Phase 2 project:

Movie Studio Analysis

Business Understanding

A company is interested in entering the movie studio industry. This is based on the performances of films from studios such as Warner Bros, Sony, and Paramount Pictures. They have no background/knowledge of the film industry, but are excited to try it out. They would like an analysis of the movies that have been performing well to make a data-driven decision.

Key focus points:

1. Which genre of movies is performing well at the Box Office
2. How much revenue are they making
3. The ratings of the movies and their respective budget

The focus points are to guide the company into ensuring the films produced and released are performing well (ratings) at the Box Office, are a good investment, and they work well with the given budget.

Datasets used:

- IMDB dataset
- bom.movie_gross dataset
- tn.movie_budgets dataset

Outcome:

- 3 or more recommendations for the potential new movie studio. This helps guide the company to make an appropriate and data-driven decision.

Data Understanding

In this section, we'll be going through the datasets and choosing the most appropriate for this analysis/project.

In [1]:
```
#importing the necessary Libraries
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
```

The provided datasets are:

- bom.movie_gross
- imdb
- rt.movie_info
- rt.reviews
- tmdb.movies
- tn.movies_budgets

In [2]:
```
movie_gross = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2
movie_gross.head(2)
```

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

In [3]:
```
rotten_tomatoes = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Pha
rotten_tomatoes.head(2)
```

Out[3]:

	id	synopsis	rating	genre	director	writer	theater_date
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971
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

In [4]:
```
reviews = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Mov
reviews.head(2)
```

Out[4]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018

In [5]:
```
tmdb = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-
tmdb.head(2)
```

Out[5]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26

In [6]:
```
movie_budgets = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase
movie_budgets.head(2)
```

Out[6]:

	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

In [7]:
```
imdb = 'C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-Project/data

# Opening up a connection
conn = sqlite3.connect(imdb)
```

In [8]:
```
table_name = """
SELECT name
AS 'Table Names'
FROM sqlite_master
WHERE type='table';"""

pd.read_sql(table_name, conn)
```

Out[8]:

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

In [9]:
```
query_one= """
SELECT *
FROM movie_basics
LIMIT 2;
"""
pd.read_sql(query_one, conn)
```

Out[9]:

	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

In [10]:
```
query_two= """
SELECT *
FROM movie_ratings
LIMIT 2;
"""
pd.read_sql(query_two, conn)
```

Out[10]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559

In [11]:
```
conn.close()
```

From viewing the data above and getting a glimpse of their columns and data in the dataset. The choices are the compulsory IMDb SQLite dataset, bom.movie_gross, and the optional tn. movie_budgets datasets.

Data Cleaning

Box Office Mojo Dataset

In [12]:
```
movie_gross.head(2)
```

Out[12]:

	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

In [13]:
```
# from looking at the first 2 rows of the dataset. We need to remove the year eg 20
# have all the letters of the title in small/lowercase

movie_gross['title_new'] = movie_gross['title'].str.lower().str.strip()
movie_gross.head(2)
```

Out[13]:

	title	studio	domestic_gross	foreign_gross	year	title_new
0	Toy Story 3	BV	415000000.0	652000000	2010	toy story 3
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010	alice in wonderland (2010)

In [14]:
```
movie_gross.columns
```

Out[14]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year',
       'title_new'],
      dtype='object')
```

In [15]:
```
# we drop the 'title' column as its not needed

movie_gross = movie_gross.drop('title', axis=1)
movie_gross.head()
```

Out[15]:

	studio	domestic_gross	foreign_gross	year	title_new
0	BV	415000000.0	652000000	2010	toy story 3
1	BV	334200000.0	691300000	2010	alice in wonderland (2010)
2	WB	296000000.0	664300000	2010	harry potter and the deathly hallows part 1
3	WB	292600000.0	535700000	2010	inception
4	P/DW	238700000.0	513900000	2010	shrek forever after

In [16]:
```
movie_gross.info()
```

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

In [17]:
```
# Convert the foreign gross column to numeric

movie_gross['foreign_gross'] = pd.to_numeric(movie_gross['foreign_gross'], errors =
movie_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   studio          3382 non-null   object 
 1   domestic_gross  3359 non-null   float64
 2   foreign_gross   2032 non-null   float64
 3   year            3387 non-null   int64  
 4   title_new       3387 non-null   object 
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
```

In [18]:
```
movie_gross.duplicated().value_counts()
```

Out[18]:
```
False    3387
Name: count, dtype: int64
```

In [19]:
```
movie_gross.shape
```

Out[19]:
```
(3387, 5)
```

In [20]:
```
# checking for columns with missing values
movie_gross.isna().sum().sort_values(ascending = True)
```

Out[20]:
```
year                 0
title_new            0
studio               5
domestic_gross      28
foreign_gross     1355
dtype: int64
```

In [21]:
```
# dropping the few rows in the domestic gross and studio columns

movie_gross = movie_gross.dropna(subset = ['studio', 'domestic_gross'])

# filling the foreign gross column with 0. This is because through research, the co
# cannot assume it to be mean due to false numbers. Foreign gross is due to the mov
```

```
# tabulated clealry or lost due to currency difference.

movie_gross['foreign_gross'] = movie_gross['foreign_gross'].fillna(0)

movie_gross.isna().sum().sort_values(ascending = True)
```

Out[21]:
```
studio            0
domestic_gross    0
foreign_gross     0
year              0
title_new         0
dtype: int64
```

The Numbers Dataset

In [22]:
```
movie_budgets.head(2)
```

Out[22]:

	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

In [23]:
```
movie_budgets.columns
```

Out[23]:
```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
```

In [24]:
```
movie_budgets.info()
```

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

In [25]:
```
movie_budgets.isna().sum()
```

Out[25]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [26]:
```
movie_budgets.shape
```

Out[26]:
```
(5782, 6)
```

In [27]:
```
#Checking for duplicates in the numbers dataset

movie_budgets.duplicated().value_counts()
```

Out[27]:
```
False    5782
Name: count, dtype: int64
```

The Numbers dataset is quite clean but we need to extract the year from the release date in order to merge the datasets well. As well as the colums need to be converted.

In [28]:
```
# create a list with the columns in it

columns = ['production_budget', 'domestic_gross','worldwide_gross']
columns
```

Out[28]:
```
['production_budget', 'domestic_gross', 'worldwide_gross']
```

In [29]:
```
# remove the dollar and commas in the 'production_budget', 'domestic_gross','worldw

for col in columns:
    movie_budgets[col] = movie_budgets[col].str.replace(r'[\$,]', '', regex=True)

movie_budgets.head(2)
```

Out[29]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875

In [30]:
```
# converting the 'production_budget', 'domestic_gross','worldwide_gross' columns in

for col in columns:
    movie_budgets[col] = pd.to_numeric(movie_budgets[col])

movie_budgets.info()
```

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

In [31]:
```
# get the year on its own eg 2010 from the release_date column

# Converting the release_date to datetime
movie_budgets['release_date'] = pd.to_datetime(movie_budgets['release_date'])

# Creating a new column called year and extracting the year from the column of rele
movie_budgets['year'] = movie_budgets['release_date'].dt.year
movie_budgets.head()
```

Out[31]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017

In [32]:
```
# converting the movie title to lowercase letters to match the other datasets

movie_budgets['title_new'] = movie_budgets['movie'].str.lower().str.strip()

# Dropping the extra movie column

movie_budgets = movie_budgets.drop('movie', axis = 1)
movie_budgets.head(2)
```

Out[32]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	year	title_new
0	1	2009-12-18	425000000	760507625	2776345279	2009	avatar
1	2	2011-05-20	410600000	241063875	1045663875	2011	pirates of the caribbean: on stranger tides

In [33]:

```
# dropping the release date column as we have extracted year

movie_budgets = movie_budgets.drop('release_date', axis = 1)
movie_budgets.head(2)
```

Out[33]:

	id	production_budget	domestic_gross	worldwide_gross	year	title_new
0	1	425000000	760507625	2776345279	2009	avatar
1	2	410600000	241063875	1045663875	2011	pirates of the caribbean: on stranger tides

IMDB Dataset

In [34]:

```
imdb = 'C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-Project/data

# Opening up a connection
conn = sqlite3.connect(imdb)
```

In [35]:

```
# when looking at the datasets to use, the 2 tables that suit best are movie_rating

query_one= """
SELECT *
FROM movie_basics;
"""
pd.read_sql(query_one, conn)
```

Out[35]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Docun
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	C
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Docun

146144 rows × 6 columns

In [36]:

```
query_two= """
SELECT *
FROM movie_ratings;
"""
pd.read_sql(query_two, conn)
```

Out[36]:

	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
...	...	...	...
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

73856 rows × 3 columns

In [37]:
```
# joining the 2 tables using the movie_id column

imdb_q = """
SELECT *
FROM movie_basics
JOIN "movie_ratings"
ON movie_basics.movie_id = "movie_ratings".movie_id;
"""
imdb = pd.read_sql(imdb_q, conn)
```

In [38]:
```
conn.close()
```

In [39]:
```
imdb.head(2)
```

Out[39]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	t
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	t

In [40]:
```
imdb.columns
```

Out[40]:
```
Index(['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'movie_id', 'averagerating', 'numvotes'],
      dtype='object')
```

In [41]:
```python
# In order to drop the duplicate column movie_id, we rename the columns first.

imdb.columns = ['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'movie_id_x', 'averagerating', 'numvotes']
imdb.columns
```

Out[41]:
```
Index(['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'movie_id_x', 'averagerating', 'numvotes'],
      dtype='object')
```

In [42]:
```python
# drop the unrequired columns; 2nd movie_id, original_title

imdb = imdb.drop(['movie_id_x', 'original_title'], axis = 1)
imdb.head(2)
```

Out[42]:

	movie_id	primary_title	start_year	runtime_minutes	genres	averagerating
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama	7.0
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2

In [43]:
```python
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   start_year       73856 non-null  int64  
 3   runtime_minutes  66236 non-null  float64
 4   genres           73052 non-null  object 
 5   averagerating    73856 non-null  float64
 6   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(3)
memory usage: 3.9+ MB
```

In [44]:
```python
imdb.duplicated().value_counts()
```

Out[44]:
```
False    73856
Name: count, dtype: int64
```

In [45]:
```python
imdb.shape
```

Out[45]:
```
(73856, 7)
```

In [46]:
```python
imdb.isna().sum().sort_values(ascending = True)
```

Out[46]:
```
movie_id              0
primary_title         0
start_year            0
averagerating         0
numvotes              0
genres              804
runtime_minutes    7620
dtype: int64
```

In [47]:
```python
# The runtime_minutes column has too many missing values therefore needs to be drop
# Fill the missing genre with unknown because it's an object and also cannot make a

# Dropping the column
imdb = imdb.drop(['runtime_minutes'], axis = 1)

# Filling the column with unknown
imdb['genres'] = imdb['genres'].fillna('Unknown')

imdb.isna().sum().sort_values(ascending = True)
```

Out[47]:
```
movie_id         0
primary_title    0
start_year       0
genres           0
averagerating    0
numvotes         0
dtype: int64
```

In [48]:
```python
# The start_year needs to be renamed to year and the primary_title to title_new to

# First change the primary title column to lowercase and drop the column as well
imdb['title_new'] = imdb['primary_title'].str.lower().str.strip()
# dropping
imdb = imdb.drop(['primary_title'], axis = 1)

imdb.head(2)
```

Out[48]:

	movie_id	start_year	genres	averagerating	numvotes	title_new
0	tt0063540	2013	Action,Crime,Drama	7.0	77	sunghursh
1	tt0066787	2019	Biography,Drama	7.2	43	one day before the rainy season

In [49]:
```python
# rename start_year to year

imdb = imdb.rename(columns={'start_year': 'year'})
imdb.head(2)
```

Out[49]:

	movie_id	year	genres	averagerating	numvotes	title_new
0	tt0063540	2013	Action,Crime,Drama	7.0	77	sunghursh
1	tt0066787	2019	Biography,Drama	7.2	43	one day before the rainy season

Checking for outliers in the 3 datasets

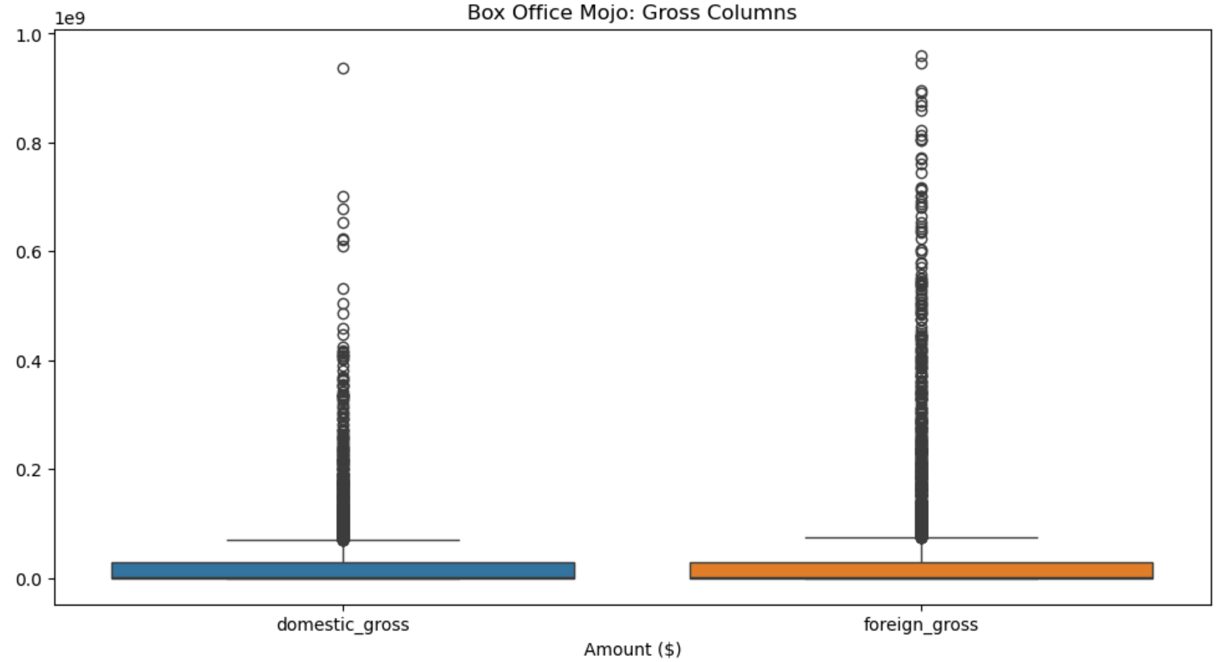
- This is to conclude in the cleaning of the 3 datasets chosen
- Saving them as csvs for merging
- EDA after

In [50]:
```
movie_gross[['domestic_gross', 'foreign_gross']].describe()
```

Out[50]:

	domestic_gross	foreign_gross
count	3.356000e+03	3.356000e+03
mean	2.877149e+07	4.532518e+07
std	6.700694e+07	1.131263e+08
min	1.000000e+02	0.000000e+00
25%	1.200000e+05	0.000000e+00
50%	1.400000e+06	1.400000e+06
75%	2.795000e+07	2.970000e+07
max	9.367000e+08	9.605000e+08

In [51]:
```
plt.figure(figsize = (12, 6))
sns.boxplot(data = movie_gross[['domestic_gross', 'foreign_gross']])
plt.title("Box Office Mojo: Gross Columns")
plt.xlabel("Amount ($)")
plt.show()
```

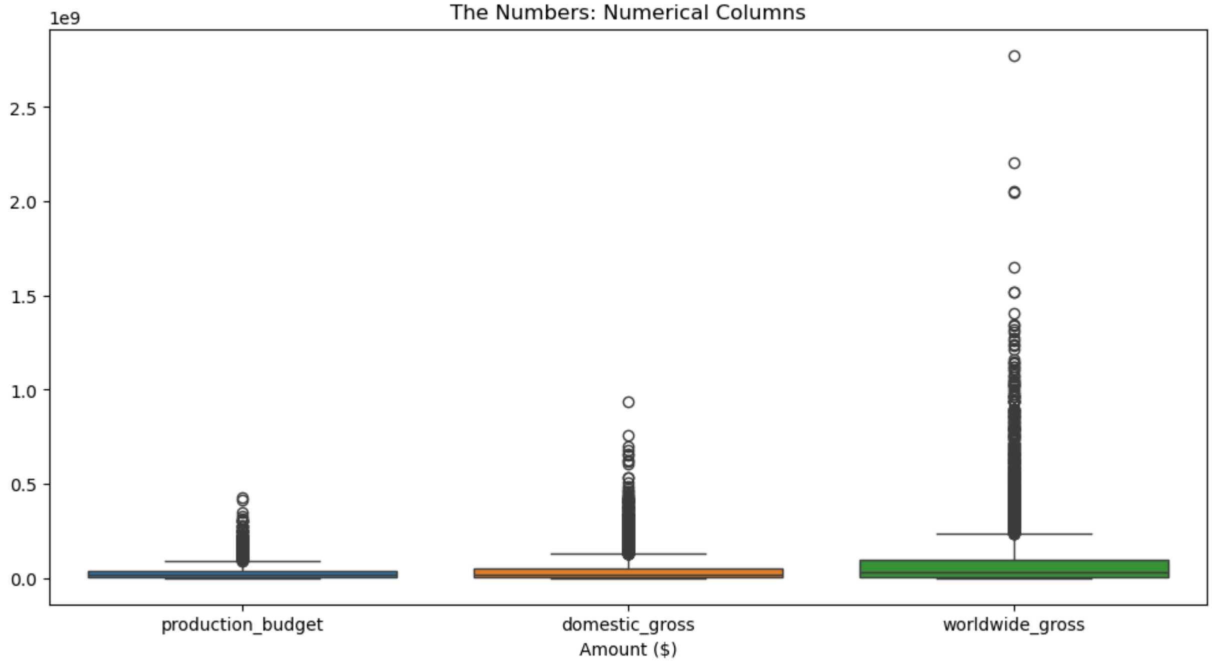


In [52]:
```
movie_budgets[['production_budget', 'domestic_gross', 'worldwide_gross']].describe(
```

Out[52]:

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

In [53]:
```
plt.figure(figsize = (12, 6))
sns.boxplot(data = movie_budgets[['production_budget', 'domestic_gross', 'worldwide
plt.title("The Numbers: Numerical Columns")
plt.xlabel("Amount ($)")
plt.show()
```

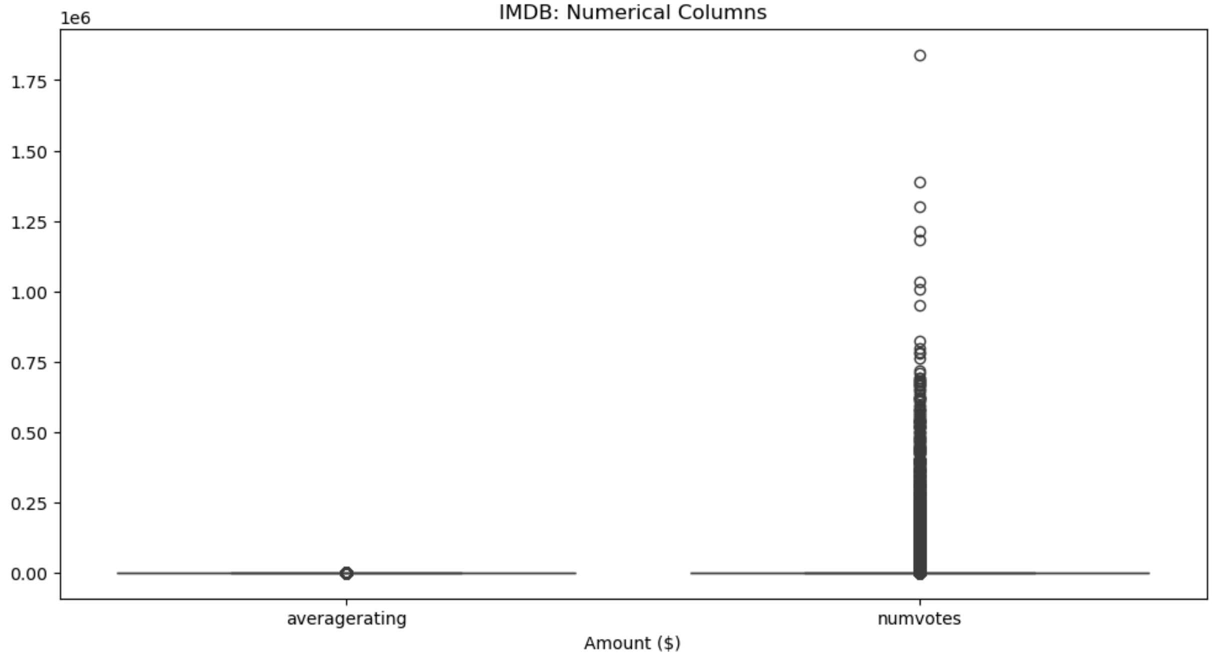


In [54]:
```
imdb[['averagerating', 'numvotes']].describe()
```

Out[54]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

In [55]:
```
plt.figure(figsize = (12, 6))
sns.boxplot(data = imdb[['averagerating', 'numvotes']])
plt.title("IMDB: Numerical Columns")
plt.xlabel("Amount ($)")
plt.show()
```



For the case of the data provided for movie analysis, it does not make sense to handle the major outliers in the respective datasets chosen. This is because:

- For the Box Office Mojo dataset and The Numbers datasets, their .describe() shows that there are outliers in the gross columns. However, there are no negative/impossible values present. Therefore, we do not remove the outliers, as they represent moments when a movie has performed exceptionally well (blockbusters) or had low production costs (small feature films, potentially).
- For the IMDB dataset, the average rating column is okay, as there are no negatives and results fall between the given 1-10 rating options. The number of votes column has outliers as it depends on the populairty of a film and how many people went ahead and rated the films. There are instances when not many people will rate a film due to the locations it's released in, or the popularity and availability.

This means that the outliers have been retained for a realistic and true analysis of the movie industry. Based on performance, popularity/audience engagement.

Saving and Merging Datasets

In [56]:
```
# saving the 3 datasets as CSVs for merging

movie_gross.to_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-

movie_budgets.to_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movi

imdb.to_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-Project
```

In [57]:
```
# Loading the clean datasets to merge

movie_gross = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2

movie_budgets = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase

imdb = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-
```

In [58]:
```
movie_gross.head()
```

Out[58]:

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

In [59]:
```
movie_budgets.head()
```

Out[59]:

	id	production_budget	domestic_gross	worldwide_gross	year	title_new
0	1	425000000	760507625	2776345279	2009	avatar
1	2	410600000	241063875	1045663875	2011	pirates of the caribbean: on stranger tides
2	3	350000000	42762350	149762350	2019	dark phoenix
3	4	330600000	459005868	1403013963	2015	avengers: age of ultron
4	5	317000000	620181382	1316721747	2017	star wars ep. viii: the last jedi

In [60]:
```
imdb.head()
```

Out[60]:

	movie_id	year	genres	averagerating	numvotes	title_new
0	tt0063540	2013	Action,Crime,Drama	7.0	77	sunghursh
1	tt0066787	2019	Biography,Drama	7.2	43	one day before the rainy season
2	tt0069049	2018	Drama	6.9	4517	the other side of the wind
3	tt0069204	2018	Comedy,Drama	6.1	13	sabse bada sukh
4	tt0100275	2017	Comedy,Drama,Fantasy	6.5	119	the wandering soap opera

In [61]:

```
print(f'Box Office Mojo Columns:{movie_gross.columns}')

print(f'The Numbers:{movie_budgets.columns}')

print(f'IMDB:{imdb.columns}')
```

```
Box Office Mojo Columns:Index(['studio', 'domestic_gross', 'foreign_gross', 'year',
'title_new'], dtype='object')
The Numbers:Index(['id', 'production_budget', 'domestic_gross', 'worldwide_gross',
'year',
       'title_new'],
      dtype='object')
IMDB:Index(['movie_id', 'year', 'genres', 'averagerating', 'numvotes', 'title_new'],
dtype='object')
```

In [62]:

```
# Merging the datasets

merged = pd.merge(movie_gross, imdb, on = ['year', 'title_new'], how='inner')

merged.head(2)
```

Out[62]:

	studio	domestic_gross	foreign_gross	year	title_new	movie_id	g
0	BV	415000000.0	652000000.0	2010	toy story 3	tt0435761	Adventure,Animation,Cc
1	WB	292600000.0	535700000.0	2010	inception	tt1375666	Action,Adventure

In [63]:

```
# last merge

df = pd.merge(merged, movie_budgets, on = ['year', 'title_new'], how='inner')

df.head()
```

Out[63]:

	studio	domestic_gross_x	foreign_gross	year	title_new	movie_id	
0	BV	415000000.0	652000000.0	2010	toy story 3	tt0435761	Adventure,Animation,
1	WB	292600000.0	535700000.0	2010	inception	tt1375666	Action,Adventu
2	P/DW	238700000.0	513900000.0	2010	shrek forever after	tt0892791	Adventure,Animation,
3	Sum.	300500000.0	398000000.0	2010	the twilight saga: eclipse	tt1325004	Adventure,Drama
4	Par.	312400000.0	311500000.0	2010	iron man 2	tt1228705	Action,Adventu

From the results above, the domestic_gross in the movie_gross dataset is rounded up to the nearest 1000 whereas for the movie_budgets it's the actual figure to the last digit. For more accuracy, we can use the domestic gross for The Numbers dataset.

In [64]:
```
# Dropping the domestic_gross_x column

df = df.drop('domestic_gross_x', axis = 1)
df.columns
```

Out[64]:
```
Index(['studio', 'foreign_gross', 'year', 'title_new', 'movie_id', 'genres',
       'averagerating', 'numvotes', 'id', 'production_budget',
       'domestic_gross_y', 'worldwide_gross'],
      dtype='object')
```

In [65]:
```
# Renaming the domestic_gross_y back to domestic_gross

df = df.rename(columns={'domestic_gross_y': 'domestic_gross'})
df.columns
```

Out[65]:
```
Index(['studio', 'foreign_gross', 'year', 'title_new', 'movie_id', 'genres',
       'averagerating', 'numvotes', 'id', 'production_budget',
       'domestic_gross', 'worldwide_gross'],
      dtype='object')
```

In [66]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1094 entries, 0 to 1093
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   studio             1094 non-null   object 
 1   foreign_gross      1094 non-null   float64
 2   year               1094 non-null   int64  
 3   title_new          1094 non-null   object 
 4   movie_id           1094 non-null   object 
 5   genres             1094 non-null   object 
 6   averagerating      1094 non-null   float64
 7   numvotes           1094 non-null   int64  
 8   id                 1094 non-null   int64  
 9   production_budget  1094 non-null   int64  
 10  domestic_gross     1094 non-null   int64  
 11  worldwide_gross    1094 non-null   int64  
dtypes: float64(2), int64(6), object(4)
memory usage: 102.7+ KB
```

In [67]:
```
df.isna().sum().sort_values(ascending = True)
```

Out[67]:
```
studio               0
foreign_gross        0
year                 0
title_new            0
movie_id             0
genres               0
averagerating        0
numvotes             0
id                   0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [68]:
```
df.duplicated().value_counts()
```

Out[68]:
```
False    1094
Name: count, dtype: int64
```

In [69]:
```
df.shape
```

Out[69]:
```
(1094, 12)
```

- Reorganzing the columns
- Droppig unneccessary columns for EDA and conclsuion analysis
- Renaming columns as well for clarity

In [70]:
```
# Dropping movie_id and id columns

df = df.drop(['movie_id', 'id'], axis = 1)
print(df.columns)
```

```
# Renaming the domestic_gross_y back to domestic_gross

df = df.rename(columns={'title_new': 'title', 'averagerating': 'rating', 'numvotes'
print(df.columns)

# Organizing the column order for ease when using Tableau

df = df[['title', 'year', 'studio', 'production_budget', 'foreign_gross','domestic_
print(df.columns)
```

```
Index(['studio', 'foreign_gross', 'year', 'title_new', 'genres',
       'averagerating', 'numvotes', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
Index(['studio', 'foreign_gross', 'year', 'title', 'genres', 'rating', 'votes',
       'production_budget', 'domestic_gross', 'worldwide_gross'],
      dtype='object')
Index(['title', 'year', 'studio', 'production_budget', 'foreign_gross',
       'domestic_gross', 'worldwide_gross', 'genres', 'rating', 'votes'],
      dtype='object')
```

The dataset merged is clean; contains no duplicates, null values and the datatypes of the columns are well allocated.

In [71]:
```
# Save the dataset for Tableau

df.to_csv("C:/Users/PC/Desktop/School work/Projects/Phase 2/Phase-2-Movie-Project/d
```

EDA

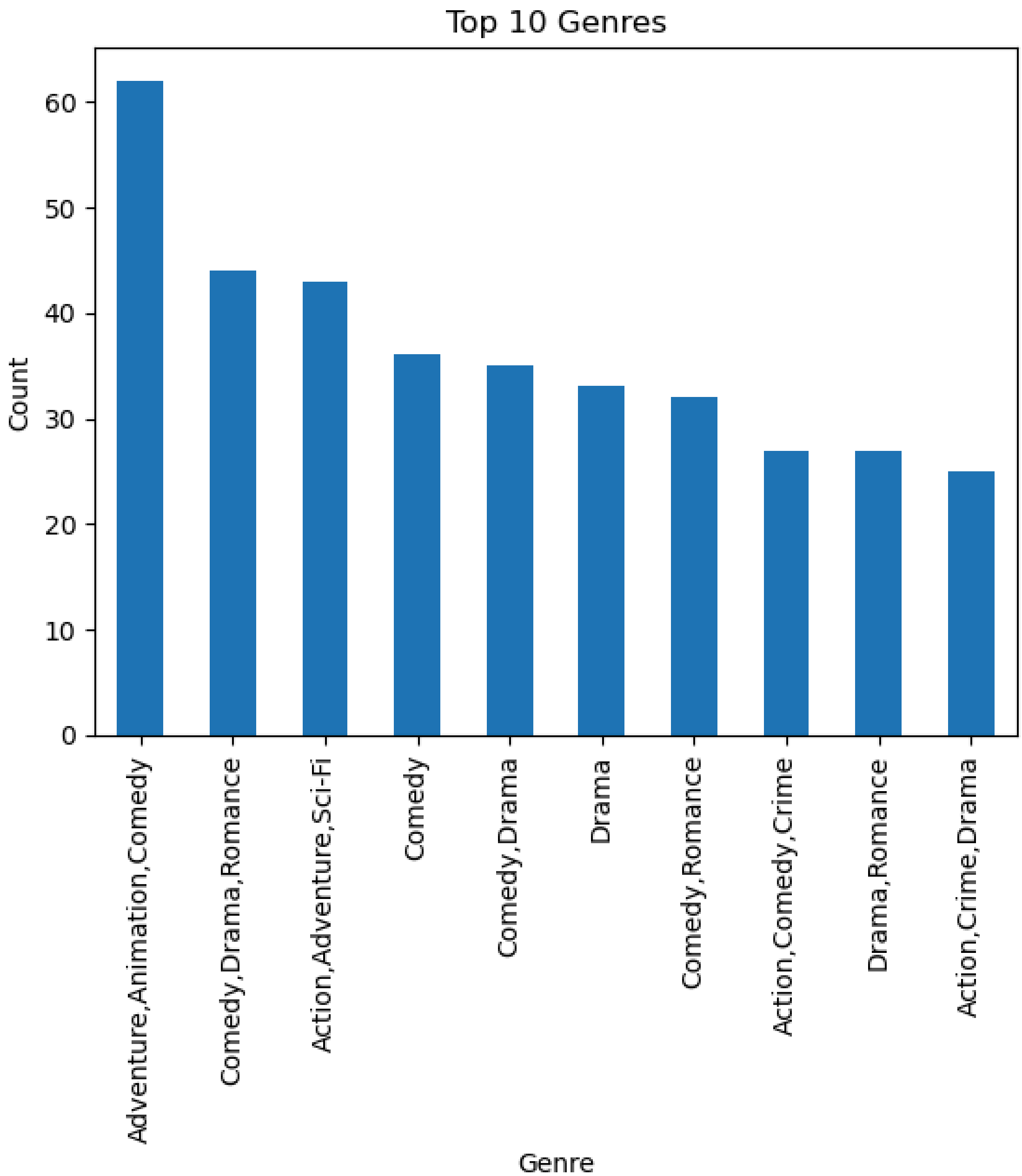
1. Univariate Analysis

In [72]:
```
df.genres.nunique()
```

Out[72]:
```
186
```

In [73]:
```
# Plot for the top 10 genres

df['genres'].value_counts(ascending = False).head(10).plot.bar()
plt.xlabel('Genre')
plt.ylabel('Count')
plt.title('Top 10 Genres')
```

Out[73]:
```
Text(0.5, 1.0, 'Top 10 Genres')
```



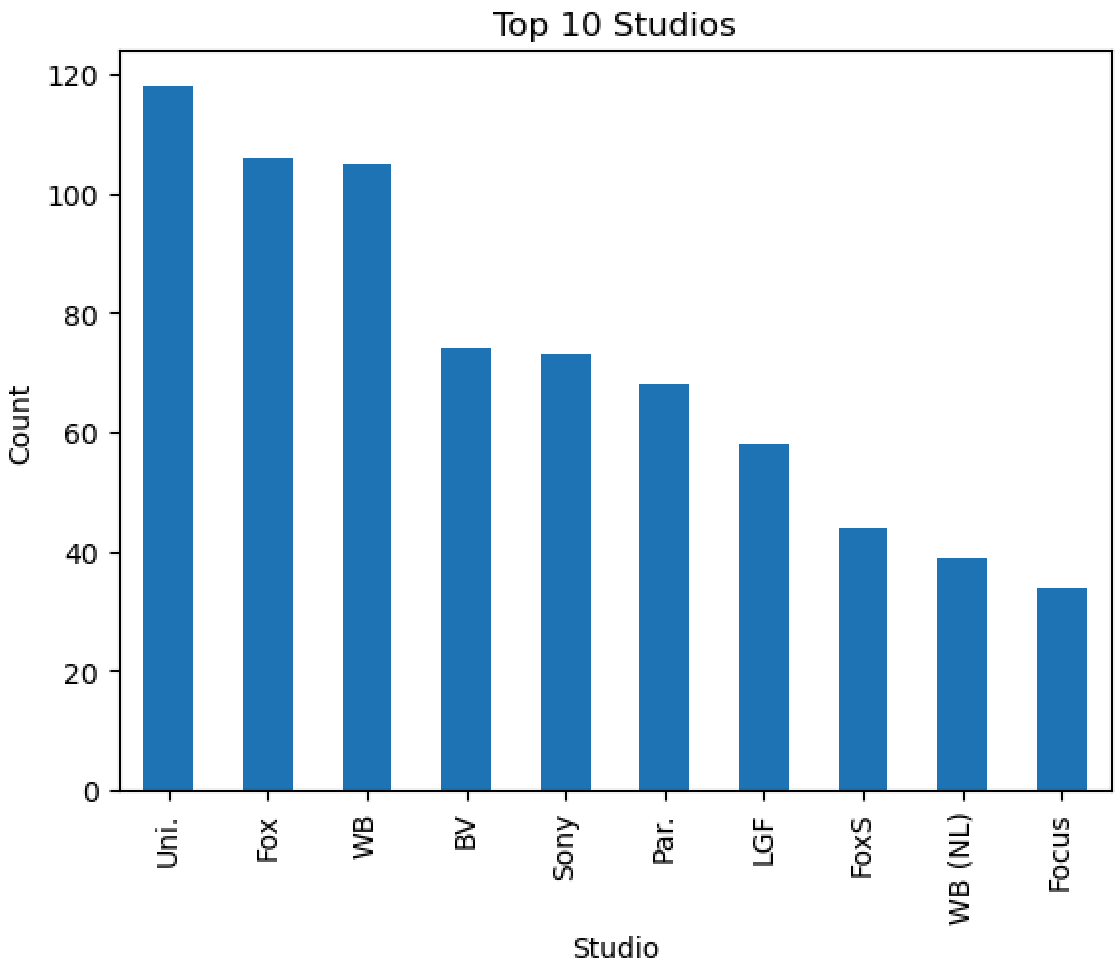
In the above diagram, we can see the top 10 genres out of the 186 different genres. These are the best genres to have the company try and focus on. They could potentially have good reception if they release them, because they are popular among the audience.

In [74]:
```
df.studio.nunique()
```

Out[74]: 78

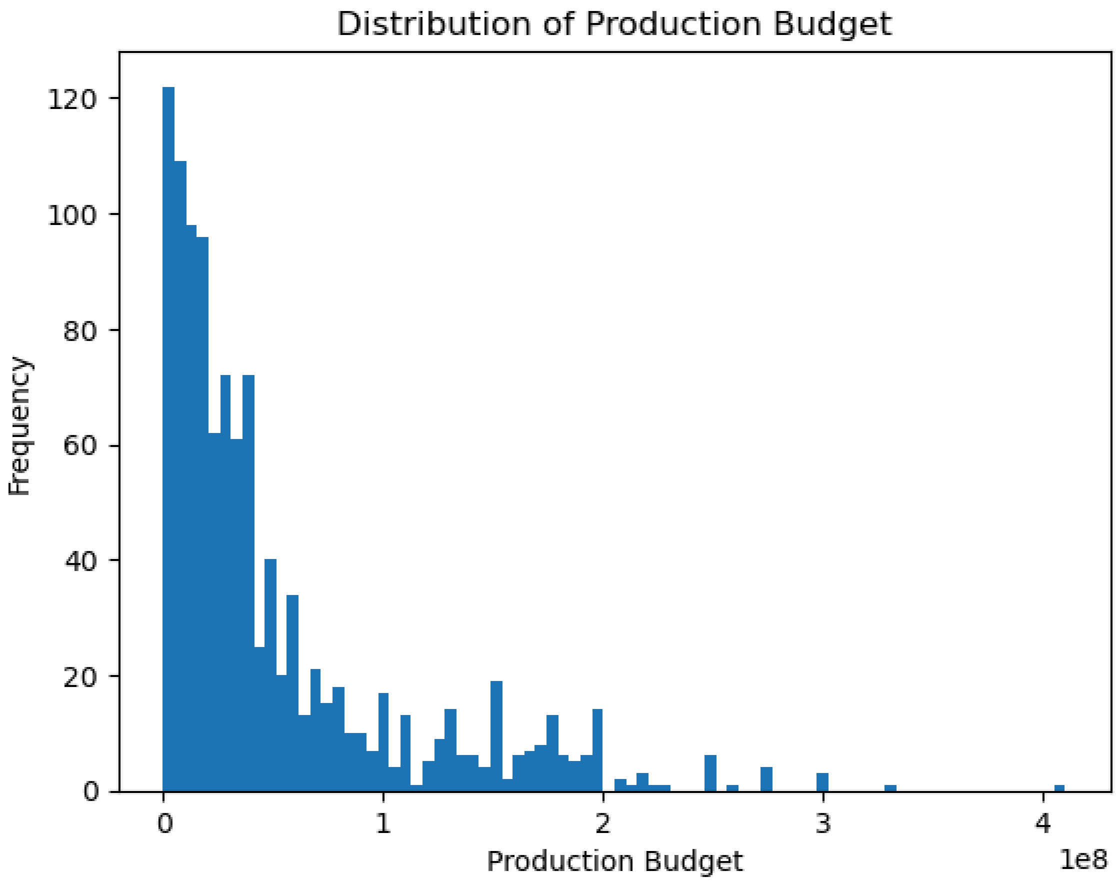
In [75]:
```
# Plot for the top 10 genres

df['studio'].value_counts(ascending = False).head(10).plot.bar()
plt.xlabel('Studio')
plt.ylabel('Count')
plt.title('Top 10 Studios')
```

Out[75]: Text(0.5, 1.0, 'Top 10 Studios')



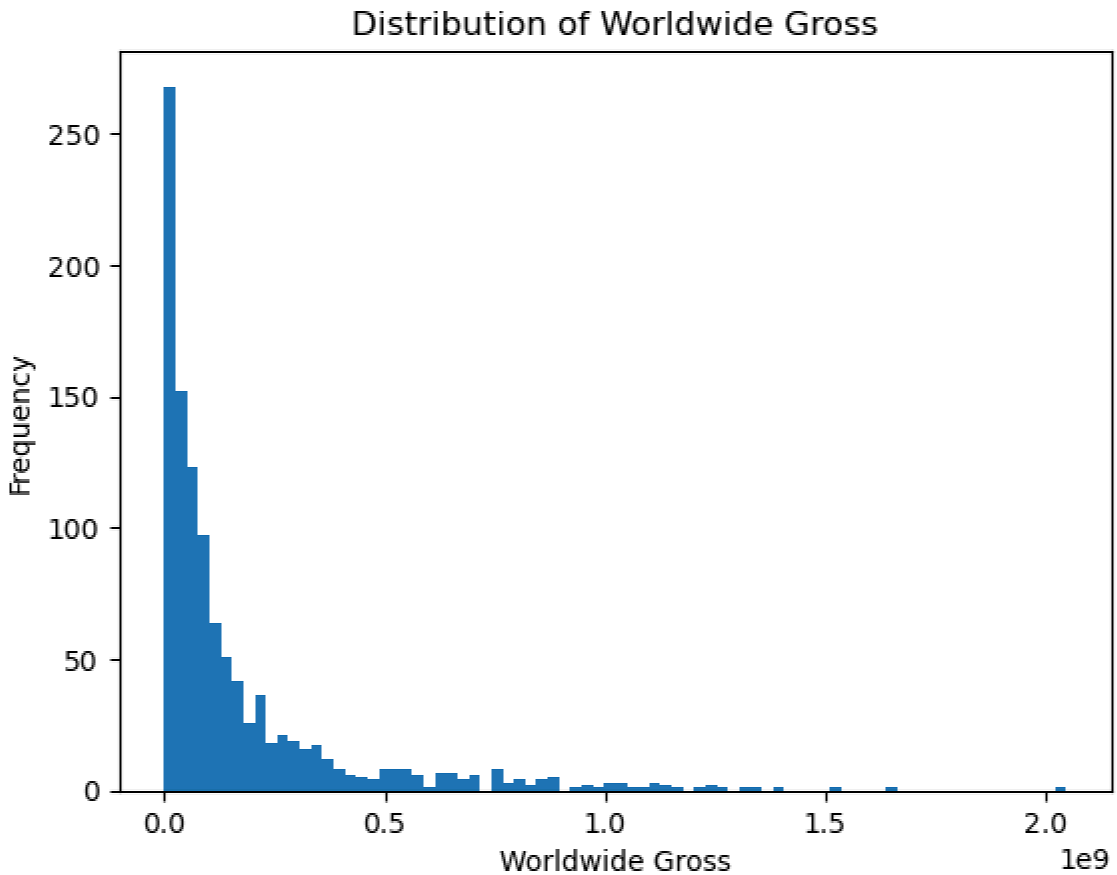
The above diagram shows some of the competitors in the industry that the company would encounter. Universal Studios, Warner Bros, and Fox are famously known, with successful films/blockbusters and regular project releases.

In [76]:
```
# Histogram for budgets for visualising the distribution

plt.hist(df['production_budget'], bins = 80)
plt.xlabel("Production Budget")
plt.ylabel("Frequency")
plt.title("Distribution of Production Budget")
plt.show()
```



The diagram shows that the production budget tends to be on the lower end. As the budget increases, the frequency decreases as well. This means that the films tend to be mostly low-budget, and unless they are intended to be a blockbuster/high-end film, like The Avengers (according to research), they will use a high budget.

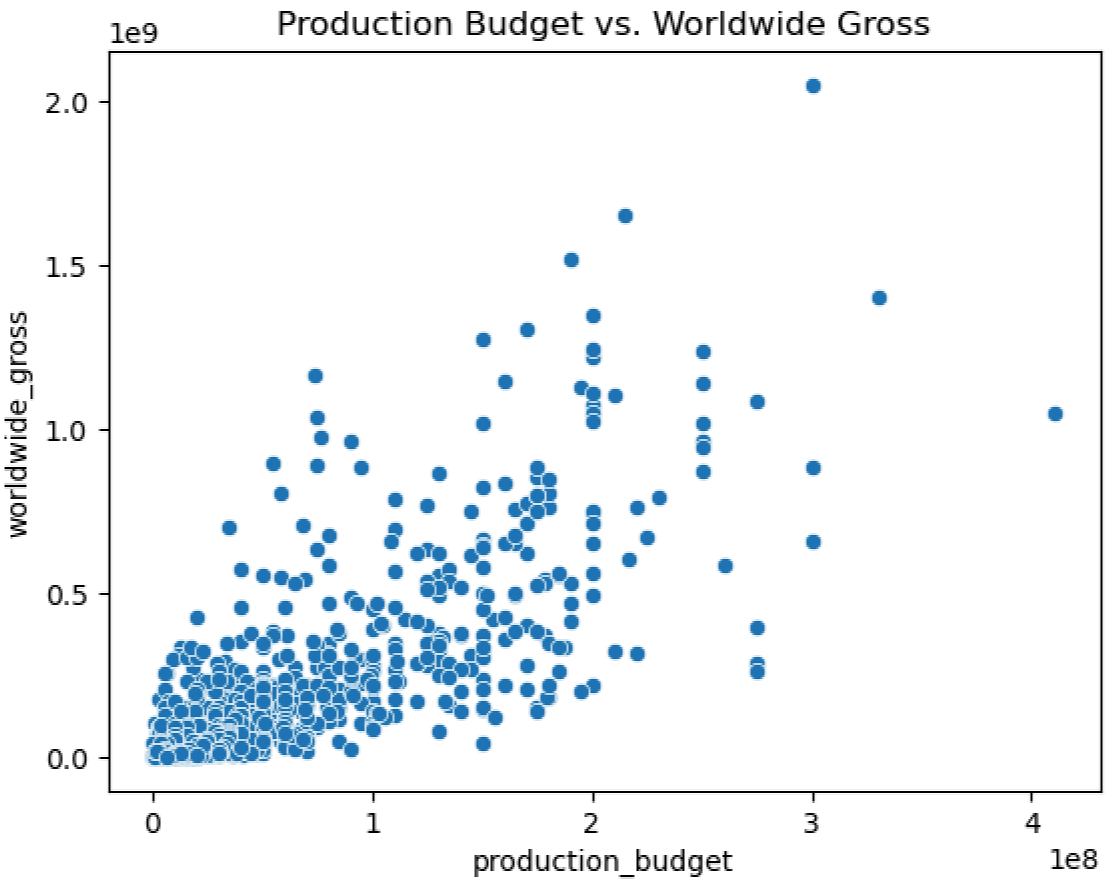
In [77]:
```
# Distribution for worldwide gross to understand the amount earned/returns from the

plt.hist(df['worldwide_gross'], bins = 80)
plt.xlabel('Worldwide Gross')
plt.ylabel('Frequency')
plt.title('Distribution of Worldwide Gross')
plt.show()
```



The frequency of films decrease as the gross increases. Only few movies/films are grossing at above 500 million dollars. Most films gross averagely below 500 million and unless they are blockbusters/huge hit they gross at even 1 billion dollars.

2. Bi-variate Analysis

In [78]:
```
# Understanding the relationship between the budget put into the film and the retur

sns.scatterplot(x = 'production_budget', y = 'worldwide_gross', data = df)
plt.title('Production Budget vs. Worldwide Gross')
plt.show()
```

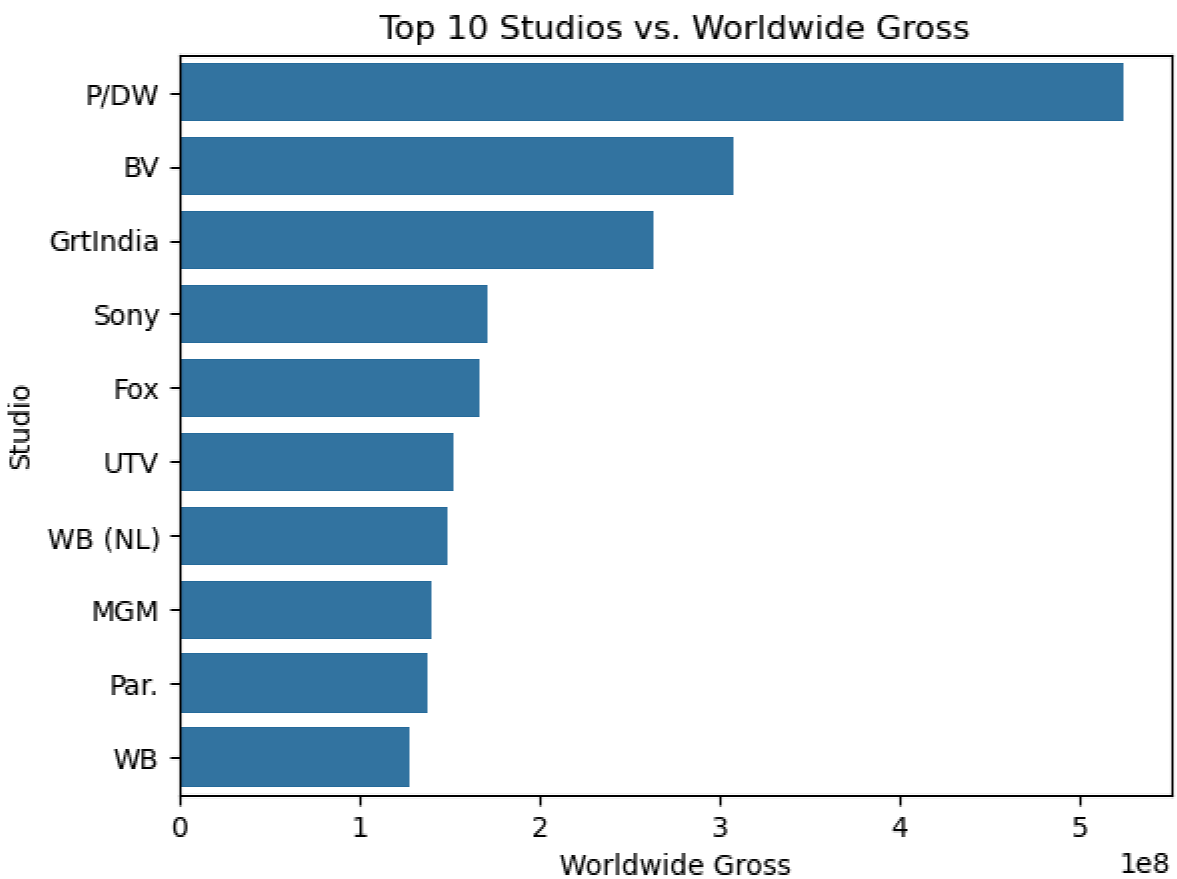


Visibly there is a relative positive relationship between the production budget and the gross. This means that the higher the budget is put into a film, it yields a higher gross. However, it is not a guarantee as well. There are moments of investing in the films with a high budget but does not perform well (yield a high gross). It can be a risk to have a high budget without the certainty of a high return.

In [79]:
```
# Grouping the data by studio and worldwide gross. The gross median is calculated b
# Therefore, using the median is a better statistical measure. Typical representati
# Studying the relationship between studio and worldwide gross. This will help unde

studio_by_gross = df.groupby('studio')['worldwide_gross'].median().sort_values(asce
studio_by_gross
```

Out[79]:
```
studio
P/DW        524929234.5
BV          308274568.5
GrtIndia    263502914.0
Sony        170936470.0
Fox         166785054.0
UTV         152395926.0
WB (NL)     148806510.0
MGM         139779636.0
Par.        137990372.0
WB          127990741.0
Name: worldwide_gross, dtype: float64
```

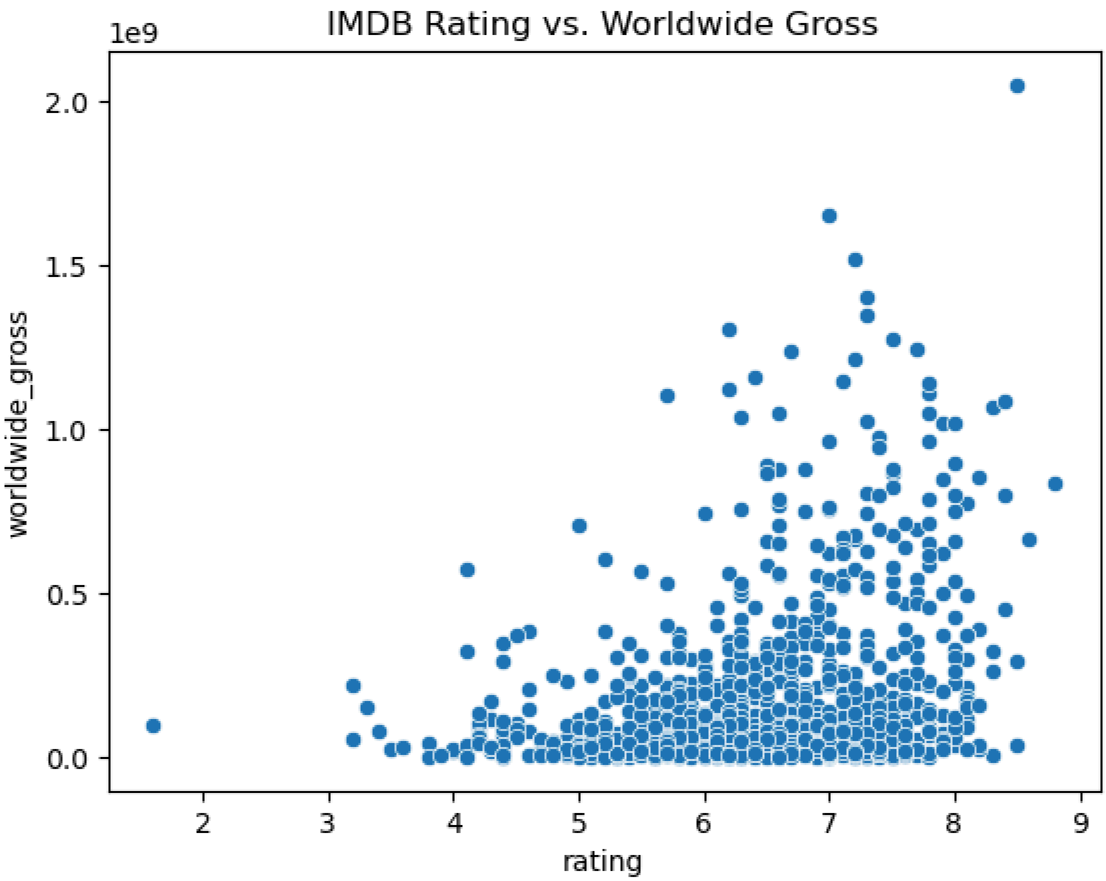
In [80]:
```
#plotting for visuals

sns.barplot(x = studio_by_gross.values, y = studio_by_gross.index)
plt.title('Top 10 Studios vs. Worldwide Gross')
plt.xlabel('Worldwide Gross')
plt.ylabel('Studio')
plt.show()
```



P/DW(DreamWork Studios), BV(Walt Disney Studios) and GrtIndia are studios that are yielding gross above 250 million dollars from their releases which is quite high. These 10 studios show their positions in the industry and the amount they are averagely grossing at from their releases.

These are studios the company would potentially like towrads emulating.

In [81]:
```
# Visualising and understanding the relationship between IMDB rating and the worldw

sns.scatterplot(x = 'rating', y = 'worldwide_gross', data = df)
plt.title('IMDB Rating vs. Worldwide Gross')
plt.show()
```

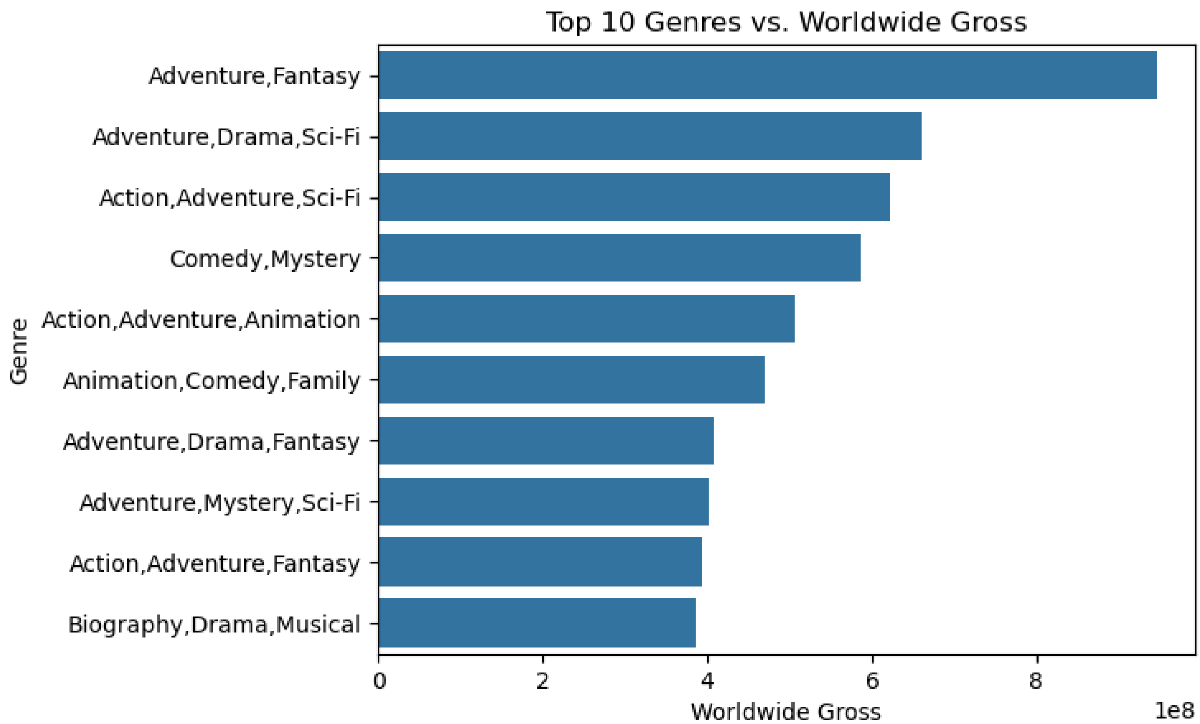


There is a visible positive relationship, however, it's not too strong as well. Highly rated movies, > 7, can gros really high such but also can gross averagely low. While a movie may be highly popular and rated, does not mean it will gross.

In [82]:
```
# Grouping the genres and worldwide gross. The gross median is calculated because t

genre_by_gross = df.groupby('genres')['worldwide_gross'].median().sort_values(ascen
genre_by_gross
```

Out[82]:
```
genres
Adventure,Fantasy              945577621.0
Adventure,Drama,Sci-Fi         660825409.0
Action,Adventure,Sci-Fi        621156389.0
Comedy,Mystery                 586464305.0
Action,Adventure,Animation     506235067.0
Animation,Comedy,Family        469500298.0
Adventure,Drama,Fantasy        408351398.5
Adventure,Mystery,Sci-Fi       402448265.0
Action,Adventure,Fantasy       393151347.0
Biography,Drama,Musical        386665550.0
Name: worldwide_gross, dtype: float64
```

In [83]:
```
sns.barplot(x = genre_by_gross.values, y = genre_by_gross.index)
plt.title('Top 10 Genres vs. Worldwide Gross')
plt.xlabel('Worldwide Gross')
plt.ylabel('Genre')
plt.show()
```



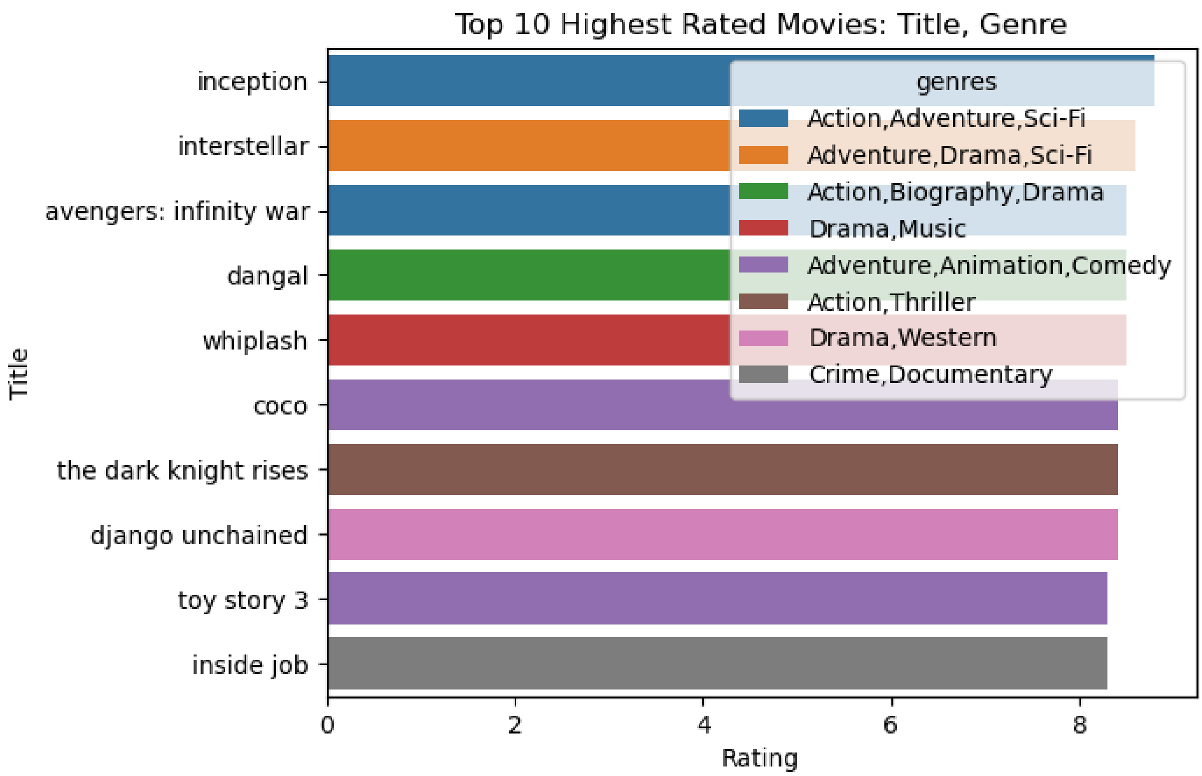
Adventure, Fantasy yields has the highest gross. The graph shows the top earning genres. Overall, family friendly and adventure themed films work well gross wise. Guaranteed a fair return.

3. Multi-variate Analysis

In [84]:
```
# Getting the top 10 movies by IMDB rating

highly_rated = df.sort_values('rating', ascending = False).head(10)
print(highly_rated[['title', 'year', 'genres', 'rating', 'studio']])
```

```
                      title  year                       genres  rating studio
1                 inception  2010      Action,Adventure,Sci-Fi     8.8     WB
548            interstellar  2014       Adventure,Drama,Sci-Fi     8.6   Par.
1001  avengers: infinity war  2018      Action,Adventure,Sci-Fi     8.5     BV
804                  dangal  2016       Action,Biography,Drama     8.5    UTV
615                whiplash  2014                  Drama,Music     8.5    SPC
913                    coco  2017   Adventure,Animation,Comedy     8.4     BV
292     the dark knight rises  2012              Action,Thriller     8.4     WB
302        django unchained  2012                Drama,Western     8.4  Wein.
0                toy story 3  2010   Adventure,Animation,Comedy     8.3     BV
122              inside job  2010            Crime,Documentary     8.3    SPC
```

In [85]:
```
# Visualizing the results above with a bar graph
# Adding the hue option for a sub-grouping, which is genres, to differentiate using

sns.barplot(x = 'rating', y = 'title', data = highly_rated, hue = 'genres')
plt.title('Top 10 Highest Rated Movies: Title, Genre')
plt.xlabel('Rating')
plt.ylabel('Title')
plt.show()
```



In the above bar graph, we can see that the highly/top rated films are inception at the top which is action, adventure, sci fi genre similar to the 3rd top rated. The 2nd is adventure, drama, sci fi, and etc. This indicates that hints of adventure, drama, sci fi and action bring in the high ratings. And would be important for the company to try and focus their scripts along these genres.

7/10 of the films are from the early 2010's (2010-2014). This indicates that over the years, the excitement within the films have decreased and would be important to study and understand what those films had that was entertaining/intriguing to the audience.

In [86]:
```
# Picking the top studios to visualise their trend over the years

top_studios = df['studio'].value_counts().head(5).index
top_studios
```

Out[86]:
```
Index(['Uni.', 'Fox', 'WB', 'BV', 'Sony'], dtype='object', name='studio')
```

In [87]:
```
# Creating a df that we can use that has the data from the top 5 studios only

top_df = df[df['studio'].isin(top_studios)]
top_df.head()
```

Out[87]:

	title	year	studio	production_budget	foreign_gross	domestic_gross	worldwide_(
0	toy story 3	2010	BV	200000000	652000000.0	415004880	106887
1	inception	2010	WB	160000000	535700000.0	292576195	83552
5	tangled	2010	BV	260000000	391000000.0	200821936	58647
6	despicable me	2010	Uni.	69000000	291600000.0	251513985	54346
8	the chronicles of narnia: the voyage of the da...	2010	Fox	155000000	311300000.0	104386950	41818

In [88]:

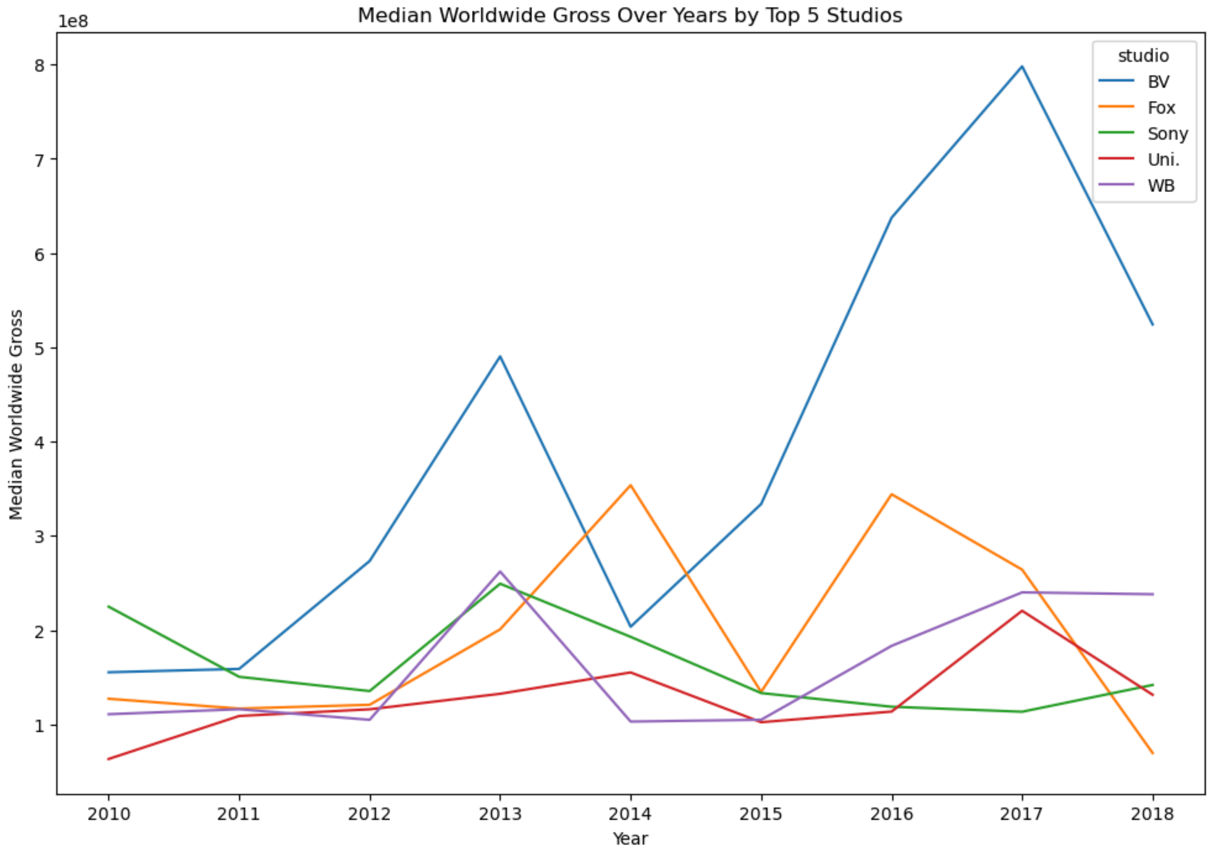
```
# Grouping year and studio columns by the median gross then go on to plot.

studio_trend = top_df.groupby(['year', 'studio'])['worldwide_gross'].median().reset
studio_trend
```

Out[88]:

	year	studio	worldwide_gross
0	2010	BV	155332634.0
1	2010	Fox	127234389.0
2	2010	Sony	224922135.0
3	2010	Uni.	63354114.0
4	2010	WB	110843326.5
5	2011	BV	158893725.5
6	2011	Fox	116809717.0
7	2011	Sony	150519217.0
8	2011	Uni.	108957098.0
9	2011	WB	116095903.5
10	2012	BV	273346281.0
11	2012	Fox	120832383.0
12	2012	Sony	135378020.0
13	2012	Uni.	116044347.0
14	2012	WB	104907746.0
15	2013	BV	490359051.0
16	2013	Fox	200859554.0
17	2013	Sony	249261736.5
18	2013	Uni.	132493015.0
19	2013	WB	262202604.0
20	2014	BV	203643010.0
21	2014	Fox	353756621.0
22	2014	Sony	192903624.0
23	2014	Uni.	155143696.0
24	2014	WB	103039258.0
25	2015	BV	333771037.0
26	2015	Fox	134491623.0
27	2015	Sony	133277985.0
28	2015	Uni.	102354238.0
29	2015	WB	104949584.0

	year	studio	worldwide_gross
30	2016	BV	637517365.0
31	2016	Fox	344150134.0
32	2016	Sony	118763442.0
33	2016	Uni.	113636174.0
34	2016	WB	183353431.0
35	2017	BV	798008101.0
36	2017	Fox	264184588.5
37	2017	Sony	113461527.0
38	2017	Uni.	220552181.5
39	2017	WB	240076708.5
40	2018	BV	524283695.0
41	2018	Fox	69693360.5
42	2018	Sony	141872305.0
43	2018	Uni.	131474527.5
44	2018	WB	238099711.0

In [89]:
```
# Plotting the graph to visualise the trend over the years of the top 5 studios

plt.figure(figsize = (12,8))
sns.lineplot(data = studio_trend, x = 'year', y = 'worldwide_gross', hue = 'studio'
plt.title('Median Worldwide Gross Over Years by Top 5 Studios')
plt.xlabel('Year')
plt.ylabel('Median Worldwide Gross')
plt.show()
```



Over the years, it is noticeable that there are years with high peaks, indicating the release of blockbuster films. BV studio has experienced the highest peaks over the years, as well as notable drops, compared to other studios. However, they can consistently stay above 1.5 dollars. Universal Studios has stayed moderately average over the years. And other studios have their peaks and drops over the years, not as large and dramatic as BV studios, and not as calm as Universal Studios.

Recommendations And Conclusion

Recommendations

1. Focus on the genres that have the highest returns.

   - Adventure, animation, comedy, action, and sci-fi have the highest return at the box office.
   - Over the years, the films that have performed well in specific studios have been family-friendly. Examples would be Avengers, Toy Story 3, which have been blockbusters and highly rated as well.
2. Work with, or learn from, the top studios in the film industry: Warner Bros, Disney, Universal Studios, Fox, and Sony. They have been able to create a name for themselves and remain successful over the many years of releasing movies. As much as they may not always gross highly in all films, they can return a solid average.

3. Monitor the industry. The trends over the years, how the potential competitors are doing, genres that are performing well in that season, the hiccups being faced, and more historical and recent data as well. The current data is just before COVID-19; hence, concluding the performance in the industry is very limited.

4. When it comes to the budget, it is important to look at the risk and reward. There are instances where the company can invest a high amount into the production of a film, and does not gross highly, and vice versa. It is a huge risk. Finding ways to invest not too much into the production, advertise it, and work on the target audience to create populairty towards the film and high ratings, can lead to a high gross.

Conclusion

In the film industry analysis above, we explored several datasets that are about the film industry. The datasets chosen and cleaned have been able to form visuals to help form recommendations for the company.

The datasets used for the analysis:

- IMDB
- The Numbers Dataset
- Box Office Mojo Dataset

The dataset was cleaned by:

- Handled missing values and duplicates in the individual datasets and merged data as well
- Understanding the outliers and whether they should be removed or retained. (Retained for maintaining real-world accuracy)
- Converted data types from object to numerical
- Standardized the formats of the data to ensure the merging works smoothly

Key findings include:

- There are specific genres that yield a high average gross, meaning they are popular with the audience. [Adventure, action, sci-fi, drama, anaimation, etc]
- There are staple film studios that are performing well in the industry and would be potential competitors/advisors/business partners. [Walt Disney Studios, Warner Bros, Sony, Fox, etc]
- Using a high production budget does not guarantee a high gross return once the film is released. Unless a blockbuster eg, Avengers.
- Over the years, the performance (yielding gross as a studio) fluctuates significantly. Moments of peaks and pits.
- Production budgets are quite skewed. Most films, apart from blockbusters, are quite low budget unless they are an anticipated blockbuster in a franchise.