Phase_Two_Project / Group one phase 2.ipynb

GatonyeW Graphs bb0ede2 · 41 minutes ago

7209 lines (7209 loc) · 737 KB

Preview Code Blame Raw

Group one

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Project Overview

This project aims to explore key trends in the movie industry, including genres, themes, and audience preferences that are driving box office performance.

1. Business Understanding

As the company ventures into the movie busness it is important to understand the key trends in the industry. These insights will help guide strategic decisions and ensure the new movie studio produces films that resonate with audiences and maximize profitability.

Hypothesis

Ho: There is no significant difference in revenue over number of votes

H1 :There is a significant difference in revenue over number of votes.

Objectives

- To identify the effect of ratings across different genres.
- To determine the genres that generates highest revenue/profit.
- To identify the trends in revenue generation.

2. Data Understanding

The Dataset is obtained from:

- imdb
- Box Offive mojo

The datasets will be merged to obtain a unique dataset that combines attributes from each individual dataset to give the best data to be used for analysis.

The final combined dataset consists of 1873 rows and 14 columns.

Key attributes

- Revenue details: *domestic_gross, foreign_gross*
- Movie details: title, year, runtime, genre, ratings

In [1]:
```
#Import necessary libraries

import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

3. Data Preparation.

- **Preprocesing.**

In [2]:
```
# Loading the DB

im_db = '/content/im.db'

# Open up a connection
conn = sqlite3.connect(im_db)
```

```
# Initialize a cursor
cursor = conn.cursor()
```

In [3]:

```
# Identify tables in our SQL DB

table_name_query = """SELECT name
                      AS 'Table Names'
                      FROM sqlite_master
                      WHERE type='table';"""

pd.read_sql(table_name_query, conn)
```

Out[3]:

	Table Names
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

In [4]:

```
#Check what we have in the movie_basics table

tbl_movie_basic = ''' select * from
movie_basics;'''

# view top 5 records as DF
basic_DF=pd.read_sql(tbl_movie_basic, conn)
basic_DF.head()
```

Out[4]:

	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

In [5]:
```
#Inspect records in the DFtable
basic_DF.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 [6]:
```
basic_DF.duplicated().sum()
```

Out[6]: 0

In [7]:
```
basic_DF.tail()
```

Out[7]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None

146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

In [8]:
```
#Check what we have in the movie_basics table

tbl_movie_rating = ''' select * from
movie_ratings;'''

# view top 5 records as DF
rating_DF = pd.read_sql(tbl_movie_rating, conn)
rating_DF.head()
```

Out[8]:

	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

In [9]:
```
rating_DF.tail()
```

Out[9]:

	movie_id	averagerating	numvotes
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

In [10]:
```
#Inspect records in the DFrating
rating_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 [11]:
```
rating_DF.duplicated().sum()
```

Out[11]: 0

In [12]:
```
BR = ''' select * from
movie_basics mb
Left Join movie_ratings mr
on mb.movie_id=mr.movie_id

;'''
```

In [13]:
```
pd.read_sql(BR, conn)
```

Out[13]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id	averagerating	r
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	tt0063540	7.0	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	tt0066787	7.2	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	tt0069049	6.9	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	tt0069204	6.1	
4	tt0100275	The Wandering	La Telenovela	2017	80.0	Comedy,Drama,Fantasy	tt0100275	6.5	

		Soap Opera	Errante					
...	...	...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama	None	NaN
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary	None	NaN
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy	None	NaN
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None	None	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary	None	NaN

146144 rows × 9 columns

In [14]:
```
combined_table=pd.read_sql(BR, conn)
combined_table.isna().sum()
#no_id = combined_table[combined_table['movie_id'].isna()]
#no_id
```

Out[14]:

	0
movie_id	0
primary_title	0
original_title	21
start_year	0
runtime_minutes	31739
genres	5408
movie_id	72288

averagerating	72288
numvotes	72288

dtype: int64

In [15]:
```
combined_table.duplicated().sum()
```

Out[15]:
```
0
```

In [16]:
```
#Load the CSV file
csvfile = pd.read_csv('./bom.movie_gross.csv.gz')
csvfile.head()
```

Out[16]:

	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

In [17]:
```
csvfile.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 [18]:
```
#Merge with the DF from the SQLite on the common field.

mergedDF= pd.merge(combined_table,csvfile,
                   left_on=['primary_title','start_year'] ,
                   right_on=['title','year'])
mergedDF
```

Out[18]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id	averagerati
0	tt0315642	Wazir	Wazir	2016	103.0	Action,Crime,Drama	tt0315642	
1	tt0337692	On the Road	On the Road	2012	124.0	Adventure,Drama,Romance	tt0337692	
2	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	tt0359950	
3	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drama	tt0365907	
4	tt0369610	Jurassic World	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	tt0369610	
...	...	...	...	...	...	...	...	
1868	tt8878922	They Shall Not Grow Old	They Shall Not Grow Old	2018	47.0	Biography,Documentary,History	None	N
1869	tt9042690	The Negotiation	The Negotiation	2018	89.0	Documentary,History,War	tt9042690	
1870	tt9078374	Last Letter	Ni hao, Zhihua	2018	114.0	Drama,Romance	tt9078374	
1871	tt9151704	Burn the Stage: The Movie	Burn the Stage: The Movie	2018	84.0	Documentary,Music	tt9151704	
1872	tt9461382	Colette	Colette	2018	29.0	Documentary,Mystery	None	N

1873 rows × 14 columns

The data is merged to obtain a combined dataset to be used for analysis

In [19]:
```
#Keep necessary columns
mergedDF = mergedDF.loc[:, ~mergedDF.columns.duplicated()]
mergedDF.columns
```

Out[19]:
```
Index(['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'averagerating', 'numvotes', 'title',
       'studio', 'domestic_gross', 'foreign_gross', 'year'],
      dtype='object')
```

In [20]:
```
DF=mergedDF[['movie_id','primary_title','runtime_minutes', 'genres','averagerating', 'numvotes',
       'studio', 'domestic_gross', 'foreign_gross', 'year']]
```

In [21]:
```
DF.head()
```

Out[21]:

	movie_id	primary_title	runtime_minutes	genres	averagerating	numvotes	studio	domestic_gross	fore
0	tt0315642	Wazir	103.0	Action,Crime,Drama	7.1	15378.0	Relbig.	1100000.0	
1	tt0337692	On the Road	124.0	Adventure,Drama,Romance	6.1	37886.0	IFC	744000.0	
2	tt0359950	The Secret Life of Walter Mitty	114.0	Adventure,Comedy,Drama	7.3	275300.0	Fox	58200000.0	
3	tt0365907	A Walk Among the Tombstones	114.0	Action,Crime,Drama	6.5	105116.0	Uni.	26300000.0	
4	tt0369610	Jurassic World	124.0	Action,Adventure,Sci-Fi	7.0	539338.0	Uni.	652300000.0	

In [22]:
```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1873 entries, 0 to 1872
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         1873 non-null   object 
 1   primary_title    1873 non-null   object 
 2   runtime_minutes  1863 non-null   float64
 3   genres           1871 non-null   object 
 4   averagerating    1847 non-null   float64
 5   numvotes         1847 non-null   float64
 6   studio           1871 non-null   object 
 7   domestic_gross   1863 non-null   float64
 8   foreign_gross    1278 non-null   object 
 9   year             1873 non-null   int64  
dtypes: float64(4), int64(1), object(5)
memory usage: 146.5+ KB
```

In [23]:

```
# Convert the Dtypes of numeric vaiables accordingly

DF['runtime_minutes']=DF['runtime_minutes'].astype(float)

DF['averagerating']=DF['averagerating'].astype(float)
DF['numvotes']=DF['numvotes'].astype(float)

DF['domestic_gross']=DF['domestic_gross'].astype(float)
DF['foreign_gross'] = pd.to_numeric(DF['foreign_gross'], errors='coerce')
DF['foreign_gross']=DF['foreign_gross'].astype(float)
DF['year'] = pd.to_numeric(DF['year'], errors='coerce')
DF['year']=DF['year'].astype(int)
```

In [24]:

```
DF.isnull().sum()
```

Out[24]:

	0
movie_id	0
primary_title	0
runtime_minutes	10
genres	2
averagerating	26

numvotes	26
studio	2
domestic_gross	10
foreign_gross	599
year	0

dtype: int64

In [25]:
```
# Drop all movies without title
DF=DF.dropna(subset=['movie_id'])
```

In [26]:
```
DF.isnull().sum()
```

Out[26]:

	0
movie_id	0
primary_title	0
runtime_minutes	10
genres	2
averagerating	26
numvotes	26
studio	2
domestic_gross	10
foreign_gross	599
year	0

dtype: int64

In [27]:
```
DF.describe()
```

Out[27]:

	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	year
count	1863.000000	1847.000000	1.847000e+03	1.863000e+03	1.274000e+03	1873.000000
mean	110.331186	6.422794	9.166869e+04	4.236055e+07	9.511677e+07	2014.002670
std	20.480174	1.004203	1.502088e+05	7.683175e+07	1.523659e+08	2.516716
min	5.000000	1.600000	6.000000e+00	3.000000e+02	6.000000e+02	2010.000000
25%	96.000000	5.800000	7.642000e+03	5.520000e+05	7.400000e+06	2012.000000
50%	107.000000	6.500000	3.546500e+04	1.050000e+07	3.130000e+07	2014.000000
75%	122.000000	7.100000	1.055535e+05	5.150000e+07	1.033750e+08	2016.000000
max	189.000000	8.800000	1.841066e+06	7.001000e+08	9.464000e+08	2018.000000

In [28]:
```
# Let add a  column that aggregates the total income but first replace missing of these columns with zero to allow
DF['domestic_gross'] = DF['domestic_gross'].fillna(0)
DF['foreign_gross'] = DF['foreign_gross'].fillna(0)
DF['Total_Revenue']=DF['domestic_gross'] + DF['foreign_gross']
DF.head()
```

Out[28]:

	movie_id	primary_title	runtime_minutes	genres	averagerating	numvotes	studio	domestic_gross	fore
0	tt0315642	Wazir	103.0	Action,Crime,Drama	7.1	15378.0	Relbig.	1100000.0	
1	tt0337692	On the Road	124.0	Adventure,Drama,Romance	6.1	37886.0	IFC	744000.0	
2	tt0359950	The Secret Life of Walter Mitty	114.0	Adventure,Comedy,Drama	7.3	275300.0	Fox	58200000.0	12
3	tt0365907	A Walk Among the Tombstones	114.0	Action,Crime,Drama	6.5	105116.0	Uni.	26300000.0	2
4	tt0369610	Jurassic World	124.0	Action,Adventure,Sci-Fi	7.0	539338.0	Uni.	652300000.0	

In [29]:
```
def RT_band(runtime_minutes):
    if(runtime_minutes <=60):
        return("1 hr and below")
    elif (runtime_minutes >60 and runtime_minutes <=120):
        return("Approx 2 hrs")
    elif (runtime_minutes >120 and runtime_minutes <=180):
        return("Approx 3 hrs")
    else:
         return("Over 3 hrs")
```

In [30]:
```
DF['RT_band']=DF['runtime_minutes'].apply(RT_band)
DF.head(3)
```

Out[30]:

	movie_id	primary_title	runtime_minutes	genres	averagerating	numvotes	studio	domestic_gross	fore
0	tt0315642	Wazir	103.0	Action,Crime,Drama	7.1	15378.0	Relbig.	1100000.0	
1	tt0337692	On the Road	124.0	Adventure,Drama,Romance	6.1	37886.0	IFC	744000.0	
2	tt0359950	The Secret Life of Walter Mitty	114.0	Adventure,Comedy,Drama	7.3	275300.0	Fox	58200000.0	12

In [31]:
```
#Recheck if we still have missing
missing_cols = DF.isnull().sum()[DF.isnull().sum() > 0]
missing_cols
```

Out[31]:

	0
runtime_minutes	10
genres	2
averagerating	26
numvotes	26

studio 2

dtype: int64

- **Feature Engineering.**

In [32]:
```
# Lets check the distribution of the numerical variables before deciding the missing replacement method
```

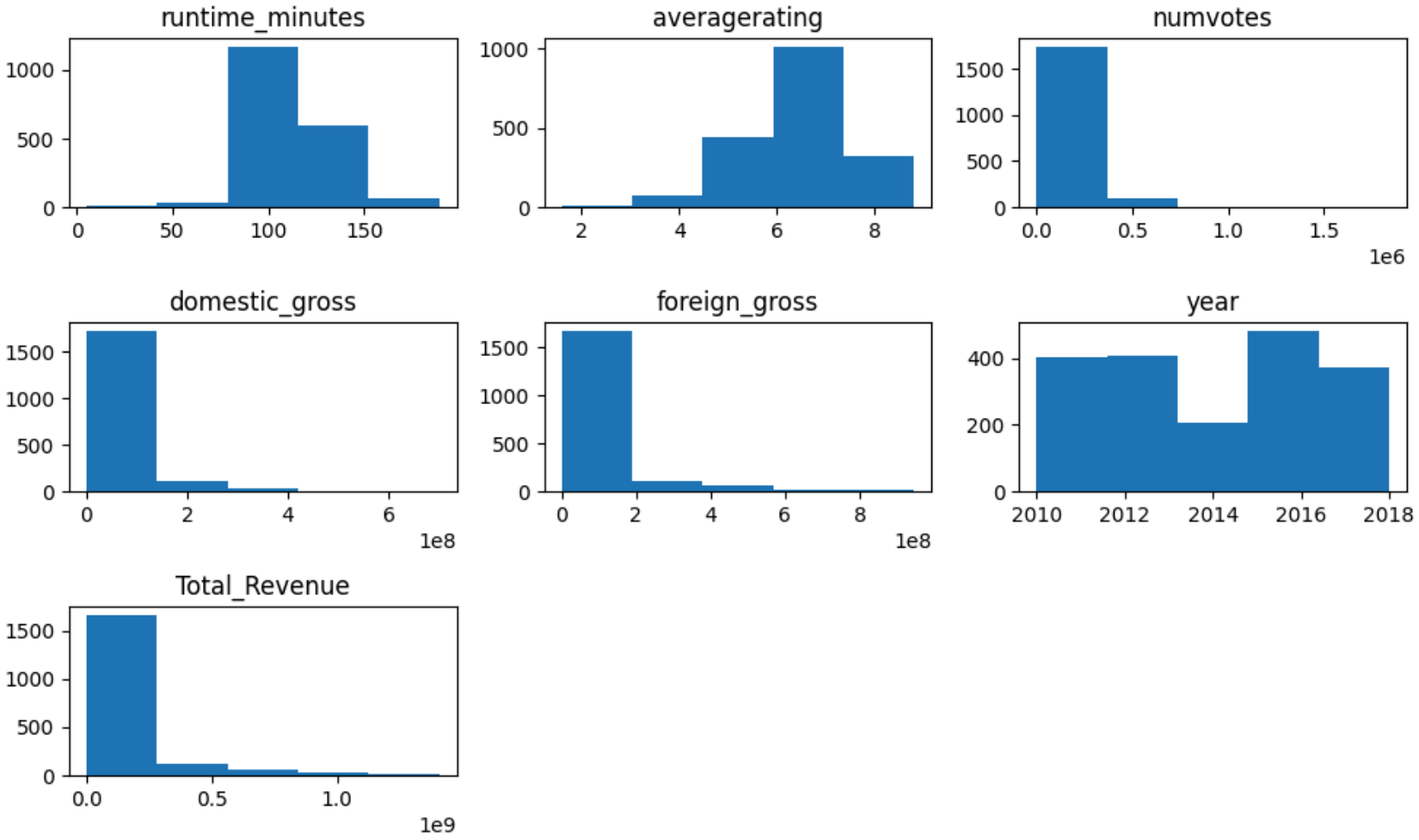
In [33]:
```
num_vars= DF.select_dtypes('number')
num_vars.head(10)
```

Out[33]:

	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	year	Total_Revenue
0	103.0	7.1	15378.0	1100000.0	0.0	2016	1100000.0
1	124.0	6.1	37886.0	744000.0	8000000.0	2012	8744000.0
2	114.0	7.3	275300.0	58200000.0	129900000.0	2013	188100000.0
3	114.0	6.5	105116.0	26300000.0	26900000.0	2014	53200000.0
4	124.0	7.0	539338.0	652300000.0	0.0	2015	652300000.0
5	119.0	6.2	94787.0	13100000.0	10800000.0	2011	23900000.0
6	108.0	6.1	12898.0	544000.0	0.0	2016	544000.0
7	92.0	5.1	28570.0	44300000.0	10500000.0	2012	54800000.0
8	100.0	7.8	366366.0	200800000.0	391000000.0	2010	591800000.0
9	132.0	6.6	241792.0	73100000.0	211100000.0	2012	284200000.0

In [34]:
```
#Plot the distributions
import matplotlib.pyplot as plt

num_vars.hist(bins=5, figsize=(10, 6), grid=False)

# Show the plots
```

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



Based on the above, Runtime and Num votes are negatively and positively skewed respectively and therefore we use the median to input the missing. While average rating exhibit almost a normal distribution, therefore we use the mean to input the missing.

In [35]:
```
DF['runtime_minutes']=DF['runtime_minutes'].fillna(DF['runtime_minutes'].median())
DF['numvotes']=DF['numvotes'].fillna(DF['numvotes'].median())
```

In [36]:
```
DF['averagerating']=DF['averagerating'].fillna(DF['averagerating'].mean())
```

In [37]:
```
# Confirm no more missing
missing_cols = DF.isnull().sum()[DF.isnull().sum() > 0]
missing_cols
```

Out[37]:

	0
genres	2
studio	2

dtype: int64

In [38]:
```
#Create the non numeric dataset
cat_vars= DF.select_dtypes(exclude='number')
cat_vars.head(3)
```

Out[38]:

	movie_id	primary_title	genres	studio	RT_band
0	tt0315642	Wazir	Action,Crime,Drama	Relbig.	Approx 2 hrs
1	tt0337692	On the Road	Adventure,Drama,Romance	IFC	Approx 3 hrs
2	tt0359950	The Secret Life of Walter Mitty	Adventure,Comedy,Drama	Fox	Approx 2 hrs

In [39]:
```
cat_vars.describe()
```

Out[39]:

	movie_id	primary_title	genres	studio	RT_band
count	1873	1873	1871	1871	1873
unique	1873	1833	262	165	4
top	tt0315642	The Wall	Drama	Uni.	Approx 2 hrs
freq	1	3	100	126	1341

In [40]:
```
#Lets check categorical data visualy
```

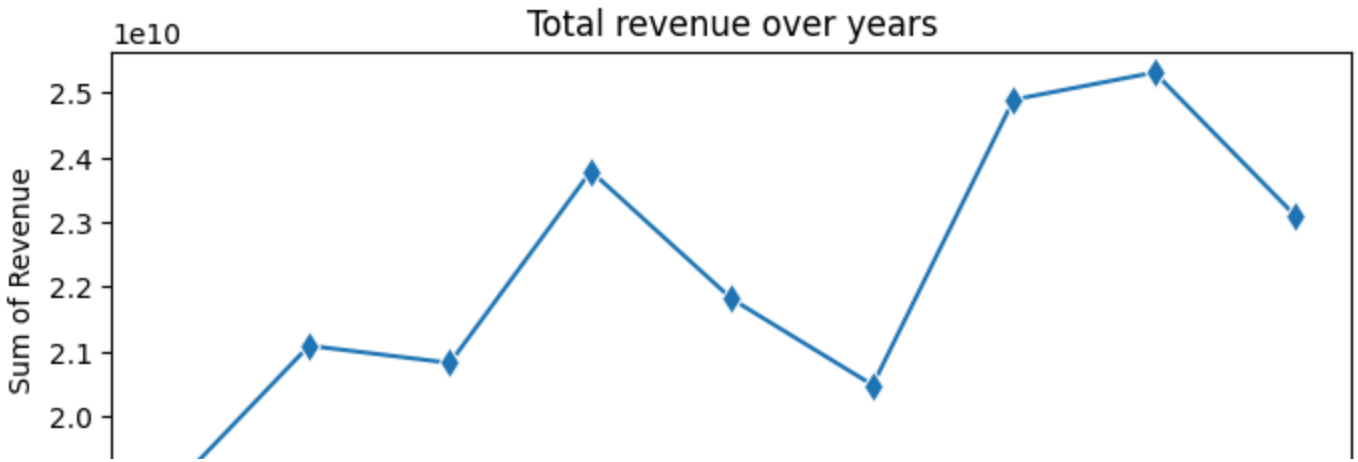
```
num_vars.describe()
```

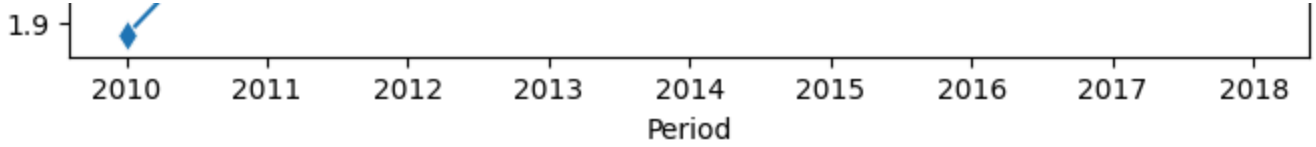
Out[40]:

	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	year	Total_Revenue
count	1863.000000	1847.000000	1.847000e+03	1.873000e+03	1.873000e+03	1873.000000	1.873000e+03
mean	110.331186	6.422794	9.166869e+04	4.213439e+07	6.469768e+07	2014.002670	1.068321e+08
std	20.480174	1.004203	1.502088e+05	7.668845e+07	1.332518e+08	2.516716	2.000485e+08
min	5.000000	1.600000	6.000000e+00	0.000000e+00	0.000000e+00	2010.000000	3.000000e+02
25%	96.000000	5.800000	7.642000e+03	5.390000e+05	0.000000e+00	2012.000000	1.300000e+06
50%	107.000000	6.500000	3.546500e+04	1.010000e+07	8.000000e+06	2014.000000	2.480000e+07
75%	122.000000	7.100000	1.055535e+05	5.090000e+07	5.840000e+07	2016.000000	1.104000e+08
max	189.000000	8.800000	1.841066e+06	7.001000e+08	9.464000e+08	2018.000000	1.405400e+09

In [41]:

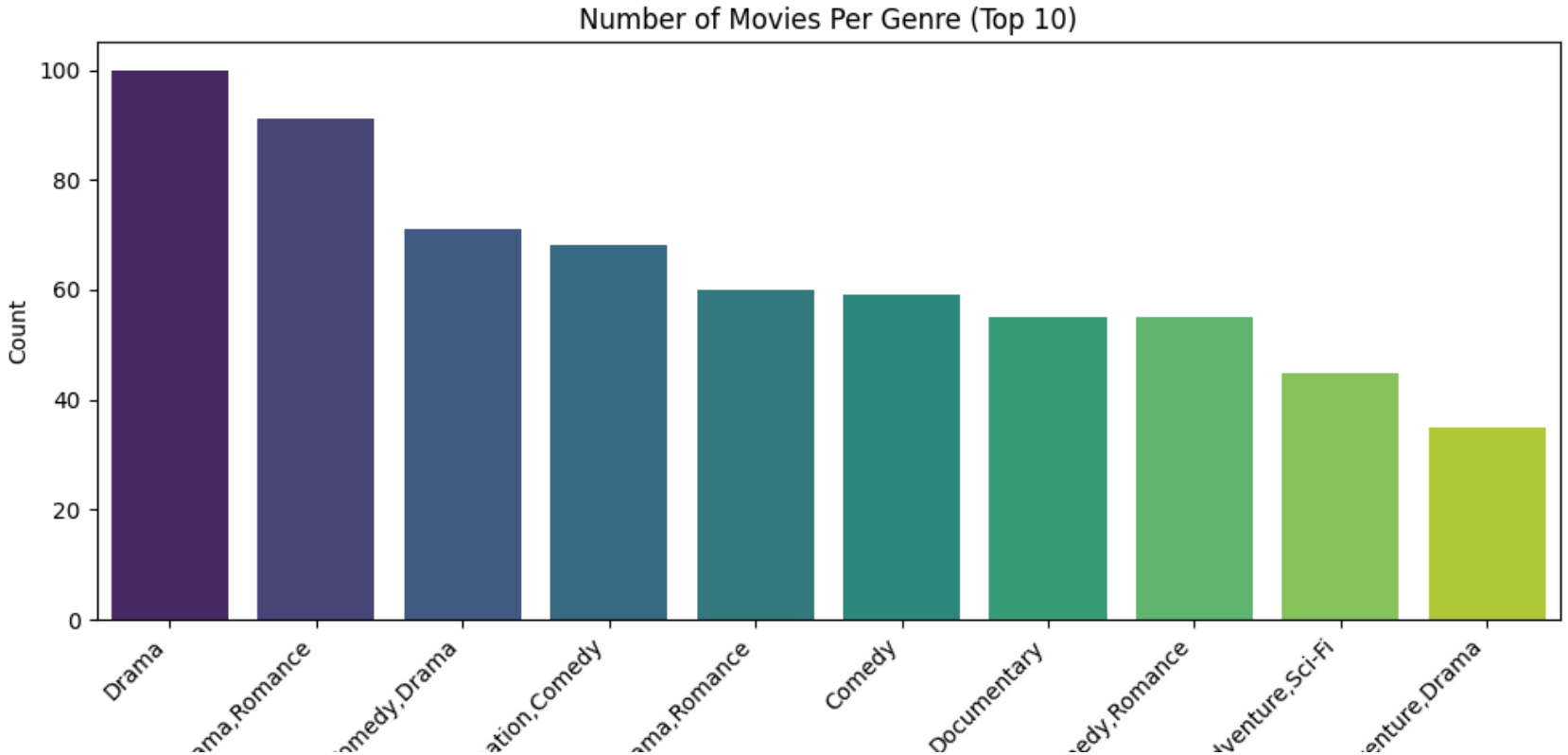
```
#Lets visualize the Revenue over years and check the pattern
import seaborn as sns

yr_rev=DF.groupby('year')['Total_Revenue'].sum().reset_index()
plt.figure(figsize=(8,3))
sns.lineplot(data=yr_rev, x='year', y='Total_Revenue', marker='d',markersize=8).set(title="Total revenue over year
#plt.savefig("Linegraph1.png", dpi=500, bbox_inches="tight")
plt.show()
```





In [42]:

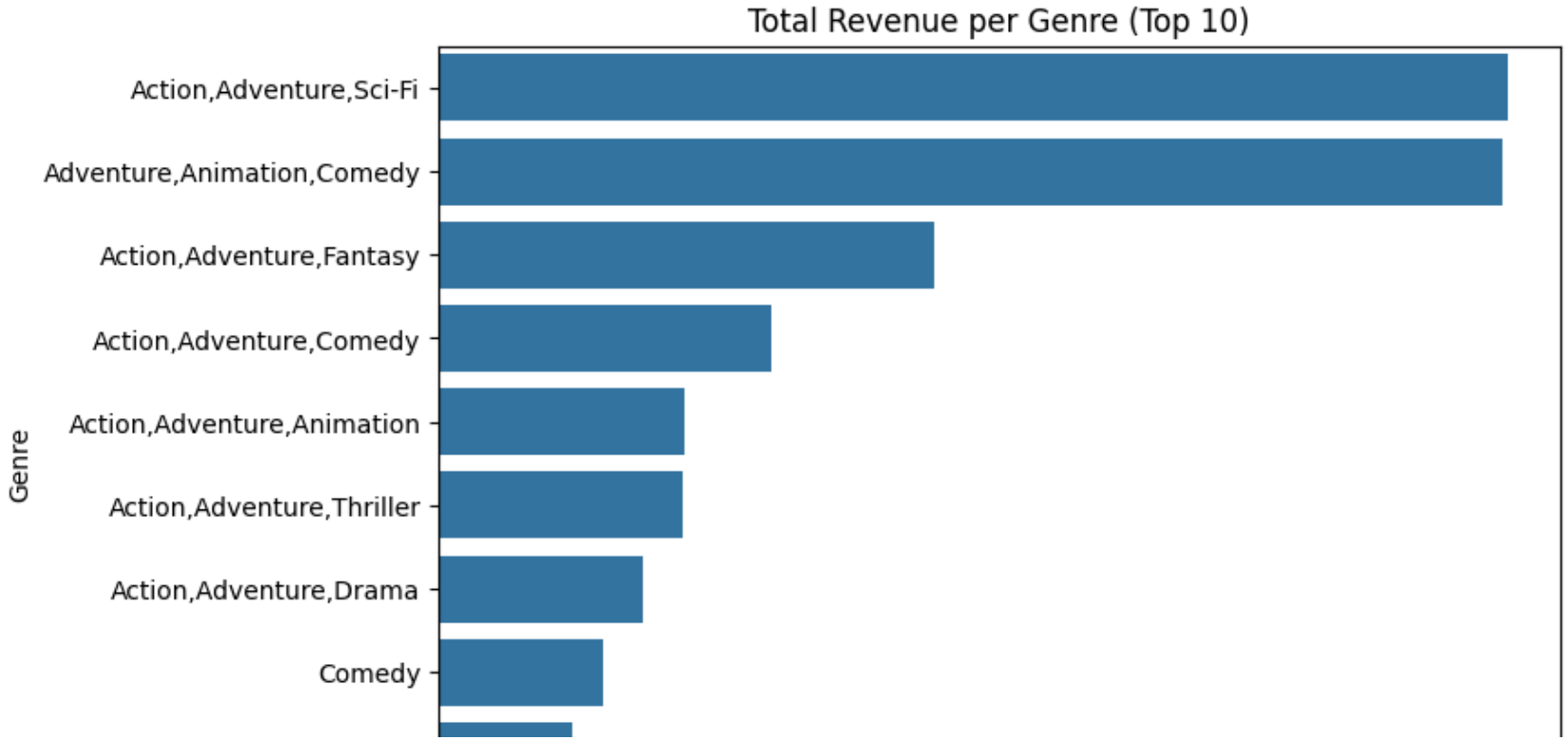
```
# Count the occurrences of each genre
genre_counts = DF['genres'].value_counts().head(10)

plt.figure(figsize=(10, 6))
sns.barplot(x=genre_counts.index, y=genre_counts.values, palette='viridis')

plt.xlabel('Genres')
plt.ylabel('Count')
plt.title('Number of Movies Per Genre (Top 10)')
plt.xticks(rotation=45, ha='right')

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

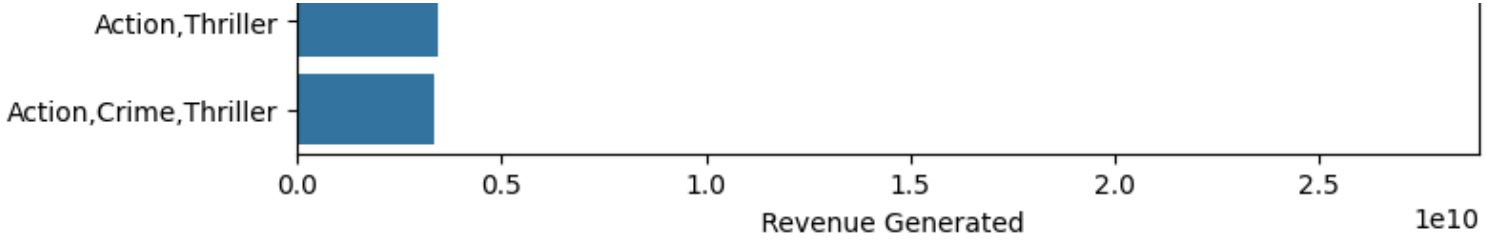


But does this translate to revenue generation?

In [43]:

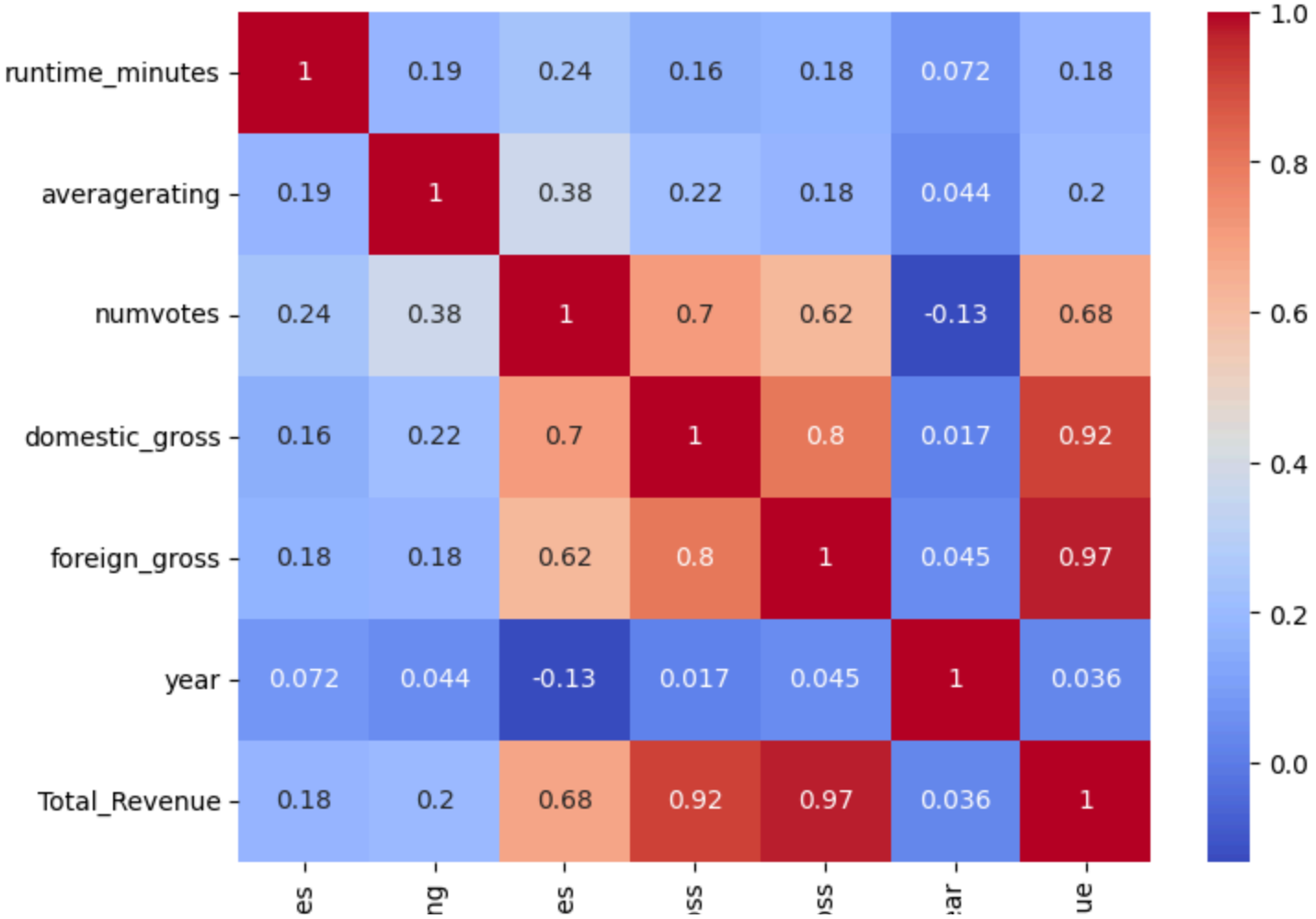
```
genSales=DF.groupby(['genres'])['Total_Revenue'].sum().reset_index().sort_values(by='Total_Revenue', ascending=Fal
plt.figure(figsize=(8,6))
sns.barplot(data=genSales, y='genres', x='Total_Revenue', orient="y").set(title="Total Revenue per Genre (Top 10)"

#Export the graph
#plt.savefig("barplot2.png", dpi=500, bbox_inches="tight")

#Render the output
plt.show()
```





In [44]:
```
plt.figure(figsize=(8,6))
sns.heatmap(num_vars.corr(),annot=True, cmap='coolwarm')
```

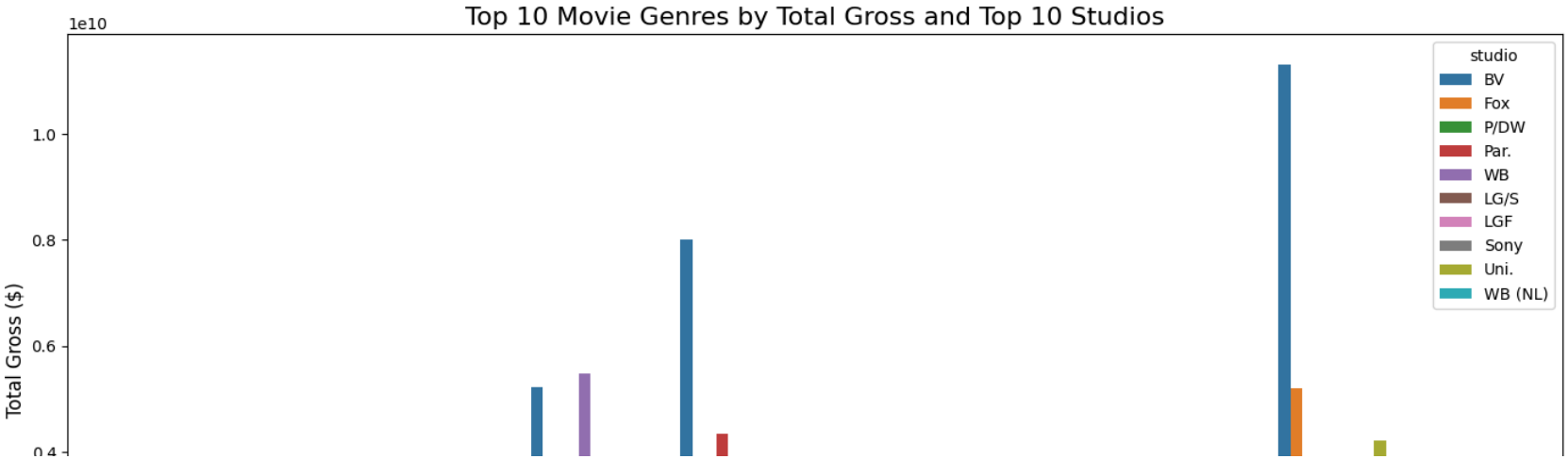
Out[44]: <Axes: >

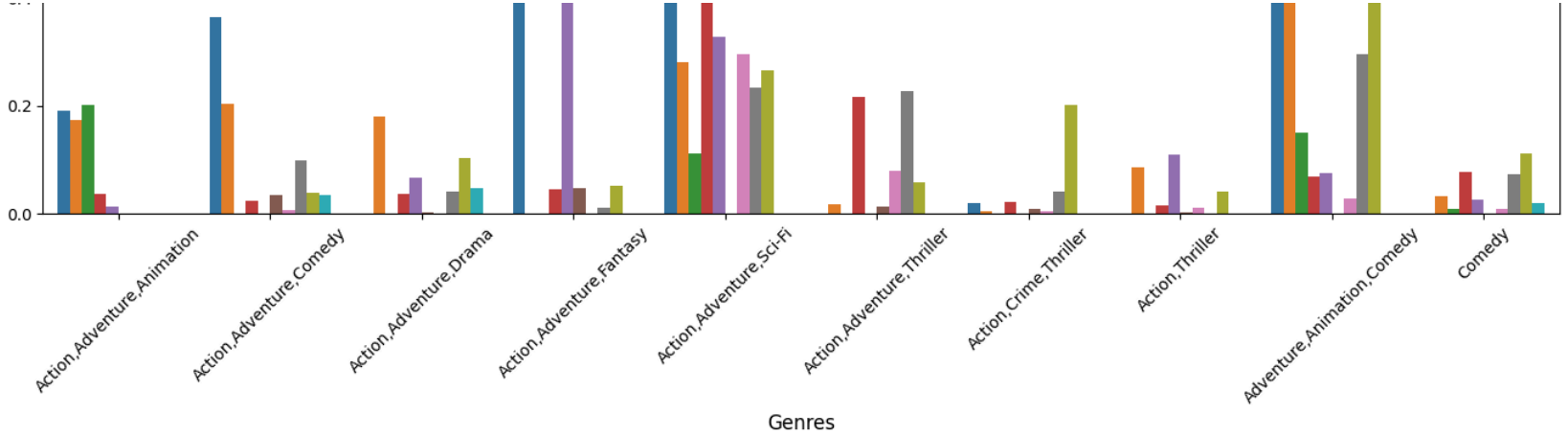


runtime_minut averagerati numvot domestic_grc foreign_grc ye Total_Reven

In [45]:

```
# Starting with Group by 'genres' and 'studio', then sum the 'Total_Revenue' for each group
grouped_df = DF.groupby(['genres', 'studio'])['Total_Revenue'].sum().reset_index()

# Getting the top 10 genres by total gross
top_genres = grouped_df.groupby('genres')['Total_Revenue'].sum().nlargest(10).index
top_genres_df = grouped_df[grouped_df['genres'].isin(top_genres)]

# Getting the top 10 studios by total gross
top_studios = top_genres_df.groupby('studio')['Total_Revenue'].sum().nlargest(10).index
top_studios_df = top_genres_df[top_genres_df['studio'].isin(top_studios)]

# Creating the bar plot
plt.figure(figsize=(14, 8))
sns.barplot(x='genres', y='Total_Revenue', hue='studio', data=top_studios_df)
plt.title('Top 10 Movie Genres by Total Gross and Top 10 Studios', fontsize=16)
plt.xlabel('Genres', fontsize=12)
plt.ylabel('Total Gross ($)', fontsize=12)
plt.xticks(rotation=45)

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





4. Modelling/Statistical analysis

Linear Regression

In [46]:
```
# Import libraries
import statsmodels.api as sm
```

In [47]:
```
# Defining the independent variable and dependent variable
X = DF[['numvotes']]
y = DF['Total_Revenue']

# Adding  a constant to the independent variable
X = sm.add_constant(X)

# Fit the simple linear regression model
model = sm.OLS(y, X).fit()

# Get the regression summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Total_Revenue   R-squared:                       0.464
Model:                            OLS   Adj. R-squared:                  0.464
Method:                 Least Squares   F-statistic:                     1620.
Date:                Sat, 25 Jan 2025   Prob (F-statistic):          1.20e-255
Time:                        07:22:45   Log-Likelihood:                -37874.
No. Observations:                1873   AIC:                          7.575e+04
```

```
No. Observations:                1873   AIC:                          7.575e+04
Df Residuals:                    1871   BIC:                          7.576e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       2.388e+07   3.96e+06      6.026      0.000    1.61e+07    3.17e+07
numvotes     912.6539     22.678     40.244      0.000     868.177     957.131
==============================================================================
Omnibus:                     1102.397   Durbin-Watson:                   1.970
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16725.422
Skew:                           2.466   Prob(JB):                         0.00
Kurtosis:                      16.784   Cond. No.                     2.05e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.05e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Relationship: There is a statistically significant positive relationship between numvotes and Total_Revenue. Each additional vote tends to increase the total revenue by approximately 912.65.

Fit: The model explains about 46.4% of the variability in Total_Revenue.

Significance: Both the model and the predictor (numvotes) are highly significant.

Residuals: The residuals might not be perfectly normal (as seen from the Omnibus and skewness/kurtosis tests), which might indicate some model misfit or the need for transformations

Since our P-value is less than 0.05 we reject the null hypothesis and conclude there is a statistical significance relationship between revenue and number of votes.

Conclusion

Revenue by Genre: Genres like Action, Adventure, and Sci-Fi consistently generate higher revenues, emphasizing the need to focus on producing films within these popular categories to capture broad audience appeal.

Audience Engagement and Revenue: Movies with higher audience engagement (reflected by the number of votes) show a significant positive correlation with total revenue. This indicates the importance of building a strong online presence and

significant positive correlation with total revenue. This indicates the importance of building a strong online presence and encouraging audience feedback to drive financial success.

Revenue Growth Over Time: Total movie revenue has steadily increased over the years, highlighting the movie industry's growth and its expanding global reach.

Model Limitations: While the linear regression model identified the number of votes as a significant predictor of revenue, its relatively low R-squared value (46.4%) and multicollinearity suggest the need to incorporate additional variables, such as genres, ratings, and studios, to improve the model's predictive accuracy.

Recommendations

Focus on High-Grossing Genres: Prioritize films in successful genres like Action and Adventure, which consistently perform well at the box office.Understanding audience preferences within these genres can significantly boost profitability

Boost Audience Engagement: Since audience votes strongly correlate with revenue, the studio should actively encourage participation through targeted campaigns and fan-driven promotions, both before and after a film's release.

Track Revenue Trends: To stay competitive in the evolving movie industry, the studio should track changes in revenue patterns over time. Monitor changes in consumer behavior, regional preferences, and technology (e.g., streaming) to stay ahead of industry shifts.

Leverage Studio Branding and Partnerships: Analyze the success patterns of top-performing studios and identify opportunities for improvement or collaboration. Partnering with leading studios or well-known directors can enhance brand visibility and drive higher revenue for films.