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1 BUSINESS UNDERSTANDING

1.1 OBJECTIVE

The company is launching a new movie studio and seeks to produce films that achieve both high box office performance and strong audience appeal. By analyzing existing market trends, the aim is to identify the types of films that are most successful, using insights from genres, budgets, ratings, and revenue data. These findings will guide decisions on what types of films to create, ensuring a profitable and competitive entry into the film industry.

1.2 WHY NOW

The movie industry is experiencing strong growth and presents a strategic opportunity for entry:

1.2.1 Revenue Growth:

Global box office revenue rebounded to 26 billion dollars in 2023 and is projected to reach 50 billion dollars by 2030, driven by increasing theatrical attendance and international market expansion.

1.2.2 Genre and Market Trends:

Action, superhero, and adventure films remain dominant, contributing to over 70% of box office revenue in 2023. Low-budget horror films, however, continue to achieve impressive 200-300% ROI, offering a lucrative segment for new studios.

1.2.3 Audience Engagement:

Movies with IMDb ratings above 7.5 generate up to 40% more revenue. Films with significant audience engagement (100,000+ votes) tend to outperform others both domestically and internationally.

1.3 KEY BUSINESS QUESTIONS

1.Which genres and themes consistently lead to high box office performance?

2.How do production budgets influence profitability and ROI?

3.What impact do ratings and audience engagement have on revenue and success?

4.How does the balance between domestic and international revenue vary across genres and film types?

5.What are the most profitable times of the year to release films?

1.4 SUCCESS CRITERIA

1.Identify Profitable Genres:

Analyze box office data to determine which genres and themes perform best.

2.Optimize Budget Allocation:

Assess the relationship between production budgets and ROI to establish profitable budget ranges.

3.Leverage Ratings and Engagement:

Explore the correlation between IMDb ratings, audience votes, and box office success to identify quality benchmarks.

4.Understand Revenue Composition:

Evaluate the contribution of domestic vs. international markets to total revenue for different genres.

5.Determine Strategic Release Windows:

Identify the best months or quarters to release films for maximum profitability.

2 DATA UNDERSTANDING

2.0.1 OVERVIEW

The datasets focus on analyzing key factors influencing movie success, aligning with the business objective of creating commercially successful and audience-captivating films. The following data sources and variables will address the outlined business questions:

2.0.2 IMDb: Movie Basics

This table provides foundational information about movies, critical for understanding trends in genres, runtime, and release years.

Columns:

movie_id: Unique identifier for each movie (joins with movie_ratings).

primary_title: Official title of the movie (used for identification in analysis).

original_title: Native language title, useful for analyzing the influence of language on commercial success.

start_year: Year of release, enabling exploration of time-based trends (e.g., genre popularity, seasonal releases).

runtime_minutes: Movie length, used to determine if runtime influences audience engagement and box office performance.

genres: Genres of the movie, critical for identifying commercially successful themes and trends.

Key Uses:

Address Q1: "What genres and themes consistently lead to box office success?"

Address Q5: What are the most profitable times of the year to release films?

2.0.3 IMDb: Movie Ratings

This table offers insights into audience reception and engagement metrics, which are critical for understanding the role of ratings and votes in a movie's financial performance.

Columns:

movie_id: Unique identifier for each movie (joins with movie_basics).

averagerating: Average IMDb rating, useful for gauging critical acclaim and audience satisfaction.

numvotes: Number of votes received, indicating audience engagement and popularity.

Key Uses:

Address Q3: "What impact do ratings and audience engagement have on revenue and success??"

2.0.4 The Numbers: Budget Data

This table provides production budget details and global revenue, essential for ROI and profitability analysis.

Columns:

movie: Name of the movie.

production_budget: Cost of production, enabling the evaluation of budget-performance relationships.

domestic_gross: Domestic revenue.

worldwide_gross: Total revenue globally.

Key Uses:

Address Q2: "How do production budgets influence profitability and ROI?"

Address Q4: "4.How does the balance between domestic and international revenue vary across genres and film types?"

2.0.5 . TMDb: Additional Metadata

This dataset supplements IMDb data with information about popularity and audience ratings.

Columns:

original_language: Language of the film, supporting analysis of language preferences.

genre_ids: Genre categorization (used alongside IMDb genres).

vote_average and vote_count: Audience ratings and engagement metrics.

release_date: Exact release date, supporting seasonal and trend analysis.

Key Uses:

Address Q3: Analyze audience engagement and its effect on financial performance.

3 Data Collection

To make informed decisions about the types of films to produce, we need to gather relevant data from various sources. The following types of data will be essential: * the imbd dataset(here we will only take two tables i.e movie_basics and movie_ratings) * tmbd dataset * tn_budget dataset

we'd then combine the dataset to one

3.1 importing datasets

[121]:
```
#load necessary libraries
import sqlite3
import pandas as pd
import numpy as np
```

[122]:
```
db_path = "im.db"

# Connect to the database
with sqlite3.connect(db_path) as conn:
    cursor = conn.cursor()

    # Get list of available tables
    cursor.execute("SELECT name FROM sqlite_master WHERE type='table';")
    available_tables = {row[0] for row in cursor.fetchall()}  # Convert to set

    print("Available tables:", available_tables)

    # Define expected tables
    tables = ["movie_basics", "directors", "known_for", "movie_akas",
              "movie_ratings", "persons", "principals", "writers"]

    # Load only existing tables
    dataframes = {
        table: pd.read_sql_query(f"SELECT * FROM {table}", conn)
        for table in tables if table in available_tables
    }

# Print which tables were loaded successfully
print("Loaded tables:", list(dataframes.keys()))
```

```
Available tables: {'persons', 'known_for', 'movie_ratings', 'writers',
'movie_akas', 'movie_basics', 'directors', 'principals'}
Loaded tables: ['movie_basics', 'directors', 'known_for', 'movie_akas',
'movie_ratings', 'persons', 'principals', 'writers']
```

[123]:
```python
# Access movie_basics table
movie_basics = dataframes["movie_basics"]
# Display the movie_basic DataFrame
print("\nmovie_basic DataFrame:")
movie_basics.head()
```

```
movie_basic DataFrame:
```

[123]:
```
    movie_id                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy
```

[124]:
```python
# access movie_ratings table
movie_ratings=dataframes['movie_ratings']
# Display the movie_ratings DataFrame
print("\nmovie_ratings DataFrame:")
movie_ratings.head()
```

```
movie_ratings DataFrame:
```

[124]:
```
     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
```

3.2 merged_df

joining movie_basics and movie_ratings as merged_df

[125]:
```python
#check the movie_rating dataset info
movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
```

```
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

[126]:
```
#check the movie_basics dataset info
movie_basics.info()
```

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

The movie ratings dataset is quite clean while the movie basic dataset contains missing values from the columns: original_title,runtime_minutes and genres. The next step is to input the missing values and drop the irrelevant columns like and original_title

[127]:
```
#dropping the original_title column
movie_basics.drop(columns=['original_title'], inplace=True)
```

[128]:
```
#handling missing values in runtime_minutes
movie_basics['runtime_minutes']=movie_basics['runtime_minutes'].
 ↪fillna(movie_basics['runtime_minutes'].median())
#handling missing values for genres
movie_basics['genres']=movie_basics['genres'].fillna('Unkown')
```

[129]:
```
# Merge the DataFrames based on 'movie_id' in movie_ratings and  movie_basics
merged_df = pd.merge(movie_basics,movie_ratings, left_on='movie_id',␣
 ↪right_on='movie_id', how='inner')

# Display the merged DataFrame
print("\nMerged DataFrame:")
merged_df.head()
```

```
Merged DataFrame:
```

[129]:
```
    movie_id                    primary_title  start_year  runtime_minutes  \
0  tt0063540                        Sunghursh        2013            175.0
1  tt0066787  One Day Before the Rainy Season        2019            114.0
2  tt0069049       The Other Side of the Wind        2018            122.0
3  tt0069204                  Sabse Bada Sukh        2018             87.0
4  tt0100275         The Wandering Soap Opera        2017             80.0

                genres  averagerating  numvotes
0   Action,Crime,Drama            7.0        77
1      Biography,Drama            7.2        43
2                Drama            6.9      4517
3         Comedy,Drama            6.1        13
4 Comedy,Drama,Fantasy            6.5       119
```

3.3 merged_df1

joining tmbd_movies to merged_df1

[130]:
```python
#load the dataset
tmbd_movies=pd.read_csv('tmdb.movies.csv')
# Display the merged DataFrame
print("\ntmbd_movies DataFrame:")
tmbd_movies.head()
```

```
tmbd_movies DataFrame:
```

[130]:
```
   Unnamed: 0            genre_ids     id original_language  \
0           0      [12, 14, 10751]  12444                en
1           1  [14, 12, 16, 10751]  10191                en
2           2        [12, 28, 878]  10138                en
3           3      [16, 35, 10751]    862                en
4           4        [28, 878, 12]  27205                en

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

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

```
4                                    Inception            8.3       22186
```

[131]:
```
#dropping columns
tmbd_movies.drop(columns=['Unnamed: 0','genre_ids','id'], inplace=True)
```

[132]:
```
#display dataset info
tmbd_movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   original_language  26517 non-null  object
 1   original_title     26517 non-null  object
 2   popularity         26517 non-null  float64
 3   release_date       26517 non-null  object
 4   title              26517 non-null  object
 5   vote_average       26517 non-null  float64
 6   vote_count         26517 non-null  int64
dtypes: float64(2), int64(1), object(4)
memory usage: 1.4+ MB
```

[133]:
```
# Merge the DataFrames based on 'primary_title' in merged_df and 'title' in␣
↪bom_movies
merged_df1 = pd.merge(merged_df,tmbd_movies, left_on='primary_title',␣
↪right_on='title', how='inner')

# Display the merged DataFrame
print("\nMerged DataFrame1:")
merged_df1.head()
```

```
Merged DataFrame1:
```

[133]:
```
    movie_id                primary_title  start_year  runtime_minutes  \
0  tt0069049  The Other Side of the Wind        2018            122.0
1  tt0112502                      Bigfoot        2017             87.0
2  tt0192528               Heaven & Hell        2018            104.0
3  tt0249516                   Foodfight!        2012             91.0
4  tt0255820            Return to Babylon        2013             75.0

                     genres  averagerating  numvotes original_language  \
0                     Drama            6.9      4517                en
1           Horror,Thriller            4.1        32                en
2                     Drama            4.0        72                en
3  Action,Animation,Comedy            1.9      8248                en
```

```
4   Biography,Comedy,Drama            5.9       123                 en

                original_title  popularity release_date  \
0  The Other Side of the Wind       9.800   2018-11-02
1                     Bigfoot       2.813   2012-06-30
2                Heaven & Hell       0.600   2018-11-06
3                   Foodfight!       4.705   2013-05-07
4             Return to Babylon       0.877   2013-08-11

                         title  vote_average  vote_count
0  The Other Side of the Wind           7.0          64
1                     Bigfoot           2.9          26
2                Heaven & Hell           7.5           2
3                   Foodfight!           2.1          46
4             Return to Babylon           7.0           1
```

[134]:
```
#display merged dataset info
merged_df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19949 entries, 0 to 19948
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           19949 non-null  object
 1   primary_title      19949 non-null  object
 2   start_year         19949 non-null  int64
 3   runtime_minutes    19949 non-null  float64
 4   genres             19949 non-null  object
 5   averagerating      19949 non-null  float64
 6   numvotes           19949 non-null  int64
 7   original_language  19949 non-null  object
 8   original_title     19949 non-null  object
 9   popularity         19949 non-null  float64
 10  release_date       19949 non-null  object
 11  title              19949 non-null  object
 12  vote_average       19949 non-null  float64
 13  vote_count         19949 non-null  int64
dtypes: float64(4), int64(3), object(7)
memory usage: 2.1+ MB
```

3.4 merged_df2

joining tn_budget to merged_df1

[135]:
```
#load the dataset
tn_budget=pd.read_csv('tn.movie_budgets.csv')
# Display the merged DataFrame
```

```
print("\ntn_budget DataFrame1:")
tn_budget.head()
```

```
tn_budget DataFrame1:
```

[135]:
```
   id  release_date                                      movie  \
0   1  Dec 18, 2009                                     Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                Dark Phoenix
3   4   May 1, 2015                     Avengers: Age of Ultron
4   5  Dec 15, 2017           Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

[136]:
```
#dropping id column
tn_budget.drop(columns=['id'], inplace=True)
```

[137]:
```
#view dataset info
tn_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 226.0+ KB
```

[138]:
```
# Merge the DataFrames based on 'primary_title' in merged_df and 'title' in
 ↪bom_movies
merged_df2 = pd.merge(merged_df1,tn_budget, left_on='primary_title',
 ↪right_on='movie', how='inner')

# Display the merged DataFrame
print("\nMerged DataFrame2:")
merged_df2.head()
```

Merged DataFrame2:

[138]:
```
    movie_id                  primary_title  start_year  runtime_minutes  \
0  tt0249516                     Foodfight!        2012             91.0
1  tt0326592                  The Overnight        2010             88.0
2  tt0337692                    On the Road        2012            124.0
3  tt0359950  The Secret Life of Walter Mitty        2013            114.0
4  tt0365907      A Walk Among the Tombstones        2014            114.0

                    genres  averagerating  numvotes original_language  \
0  Action,Animation,Comedy            1.9      8248                en
1                   Unkown            7.5        24                en
2  Adventure,Drama,Romance            6.1     37886                en
3   Adventure,Comedy,Drama            7.3    275300                en
4       Action,Crime,Drama            6.5    105116                en

                    original_title  popularity release_date_x  \
0                       Foodfight!       4.705     2013-05-07
1                    The Overnight       6.576     2015-06-19
2                      On the Road       8.919     2012-12-21
3  The Secret Life of Walter Mitty      10.743     2013-12-25
4      A Walk Among the Tombstones      19.373     2014-09-19

                             title  vote_average  vote_count release_date_y  \
0                       Foodfight!           2.1          46   Dec 31, 2012
1                    The Overnight           6.0         200   Jun 19, 2015
2                      On the Road           5.6         518   Mar 22, 2013
3  The Secret Life of Walter Mitty           7.1        4859   Dec 25, 2013
4      A Walk Among the Tombstones           6.3        1685   Sep 19, 2014

                             movie production_budget domestic_gross  \
0                       Foodfight!       $45,000,000             $0
1                    The Overnight          $200,000     $1,109,808
2                      On the Road       $25,000,000       $720,828
3  The Secret Life of Walter Mitty       $91,000,000    $58,236,838
4      A Walk Among the Tombstones       $28,000,000    $26,017,685

  worldwide_gross
0         $73,706
1      $1,165,996
2      $9,313,302
3    $187,861,183
4     $62,108,587
```

[139]:
```
#display dataset info
merged_df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3361 entries, 0 to 3360
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           3361 non-null   object
 1   primary_title      3361 non-null   object
 2   start_year         3361 non-null   int64
 3   runtime_minutes    3361 non-null   float64
 4   genres             3361 non-null   object
 5   averagerating      3361 non-null   float64
 6   numvotes           3361 non-null   int64
 7   original_language  3361 non-null   object
 8   original_title     3361 non-null   object
 9   popularity         3361 non-null   float64
 10  release_date_x     3361 non-null   object
 11  title              3361 non-null   object
 12  vote_average       3361 non-null   float64
 13  vote_count         3361 non-null   int64
 14  release_date_y     3361 non-null   object
 15  movie              3361 non-null   object
 16  production_budget  3361 non-null   object
 17  domestic_gross     3361 non-null   object
 18  worldwide_gross    3361 non-null   object
dtypes: float64(4), int64(3), object(12)
memory usage: 499.0+ KB
```

[140]:
```
# Save the DataFrame to a CSV file
merged_df2.to_csv('combined_dataset.csv', index=False)
```

4 Data preparation

4.1 Data Cleaning

This includes * exploring our data using methods like(df.head,df.describe,df.info)to get a sense of the data structure,data types and summary statistics * manipulating column names for better readability * dropping unnecessary columns * identify missing values using df.isnull().sum() then fill the missing values appropriately if any,or drop them * identify duplicates(df.duplicated() and remove them using df.drop_duplicated * check the data types if they are appropriate for each column if not correct them * check and handle outliers appropriately * create new features * do final checks then save the cleaned data

4.1.1 Explore the data

This is done to get a sense of the data structure,data types and summary statistics

view the dataset to see how our data looks like

[141]:
```python
#load the combined dataset
combined=pd.read_csv('combined_dataset.csv')
#view the dataset
combined.head()
```

[141]:
```
    movie_id                     primary_title  start_year  runtime_minutes  \
0  tt0249516                        Foodfight!        2012             91.0
1  tt0326592                     The Overnight        2010             88.0
2  tt0337692                       On the Road        2012            124.0
3  tt0359950  The Secret Life of Walter Mitty        2013            114.0
4  tt0365907      A Walk Among the Tombstones        2014            114.0

                      genres  averagerating  numvotes original_language  \
0  Action,Animation,Comedy            1.9      8248                en
1                   Unkown            7.5        24                en
2   Adventure,Drama,Romance            6.1     37886                en
3    Adventure,Comedy,Drama            7.3    275300                en
4        Action,Crime,Drama            6.5    105116                en

                    original_title  popularity release_date_x  \
0                       Foodfight!       4.705     2013-05-07
1                    The Overnight       6.576     2015-06-19
2                      On the Road       8.919     2012-12-21
3  The Secret Life of Walter Mitty      10.743     2013-12-25
4      A Walk Among the Tombstones      19.373     2014-09-19

                             title  vote_average  vote_count release_date_y  \
0                       Foodfight!           2.1          46   Dec 31, 2012
1                    The Overnight           6.0         200   Jun 19, 2015
2                      On the Road           5.6         518   Mar 22, 2013
3  The Secret Life of Walter Mitty           7.1        4859   Dec 25, 2013
4      A Walk Among the Tombstones           6.3        1685   Sep 19, 2014

                             movie production_budget domestic_gross  \
0                       Foodfight!       $45,000,000             $0
1                    The Overnight          $200,000     $1,109,808
2                      On the Road       $25,000,000       $720,828
3  The Secret Life of Walter Mitty       $91,000,000    $58,236,838
4      A Walk Among the Tombstones       $28,000,000    $26,017,685

  worldwide_gross
0         $73,706
1      $1,165,996
2      $9,313,302
3    $187,861,183
4     $62,108,587
```

get statistic summary for our dataset

[142]:
```
#view statistics for our dataset
combined.describe()
```

[142]:

	start_year	runtime_minutes	averagerating	numvotes	popularity
count	3361.000000	3361.000000	3361.000000	3.361000e+03	3361.000000
mean	2013.939601	102.645641	6.294347	6.862621e+04	9.022082
std	2.490502	20.396231	1.178406	1.330570e+05	8.167201
min	2010.000000	3.000000	1.600000	5.000000e+00	0.600000
25%	2012.000000	90.000000	5.700000	1.830000e+02	1.823000
50%	2014.000000	100.000000	6.400000	8.553000e+03	8.166000
75%	2016.000000	113.000000	7.100000	8.300900e+04	12.817000
max	2019.000000	280.000000	9.300000	1.841066e+06	80.773000

	vote_average	vote_count
count	3361.000000	3361.000000
mean	6.158643	1383.335019
std	1.271010	2485.514931
min	0.000000	1.000000
25%	5.500000	11.000000
50%	6.200000	312.000000
75%	7.000000	1684.000000
max	10.000000	22186.000000

[143]:
```
#summary statistic for numerical columns
combined.describe(include='O')
```

[143]:

	movie_id	primary_title	genres	original_language	original_title
count	3361	3361	3361	3361	3361
unique	2315	1779	292	31	1821
top	tt2372760	Home	Drama	en	Home
freq	21	168	427	3123	144

	release_date_x	title	release_date_y	movie	production_budget
count	3361	3361	3361	3361	3361
unique	956	1779	794	1779	288
top	2015-06-19	Home	Mar 27, 2015	Home	$10,000,000
freq	42	168	59	168	166

	domestic_gross	worldwide_gross
count	3361	3361
unique	1614	1680
top	$0	$0
freq	470	357

dataset info

[144]:
```
#checking dataset info
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3361 entries, 0 to 3360
Data columns (total 19 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   movie_id            3361 non-null   object
 1   primary_title       3361 non-null   object
 2   start_year          3361 non-null   int64
 3   runtime_minutes     3361 non-null   float64
 4   genres              3361 non-null   object
 5   averagerating       3361 non-null   float64
 6   numvotes            3361 non-null   int64
 7   original_language   3361 non-null   object
 8   original_title      3361 non-null   object
 9   popularity          3361 non-null   float64
 10  release_date_x      3361 non-null   object
 11  title               3361 non-null   object
 12  vote_average        3361 non-null   float64
 13  vote_count          3361 non-null   int64
 14  release_date_y      3361 non-null   object
 15  movie               3361 non-null   object
 16  production_budget   3361 non-null   object
 17  domestic_gross      3361 non-null   object
 18  worldwide_gross     3361 non-null   object
dtypes: float64(4), int64(3), object(12)
memory usage: 499.0+ KB
```

4.1.2 Column manipulation

now that we have a sense of how our data is lets begin with column manipulation.

this includes:checking column names to see they are same,change the name to lowercase if necessary,remove whitespaces in the column names and also in the data,rename columns for better understanding and drop unnecessary columns.

check column names

[145]:
```
#check columns
combined.columns
```

[145]:
```
Index(['movie_id', 'primary_title', 'start_year', 'runtime_minutes', 'genres',
       'averagerating', 'numvotes', 'original_language', 'original_title',
       'popularity', 'release_date_x', 'title', 'vote_average', 'vote_count',
       'release_date_y', 'movie', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
```

remove whitespaces Here we are removing the whitepaces found in the column names and ensure that all string and categorical values are clean and consistent

[146]:
```
# Strip white spaces in values
combined = combined.apply(lambda col: col.str.strip() if col.dtype ==␣
↪["object", "number", "category"] else col)
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3361 entries, 0 to 3360
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           3361 non-null   object
 1   primary_title      3361 non-null   object
 2   start_year         3361 non-null   int64
 3   runtime_minutes    3361 non-null   float64
 4   genres             3361 non-null   object
 5   averagerating      3361 non-null   float64
 6   numvotes           3361 non-null   int64
 7   original_language  3361 non-null   object
 8   original_title     3361 non-null   object
 9   popularity         3361 non-null   float64
 10  release_date_x     3361 non-null   object
 11  title              3361 non-null   object
 12  vote_average       3361 non-null   float64
 13  vote_count         3361 non-null   int64
 14  release_date_y     3361 non-null   object
 15  movie              3361 non-null   object
 16  production_budget  3361 non-null   object
 17  domestic_gross     3361 non-null   object
 18  worldwide_gross    3361 non-null   object
dtypes: float64(4), int64(3), object(12)
memory usage: 499.0+ KB
```

renaming columns

[147]:
```
#renaming column names
combined = combined.rename(columns = {'averagerating':'average_ratings',␣
↪'movie_id':'id','numvotes':'number_of_votes','release_date_x':
↪'release_date'})
#check column names
combined.columns
```

[147]:
```
Index(['id', 'primary_title', 'start_year', 'runtime_minutes', 'genres',
       'average_ratings', 'number_of_votes', 'original_language',
       'original_title', 'popularity', 'release_date', 'title', 'vote_average',
       'vote_count', 'release_date_y', 'movie', 'production_budget',
```

```
        'domestic_gross', 'worldwide_gross'],
       dtype='object')
```

drop unnecessary columns

[148]:
```
#drop unnecessary columns
combined = combined.drop(columns=['id', 'primary_title',␣
↪'start_year','original_language', 'popularity',
                            ␣
↪'original_title','release_date_y','movie','vote_count', 'id_x',␣
↪'vote_average' ], errors="ignore")
#view the dataset
combined.head()
```

[148]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0             91.0  Action,Animation,Comedy              1.9             8248
1             88.0                   Unkown              7.5               24
2            124.0  Adventure,Drama,Romance              6.1            37886
3            114.0   Adventure,Comedy,Drama              7.3           275300
4            114.0       Action,Crime,Drama              6.5           105116

  release_date                          title production_budget  \
0   2013-05-07                     Foodfight!       $45,000,000
1   2015-06-19                  The Overnight          $200,000
2   2012-12-21                    On the Road       $25,000,000
3   2013-12-25  The Secret Life of Walter Mitty       $91,000,000
4   2014-09-19      A Walk Among the Tombstones       $28,000,000

  domestic_gross worldwide_gross
0             $0         $73,706
1     $1,109,808      $1,165,996
2       $720,828      $9,313,302
3    $58,236,838    $187,861,183
4    $26,017,685     $62,108,587
```

removing dollar signs and commas in production__budget,domestic__gross,worldwide__gross

[149]:
```
# Convert financial columns by removing $ and , then converting to numeric
def clean_currency_column(df, column):
    df[column] = df[column].replace(r'[\$,]', '', regex=True).astype(float)

# Apply cleaning function to relevant columns
for col in ['production_budget', 'domestic_gross', 'worldwide_gross']:
    clean_currency_column(combined, col)

# Verify changes
combined.head()
```

[149]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0             91.0  Action,Animation,Comedy              1.9             8248
1             88.0                   Unkown              7.5               24
2            124.0  Adventure,Drama,Romance              6.1            37886
3            114.0   Adventure,Comedy,Drama              7.3           275300
4            114.0       Action,Crime,Drama              6.5           105116

  release_date                            title  production_budget  \
0   2013-05-07                       Foodfight!         45000000.0
1   2015-06-19                    The Overnight           200000.0
2   2012-12-21                      On the Road         25000000.0
3   2013-12-25  The Secret Life of Walter Mitty         91000000.0
4   2014-09-19      A Walk Among the Tombstones         28000000.0

   domestic_gross  worldwide_gross
0             0.0          73706.0
1       1109808.0        1165996.0
2        720828.0        9313302.0
3      58236838.0      187861183.0
4      26017685.0       62108587.0
```

4.1.3 Missing values

[150]:
```python
mis=combined.isna().any().sum()
if mis > 0:
    print(f'\nThere are {mis} missing values present in our data.')
else:
    print('There are no missing values in our data.')
```

```
There are no missing values in our data.
```

4.1.4 Checking for duplicate

[151]:
```python
#check for duplicates
dup = combined.duplicated().sum()
if dup > 0:
    print(f'\nThere are {dup} duplicates present in our data.')
else:
    print('There are no duplicates in our data.')
```

```

There are 212 duplicates present in our data.
```

[152]:
```python
# Remove duplicates (inplace to modify the original DataFrame)
combined.drop_duplicates(inplace=True)

# Check for duplicates
```

```
dup = combined.duplicated().sum()
if dup > 0:
    print(f'\nThere are {dup} duplicates present in our data.')
else:
    print('There are no duplicates in our data.')
```

```
There are no duplicates in our data.
```

4.1.5 Checking the data types

to see if they are appropriate for each column

[153]:
```
combined.dtypes
```

[153]:
```
runtime_minutes      float64
genres                object
average_ratings      float64
number_of_votes        int64
release_date          object
title                 object
production_budget    float64
domestic_gross       float64
worldwide_gross      float64
dtype: object
```

[154]:
```
# Change data types
combined['runtime_minutes'] = combined['runtime_minutes'].astype('int64')
combined['average_ratings'] = combined['average_ratings'].astype('int64')
combined['release_date'] = pd.to_datetime(combined['release_date'])
combined['production_budget'] = combined['production_budget'].astype('int64')
combined['worldwide_gross'] = combined['worldwide_gross'].astype('int64')
combined['domestic_gross'] = combined['domestic_gross'].astype('int64')

# Display updated dtypes
print("\nUpdated Data Types:")
combined.dtypes
```

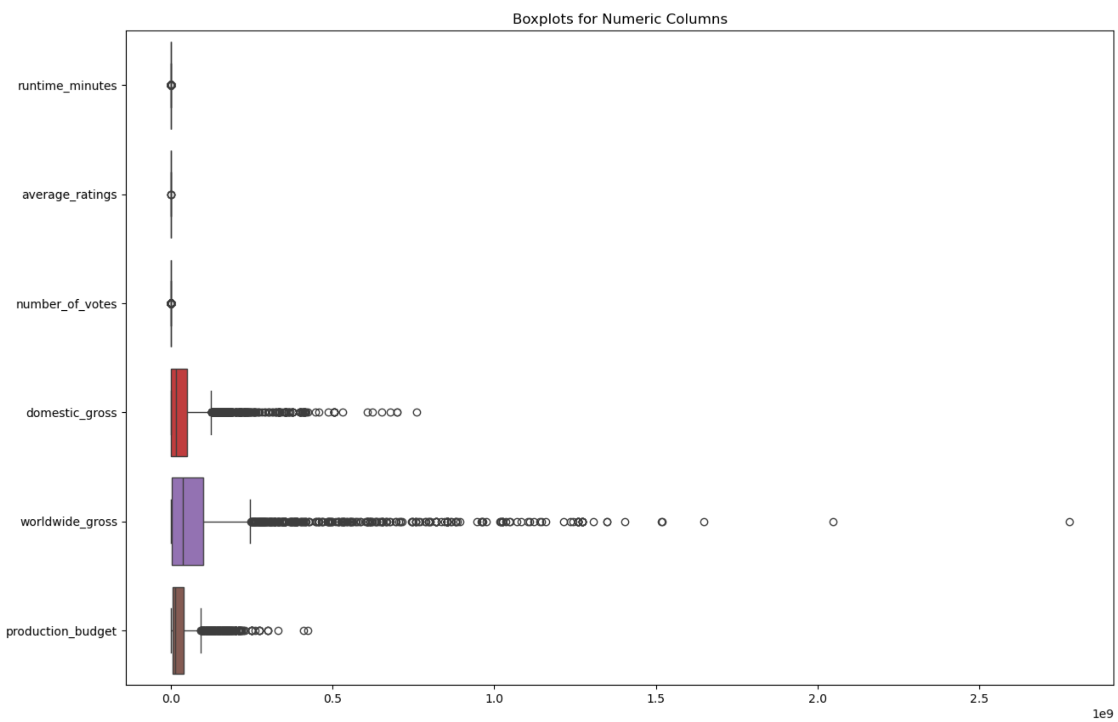
```

Updated Data Types:
```

[154]:
```
runtime_minutes               int64
genres                       object
average_ratings               int64
number_of_votes               int64
release_date         datetime64[ns]
title                        object
production_budget             int64
domestic_gross                int64
```

```
worldwide_gross                int64
dtype: object
```

4.1.6 Checking outliers

[155]:
```python
#import libraries
import matplotlib.pyplot as plt
import seaborn as sns
#select numerical columns
numeric_columns=combined[['runtime_minutes','average_ratings','number_of_votes','domestic_gros
# Plot boxplots for all numeric columns
plt.figure(figsize=(15, 10))
sns.boxplot(data=numeric_columns, orient='h')
plt.title("Boxplots for Numeric Columns")
plt.show()
```



there's plenty of outliers in domestic_gross,production_budget and worldwide_gross but we decided to keep them since they are sensitive columns

4.1.7 Feature engineering

this involes making of new columns or transforming existing features

total gross

[156]:
```python
#creating new features
combined['Total_gross']=(combined['domestic_gross']+combined['worldwide_gross'])
combined.head()
```

[156]:
```
   runtime_minutes                       genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124   Adventure,Drama,Romance                6            37886
3              114    Adventure,Comedy,Drama                7           275300
4              114        Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty          91000000
4   2014-09-19      A Walk Among the Tombstones         28000000

   domestic_gross  worldwide_gross  Total_gross
0               0            73706        73706
1         1109808          1165996      2275804
2          720828          9313302     10034130
3        58236838        187861183    246098021
4        26017685         62108587     88126272
```

ROI Return on Investment (ROI) is a financial metric used to evaluate the profitability or performance of an investment relative to its cost.

It is often expressed as a percentage and helps investors and businesses assess the efficiency and potential return of an investment.

Return on Investment (ROI):(gross—Budget)/Budget

[157]:
```python
#creating new features
combined['ROI']=((combined['Total_gross']-combined['production_budget'])/
 ↪combined['production_budget'])*100
combined.head()
```

[157]:
```
   runtime_minutes                       genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124   Adventure,Drama,Romance                6            37886
3              114    Adventure,Comedy,Drama                7           275300
4              114        Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
```

```
2   2012-12-21                        On the Road          25000000
3   2013-12-25  The Secret Life of Walter Mitty          91000000
4   2014-09-19      A Walk Among the Tombstones          28000000

   domestic_gross  worldwide_gross  Total_gross          ROI
0               0            73706        73706   -99.836209
1         1109808          1165996      2275804  1037.902000
2          720828          9313302     10034130   -59.863480
3        58236838        187861183    246098021   170.437386
4        26017685         62108587     88126272   214.736686
```

seasons column

[158]:
```
# Extract 'Year' from the 'Date' column
combined['month'] = combined['release_date'].dt.month

#create a function to categorize the months in seasons
def categorize_seasons(month):

    if month in [12, 1, 2]:
        return 'Winter'

    elif month in [3, 4, 5]:
        return 'Spring'

    elif month in [6, 7, 8]:
        return 'Summer'

    elif month in [9, 10, 11]:
        return 'Fall'
#apply the categorize_seasons function
combined['season'] = combined['month'].apply(categorize_seasons)
#view the dataset
combined.head()
```

[158]:
```
   runtime_minutes                   genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124  Adventure,Drama,Romance                 6            37886
3              114   Adventure,Comedy,Drama                 7           275300
4              114       Action,Crime,Drama                 6           105116

  release_date                            title  production_budget  \
0   2013-05-07                       Foodfight!           45000000
1   2015-06-19                    The Overnight             200000
2   2012-12-21                       On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
```

```
4   2014-09-19      A Walk Among the Tombstones          28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall
```

movie ratings

[159]:
```python
#create a movie_ratings function
def movie_ratings(value):
    if value <= 4:
        return 'low'

    elif 5 <= value <= 7:
        return 'Average'

    else:
        return 'High'
#apply the function
combined['movie_rating'] = combined['average_ratings'].apply(movie_ratings)
#view the dataset
combined.head()
```

[159]:
```
   runtime_minutes                      genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                     Unkown                7               24
2              124   Adventure,Drama,Romance                6            37886
3              114    Adventure,Comedy,Drama                7           275300
4              114        Action,Crime,Drama                6           105116

  release_date                         title  production_budget  \
0   2013-05-07                    Foodfight!           45000000
1   2015-06-19                 The Overnight             200000
2   2012-12-21                   On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty        91000000
4   2014-09-19      A Walk Among the Tombstones          28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall
```

```
  movie_rating
0          low
1      Average
2      Average
3      Average
4      Average
```

movie_length

[160]:
```python
#create a movie duration function to classify the duration
def movie_duration(value):
    if value <= 60:
        return 'Short'

    elif 60 <= value <= 120:
        return 'Medium'

    else:
        return 'Long'
#apply the function
combined['movie_length'] = combined['runtime_minutes'].apply(movie_duration)
#view the dataset
combined.head()
```

[160]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length
0          low       Medium
```

```
1      Average       Medium
2      Average         Long
3      Average       Medium
4      Average       Medium
```

splitting the genre column

[161]:
```
# Split the 'genres' column into a list but keep the original column
combined['genres_list'] = combined['genres'].str.split(',')

# Expand the 'genres_list' into separate columns
genres_expanded = combined['genres_list'].apply(pd.Series)
genres_expanded = genres_expanded.rename(columns=lambda x: f'genre_{x+1}')  #␣
 ↪Rename the columns

# Concatenate the new columns with the original DataFrame
combined = pd.concat([combined, genres_expanded], axis=1)
```

[162]:
```
#viewing the dataset
combined.head()
```

[162]:
```
   runtime_minutes                  genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                            title  production_budget  \
0   2013-05-07                       Foodfight!           45000000
1   2015-06-19                    The Overnight             200000
2   2012-12-21                      On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length                  genres_list    genre_1  \
0          low       Medium  [Action, Animation, Comedy]     Action
1      Average       Medium                     [Unkown]     Unkown
2      Average         Long  [Adventure, Drama, Romance]  Adventure
3      Average       Medium   [Adventure, Comedy, Drama]  Adventure
```

```
4      Average       Medium       [Action, Crime, Drama]     Action

     genre_2  genre_3
0  Animation   Comedy
1        NaN      NaN
2      Drama  Romance
3     Comedy    Drama
4      Crime    Drama
```

[163]:
```
#dropping irrelevant columns
combined = combined.drop(columns=['genre_2', 'genre_3','genres_list'],␣
 ↪errors='ignore')
combined.head()
```

[163]:
```
   runtime_minutes                   genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1
0          low       Medium     Action
1      Average       Medium     Unkown
2      Average         Long  Adventure
3      Average       Medium  Adventure
4      Average       Medium     Action
```

[164]:
```
#Create a new column for processing
combined['genre_processed'] = combined['genres'].str.split(',')

# Apply transformations according to the specifications
def process_genres(genre_list):
```

```
    if len(genre_list) == 1:
        return genre_list[0]  # Leave single genre as it is
    elif len(genre_list) == 2:
        return f"{genre_list[0]} & {genre_list[1]}"  # Replace comma with '&'
    else:
        return f"{genre_list[0]} & {genre_list[1]}"  # Keep only the first two,␣
 ↪use '&'

# Apply the function to 'genre_processed' and store the result in a new column
combined['genre_combined'] = combined['genre_processed'].apply(process_genres)

# Check the result
combined[['genres', 'genre_combined']]
```

[164]:

```
                        genres      genre_combined
0     Action,Animation,Comedy  Action & Animation
1                      Unkown              Unkown
2      Adventure,Drama,Romance  Adventure & Drama
3       Adventure,Comedy,Drama  Adventure & Comedy
4           Action,Crime,Drama      Action & Crime
…                          …                 …
3356                   Comedy              Comedy
3357             Action,Drama      Action & Drama
3358                   Comedy              Comedy
3359              Documentary         Documentary
3360              Documentary         Documentary

[3149 rows x 2 columns]
```

[165]:

```
#view the dataset
combined.head()
```

[165]:

```
   runtime_minutes                   genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross        ROI  month  season  \
```

```
0          0        73706      73706   -99.836209    5  Spring
1    1109808      1165996    2275804  1037.902000    6  Summer
2     720828      9313302   10034130   -59.863480   12  Winter
3   58236838    187861183  246098021   170.437386   12  Winter
4   26017685     62108587   88126272   214.736686    9    Fall

  movie_rating movie_length    genre_1              genre_processed  \
0          low       Medium     Action  [Action, Animation, Comedy]
1      Average       Medium     Unkown                     [Unkown]
2      Average         Long  Adventure  [Adventure, Drama, Romance]
3      Average       Medium  Adventure   [Adventure, Comedy, Drama]
4      Average       Medium     Action       [Action, Crime, Drama]

       genre_combined
0  Action & Animation
1              Unkown
2   Adventure & Drama
3  Adventure & Comedy
4      Action & Crime
```

[166]:
```python
#drop irrelevant columns
combined = combined.drop(columns=['genre_processed'], errors='ignore')
#view the dataset
combined.head()
```

[166]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined
```

```
0         low       Medium     Action  Action & Animation
1     Average       Medium     Unkown              Unkown
2     Average         Long  Adventure   Adventure & Drama
3     Average       Medium  Adventure  Adventure & Comedy
4     Average       Medium     Action      Action & Crime
```

[167]:
```
#check for missing values
combined.isna().sum()
```

[167]:
```
runtime_minutes      0
genres               0
average_ratings      0
number_of_votes      0
release_date         0
title                0
production_budget    0
domestic_gross       0
worldwide_gross      0
Total_gross          0
ROI                  0
month                0
season               0
movie_rating         0
movie_length         0
genre_1              0
genre_combined       0
dtype: int64
```

budget category

[168]:
```
# Categorize budgets
def categorize_budget(budget):
    if budget < 20_000_000:  # Low budget
        return 'Low'
    elif 20_000_000 <= budget <= 80_000_000:  # Medium budget
        return 'Medium'
    else:  # High budget
        return 'High'
#apply the function
combined['Budget_Category'] = combined['production_budget'].
 ↪apply(categorize_budget)
#view the dataset
combined.head()
```

[168]:
```
   runtime_minutes                   genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
```

```
2             124  Adventure,Drama,Romance               6         37886
3             114   Adventure,Comedy,Drama               7        275300
4             114       Action,Crime,Drama               6        105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                     On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure   Adventure & Drama          Medium
3      Average       Medium  Adventure  Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium
```

break even point The break-even point in movie production refers to the minimum box office revenue a film needs to generate to cover its production costs, meaning no profit and no loss.

The break-even point is when Box Office Revenue >= Production Budget.

[169]:
```
# Create a break-even indicator
combined["Break_Even"] = combined["Total_gross"] >=␣
 ↪combined["production_budget"]
#view the dataset
combined.head()
```

[169]:
```
   runtime_minutes                   genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                     On the Road           25000000
```

```
3   2013-12-25  The Secret Life of Walter Mitty          91000000
4   2014-09-19      A Walk Among the Tombstones          28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1       genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure    Adventure & Drama          Medium
3      Average       Medium  Adventure   Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium

   Break_Even
0       False
1        True
2       False
3        True
4        True
```

profit margin

[170]:
```
# Calculate Profit Margin
combined['Profit_Margin'] = (combined['Total_gross'] -
 ↪combined['production_budget']) / combined['Total_gross']
#view the dataset
combined.head()
```

[170]:
```
   runtime_minutes                 genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                  Unkown                7               24
2              124   Adventure,Drama,Romance                6            37886
3              114    Adventure,Comedy,Drama                7           275300
4              114        Action,Crime,Drama                6           105116

  release_date                        title  production_budget  \
0   2013-05-07                   Foodfight!           45000000
1   2015-06-19                The Overnight             200000
2   2012-12-21                  On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty        91000000
4   2014-09-19      A Walk Among the Tombstones        28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
```

```
0          0      73706      73706   -99.836209      5  Spring
1    1109808    1165996    2275804  1037.902000      6  Summer
2     720828    9313302   10034130   -59.863480     12  Winter
3   58236838  187861183  246098021   170.437386     12  Winter
4   26017685   62108587   88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure   Adventure & Drama          Medium
3      Average       Medium  Adventure  Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium

   Break_Even  Profit_Margin
0       False    -609.533742
1        True       0.912119
2       False      -1.491497
3        True       0.630229
4        True       0.682274
```

quarter and monthly

[171]:
```python
# Extract quarter from release_date_x
combined['quarter'] =combined['release_date'].dt.to_period('Q')

#view the dataset
combined.head()
```

[171]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19       A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
```

```
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure   Adventure & Drama          Medium
3      Average       Medium  Adventure  Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium

   Break_Even  Profit_Margin quarter
0       False    -609.533742  2013Q2
1        True       0.912119  2015Q2
2       False      -1.491497  2012Q4
3        True       0.630229  2013Q4
4        True       0.682274  2014Q3
```

year

[172]:
```python
# Extract year, month, and quarter from release_date_x
combined['year'] =combined['release_date'].dt.year
#view the dataset
combined.head()
```

[172]:
```
   runtime_minutes                     genres  average_ratings  number_of_votes  \
0               91   Action,Animation,Comedy                1             8248
1               88                     Unkown                7               24
2              124   Adventure,Drama,Romance                6            37886
3              114    Adventure,Comedy,Drama                7           275300
4              114        Action,Crime,Drama                6           105116

  release_date                            title  production_budget  \
0   2013-05-07                       Foodfight!           45000000
1   2015-06-19                    The Overnight             200000
2   2012-12-21                      On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19       A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
```

```
2      Average         Long  Adventure   Adventure & Drama           Medium
3      Average       Medium  Adventure  Adventure & Comedy             High
4      Average       Medium     Action      Action & Crime           Medium

   Break_Even  Profit_Margin quarter  year
0       False    -609.533742  2013Q2  2013
1        True       0.912119  2015Q2  2015
2       False      -1.491497  2012Q4  2012
3        True       0.630229  2013Q4  2013
4        True       0.682274  2014Q3  2014
```

peak season

[173]:
```
# Define peak season (Summer & Holiday)
combined['peak_season'] = combined['month'].apply(lambda x: 'Peak' if x in [6,␣
↪7, 11, 12] else 'Non-Peak')
#view dataset
combined.head()
```

[173]:
```
   runtime_minutes                    genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                   Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure   Adventure & Drama          Medium
3      Average       Medium  Adventure  Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium
```

```
   Break_Even  Profit_Margin quarter  year peak_season
0       False    -609.533742  2013Q2  2013    Non-Peak
1        True       0.912119  2015Q2  2015        Peak
2       False      -1.491497  2012Q4  2012        Peak
3        True       0.630229  2013Q4  2013        Peak
4        True       0.682274  2014Q3  2014    Non-Peak
```

4.1.8 final checks

we review the data to ensure the cleaning steps have been applied correctly

[174]:
```
#view the dataset
combined.head()
```

[174]:
```
   runtime_minutes                      genres  average_ratings  number_of_votes  \
0               91  Action,Animation,Comedy                1             8248
1               88                    Unkown                7               24
2              124  Adventure,Drama,Romance                6            37886
3              114   Adventure,Comedy,Drama                7           275300
4              114       Action,Crime,Drama                6           105116

  release_date                          title  production_budget  \
0   2013-05-07                     Foodfight!           45000000
1   2015-06-19                  The Overnight             200000
2   2012-12-21                    On the Road           25000000
3   2013-12-25  The Secret Life of Walter Mitty           91000000
4   2014-09-19      A Walk Among the Tombstones           28000000

   domestic_gross  worldwide_gross  Total_gross          ROI  month  season  \
0               0            73706        73706   -99.836209      5  Spring
1         1109808          1165996      2275804  1037.902000      6  Summer
2          720828          9313302     10034130   -59.863480     12  Winter
3        58236838        187861183    246098021   170.437386     12  Winter
4        26017685         62108587     88126272   214.736686      9    Fall

  movie_rating movie_length    genre_1      genre_combined Budget_Category  \
0          low       Medium     Action  Action & Animation          Medium
1      Average       Medium     Unkown              Unkown             Low
2      Average         Long  Adventure   Adventure & Drama          Medium
3      Average       Medium  Adventure  Adventure & Comedy            High
4      Average       Medium     Action      Action & Crime          Medium

   Break_Even  Profit_Margin quarter  year peak_season
0       False    -609.533742  2013Q2  2013    Non-Peak
1        True       0.912119  2015Q2  2015        Peak
2       False      -1.491497  2012Q4  2012        Peak
3        True       0.630229  2013Q4  2013        Peak
```

```
4        True       0.682274  2014Q3  2014    Non-Peak
```

[175]:

```python
#check dataset info
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3149 entries, 0 to 3360
Data columns (total 23 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   runtime_minutes    3149 non-null   int64
 1   genres             3149 non-null   object
 2   average_ratings    3149 non-null   int64
 3   number_of_votes    3149 non-null   int64
 4   release_date       3149 non-null   datetime64[ns]
 5   title              3149 non-null   object
 6   production_budget  3149 non-null   int64
 7   domestic_gross     3149 non-null   int64
 8   worldwide_gross    3149 non-null   int64
 9   Total_gross        3149 non-null   int64
 10  ROI                3149 non-null   float64
 11  month              3149 non-null   int32
 12  season             3149 non-null   object
 13  movie_rating       3149 non-null   object
 14  movie_length       3149 non-null   object
 15  genre_1            3149 non-null   object
 16  genre_combined     3149 non-null   object
 17  Budget_Category    3149 non-null   object
 18  Break_Even         3149 non-null   bool
 19  Profit_Margin      3149 non-null   float64
 20  quarter            3149 non-null   period[Q-DEC]
 21  year               3149 non-null   int32
 22  peak_season        3149 non-null   object
dtypes: bool(1), datetime64[ns](1), float64(2), int32(2), int64(7), object(9),
period[Q-DEC](1)
memory usage: 544.3+ KB
```

[176]:

```python
#reset index
combined.reset_index(drop=True, inplace=True)
```

[177]:

```python
#review the dataset info
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3149 entries, 0 to 3148
Data columns (total 23 columns):
 #   Column             Non-Null Count  Dtype
```

```
---  ------              --------------  -----
 0   runtime_minutes    3149 non-null   int64
 1   genres             3149 non-null   object
 2   average_ratings    3149 non-null   int64
 3   number_of_votes    3149 non-null   int64
 4   release_date       3149 non-null   datetime64[ns]
 5   title              3149 non-null   object
 6   production_budget  3149 non-null   int64
 7   domestic_gross     3149 non-null   int64
 8   worldwide_gross    3149 non-null   int64
 9   Total_gross        3149 non-null   int64
 10  ROI                3149 non-null   float64
 11  month              3149 non-null   int32
 12  season             3149 non-null   object
 13  movie_rating       3149 non-null   object
 14  movie_length       3149 non-null   object
 15  genre_1            3149 non-null   object
 16  genre_combined     3149 non-null   object
 17  Budget_Category    3149 non-null   object
 18  Break_Even         3149 non-null   bool
 19  Profit_Margin      3149 non-null   float64
 20  quarter            3149 non-null   period[Q-DEC]
 21  year               3149 non-null   int32
 22  peak_season        3149 non-null   object
dtypes: bool(1), datetime64[ns](1), float64(2), int32(2), int64(7), object(9),
period[Q-DEC](1)
memory usage: 519.8+ KB
```

[178]:
```
# Save the DataFrame to a CSV file
combined.to_csv('combined_cleaned_dataset.csv', index=False)
```

5 EXPLORATORY DATA ANALYSIS

Here we would do visualization based on our previous business questions and get recomendations

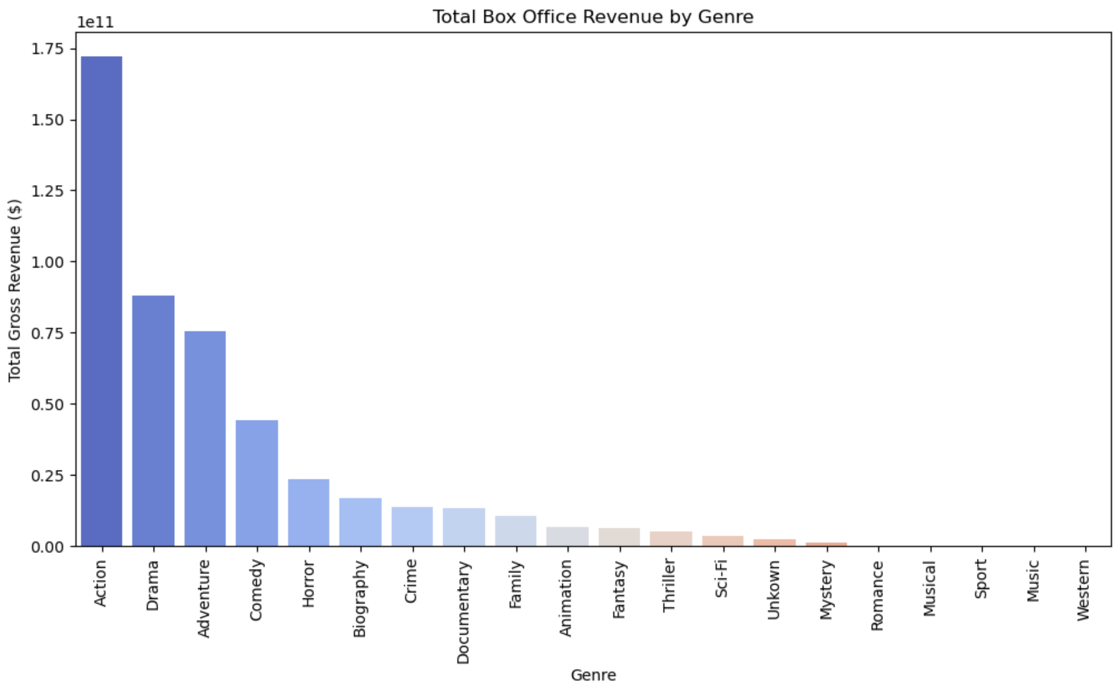
5.1 What genre and themes consistently leads to box office success?

5.1.1 Univariate Analysis

Identify Top-Performing Genres by Total Gross Revenue We will group by genres and analyze the total earnings.

[179]:
```
# Group by genre and calculate total revenue
genre_revenue = combined.groupby("genre_1")["Total_gross"].sum().
 ↪sort_values(ascending=False)

# Plot
# Plot with updated parameters
```

```
plt.figure(figsize=(12, 6))
sns.barplot(
    x=genre_revenue.index,
    y=genre_revenue.values,
    hue=genre_revenue.index,  # Assign x variable to hue
    palette="coolwarm",
    dodge=False,
    legend=False  # Remove legend
)
plt.xticks(rotation=90)
plt.title("Total Box Office Revenue by Genre")
plt.xlabel("Genre")
plt.ylabel("Total Gross Revenue ($)")
plt.show()
```

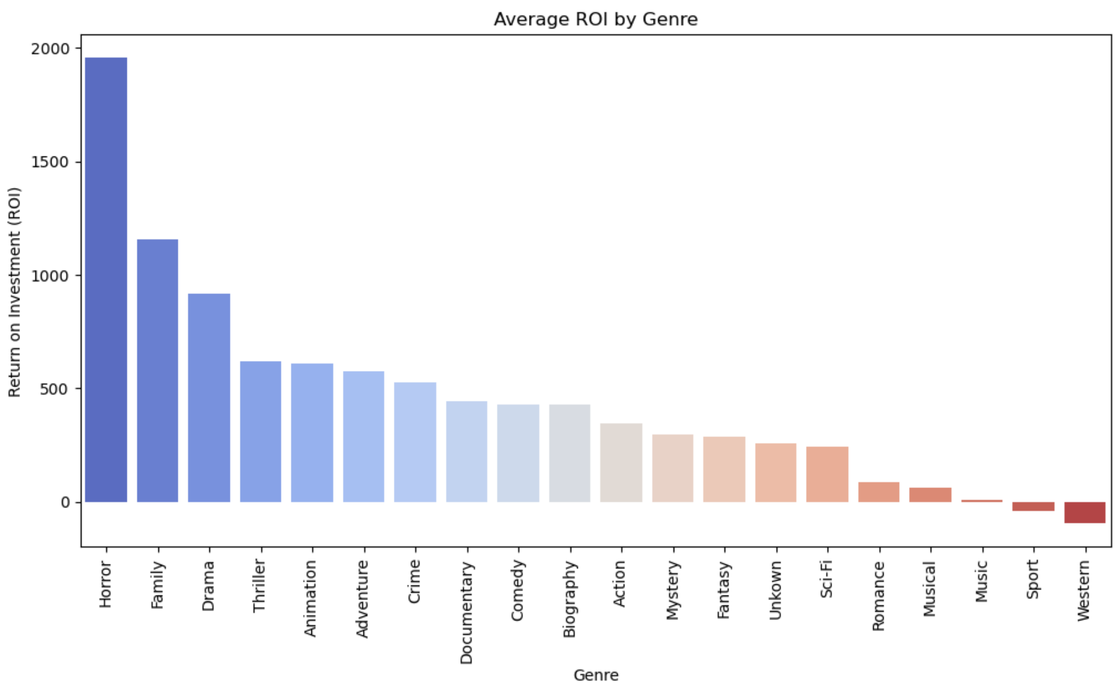


Insight: Genres with the highest total revenue indicate which are the most financially successful.for our case that is action,drama and adventure

Which Genres Have the Highest ROI? Some genres may have high revenue but also high production costs. To measure profitability, we analyze ROI.

[180]:
```
# Group by genre and calculate average ROI
genre_roi = combined.groupby("genre_1")["ROI"].mean().
    ↪sort_values(ascending=False)
```

```
# Plot
plt.figure(figsize=(12, 6))
sns.barplot(
    x=genre_roi.index,
    y=genre_roi.values,
    hue=genre_roi.index,  # Assign x to hue for palette compatibility
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress redundant legend
)
plt.xticks(rotation=90)
plt.title("Average ROI by Genre")
plt.xlabel("Genre")
plt.ylabel("Return on Investment (ROI)")
plt.show()
```

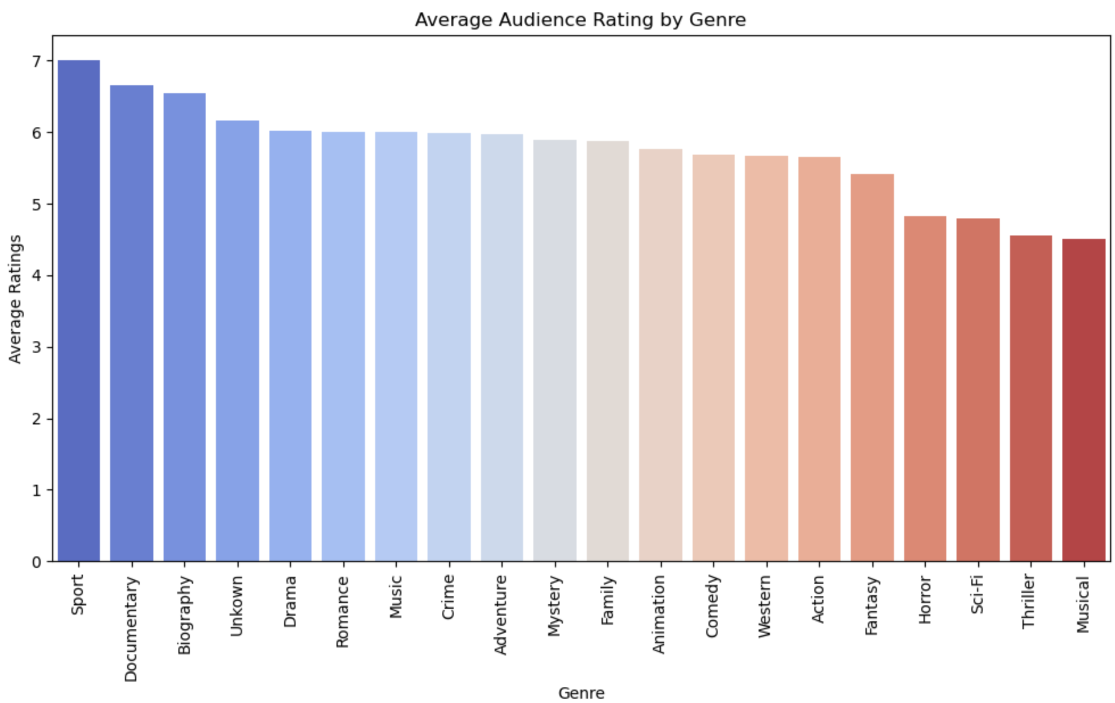


Insight: Genres with the highest ROI are the most profitable, even if their revenue isn't the highest. in this case that is horror and family

Audience Ratings by Genre High audience ratings indicate genre satisfaction.

[181]:
```
# Group by genre and calculate average rating
genre_ratings = combined.groupby("genre_1")["average_ratings"].mean().
↪sort_values(ascending=False)
```

```python
# Plot
plt.figure(figsize=(12, 6))
sns.barplot(
    x=genre_ratings.index,
    y=genre_ratings.values,
    hue=genre_ratings.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress legend
)
plt.xticks(rotation=90)
plt.title("Average Audience Rating by Genre")
plt.xlabel("Genre")
plt.ylabel("Average Ratings")
plt.show()
```

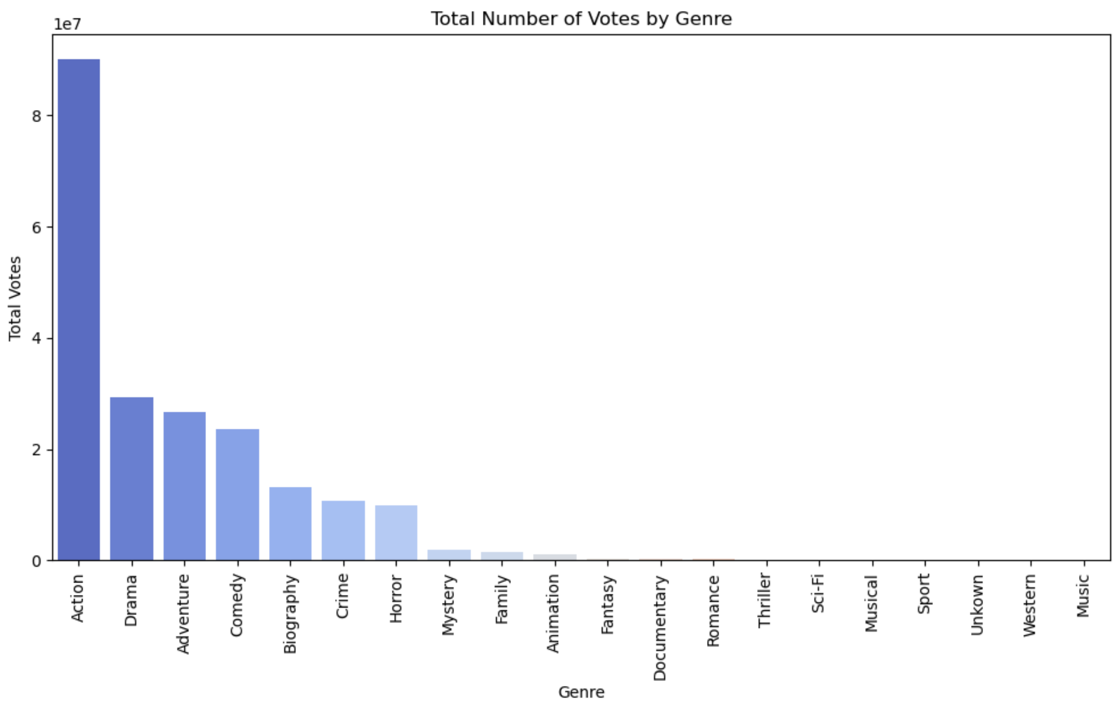


Insight: This tells us which genres are most appreciated by audiences, not just financially successful.

Audience Engagement: Number of Votes by Genre A highly rated genre with few votes might not be popular.

[182]:

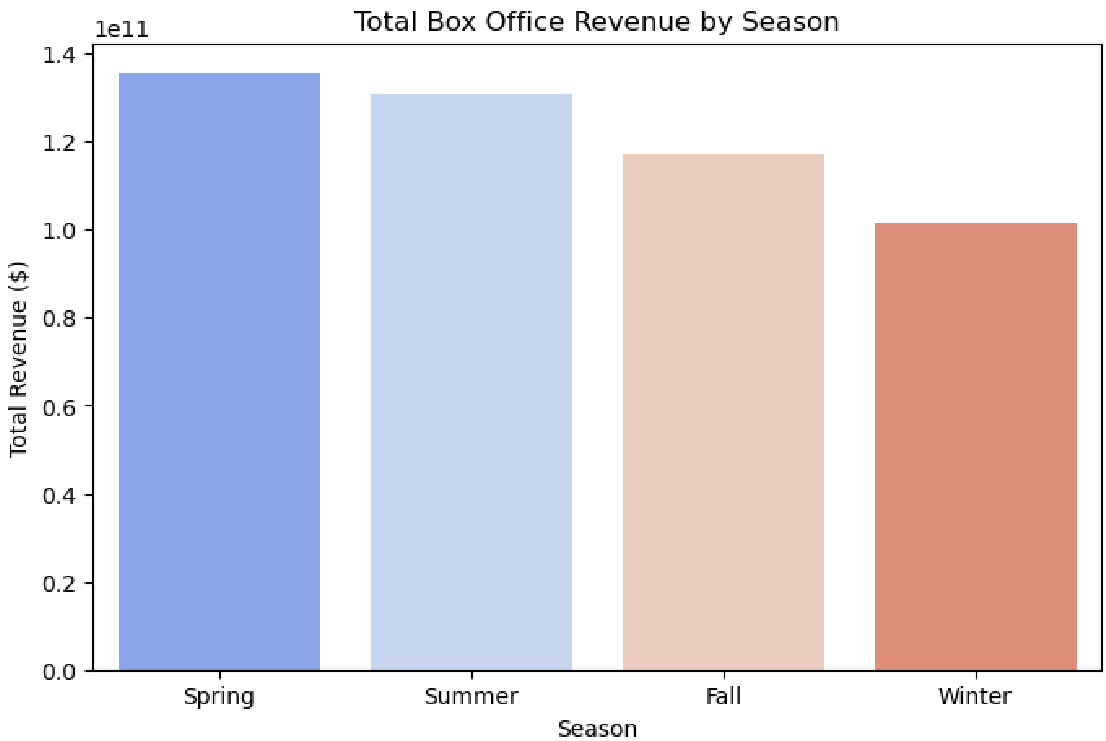
```python
# Group by genre and count total votes
genre_votes = combined.groupby("genre_1")["number_of_votes"].sum().
    ↪sort_values(ascending=False)

#plot
plt.figure(figsize=(12, 6))
sns.barplot(
    x=genre_votes.index,
    y=genre_votes.values,
    hue=genre_votes.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False
)
plt.xticks(rotation=90)
plt.title("Total Number of Votes by Genre")
plt.xlabel("Genre")
plt.ylabel("Total Votes")
plt.show()
```



Insight: Genres with high votes indicate high audience engagement and demand. for our case that would be action

Best Release Season for Success Does seasonality impact success?

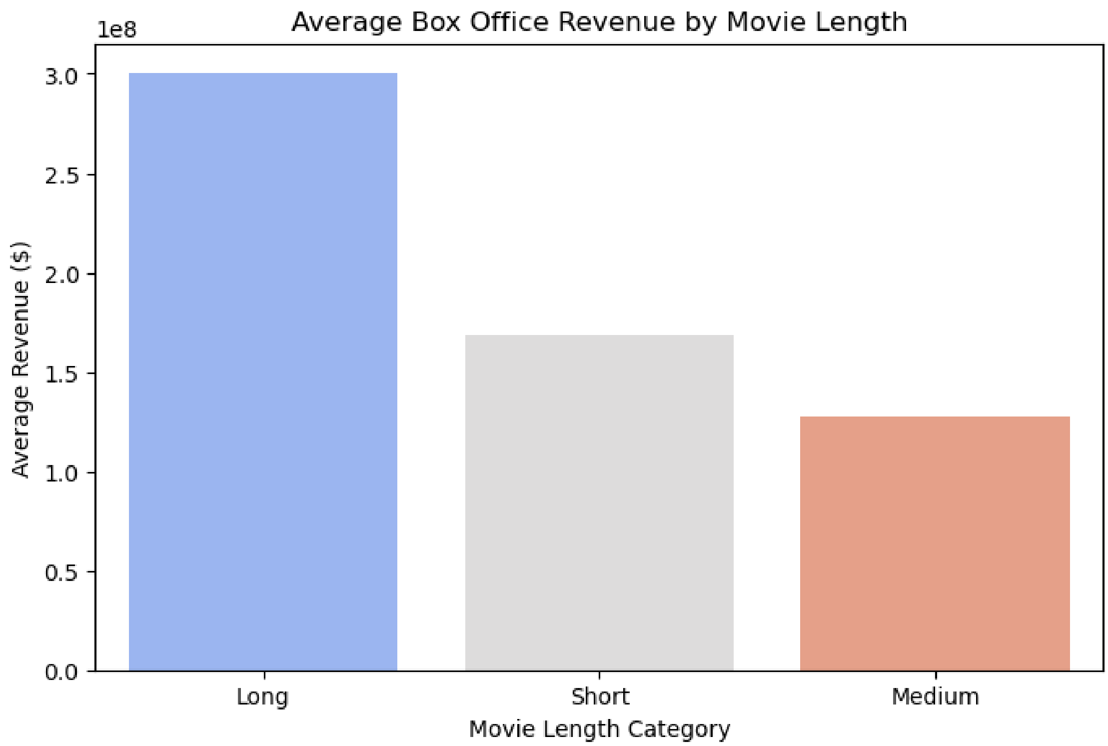
[183]:
```
# Group by season and sum total revenue
season_revenue = combined.groupby("season")["Total_gross"].sum().
 ↪sort_values(ascending=False)

# plot
plt.figure(figsize=(8, 5))
sns.barplot(
    x=season_revenue.index,
    y=season_revenue.values,
    hue=season_revenue.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False
)
plt.title("Total Box Office Revenue by Season")
plt.xlabel("Season")
plt.ylabel("Total Revenue ($)")
plt.show()
```



Insight: Determines whether summer blockbusters or holiday releases perform better. and according to our data summer is better

Does Movie Length Affect Box Office Success? Are longer movies more successful?

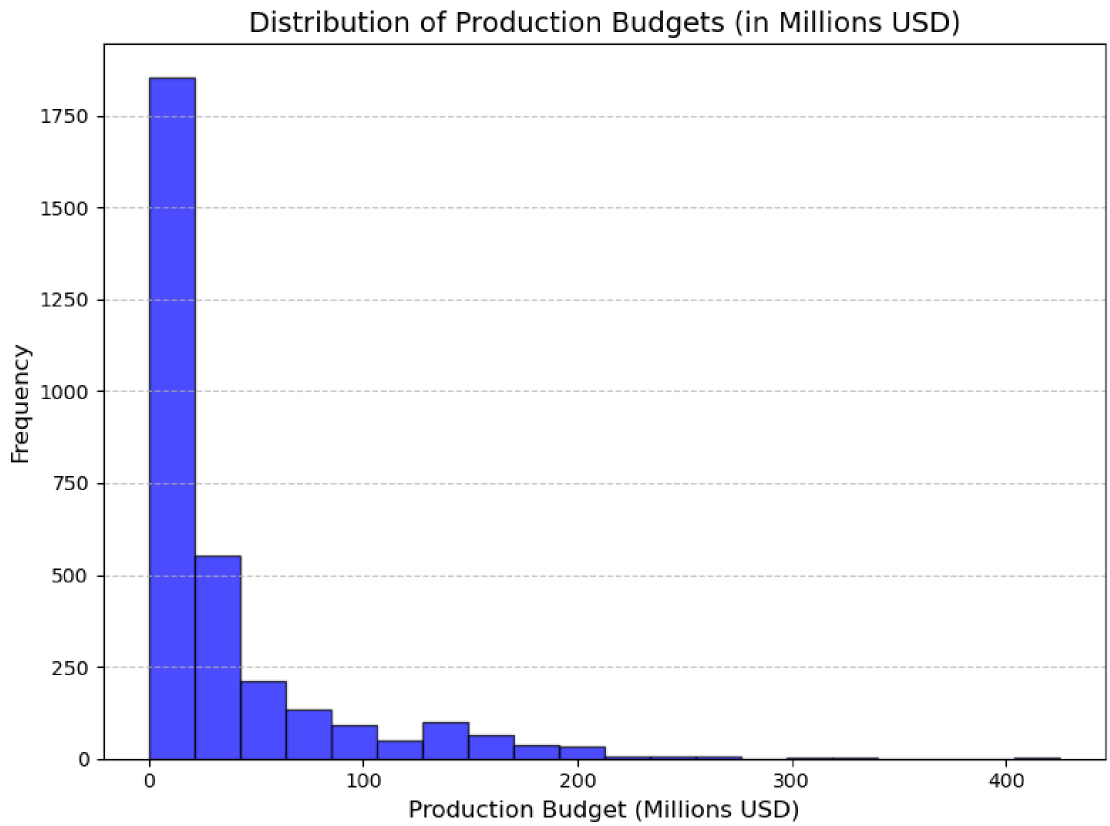
[184]:
```python
# Group by movie length category and sum revenue
length_revenue = combined.groupby("movie_length")["Total_gross"].mean().
 ↪sort_values(ascending=False)

# Plot
plt.figure(figsize=(8, 5))
sns.barplot(
    x=length_revenue.index,
    y=length_revenue.values,
    hue=length_revenue.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False
)
plt.title("Average Box Office Revenue by Movie Length")
plt.xlabel("Movie Length Category")
plt.ylabel("Average Revenue ($)")
plt.show()
```



Insight: Does a longer runtime correlate with box office success? yes

ANALYZE AVERAGE BUDGET OF MOVIES Most movies have production budgets below $40 million with a small number of high-budget movies exceed 200 million usd, indicating big-budget blockbusters.

[185]:
```
# Calculate the average production budget
average_budget = combined['production_budget'].mean()

# Generate descriptive statistics for the production budget
budget_stats = combined['production_budget'].describe()

# Visualize the distribution of production budgets
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
plt.hist(combined['production_budget'] / 1e6, bins=20, edgecolor='black',␣
↪color='blue', alpha=0.7)
plt.title('Distribution of Production Budgets (in Millions USD)', fontsize=14)
plt.xlabel('Production Budget (Millions USD)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Display average budget and statistics
average_budget, budget_stats
```



[185]:
```
(35052331.44204509,
 count    3.149000e+03
 mean     3.505233e+07
 std      4.899110e+07
 min      9.000000e+03
 25%      5.000000e+06
 50%      1.500000e+07
 75%      4.000000e+07
 max      4.250000e+08
 Name: production_budget, dtype: float64)
```

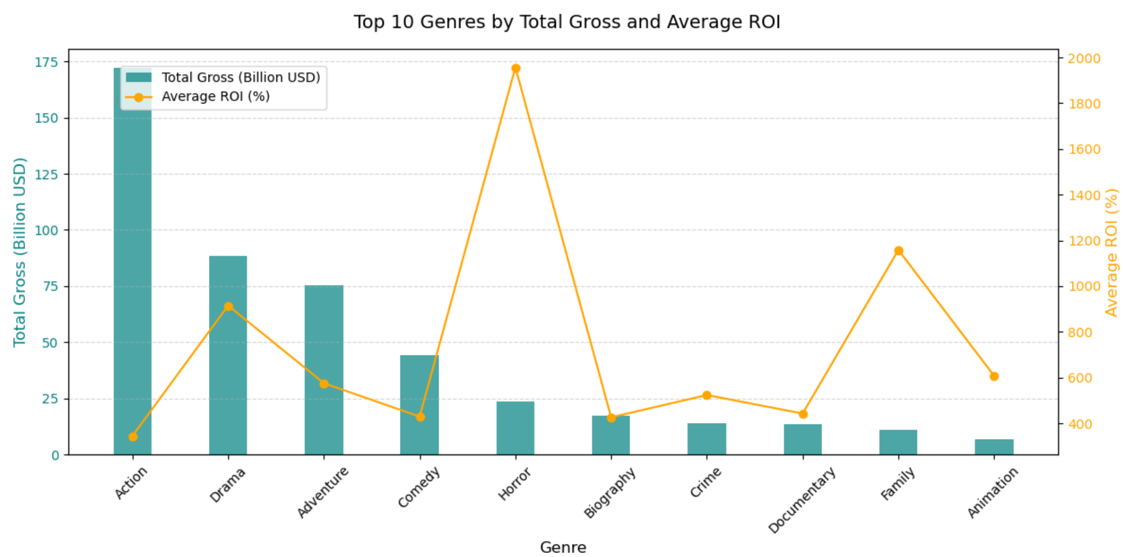
5.1.2 Multivariate analysis

ANALYZE GENRES BY TOTAL GROSS REVENUE AND ROI Adventure, Action, and Drama dominate in total gross revenue while Horror leads in ROI,Animation and Fantasy strike a balance, achieving both strong total gross and high ROI.

[186]:
```
# Calculate total and average gross revenue and ROI by genre
genre_performance = combined.groupby('genre_1').agg(
    total_gross=('Total_gross', 'sum'),
    avg_gross=('Total_gross', 'mean'),
    avg_ROI=('ROI', 'mean')
).sort_values(by='total_gross', ascending=False)
```

[187]:
```
# Combine Total Gross and ROI into a single visualization for top-performing␣
↪genres
fig, ax1 = plt.subplots(figsize=(12, 6))

# Bar graph for Total Gross Revenue
bar_width = 0.4
x = range(len(genre_performance.head(10)))

ax1.bar(
    x,
    genre_performance['total_gross'].head(10) / 1e9,  # Convert to billions for␣
↪readability
    width=bar_width,
    label='Total Gross (Billion USD)',
    color='teal',
    alpha=0.7
)
ax1.set_xlabel('Genre', fontsize=12)
ax1.set_ylabel('Total Gross (Billion USD)', fontsize=12, color='teal')
ax1.tick_params(axis='y', labelcolor='teal')
ax1.set_xticks(x)
```

```
ax1.set_xticklabels(genre_performance.head(10).index, rotation=45, fontsize=10)
ax1.grid(axis='y', linestyle='--', alpha=0.5)

# Add secondary axis for ROI
ax2 = ax1.twinx()
ax2.plot(
    x,
    genre_performance['avg_ROI'].head(10),
    color='orange',
    marker='o',
    label='Average ROI (%)'
)
ax2.set_ylabel('Average ROI (%)', fontsize=12, color='orange')
ax2.tick_params(axis='y', labelcolor='orange')

# Add legends and title
fig.suptitle('Top 10 Genres by Total Gross and Average ROI', fontsize=14)
fig.legend(loc='upper left', bbox_to_anchor=(0.1, 0.9), fontsize=10)
plt.tight_layout()
plt.show()
```



1. Budget Recommendation

Focus on production budgets between 10 million usd and 40 million usd , aligning with the 25th to 75th percentile, to capture consistent ROI opportunities while occasionally considering high-budget films ($100M+) to capitalize on blockbuster trends, but prioritize efficient mid-budget films for stability

2. Genre's Recommendation

Focus on producing high-revenue films in Adventure, Action, and Drama genres to target global audiences, incorporating occasional high-budget blockbusters for significant market impact, while leveraging Horror and Animation genres for low-risk, high-ROI projects to ensure a balanced and profitable portfolio.

Final Answer

By analyzing these metrics, we can determine:

- Which genres consistently generate the most revenue.(horror and family)
- Which genres are the most profitable (ROI).(action
- What audiences enjoy the most (Ratings & Votes).
- When movies should be released for the best results.
- Whether movie length affects box office success.

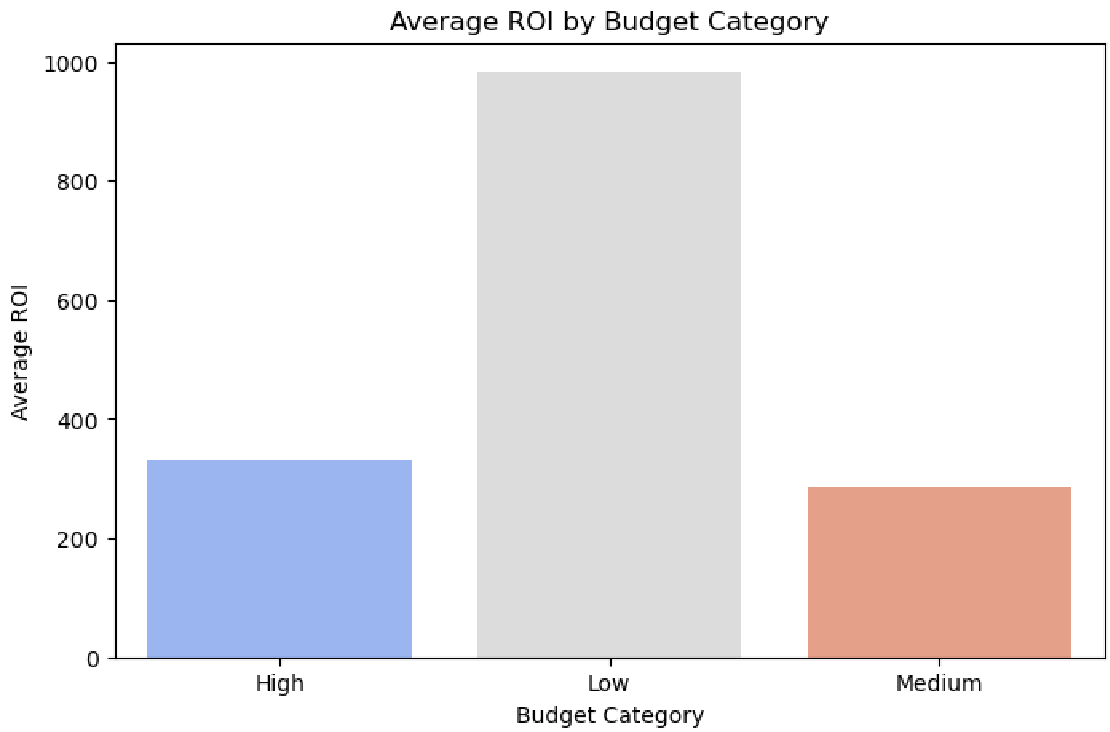
5.2 How do production budgets influence profitability and ROI?

5.2.1 Univariate Analysis

Budget Categories Analysis

- Compare average ROI for each category.

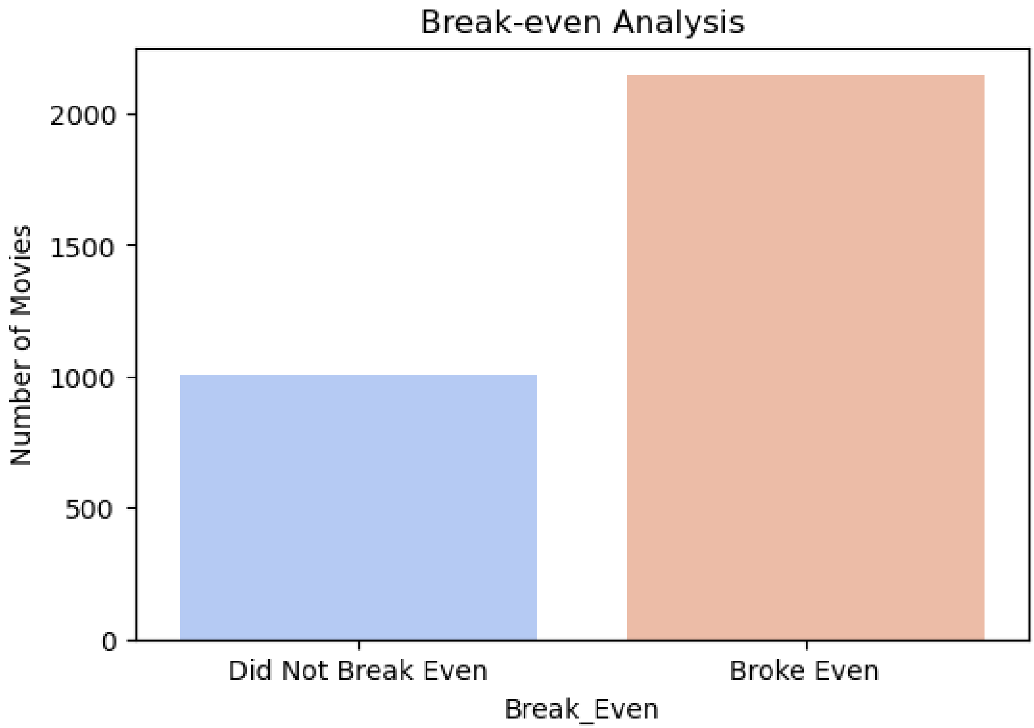
[188]:
```
# Group by budget category and calculate average ROI
budget_roi = combined.groupby('Budget_Category')['ROI'].mean()

# Plot
plt.figure(figsize=(8, 5))
sns.barplot(
    x=budget_roi.index,
    y=budget_roi.values,
    hue=budget_roi.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False
)
plt.title("Average ROI by Budget Category")
plt.xlabel("Budget Category")
plt.ylabel("Average ROI")
plt.show()
```



Insight: This bar chart reveals which budget category (low, medium, or high) has the highest ROI, guiding decisions on budget allocation. that is the low budget category

Break-even Point

[189]:
```
# Count break-even movies
break_even_counts = combined["Break_Even"].value_counts()
# Plot
plt.figure(figsize=(6, 4))
sns.barplot(
    x=break_even_counts.index,
    y=break_even_counts.values,
    hue=break_even_counts.index,  # Explicitly associate palette with hue
    palette="coolwarm",
    dodge=False,
    legend=False
)
plt.xticks([0, 1], ["Did Not Break Even", "Broke Even"])
plt.title("Break-even Analysis")
plt.ylabel("Number of Movies")
plt.show()
```

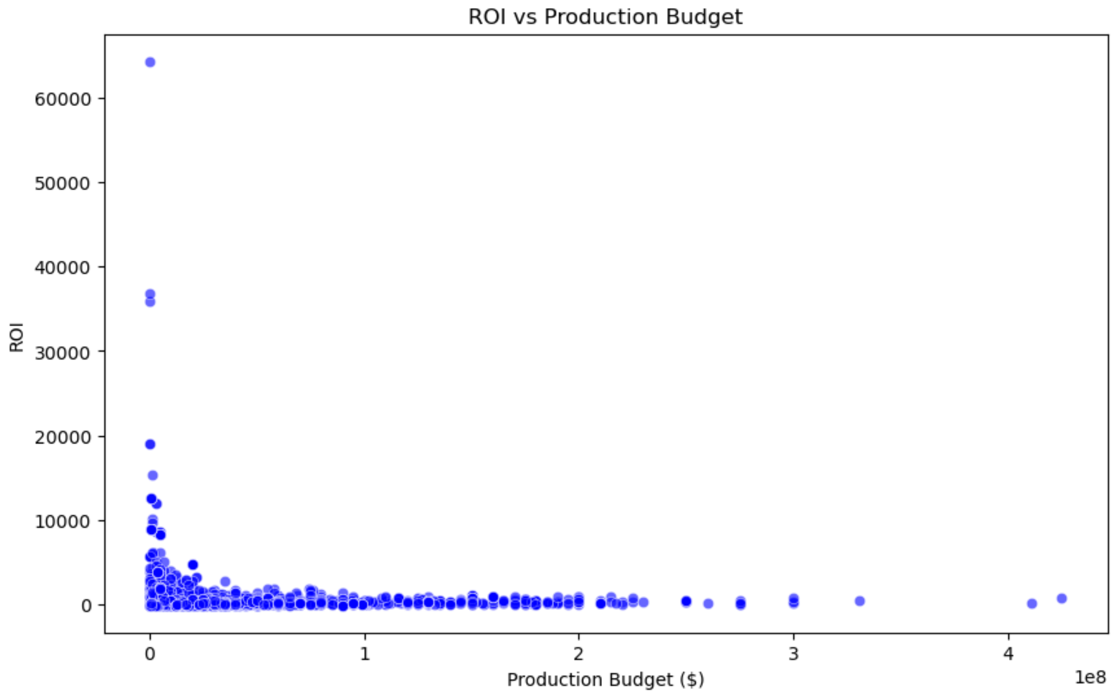


Insight: Determines how many movies recover their production costs.

5.2.2 Bivariate analysis

Return on Investment (ROI)

[190]:
```
# Plot ROI vs. Budget
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='ROI', data=combined, color='blue',␣
↪alpha=0.6)
plt.title("ROI vs Production Budget")
plt.xlabel("Production Budget ($)")
plt.ylabel("ROI")
plt.show()
```



Explanation

Key Observations:

Negative Correlation Between Budget and ROI

As the production budget increases (moving right along the X-axis), the ROI generally decreases, clustering near zero. High-budget movies (above 100 million) show lower ROI, meaning they do not always generate proportionally high profits.

High ROI for Low-Budget Films

Some low-budget films (left side of the plot) show extremely high ROI, suggesting that low-budget films can be highly profitable.

Wide ROI Variability in Low-Budget Films

The leftmost side of the plot (low-budget films) has a large spread in ROI, meaning some films generate very high returns while others fail.

Stable ROI for High-Budget Films

The right side (high-budget films) has a narrower spread in ROI, suggesting that blockbuster movies have more predictable but lower returns.

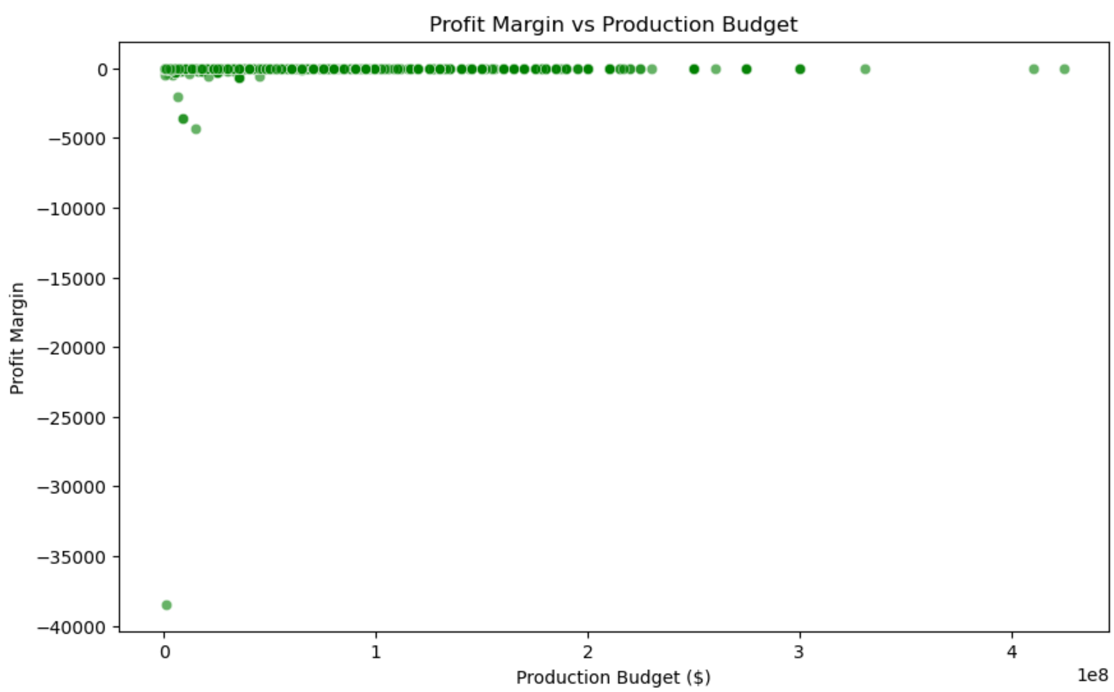
Insights & Implications:

- Higher budgets do not guarantee high ROI. Studios should carefully analyze the risk of large investments.

- Low-budget films have higher profit potential but higher risk. Some achieve massive ROI, while others fail entirely.
- Medium-budget films might offer a balance. Further analysis of budget categories is needed to determine an optimal investment range.

Profit Margin

[191]:
```
# Plot Profit Margin vs Budget
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='Profit_Margin', data=combined,␣
↪color='green', alpha=0.6)
plt.title("Profit Margin vs Production Budget")
plt.xlabel("Production Budget ($)")
plt.ylabel("Profit Margin")
plt.show()
```



Explanation Key Observations: Profit Margins Cluster Near Zero

Most data points are very close to the zero line, meaning many movies barely make a profit or just break even.

High Profit Margins for Some Low-Budget Films

The few low-budget films (left side of the plot) have significantly higher profit margins, indicating that some smaller productions generate substantial returns relative to their cost.

Very Few High-Profit Outliers

A handful of points show extremely high profit margins, meaning some films were produced at a low cost and earned massive box office revenue.

High-Budget Films Have Lower and More Stable Profit Margins

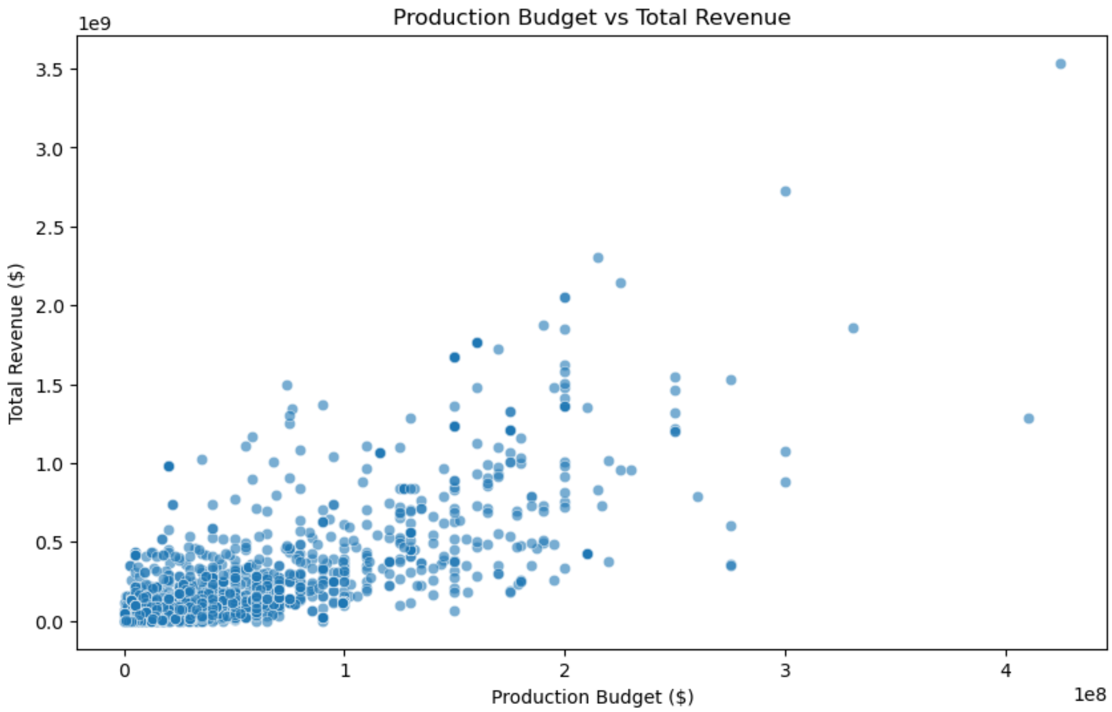
The right side of the plot (higher budgets) shows a more consistent trend with profit margins staying closer to zero, meaning big-budget films often operate on smaller percentage margins.

Insights & Implications: * Low-budget films have a higher potential for massive profit margins but also higher risk. * Big-budget films tend to have more stable but lower profit margins, likely due to high production and marketing costs. * Further investigation is needed to determine why some low-budget films achieve extreme profit margins while others do not.

Correlation Analysis Steps: * Compute correlation between budget and revenue. * Visualize with a scatter plot.

[192]:
```
# Calculate correlation
correlation = combined['production_budget'].corr(combined['Total_gross'])
print(f"Correlation between production budget and total revenue: {correlation}")

# Plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='Total_gross', data=combined, alpha=0.
↪6)
plt.title("Production Budget vs Total Revenue")
plt.xlabel("Production Budget ($)")
plt.ylabel("Total Revenue ($)")
plt.show()
```

```
Correlation between production budget and total revenue: 0.7783149247538605
```



Insight: A high positive correlation indicates that higher budgets generally lead to higher revenue, but this doesn't guarantee higher profitability.

5.3 What role do ratings and audience engagement play in financial performance?

5.3.1 Correlation Between Ratings and Revenue

We'll calculate the Pearson correlation coefficient between average_ratings and Total_gross to see if higher ratings correlate with higher box office performance.

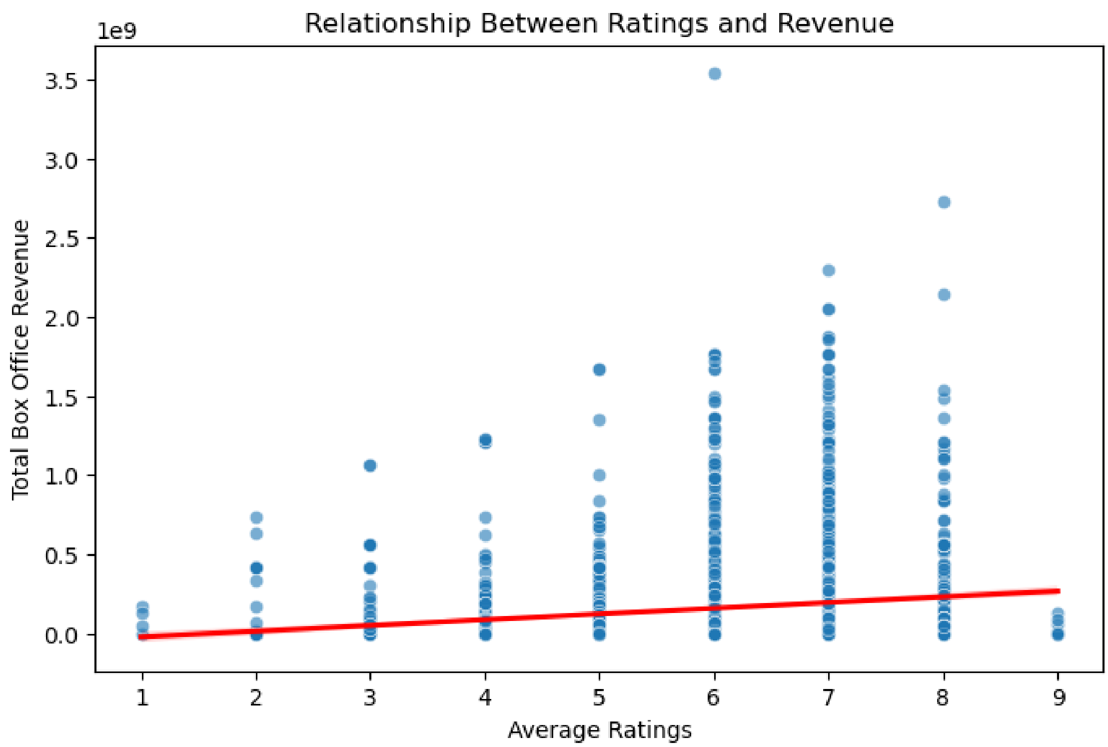
[193]:
```
#import libraries
from scipy.stats import pearsonr
import statsmodels.api as sm
```

[194]:
```
# Correlation coefficient
corr_rating, p_value = pearsonr(combined['average_ratings'],␣
↪combined['Total_gross'])
print(f"Correlation between Ratings and Revenue: {corr_rating:.4f}, p-value:␣
↪{p_value:.4f}")
```

```
Correlation between Ratings and Revenue: 0.1565, p-value: 0.0000
```

Interpretation: * Positive correlation: Higher ratings lead to higher revenue. * Negative correlation: Higher ratings do not influence revenue. * p-value < 0.05: The relationship is statistically significant.

```
[195]: #plot
plt.figure(figsize=(8, 5))
sns.scatterplot(x=combined['average_ratings'], y=combined['Total_gross'],␣
 ↪alpha=0.6)
sns.regplot(x=combined['average_ratings'], y=combined['Total_gross'],␣
 ↪scatter=False, color='red')  # Regression line
plt.title("Relationship Between Ratings and Revenue")
plt.xlabel("Average Ratings")
plt.ylabel("Total Box Office Revenue")
plt.show()
```



Scatter Distribution: Each blue dot represents a movie, showing its rating and corresponding revenue.

Trendline (Red Line): A fitted regression line shows the overall trend, suggesting a slight positive correlation between ratings and revenue.

Variance in Revenue: While higher-rated movies tend to earn more, the spread of revenue is wide at each rating level, meaning other factors (e.g., budget, marketing) also influence earnings.

High Revenue Outliers: Some movies with ratings around 6-8 have exceptionally high revenues (over 1 billion), likely representing blockbuster hits.

Interpretation:

Movies with higher ratings generally earn more revenue, but ratings alone are not a strong predictor of box office success.

Other factors such as franchise value, marketing, and production budget significantly impact earnings.

5.3.2 Audience Engagement and Box Office Performance

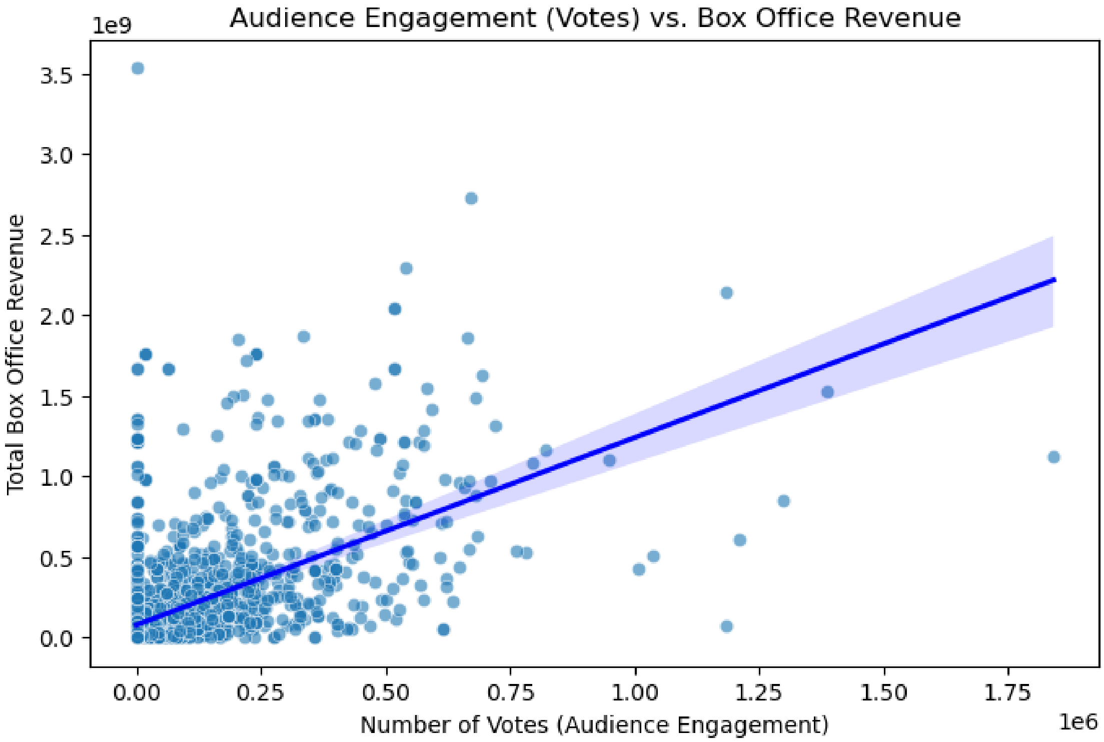
We'll investigate the relationship between audience engagement (number_of_votes) and box office revenue.

[196]:
```
# Correlation between number of votes and revenue
corr_votes, p_value_votes = pearsonr(combined['number_of_votes'],␣
↪combined['Total_gross'])
print(f"Correlation between Number of Votes and Revenue: {corr_votes:.4f},␣
↪p-value: {p_value_votes:.4f}")
```

```
Correlation between Number of Votes and Revenue: 0.5397, p-value: 0.0000
```

Interpretation: * High correlation: More reviews may indicate greater audience engagement, leading to higher revenue. * Low correlation: Engagement might not be a significant factor in box office performance.

[197]:
```
#plot .
plt.figure(figsize=(8, 5))
sns.scatterplot(x=combined['number_of_votes'], y=combined['Total_gross'],␣
↪alpha=0.6)
sns.regplot(x=combined['number_of_votes'], y=combined['Total_gross'],␣
↪scatter=False, color='blue')
plt.title("Audience Engagement (Votes) vs. Box Office Revenue")
plt.xlabel("Number of Votes (Audience Engagement)")
plt.ylabel("Total Box Office Revenue")
plt.show()
```



Scatter Distribution (Blue Dots)

Each dot represents a movie.

A noticeable concentration of movies with low to moderate audience votes (below ~500,000) but varying revenue levels.

Some movies have very high votes (1.5M+) and high revenues (over 1B), likely indicating major blockbuster films.

Regression Line (Dark Blue) and Confidence Interval (Shaded Area)

The regression line shows a positive correlation between audience engagement and revenue.

The confidence interval suggests some variance, meaning while the trend is generally upward, individual cases may vary significantly.

Interpretation and Insights: Stronger Correlation Than Ratings vs. Revenue * Unlike average ratings (which had a weak effect on revenue), the number of votes shows a clearer upward trend. * More engagement often means a larger audience, leading to higher revenue.

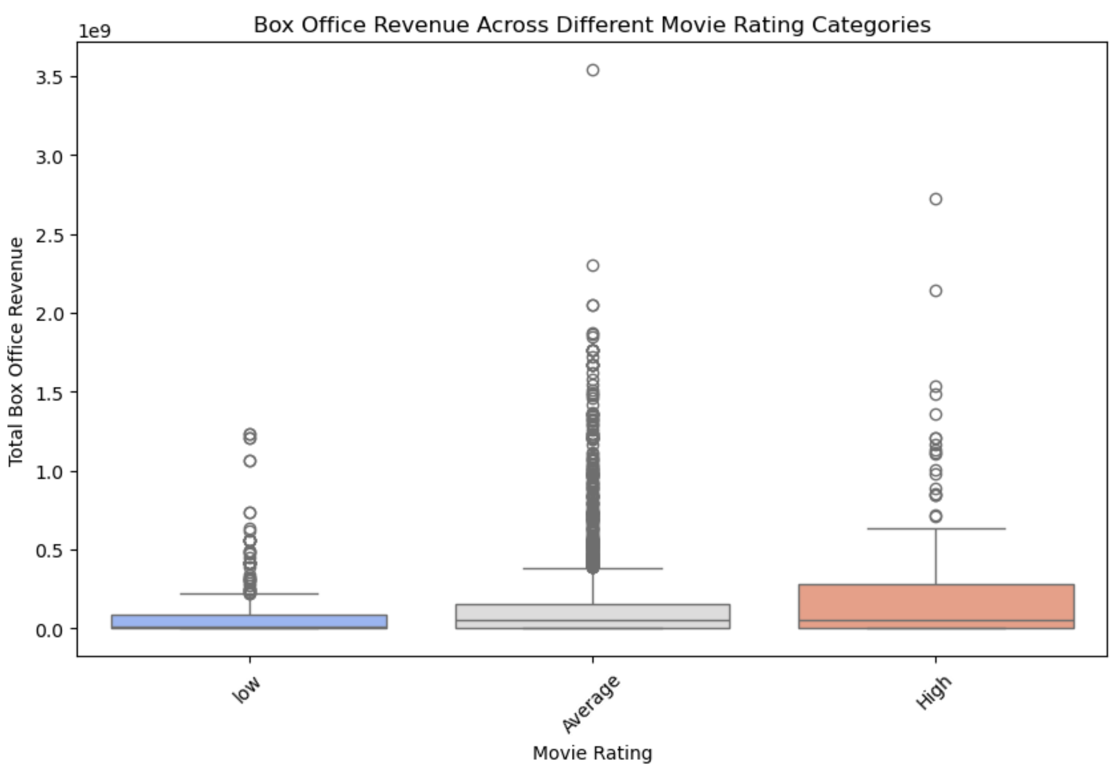
Popular Movies Are More Profitable * Movies with a high number of votes tend to generate more revenue. * This suggests that audience size (engagement) is a better predictor of box office success than just the rating score.

Outliers Exist * Some movies with low votes still have high revenue (possibly due to marketing, franchise popularity, or blockbuster status). * Some movies with high votes but lower revenue might have gained popularity post-theatrical release (e.g., cult classics or streaming success).

Causation vs. Correlation * High engagement likely leads to higher revenue, but marketing, production budget, and franchise status also contribute significantly.

5.3.3 Ratings Distribution by Revenue

[198]:
```
#plot
plt.figure(figsize=(10, 6))
sns.boxplot(
    x=combined['movie_rating'],
    y=combined['Total_gross'],
    hue=combined['movie_rating'],  # Explicitly associate palette with hue
    palette="coolwarm"
)
plt.title("Box Office Revenue Across Different Movie Rating Categories")
plt.xlabel("Movie Rating")
plt.ylabel("Total Box Office Revenue")
plt.xticks(rotation=45)
plt.show()
```



Key Observations: 1. Box Plot Interpretation * The x-axis represents movie rating categories (Low, Average, High). * The y-axis represents total box office revenue. * The box represents the interquartile range (IQR) (middle 50% of the data). * The horizontal line inside the box is the median revenue for each category. * The whiskers extend to data points within 1.5 times the IQR.

* The dots outside the whiskers are outliers, indicating extreme revenue values.

2. Insights from the Data

a) Revenue Distribution Across Ratings

- Low-rated movies (blue box)
  - Tend to have lower revenue overall, with most movies earning relatively little.
  - A few outliers (successful low-rated films) reach high revenue, but these are rare.
- Average-rated movies (gray box)
  - Show a slightly higher median revenue than low-rated movies.
  - There is a broader spread of revenue values, with some movies earning over 2 billion.
  - The number of high-revenue outliers is significant, suggesting some mid-rated films perform exceptionally well.
- High-rated movies (orange box)
  - Have the highest median revenue, meaning most high-rated movies tend to perform better.
  - However, the spread is also wide, indicating that some high-rated films do not always achieve high box office revenue.
  - The number of outliers is similar to the "Average" category, suggesting that critical acclaim does not always guarantee massive earnings.

Key Takeaways * High-rated movies generally earn more revenue, but the advantage is not absolute. * While median revenue increases with rating, the presence of high-revenue outliers in both average- and low-rated films suggests that other factors (e.g., budget, marketing, franchise strength) play a critical role.

- Some low-rated films can still perform well.
  - The presence of outliers in the "Low" category suggests that certain movies succeed despite poor reviews—possibly due to strong marketing, established fan bases, or niche appeal.
- The "Average" rating category has the highest variation.
  - Many blockbusters fall into this category, showing that critical reception is not the only predictor of financial success.

Recommendations for the Film Industry 1. Invest in High-Quality Productions (But Don't Ignore Other Factors) * Since higher-rated movies tend to perform better on average, studios should prioritize quality storytelling, strong scripts, and production value. * However, high ratings do not guarantee high revenue, so marketing and distribution strategies remain crucial.

2. Focus on Marketing and Franchise Potential

- Some low-rated movies (outliers) achieve high revenue, likely due to franchise popularity or strong branding (e.g., superhero movies, action franchises).
- Marketing campaigns, strategic release timing, and audience engagement play a crucial role in box office performance.

3. Target Broad Audiences for Mid-Tier Movies

- Mid-rated films (5-7/10 range) still have strong revenue potential.
- Instead of focusing only on critic scores, studios should leverage audience preferences, genre appeal, and accessibility to maximize profits.

4. Utilize Streaming and Digital Platforms

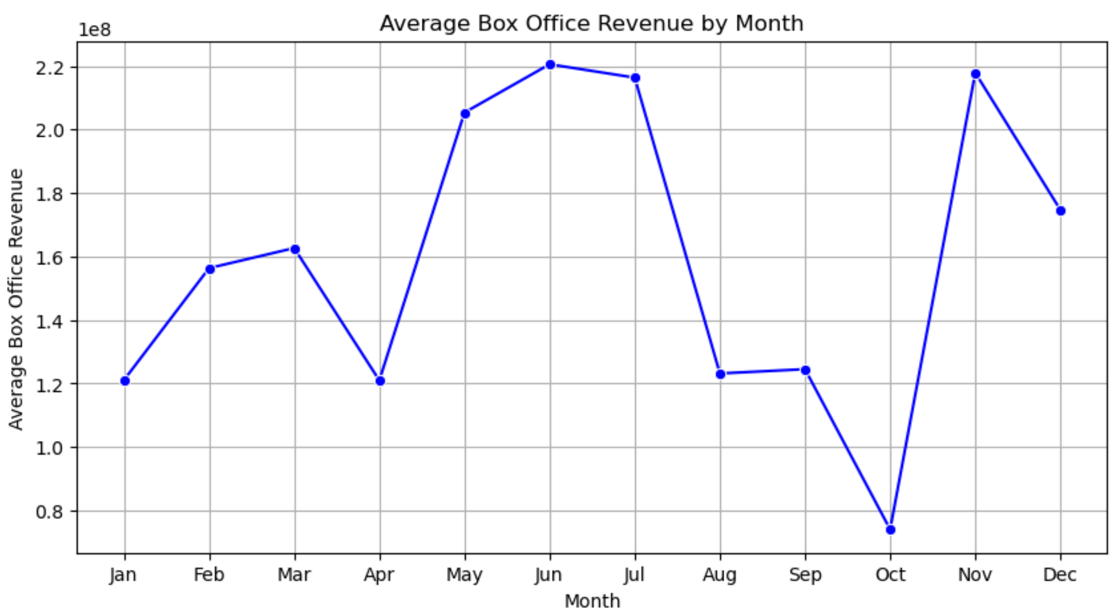
- Movies that do not perform well in theaters can gain popularity post-release through streaming services, leading to increased revenue over time.
- Investing in alternative revenue streams (digital rentals, merchandise, special editions) can boost profitability for movies that underperform in theaters.

Final Thoughts

While higher ratings generally lead to better revenue, there is no absolute guarantee of success. Successful films often rely on a combination of quality, marketing, franchise value, and audience reach. Studios should adopt a balanced strategy, focusing not just on critic scores but also on audience preferences, effective distribution, and strong marketing efforts.

5.4 Are there seasonal or year-based trends that affect revenue potential

[199]:
```
# Group by month to see revenue trends
monthly_revenue =combined.groupby('month')['Total_gross'].mean()

# Plot monthly revenue trends
plt.figure(figsize=(10, 5))
sns.lineplot(x=monthly_revenue.index, y=monthly_revenue.values, marker="o",␣
 ↪color="b")
plt.title("Average Box Office Revenue by Month")
plt.xlabel("Month")
plt.ylabel("Average Box Office Revenue")
plt.xticks(range(1, 13),
           ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
            'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid()
plt.show()
```

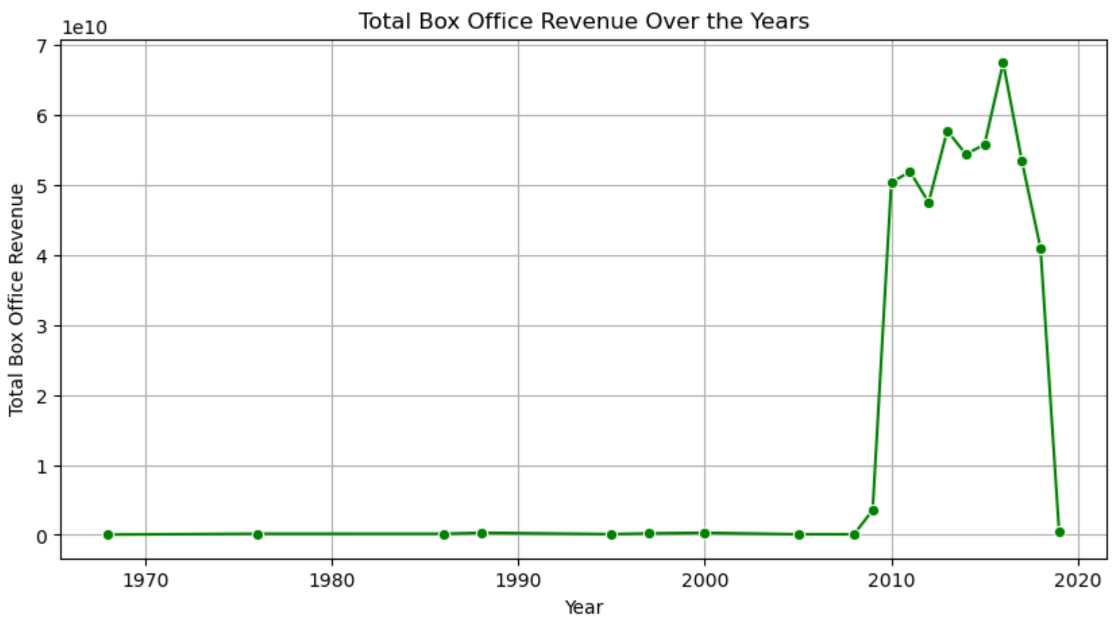


Highest Revenue: * The highest average revenue occurs in June, followed closely by May and July. **Lowest Revenue:** * The lowest average revenue occurs in October, followed by April. **Trends:** * The revenue generally increases from January to June, drops significantly in August, experiences a slight increase in September, and then drops again in October. There's a sharp rise in November followed by a decline in December.

5.4.1 Year-on-Year Revenue Analysis

This analysis identifies revenue trends over the years.

[200]:
```
# Yearly revenue trend
yearly_revenue = combined.groupby('year')['Total_gross'].sum()
#plot
plt.figure(figsize=(10, 5))
sns.lineplot(x=yearly_revenue.index, y=yearly_revenue.values, marker="o",␣
↪color="g")
plt.title("Total Box Office Revenue Over the Years")
plt.xlabel("Year")
plt.ylabel("Total Box Office Revenue")
plt.grid()
plt.show()
```



Exponential Growth (2009-2016): * A sharp rise in revenue begins around 2009, indicating a significant shift in the industry.

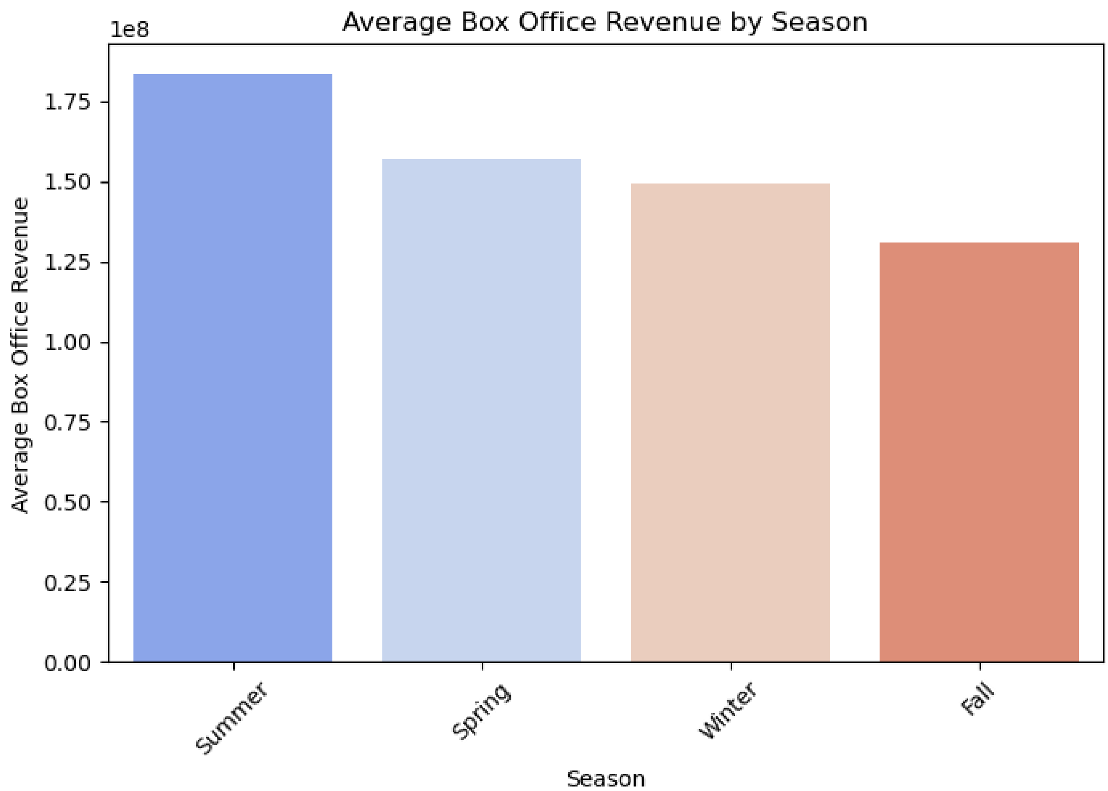
Peak and Decline (2017-2020): * The revenue reaches its zenith around 2017, followed by a noticeable decline.

Interpretations: * **Industry Transformation:** * The drastic growth from 2009 onwards indicates a transformative period in the film industry, likely driven by technological advancements and changing consumer preferences.

Impact of External Factors: * The decline after 2017 suggests that the industry is susceptible to external forces such as economic downturns, global events, and competition from alternative entertainment sources.

Holiday/Peak Season Performance We categorize movies into seasons (Winter, Spring, Summer, Fall) and compare revenues.

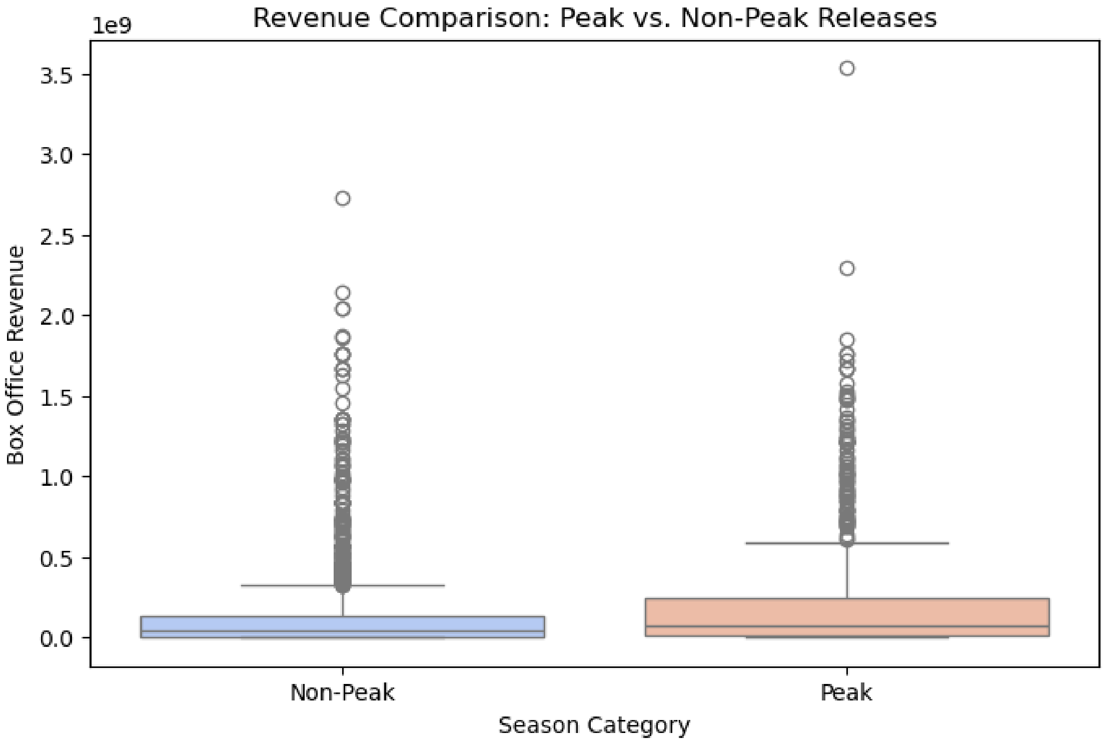
[201]:
```python
# Group by season
seasonal_revenue = combined.groupby('season')['Total_gross'].mean()

# Sort the data in descending order
sorted_seasonal_revenue = seasonal_revenue.sort_values(ascending=False)

# Plot
plt.figure(figsize=(8, 5))
sns.barplot(
    x=sorted_seasonal_revenue.index,
    y=sorted_seasonal_revenue.values,
    hue=sorted_seasonal_revenue.index,  # Assign x variable to hue to avoid␣
 ↪FutureWarning
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress the legend
)
plt.title("Average Box Office Revenue by Season")
plt.xlabel("Season")
plt.ylabel("Average Box Office Revenue")
plt.xticks(rotation=45)
plt.show()
```



5.4.2 Release Timing Analysis: Summer vs. Holiday Releases

This analysis compares box office performance of summer blockbusters vs. holiday releases.

[202]:
```
# Boxplot to compare revenues
plt.figure(figsize=(8, 5))
sns.boxplot(
    x=combined['peak_season'],
    y=combined['Total_gross'],
    hue=combined['peak_season'],  # Explicitly assign x to hue
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress legend to avoid unnecessary output
)
plt.title("Revenue Comparison: Peak vs. Non-Peak Releases")
plt.xlabel("Season Category")
plt.ylabel("Box Office Revenue")
plt.show()
```



Explanation: The boxes: represent the interquartile range (IQR), which contains the middle 50% of the data. The bottom of the box is the first quartile (25th percentile), the top is the third quartile (75th percentile), and the line inside the box is the median (50th percentile).

The whiskers: extend from the box to the minimum and maximum values within 1.5 times the IQR.

The circles: represent outliers, which are data points that fall outside the whiskers.

Interpretation:

Peak season releases: * tend to have higher median revenue than non-peak releases, indicating that they generally make more money. * also have a wider range of revenue, with more outliers, indicating that there's more variability in their performance. Some peak season movies can be extremely successful, while others may not perform as well.

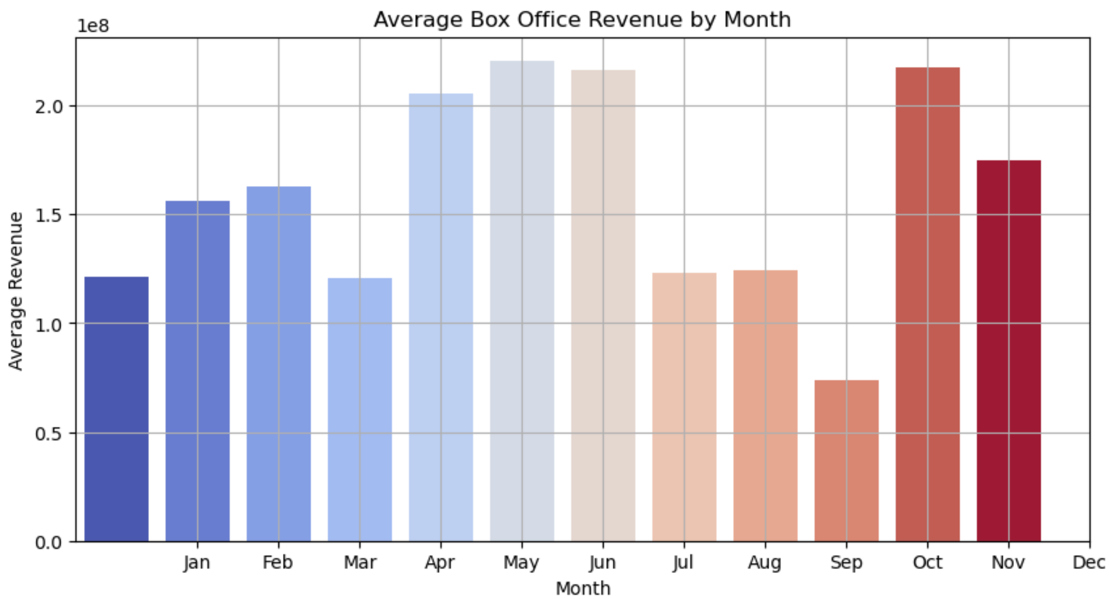
Non-peak season releases: * have a narrower range of revenue and fewer outliers, indicating that their performance is more consistent.

5.5 What are the most profitable release windows?

5.5.1 Revenue Distribution by Week/Month

We will analyze how box office revenue varies month by month.

[203]:
```
# Group by month to analyze revenue trends
monthly_revenue = combined.groupby('month')['Total_gross'].mean()

# Plot Monthly Revenue Trends

plt.figure(figsize=(10, 5))
sns.barplot(
    x=monthly_revenue.index,
    y=monthly_revenue.values,
    hue=monthly_revenue.index,  # Explicitly assign x variable to hue
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress legend to avoid unnecessary output
)
plt.title("Average Box Office Revenue by Month")
plt.xlabel("Month")
plt.ylabel("Average Revenue")
plt.xticks(range(1, 13),
           ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
            'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid()
plt.show()
```

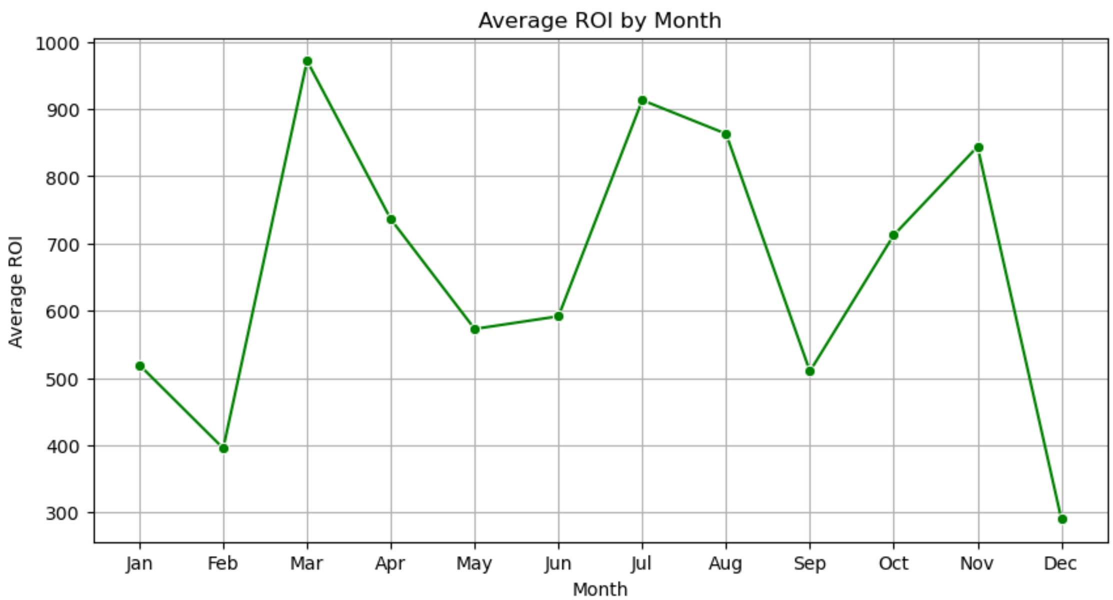


Insights: This will highlight which months tend to generate the most revenue.

5.5.2 Profitability by Release Date (ROI Analysis)

Next, we assess Return on Investment (ROI) across different release periods.

[204]:
```python
# Group by month and calculate average ROI
monthly_roi = combined.groupby('month')['ROI'].mean()

plt.figure(figsize=(10, 5))
sns.lineplot(x=monthly_roi.index, y=monthly_roi.values, marker="o", color="g")
plt.title("Average ROI by Month")
plt.xlabel("Month")
plt.ylabel("Average ROI")
plt.xticks(range(1, 13),
           ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
            'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid()
plt.show()
```



The x-axis represents the months of the year, from January to December.

The y-axis represents the average ROI, ranging from 300 to 1000.

The highest average ROI occurs in March, reaching approximately 960.

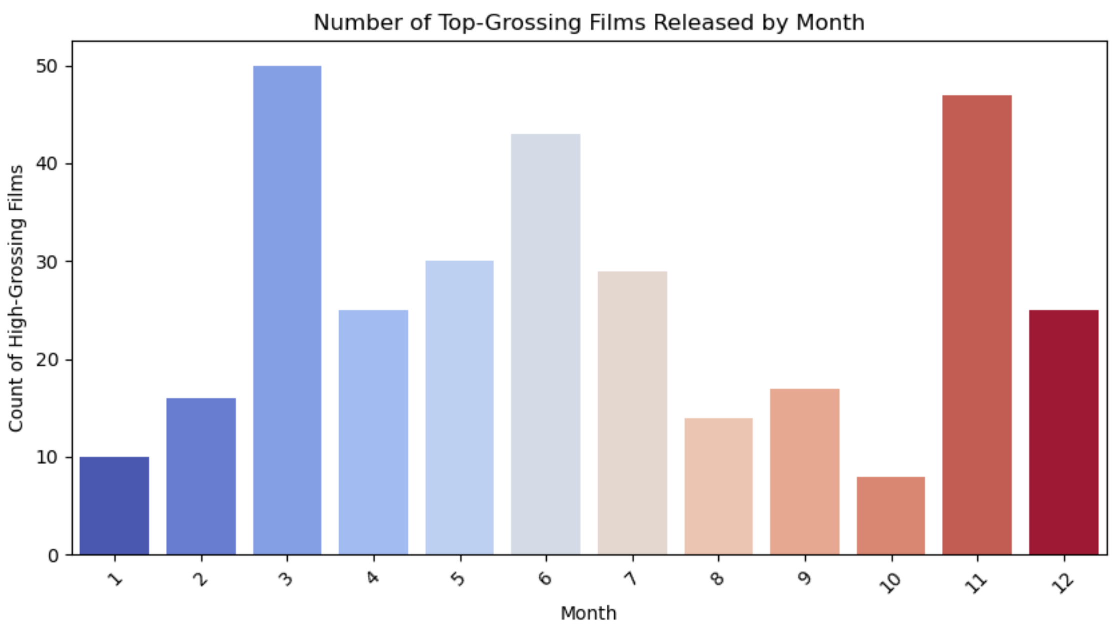
The lowest average ROI occurs in December, at around 300.

There's a significant fluctuation in average ROI throughout the year, with peaks in March and July, and troughs in February and December.

5.5.3 Competitor Analysis: Release Timing of Top Films

To understand competition, we analyze when the highest-grossing films are released.

[205]:
```
# Find top 10% highest-grossing films
top_movies = combined.nlargest(int(len(combined) * 0.1), 'Total_gross')

# Count releases per month for top films
top_releases_per_month = top_movies['month'].value_counts().sort_index()

# Plot
plt.figure(figsize=(10, 5))
sns.barplot(
    x=top_releases_per_month.index,
    y=top_releases_per_month.values,
    hue=top_releases_per_month.index,  # Assign x to hue to avoid FutureWarning
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress the legend
)
plt.title("Number of Top-Grossing Films Released by Month")
plt.xlabel("Month")
plt.ylabel("Count of High-Grossing Films")
plt.xticks(rotation=45)
plt.show()
```

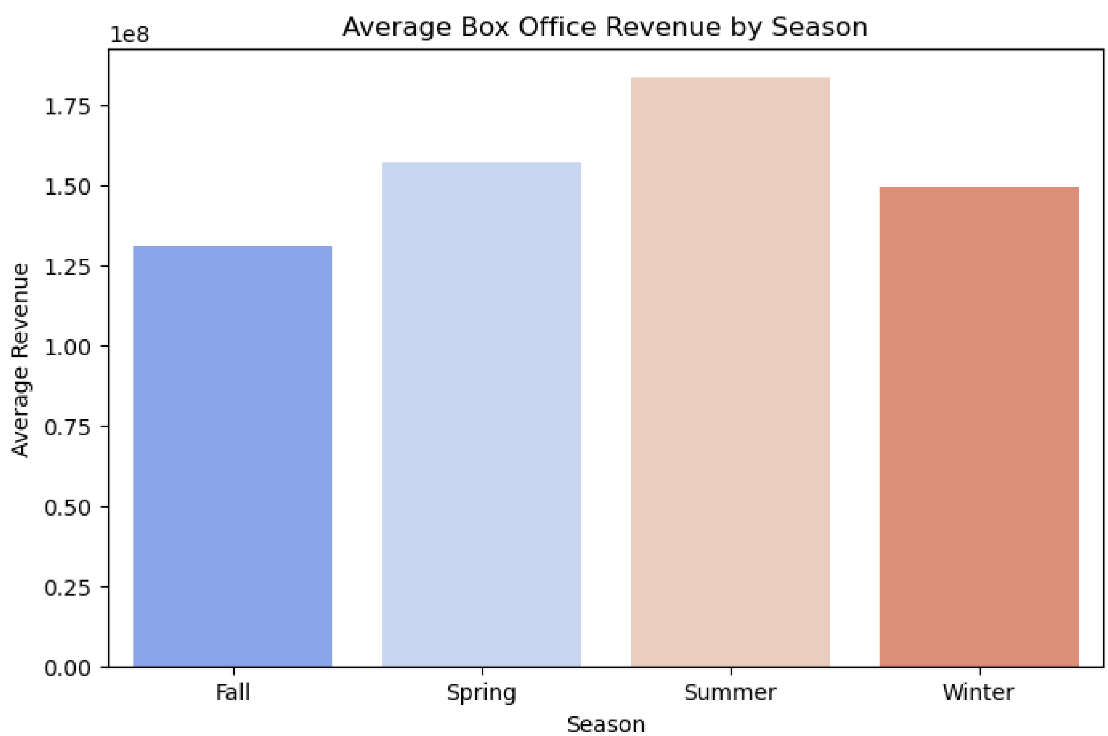


Insights: If most top films are released during summer or holiday periods, it suggests a strategic pattern in release timing

5.5.4 Average Revenue by Release Window

We categorize movies into seasons to compare revenue performance.

[206]:
```
# Average revenue per season
seasonal_revenue = combined.groupby('season')['Total_gross'].mean()

# Plot
plt.figure(figsize=(8, 5))
sns.barplot(
    x=seasonal_revenue.index,
    y=seasonal_revenue.values,
    hue=seasonal_revenue.index,  # Assign x variable to hue to avoid the␣
↪FutureWarning
    palette="coolwarm",
    dodge=False,
    legend=False  # Suppress legend
)
plt.title("Average Box Office Revenue by Season")
plt.xlabel("Season")
plt.ylabel("Average Revenue")
plt.show()
```



The bar graph illustrates the average box office revenue across different seasons. Here's

a breakdown:

- **Summer:**
  - This season boasts the highest average box office revenue, exceeding 175 million dollars.
- **Spring:**
  - It follows with an average revenue slightly above 150 million dollars.
- **Winter:**
  - The season secures the third spot with an average revenue around 150 million dollars.
- **Fall:**
  - It records the lowest average revenue, slightly surpassing 125 million dollars.

This data highlights the significant impact of the season on movie earnings, with summer being the most lucrative period for the film industry.

6 Preprocessing

Preprocessing is the crucial first step in preparing raw data for analysis or machine learning models. It involves cleaning, transforming, and structuring data to improve accuracy and efficiency.

6.1 import libraries

[207]:
```
#import the libraries
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
import scipy.stats as statsmodels

# Preprocessing

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

# time
import time
```

6.2 clean the dataset

[208]:
```
#check the dataset info
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3149 entries, 0 to 3148
Data columns (total 23 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   runtime_minutes     3149 non-null   int64
 1   genres              3149 non-null   object
```

```
 2   average_ratings    3149 non-null   int64
 3   number_of_votes    3149 non-null   int64
 4   release_date       3149 non-null   datetime64[ns]
 5   title              3149 non-null   object
 6   production_budget  3149 non-null   int64
 7   domestic_gross     3149 non-null   int64
 8   worldwide_gross    3149 non-null   int64
 9   Total_gross        3149 non-null   int64
 10  ROI                3149 non-null   float64
 11  month              3149 non-null   int32
 12  season             3149 non-null   object
 13  movie_rating       3149 non-null   object
 14  movie_length       3149 non-null   object
 15  genre_1            3149 non-null   object
 16  genre_combined     3149 non-null   object
 17  Budget_Category    3149 non-null   object
 18  Break_Even         3149 non-null   bool
 19  Profit_Margin      3149 non-null   float64
 20  quarter            3149 non-null   period[Q-DEC]
 21  year               3149 non-null   int32
 22  peak_season        3149 non-null   object
dtypes: bool(1), datetime64[ns](1), float64(2), int32(2), int64(7), object(9),
period[Q-DEC](1)
memory usage: 519.8+ KB
```

[209]:
```
#drop irrelevant columns
combined = combined.
 ↪drop(columns=['release_date','title','movie_age_label','quarter','movie_length',␣
 ↪'genres_list',
       'Break_Even','quarter','genres','genre_combined','genre_1'], axis=1,␣
 ↪errors='ignore')
#combined=combined.drop(columns=['genres'],axis=1,errors='ignore')
#combined=combined.drop(columns=['genre_1'],axis=1,errors='ignore')
#combined=combined.drop(columns=['genre_combined'],axis=1,errors='ignore')
```

[210]:
```
#check columns
combined.columns
```

[210]:
```
Index(['runtime_minutes', 'average_ratings', 'number_of_votes',
       'production_budget', 'domestic_gross', 'worldwide_gross', 'Total_gross',
       'ROI', 'month', 'season', 'movie_rating', 'Budget_Category',
       'Profit_Margin', 'year', 'peak_season'],
      dtype='object')
```

[211]:
```
#check dataset info
combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 3149 entries, 0 to 3148
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   runtime_minutes    3149 non-null   int64
 1   average_ratings    3149 non-null   int64
 2   number_of_votes    3149 non-null   int64
 3   production_budget  3149 non-null   int64
 4   domestic_gross     3149 non-null   int64
 5   worldwide_gross    3149 non-null   int64
 6   Total_gross        3149 non-null   int64
 7   ROI                3149 non-null   float64
 8   month              3149 non-null   int32
 9   season             3149 non-null   object
 10  movie_rating       3149 non-null   object
 11  Budget_Category    3149 non-null   object
 12  Profit_Margin      3149 non-null   float64
 13  year               3149 non-null   int32
 14  peak_season        3149 non-null   object
dtypes: float64(2), int32(2), int64(7), object(4)
memory usage: 344.6+ KB
```

[212]:
```
combined['ROI']=round(combined['ROI'],0)
combined['Profit_Margin']=round(combined['ROI'],0)
```

[213]:
```
# Change data types
combined['ROI'] = combined['ROI'].astype('int64')
combined['Profit_Margin'] = combined['Profit_Margin'].astype('int64')
```

[214]:
```
#view dataset
combined.head()
```

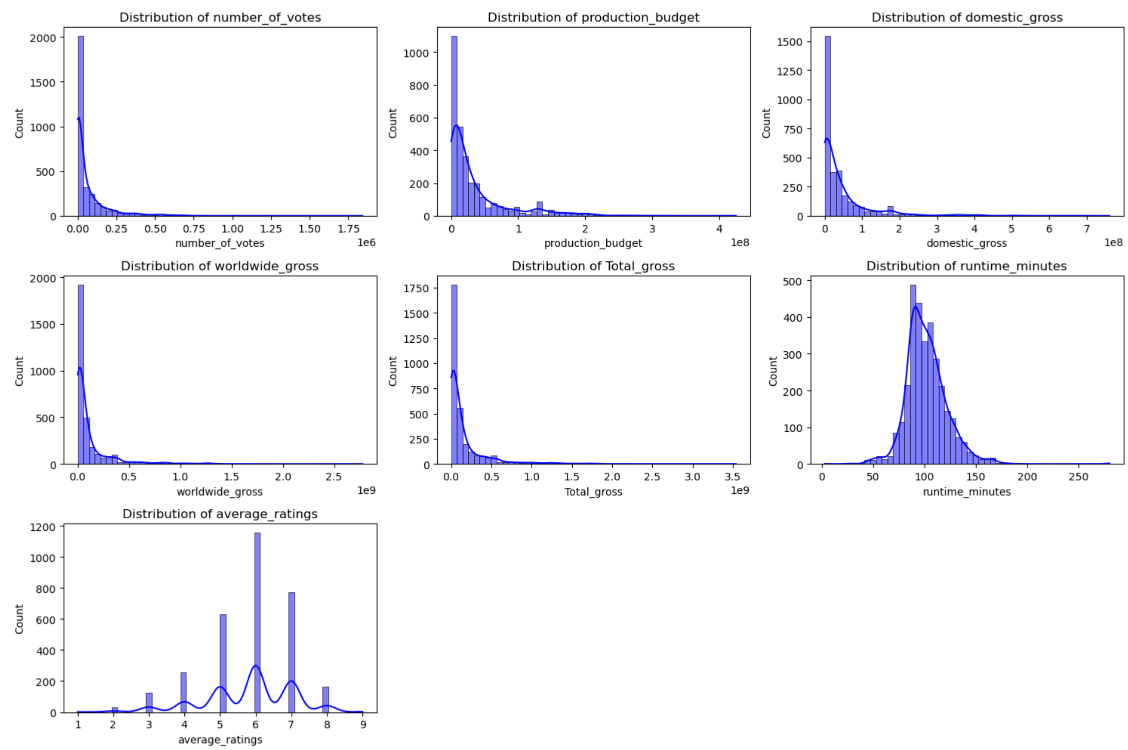
[214]:
```
   runtime_minutes  average_ratings  number_of_votes  production_budget  \
0               91                1             8248           45000000
1               88                7               24             200000
2              124                6            37886           25000000
3              114                7           275300           91000000
4              114                6           105116           28000000

   domestic_gross  worldwide_gross  Total_gross   ROI  month  season  \
0               0            73706        73706  -100      5  Spring
1         1109808          1165996      2275804  1038      6  Summer
2          720828          9313302     10034130   -60     12  Winter
3        58236838        187861183    246098021   170     12  Winter
4        26017685         62108587     88126272   215      9    Fall

  movie_rating Budget_Category  Profit_Margin  year peak_season
```

```
0         low          Medium          -100  2013    Non-Peak
1     Average             Low          1038  2015        Peak
2     Average          Medium           -60  2012        Peak
3     Average            High           170  2013        Peak
4     Average          Medium           215  2014    Non-Peak
```

[215]:
```
#check for missing values
combined.isna().sum()
```

[215]:
```
runtime_minutes      0
average_ratings      0
number_of_votes      0
production_budget    0
domestic_gross       0
worldwide_gross      0
Total_gross          0
ROI                  0
month                0
season               0
movie_rating         0
Budget_Category      0
Profit_Margin        0
year                 0
peak_season          0
dtype: int64
```

[216]:
```
# List of numerical features
numerical_features = ['number_of_votes', 'production_budget', 'domestic_gross',␣
 ↪'worldwide_gross',
                      'Total_gross', 'runtime_minutes', 'average_ratings']

# Plot histograms for all numerical features
plt.figure(figsize=(15, 10))
for i, feature in enumerate(numerical_features, 1):
    plt.subplot(3, 3, i)  # Creating a 3x3 grid
    sns.histplot(combined[feature], bins=50, kde=True, color="blue")
    plt.title(f"Distribution of {feature}")
plt.tight_layout()
plt.show()
```



[217]:

```
from scipy.stats import skew

# Calculate skewness for all numerical columns
skewness_values = combined[numerical_features].apply(lambda x: skew(x, nan_policy='omit'))
print(skewness_values.sort_values(ascending=False))  # Sort to see most skewed first
```

```
number_of_votes      4.149164
worldwide_gross      3.902812
Total_gross          3.739693
domestic_gross       3.494778
production_budget    2.372282
runtime_minutes      1.063995
average_ratings     -0.633061
dtype: float64
```

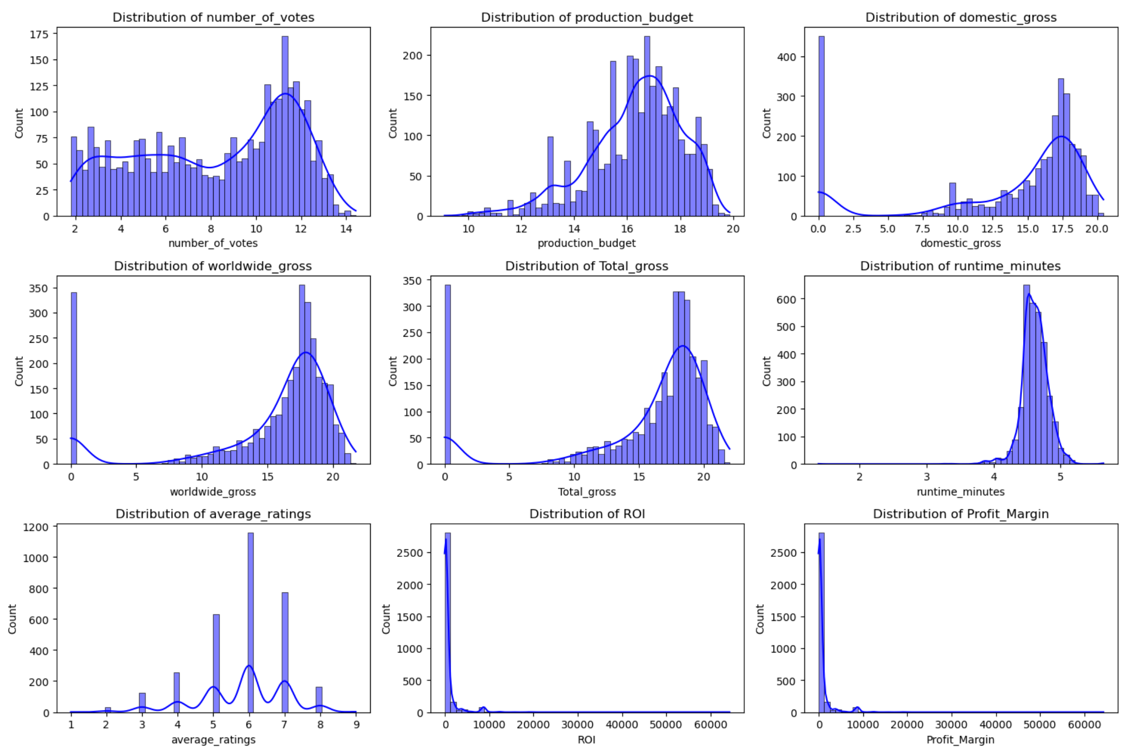
[218]:

```
# Select features with high skewness (skewness > 1)
skewed_features = skewness_values[skewness_values > 1].index.tolist()
print("\nHighly Skewed Features:\n", skewed_features)

# Apply log transformation safely (using log1p to handle zeros)
```

```
combined[skewed_features] = combined[skewed_features].apply(lambda x: np.
 ↪log1p(x))

# Recalculate skewness after transformation
new_skewness = combined[skewed_features].apply(lambda x: skew(x,␣
 ↪nan_policy='omit'))
print("\nNew Skewness After Log Transformation:\n", new_skewness.
 ↪sort_values(ascending=False))
```

```
Highly Skewed Features:
 ['number_of_votes', 'production_budget', 'domestic_gross', 'worldwide_gross',
'Total_gross', 'runtime_minutes']

New Skewness After Log Transformation:
 number_of_votes      -0.321272
production_budget    -0.758359
domestic_gross       -1.453697
runtime_minutes      -1.600740
worldwide_gross      -1.812011
Total_gross          -1.844406
dtype: float64
```

[219]:
```
# List of numerical features
numerical_features = ['number_of_votes', 'production_budget', 'domestic_gross',␣
 ↪'worldwide_gross',
                      'Total_gross', 'runtime_minutes', 'average_ratings',␣
 ↪'ROI', 'Profit_Margin']

# Plot histograms for all numerical features
plt.figure(figsize=(15, 10))
for i, feature in enumerate(numerical_features, 1):
    plt.subplot(3, 3, i)  # Creating a 3x3 grid
    sns.histplot(combined[feature], bins=50, kde=True, color="blue")
    plt.title(f"Distribution of {feature}")
plt.tight_layout()
plt.show()
```



[220]:
```
combined.dropna(inplace=True)
```

7 modelling

7.1 onehot encoding

[221]:
```
from sklearn.preprocessing import OneHotEncoder
# Create a list of columns to encode
categorical_columns = ['season', 'movie_rating','Budget_Category',␣
↪'peak_season']

# Create a copy of the DataFrame with the selected columns
encoded_df = combined.copy()

# Create an instance of OneHotEncoder
# sparse=False to produce a dense array and drop='first' to drop the first␣
↪category of each variable
encoder = OneHotEncoder(sparse_output=False, drop='first')

# Iterate through each categorical column

for column in categorical_columns:
    # Fit and transform the selected column
```

```
    one_hot_encoded = encoder.fit_transform(encoded_df[[column]])

    # Create a DataFrame with one-hot encoded columns
    one_hot_df = pd.DataFrame(one_hot_encoded, columns=encoder.
 ↪get_feature_names_out([column]))

    # Concatenate the one-hot encoded DataFrame with the original DataFrame
    encoded_df = pd.concat([encoded_df, one_hot_df], axis=1)

    # Drop the original categorical column
    encoded_df = encoded_df.drop([column], axis=1)

# Display the resulting DataFrame
combined_1= encoded_df.copy()
```

[222]:
```
# For default view
pd.set_option("display.max_columns", 100)
combined_1.head()
```

[222]:
```
   runtime_minutes  average_ratings  number_of_votes  production_budget  \
0         4.521789                1         9.017847          17.622173
1         4.488636                7         3.218876          12.206078
2         4.828314                6        10.542363          17.034386
3         4.744932                7        12.525620          18.326370
4         4.744932                6        11.562829          17.147715

   domestic_gross  worldwide_gross  Total_gross   ROI  month  Profit_Margin  \
0        0.000000        11.207853    11.207853  -100      5           -100
1       13.919698        13.969087    14.637844  1038      6           1038
2       13.488157        16.046954    16.121503   -60     12            -60
3       17.880029        19.051214    19.321240   170     12            170
4       17.074287        17.944395    18.294281   215      9            215

   year  season_Spring  season_Summer  season_Winter  movie_rating_High  \
0  2013            1.0            0.0            0.0                0.0
1  2015            0.0            1.0            0.0                0.0
2  2012            0.0            0.0            1.0                0.0
3  2013            0.0            0.0            1.0                0.0
4  2014            0.0            0.0            0.0                0.0

   movie_rating_low  Budget_Category_Low  Budget_Category_Medium  \
0               1.0                  0.0                     1.0
1               0.0                  1.0                     0.0
2               0.0                  0.0                     1.0
3               0.0                  0.0                     0.0
4               0.0                  0.0                     1.0
```

```
   peak_season_Peak
0               0.0
1               1.0
2               1.0
3               1.0
4               0.0
```

7.2 Feature Selection: Identify the features that will be used for the model.

[223]:
```
# Select features and target variable
X = combined_1.drop('production_budget', axis=1)  # X is the target␣
↪variable(independent)
y = combined_1['production_budget']#dependent variable
```

7.3 splitting data

[224]:
```
# split the data into training set and testing split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
↪random_state=127)
```

7.4 Scaling the features

[225]:
```
# Initialize the scaler
scaler = MinMaxScaler()#It scales the data so that all features are in the␣
↪range between 0 and 1 (by default).

# Fit and transform the training data
X_train_scaled = scaler.fit_transform(X_train)

# Transform the testing data
X_test_scaled = scaler.transform(X_test)
```

7.5 modeling

[226]:
```
!pip install lightgbm
!pip install catboost
!pip install xgboost


#import libraries
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
from xgboost import XGBRegressor

# Define the model
```

```python
models = {
    'linear regressor':LinearRegression(),
    'LGBM Regressor': LGBMRegressor(verbose=0),
    'CatBoost Regressor': CatBoostRegressor(verbose=0),
    'XGB Regressor': XGBRegressor()
}

# Initialize a dictionary to store results
results = {
    'Model': [], 'MAE': [], 'MSE': [], 'RMSE': [], 'MAPE': [], 'R2': [],
    'Training Time (s)': [], 'Prediction Time (s)': []
}

# Create a loop to iterate over the models
for model_name, model in models.items():
    # Measure the training time
    start_time = time.time()
    model.fit(X_train_scaled, y_train)
    training_time = time.time() - start_time

    # Measure the prediction time
    start_time = time.time()
    y_pred = model.predict(X_test_scaled)
    prediction_time = time.time() - start_time

    # Evaluating the model
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100
    r2 = r2_score(y_test, y_pred)

    # Store results in a dictionary
    results['Model'].append(model_name)
    results['MAE'].append(mae)
    results['MSE'].append(mse)
    results['RMSE'].append(rmse)
    results['R2'].append(r2)
    results['MAPE'].append(mape)
    results['Training Time (s)'].append(training_time)
    results['Prediction Time (s)'].append(prediction_time)

# Create a DataFrame for results in dictionary
results_combined = pd.DataFrame(results)

# Display the results
results_combined
```

```
Requirement already satisfied: lightgbm in c:\users\admin\anaconda4\lib\site-
packages (4.5.0)
Requirement already satisfied: numpy>=1.17.0 in
c:\users\admin\anaconda4\lib\site-packages (from lightgbm) (1.26.4)
Requirement already satisfied: scipy in c:\users\admin\anaconda4\lib\site-
packages (from lightgbm) (1.13.1)
Requirement already satisfied: catboost in c:\users\admin\anaconda4\lib\site-
packages (1.2.7)
Requirement already satisfied: graphviz in c:\users\admin\anaconda4\lib\site-
packages (from catboost) (0.20.3)
Requirement already satisfied: matplotlib in c:\users\admin\anaconda4\lib\site-
packages (from catboost) (3.9.2)
Requirement already satisfied: numpy<2.0,>=1.16.0 in
c:\users\admin\anaconda4\lib\site-packages (from catboost) (1.26.4)
Requirement already satisfied: pandas>=0.24 in
c:\users\admin\anaconda4\lib\site-packages (from catboost) (2.2.3)
Requirement already satisfied: scipy in c:\users\admin\anaconda4\lib\site-
packages (from catboost) (1.13.1)
Requirement already satisfied: plotly in c:\users\admin\anaconda4\lib\site-
packages (from catboost) (5.24.1)
Requirement already satisfied: six in c:\users\admin\anaconda4\lib\site-packages
(from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\admin\anaconda4\lib\site-packages (from pandas>=0.24->catboost)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
c:\users\admin\anaconda4\lib\site-packages (from pandas>=0.24->catboost)
(2024.1)
Requirement already satisfied: tzdata>=2022.7 in
c:\users\admin\anaconda4\lib\site-packages (from pandas>=0.24->catboost)
(2023.3)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (1.2.0)
Requirement already satisfied: cycler>=0.10 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (1.4.4)
Requirement already satisfied: packaging>=20.0 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (24.1)
Requirement already satisfied: pillow>=8 in c:\users\admin\anaconda4\lib\site-
packages (from matplotlib->catboost) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\admin\anaconda4\lib\site-packages (from matplotlib->catboost) (3.1.2)
Requirement already satisfied: tenacity>=6.2.0 in
c:\users\admin\anaconda4\lib\site-packages (from plotly->catboost) (8.2.3)
Requirement already satisfied: xgboost in c:\users\admin\anaconda4\lib\site-
```

```
packages (2.1.3)
Requirement already satisfied: numpy in c:\users\admin\anaconda4\lib\site-
packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\admin\anaconda4\lib\site-
packages (from xgboost) (1.13.1)
```

[226]:

```
                Model       MAE       MSE      RMSE      MAPE        R2  \
0    linear regressor  0.629835  0.909450  0.953651  4.373720  0.733053
1      LGBM Regressor  0.239017  0.270801  0.520385  1.698241  0.920513
2  CatBoost Regressor  0.205437  0.255286  0.505258  1.475397  0.925067
3       XGB Regressor  0.217833  0.266667  0.516398  1.572617  0.921726

   Training Time (s)  Prediction Time (s)
0           0.004351             0.000634
1           0.257313             0.007991
2           6.529149             0.004013
3           0.350064             0.002992
```

The table above compares the performance of different regression models based on several evaluation metrics.

Metrics:

- **MAE (Mean Absolute Error):**
  - Represents the average absolute difference between the predicted and actual values. Lower MAE indicates better accuracy.
- **MSE (Mean Squared Error):**
  - Measures the average squared difference between the predicted and actual values. MSE gives higher weight to larger errors.
- **RMSE (Root Mean Squared Error):**
  - The square root of MSE, providing an interpretable metric in the same units as the target variable. Lower RMSE indicates better accuracy.
- **MAPE (Mean Absolute Percentage Error):**
  - Represents the average percentage difference between the predicted and actual values. Lower MAPE indicates better accuracy.
- **R2 (R-squared):**
  - Measures the proportion of variance in the target variable that is explained by the model. Higher R2 indicates a better fit.
- **Training Time (s):**
  - The time taken by the model to train on the data.
- **Prediction Time (s):**
  - The time taken by the model to make predictions on new data.

Interpretation:

- **CatBoost Regressor:**
  - Achieves the lowest MAE, MSE, RMSE, and MAPE, indicating the best overall performance in terms of accuracy. However, it has the longest training time.
- **LGBM Regressor:**

  - Performs well across all metrics, with a slightly higher MAE and RMSE compared to CatBoost. It has a faster training time than CatBoost but slower than XGBoost.
- **XGBoost Regressor:**
  - Performs similarly to LGBM Regressor, with slightly higher errors. It has the fastest training time among the three.
- **Linear Regressor:**
  - Has the highest errors across all metrics, indicating the least accurate performance. It has a relatively fast training time.

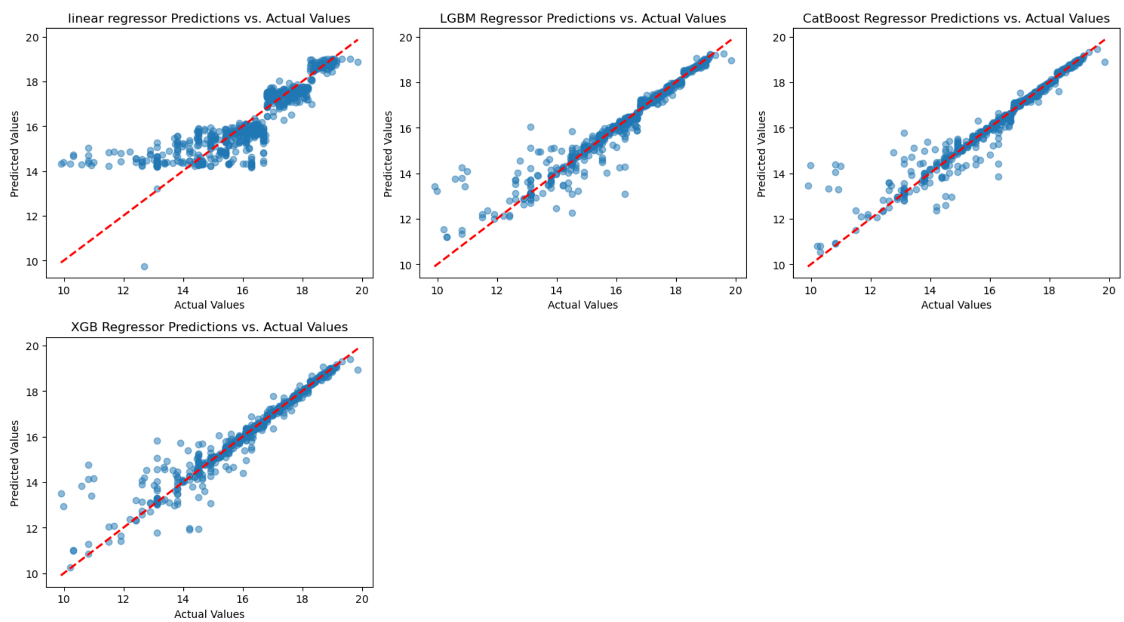
7.6 visualization of the best model

[227]:
```
import plotly.express as px

# Plotting a grouped bar graph
fig = px.bar(results_combined, x='Model',
             y=['MAE', 'MSE', 'RMSE', 'MAPE', 'R2', 'Training Time (s)',␣
 ↪'Prediction Time (s)'],
             labels={'value': 'Metric Value'},
             title='Best Model',
             barmode = 'group')

# Update layout to vary length and width
fig.update_layout(
    width=1000,  # Set the width of the entire plot
    height=700,  # Set the height of the entire plot
    bargap=0.2,  # Set the gap between bars
)

fig.show()
```

7.7 prediction vs actual for all the models

[228]:
```
# Define the grid layout
rows, cols = 3, 3

# Specify the figure size for the entire grid
plt.figure(figsize=(15, 12))

# Loop over models
for idx, (model_name, model) in enumerate(models.items(), 1):
    # Fit the model to training data
    model.fit(X_train_scaled, y_train)

    # Make predictions on the testing data
    y_pred = model.predict(X_test_scaled)

    # Scatter plot of Predictions vs. Actual Values for each model
```

```python
    plt.subplot(rows, cols, idx)
    plt.scatter(y_test, y_pred, alpha=0.5)
    plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color='red', linewidth=2)  # Diagonal line for perfect predictions
    plt.title(f'{model_name} Predictions vs. Actual Values')
    plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')

# Adjust layout
plt.tight_layout()
plt.show()
```



The graph showcases the performance of four different regression models by comparing their predicted values to the actual values.

Interpretation:

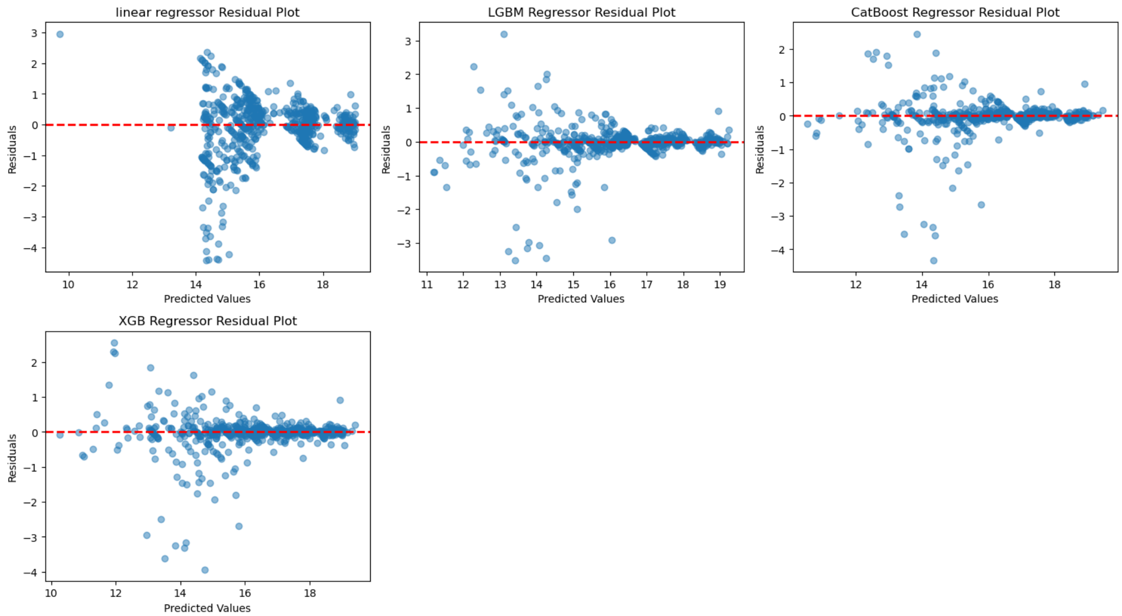
- **Ideal Scenario:**
  - The red dashed line represents the perfect prediction where predicted values equal actual values. The closer the data points are to this line, the better the model's performance.
- **Model Performance:**
  - All four models demonstrate good performance, with the data points closely aligned with the diagonal line. This suggests that the models are accurately predicting the target variable.
- **Comparison:**
  - Among the four, the XGB Regressor seems to have the tightest clustering of points around the diagonal line, indicating it might be the most accurate model in this com-

parison.

Overall, the graph illustrates the accuracy of the regression models in predicting the target variable.

7.8 Residuals

[229]:
```
# Define the grid layout
rows, cols = 3, 3
plt.figure(figsize=(15, 12))

# Loop over models
for idx, (model_name, model) in enumerate(models.items(), 1):
    # Fit the model to training data
    model.fit(X_train_scaled, y_train)

    # Make predictions on the testing data
    y_pred = model.predict(X_test_scaled)

    # Calculate residuals
    residuals = y_test - y_pred

    # Residual plot for each model
    plt.subplot(rows, cols, idx)
    plt.scatter(y_pred, residuals, alpha=0.5)
    plt.axhline(y=0, color='red', linestyle='--', linewidth=2)
    plt.title(f'{model_name} Residual Plot')
    plt.xlabel('Predicted Values')
    plt.ylabel('Residuals')

# Adjust layout
plt.tight_layout()
plt.show()
```



Understanding Residual Plots * A residual plot is a diagnostic tool used in regression analysis to assess the quality of the model fit. * It plots the residuals (the difference between the observed values and the predicted values) on the vertical axis against the predicted values on the horizontal axis.

Ideal Residual Plot * In an ideal scenario, the points in a residual plot should be randomly scattered around the horizontal line at zero, indicating that the model's errors are random and have a mean of zero. * This suggests that the model is capturing the underlying pattern in the data well.

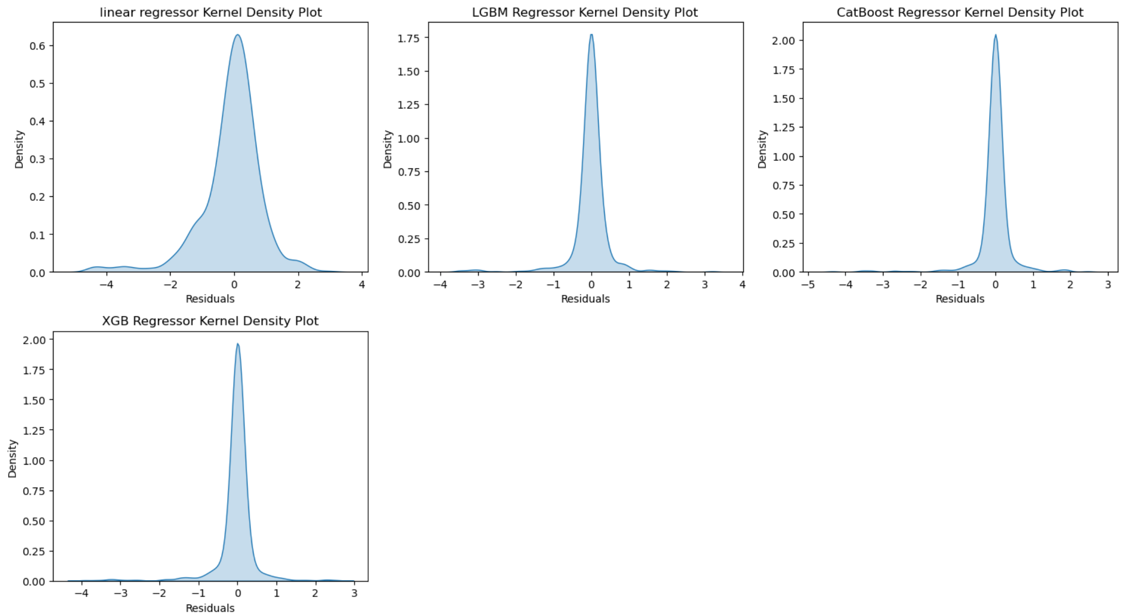
Interpreting the Plots

- **Linear Regressor:**
  - The plot shows a slight funnel shape, indicating that the model's errors are not constant across the range of predicted values. There might be some non-linearity in the data that the linear model is not capturing.
- **LGBM Regressor:**
  - This plot shows a relatively random pattern, indicating a good fit for the model. However, there are a few outliers, which are points that are far away from the zero line. These outliers might be due to unusual data points or errors in the data.
- **CatBoost Regressor:**
  - This plot is similar to the LGBM Regressor, indicating a good fit with a few outliers.
- **XGB Regressor:**
  - The plot shows a similar pattern to the LGBM and CatBoost Regressors, indicating a good fit with a few outliers.

Overall Interpretation * Based on the residual plots, all four models seem to provide a reasonable fit to the data. * However, the non-linear pattern observed in the Linear Regressor plot suggests that a more complex model might be able to capture the data better. * The LGBM, CatBoost, and XGB Regressors all show a random pattern, indicating that they are capturing the underlying patterns in the data well. * However, the presence of outliers suggests that further investigation of these data points might be necessary.

7.9 Kernel density

[230]:
```
# Kernel Density Plot
# Define the grid layout
rows, cols = 3, 3
plt.figure(figsize=(15, 12))

# Loop over models
for idx, (model_name, model) in enumerate(models.items(), 1):
    # Fit the model to training data
    model.fit(X_train_scaled, y_train)

    # Make predictions on the testing data
    y_pred = model.predict(X_test_scaled)

    # Calculate residuals
    residuals = y_test - y_pred

    # Kernel density plot for residuals of each model
    plt.subplot(rows, cols, idx)
    sns.kdeplot(residuals, fill=True)
    plt.title(f'{model_name} Kernel Density Plot')
    plt.xlabel('Residuals')
    plt.ylabel('Density')

# Adjust layout
plt.tight_layout()
plt.show()
```



Here's an explanation and interpretation:

What is a kernel density plot? * A kernel density plot is a way to visualize the probability density function of a continuous variable. * It's a smoothed version of a histogram, providing a clearer picture of the underlying distribution.

What are residuals? * Residuals are the differences between the actual observed values and the values predicted by a regression model. * Ideally, the residuals should be normally distributed with a mean of zero, indicating that the model is capturing the underlying patterns well.

Interpretation of the plots: * **All four plots:** * They all exhibit a roughly bell-shaped curve, suggesting that the residuals are approximately normally distributed, which is a good sign for the models' performance. * The peaks of the curves are centered around zero, further supporting the assumption that the models are unbiased.

Comparing the plots: * The XGB Regressor appears to have the narrowest and tallest peak, indicating that its residuals are more tightly clustered around zero. This suggests that the XGB Regressor is potentially the most accurate of the four models. * The Linear Regressor and LGBM Regressor have slightly wider distributions, indicating a bit more variability in their predictions. * The CatBoost Regressor has a slightly wider distribution than the XGB Regressor, but still narrower than the Linear and LGBM Regressors. Overall, the plots suggest that all four regression models are performing reasonably well, with the XGB Regressor potentially having the best performance.

our best model so far is XGB regressor so we'd look at it n evaluate it individually

8 xgboost Model

[231]:
```
# Initialize the XGB Regressor
XGB_model = XGBRegressor()

# Initialize a dictionary to store results
results = {
    'Model': [], 'MAE': [], 'MSE': [], 'RMSE': [], 'MAPE': [], 'R2': [],
    'Adjusted R2': []
}

# Fit the model
XGB_model.fit(X_train_scaled, y_train)

# Make prediction
y_pred = XGB_model.predict(X_test_scaled)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100
r2 = r2_score(y_test, y_pred)

# Calculate Adjusted R2
n = X_test_scaled.shape[0]  # Number of samples
p = X_test_scaled.shape[1]  # Number of features
adjusted_r2 = 1 - ((1 - r2) * (n - 1) / (n - p - 1))

# Display the metrics
print("Model Evaluation Metrics:")
print(f"MAE: {mae:.2f}")
print(f"MSE: {mse:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"MAPE: {mape:.2f}")
print(f"R²: {r2:.2f}")
print(f"Adjusted R²: {adjusted_r2:.2f}")
```

```
Model Evaluation Metrics:
MAE: 0.22
MSE: 0.27
RMSE: 0.52
MAPE: 1.57
R²: 0.92
Adjusted R²: 0.92
```

Model Evaluation Metrics

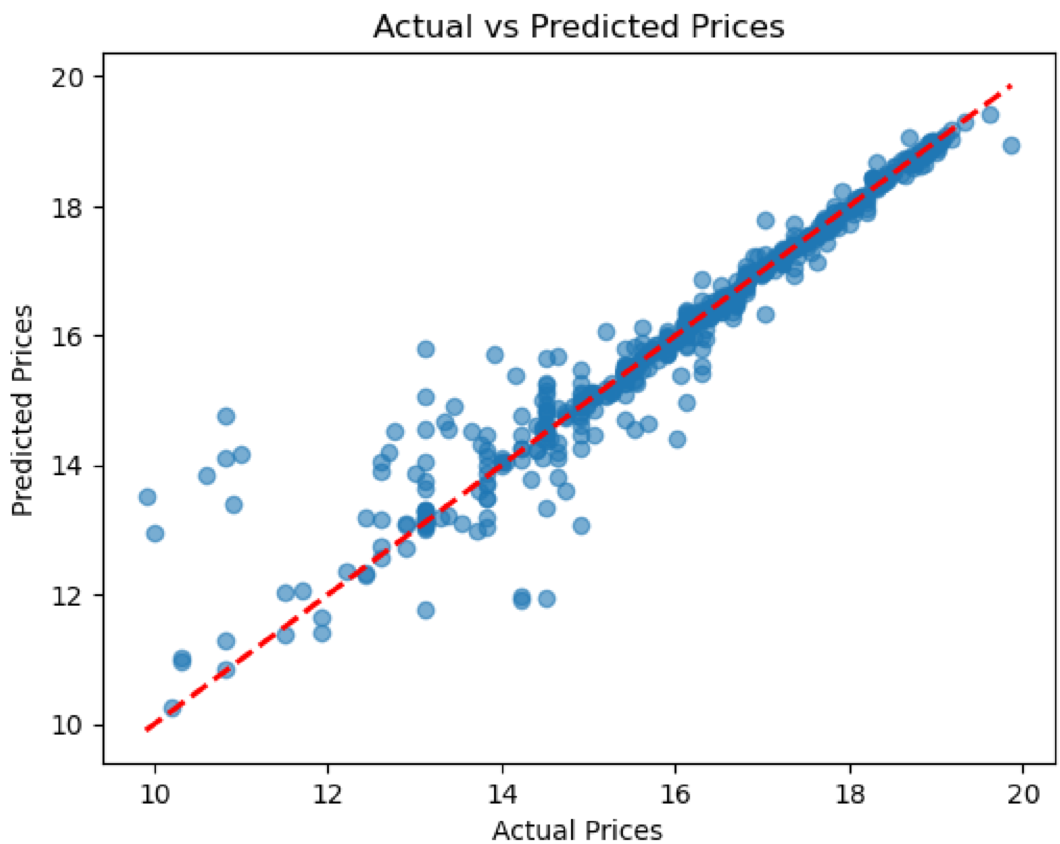
Metric	Value	Interpretation
MAE	0.22	On average, predictions are **0.22 units** away from actual values. Good result!
MSE	0.27	Low MSE indicates small squared errors, meaning the model makes few large mistakes.
RMSE	0.52	Predictions deviate **by about 0.52 units** from actual values on average. A lower RMSE is ideal.
MAPE	1.57%	Model's average percentage error is **1.57%**, meaning it's **highly accurate**.
R^2	0.92	The model explains **92% of the variance** in the target variable, indicating a **strong fit**.
Adjusted R^2	0.92	High value confirms the model is effective **even after adjusting for multiple predictors**.

Overall Evaluation: - **The model is performing very well** with an **R^2 of 0.92**, meaning it explains **92% of the variation** in the target variable. - **Low error values (MAE = 0.22, RMSE = 0.52, MAPE = 1.57%)** indicate high accuracy. - **Adjusted R^2 = 0.92** suggests that adding more features didn't significantly degrade performance.

8.1 Model Evaluation

8.2 Predicted vs Actual

[232]:
```
#plot
plt.scatter(y_test, y_pred, alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
 ↪lw=2)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
plt.show()
```



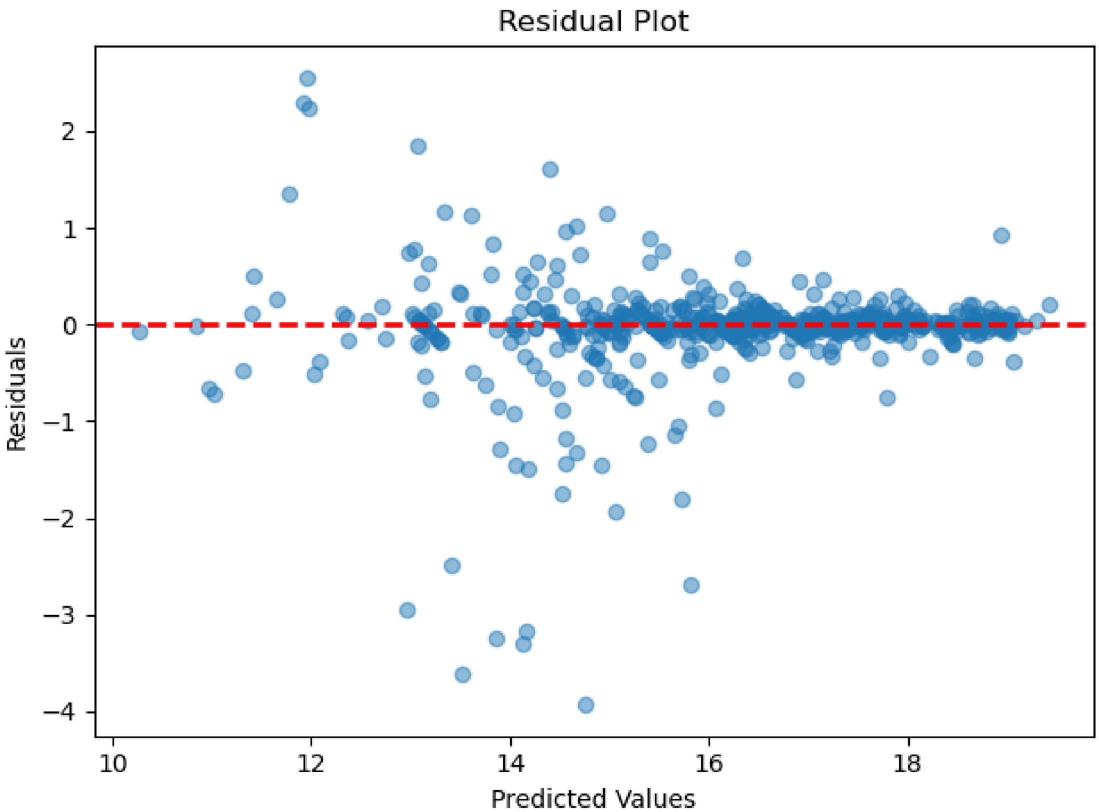
This scatter plot compares actual prices to predicted prices, likely from a predictive model.

Interpretation: * The red dashed line represents the ideal scenario: where the predicted price perfectly matches the actual price. * The blue dots represent individual data points, showing the actual price on the x-axis and the corresponding predicted price on the y-axis. * The closer the blue dots are to the red line, the more accurate the predictions are. * In this case, the dots are clustered closely around the red line, indicating a strong correlation between predicted and actual prices. This suggests the model is performing well in predicting prices.

8.3 Residuals

[233]:
```
# Calculate residuals
residuals = y_test - y_pred

# Residual plot for each model
plt.scatter(y_pred, residuals, alpha=0.5)
plt.axhline(y=0, color='red', linestyle='--', linewidth=2)
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
```

```
# Adjust layout
plt.tight_layout()
plt.show()
```



This is a residual plot, a crucial diagnostic tool used in regression analysis to assess the quality of a model's fit.

Explanation: * The x-axis represents the predicted values from the regression model. * The y-axis represents the residuals, which are the differences between the actual observed values and the predicted values. * The red line represents the zero line, indicating where residuals would be if the model perfectly predicted all data points.

Interpretation: * **Randomness:** * Ideally, the points in a residual plot should be randomly scattered around the zero line without any discernible pattern. This indicates that the model's errors are random, which is a key assumption in regression analysis.

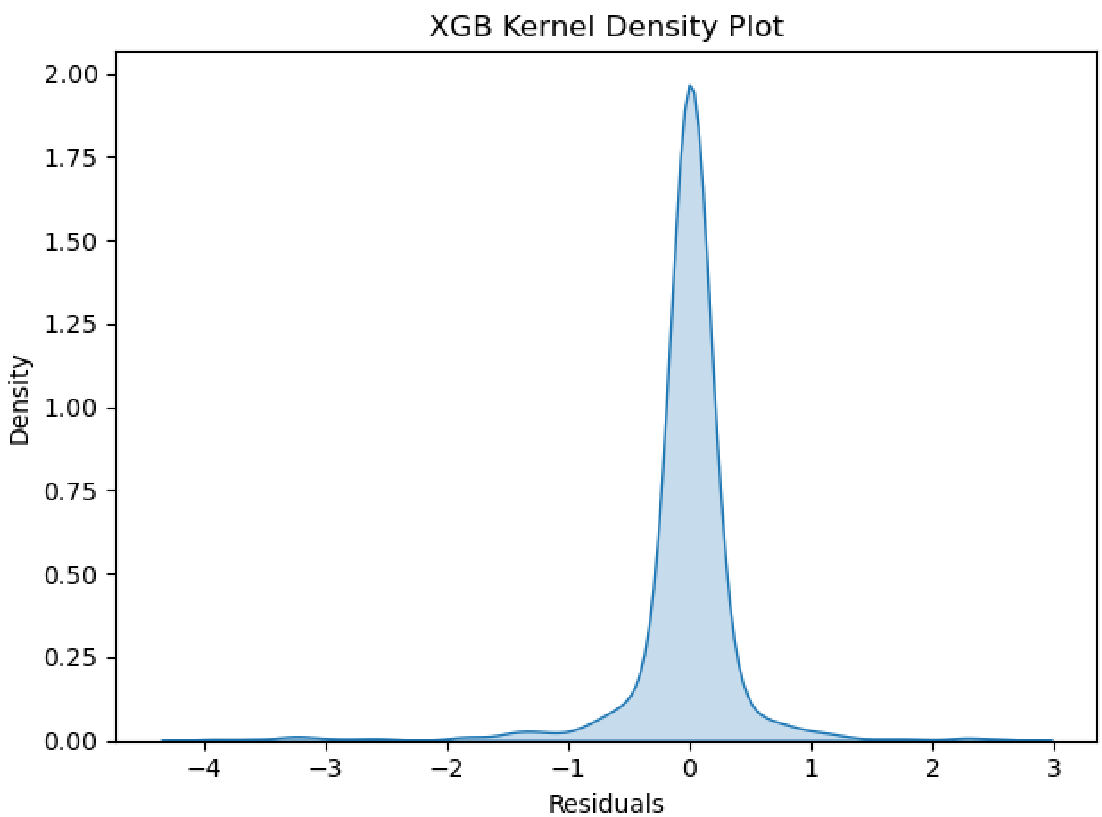
- **Homoscedasticity:**
  - The spread of the residuals should be relatively constant across the entire range of predicted values. This means the model's accuracy is consistent across different levels of the predictor variables.
- **No Outliers:**
  - Extreme outliers can significantly affect the regression model's fit.

In this particular graph: * The residuals appear to be randomly scattered around the zero line with no obvious patterns, suggesting the model is a good fit. * The spread of the residuals appears to be fairly constant, indicating homoscedasticity. * There might be a few potential outliers, but overall, the plot suggests the regression model is a good fit for the data.

8.4 Normality Assumption

[234]:

```
# KDE plot
# Kernel density plot for residuals of each model
sns.kdeplot(residuals, fill=True)
plt.title('XGB Kernel Density Plot')
plt.xlabel('Residuals')
plt.ylabel('Density')

# Adjust layout
plt.tight_layout()
plt.show()
```



This is a kernel density plot of residuals from an XGBoost model.

Explanation: * **Kernel density estimation (KDE):** * This is a method to visualize the distribution of a dataset by smoothing out individual data points into a continuous curve.

- **Residuals:**
  - These are the differences between the actual values and the values predicted by the model.
- **XGBoost:**
  - This is a powerful machine learning algorithm known for its accuracy and speed.

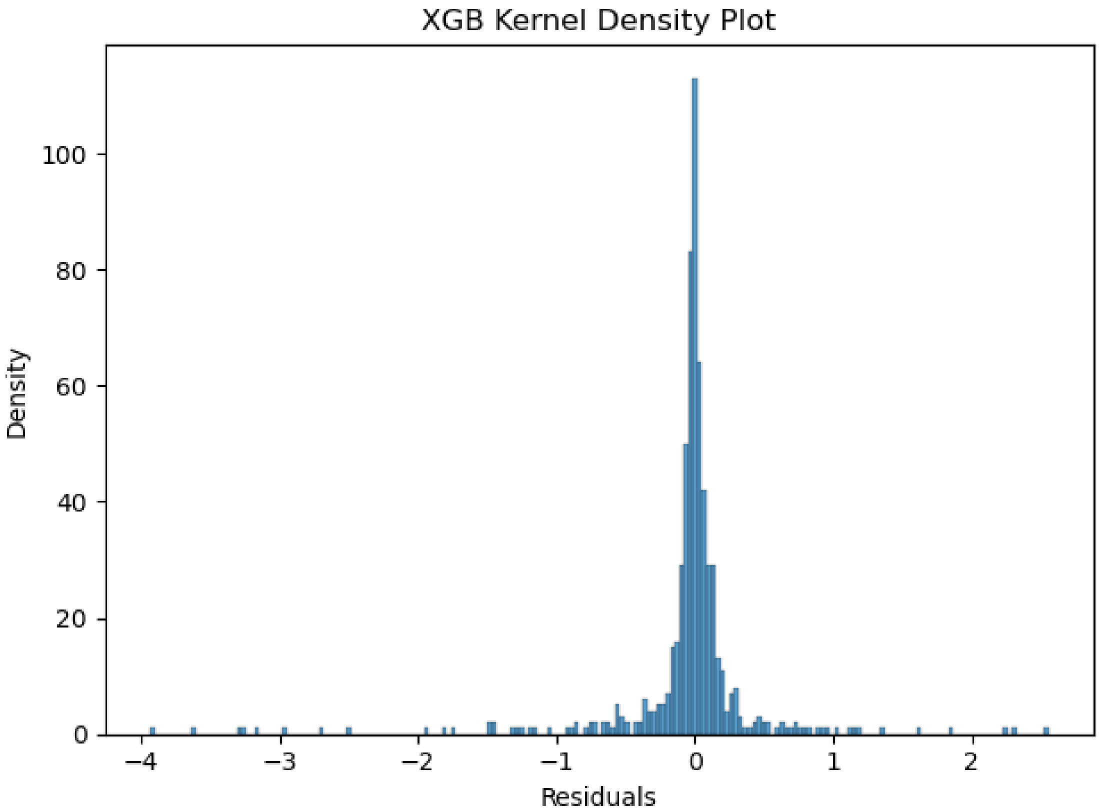
Interpretation: * **Shape:** * The plot shows a sharp peak around zero, indicating that most predictions are close to the actual values. This is desirable, as it suggests the model is making accurate predictions.

- **Tails:**
  - The tails of the distribution are relatively thin, meaning there are few extreme residuals (large prediction errors). This is also a good sign, as it indicates that the model is performing well even on data points that are different from the ones it was trained on.

Symmetry: The distribution is nearly symmetrical, which indicates that the model is not biased towards over-predicting or under-predicting.

8.5 Histogram plot for Normality

[235]:
```
#plot
sns.histplot(residuals, fill=True)
plt.title('XGB Kernel Density Plot')
plt.xlabel('Residuals')
plt.ylabel('Density')

# Adjust layout
plt.tight_layout()
plt.show()
```



This is a kernel density plot of residuals from a XGB model.

Explanation:

- **Residuals:**
  - The difference between the actual observed values and the values predicted by the model.
- **Kernel Density Plot:**
  - A smoothed histogram that visualizes the distribution of a dataset.
- **Random Forest:**
  - An ensemble machine learning method that builds multiple decision trees and combines their predictions.

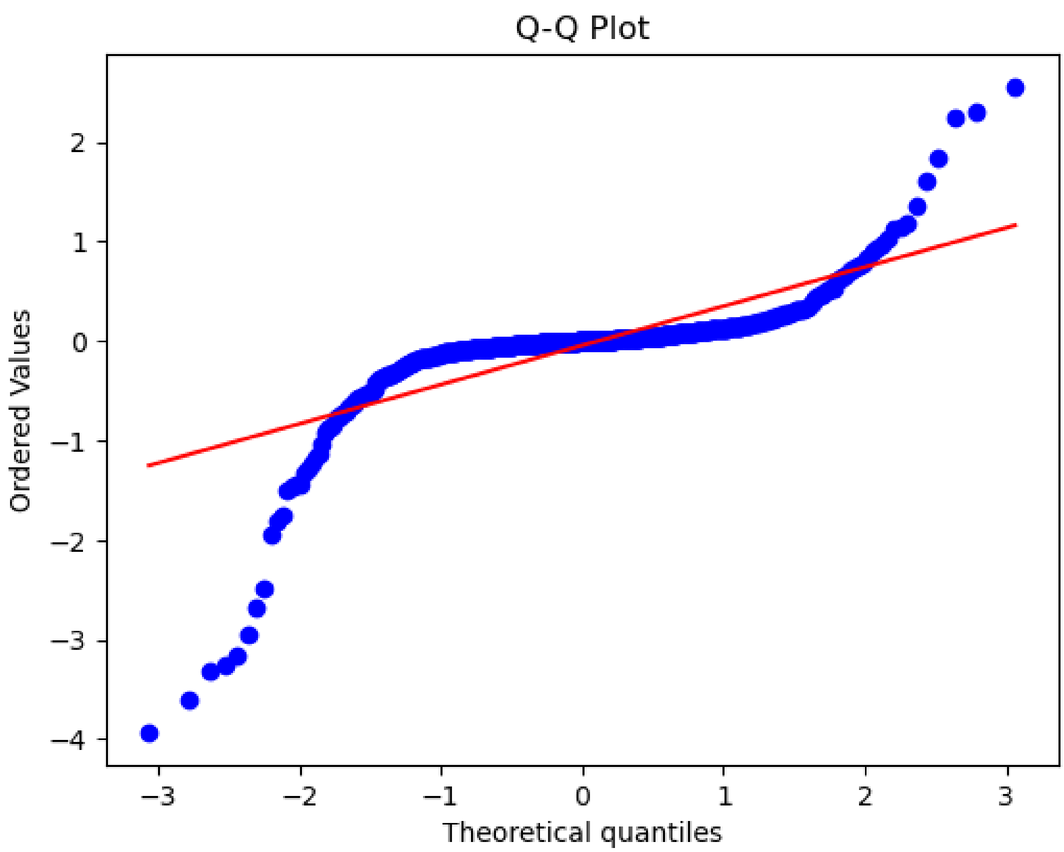
Interpretation:

- **Shape:**
  - The distribution is roughly centered around zero, which is ideal for a well-performing model. The high peak indicates that most of the residuals are close to zero, suggesting that the model is making accurate predictions for most data points.
- **Spread:**
  - The spread of the distribution provides insight into the model's accuracy. A narrow distribution implies that the model's predictions are consistently close to the actual values, while a wide distribution suggests greater variability in the model's performance.
- **Outliers:**

  - The presence of any long tails or points far from zero indicates outliers, where the model's predictions were significantly off. These outliers could be due to noisy data, unusual patterns in the data, or limitations of the model itself.

8.6 Q-Q Plot

[236]:
```
import scipy.stats as stats
stats.probplot(residuals, dist="norm", plot=plt)
plt.title("Q-Q Plot")
plt.show()
```



This is a Q-Q plot (Quantile-Quantile plot), a graphical tool used to assess whether a dataset follows a particular theoretical distribution, like the normal distribution.

How to interpret it: * **The x-axis:** * Represents the theoretical quantiles of the distribution you're comparing against (often the standard normal distribution).

- **The y-axis:**
  - Represents the ordered values (quantiles) of your observed data.
- **The red line:**
  - Represents the line of perfect fit. If the points fall exactly on this line, it indicates that

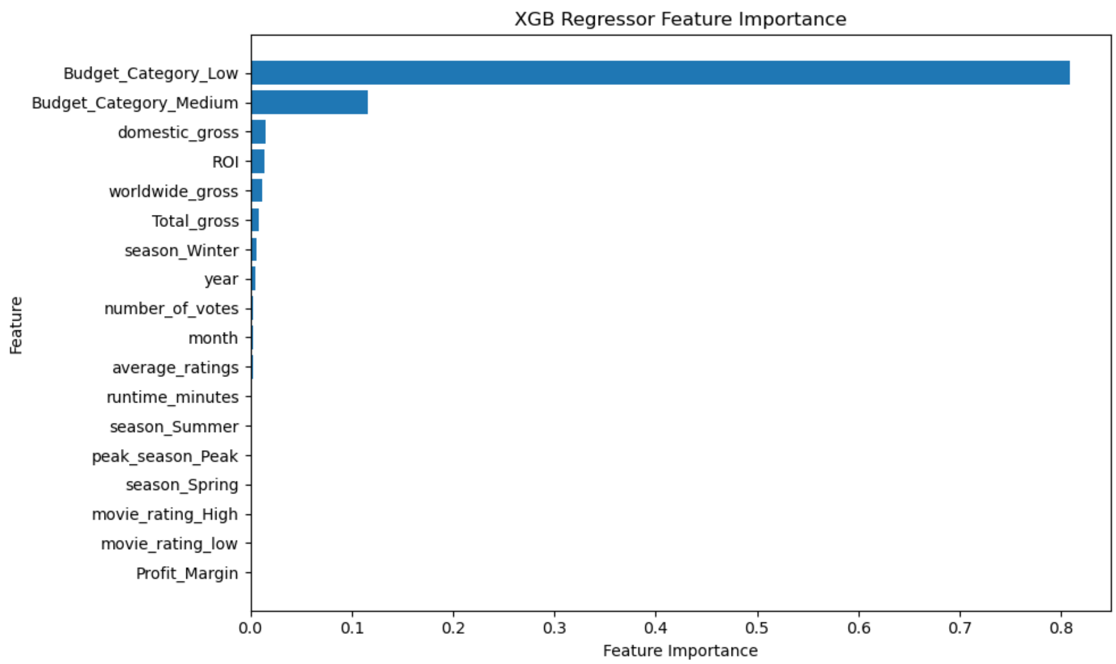
your data perfectly matches the theoretical distribution.

Interpreting this specific Q-Q plot: * **The points deviate from the line at both tails:** * This indicates that the data has heavier tails than the normal distribution. In other words, there are more extreme values (both high and low) in the data than would be expected in a normal distribution.

- **The points generally follow the line in the middle:**
  - This suggests that the data is reasonably close to normal in the central region.

8.7 Feature importance

[237]:
```
# Get Feature Importance
feature_importance = XGB_model.feature_importances_

# Create a DataFrame to view feature importance
feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance':␣
↪feature_importance})

# Sort by Importance (descending order) and limit to the top 20 most important␣
↪features
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
↪ascending=False).head(20)

# Plot Horizontal Bar Graph
plt.figure(figsize=(10, 6))  # Adjust figure size as needed
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('XGB Regressor Feature Importance')
plt.gca().invert_yaxis()  # Invert the y-axis to have most important at the top
plt.tight_layout()  # Adjust layout for better visualization
plt.show()
```



This feature importance graph shows the relative importance of different features in a machine learning model.

The features are listed on the y-axis, and their importance is indicated by the length of the bars on the x-axis.

Interpretation:

- **Top Features:**
  - The most important feature in this model is "Budget_Category_Low," followed closely by "Budget_Category_Medium."
  - This suggests that the budget category of a movie plays a significant role in predicting the target variable (which is not specified in the graph).
- **Other Important Features:**
  - Features like "domestic_gross," "ROI," and "worldwide_gross" also have a notable impact on the model's predictions.
- **Least Important Features:**
  - Features at the bottom of the graph, such as "movie_rating_low" and "Profit_Margin," have minimal influence on the model's predictions.

Uses of this Graph:

- **Feature Selection:**
  - This graph can help you select the most relevant features for your model. You might choose to keep only the top few features, or experiment with different combinations to find the optimal set.
- **Model Understanding:**
  - By examining the feature importance, you can gain insights into how the model makes

    predictions and which factors are most influential.
- **Communication:**
  - This graph can be used to communicate the model's behavior to stakeholders, helping them understand which features are driving the predictions.

Recomendations * drop the features with least importance and redo the model for better results

```
[ ]:
```