	20.340	2010-06-23	∠
4	iron man 2	Par.	311500000.0	2010	en	28.515	2010-05-07	1:

5 rows × 21 columns

In [37]:
```
print(merged_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1241 entries, 0 to 1240
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              1241 non-null   object
 1   studio             1241 non-null   object
 2   foreign_gross      1241 non-null   float64
 3   year               1241 non-null   Int64
 4   original_language  1241 non-null   object
 5   popularity         1241 non-null   float64
 6   release_date       1241 non-null   datetime64[ns]
 7   vote_count         1241 non-null   int64
 8   movie              1241 non-null   object
 9   production_budget  1241 non-null   float64
 10  domestic_gross     1241 non-null   float64
 11  worldwide_gross    1241 non-null   float64
 12  vote_average       1241 non-null   float64
 13  movie_id           1241 non-null   object
 14  primary_title      1241 non-null   object
 15  original_title     1241 non-null   object
 16  start_year         1241 non-null   int64
 17  runtime_minutes    1241 non-null   float64
 18  genres             1241 non-null   object
 19  averagerating      1241 non-null   float64
 20  numvotes           1241 non-null   int64
dtypes: Int64(1), datetime64[ns](1), float64(8), int64(3), object(8)
memory usage: 214.5+ KB
None
```

In [38]:
```
# Drop redundant columns
merged_data.drop(['original_title', 'movie', 'primary_title','movie_id'], axis=1, i
```

In [39]:
```
merged_data.info()
merged_data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1241 entries, 0 to 1240
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   title               1241 non-null   object
 1   studio              1241 non-null   object
 2   foreign_gross       1241 non-null   float64
 3   year                1241 non-null   Int64
 4   original_language   1241 non-null   object
 5   popularity          1241 non-null   float64
 6   release_date        1241 non-null   datetime64[ns]
 7   vote_count          1241 non-null   int64
 8   production_budget   1241 non-null   float64
 9   domestic_gross      1241 non-null   float64
 10  worldwide_gross     1241 non-null   float64
 11  vote_average        1241 non-null   float64
 12  start_year          1241 non-null   int64
 13  runtime_minutes     1241 non-null   float64
 14  genres              1241 non-null   object
 15  averagerating       1241 non-null   float64
 16  numvotes            1241 non-null   int64
dtypes: Int64(1), datetime64[ns](1), float64(8), int64(3), object(4)
memory usage: 175.7+ KB
```

Out[39]:

	title	studio	foreign_gross	year	original_language	popularity	release_date	vote_
0	toy story 3	BV	652000000.0	2010	en	24.445	2010-06-17	
1	inception	WB	535700000.0	2010	en	27.920	2010-07-16	
2	shrek forever after	P/DW	513900000.0	2010	en	15.041	2010-05-16	
3	the twilight saga eclipse	Sum.	398000000.0	2010	en	20.340	2010-06-23	
4	iron man 2	Par.	311500000.0	2010	en	28.515	2010-05-07	

3.1. Derived Metrics

a. Profit and Profit Margin

In [40]:
```
# Calculate profit by subtracting the production budget from the worldwide gross
merged_data['profit'] = merged_data['worldwide_gross'] - merged_data['production_bu
# 'profit' is the difference between how much the movie made globally ('worldwide_g

# Calculate profit margin by dividing the profit by the production budget
merged_data['profit_margin'] = merged_data['profit'] / merged_data['production_budg
# 'profit_margin' is the ratio of profit to production budget, indicating the retur
```

b. Release Windows

In [41]:
```
# Extract the month from the 'release_date' column and store it in a new column 're
merged_data['release_month'] = merged_data['release_date'].dt.month

# Create a dictionary that maps month numbers to their corresponding month names
month_mapping = {
    1: 'January', 2: 'February', 3: 'March', 4: 'April', 5: 'May', 6: 'June',
    7: 'July', 8: 'August', 9: 'September', 10: 'October', 11: 'November', 12: 'Dec
}

# Map the 'release_month' column to month names using the dictionary
merged_data['release_month_name'] = merged_data['release_month'].map(month_mapping)


# Extract the quarter from the 'release_date' column and store it in a new column '
merged_data['release_quarter'] = merged_data['release_date'].dt.quarter
# The '.dt.quarter' function extracts the quarter of the year (1, 2, 3, or 4) based
# Quarters are typically divided as:
#  - Q1: January, February, March
#  - Q2: April, May, June
#  - Q3: July, August, September
#  - Q4: October, November, December
```

In [42]:
```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1241 entries, 0 to 1240
Data columns (total 22 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   title                1241 non-null   object
 1   studio               1241 non-null   object
 2   foreign_gross        1241 non-null   float64
 3   year                 1241 non-null   Int64
 4   original_language    1241 non-null   object
 5   popularity           1241 non-null   float64
 6   release_date         1241 non-null   datetime64[ns]
 7   vote_count           1241 non-null   int64
 8   production_budget    1241 non-null   float64
 9   domestic_gross       1241 non-null   float64
 10  worldwide_gross      1241 non-null   float64
 11  vote_average         1241 non-null   float64
 12  start_year           1241 non-null   int64
 13  runtime_minutes      1241 non-null   float64
 14  genres               1241 non-null   object
 15  averagerating        1241 non-null   float64
 16  numvotes             1241 non-null   int64
 17  profit               1241 non-null   float64
 18  profit_margin        1241 non-null   float64
 19  release_month        1241 non-null   int64
 20  release_month_name   1241 non-null   object
 21  release_quarter      1241 non-null   int64
dtypes: Int64(1), datetime64[ns](1), float64(10), int64(5), object(5)
memory usage: 224.2+ KB
```

c. Genre Analysis

In [43]:
```python
genres_split = merged_data.assign(genres=merged_data['genres'].str.split(',')).expl
```

In [44]:
```python
# Save the DataFrame to a CSV file
merged_data.to_csv('C:/Users/USER/Desktop/movie_insights/zippedData/processed/merge
print("Dataset saved as 'merged_movie_clean.csv'.")
```

```
Dataset saved as 'merged_movie_clean.csv'.
```

Exploratory Data Analysis

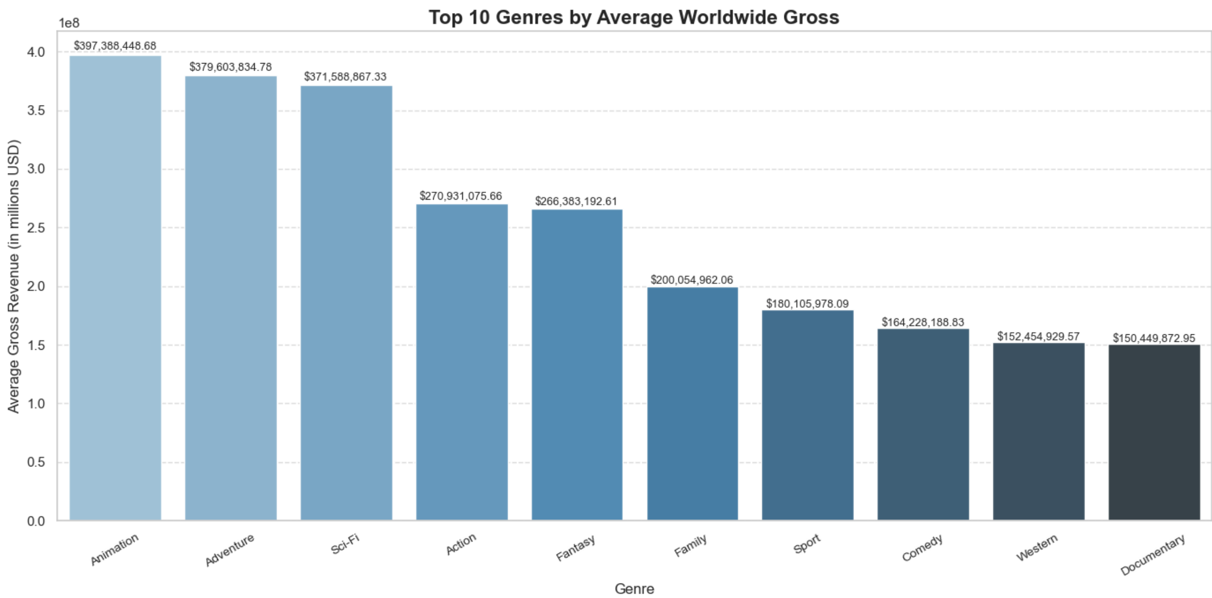
Q1: Which genres consistently generate the highest revenue?

I will analyze which genres consistently generate the highest revenue by examining the average revenue for each genre. To identify trends, I'll use visualizations like bar plots

In [45]:
```python
# Group the dataframe by 'genres' to aggregate movies by their genre
# For each genre group,I calculate the mean of 'worldwide_gross' (average revenue p
genres_revenue = genres_split.groupby('genres')['worldwide_gross'].mean()

# Sort the resulting series in descending order based on the average worldwide gros
```

```
# This will display the genres with the highest average revenue at the top
genres_revenue = genres_revenue.sort_values(ascending=False)

display(genres_revenue)

# Select the top 10 genres based on average worldwide gross
top_10_genres = genres_revenue.head(10)

# Visualization of Top 10 Genres by Average Worldwide Gross
plt.figure(figsize=(14, 7))

# Use a seaborn color palette for aesthetics
sns.barplot(
    x=top_10_genres.index,
    y=top_10_genres.values,
    palette="Blues_d"
)

# Title and labels
plt.title('Top 10 Genres by Average Worldwide Gross', fontsize=16, weight='bold')
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Average Gross Revenue (in millions USD)', fontsize=12)

# Rotate x-axis labels and add gridlines
plt.xticks(rotation=30, fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with their values
for index, value in enumerate(top_10_genres.values):
    plt.text(index, value + (value * 0.01), f"${value:,.2f}", ha='center', fontsize

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

```
genres
Animation      3.973884e+08
Adventure      3.796038e+08
Sci-Fi         3.715889e+08
Action         2.709311e+08
Fantasy        2.663832e+08
Family         2.000550e+08
Sport          1.801060e+08
Comedy         1.642282e+08
Western        1.524549e+08
Documentary    1.504499e+08
Musical        1.500816e+08
Thriller       1.437951e+08
History        1.155057e+08
Horror         1.101223e+08
Biography      1.093106e+08
Mystery        1.070858e+08
Crime          1.048086e+08
Music          1.036456e+08
Drama          1.023338e+08
War            9.268191e+07
Romance        9.153810e+07
News           6.283172e+07
Name: worldwide_gross, dtype: float64
```

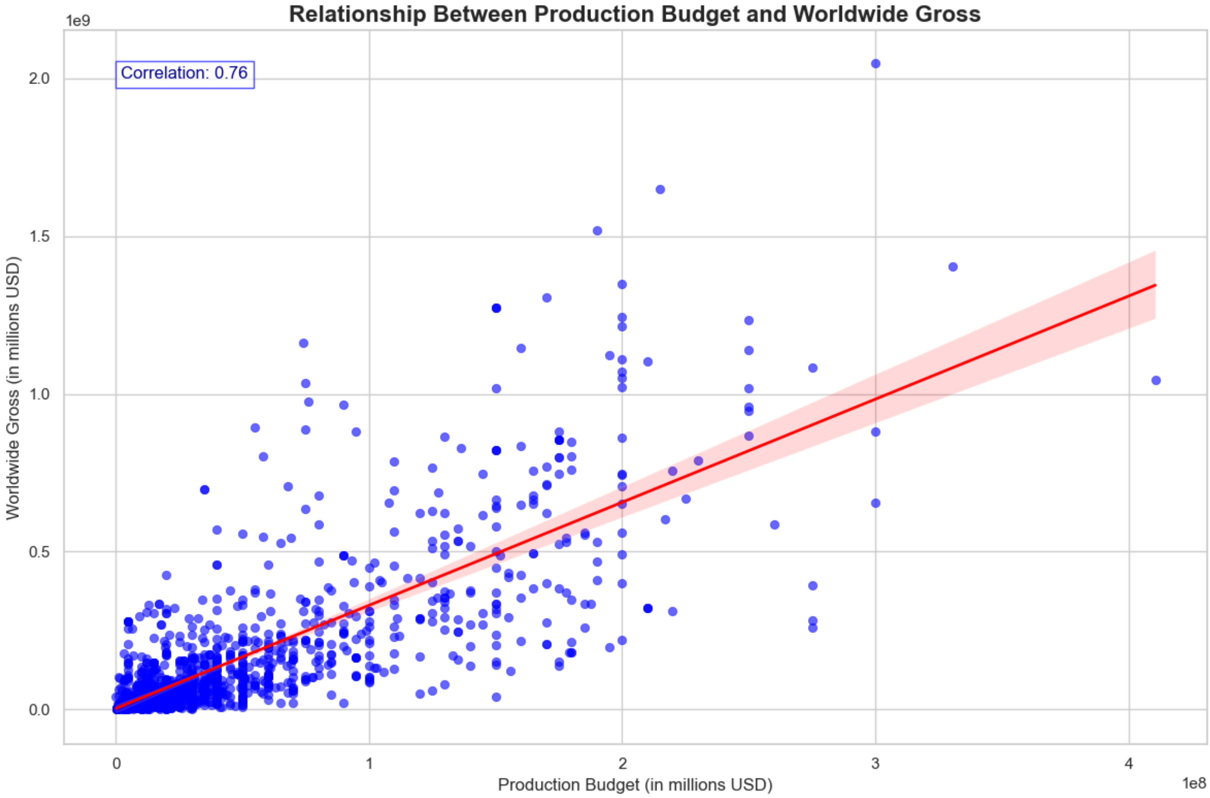


How do budgets correlate with worldwide gross?

I'm interested in exploring how production budgets correlate with worldwide gross revenue. To investigate this, I'll use scatter plots to visualize the relationship and calculate correlation coefficients to quantify the strength of the association.

In [46]:
```
# Scatter plot of production budget vs worldwide gross
# Figure size for better clarity
plt.figure(figsize=(12, 8))
```

```
# Scatter plot of Production Budget vs Worldwide Gross
sns.scatterplot(
    data=merged_data,
    x='production_budget',
    y='worldwide_gross',
    alpha=0.6,
    edgecolor=None,
    color='blue'
)

# Add a regression line to visualize the trend
sns.regplot(
    data=merged_data,
    x='production_budget',
    y='worldwide_gross',
    scatter=False,
    color='red',
    line_kws={'linewidth': 2}
)

# Title and axis labels
plt.title('Relationship Between Production Budget and Worldwide Gross', fontsize=16
plt.xlabel('Production Budget (in millions USD)', fontsize=12)
plt.ylabel('Worldwide Gross (in millions USD)', fontsize=12)

# Display the correlation coefficient on the plot
correlation = merged_data['production_budget'].corr(merged_data['worldwide_gross'])
plt.text(
    0.05, 0.95,
    f'Correlation: {correlation:.2f}',
    ha='left', va='top',
    transform=plt.gca().transAxes,
    fontsize=12, color='darkblue',
    bbox=dict(facecolor='white', alpha=0.7, edgecolor='blue')
)

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



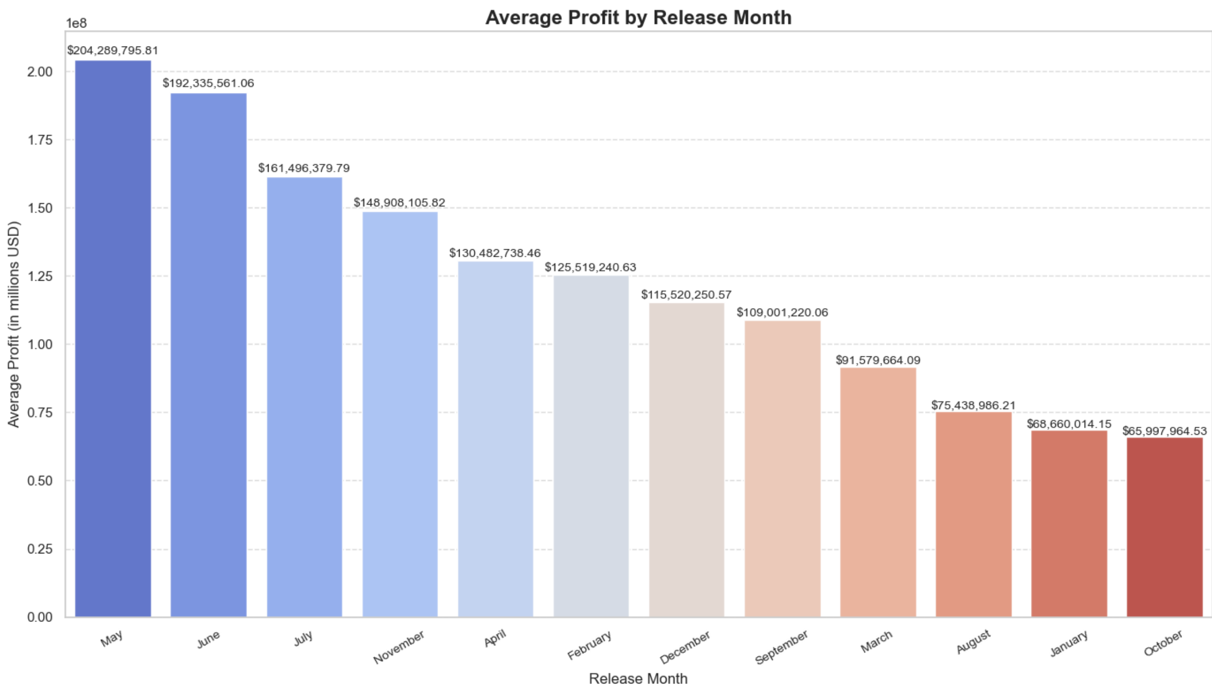
Q3: What are the most profitable release windows for movies?

I want to find out which release windows are the most profitable for movies. By analyzing the average revenue of films released in different months

In [47]:
```
# Group the data by 'release_month' and calculate the average 'profit' for each mon
# Then, sort the resulting values in descending order to find the months with the h
release_profit = merged_data.groupby('release_month_name')['profit'].mean().sort_va
display(release_profit)


# Visualization of Average profit by release month
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate average profit by release month
release_profit = merged_data.groupby('release_month_name')['profit'].mean().sort_va

# Set a consistent style
sns.set_style("whitegrid")

# Create the bar plot
plt.figure(figsize=(14, 8))
sns.barplot(
    x=release_profit.index,
    y=release_profit.values,
    palette="coolwarm"
)

# Add title and labels
```

```
plt.title('Average Profit by Release Month', fontsize=16, weight='bold')
plt.xlabel('Release Month', fontsize=12)
plt.ylabel('Average Profit (in millions USD)', fontsize=12)

# Rotate x-axis labels and add gridlines
plt.xticks(rotation=30, fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with their values
for index, value in enumerate(release_profit.values):
    plt.text(index, value + (value * 0.01), f"${value:,.2f}", ha='center', fontsize

# Ensure proper layout
plt.tight_layout()
plt.show()
```

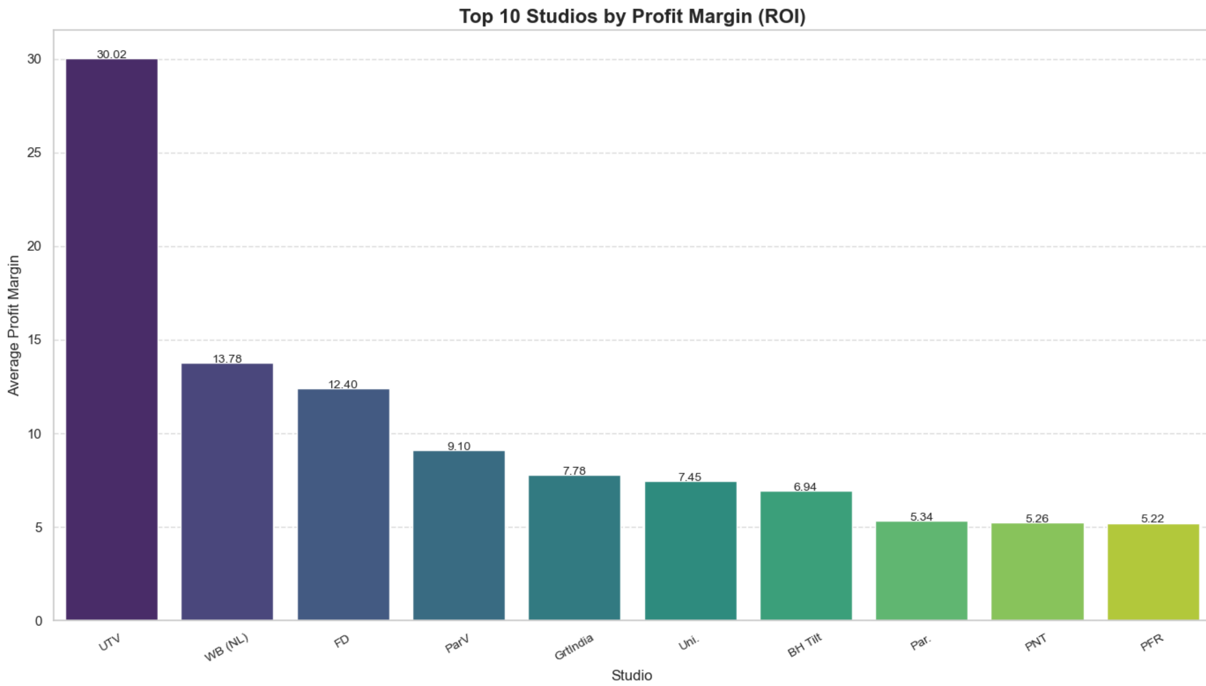
```
release_month_name
May          2.042898e+08
June         1.923356e+08
July         1.614964e+08
November     1.489081e+08
April        1.304827e+08
February     1.255192e+08
December     1.155203e+08
September    1.090012e+08
March        9.157966e+07
August       7.543899e+07
January      6.866001e+07
October      6.599796e+07
Name: profit, dtype: float64
```



Q4: Which studios have the highest profit margins?

I'm curious about which studios achieve the highest profit margins. To compare profitability —calculated as worldwidegross minus budget—across production studios, I'll use visualizations like box plots or bar charts to present the data effectively

In [48]:
```
# Group the data by 'studio' and calculate the average 'profit_margin' for each stu
# The 'profit_margin' is the ratio of profit to the production budget, which measur
studio_profit = merged_data.groupby('studio')['profit_margin'].mean()

# Sort the resulting series in descending order to find the studios with the highes
# This step ensures that the studios with the highest ROI are shown at the top
studio_profit = studio_profit.sort_values(ascending=False)

# Display the resulting series
# Display the top 10 studios with the highest profit margin
top_10_studios = studio_profit.head(10)

# Set a consistent style for the plot
sns.set_style("whitegrid")

# Visualization of top 10 studios by profit margin
plt.figure(figsize=(14, 8))

# Use seaborn's barplot for a cleaner look
sns.barplot(
    x=top_10_studios.index,
    y=top_10_studios.values,
    palette="viridis"
)

# Add title and axis labels
plt.title('Top 10 Studios by Profit Margin (ROI)', fontsize=16, weight='bold')
plt.xlabel('Studio', fontsize=12)
plt.ylabel('Average Profit Margin', fontsize=12)

# Rotate x-axis labels for readability and add gridlines
plt.xticks(rotation=30, fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with their values
for index, value in enumerate(top_10_studios.values):
    plt.text(index, value + 0.01, f"{value:.2f}", ha='center', fontsize=10)

# Adjust layout to prevent clipping
plt.tight_layout()
plt.show()
```



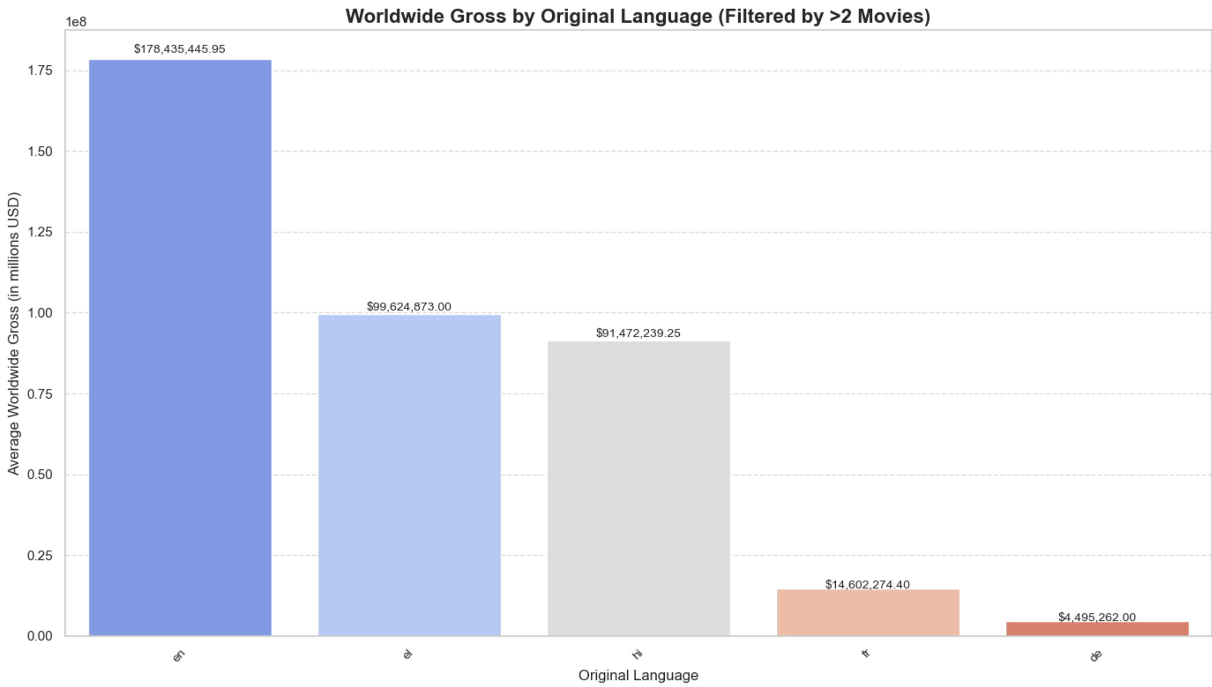
Q5: Does the original language influence global performance?

In [49]:

```
# Group the data by original language and calculate average worldwide gross and cou
language_stats = merged_data.groupby('original_language').agg(
    average_worldwide_gross=('worldwide_gross', 'mean'),  # Calculate the average w
    number_of_movies=('worldwide_gross', 'count')          # Count the number of mov
)

# Filter the data to include only languages with more than 2 movies
language_stats_filtered = language_stats[language_stats['number_of_movies'] > 2]

# Sort the filtered data by average worldwide gross
language_stats_filtered = language_stats_filtered.sort_values(by='average_worldwide

# Display the filtered and sorted dataframe
display(language_stats_filtered)

# Prepare the data for visualization
language_revenue = language_stats_filtered['average_worldwide_gross']

# Set a consistent style for the plot
sns.set_style("whitegrid")

# Create a bar plot for average worldwide gross by original language
plt.figure(figsize=(14, 8))
sns.barplot(
    x=language_revenue.index,
    y=language_revenue.values,
    palette="coolwarm"
)

# Add titles and labels
plt.title('Worldwide Gross by Original Language (Filtered by >2 Movies)', fontsize=
plt.xlabel('Original Language', fontsize=12)
```

```
plt.ylabel('Average Worldwide Gross (in millions USD)', fontsize=12)

# Rotate x-axis labels for better readability and add gridlines
plt.xticks(rotation=45, fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with their values
for index, value in enumerate(language_revenue.values):
    plt.text(index, value + (value * 0.01), f"${value:,.2f}", ha='center', fontsize

# Ensure layout doesn't get cut off
plt.tight_layout()
plt.show()
```

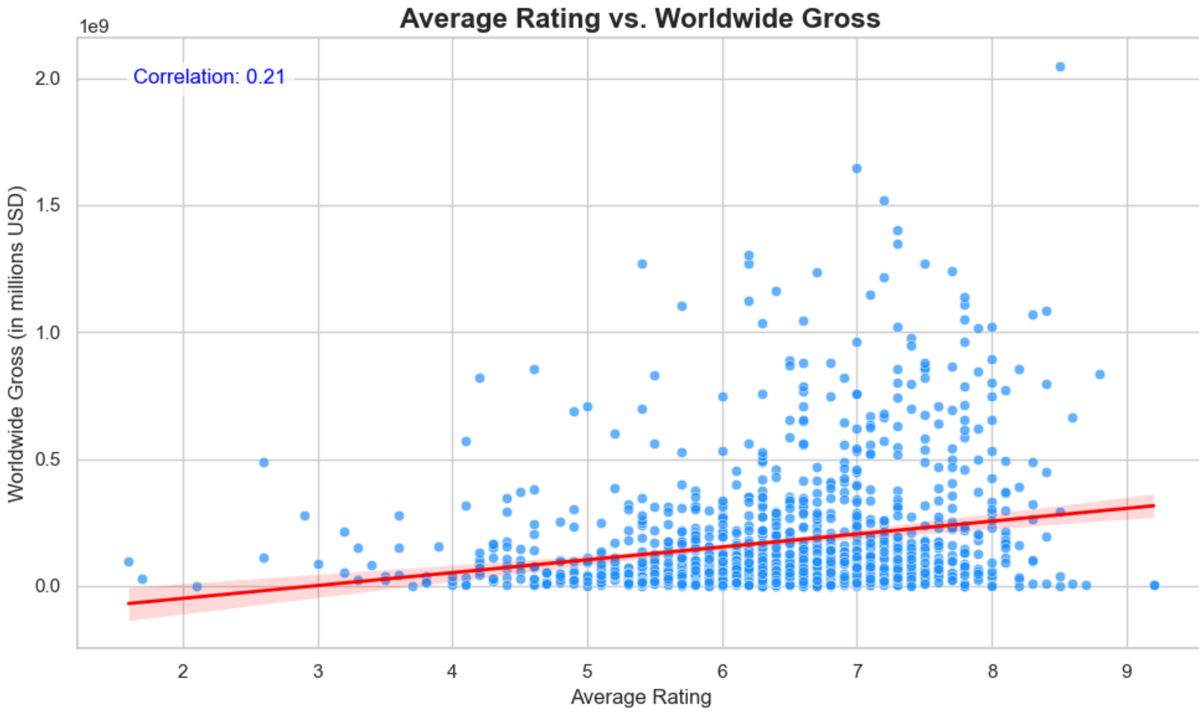
original_language	average_worldwide_gross	number_of_movies
en	1.784354e+08	1214
el	9.962487e+07	3
hi	9.147224e+07	4
fr	1.460227e+07	5
de	4.495262e+06	4

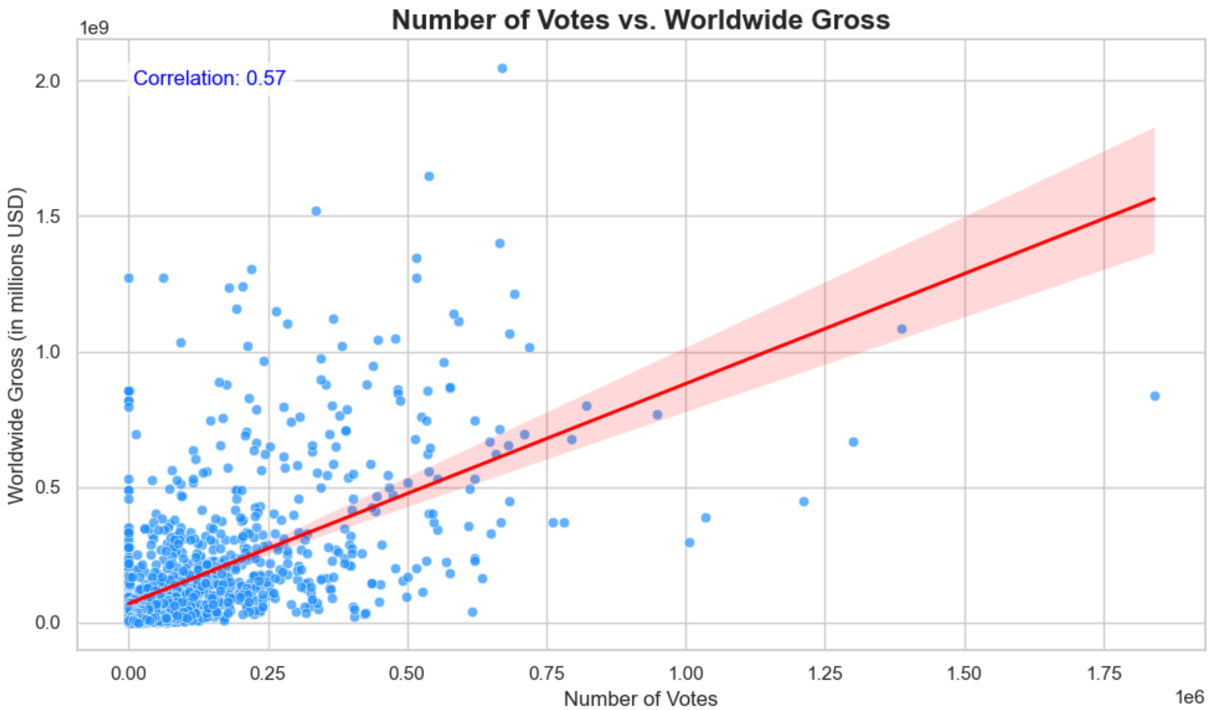


Q6: How do ratings (average and votes) correlate with revenue?

In [50]:
```
# Define colors for consistency
scatter_color = 'dodgerblue'   # Blue for scatter points
regression_color = 'red'       # Red for regression line
```

```
# Scatter plot: Average Rating vs Worldwide Gross
plt.figure(figsize=(10, 6))

# Scatter plot for Average Rating vs Worldwide Gross with uniform color
sns.scatterplot(data=merged_data, x='averagerating', y='worldwide_gross', alpha=0.7

# Add regression line with the same color scheme
sns.regplot(data=merged_data, x='averagerating', y='worldwide_gross', scatter=False

# Title and labels
plt.title('Average Rating vs. Worldwide Gross', fontsize=16, weight='bold')
plt.xlabel('Average Rating', fontsize=12)
plt.ylabel('Worldwide Gross (in millions USD)', fontsize=12)

# Add the correlation coefficient
correlation_rating_gross = merged_data['averagerating'].corr(merged_data['worldwide
plt.text(0.05, 0.95, f'Correlation: {correlation_rating_gross:.2f}', ha='left', va=

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

# Scatter plot: Number of Votes vs Worldwide Gross
plt.figure(figsize=(10, 6))

# Scatter plot for Number of Votes vs Worldwide Gross with uniform color
sns.scatterplot(data=merged_data, x='numvotes', y='worldwide_gross', alpha=0.7, col

# Add regression line with the same color scheme
sns.regplot(data=merged_data, x='numvotes', y='worldwide_gross', scatter=False, col

# Title and labels
plt.title('Number of Votes vs. Worldwide Gross', fontsize=16, weight='bold')
plt.xlabel('Number of Votes', fontsize=12)
plt.ylabel('Worldwide Gross (in millions USD)', fontsize=12)

# Add the correlation coefficient
correlation_votes_gross = merged_data['numvotes'].corr(merged_data['worldwide_gross
plt.text(0.05, 0.95, f'Correlation: {correlation_votes_gross:.2f}', ha='left', va='

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





4. Conclusion

Key Insights:

1. Action and Adventure genres generate the highest revenue.
2. Higher budgets tend to result in higher worldwide gross.
3. Summer and holiday release windows are the most profitable.
4. Major studios with large budgets dominate profit margins.
5. English-language movies lead in global performance, but specific non-English movies

perform well in niche markets.

6. Audience engagement (via votes) correlates strongly with revenue, while high ratings alone are not a guarantee of success.

Recommendations:

- Prioritize high-budget Action and Adventure films for global appeal.
- Align release schedules with profitable months (summer, holidays).
- Foster partnerships with top-performing studios.
- Invest in marketing strategies to increase audience engagement and votes.

In [ ]: