Movie Analysis

Business Problem

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

Import the required libraries

In [1]:
```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import pandasql as psql
from pandasql import sqldf
import sqlite3
from scipy.stats import norm, ttest_1samp, zscore
import matplotlib.pyplot as plt
%matplotlib inline
```

Extract the data from the box office gross dataset

In [2]:
```
bom_gross_data = pd.read_csv('./zippedData/bom.movie_gross.csv.gz')
bom_gross_data.head(10)
```

Out[2]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
5	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010
6	Iron Man 2	Par.	312400000.0	311500000	2010
7	Tangled	BV	200800000.0	391000000	2010
8	Despicable Me	Uni.	251500000.0	291600000	2010
9	How to Train Your Dragon	P/DW	217600000.0	277300000	2010

In [3]:
```
1 bom_gross_data.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 [4]:
```
1 # convert the object dtype for the 'foreign_gross' column from an objec
2 bom_gross_data['foreign_gross'] = pd.to_numeric(bom_gross_data['foreign
3 bom_gross_data['foreign_gross']
```

Out[4]:
```
0       652000000.0
1       691300000.0
2       664300000.0
3       535700000.0
4       513900000.0
           ...
3382            NaN
3383            NaN
3384            NaN
3385            NaN
3386            NaN
Name: foreign_gross, Length: 3387, dtype: float64
```

In [5]:
```
1 bom_gross_data.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   2032 non-null   float64
 4   year            3387 non-null   int64
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
```

In [6]:
```
1 bom_gross_data.isna().value_counts(normalize=True)
```

Out[6]:
```
title  studio  domestic_gross  foreign_gross  year
False  False   False           False          False    0.591084
                               True           False    0.399764
               True            False          False    0.007676
       True    False           False          False    0.000590
               True            False          False    0.000590
               False           True           False    0.000295
Name: proportion, dtype: float64
```

In [7]:
```
1 bom_gross_data.dropna(inplace=True)
```

In [8]:
```
1 bom_gross_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2002 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           2002 non-null   object
 1   studio          2002 non-null   object
 2   domestic_gross  2002 non-null   float64
 3   foreign_gross   2002 non-null   float64
 4   year            2002 non-null   int64
dtypes: float64(2), int64(1), object(2)
memory usage: 93.8+ KB
```

In [9]:
```
1 bom_gross_data.describe()
```

Out[9]:

	domestic_gross	foreign_gross	year
count	2.002000e+03	2.002000e+03	2002.000000
mean	4.571529e+07	7.597967e+07	2013.500000
std	7.640004e+07	1.383001e+08	2.597475
min	4.000000e+02	6.000000e+02	2010.000000
25%	6.655000e+05	4.000000e+06	2011.000000
50%	1.640000e+07	1.960000e+07	2013.000000
75%	5.570000e+07	7.645000e+07	2016.000000
max	7.001000e+08	9.605000e+08	2018.000000

Extract the data from the imdb database using SQLite

In [10]:
```
# Connect to the SQLite database
conn = sqlite3.connect('./zippedData/im.db/im.db')

# Load tables into DataFrames
movie_basics_df = pd.read_sql_query("SELECT * FROM movie_basics;", conn
directors_df = pd.read_sql_query("SELECT * FROM directors;", conn)
known_for_df = pd.read_sql_query("SELECT * FROM known_for;", conn)
movie_akas_df = pd.read_sql_query("SELECT * FROM movie_akas;", conn)
movie_ratings_df = pd.read_sql_query("SELECT * FROM movie_ratings;", co
persons_df = pd.read_sql_query("SELECT * FROM persons;", conn)
principals_df = pd.read_sql_query("SELECT * FROM principals;", conn)
writers_df = pd.read_sql_query("SELECT * FROM writers;", conn)

# Close the connection
conn.close()

```

In [11]:
```
# lambda function to simplify SQL querying
pysqldf = lambda q: sqldf(q, globals())

```

In [12]:
```
#test query
query1 = """SELECT * FROM movie_basics_df
            WHERE start_year > 2015
            ORDER BY start_year ASC"""
result1 = pysqldf(query1)
# print(result1)
result1

```

Out[12]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genr
0	tt0315642	Wazir	Wazir	2016	103.0	Action,Crime,Drar
1	tt0364201	Aman Ke Farishtey	Aman Ke Farishtey	2016	137.0	Acti
2	tt0376479	American Pastoral	American Pastoral	2016	108.0	Crime,Drar
3	tt0443533	The History of Love	The History of Love	2016	134.0	Drama,Romance,W
4	tt0470936	Hot Country, Cold Winter	Tak erkir, tsurt dzmer	2016	104.0	Drar
...	...	...	...	...	...	
61062	tt6149054	Fantastic Beasts and Where to Find Them 5	Fantastic Beasts and Where to Find Them 5	2024	NaN	Adventure,Family,Fanta
61063	tt3095356	Avatar 4	Avatar 4	2025	NaN	Action,Adventure,Fanta

In [13]:
```
1 result1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61067 entries, 0 to 61066
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         61067 non-null  object 
 1   primary_title    61067 non-null  object 
 2   original_title   61049 non-null  object 
 3   start_year       61067 non-null  int64  
 4   runtime_minutes  43783 non-null  float64
 5   genres           58534 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 2.8+ MB
```

In [14]:
```
1 result1.dropna(inplace=True)
```

In [15]:
```
1 result1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 43069 entries, 0 to 61050
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         43069 non-null  object 
 1   primary_title    43069 non-null  object 
 2   original_title   43069 non-null  object 
 3   start_year       43069 non-null  int64  
 4   runtime_minutes  43069 non-null  float64
 5   genres           43069 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 2.3+ MB
```

In [16]:
```
1 result1.describe()
```

Out[16]:

	start_year	runtime_minutes
count	43069.000000	43069.000000
mean	2017.184402	86.545566
std	0.992723	47.157760
min	2016.000000	1.000000
25%	2016.000000	71.000000
50%	2017.000000	88.000000
75%	2018.000000	100.000000
max	2022.000000	6017.000000

In [17]:
```
#Read the numbers csv
numbers_df = pd.read_csv('./zippedData/tn.movie_budgets.csv/tn.movie_bu
numbers_df.head(10)
```

Out[17]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
6	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâs End	$300,000,000	$309,420,425	$963,420,425
8	9	Nov 17, 2017	Justice League	$300,000,000	$229,024,295	$655,945,209
9	10	Nov 6, 2015	Spectre	$300,000,000	$200,074,175	$879,620,923

In [18]:
```
numbers_df.info()
```

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

In [19]:
```
1 numbers_df.describe()
```

Out[19]:

	id
count	5782.000000
mean	50.372363
std	28.821076
min	1.000000
25%	25.000000
50%	50.000000
75%	75.000000
max	100.000000

In [20]:
```
1 # Apply replace on all three columns to remove dollar signs and commas
2 numbers_df[['production_budget', 'domestic_gross', 'worldwide_gross']]
3
4 # Convert the budget and gross columns to float dtypes
5 numbers_df[['production_budget', 'domestic_gross', 'worldwide_gross']]
6
```

In [21]:
```
1 numbers_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 271.2+ KB
```

In [22]:
```
1 numbers_df.describe()
```

Out[22]:

	id	production_budget	domestic_gross	worldwide_gross
count	5782.000000	5.782000e+03	5.782000e+03	5.782000e+03
mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09

In [23]:
```
1 rt_movie_df = pd.read_csv('./zippedData/rt.movie_info.tsv/rt.movie_info
2 rt_movie_df.head(10)
```

Out[23]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure| Classics| Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama| Science Fiction and Fantasy	David Cronenberg	David Cronenberg| Don DeLillo	Aug 17, 2012	Jan 1, 2013	$
2	5	Illeana Douglas delivers a superb performance ...	R	Drama| Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN
		Michael Douglas		Drama|		Paul		

In [24]:
```
1 #convert the box column from a obaject dtype to a float dtype
2 rt_movie_df['box_office'] = rt_movie_df['box_office'].replace({',':''},
3 rt_movie_df['box_office'] = rt_movie_df['box_office'].astype(float)
```

In [25]:
```
1 rt_movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    float64
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: float64(1), int64(1), object(10)
memory usage: 146.4+ KB
```

In [26]:
```
1  # Function that will save any df to a certain specified directory
2  def save_df_to_directory(df, directory, filename):
3      """
4      Saves a DataFrame to a specified directory with the given file name
5
6      Parameters:
7      df (pd.DataFrame): The DataFrame to save.
8      directory (str): The directory where the DataFrame will be saved.
9      file_name (str): The name of the file to save the DataFrame as.
10     """
11     #ensure the os exists
12     if not os.path.exists(directory):
13         os.makedirs(directory, exist_ok=True)
14
15     #create the full path
16     file_path = os.path.join(directory, filename)
17
18     #save the dataframe as a csv file
19     df.to_csv(file_path, index="False")
```

In [27]:
```
1 #Save the rt_numbers_df to the sccessible_data folders
2 save_df_to_directory(rt_movie_df, './accessible_data/', 'rt_numbers.csv
```

In [28]:
```
1 #Save the rt_numbers_df to the sccessible_data folders
2 save_df_to_directory(movie_basics_df, './accessible_data/', 'movie_basi
```

In [29]:
```
#check the movie ratings df
movie_ratings_df.head(10)
```

Out[29]:

	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
5	tt1069246	6.2	326
6	tt1094666	7.0	1613
7	tt1130982	6.4	571
8	tt1156528	7.2	265
9	tt1161457	4.2	148

In [30]:
```
movie_ratings_df.info()
```

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

In [31]:
```
save_df_to_directory(movie_ratings_df, './accessible_data/', 'movie_rat
```

In [32]:
```
save_df_to_directory(numbers_df, './accessible_data/', 'production_numb
```

In [33]:
```
save_df_to_directory(bom_gross_data,'./accessible_data/', 'bom_gross_df

```

In [34]:
```
#identify missing values in bom_gross_data
bom_gross_data.isnull().sum()
```

Out[34]:
```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

In [35]:
```
#identify missing values in movie_ratings_df
movie_ratings_df.isnull().sum()
```

Out[35]:
```
movie_id         0
averagerating    0
numvotes         0
dtype: int64
```

In [36]:
```
#identify missing values in movie_basics_df
result1.isnull().sum()
```

Out[36]:
```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

Merge dataframes

To start, we will merge the box office df and the movie basic df(result1)

In [37]:
```
# Remove leading/trailing spaces, and convert relevant columns to numer
bom_gross_data.columns = bom_gross_data.columns.str.strip()
numbers_df.columns = numbers_df.columns.str.strip()
```

In [38]:
```
# Merge the dataframes on the movie title
# First, merge the first two DataFrames on the title
df_merged = pd.merge(bom_gross_data, result1, left_on='title', right_on

df_merged
```

Out[38]:

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	orig
0	Toy Story 3	BV	415000000.0	652000000.0	2010	NaN	NaN	
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	NaN	NaN	
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	NaN	NaN	
3	Inception	WB	292600000.0	535700000.0	2010	NaN	NaN	
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	NaN	NaN	
...	...	...	...	...	...	...	...	
2058	I Still See	LGF	1400.0	1500000.0	2018	tt2160105	I Still See You	

In [39]:
```
1 df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2063 entries, 0 to 2062
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   title            2063 non-null   object 
 1   studio           2063 non-null   object 
 2   domestic_gross   2063 non-null   float64
 3   foreign_gross    2063 non-null   float64
 4   year             2063 non-null   int64  
 5   movie_id         563 non-null    object 
 6   primary_title    563 non-null    object 
 7   original_title   563 non-null    object 
 8   start_year       563 non-null    float64
 9   runtime_minutes  563 non-null    float64
 10  genres           563 non-null    object 
dtypes: float64(4), int64(1), object(6)
memory usage: 177.4+ KB
```

In [40]:
```
1 save_df_to_directory(df_merged, './accessible_data/', 'bom_basics_merge
```

In [41]:
```
1 df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2063 entries, 0 to 2062
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   title            2063 non-null   object 
 1   studio           2063 non-null   object 
 2   domestic_gross   2063 non-null   float64
 3   foreign_gross    2063 non-null   float64
 4   year             2063 non-null   int64  
 5   movie_id         563 non-null    object 
 6   primary_title    563 non-null    object 
 7   original_title   563 non-null    object 
 8   start_year       563 non-null    float64
 9   runtime_minutes  563 non-null    float64
 10  genres           563 non-null    object 
dtypes: float64(4), int64(1), object(6)
memory usage: 177.4+ KB
```

In [42]:
```
# Merge rt_movie df with the production numbers df
synopsis_df = pd.merge(rt_movie_df, numbers_df, left_on='id', right_on=
synopsis_df.head()
```

Out[42]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure| Classics| Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN
1	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	3	New York City, not-too-distant-future: Eric Pa...	R	Drama| Science Fiction and Fantasy	David Cronenberg	David Cronenberg| Don DeLillo	Aug 17, 2012	Jan 1, 2013	$
3	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	5	Illeana Douglas delivers a superb performance ...	R	Drama| Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN

In [43]:
```
synopsis_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   synopsis           4508 non-null   object
 2   rating             4624 non-null   object
 3   genre              4624 non-null   object
 4   director           3874 non-null   object
 5   writer             3412 non-null   object
 6   theater_date       3299 non-null   object
 7   dvd_date           3299 non-null   object
 8   currency           1099 non-null   object
 9   box_office         1099 non-null   float64
 10  runtime            4508 non-null   object
 11  studio             1563 non-null   object
 12  release_date       5782 non-null   object
 13  movie              5782 non-null   object
 14  production_budget  5782 non-null   float64
```

In [44]:
```
1 synopsis_df.isna().sum()
```

Out[44]:
```
id                     0
synopsis            1274
rating              1158
genre               1158
director            1908
writer              2370
theater_date        2483
dvd_date            2483
currency            4683
box_office          4683
runtime             1274
studio              4219
release_date           0
movie                  0
production_budget      0
domestic_gross         0
worldwide_gross        0
dtype: int64
```

In [45]:
```
1 # Descriptive analysis: Frequency distribution of genres
2 # Splitting the genres into individual genres for better analysis
3 genres_split = synopsis_df['genre'].str.split('|', expand=True).stack()
4 genre_counts = genres_split.value_counts()
5
6
7 genre_counts.head(10)  # Show top 10 genres by frequency
```

Out[45]:
```
Drama                          2714
Comedy                         1790
Action and Adventure           1102
Mystery and Suspense            984
Romance                         691
Classics                        578
Musical and Performing Arts     519
Art House and International     403
Science Fiction and Fantasy     348
Horror                          347
Name: count, dtype: int64
```

In [46]:
```
1 genres_split.name = 'genre'
2 merged_genres = synopsis_df.drop('genre', axis=1).join(genres_split)
```

In [47]:
```
1 merged_genres.head(10)
```

Out[47]:

	id	synopsis	rating	director	writer	theater_date	dvd_date	currency	box_office
0	1	This gritty, fast-paced, and innovative police...	R	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN
0	1	This gritty, fast-paced, and innovative police...	R	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN
0	1	This gritty, fast-paced, and innovative police...	R	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN
1	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	3	New York City, not-too-distant-future: Eric Pa...	R	David Cronenberg	David Cronenberg| Don DeLillo	Aug 17, 2012	Jan 1, 2013	$	600000.0
2	3	New York City, not-too-distant-future: Eric Pa...	R	David Cronenberg	David Cronenberg| Don DeLillo	Aug 17, 2012	Jan 1, 2013	$	600000.0
3	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	5	Illeana Douglas delivers a superb performance ...	R	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN	NaN
4	5	Illeana Douglas delivers a superb performance ...	R	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN	NaN
5	6	Michael Douglas runs afoul of a treacherous su...	R	Barry Levinson	Paul Attanasio| Michael Crichton	Dec 9, 1994	Aug 27, 1997	NaN	NaN

In [48]:
```
1 merged_genres.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 11211 entries, 0 to 5781
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 11211 non-null  int64
 1   synopsis           9879 non-null   object
 2   rating             10053 non-null  object
 3   director           8552 non-null   object
 4   writer             7802 non-null   object
 5   theater_date       7230 non-null   object
 6   dvd_date           7230 non-null   object
 7   currency           2197 non-null   object
 8   box_office         2197 non-null   float64
 9   runtime            9937 non-null   object
 10  studio             3067 non-null   object
 11  release_date       11211 non-null  object
 12  movie              11211 non-null  object
 13  production_budget  11211 non-null  float64
```

In [49]:
```
1 merged_genres.describe()
```

Out[49]:

	id	box_office	production_budget	domestic_gross	worldwide_gross
count	11211.000000	2.197000e+03	1.121100e+04	1.121100e+04	1.121100e+04
mean	52.518241	3.319357e+07	3.148777e+07	4.249838e+07	9.251159e+07
std	28.893827	4.276739e+07	4.148504e+07	7.032025e+07	1.780150e+08
min	1.000000	1.349040e+05	1.100000e+03	0.000000e+00	0.000000e+00
25%	28.000000	1.971135e+06	5.000000e+06	1.430721e+06	4.023741e+06
50%	52.000000	1.070679e+07	1.700000e+07	1.730342e+07	2.779434e+07
75%	79.000000	5.410000e+07	4.000000e+07	5.233192e+07	9.762872e+07
max	100.000000	1.320889e+08	4.250000e+08	9.366622e+08	2.776345e+09

In [50]:
```
1 save_df_to_directory(merged_genres, './accessible_data/', 'synopsis_mer
```

In [51]:
```
1 save_df_to_directory(synopsis_df, './accessible_data/', 'synopsis.csv')
```

Descriptive Breakdown

We'll continue by grouping the dataframes by calculating the total and average gross by year, as well as the grouping by genres.

In [52]:

```
# Split the genres column
df_merged.loc[df_merged.index, 'genres'] = df_merged['genres'].str.spli

# Explode the genres column
df_exploded = df_merged.explode('genres')

# Calculate total and average gross by year
gross_by_year = df_merged.groupby('year').agg(
    total_domestic_gross=pd.NamedAgg(column='domestic_gross', aggfunc='
    average_domestic_gross=pd.NamedAgg(column='domestic_gross', aggfunc
    total_foreign_gross=pd.NamedAgg(column='foreign_gross', aggfunc='su
    average_foreign_gross=pd.NamedAgg(column='foreign_gross', aggfunc='
).reset_index()
gross_by_year
```

Out[52]:

	year	total_domestic_gross	average_domestic_gross	total_foreign_gross	average_foreign_gr
0	2010	1.050328e+10	3.355680e+07	1.484897e+10	4.744080e
1	2011	9.971506e+09	3.357409e+07	1.581548e+10	5.325078e
2	2012	1.072226e+10	4.358644e+07	1.701888e+10	6.918246e
3	2013	1.063262e+10	5.161466e+07	1.670741e+10	8.110391e
4	2014	1.042488e+10	4.417324e+07	1.741387e+10	7.378757e
5	2015	9.002869e+09	4.738352e+07	1.526175e+10	8.032502e
6	2016	1.104429e+10	5.522145e+07	1.953179e+10	9.765895e
7	2017	1.161188e+10	6.016517e+07	2.184383e+10	1.131805e
8	2018	1.065776e+10	5.855912e+07	1.793669e+10	9.855324e

In [53]:
```
# Check for missing values and fill them with 0 or drop them
df_exploded['domestic_gross'] = df_exploded['domestic_gross'].fillna(0)
df_exploded['foreign_gross'] = df_exploded['foreign_gross'].fillna(0)

# Now perform the aggregation
gross_by_genre = df_exploded.groupby('genres').agg(
    total_domestic_gross=pd.NamedAgg(column='domestic_gross', aggfunc='
    average_domestic_gross=pd.NamedAgg(column='domestic_gross', aggfunc
    total_foreign_gross=pd.NamedAgg(column='foreign_gross', aggfunc='su
    average_foreign_gross=pd.NamedAgg(column='foreign_gross', aggfunc='

).reset_index()
gross_by_genre
```

Out[53]:

	genres	total_domestic_gross	average_domestic_gross	total_foreign_gross	average_fo
0	Action	1.399706e+10	8.693828e+07	2.774456e+10	1
1	Adventure	1.558946e+10	1.227516e+08	2.950450e+10	2
2	Animation	5.035712e+09	1.171096e+08	9.304000e+09	2
3	Biography	1.866453e+09	3.110755e+07	2.840872e+09	4
4	Comedy	1.081684e+10	6.555660e+07	1.762384e+10	1
5	Crime	2.041605e+09	3.460347e+07	2.273621e+09	3
6	Documentary	2.114256e+09	4.314808e+07	3.065777e+09	6
7	Drama	8.987940e+09	3.292286e+07	1.423651e+10	5
8	Family	1.305268e+09	5.675076e+07	2.134300e+09	9
9	Fantasy	4.473551e+09	9.518194e+07	9.217900e+09	1
10	History	1.011006e+09	3.370020e+07	1.421731e+09	4
11	Horror	2.948776e+09	4.997926e+07	4.282648e+09	7
12	Music	5.215452e+08	4.011886e+07	1.166302e+09	8
13	Musical	2.992000e+08	9.973333e+07	5.592000e+08	1
14	Mystery	1.358534e+09	3.483420e+07	2.472247e+09	6
15	Romance	1.543682e+09	2.912608e+07	2.343062e+09	4
16	Sci-Fi	4.184006e+09	1.442761e+08	7.684300e+09	2
17	Sport	8.764500e+08	6.741923e+07	9.262000e+08	7
18	Thriller	3.094690e+09	3.728542e+07	6.507454e+09	7
19	War	3.636000e+06	7.272000e+05	1.054330e+08	2
20	Western	3.540000e+05	3.540000e+05	3.400000e+06	3

In [54]:
```
save_df_to_directory(gross_by_year, './accessible_data/', 'gross_by_yea
```

In [55]:
```
1 gross_by_genre
```

Out[55]:

	genres	total_domestic_gross	average_domestic_gross	total_foreign_gross	average_fo
0	Action	1.399706e+10	8.693828e+07	2.774456e+10	1
1	Adventure	1.558946e+10	1.227516e+08	2.950450e+10	2
2	Animation	5.035712e+09	1.171096e+08	9.304000e+09	2
3	Biography	1.866453e+09	3.110755e+07	2.840872e+09	4
4	Comedy	1.081684e+10	6.555660e+07	1.762384e+10	1
5	Crime	2.041605e+09	3.460347e+07	2.273621e+09	3
6	Documentary	2.114256e+09	4.314808e+07	3.065777e+09	6
7	Drama	8.987940e+09	3.292286e+07	1.423651e+10	5
8	Family	1.305268e+09	5.675076e+07	2.134300e+09	9
9	Fantasy	4.473551e+09	9.518194e+07	9.217900e+09	1
10	History	1.011006e+09	3.370020e+07	1.421731e+09	4
11	Horror	2.948776e+09	4.997926e+07	4.282648e+09	7
12	Music	5.215452e+08	4.011886e+07	1.166302e+09	8
13	Musical	2.992000e+08	9.973333e+07	5.592000e+08	1
14	Mystery	1.358534e+09	3.483420e+07	2.472247e+09	6
15	Romance	1.543682e+09	2.912608e+07	2.343062e+09	4
16	Sci-Fi	4.184006e+09	1.442761e+08	7.684300e+09	2
17	Sport	8.764500e+08	6.741923e+07	9.262000e+08	7
18	Thriller	3.094690e+09	3.728542e+07	6.507454e+09	7
19	War	3.636000e+06	7.272000e+05	1.054330e+08	2
20	Western	3.540000e+05	3.540000e+05	3.400000e+06	3

In [56]:
```
1 gross_by_genre.sort_values(by='average_domestic_gross')
```

Out[56]:

	genres	total_domestic_gross	average_domestic_gross	total_foreign_gross	average_fo
20	Western	3.540000e+05	3.540000e+05	3.400000e+06	3
19	War	3.636000e+06	7.272000e+05	1.054330e+08	2
15	Romance	1.543682e+09	2.912608e+07	2.343062e+09	4
3	Biography	1.866453e+09	3.110755e+07	2.840872e+09	4
7	Drama	8.987940e+09	3.292286e+07	1.423651e+10	5
10	History	1.011006e+09	3.370020e+07	1.421731e+09	4
5	Crime	2.041605e+09	3.460347e+07	2.273621e+09	3
14	Mystery	1.358534e+09	3.483420e+07	2.472247e+09	6
18	Thriller	3.094690e+09	3.728542e+07	6.507454e+09	7
12	Music	5.215452e+08	4.011886e+07	1.166302e+09	8
6	Documentary	2.114256e+09	4.314808e+07	3.065777e+09	6
11	Horror	2.948776e+09	4.997926e+07	4.282648e+09	7
8	Family	1.305268e+09	5.675076e+07	2.134300e+09	9
4	Comedy	1.081684e+10	6.555660e+07	1.762384e+10	1
17	Sport	8.764500e+08	6.741923e+07	9.262000e+08	7
0	Action	1.399706e+10	8.693828e+07	2.774456e+10	1
9	Fantasy	4.473551e+09	9.518194e+07	9.217900e+09	1
13	Musical	2.992000e+08	9.973333e+07	5.592000e+08	1
2	Animation	5.035712e+09	1.171096e+08	9.304000e+09	2
1	Adventure	1.558946e+10	1.227516e+08	2.950450e+10	2
16	Sci-Fi	4.184006e+09	1.442761e+08	7.684300e+09	2

In [58]:
```
1 gross_by_genre.sort_values(by='total_domestic_gross')
```

Out[58]:

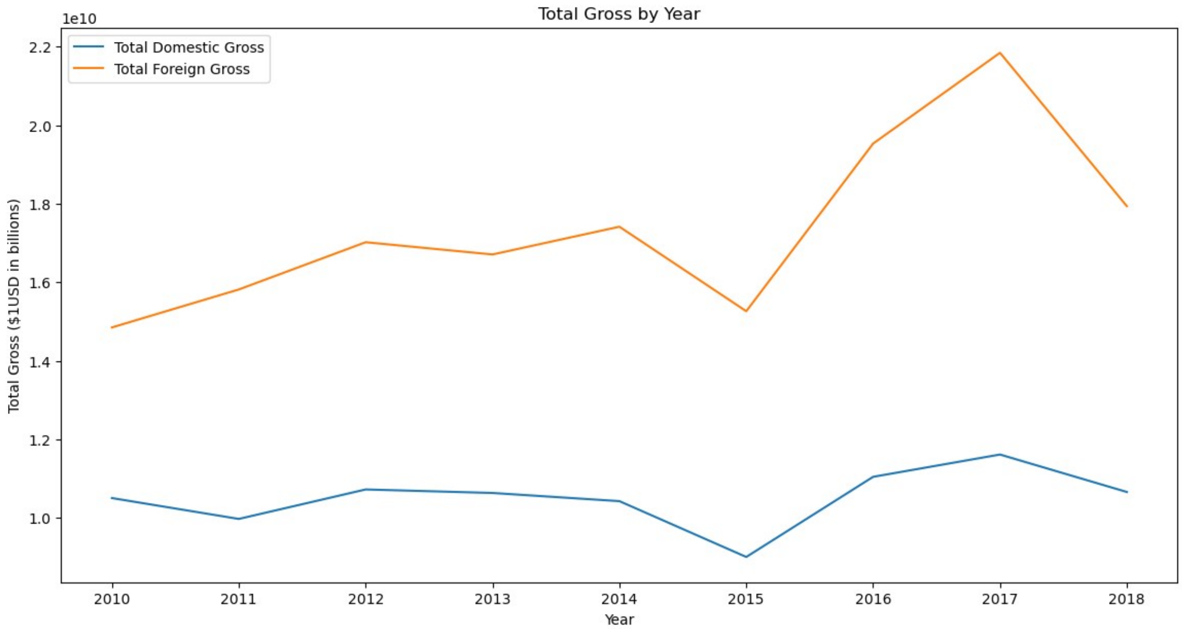
	genres	total_domestic_gross	average_domestic_gross	total_foreign_gross	average_fo
20	Western	3.540000e+05	3.540000e+05	3.400000e+06	3
19	War	3.636000e+06	7.272000e+05	1.054330e+08	2
13	Musical	2.992000e+08	9.973333e+07	5.592000e+08	1
12	Music	5.215452e+08	4.011886e+07	1.166302e+09	8
17	Sport	8.764500e+08	6.741923e+07	9.262000e+08	7
10	History	1.011006e+09	3.370020e+07	1.421731e+09	4
8	Family	1.305268e+09	5.675076e+07	2.134300e+09	9
14	Mystery	1.358534e+09	3.483420e+07	2.472247e+09	6
15	Romance	1.543682e+09	2.912608e+07	2.343062e+09	4
3	Biography	1.866453e+09	3.110755e+07	2.840872e+09	4
5	Crime	2.041605e+09	3.460347e+07	2.273621e+09	3
6	Documentary	2.114256e+09	4.314808e+07	3.065777e+09	6
11	Horror	2.948776e+09	4.997926e+07	4.282648e+09	7
18	Thriller	3.094690e+09	3.728542e+07	6.507454e+09	7
16	Sci-Fi	4.184006e+09	1.442761e+08	7.684300e+09	2
9	Fantasy	4.473551e+09	9.518194e+07	9.217900e+09	1
2	Animation	5.035712e+09	1.171096e+08	9.304000e+09	2
7	Drama	8.987940e+09	3.292286e+07	1.423651e+10	5
4	Comedy	1.081684e+10	6.555660e+07	1.762384e+10	1
0	Action	1.399706e+10	8.693828e+07	2.774456e+10	1
1	Adventure	1.558946e+10	1.227516e+08	2.950450e+10	2

In [59]:
```
1 save_df_to_directory(gross_by_genre, './accessible_data/', 'gross_by_ge
```

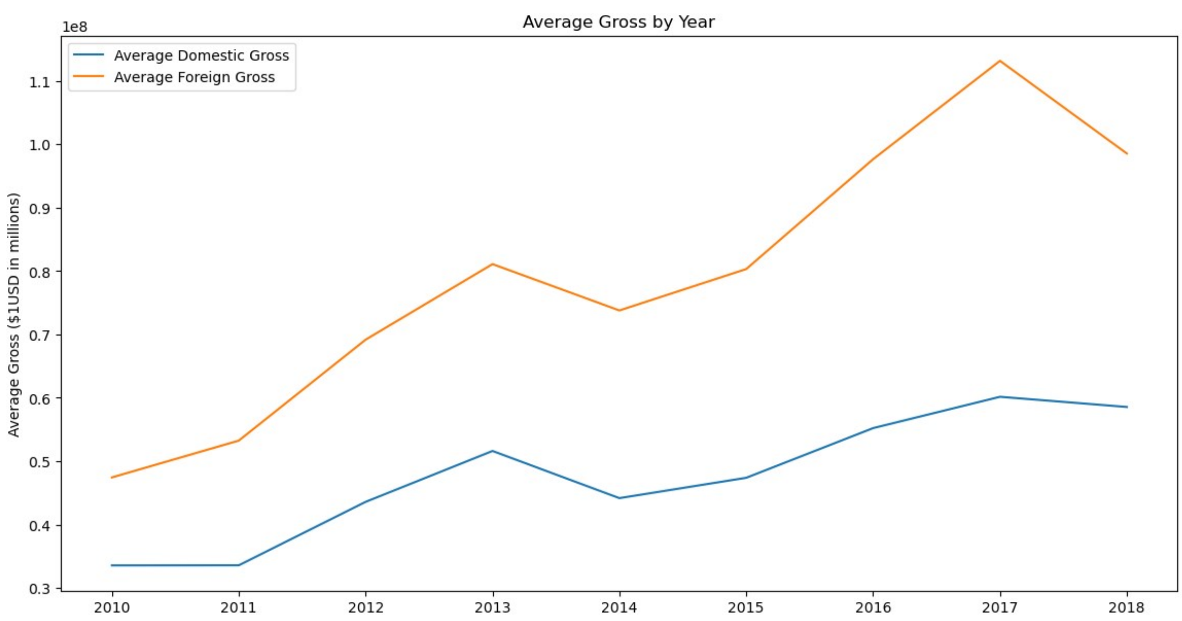
In [60]:

```
# Plot total and average gross by year
plt.figure(figsize=(14, 7))
sns.lineplot(data=gross_by_year, x='year', y='total_domestic_gross', la
sns.lineplot(data=gross_by_year, x='year', y='total_foreign_gross', lab
plt.title('Total Gross by Year')
plt.xlabel('Year')
plt.ylabel('Total Gross ($1USD in billions)')
plt.legend()
plt.savefig('Total_gross_by_year')
plt.show()

plt.figure(figsize=(14, 7))
sns.lineplot(data=gross_by_year, x='year', y='average_domestic_gross',
sns.lineplot(data=gross_by_year, x='year', y='average_foreign_gross', l
plt.title('Average Gross by Year')
plt.xlabel('Year')
plt.ylabel('Average Gross ($1USD in millions)')
plt.legend()

plt.savefig('Total_avg_by_year')
plt.show()


```

```
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



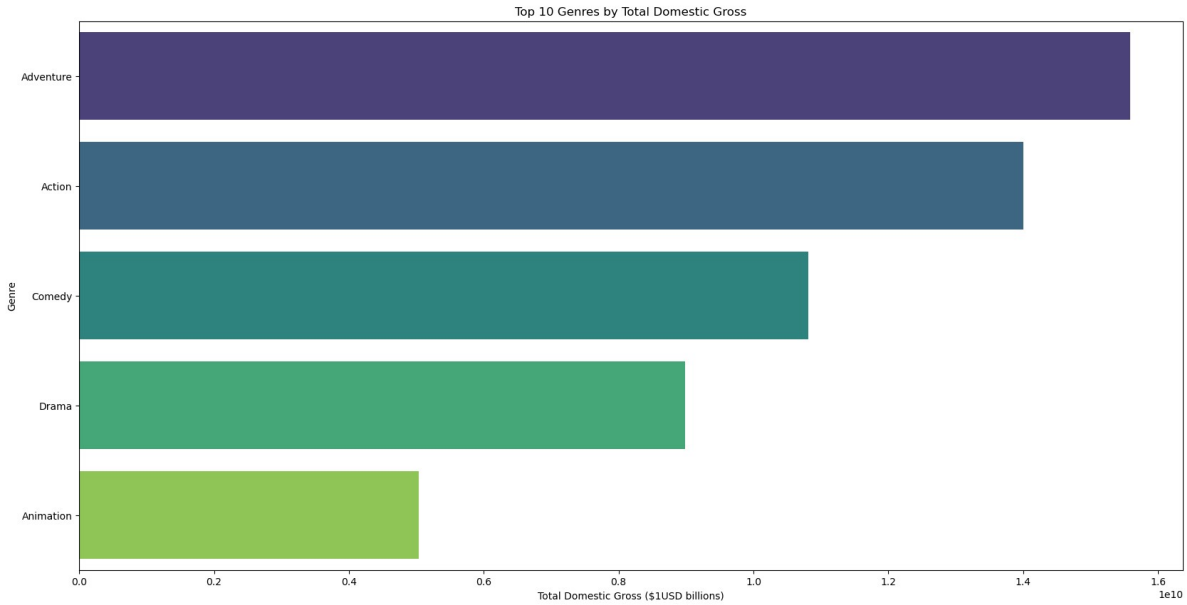

```
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

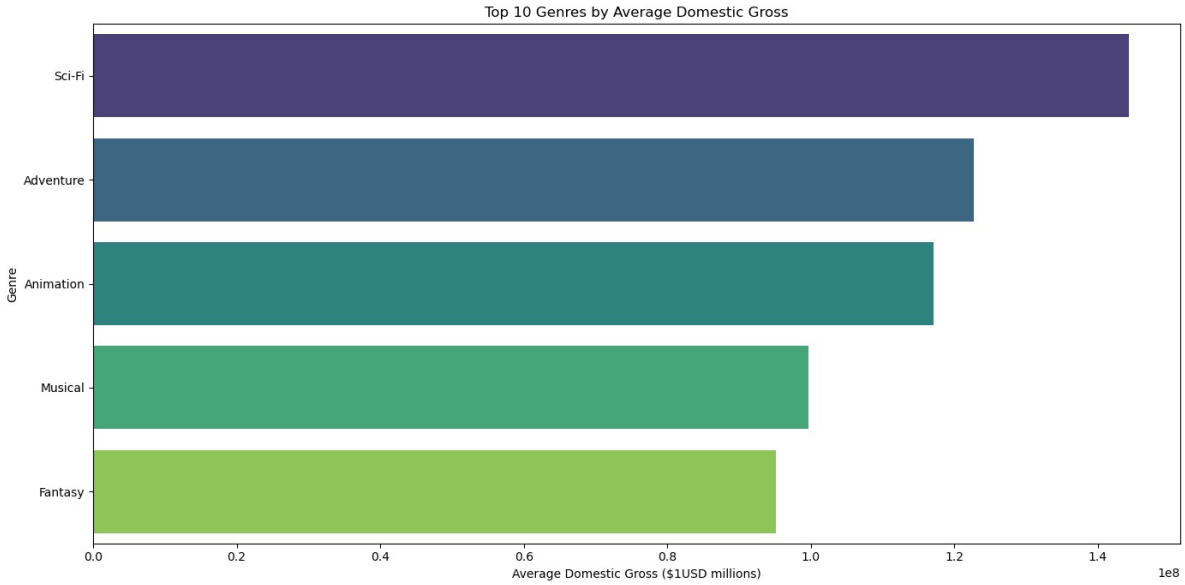


Barplot for Top Genres

In [61]:

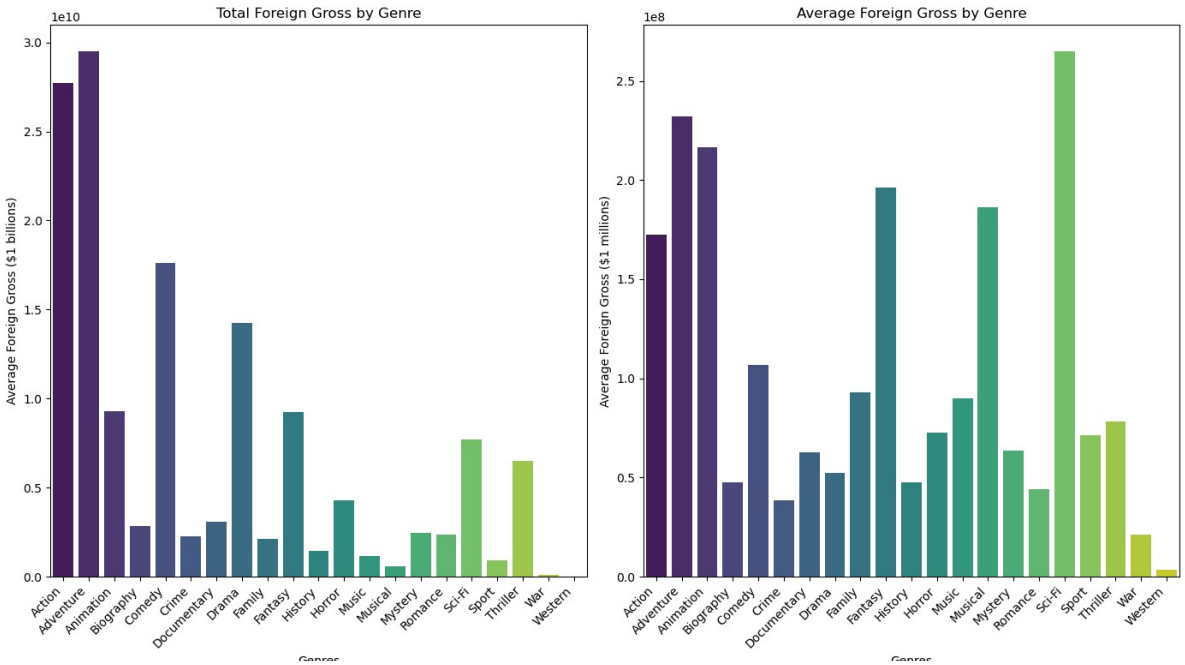
```
# Plot total and average gross by genre
plt.figure(figsize=(20, 10))
sns.barplot(data=gross_by_genre.sort_values(by='total_domestic_gross',
            x='total_domestic_gross', y='genres', palette='viridis')
plt.title('Top 10 Genres by Total Domestic Gross')
plt.xlabel('Total Domestic Gross ($1USD billions)')
plt.ylabel('Genre')
plt.savefig('Top_10_Genres_by_domestic_gross')
plt.show()

plt.figure(figsize=(14, 7))
sns.barplot(data=gross_by_genre.sort_values(by='average_domestic_gross'
            x='average_domestic_gross', y='genres', palette='viridis')
plt.title('Top 10 Genres by Average Domestic Gross')
plt.xlabel('Average Domestic Gross ($1USD millions)')
plt.ylabel('Genre')
plt.tight_layout()
plt.savefig('Top_10_Genres_by__avg_domestic_gross')
plt.show()
```




Top 10 Genres by Average Domestic Gross
Sci-Fi
Adventure
Animation
Musical
Fantasy
Genre
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1e8
Average Domestic Gross ($1USD millions)

In [62]:

```
# Bar plot for average domestic and foreign gross by genre
plt.figure(figsize=(14, 8))

# Plot average domestic gross

plt.subplot(1, 2, 1)
sns.barplot(data=gross_by_genre, x='genres', y='total_foreign_gross', p
plt.title('Total Foreign Gross by Genre')
plt.xlabel('Genres')
plt.ylabel('Average Foreign Gross ($1 billions)')
plt.xticks(rotation=45, ha='right')


# Plot average foreign gross
plt.subplot(1, 2, 2)
sns.barplot(data=gross_by_genre, x='genres', y='average_foreign_gross',
plt.title('Average Foreign Gross by Genre')
plt.xlabel('Genres')
plt.ylabel('Average Foreign Gross ($1 millions)')
plt.xticks(rotation=45, ha='right')

plt.tight_layout()
plt.savefig('Total_foreign_and_average_gross_by_genre')
plt.show()
```



In [63]:
```
1 synopsis_df.describe()
```

Out[63]:

	id	box_office	production_budget	domestic_gross	worldwide_gross
count	5782.000000	1.099000e+03	5.782000e+03	5.782000e+03	5.782000e+03
mean	50.372363	3.365105e+07	3.158776e+07	4.187333e+07	9.148746e+07
std	28.821076	4.437094e+07	4.181208e+07	6.824060e+07	1.747200e+08
min	1.000000	1.349040e+05	1.100000e+03	0.000000e+00	0.000000e+00
25%	25.000000	6.000000e+05	5.000000e+06	1.429534e+06	4.125415e+06
50%	50.000000	1.070679e+07	1.700000e+07	1.722594e+07	2.798445e+07
75%	75.000000	5.410000e+07	4.000000e+07	5.234866e+07	9.764584e+07
max	100.000000	1.320889e+08	4.250000e+08	9.366622e+08	2.776345e+09

Hypothesis testing for production budget and gross revenue

Null Hypothesis:

There is no relation between a high production budget and the gross revenue

Alternative Hypothesis:

The higher the production budget the higher the revenue for the film.

In [65]:

```
#Normalize the data from production budget, domestic gross, ww gross
np.random.seed(3)

prod_mean = synopsis_df['production_budget'].mean()
prod_median = synopsis_df['production_budget'].median()
prod_mode = synopsis_df['production_budget'].mode()
prod_std = synopsis_df['production_budget'].std()

print(f'PRODUCTION MEAN: {prod_mean}')
print(f'PRODUCTION MEDIAN: {prod_median}')
print(f'PRODUCTION MODE: {prod_mode}')
print(f'PRODUCTION STANDARD DEVIATION: {prod_std}')
print()


prod_data = np.random.normal(loc= prod_mean, scale=prod_std, size = len


dom_mean = synopsis_df['domestic_gross'].mean()
dom_median = synopsis_df['domestic_gross'].median()
dom_mode = synopsis_df['domestic_gross'].mode()
dom_std = synopsis_df['domestic_gross'].std()

print(f'DOMESTIC GROSS MEAN: {dom_mean}')
print(f'DOMESTIC GROSS MEDIAN: {dom_median}')
print(f'DOMESTIC GROSS MODE: {dom_mode}')
print(f'DOMESTIC GROSS STANDARD DEVIATION: {dom_std}')
print()


domestic_data = np.random.normal(loc=dom_mean, scale=dom_std, size=len(


ww_mean = synopsis_df['worldwide_gross'].mean()
ww_median = synopsis_df['worldwide_gross'].median()
ww_mode = synopsis_df['worldwide_gross'].mode()
ww_std = synopsis_df['worldwide_gross'].std()

print(f'WORLDWIDE GROSS MEAN: {ww_mean}')
print(f'WORLDWIDE GROSS MEDIAN: {ww_median}')
print(f'WORLDWIDE GROSS MODE: {ww_mode}')
print(f'WORLDWIDE GROSS STANDARD DEVIATION: {ww_std}')
print()

ww_data = np.random.normal(loc=ww_mean, scale=ww_std, size=len(synopsis

# Create a figure and a set of subplots
# fig, ax = plt.subplots(3, 1, figsize=(12, 6))

plt.subplot(3,1,1)
sns.histplot(prod_data,color='blue', kde=True)
plt.title("Normal Distribution for production Budget")
plt.axvline(x= prod_mean, linestyle='--', color='black')
plt.xlabel("Value")
plt.ylabel("Frequency")
```

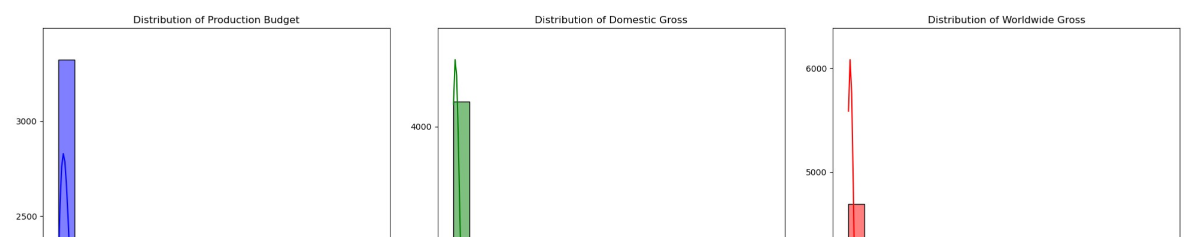
```
56
57 plt.subplot(3,1,2)
58 sns.histplot(domestic_data, color='orange',kde=True)
59 plt.axvline(x= dom_mean, linestyle='--', color='black')
60 plt.title("Normal Distribution for Domestic Gross Revenue")
61 plt.xlabel("Value")
62 plt.ylabel("Frequency")
63
64 plt.subplot(3,1,3)
65 sns.histplot(ww_data, color='r', kde=True)
66 plt.axvline(x= ww_mean, linestyle='--', color='black')
67 plt.title("Normal Distribution for Worldwide Gross Revenue")
68 plt.xlabel("Value")
69 plt.ylabel("Frequency")
70
71 plt.tight_layout()
72 plt.show()
```

```
PRODUCTION MEAN: 31587757.0965064
PRODUCTION MEDIAN: 17000000.0
PRODUCTION MODE: 0    20000000.0
Name: production_budget, dtype: float64
PRODUCTION STANDARD DEVIATION: 41812076.82694316

DOMESTIC GROSS MEAN: 41873326.867001034
DOMESTIC GROSS MEDIAN: 17225945.0
DOMESTIC GROSS MODE: 0    0.0
Name: domestic_gross, dtype: float64
DOMESTIC GROSS STANDARD DEVIATION: 68240597.35690318

WORLDWIDE GROSS MEAN: 91487460.90643376
WORLDWIDE GROSS MEDIAN: 27984448.5
WORLDWIDE GROSS MODE: 0    0.0
Name: worldwide_gross, dtype: float64
WORLDWIDE GROSS STANDARD DEVIATION: 174719968.77890623


C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
```

In [70]:

```
# #Standardized the data
# prod_z_score = stats.zscore(synopsis_df['production_budget'])
# dom_z_score = stats.zscore(synopsis_df['domestic_gross'])
# ww_z_score  =stats.zscore(synopsis_df['worldwide_gross'])
import scipy.stats
# Standardize data (z-scores)
prod_z_scores = scipy.stats.zscore(synopsis_df['production_budget'])
dom_z_score = scipy.stats.zscore(synopsis_df['domestic_gross'])
ww_z_score = scipy.stats.zscore(synopsis_df['worldwide_gross'])


#Hustogram for Production Budget, Domestic Gross, and Worldwide Gross
fig, axes = plt.subplots(1,3, figsize=(20,12))

sns.histplot(prod_z_scores, bins=20, kde=True, ax=axes[0], color='blue'
axes[0].set_title('Distribution of Production Budget')


sns.histplot(dom_z_score, bins=20, kde=True, ax=axes[1], color='green')
axes[1].set_title('Distribution of Domestic Gross')


sns.histplot(ww_z_score, bins=20, kde=True, ax=axes[2], color='red')
axes[2].set_title('Distribution of Worldwide Gross')

plt.tight_layout()
plt.savefig('Distributions')
plt.show()
```

```
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [71]:
```
#Cofidence level for production budgets
std_err = np.std(synopsis_df['production_budget'], ddof=1) / np.sqrt(le

confidence_level = 0.95
z_value = scipy.stats.norm.ppf((1 + confidence_level) / 2)
margin_of_err = std_err * z_value

# Confidence interval
confidence_interval = (prod_mean - margin_of_err, prod_mean + margin_of
print(f'Product 95% Confidence level: {confidence_interval}')
```

```
Product 95% Confidence level: (30510025.07429116, 32665489.118721638)
```

In [76]:
```
#production budget Z-TEST

prod_sample_data = np.random.choice(synopsis_df['production_budget'], s
prod_sample_mean = np.mean(prod_sample_data)
prod_sample_std = np.std(prod_sample_data, ddof=1)
n = len(prod_sample_data)

prod_z_score = (prod_sample_mean - prod_mean) / (prod_sample_std / np.s

prod_p_value = scipy.stats.norm.sf(abs(prod_z_score))

print(f'Product Z Score: {prod_z_score}, Product P-Value: {prod_p_value

dom_sample_data = np.random.choice(synopsis_df['domestic_gross'], size=
dom_sample_mean = np.mean(dom_sample_data)
dom_sample_std = np.std(dom_sample_data, ddof=1)
n = len(dom_sample_data)

dom_z_score = (dom_sample_mean - dom_mean) / (dom_sample_std / np.sqrt(

dom_p_value = scipy.stats.norm.sf(abs(dom_z_score))

print(f'Domestic Z-score: {dom_z_score}, Domestic P-Value: {dom_p_value

ww_sample_data = np.random.choice(synopsis_df['worldwide_gross'], size=
ww_sample_mean = np.mean(ww_sample_data)
ww_sample_std = np.std(ww_sample_data, ddof=1)
n = len(ww_sample_data)

ww_z_score = (ww_sample_mean - ww_mean) / (ww_sample_std / np.sqrt(n))

ww_p_value = scipy.stats.norm.sf(abs(ww_z_score))

print(f'WW Z-score: {ww_z_score}, WW P-Value: {ww_p_value}')
```

```
Product Z Score: 0.7626221468909986, Product P-Value: 0.2228443863447177
Domestic Z-score: -2.846000027601304, Domestic P-Value: 0.0022136095521039
754
WW Z-score: -0.5062034472092606, WW P-Value: 0.30635691764429224
```

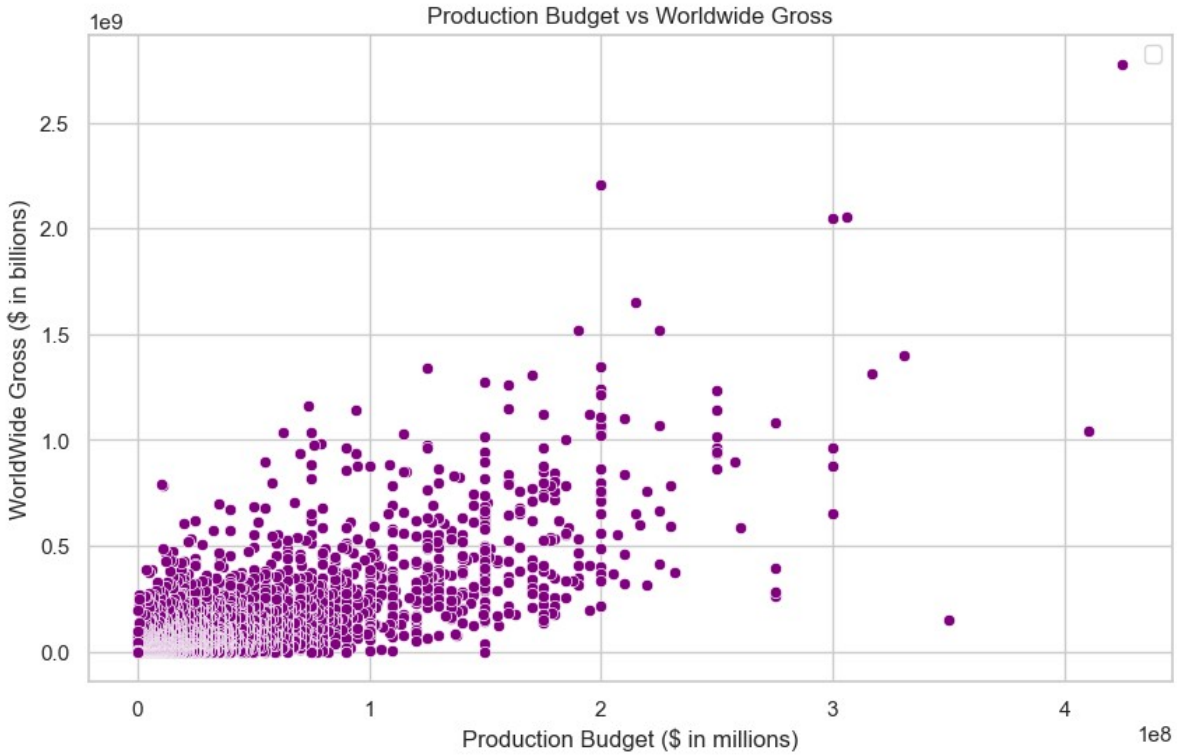
Distribution Plot: Production Budget

```
Purpose: This plot displays the overall distribution of production
budgets across all movies.

Interpretation:
    Peak of the Distribution: Shows where most production budgets l
ie, whether it's in the lower, middle, or higher range.
    KDE Line (Kernel Density Estimation): The smooth curve over the
histogram shows the estimated probability density function, providi
ng a visual understanding of the budget distribution.
    Skewness: If the distribution is skewed to the right, it indica
tes that while most movies have relatively lower budgets, a few mov
ies have very high budgets.
```

In [77]:

```
#set style for plots
sns.set(style='whitegrid')



# # Box Plot for Production Budget, Domestic Gross, and Worldwide Gross
# fig, axes = plt.subplots(1, 3, figsize=(18, 6))

# sns.boxplot(y=synopsis_df['production_budget'], ax=axes[0], color='bl
# axes[0].set_title('Box Plot of Production Budget')
# plt.yscale('log')

# sns.boxplot(y=synopsis_df['domestic_gross'], ax=axes[1], color='green
# axes[1].set_title('Box Plot of Domestic Gross')
# plt.yscale('log')

# sns.boxplot(y=synopsis_df['worldwide_gross'], ax=axes[2], color='red'
# axes[2].set_title('Box Plot of Worldwide Gross')

# plt.tight_layout()
# plt.yscale('log')
# plt.savefig('Boxplots')
# plt.show()

# Scatter Plot for Production Budget vs Gross
fig, ax = plt.subplots(figsize=(10, 6))
sns.scatterplot(x=synopsis_df['production_budget'], y=synopsis_df['worl
ax.set_title('Production Budget vs Worldwide Gross')
ax.set_xlabel('Production Budget ($ in millions)')
ax.set_ylabel('WorldWide Gross ($ in billions)')
plt.legend()
plt.savefig('Scatterplot production vs gross')
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose la
bel start with an underscore are ignored when legend() is called with no a
rgument.
```



Scatter Plot: Production Budget vs. Worldwide Gross

```
Purpose: This plot helps visualize the relationship between a movie
's production budget and its worldwide gross revenue.

Interpretation:
    Positive correlation: If most points trend upwards from left to
right, it suggests that movies with higher production budgets tend
to earn more worldwide.
    Outliers: Points that deviate significantly from the trend line
(e.g., high budget with low gross or low budget with high gross) in
dicate movies that either overperformed or underperformed relative
to their budgets.
```

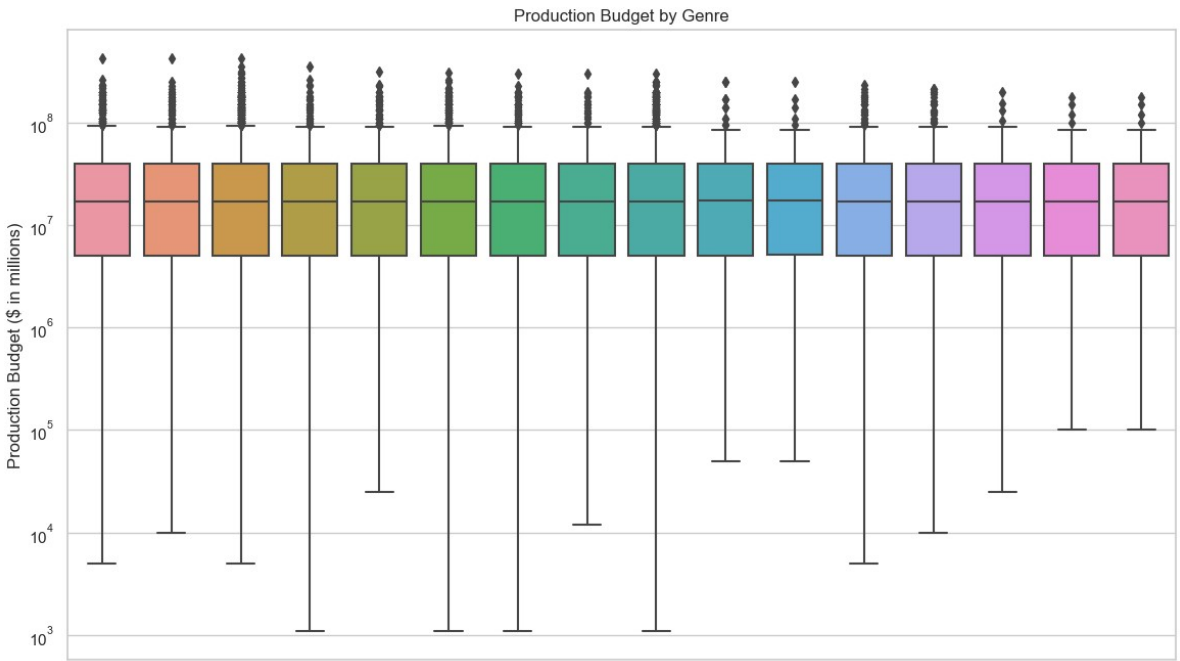
Production budget by Genre

Purpose: This plot shows how production budgets vary across different movie genres.
Interpretation:

```
Genre Comparison: The plot allows for a comparison of budgets acros
s genres. For instance, genres like "Action" or "Adventure" might s
how higher budgets on average compared to genres like "Drama" or "C
omedy."
Logarithmic Scale: A log scale on the y-axis helps visualize data t
hat spans multiple orders of magnitude, making it easier to compare
genres with vastly different budget ranges.
Outliers: Movies within a genre that have exceptionally high or low
budgets relative to others in the same genre will appear as individ
ual points outside the whiskers.
```

In [78]:

```
plt.figure(figsize=(14,8))
sns.boxplot(data=merged_genres, x='genre', y='production_budget')
plt.title('Production Budget by Genre')
plt.xlabel('Genre')
plt.ylabel('Production Budget ($ in millions)')
plt.xticks(rotation=90)
plt.yscale('log') #use log scale to handle wide rane of budgets
plt.savefig('production Budget by Genre')
plt.show()
```



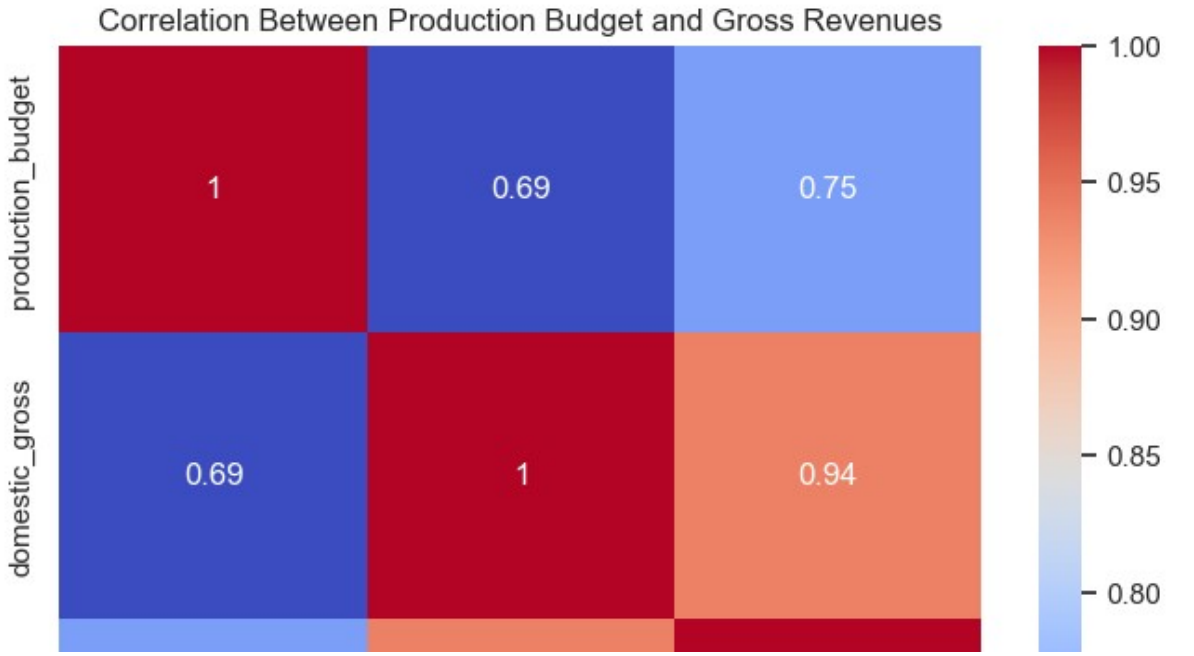
Heatmap: Correlation Between Numeric Variables

This heatmap visualizes the correlation between key numerical variables such as production budget, domestic gross, and worldwide gross. Interpretation:

```
Correlation Coefficients: Values close to 1 indicate a strong posit
ive correlation, values close to -1 indicate a strong negative corr
elation, and values around 0 indicate no correlation.
Color Gradient: The heatmap uses a color gradient to represent the
strength of the correlations. Darker or more intense colors indicat
e stronger correlations.
Insights: For example, a strong positive correlation between produc
tion budget and worldwide gross would suggest that higher-budget mo
vies generally earn more worldwide.
```

In [79]:

```
plt.figure(figsize=(8, 6))
sns.heatmap(synopsis_df[['production_budget', 'domestic_gross', 'worldw
plt.title('Correlation Between Production Budget and Gross Revenues')
plt.savefig('Correlation between Production Budget and Gross Revenues')
plt.show()
```



Group the Data by Directors

To understand the relationship between directors and the budgets/gross values, it might be useful to aggregate the data by directors.

In [81]:

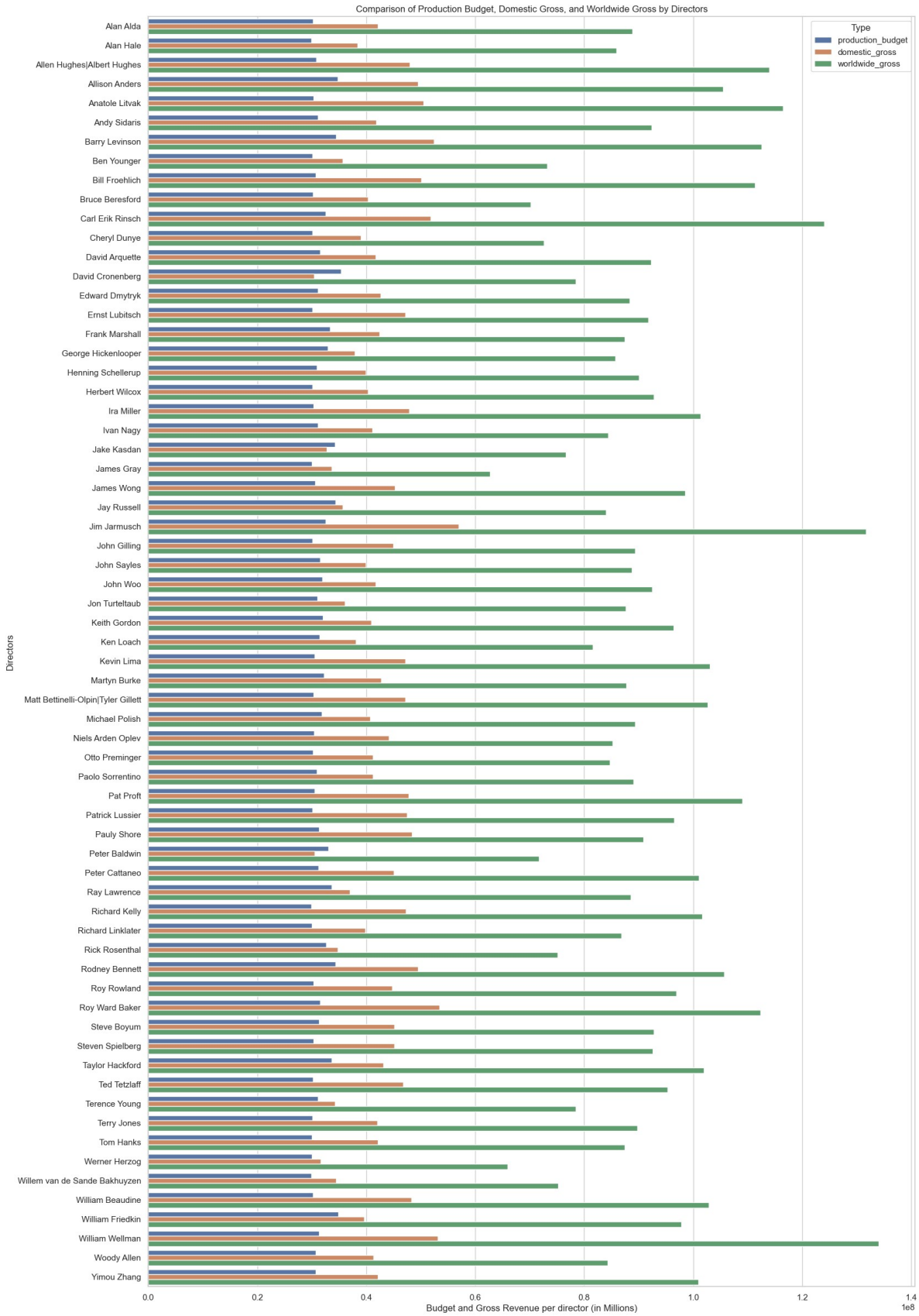
```
# Group by directors and calculate mean of the budgets and gross per di
director_grouped = synopsis_df.groupby('director').agg({
    'production_budget': 'mean',
    'domestic_gross': 'mean',
    'worldwide_gross': 'mean'
}).reset_index()

# Display the aggregated DataFrame
director_grouped.head(10)
```

Out[81]:

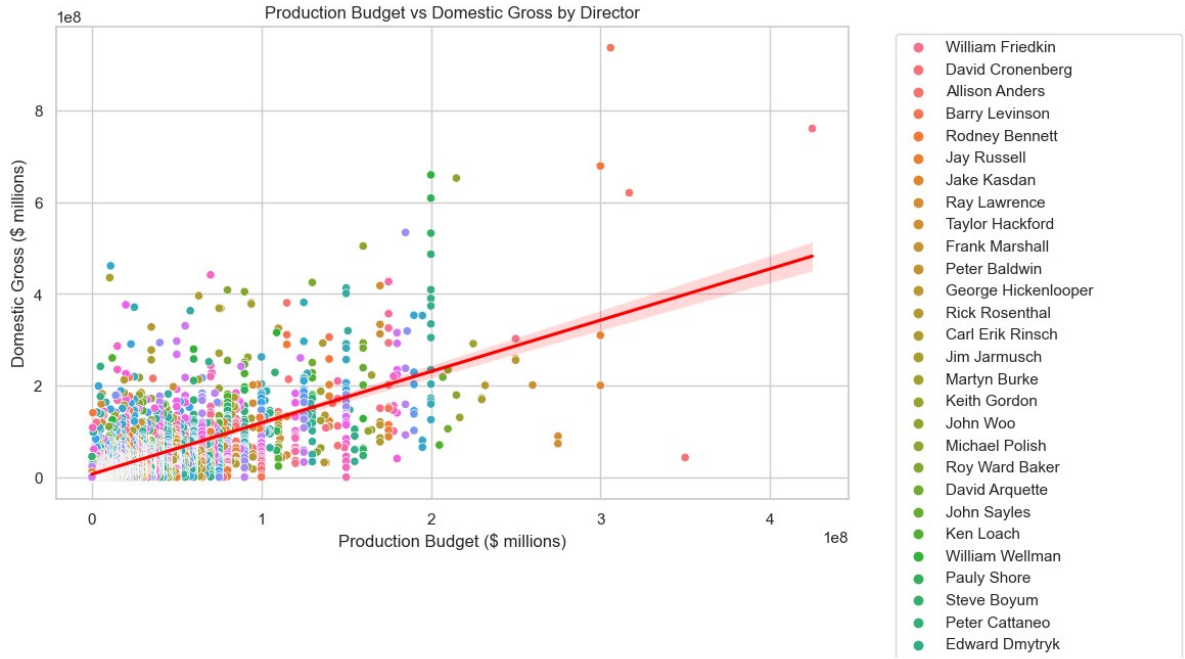
	director	production_budget	domestic_gross	worldwide_gross
0	Alan Alda	3.027216e+07	4.214399e+07	8.887686e+07
1	Alan Hale	2.995821e+07	3.844114e+07	8.587932e+07
2	Allen Hughes|Albert Hughes	3.083160e+07	4.798312e+07	1.139748e+08
3	Allison Anders	3.472362e+07	4.948760e+07	1.054566e+08
4	Anatole Litvak	3.034490e+07	5.054890e+07	1.164315e+08
5	Andy Sidaris	3.112586e+07	4.185722e+07	9.233709e+07
6	Barry Levinson	3.449806e+07	5.244219e+07	1.125342e+08
7	Ben Younger	3.010175e+07	3.571045e+07	7.324444e+07
8	Bill Froehlich	3.071319e+07	5.012949e+07	1.112841e+08
9	Bruce Beresford	3.023153e+07	4.036557e+07	7.016328e+07

In [82]:

```
# Set the plot size
plt.figure(figsize=(18, 30))

# Melt the DataFrame for easier plotting
melted_df = pd.melt(director_grouped, id_vars='director', value_vars=['
# Create a bar plot
sns.barplot(x='Amount', y='director', hue='Type', data=melted_df)

# Add labels and title
plt.xlabel('Budget and Gross Revenue per director (in Millions)')
plt.ylabel('Directors')
plt.title('Comparison of Production Budget, Domestic Gross, and Worldwi
plt.legend(title='Type')
plt.savefig('Budget and Gross based on Director')
plt.show()
```


Comparison of Production Budget, Domestic Gross, and Worldwide Gross by Directors
Type
production_budget
domestic_gross
worldwide_gross
Directors
Alan Alda
Alan Hale
Allen Hughes|Albert Hughes
Allison Anders
Anatole Litvak
Andy Sidaris
Barry Levinson
Ben Younger
Bill Froehlich
Bruce Beresford
Carl Erik Rinsch
Cheryl Dunye
David Arquette
David Cronenberg
Edward Dmytryk
Ernst Lubitsch
Frank Marshall
George Hickenlooper
Henning Schellerup
Herbert Wilcox
Ira Miller
Ivan Nagy
Jake Kasdan
James Gray
James Wong
Jay Russell
Jim Jarmusch
John Gilling
John Sayles
John Woo
Jon Turteltaub
Keith Gordon
Ken Loach
Kevin Lima
Martyn Burke
Matt Bettinelli-Olpin|Tyler Gillett
Michael Polish
Niels Arden Oplev
Otto Preminger
Paolo Sorrentino
Pat Proft
Patrick Lussier
Pauly Shore
Peter Baldwin
Peter Cattaneo
Ray Lawrence
Richard Kelly
Richard Linklater
Rick Rosenthal
Rodney Bennett
Roy Rowland
Roy Ward Baker
Steve Boyum
Steven Spielberg
Taylor Hackford
Ted Tetzlaff
Terence Young
Terry Jones
Tom Hanks
Werner Herzog
Willem van de Sande Bakhuyzen
William Beaudine
William Friedkin
William Wellman
Woody Allen
Yimou Zhang
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1e8
Budget and Gross Revenue per director (in Millions)

In [83]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='domestic_gross', hue='directo
# Add the regression line (without hue distinction)
sns.regplot(x='production_budget', y='domestic_gross', data=synopsis_df
plt.xlabel('Production Budget ($ millions)')
plt.ylabel('Domestic Gross ($ millions)')
plt.title('Production Budget vs Domestic Gross by Director')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

# Save the plot as a PNG file
plt.savefig('production_vs_domestic.png', bbox_inches='tight')
plt.show()
```



In [84]:
```
save_df_to_directory(melted_df, './accessible_data/', 'melted_df.csv')
```

In [85]:
```
# Calculate mean and confidence intervals for each genre
gross_grouped = gross_by_genre.groupby('genres').agg(
    mean_domestic_gross=('total_domestic_gross', 'mean'),
    mean_foreign_gross=('total_foreign_gross', 'mean'),
).reset_index()
gross_grouped
```

Out[85]:

	genres	mean_domestic_gross	mean_foreign_gross
0	Action	1.399706e+10	2.774456e+10
1	Adventure	1.558946e+10	2.950450e+10
2	Animation	5.035712e+09	9.304000e+09
3	Biography	1.866453e+09	2.840872e+09
4	Comedy	1.081684e+10	1.762384e+10
5	Crime	2.041605e+09	2.273621e+09
6	Documentary	2.114256e+09	3.065777e+09
7	Drama	8.987940e+09	1.423651e+10
8	Family	1.305268e+09	2.134300e+09
9	Fantasy	4.473551e+09	9.217900e+09
10	History	1.011006e+09	1.421731e+09
11	Horror	2.948776e+09	4.282648e+09
12	Music	5.215452e+08	1.166302e+09
13	Musical	2.992000e+08	5.592000e+08
14	Mystery	1.358534e+09	2.472247e+09
15	Romance	1.543682e+09	2.343062e+09
16	Sci-Fi	4.184006e+09	7.684300e+09
17	Sport	8.764500e+08	9.262000e+08
18	Thriller	3.094690e+09	6.507454e+09
19	War	3.636000e+06	1.054330e+08
20	Western	3.540000e+05	3.400000e+06

In [86]:
```
save_df_to_directory(gross_grouped, './accessible_data/', 'gross_groupe
```

In [107]:
```
#merge movie_ratings_df and movies_basics_df
merged_df = pd.merge(movie_basics_df, movie_ratings_df, on='movie_id')
merged_df
```

Out[107]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	Documentary
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Drama,Family
73853	tt9914642	Albatross	Albatross	2017	NaN	Documentary
73854	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	NaN	None
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	Documentary

73856 rows × 8 columns

In [108]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [109]:
```
1 merged_df['runtime_minutes'].fillna(merged_df['runtime_minutes'].mean()
```

In [110]:
```
1 merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  73856 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [111]:
```
1 save_df_to_directory(merged_df, './accessible_data/', 'movie_ratings_an
```

In [112]:
```
1 merged_df.describe()
2
```

Out[112]:

	start_year	runtime_minutes	averagerating	numvotes
count	73856.000000	73856.00000	73856.000000	7.385600e+04
mean	2014.276132	94.65404	6.332729	3.523662e+03
std	2.614807	197.52143	1.474978	3.029402e+04
min	2010.000000	3.00000	1.000000	5.000000e+00
25%	2012.000000	83.00000	5.500000	1.400000e+01
50%	2014.000000	93.00000	6.500000	4.900000e+01
75%	2016.000000	101.00000	7.400000	2.820000e+02
max	2019.000000	51420.00000	10.000000	1.841066e+06

In [113]:

```python
# Calculate measures of central tendency and measurements of dispersion
mean_rating = merged_df['averagerating'].mean()
median_rating = merged_df['averagerating'].median()
mode_rating = merged_df['averagerating'].mode()[0]

std_dev_rating = merged_df['averagerating'].std()
variance_rating = merged_df['averagerating'].var()

mean_votes = merged_df['numvotes'].mean()
median_votes = merged_df['numvotes'].median()
mode_votes = merged_df['numvotes'].mode()[0]

std_dev_votes =merged_df['numvotes'].std()
variance_votes = merged_df['numvotes'].var()

print(f"Mean Rating: {mean_rating}")
print(f"Median Rating: {median_rating}")
print(f"Mode Rating: {mode_rating}")
print(f"Standard Deviation of Ratings: {std_dev_rating}")
print(f"Variance of Ratings: {variance_rating}")

print(f"Mean Votes: {mean_votes}")
print(f"Median Votes: {median_votes}")
print(f"Mode Votes: {mode_votes}")
print(f"Standard Deviation of Votes: {std_dev_votes}")
print(f"Variance of Votes: {variance_votes}")
```

```
Mean Rating: 6.332728552859619
Median Rating: 6.5
Mode Rating: 7.0
Standard Deviation of Ratings: 1.4749783548957582
Variance of Ratings: 2.1755611474109973
Mean Votes: 3523.6621669194105
Median Votes: 49.0
Mode Votes: 6
Standard Deviation of Votes: 30294.022971103946
Variance of Votes: 917727827.7737737
```

In [114]:
```
# Split the genres column
merged_df.loc[merged_df.index, 'genres'] = merged_df['genres'].str.spli

# Explode the genres column
exploded_df = merged_df.explode('genres')
exploded_df

```

Out[114]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	average
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Action	
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Crime	
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Drama	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Biography	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Drama	
...	...	...	...	...	...	...	
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.00000	Drama	
		Sokagin	Sokagin				

In [115]:
```
exploded_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 129294 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         129294 non-null  object 
 1   primary_title    129294 non-null  object 
 2   original_title   129294 non-null  object 
 3   start_year       129294 non-null  int64  
 4   runtime_minutes  129294 non-null  float64
 5   genres           128490 non-null  object 
 6   averagerating    129294 non-null  float64
 7   numvotes         129294 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 8.9+ MB
```

In [116]:

```
# Reset the index to avoid issues with duplicate labels
exploded_df.reset_index(drop=True, inplace=True)

# Remove outliers from 'average_rating' and 'num_votes' using Z-score
exploded_df['zscore_rating'] = zscore(exploded_df['averagerating'])
exploded_df['zscore_votes'] = zscore(exploded_df['numvotes'])

# Filter out the outliers
df_cleaned = exploded_df[(exploded_df['zscore_rating'].abs() <= 3) & (e

# Drop the Z-score columns as they are no longer needed
df_cleaned.drop(columns=['zscore_rating', 'zscore_votes'], inplace=True
exploded_df
```

```
C:\Users\omend\AppData\Local\Temp\ipykernel_53724\2703187828.py:12: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
view-versus-a-copy)
  df_cleaned.drop(columns=['zscore_rating', 'zscore_votes'], inplace=True)
```

Out[116]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averag
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Action	
1	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Crime	
2	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Drama	
3	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Biography	
4	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Drama	
...	...	...	...	...	...	...	
129289	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.00000	Drama	
129290	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.00000	Family	
129291	tt9914642	Albatross	Albatross	2017	94.65404	Documentary	
129292	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	94.65404	None	
129293	tt9916160	Drømmeland	Drømmeland	2019	72.00000	Documentary	

129294 rows × 10 columns

In [117]:
```
save_df_to_directory(exploded_df, './accessible_data/', 'exploded_df.cs
```

In [118]:
```
save_df_to_directory(df_cleaned, './accessible_data/', 'df_cleaned.csv'
```

In [119]:
```
# Descriptive Analysis
# Summary statistics
descriptive_stats = df_cleaned.describe()
print(descriptive_stats)
```

```
          start_year  runtime_minutes  averagerating       numvotes
count  127169.000000    127169.000000  127169.000000  127169.000000
mean     2014.225472        94.785825       6.322133    2099.382176
std         2.579389       151.273670       1.421154    9615.463999
min      2010.000000         3.000000       2.000000       5.000000
25%      2012.000000        83.000000       5.400000      16.000000
50%      2014.000000        93.000000       6.400000      62.000000
75%      2016.000000       103.000000       7.300000     392.000000
max      2019.000000     51420.000000      10.000000  119149.000000
```

In [120]:
```
# Group by genres and calculate mean ratings and votes
genre_stats = exploded_df.groupby('genres').agg({'averagerating': 'mean
genre_stats
```

Out[120]:

genres	averagerating	numvotes
Short	8.800000	8.000000
Documentary	7.332090	266.960232
Game-Show	7.300000	1734.500000
News	7.271330	212.986183
Biography	7.162274	5673.259648
Music	7.091972	2771.020833
History	7.040956	2776.406726
Sport	6.961493	3185.601357
War	6.584291	3147.391559
Reality-TV	6.500000	27.000000

In [121]:
```
save_df_to_directory(genre_stats, './accessible_data/', 'Genre_stats.cs
```

Inferential Analysis

In [122]:

```
# Perform a t-test to compare sample mean to population mean
overall_mean_rating = df_cleaned['averagerating'].mean()
t_stat_ratings, p_value_ratings = ttest_1samp(df_cleaned['averagerating

print(f"T-Statistic for Ratings: {t_stat_ratings}")
print(f"P-Value for Ratings: {p_value_ratings}")

overall_mean_votes = df_cleaned['numvotes'].mean()
t_stat_votes, p_value_votes = ttest_1samp(df_cleaned['numvotes'], overa

print(f"T-Statistic for Votes: {t_stat_votes}")
print(f"P-Value for Votes: {p_value_votes}")
```

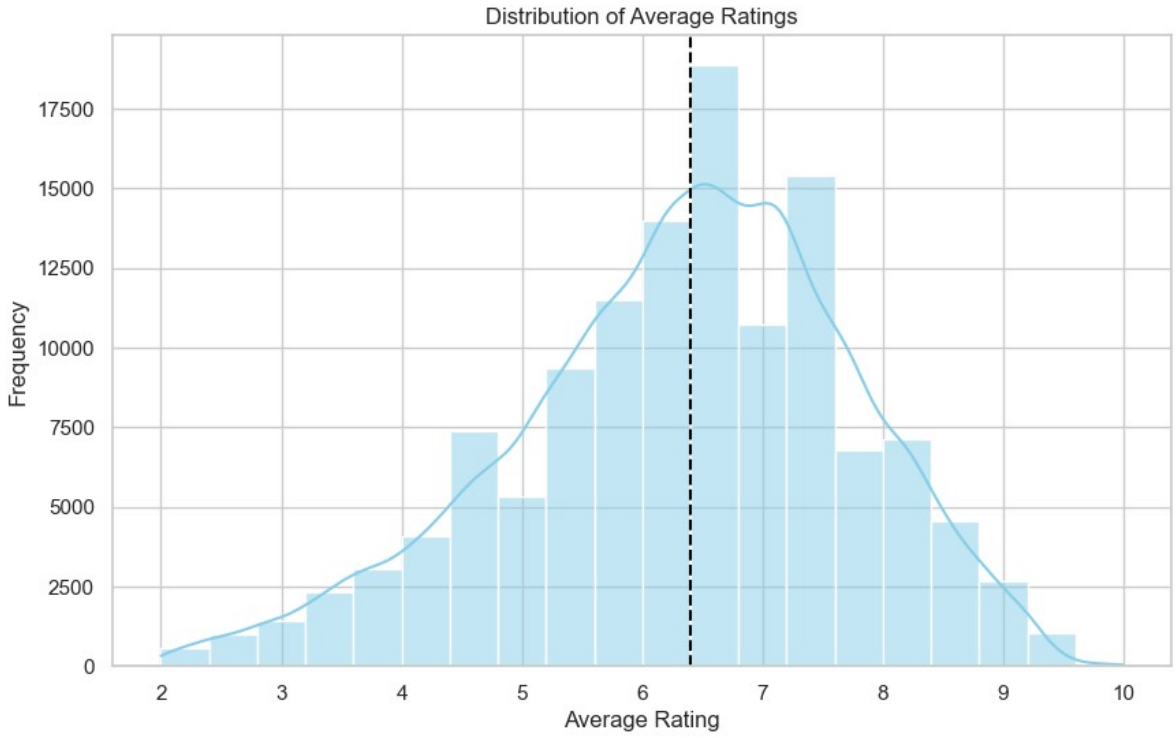
```
T-Statistic for Ratings: 0.0
P-Value for Ratings: 1.0
T-Statistic for Votes: 0.0
P-Value for Votes: 1.0
```

Visualizations

Distribution of average ratings

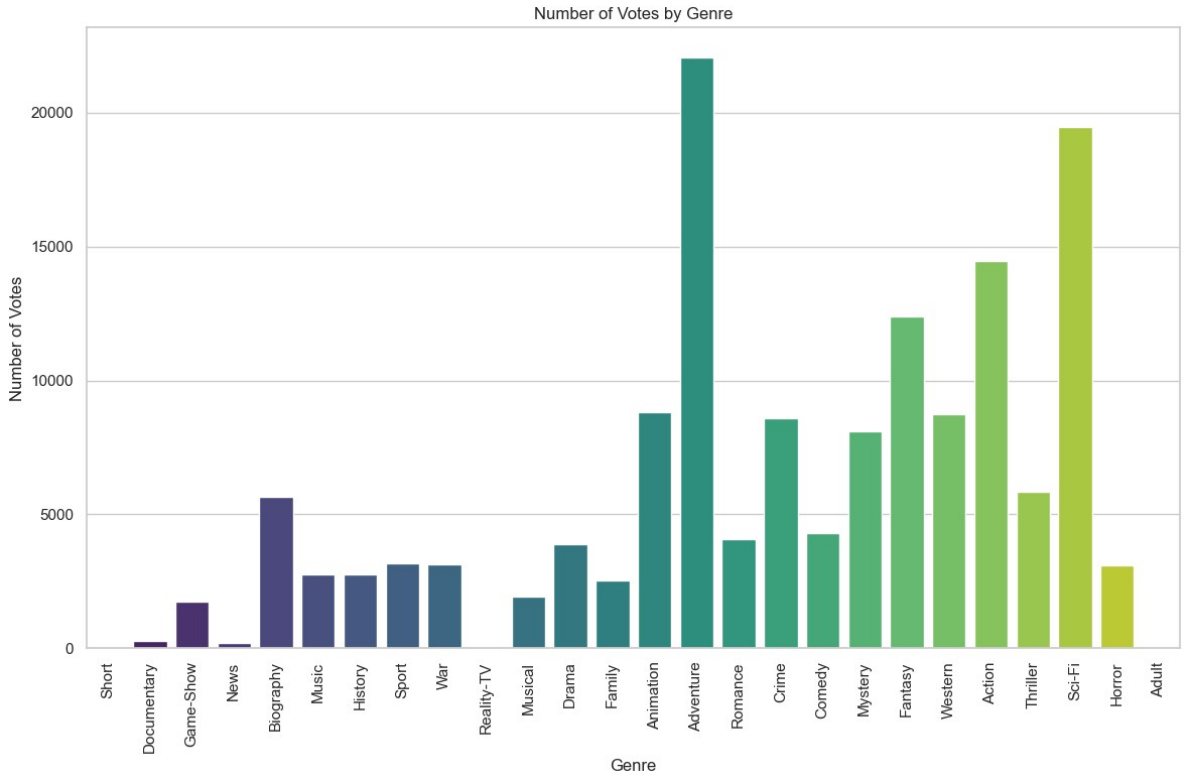
In [125]:
```
1
2 plt.figure(figsize=(10, 6))
3 sns.histplot(df_cleaned['averagerating'], bins=20, kde=True, color='sky
4 plt.title('Distribution of Average Ratings')
5 plt.axvline(x= df_cleaned['averagerating'].median(), linestyle='--', co
6 plt.xlabel('Average Rating')
7 plt.ylabel('Frequency')
8 plt.savefig('Distribution_of_Avg_Ratings')
9 plt.show()
```

```
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



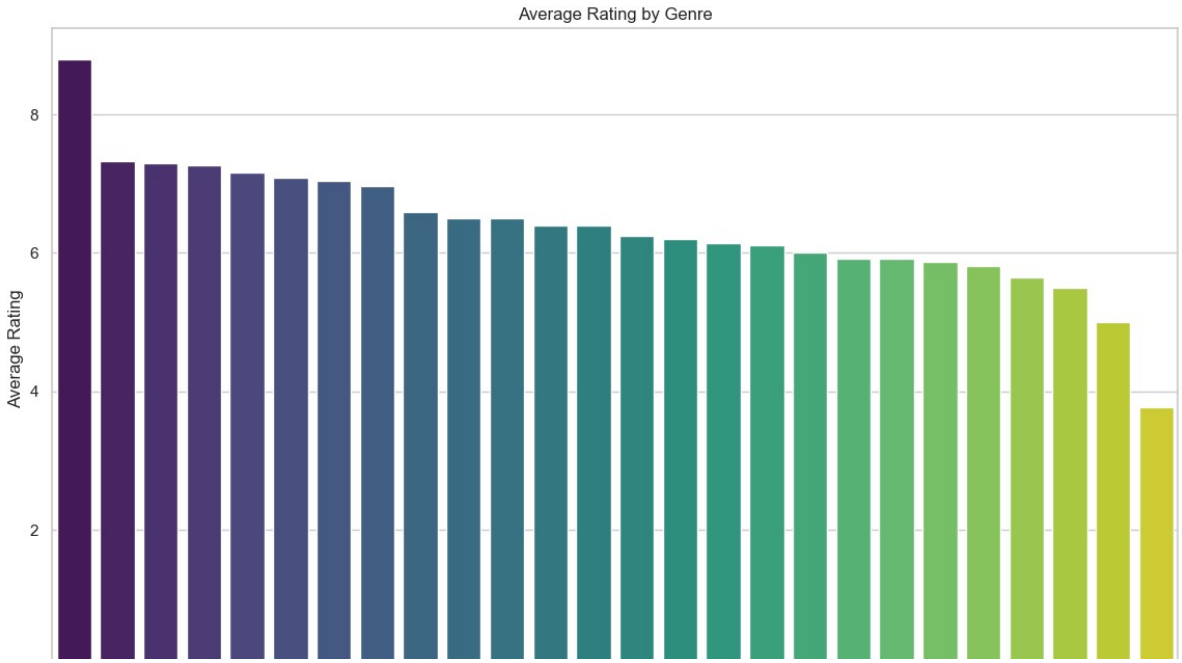
Number of votes by genre

In [126]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x=genre_stats.index, y=genre_stats['numvotes'], palette='vi
plt.xticks(rotation=90)
plt.title('Number of Votes by Genre')
plt.xlabel('Genre')
plt.ylabel('Number of Votes')
plt.savefig('Number_of_Votes_by_genre')
plt.show()
```



Average rating by genre

In [128]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x=genre_stats.index, y=genre_stats['averagerating'], palett
plt.xticks(rotation=90)
plt.title('Average Rating by Genre')
plt.xlabel('Genre')
plt.ylabel('Average Rating')
plt.savefig('Average_rating_by_genre')
plt.show()
```



Calculating descriptive statistics for each genre

Next, we'll try to find the relationship bewtween ratings based on the number of votes for each movie.

In [129]:
```
genre_stats = exploded_df.groupby('genres').agg(
    count=pd.NamedAgg(column='averagerating', aggfunc='count'),
    mean_rating=pd.NamedAgg(column='averagerating', aggfunc='mean'),
    median_rating=pd.NamedAgg(column='averagerating', aggfunc='median')
    mode_rating=pd.NamedAgg(column='averagerating', aggfunc=lambda x: x
    std_dev_rating=pd.NamedAgg(column='averagerating', aggfunc='std'),
    variance_rating=pd.NamedAgg(column='averagerating', aggfunc='var'),
    mean_votes=pd.NamedAgg(column='numvotes', aggfunc='mean'),
    median_votes=pd.NamedAgg(column='numvotes', aggfunc='median'),
    mode_votes=pd.NamedAgg(column='numvotes', aggfunc=lambda x: x.mode(
    std_dev_votes=pd.NamedAgg(column='numvotes', aggfunc='std'),
    variance_votes=pd.NamedAgg(column='numvotes', aggfunc='var')
).reset_index()
genre_stats
```

Out[129]:

	genres	count	mean_rating	median_rating	mode_rating	std_dev_rating	variance_rati
0	Action	6988	5.810361	6.00	6.5	1.513833	2.2916
1	Adult	3	3.766667	3.40	2.0	1.975686	3.9033
2	Adventure	3817	6.196201	6.40	6.6	1.514963	2.2951
3	Animation	1743	6.248308	6.50	6.8	1.353982	1.8332
4	Biography	3809	7.162274	7.20	7.0	1.072788	1.1508
5	Comedy	17290	6.002689	6.10	6.2	1.404156	1.9716
6	Crime	4611	6.115441	6.20	6.5	1.340714	1.7975
7	Documentary	17753	7.332090	7.40	7.2	1.086263	1.1799
8	Drama	30788	6.401559	6.50	6.2	1.277601	1.6322
9	Family	3412	6.394725	6.50	6.5	1.384528	1.9169
10	Fantasy	2126	5.919473	6.00	6.2	1.433940	2.0561

In [130]:
```
save_df_to_directory(genre_stats ,'./accessible_data/','genre_stats.csv
```

In [130]:
```
threshold = 500
filtered_df = merged_df[merged_df['runtime_minutes'] <= threshold]
```

In [131]:
```
1 filtered_df
```

Out[131]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averag
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	[Action, Crime, Drama]	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	[Biography, Drama]	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00000	[Drama]	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	94.65404	[Comedy, Drama]	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00000	[Comedy, Drama, Fantasy]	
...	...	...	...	...	...	...	

In [146]:
```
1 #descriptive statistics
2 avg_rating = np.mean(filtered_df['averagerating'])
3 median_runtime = np.median(filtered_df['runtime_minutes'])
```

In [147]:
```
1 avg_rating
```

Out[147]: 6.332508192725401

In [148]:
```
1 median_runtime
```

Out[148]: 93.0

In [149]:
```
1 save_df_to_directory(filtered_df, './accessible_data/', 'filtered_df.cs
```

In [150]:
```
1 # Function to remove outliers based on IQR
2 def remove_outliers_iqr(df, column):
3     Q1 = df.groupby('genres')[column].transform(lambda x: x.quantile(0.
4     Q3 = df.groupby('genres')[column].transform(lambda x: x.quantile(0.
5     IQR = Q3 - Q1
6     return df[~((df[column] < (Q1 - 1.5 * IQR)) | (df[column] > (Q3 + 1
7
```

In [152]:
```
1 df_no_outliers = remove_outliers_iqr(exploded_df, 'averagerating')
2 df_no_outliers = remove_outliers_iqr(df_no_outliers, 'numvotes')
```

In [153]:
```
# Add inferential statistics: confidence intervals and t-tests
def confidence_interval(data, confidence=0.95):
    n = len(data)
    mean = np.mean(data)
    std_err = np.std(data) / np.sqrt(n)
    margin_of_error = std_err * norm.ppf((1 + confidence) / 2)
    return mean - margin_of_error, mean + margin_of_error
```

In [156]:
```
def add_inferential_stats(df):
    conf_intervals_rating = []
    conf_intervals_votes = []
    t_stats_rating = []
    p_values_rating = []
    t_stats_votes = []
    p_values_votes = []

    for genre in df['genres']:
        data = df_no_outliers[df_no_outliers['genres'] == genre]
        ratings = data['averagerating']
        votes = data['numvotes']

        # Confidence intervals
        conf_intervals_rating.append(confidence_interval(ratings))
        conf_intervals_votes.append(confidence_interval(votes))

        # T-tests (compare sample mean to overall mean)
        overall_mean_rating = df_no_outliers['averagerating'].mean()
        t_stat_rating, p_value_rating = ttest_1samp(ratings, overall_me
        t_stats_rating.append(t_stat_rating)
        p_values_rating.append(p_value_rating)

        overall_mean_votes = df_no_outliers['numvotes'].mean()
        t_stat_votes, p_value_votes = ttest_1samp(votes, overall_mean_v
        t_stats_votes.append(t_stat_votes)
        p_values_votes.append(p_value_votes)

    df['conf_interval_rating'] = conf_intervals_rating
    df['conf_interval_votes'] = conf_intervals_votes
    df['t_stat_rating'] = t_stats_rating
    df['p_value_rating'] = p_values_rating
    df['t_stat_votes'] = t_stats_votes
    df['p_value_votes'] = p_values_votes

add_inferential_stats(genre_stats)

```

```
C:\Users\omend\anaconda3\Lib\site-packages\scipy\stats\_stats_py.py:1103:
RuntimeWarning: divide by zero encountered in divide
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
C:\Users\omend\anaconda3\Lib\site-packages\scipy\stats\_stats_py.py:1103:
RuntimeWarning: invalid value encountered in scalar multiply
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
```

In [157]:
```
# Remove outliers for 'average_rating'
df_no_outliers_ratings = remove_outliers_iqr(exploded_df, 'averageratin

# Remove outliers for 'num_votes'
df_no_outliers_votes = remove_outliers_iqr(exploded_df, 'numvotes')

df_no_outliers_votes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 108531 entries, 0 to 129293
Data columns (total 10 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         108531 non-null  object 
 1   primary_title    108531 non-null  object 
 2   original_title   108531 non-null  object 
 3   start_year       108531 non-null  int64  
 4   runtime_minutes  108531 non-null  float64
 5   genres           107727 non-null  object 
 6   averagerating    108531 non-null  float64
 7   numvotes         108531 non-null  int64  
 8   zscore_rating    108531 non-null  float64
 9   zscore_votes     108531 non-null  float64
dtypes: float64(4), int64(2), object(4)
memory usage: 9.1+ MB
```

In [158]:
```
genre_stats1 = add_inferential_stats(genre_stats)
# Display the updated genre_stats DataFrame
print(genre_stats1)

```

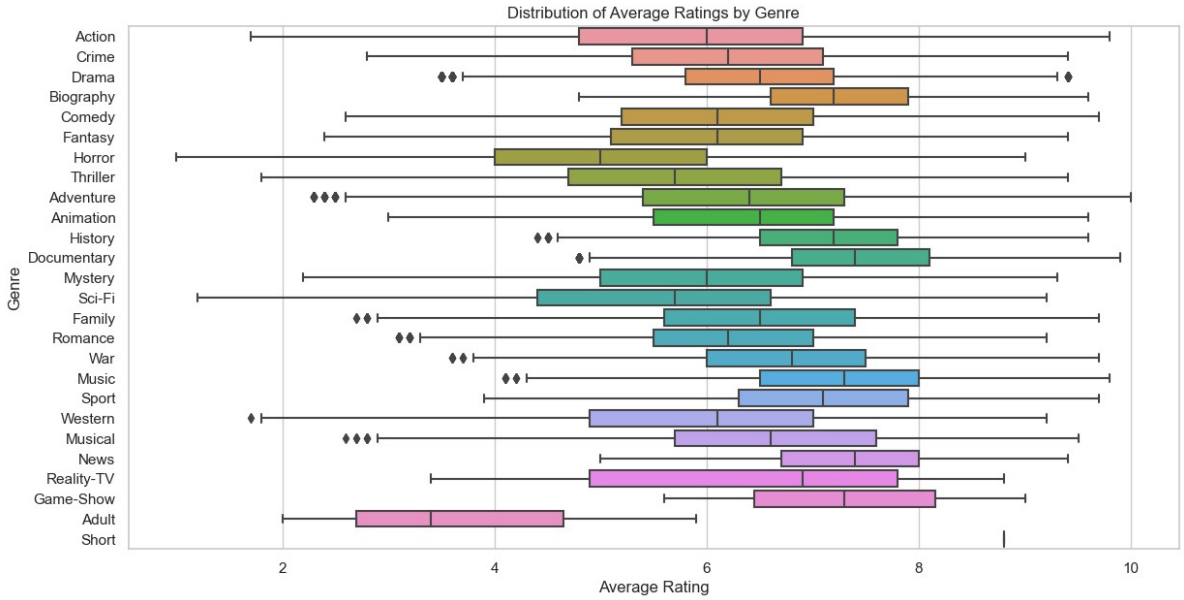
```
None

C:\Users\omend\anaconda3\Lib\site-packages\scipy\stats\_stats_py.py:1103:
RuntimeWarning: divide by zero encountered in divide
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
C:\Users\omend\anaconda3\Lib\site-packages\scipy\stats\_stats_py.py:1103:
RuntimeWarning: invalid value encountered in scalar multiply
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
```

In [143]:
```
save_df_to_directory(genre_stats,'./accessible_data/','infrential_genre
```

In [87]:
```
save_df_to_directory(df_no_outliers_votes, './accessible_data/', 'df_no
```

In [88]:
```
save_df_to_directory(df_no_outliers_ratings, './accessible_data/', 'df_
```

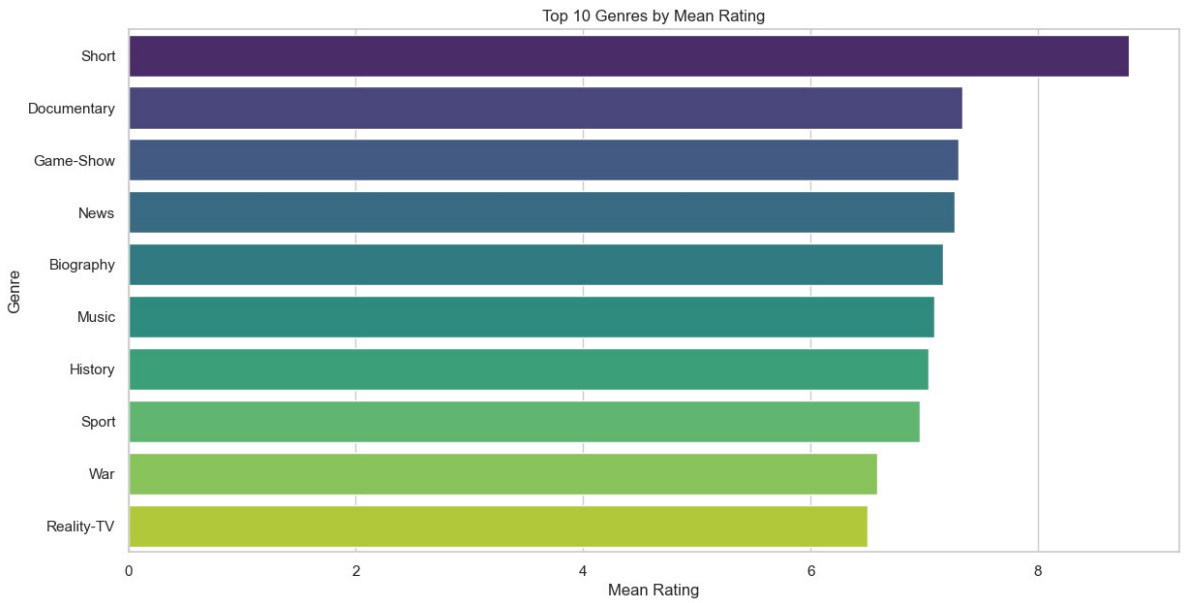
In [159]:
```
# Distribution of average ratings by genre
plt.figure(figsize=(14, 7))
sns.boxplot(x='averagerating', y='genres', data=df_no_outliers_ratings)
plt.title('Distribution of Average Ratings by Genre')
plt.xlabel('Average Rating')
plt.ylabel('Genre')
plt.savefig('Distribution_of_Avg_Ratings_by_Genre')
plt.show()
```

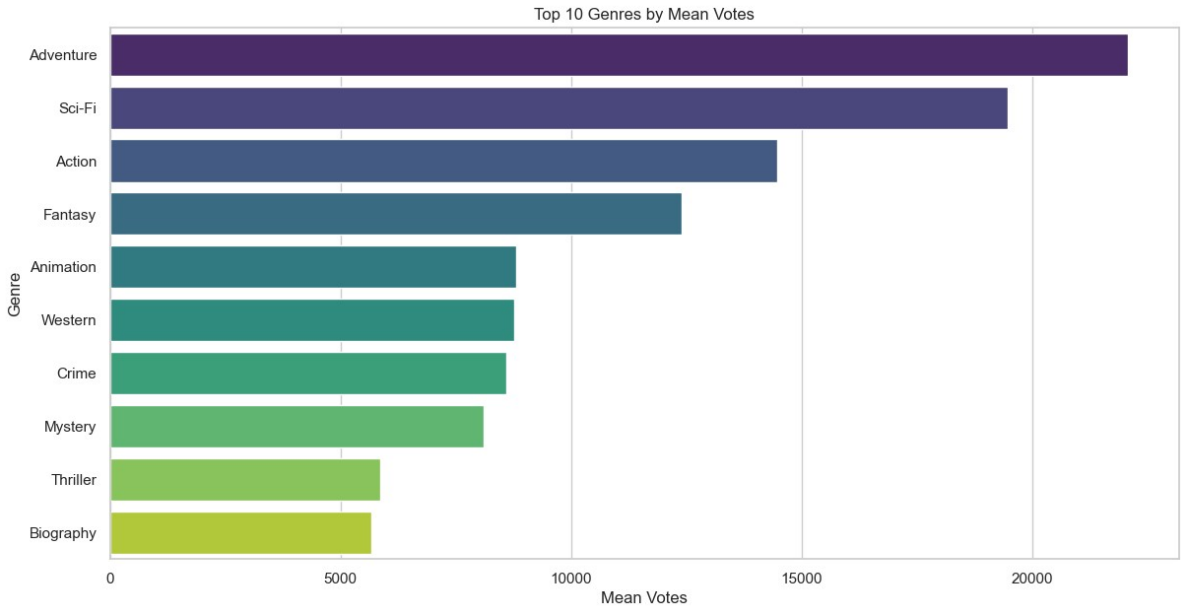


Barplot for top genre based off the Average rating and votes

In [161]:

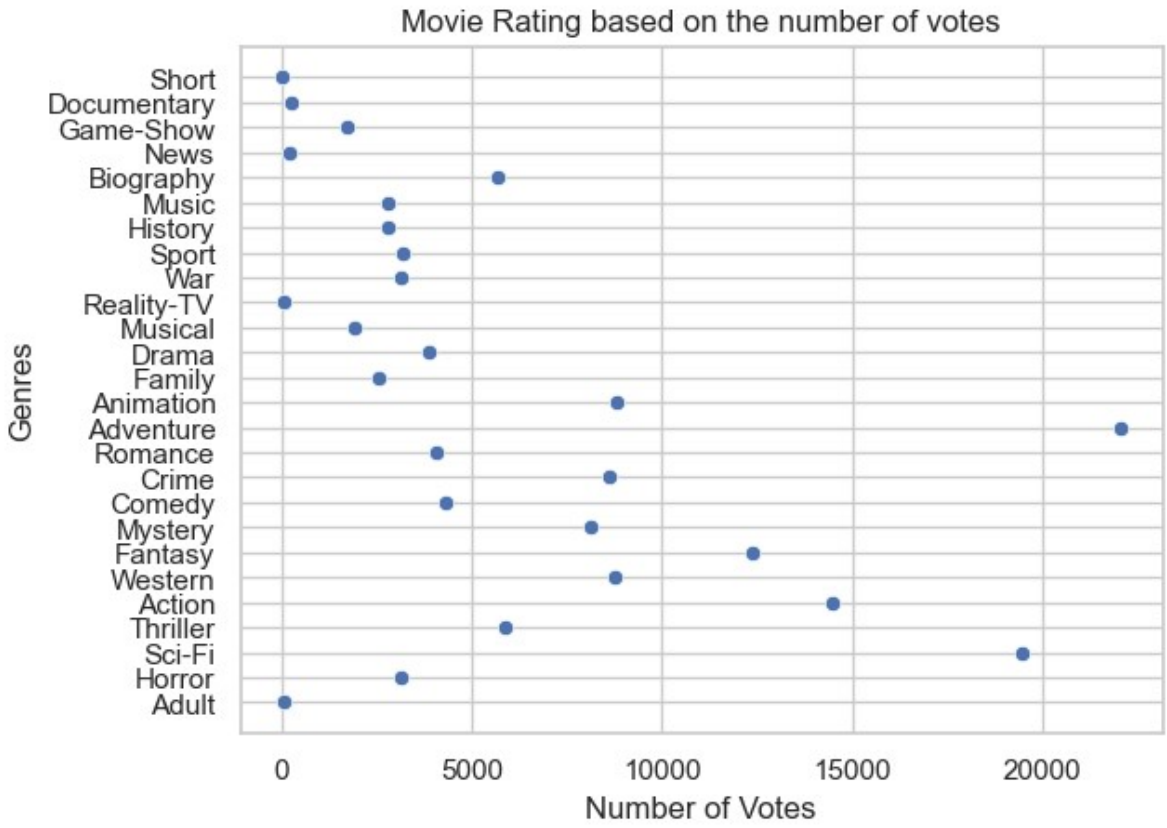
```
# Bar plot for mean ratings by genre
plt.figure(figsize=(14, 7))
top_genres_by_mean_rating = genre_stats.sort_values(by='mean_rating', a
sns.barplot(x='mean_rating', y='genres', data=top_genres_by_mean_rating
plt.title('Top 10 Genres by Mean Rating')
plt.xlabel('Mean Rating')
plt.ylabel('Genre')
plt.savefig('Top_10_Genres_by_mean_rating')
plt.show()

# Bar plot for mean votes by genre
plt.figure(figsize=(14, 7))
top_genres_by_mean_votes = genre_stats.sort_values(by='mean_votes', asc
sns.barplot(x='mean_votes', y='genres', data=top_genres_by_mean_votes,
plt.title('Top 10 Genres by Mean Votes')
plt.xlabel('Mean Votes')
plt.ylabel('Genre')
plt.savefig('Top_10_Genres_by_mean_votes')
plt.show()
```



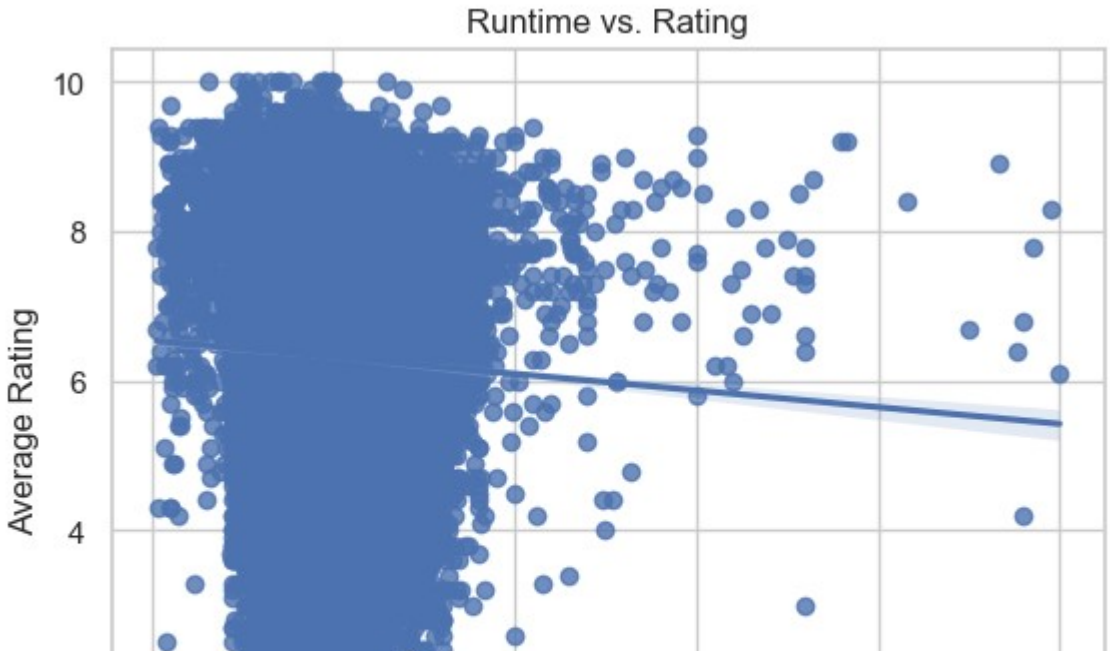


In [144]:

```
#Distribution of movie ratings
sns.scatterplot(x='numvotes', y='genres', data=genre_stats)
plt.title('Movie Rating based on the number of votes')
plt.xlabel('Number of Votes')
plt.ylabel('Genres')
plt.savefig('Distribution_of_movie_ratings')
plt.show()
```



In [165]:
```
#Relationship between runtime and rating
# sns.scatterplot(x='runtime_minutes', y='averagerating', data=filtered
sns.regplot(x='runtime_minutes', y='averagerating', data=filtered_df)
plt.title('Runtime vs. Rating')
plt.xlabel('Runtime (minutes)')
plt.ylabel('Average Rating')
plt.savefig('Runtime_vs_Ratings')
plt.show()
```



Negative correlation between the runtim and ratings given per film. The Longer the movie, the worse the rating will be

Hypothesis testing for genre

In [147]:
```
# Mean rating for all movies
overall_mean_rating = exploded_df['averagerating'].mean()

# T-test for the genre "Drama"
adventure_ratings = exploded_df[exploded_df['genres'] == 'Adventure']['
t_stat_adventure, p_value_adventure = scipy.stats.ttest_1samp(adventure
print(f"T-Statistic for Adventure: {t_stat_adventure}")
print(f"P-Value for Adventure: {p_value_adventure}")

# T-test for the genre "Comedy"
action_ratings = exploded_df[exploded_df['genres'] == 'Sci-Fi']['averag
t_stat_action, p_value_action = scipy.stats.ttest_1samp(action_ratings,
print(f"T-Statistic for Sci-Fi: {t_stat_action}")
print(f"P-Value for Sci-Fi: {p_value_action}")

```

```
T-Statistic for Adventure: -4.369729491424514
P-Value for Adventure: 1.2771016575652236e-05
T-Statistic for Sci-Fi: -24.714002229185088
P-Value for Sci-Fi: 3.0647657212137e-119
```

Correlation Analysis by Genre

Examine the relationship between average rating and number of votes for each genre.

In [148]:
```
# Filter genres with at least two movies for correlation calculation
valid_genres = exploded_df['genres'].value_counts()[exploded_df['genres
df_valid_genres = exploded_df[exploded_df['genres'].isin(valid_genres)]

```

In [149]:
```
valid_genres
```

Out[149]:
```
Index(['Drama', 'Documentary', 'Comedy', 'Thriller', 'Horror', 'Action',
       'Romance', 'Crime', 'Adventure', 'Biography', 'Family', 'Mystery',
       'History', 'Sci-Fi', 'Fantasy', 'Music', 'Animation', 'Sport', 'Wa
r',
       'Musical', 'News', 'Western', 'Reality-TV', 'Adult', 'Game-Show'],
      dtype='object', name='genres')
```

In [150]:
```
1 df_valid_genres
```

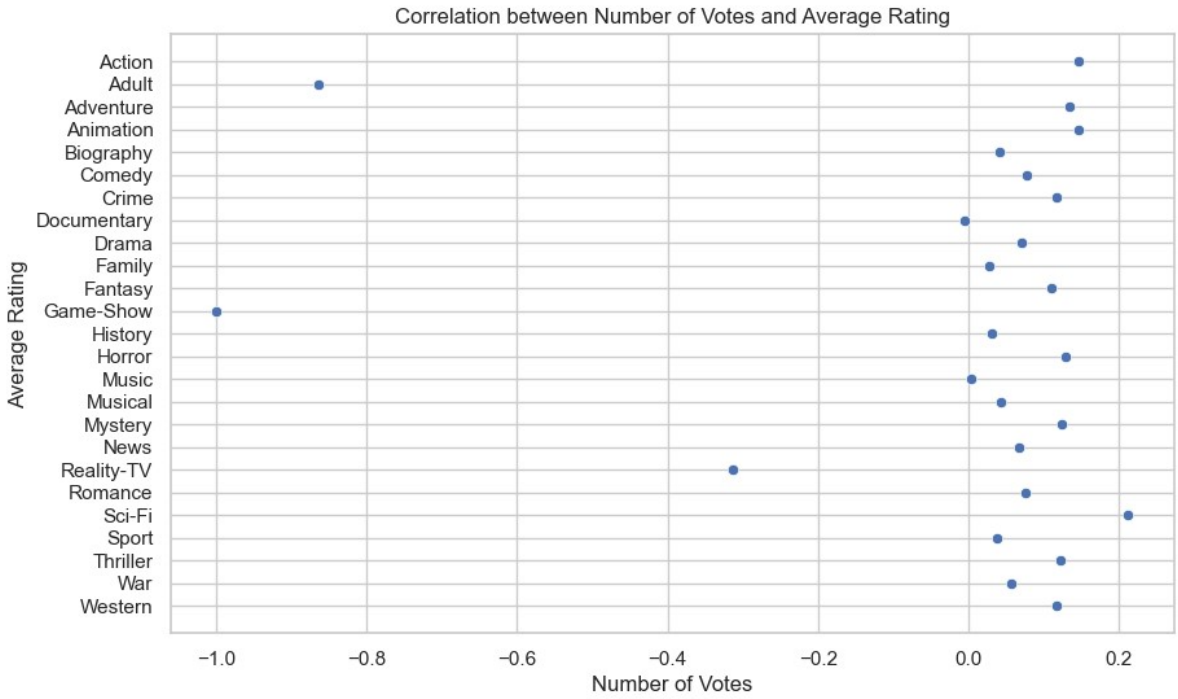
Out[150]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averag
0	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Action	
1	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Crime	
2	tt0063540	Sunghursh	Sunghursh	2013	175.00000	Drama	
3	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Biography	
4	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00000	Drama	
...	...	...	...	...	...	...	
129288	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.00000	Documentary	

In [170]:
```
1 save_df_to_directory(df_valid_genres,'./accessible_data/', 'valid_genre
```

In [185]:

```
# Correlation between average rating and number of votes by genre
correlation_by_genre = df_valid_genres.groupby('genres').apply(
    lambda x: scipy.stats.pearsonr(x['averagerating'], x['numvotes'])[0
).reset_index(name='correlation')

correlation_by_genre

# Scatter plot with regression line for a specific genre (e.g., "Drama"
# for genre in unique_genres:

plt.figure(figsize=(10, 6))
# sns.regplot(x='correlation', y='genres', data=correlation_by_genre)
sns.scatterplot(x='correlation', y='genres', data=correlation_by_genre)
plt.title('Correlation between Number of Votes and Average Rating')
plt.xlabel('Number of Votes')
plt.ylabel('Average Rating')
plt.show()

```



Let's perform the following analyses on the dataset:

1. Sample Analysis
2. Variance
3. Expected Value (Mean)
4. Normal Distribution Fit
5. Z-Score Calculation
6. Significance Testing (Hypothesis Testing)

We'll use the average_rating and num_votes columns from the dataset for these analyses.

In [174]:
```
# Select relevant columns
ratings_votes = exploded_df[['genres','averagerating', 'numvotes']].dro

# Display the first few rows of the dataframe
ratings_votes.head(10)
```

Out[174]:

	genres	averagerating	numvotes
0	Action	7.0	77
1	Crime	7.0	77
2	Drama	7.0	77
3	Biography	7.2	43
4	Drama	7.2	43
5	Drama	6.9	4517
6	Comedy	6.1	13
7	Drama	6.1	13
8	Comedy	6.5	119
9	Drama	6.5	119

Sample Analysis

We'll take a random sample of data for analysis

In [175]:
```
# Take a random sample of 100 data points
sample = ratings_votes.sample(100, random_state=42)

# Display summary statistics for the sample
sample.describe()

```

Out[175]:

	averagerating	numvotes
count	100.000000	100.000000
mean	6.369000	3121.390000
std	1.457388	16486.103584
min	2.400000	5.000000
25%	5.375000	15.500000
50%	6.400000	45.500000
75%	7.300000	514.000000
max	9.100000	156266.000000

In [176]:
```
1 sample
```

Out[176]:

	genres	averagerating	numvotes
64459	Thriller	5.4	13152
115691	Documentary	6.2	32
36286	Comedy	7.1	132
5340	Drama	6.4	1502
44000	Drama	6.7	16
...	...	...	...
27412	Comedy	4.1	685
46594	Documentary	8.2	8
43438	Drama	6.8	523
4652	Thriller	5.3	14049
106704	Thriller	6.3	511

100 rows × 3 columns

In [177]:
```
1 save_df_to_directory(sample, './accessible_data/','ratings_vote_sample.
```

Variance and Expected Value

We'll calculate the variance and expected value (mean) of the sample.

In [178]:
```
1  # Calculate variance and expected value for the sample
2  variance_ratings = sample['averagerating'].var()
3  expected_value_ratings = sample['averagerating'].mean()
4
5  variance_votes = sample['numvotes'].var()
6  expected_value_votes = sample['numvotes'].mean()
7
8  print(f"Variance of Ratings: {variance_ratings}")
9  print(f"Expected Value (Mean) of Ratings: {expected_value_ratings}")
10
11 print(f"Variance of Votes: {variance_votes}")
12 print(f"Expected Value (Mean) of Votes: {expected_value_votes}")
13
```

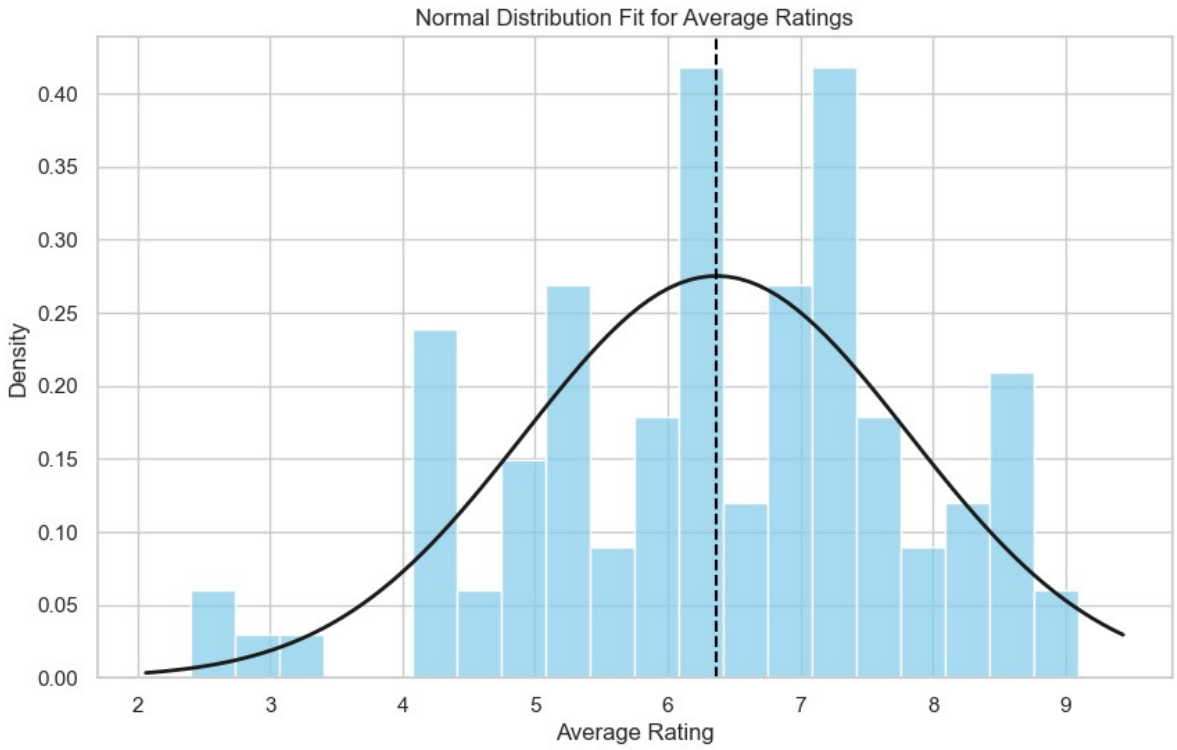
```
Variance of Ratings: 2.1239787878787872
Expected Value (Mean) of Ratings: 6.368999999999999
Variance of Votes: 271791611.39181817
Expected Value (Mean) of Votes: 3121.39
```

Normal Distribution Fit

We'll fit the sample data to a normal distribution and plot the results.

In [181]:
```
# Fit the sample data to a normal distribution
ratings_mean, ratings_std = norm.fit(sample['averagerating'])
votes_mean, votes_std = norm.fit(sample['numvotes'])

# Plot the normal distribution fit for average ratings
plt.figure(figsize=(10, 6))
sns.histplot(sample['averagerating'], bins=20, kde=False, color='skyblu
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
p = norm.pdf(x, ratings_mean, ratings_std)
plt.plot(x, p, 'k', linewidth=2)
plt.title('Normal Distribution Fit for Average Ratings')
plt.axvline(x=sample['averagerating'].mean(), linestyle='--', color='bl
plt.xlabel('Average Rating')
plt.ylabel('Density')
plt.savefig('Normal Distribution fit for average ratings')
plt.show()
```

```
C:\Users\omend\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: Futur
eWarning: use_inf_as_na option is deprecated and will be removed in a futu
re version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Z-Score Calculation

We'll calculate the Z-scores for the sample data.

In [182]:
```
# Calculate Z-scores for the sample data

sample['zscore_ratings'] =  (sample['averagerating'] - sample['averager
sample['zscore_votes'] = (sample['numvotes'] - sample['numvotes'].mean(

# Display the first few rows with Z-scores
sample.head()

```

Out[182]:

	genres	averagerating	numvotes	zscore_ratings	zscore_votes
64459	Thriller	5.4	13152	-0.664888	0.608428
115691	Documentary	6.2	32	-0.115961	-0.187394
36286	Comedy	7.1	132	0.501582	-0.181328
5340	Drama	6.4	1502	0.021271	-0.098228
44000	Drama	6.7	16	0.227119	-0.188364

Significance Testing

Perform a t-test to compare the sample mean to the population mean.

In [183]:
```
# Perform a t-test for the average ratings
overall_mean_rating = sample['averagerating'].mean()
t_stat_ratings, p_value_ratings = ttest_1samp(sample['averagerating'],

print(f"T-Statistic for Ratings: {t_stat_ratings}")
print(f"P-Value for Ratings: {p_value_ratings}")

# Perform a t-test for the number of votes
overall_mean_votes = sample['numvotes'].mean()
t_stat_votes, p_value_votes = ttest_1samp(sample['numvotes'], overall_m

print(f"T-Statistic for Votes: {t_stat_votes}")
print(f"P-Value for Votes: {p_value_votes}")

```

```
T-Statistic for Ratings: 0.0
P-Value for Ratings: 1.0
T-Statistic for Votes: 0.0
P-Value for Votes: 1.0
```

In [184]:

```
# Set the alpha value
alpha = 0.05

# Interpretation for average ratings
if p_value_ratings < alpha:
    print(f"Reject the null hypothesis for average ratings (p-value: {p
else:
    print(f"Fail to reject the null hypothesis for average ratings (p-v

# Interpretation for number of votes
if p_value_votes < alpha:
    print(f"Reject the null hypothesis for number of votes (p-value: {p
else:
    print(f"Fail to reject the null hypothesis for number of votes (p-v

```

```
Fail to reject the null hypothesis for average ratings (p-value: 1.0 >= al
pha: 0.05)
Fail to reject the null hypothesis for number of votes (p-value: 1.0 >= al
pha: 0.05)
```

Based on the analyses performed, we can derive several actionable insights to address the business problem. Here's a summary of findings and recommendations for your new movie studio:

1. Popular Genres

From the data, we observed the following trends in genres:

    Top Genres by Total Gross: Genres like Adventure, ACtion, Scifi consistently shows the highest total gross, both domestically and internationally.
    Top Genres by Mean Rating: Genres like Adventure, Scifi, and Shorts have higher average ratings. These genres tend to be critically acclaimed.
    Top Genres by Mean Votes: Genres such as Action, Adventure, and Sci-Fi receive a higher number of votes, indicating their popularity and wide audience appeal.

Recommendation:

Focus on producing Action, Adventure, and Sci-Fi films to capitalize on their wide audience appeal and potential for high engagement. Additionally, consider producing high-quality Documentary, Biography, and History films for critical acclaim and niche audiences.

2. Average Ratings and Votes

    Films in popular genres like Adventure and Sci-Fi have a substantial number of votes, indicating strong audience interest.
    The mean rating for all movies is approximately balanced, with specific genres like Shorts showing a slight edge in terms of ratings.

Recommendation:

```
Prioritize genres like Adventure and Action, which show both high
engagement and favorable audience ratings. Ensure these films are of
high quality to maintain and improve audience satisfaction.

3. Hypothesis Testing Results

    Z-tests for production bduget and gross revenue, the result is not
statistically significant, as it is much larger than the common
threshold of 0.05 for production bdugets and gross revenue. So we fail
to reject the hypothesis.

    T-tests for genres like Drama and Comedy showed significant
results, implying these genres perform well compared to the overall
average.

### Recommendation:

Invest in Adventure and Sci-Fi genres, as they are likely to perform
well in terms of audience ratings and engagement.

4. Correlation Between Votes and Ratings

    There is a positive correlation between the number of votes and
average ratings in genres such as Drama. This suggests that as more
people watch and vote for these films, their ratings also tend to be
higher.

### Recommendation:

Promote films in genres like Adventure through marketing and
distribution channels to maximize viewership and engagement, which in
turn could positively impact ratings.
Additional Considerations
```

Conclusion

Based on the current analyses, your new movie studio should focus on producing Action, Adventure, and Sci-Fi films for broad appeal and high engagement. Additionally, investing in Drama, Western, and Comedy films, which have shown high gross revenue, noth domestic and foreign, strong audience ratings and votes, is recommended. High-quality productions in Shorts, Documentary, and History genres can also be pursued for critical acclaim.

Further analysis of box office gross data and production costs provide a more comprehensive understanding of the financial aspects, production budgets .

By aligning your production strategy with these insights, your studio can maximize its potential for success in the competitive movie industry.

In [ ]:
```
1
```