Exploratory Data Analysis for Microsoft's New Movie Studio

Overview

In this project, we will perform exploratory data analysis (EDA) to generate insights for Microsoft, helping them decide what type of films to create for their new movie studio. We will use various datasets related to movies, analyze trends, and provide actionable recommendations based on our findings.

Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio but lack knowledge about creating movies. Our task is to explore what types of films are currently doing the best at the box office and translate those findings into actionable insights for Microsoft's new movie studio.

Objectives

The objectives of this project are to:

1. Compare budget to profitability.
2. Identify the top-performing genres.
3. Assess profitability by genre.

Loading Data

In [ ]:
```
import pandas as pd
import numpy as np
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import ScalarFormatter
```

In [ ]:
```
bom_movie_gross = pd.read_csv('data/bom.movie_gross.csv')
rt_movie_info = pd.read_csv('data/rt.movie_info.tsv', sep='\t')
rt_reviews = pd.read_csv('data/rt.reviews.tsv', sep='\t', encoding='ISO-8859-1')
tmdb_movies = pd.read_csv('data/tmdb.movies.csv')
tn_movie_budgets = pd.read_csv('data/tn.movie_budgets.csv')

conn = sqlite3.connect('data/im.db')
imdb_movie_basics = pd.read_sql_query("SELECT * FROM movie_basics", conn)
imdb_movie_ratings = pd.read_sql_query("SELECT * FROM movie_ratings", conn)
```

Displaying the first few rows of each dataframe.

In [ ]:
```
print("Movie Gross Data:")
print(bom_movie_gross.head())
```

```
print("------------------------------------------------------------")

print("Movie Info Data:")
print(rt_movie_info.head())
print("------------------------------------------------------------")

print("Reviews Data:")
print(rt_reviews.head())
print("------------------------------------------------------------")

print("TMDB Movies Data:")
print(tmdb_movies.head())
print("------------------------------------------------------------")

print("Movie Budgets Data:")
print(tn_movie_budgets.head())
print("------------------------------------------------------------")

print("Movie Basics Data:")
print(imdb_movie_basics.head())
print("------------------------------------------------------------")

print("Movie Ratings Data:")
print(imdb_movie_ratings.head())
```

```
Movie Gross Data:
                                       title studio  domestic_gross  \
0                                Toy Story 3     BV     415000000.0
1                  Alice in Wonderland (2010)     BV     334200000.0
2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0
3                                  Inception     WB     292600000.0
4                       Shrek Forever After   P/DW     238700000.0

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
------------------------------------------------------------
Movie Info Data:
   id                                           synopsis rating  \
0   1  This gritty, fast-paced, and innovative police...      R
1   3  New York City, not-too-distant-future: Eric Pa...      R
2   5  Illeana Douglas delivers a superb performance ...      R
3   6  Michael Douglas runs afoul of a treacherous su...      R
4   7                                                NaN     NR

                              genre          director  \
0  Action and Adventure|Classics|Drama  William Friedkin
1    Drama|Science Fiction and Fantasy  David Cronenberg
2    Drama|Musical and Performing Arts    Allison Anders
3          Drama|Mystery and Suspense    Barry Levinson
4                      Drama|Romance    Rodney Bennett

                         writer  theater_date      dvd_date currency  \
0                  Ernest Tidyman   Oct 9, 1971  Sep 25, 2001      NaN
1     David Cronenberg|Don DeLillo  Aug 17, 2012   Jan 1, 2013        $
2                  Allison Anders  Sep 13, 1996  Apr 18, 2000      NaN
3  Paul Attanasio|Michael Crichton   Dec 9, 1994  Aug 27, 1997      NaN
4                    Giles Cooper           NaN           NaN      NaN

  box_office      runtime             studio
```

```
0        NaN  104 minutes                NaN
1    600,000  108 minutes  Entertainment One
2        NaN  116 minutes                NaN
3        NaN  128 minutes                NaN
4        NaN  200 minutes                NaN
------------------------------------------------------------
Reviews Data:
   id                                             review rating   fresh  \
0   3  A distinctly gallows take on contemporary fina...    3/5   fresh
1   3  It's an allegory in search of a meaning that n...    NaN  rotten
2   3  ... life lived in a bubble in financial dealin...    NaN   fresh
3   3  Continuing along a line introduced in last yea...    NaN   fresh
4   3             ... a perverse twist on neorealism...     NaN   fresh

           critic  top_critic         publisher               date
0      PJ Nabarro           0   Patrick Nabarro  November 10, 2018
1  Annalee Newitz           0           io9.com       May 23, 2018
2    Sean Axmaker           0  Stream on Demand    January 4, 2018
3   Daniel Kasman           0              MUBI  November 16, 2017
4             NaN           0      Cinema Scope   October 12, 2017
------------------------------------------------------------
TMDB Movies Data:
   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
------------------------------------------------------------
Movie Budgets Data:
   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
------------------------------------------------------------
Movie Basics Data:
    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
------------------------------------------------------------
Movie Ratings Data:
     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
```

Upon initial examination of the dataframes, the following datasets were selected as they contain the necessary information to meet the project objectives:

- bom_movie_gross
- tn_movie_budgets
- imdb_movie_basics
- imdb_movie_ratings

Inspecting the selected datasets

1. bom_movie_gross

In [ ]:
```
#Examining the total number of rows, columns, non-null values and datatypes in the data
bom_movie_gross.info()
```

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

In [ ]:
```
# Checking for null values
bom_movie_gross.isna().sum()
```

Out[ ]:
```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

In [ ]:
```
#checking for duplicetes
bom_movie_gross.duplicated().sum()
```

Out[ ]:
```
0
```

2. tn_movie_budgets

In [ ]:
```
#Examining the total number of rows, columns, non-null values and datatypes in the data
tn_movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

In [ ]:
```
# Checking for null values
tn_movie_budgets.isna().sum()
```

Out[ ]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [ ]:
```
#checking for duplicetes
tn_movie_budgets.duplicated().sum()
```

Out[ ]:
```
0
```

3. imdb_movie_basics

In [ ]:
```
#Examining the total number of rows, columns, non-null values and datatypes in the data
imdb_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
```

In [ ]:
```
# Checking for null values
imdb_movie_basics.isna().sum()
```

Out[ ]:
```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [ ]:
```
#checking for duplicetes
imdb_movie_basics.duplicated().sum()
```

Out[ ]:
```
0
```

4. imdb_movie_ratings

In [ ]:
```
#Examining the total number of rows, columns, non-null values and datatypes in the data
imdb_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
```

In [ ]:
```
# Checking for null values
imdb_movie_ratings.isna().sum()
```

Out[ ]:
```
movie_id         0
averagerating    0
numvotes         0
dtype: int64
```

In [ ]:
```
#checking for duplicetes
imdb_movie_ratings.duplicated().sum()
```

Out[ ]:
```
0
```

Upon inspecting the datasets, the bom_movie_gross dataframe was dropped since its data is available in other datasets. Additionally, the foreign_gross column had 1,350 missing values out of a total of 3,387 rows.

Data Cleaning

Missing Values

imdb_movie_basics

In [ ]:
```
#checking the percentages of the missing data
missing_data = imdb_movie_basics.isnull().sum()

missing_percentage = (missing_data / len(imdb_movie_basics)) * 100


missing_data_df = pd.DataFrame({
    'Missing Values': missing_data,
    'Percentage': missing_percentage
}).sort_values(by='Percentage', ascending=False)


print(missing_data_df)
```

```
                 Missing Values  Percentage
runtime_minutes           31739   21.717621
genres                     5408    3.700460
original_title               21    0.014369
movie_id                      0    0.000000
primary_title                 0    0.000000
start_year                    0    0.000000
```

There are 21 missing values in the original_title column, 31,739 missing values in the runtime_minutes column, and 5,408 missing values in the genres column. These were dropped due to their relatively small number compared to the entire dataset.

In [ ]:
```
imdb_movie_basics.dropna(inplace=True)
```

In [ ]:
```
imdb_movie_basics.isna().sum()
```

Out[ ]:
```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

In [ ]:
```
#merging the imdb dataframes
imdb_merged = pd.merge(imdb_movie_basics, imdb_movie_ratings, how='inner', on='movie_id

#checking the fisrt five rows of the merged dataframe
imdb_merged.head()
```

Out[ ]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	avera
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	
3	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	
4	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	

In [ ]:
```
#checking the shape of the merged object
imdb_merged.shape
```

Out[ ]:
```
(65720, 8)
```

After cleaning the data, the remaining dataframes containing the cleaned data are:

- tn_movie_budgets
- imdb_merged

Creating New Variables for Analysis

Analyzing revenue

In [ ]:
```
#converting production_budget, domestic_gross, and worldwide_gross columns in tn_movie_
tn_movie_budgets['production_budget'] = tn_movie_budgets['production_budget'].replace('
tn_movie_budgets['domestic_gross'] = tn_movie_budgets['domestic_gross'].replace('[\$,]'
tn_movie_budgets['worldwide_gross'] = tn_movie_budgets['worldwide_gross'].replace('[\$,

#calculating profit
tn_movie_budgets['domestic_profit'] = tn_movie_budgets['domestic_gross'] - tn_movie_bud
tn_movie_budgets['worldwide_profit'] = tn_movie_budgets['worldwide_gross'] - tn_movie_b

#calcultaing return on investment
tn_movie_budgets['domestic_roi'] = (tn_movie_budgets['domestic_profit'] / tn_movie_budg
tn_movie_budgets['worldwide_roi'] = (tn_movie_budgets['worldwide_profit'] / tn_movie_bu

#Extracting year from release date
tn_movie_budgets['release_year'] = pd.to_datetime(tn_movie_budgets['release_date']).dt.

tn_movie_budgets.head()
```

Out[ ]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	domestic_profit	wo
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	335507625	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	-169536125	
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-307237650	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	128405868	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	303181382	

Seperating Genres

In [ ]:
```
#using one-hot encoding to seperate the genres

genres = imdb_merged['genres'].str.get_dummies(sep=',')
imdb_merged = pd.concat([imdb_merged, genres], axis=1)
```

In [ ]:
```
imdb_merged.head()
```

Out[ ]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	avera
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	
3	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	
4	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	

5 rows × 34 columns

In [ ]:
```
#merging the tn_movie_budgets and the imdb_merged dataframe

tn_movie_budgets = tn_movie_budgets.rename(columns={'movie': 'primary_title'})
combined_data = pd.merge(tn_movie_budgets, imdb_merged, on='primary_title', how='inner'
```

In [ ]:
```
combined_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2752 entries, 0 to 2751
Data columns (total 44 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 2752 non-null   int64  
 1   release_date       2752 non-null   object 
 2   primary_title      2752 non-null   object 
 3   production_budget  2752 non-null   int64  
 4   domestic_gross     2752 non-null   int64  
 5   worldwide_gross    2752 non-null   int64  
 6   domestic_profit    2752 non-null   int64  
 7   worldwide_profit   2752 non-null   int64  
 8   domestic_roi       2752 non-null   float64
 9   worldwide_roi      2752 non-null   float64
 10  release_year       2752 non-null   int64  
 11  movie_id           2752 non-null   object 
 12  original_title     2752 non-null   object 
 13  start_year         2752 non-null   int64  
 14  runtime_minutes    2752 non-null   float64
 15  genres             2752 non-null   object 
 16  averagerating      2752 non-null   float64
 17  numvotes           2752 non-null   int64  
 18  Action             2752 non-null   int64  
 19  Adult              2752 non-null   int64  
 20  Adventure          2752 non-null   int64  
 21  Animation          2752 non-null   int64  
 22  Biography          2752 non-null   int64  
 23  Comedy             2752 non-null   int64  
 24  Crime              2752 non-null   int64  
 25  Documentary        2752 non-null   int64  
```

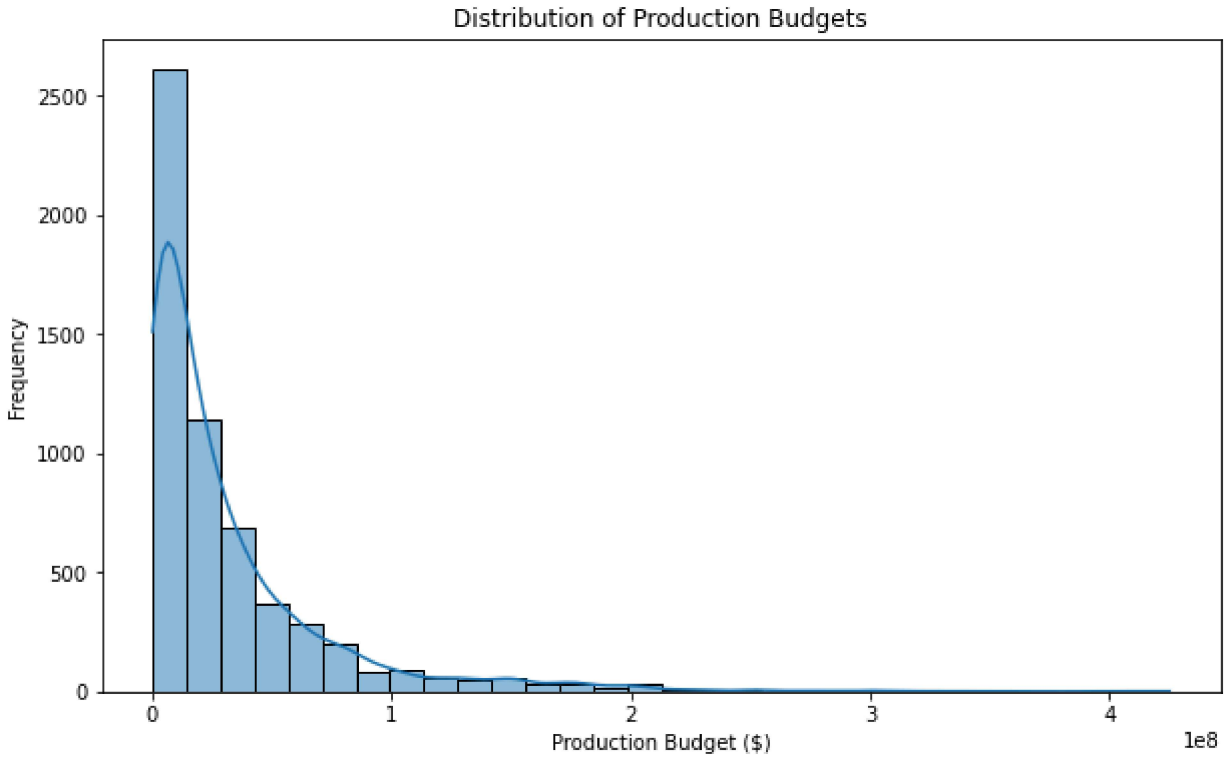
```
 26  Drama              2752 non-null   int64
 27  Family             2752 non-null   int64
 28  Fantasy            2752 non-null   int64
 29  Game-Show          2752 non-null   int64
 30  History            2752 non-null   int64
 31  Horror             2752 non-null   int64
 32  Music              2752 non-null   int64
 33  Musical            2752 non-null   int64
 34  Mystery            2752 non-null   int64
 35  News               2752 non-null   int64
 36  Reality-TV         2752 non-null   int64
 37  Romance            2752 non-null   int64
 38  Sci-Fi             2752 non-null   int64
 39  Short              2752 non-null   int64
 40  Sport              2752 non-null   int64
 41  Thriller           2752 non-null   int64
 42  War                2752 non-null   int64
 43  Western            2752 non-null   int64
dtypes: float64(4), int64(35), object(5)
memory usage: 967.5+ KB
```

Exploratory Data Analysis (EDA)

Examining the distribution of the variables

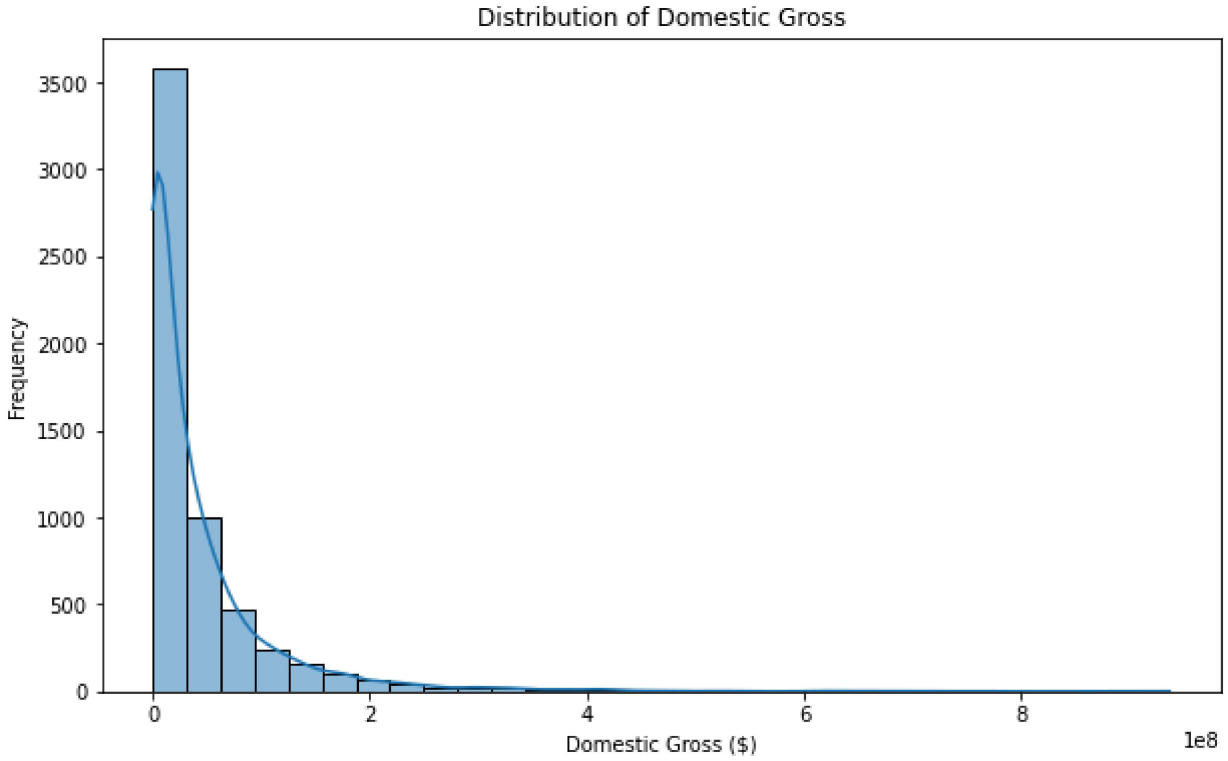
Distribution of Production Budgets

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(tn_movie_budgets['production_budget'], bins=30, kde=True)
plt.title('Distribution of Production Budgets')
plt.xlabel('Production Budget ($)')
plt.ylabel('Frequency')
plt.show()
```



Distribution of Domestic Gross

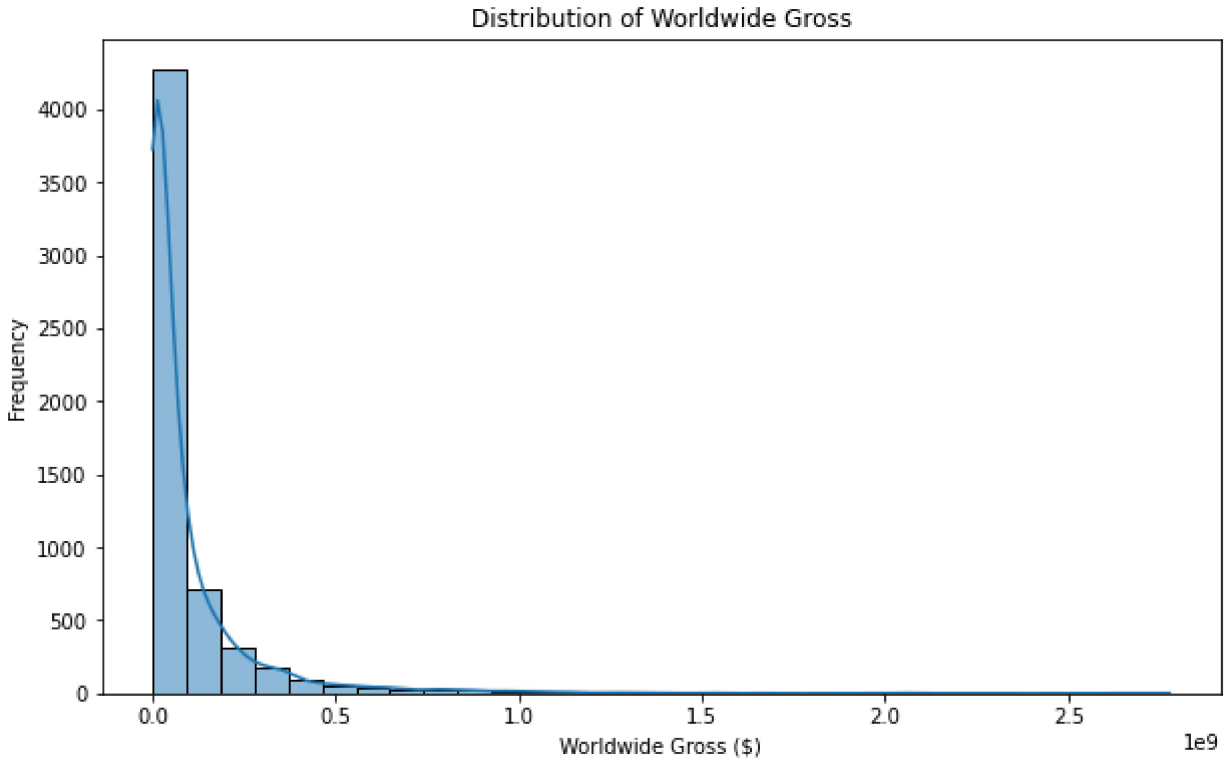
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(tn_movie_budgets['domestic_gross'], bins=30, kde=True)
plt.title('Distribution of Domestic Gross')
plt.xlabel('Domestic Gross ($)')
plt.ylabel('Frequency')
plt.show()
```



The histogram shows the distribution of production budgets for movies in the dataset. This helps identify the most common budget ranges and outliers.

Distribution of Worldwide Gross

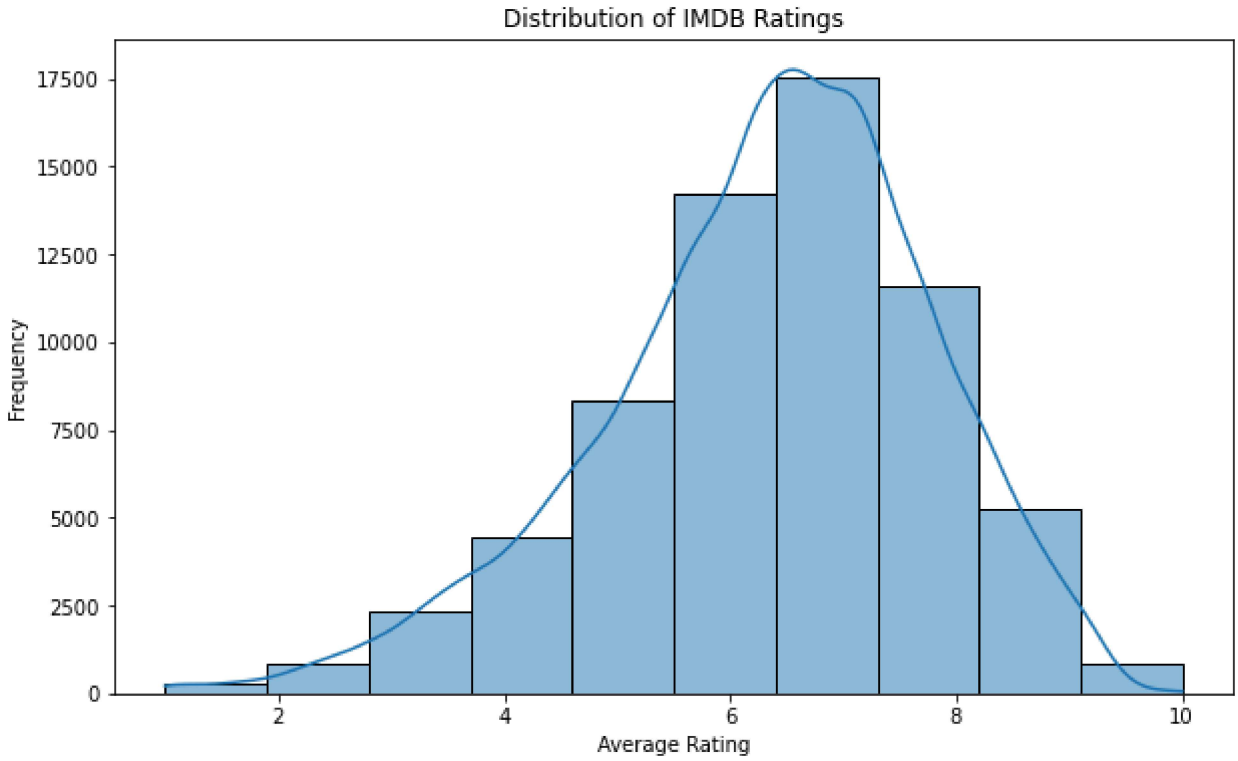
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(tn_movie_budgets['worldwide_gross'], bins=30, kde=True)
plt.title('Distribution of Worldwide Gross')
plt.xlabel('Worldwide Gross ($)')
plt.ylabel('Frequency')
plt.show()
```



The histogram shows the distribution of worldwide gross earnings. This helps understand global revenue patterns for movies.

Distribution of IMDB Ratings

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(imdb_merged['averagerating'], bins=10, kde=True)
plt.title('Distribution of IMDB Ratings')
plt.xlabel('Average Rating')
plt.ylabel('Frequency')
plt.show()
```

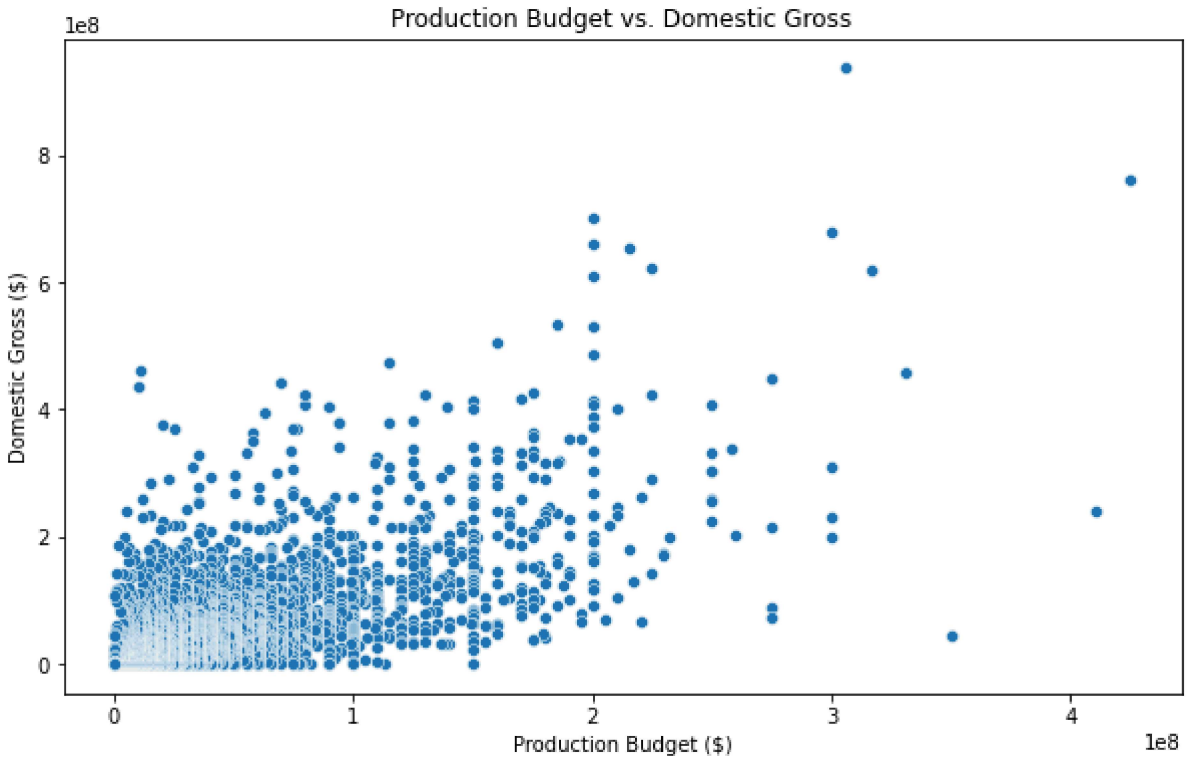


The histogram shows the distribution of average IMDB ratings. This helps identify the typical rating range for movies and any outliers.

Comparing the variables

Production Budget vs. Domestic Gross

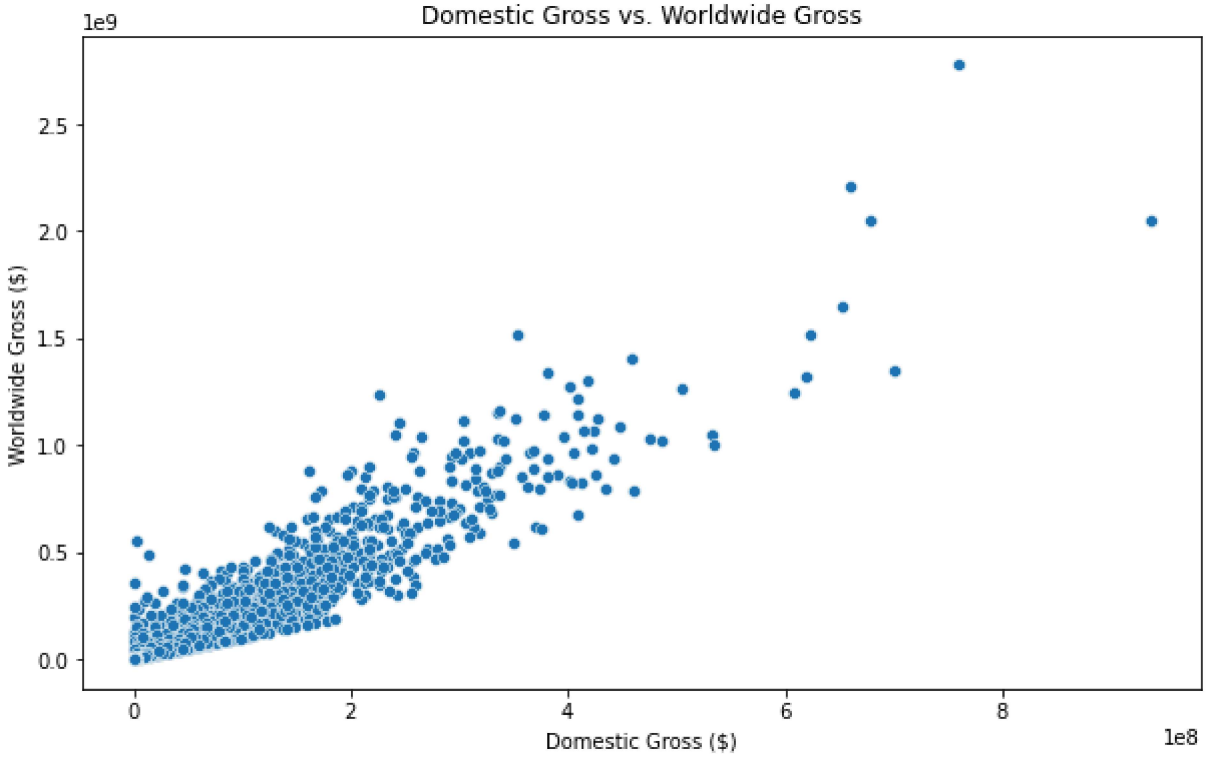
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='domestic_gross', data=tn_movie_budgets)
plt.title('Production Budget vs. Domestic Gross')
plt.xlabel('Production Budget ($)')
plt.ylabel('Domestic Gross ($)')
plt.show()
```



The scatter plot shows that as budgets increase, domestic revenues also tend to go up.

Domestic Gross vs. Worldwide Gross

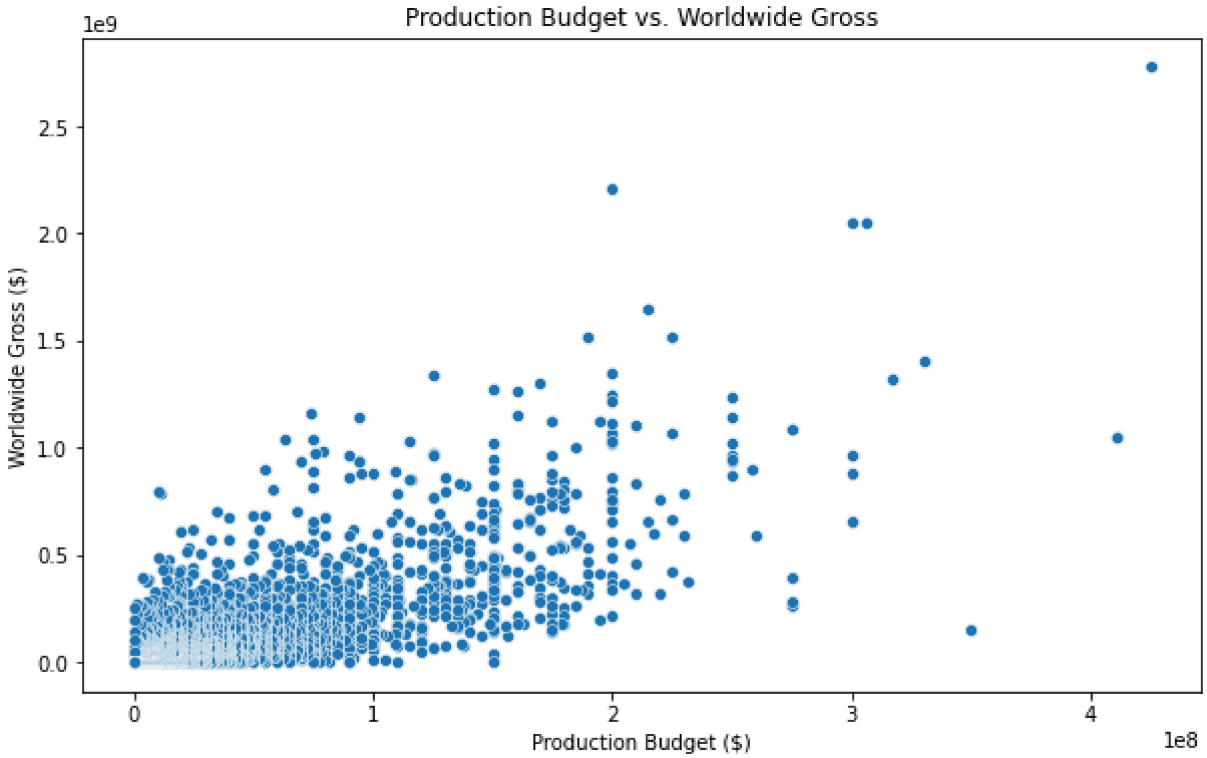
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='domestic_gross', y='worldwide_gross', data=tn_movie_budgets)
plt.title('Domestic Gross vs. Worldwide Gross')
plt.xlabel('Domestic Gross ($)')
plt.ylabel('Worldwide Gross ($)')
plt.show()
```



The scatter plot shows an upward trend, suggesting that higher domestic gross tend to yield higher worldwide revenues.

Production Budget vs. Worldwide Gross

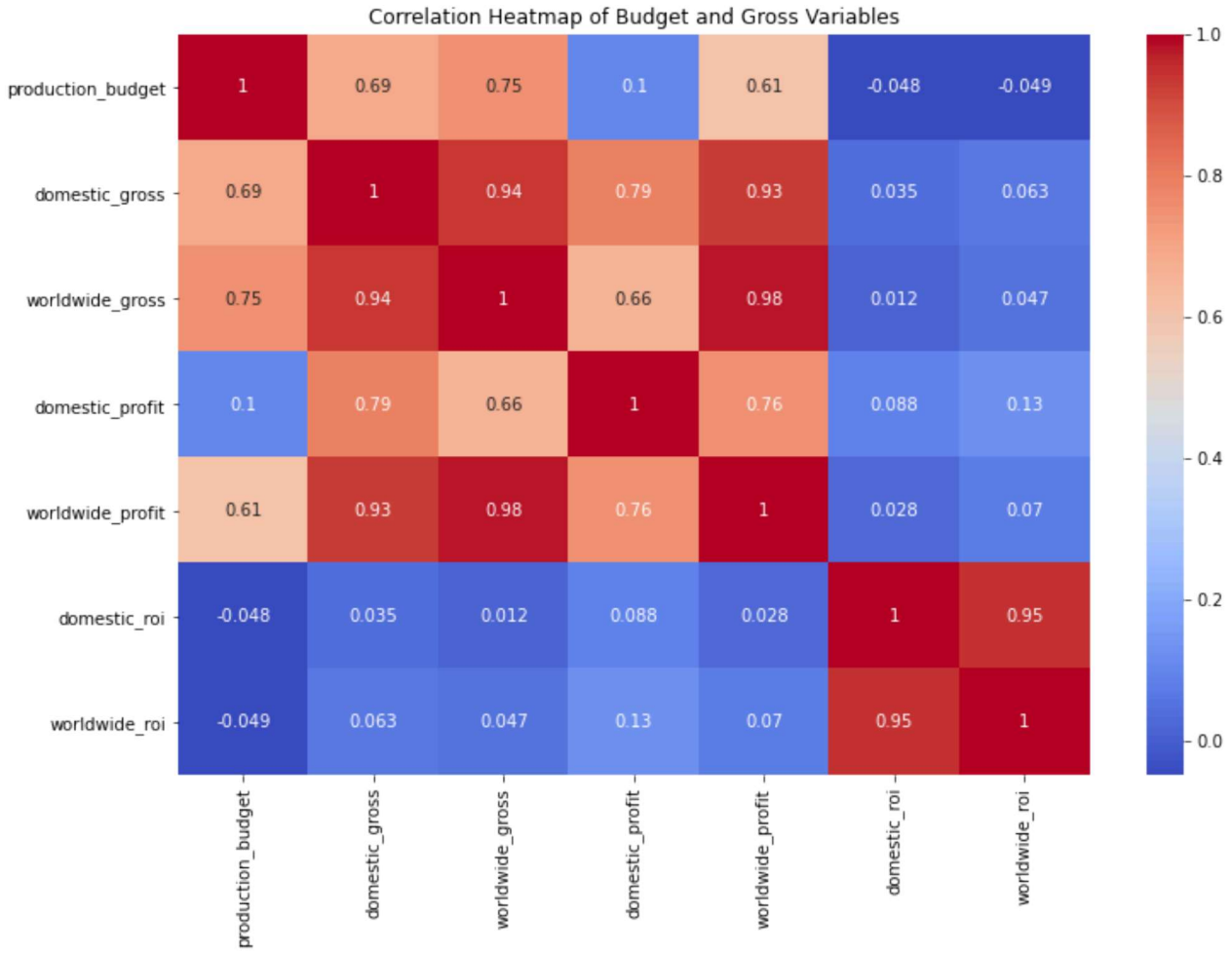
In [ ]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='worldwide_gross', data=tn_movie_budgets)
plt.title('Production Budget vs. Worldwide Gross')
plt.xlabel('Production Budget ($)')
plt.ylabel('Worldwide Gross ($)')
plt.show()
```



The scatter plot suggests that as budgets increase, worldwide revenues also tend to go up.

Multivariate Analysis: Heatmap of Correlations in tn_movie_budgets

In [ ]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(tn_movie_budgets[['production_budget', 'domestic_gross', 'worldwide_gross',
plt.title('Correlation Heatmap of Budget and Gross Variables')
plt.show()
```



There is a strong positive correlation between production budget and gross revenues for both domestic and worldwide, and between gross revenues and profits.

Identifying the most profitable genres

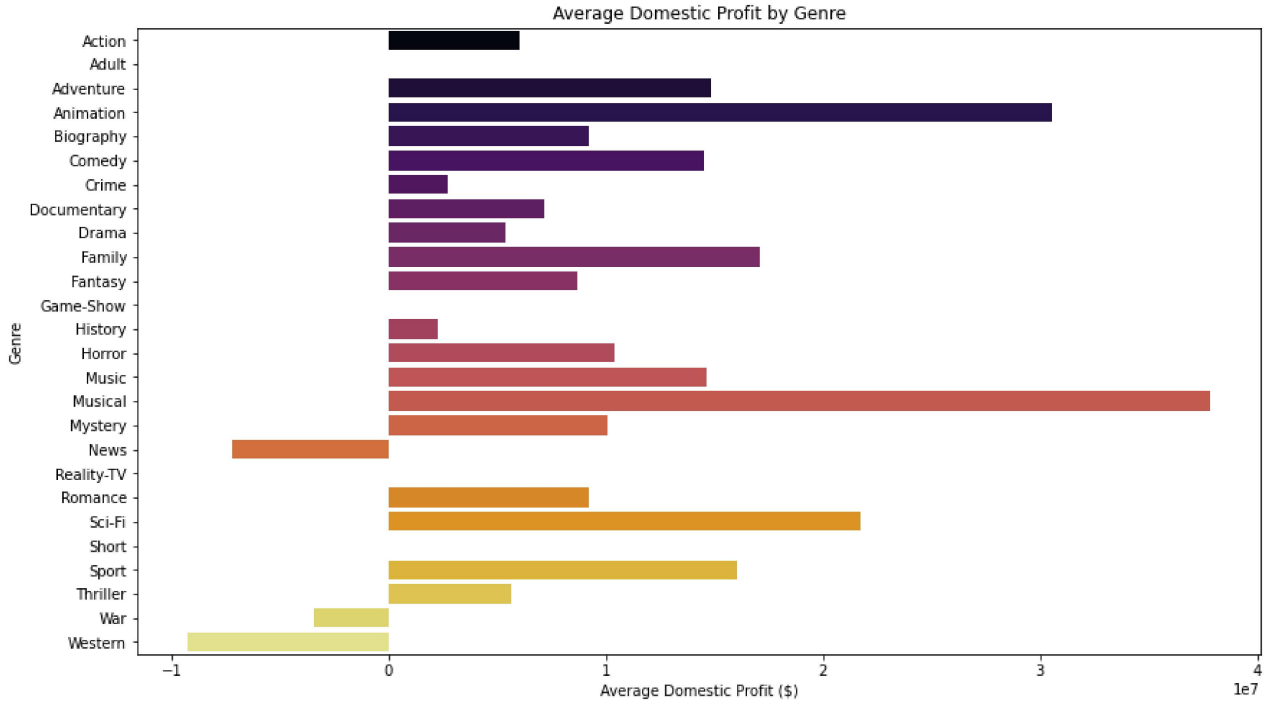
In [ ]:
```
genre_columns = ['Action', 'Adult', 'Adventure','Animation', 'Biography', 'Comedy', 'Cr

genre_profit_df = pd.DataFrame()

for genre in genre_columns:
    genre_profit_df.loc[genre, 'avg_domestic_profit'] = combined_data.loc[combined_data
    genre_profit_df.loc[genre, 'avg_worldwide_profit'] = combined_data.loc[combined_dat

genre_profit_df = genre_profit_df.reset_index().rename(columns={'index': 'genre'})

genre_profit_df
```

Out[ ]:

	genre	avg_domestic_profit	avg_worldwide_profit
0	Action	6.009706e+06	1.277744e+08
1	Adult	NaN	NaN
2	Adventure	1.482112e+07	2.059963e+08
3	Animation	3.054870e+07	2.347626e+08
4	Biography	9.240125e+06	4.685618e+07

	genre	avg_domestic_profit	avg_worldwide_profit
5	Comedy	1.453542e+07	7.415582e+07
6	Crime	2.745059e+06	3.870504e+07
7	Documentary	7.144900e+06	3.589637e+07
8	Drama	5.382601e+06	3.806185e+07
9	Family	1.706532e+07	1.135383e+08
10	Fantasy	8.690764e+06	1.480807e+08
11	Game-Show	NaN	NaN
12	History	2.249297e+06	3.919284e+07
13	Horror	1.037547e+07	4.676660e+07
14	Music	1.466438e+07	4.775460e+07
15	Musical	3.780470e+07	1.374225e+08
16	Mystery	1.006663e+07	4.876315e+07
17	News	-7.196259e+06	2.008208e+07
18	Reality-TV	NaN	NaN
19	Romance	9.182224e+06	4.312345e+07
20	Sci-Fi	2.172206e+07	1.789648e+08
21	Short	NaN	NaN
22	Sport	1.602454e+07	5.482649e+07
23	Thriller	5.625565e+06	5.449042e+07
24	War	-3.428482e+06	1.947261e+07
25	Western	-9.238052e+06	3.231587e+07

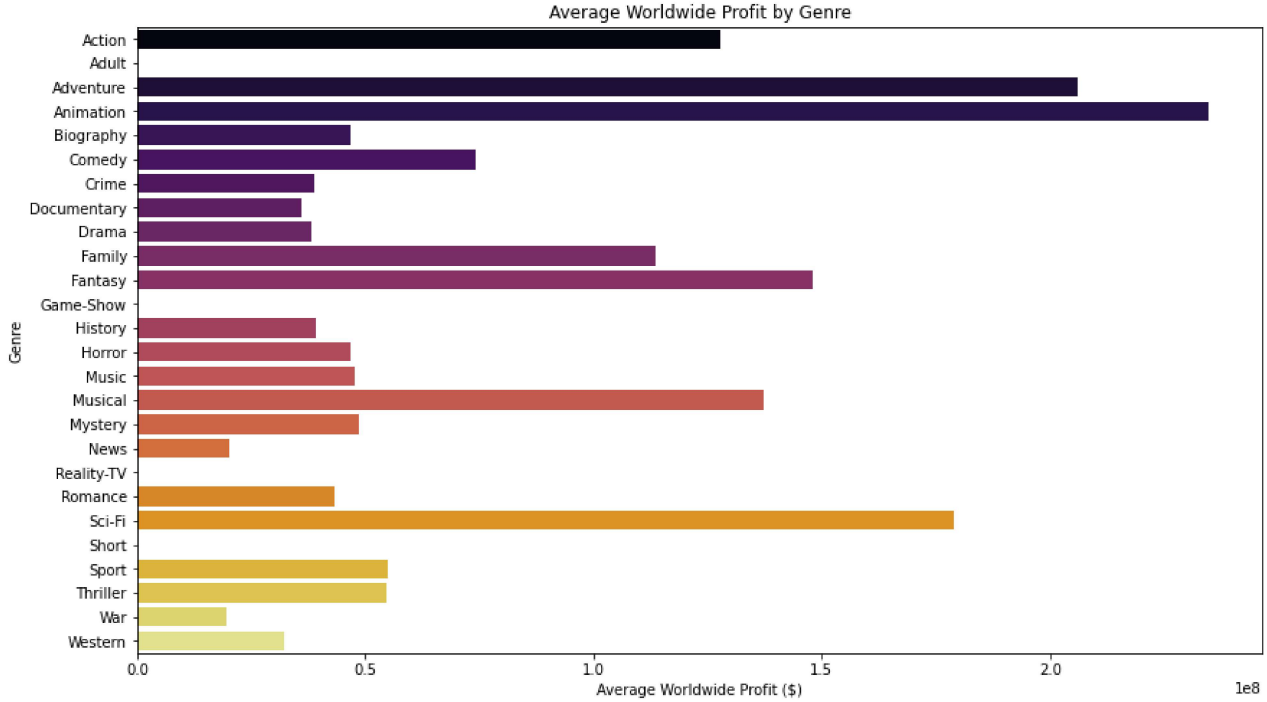
In [ ]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x='avg_domestic_profit', y='genre', data=genre_profit_df, palette='inferno'
plt.title('Average Domestic Profit by Genre')
plt.xlabel('Average Domestic Profit ($)')
plt.ylabel('Genre')
plt.show()
```



The bar chart shows the average domestic profit for each genre. This helps identify the most profitable genres domestically.

Average Worldwide Profit by Genre

In [ ]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x='avg_worldwide_profit', y='genre', data=genre_profit_df, palette='inferno
plt.title('Average Worldwide Profit by Genre')
plt.xlabel('Average Worldwide Profit ($)')
plt.ylabel('Genre')
plt.show()
```



The genres with the tallest bars are the most profitable on a global scale. Animation, adventure and Sci-Fi have the tallest bars. These genres generate the highest average worldwide profits.

Conclusion and Recommendations

Conclusion:

The analysis reveals that certain genres consistently perform better both domestically and worldwide. Action, Science Fiction, and Adventure films generally generate the highest average revenues and profits. Furthermore, the analysis of different budget ranges reveals that mid-range to high-range budgets often result in the most profitable movies.

Recommendations:

1. Prioritize Profitable Genres: Concentrate your efforts and resources on developing films within the Action, Science Fiction, and Adventure genres, as the analysis indicates these genres consistently generate the highest profits.

2. Strategic Budget Management: When allocating budgets for film productions, aim for the mid range. This budget range has been shown to yield the highest profits. Steer clear of excessively high budgets unless the potential returns are projected to be remarkably high and well-justified.