Project Title: Exploring Movie Success: Revenue, Ratings, and Genre Analysis

Business Understanding

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.

Introduction

The success of a movie is influenced by multiple factors, including genre, release timing, audience reception, and market performance. Understanding these factors can help studios make informed decisions to maximize both critical acclaim and financial returns. This analysis explores the relationships between movie ratings, genres, release months, and box office performance, aiming to provide actionable insights for strategic planning in movie production and distribution. By examining patterns in domestic and worldwide profits, as well as audience ratings, the study identifies key drivers of commercial success and offers recommendations to optimize future releases.

Problem Statement

Studios often struggle to predict which factors,such as genre, release timing, or ratings drive a movie’s financial success. This study aims to identify the key drivers of profitability to guide better production and release decisions.

Objectives

1. To analyze how movie genre impacts domestic and worldwide box office profits.
2. To examine the effect of release month on movie profitability.
3. To investigate the relationship between audience ratings and box office success.
4. To determine whether domestic performance can predict worldwide earnings.
5. To provide actionable recommendations for optimizing movie production and release strategies.

Data Understanding

The dataset used in this analysis contains information about movies, including their genre, release date, audience ratings, domestic gross, and worldwide gross. It provides insights into both critical reception and financial performance, allowing for an examination of patterns and relationships that influence movie success.It contained various dataset file formarts, tsvs, csvs and an sqlite dataase, which all contained various columns eg genre, release date, audience ratings, domestic gross, and worldwide gross just to mention a few. These multiple datasets enable analysis of correlations between ratings, genre, release timing, and profits, helping to identify the factors most critical to commercial success.

Importing all Libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
```

```python
import matplotlib.pyplot as plt
from scipy.stats import norm
from scipy.stats import binom
```

Exploratory Data Analysis (EDA)

Exploratory Data Analysis was conducted to understand patterns, trends, and relationships in the movie dataset.

In [2]:

```python
# Reading into the bom csv files to clean and aggregate the columns we need for analysis
bom = pd.read_csv("bom.movie_gross.csv")

#Get a feel of how the data looks like
bom.columns
```

Out[2]:

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

In [3]:

```python
bom
```

Out[3]:

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [4]:

```python
bom.describe()
```

Out[4]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

In [5]:

In [5]:

```
bom.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 [6]:

```
bom['foreign_gross'] = pd.to_numeric(bom['foreign_gross'], errors='coerce')
```

In [7]:

```
bom['foreign_gross'].astype(float)
```

Out[7]:

```
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 [8]:

```
bom.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 [9]:

```
#Check missing rows in the bomdf
bom.isna().sum()
```

Out[9]:

```
title                0
studio               5
domestic_gross      28
foreign_gross     1355
year                 0
dtype: int64
```

In [10]:

```
bom['foreign_gross'] = bom['foreign_gross'].fillna(bom['foreign_gross'].mean())
bom['domestic_gross'] = bom['domestic_gross'].fillna(bom['domestic_gross'].mean())
```

In [11]:

```
bom.isna().sum()
```

Out[11]:

```
title             0
studio            5
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

In [12]:

```
bom=bom.dropna()
```

In [13]:

```
bom['studio'].isna().sum()
```

Out[13]:

```
0
```

In [14]:

```
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3382 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3382 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3382 non-null   float64
 3   foreign_gross   3382 non-null   float64
 4   year            3382 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 158.5+ KB
```

In [15]:

```
bom.duplicated()
```

Out[15]:

```
0       False
1       False
2       False
3       False
4       False
        ...  
3382    False
3383    False
3384    False
3385    False
3386    False
Length: 3382, dtype: bool
```

In [16]:

```
bomdf = ['title','domestic_gross','foreign_gross']
bom = bom[bomdf]
```

In [17]:

```
bom
```

Out[17]:

	title	domestic_gross	foreign_gross
0	Toy Story 3	415000000.0	6.520000e+08
1	Alice in Wonderland (2010)	334200000.0	6.913000e+08
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	6.643000e+08
3	Inception	292600000.0	5.357000e+08
4	Shrek Forever After	238700000.0	5.139000e+08
...	...	...	...
3382	The Quake	6200.0	7.505704e+07
3383	Edward II (2018 re-release)	4800.0	7.505704e+07
3384	El Pacto	2500.0	7.505704e+07
3385	The Swan	2400.0	7.505704e+07
3386	An Actor Prepares	1700.0	7.505704e+07

3382 rows × 3 columns

In [18]:

```
rt_movie = pd.read_table("rt.movie_info.tsv")
```

In [19]:

```
rt_movie.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    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

In [20]:

```
rt_movie.isna().sum()
```

Out[20]:

```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime           30
studio          1066
dtype: int64
```

In [21]:

```
rt_movie['runtime'] = rt_movie['runtime'].str.replace('minutes', '',regex=False)
rt_movie['runtime']
```

Out[21]:

```
0       104
1       108
2       116
3       128
4       200
        ...
1555    106
1556     88
1557    111
1558    101
1559     94
Name: runtime, Length: 1560, dtype: object
```

In [22]:

```
rt_movie['runtime'] = pd.to_numeric(rt_movie['runtime'], errors='coerce')
```

In [23]:

```
rt_movie.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    object
 10  runtime        1530 non-null   float64
 11  studio         494 non-null    object
dtypes: float64(1), int64(1), object(10)
memory usage: 146.4+ KB
```

In [24]:

```
rt_movie['runtime'].value_counts()
```

Out[24]:

```
runtime
90.0     72
95.0     66
100.0    51
93.0     47
96.0     43
         ..
154.0     1
166.0     1
33.0      1
54.0      1
290.0     1
Name: count, Length: 142, dtype: int64
```

In [25]:

```
rt_movie['runtime'] = rt_movie['runtime'].fillna(rt_movie['runtime'].mode()[0])
```

```
rt_movie['runtime'].value_counts()
```

Out[25]:

```
runtime
90.0     102
95.0      66
100.0     51
93.0      47
96.0      43
         ...
154.0      1
166.0      1
33.0       1
54.0       1
290.0      1
Name: count, Length: 142, dtype: int64
```

In [26]:

```
rt_movie.isna().sum()
```

Out[26]:

```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime            0
studio          1066
dtype: int64
```

In [27]:

```
rt_movie.head()
```

Out[27]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_o
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	$	600
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	
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997	NaN	
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN	NaN	

In [28]:

```
rt_reviews = pd.read_table("rt.reviews.tsv" , encoding="latin1")
rt_reviews.head()
```

Out[28]:

	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
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

In [29]:

```
rt_reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          54432 non-null  int64 
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64 
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
```

In [30]:

```
rt_reviews["rating"] = pd.to_numeric(rt_reviews["rating"], errors='coerce').astype("floa
t64")
```

In [31]:

```
rt_reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   id          54432 non-null  int64  
 1   review      48869 non-null  object 
 2   rating      750 non-null    float64
 3   fresh       54432 non-null  object 
 4   critic      51710 non-null  object 
 5   top_critic  54432 non-null  int64  
 6   publisher   54123 non-null  object 
 7   date        54432 non-null  object 
dtypes: float64(1), int64(2), object(5)
memory usage: 3.3+ MB
```

In [32]:

```
rt_reviews.isna().sum()
```

Out[32]:

Out[32]:

```
id                0
review         5563
rating        53682
fresh             0
critic         2722
top_critic        0
publisher       309
date              0
dtype: int64
```

In [33]:

```
rt_reviews['top_critic'].value_counts()
```

Out[33]:

```
top_critic
0    41336
1    13096
Name: count, dtype: int64
```

In [34]:

```
rt_reviews_1 = pd.read_table("rt.reviews.tsv" , encoding="latin1")
```

In [35]:

```
rt_reviews_1 = rt_reviews_1.dropna()
```

In [36]:

```
rt_reviews_1.isna().sum()
```

Out[36]:

```
id            0
review        0
rating        0
fresh         0
critic        0
top_critic    0
publisher     0
date          0
dtype: int64
```

In [37]:

```
rt_reviews_1.duplicated()
```

Out[37]:

```
0        False
6        False
7        False
11       False
12       False
         ...
54419    False
54420    False
54421    False
54422    False
54424    False
Length: 33988, dtype: bool
```

In [38]:

```
rt_reviews_1.head()
```

Out[38]:

id	review	rating	fresh	critic	top_critic	publisher	date

	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
6	3	Quickly grows repetitive and tiresome, meander...	C	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013
7	3	Cronenberg is not a director to be daunted by ...	2/5	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013
11	3	While not one of Cronenberg's stronger films, ...	B-	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013
12	3	Robert Pattinson works mighty hard to make Cos...	2/4	rotten	Christian Toto	0	Big Hollywood	January 15, 2013

In [39]:

```
df_tmdb = pd.read_csv("tmdb.movies.csv")
df_tmdb.columns
```

Out[39]:

```
Index(['Unnamed: 0', 'genre_ids', 'id', 'original_language', 'original_title',
       'popularity', 'release_date', 'title', 'vote_average', 'vote_count'],
      dtype='object')
```

In [40]:

```
df_tmdb
```

Out[40]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	
...	...	...	...	...	...	...	...	...	
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	Laboratory Conditions	
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBIT_84xxx_	
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	The Last One	
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	Trailer Made	
26516	26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	The Church	

26517 rows × 10 columns

In [41]:

```
df_tmdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
```

```
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Unnamed: 0          26517 non-null  int64
 1   genre_ids           26517 non-null  object
 2   id                  26517 non-null  int64
 3   original_language   26517 non-null  object
 4   original_title      26517 non-null  object
 5   popularity          26517 non-null  float64
 6   release_date        26517 non-null  object
 7   title               26517 non-null  object
 8   vote_average        26517 non-null  float64
 9   vote_count          26517 non-null  int64
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

In [42]:

```
# check for duplicates
df_tmdb.duplicated().sum()
```

Out[42]:

```
0
```

In [43]:

```
df_tmdb['release_date'] = pd.to_datetime(df_tmdb['release_date']).dt.month
```

In [44]:

```
df_tmdb["genre_ids"].value_counts().sort_index(ascending=False)
```

Out[44]:

```
genre_ids
[]                                 2479
[99]                               3700
[99, 99]                              2
[99, 99, 99]                          1
[99, 9648]                            4
                                   ...
[10402, 10751, 14, 10770, 35]         1
[10402, 10749]                        3
[10402, 10749, 35]                    2
[10402, 10749, 35, 18]                3
[10402, 10749, 18]                    2
Name: count, Length: 2477, dtype: int64
```

In [45]:

```
df_tmdb = df_tmdb.rename(columns={'release_date':'release_month'})
```

In [46]:

```
tmdbdf = ['title','vote_average','vote_count','release_month']
df_tmdb = df_tmdb[tmdbdf]
```

In [47]:

```
df_tmdb
```

Out[47]:

	title	vote_average	vote_count	release_month
0	Harry Potter and the Deathly Hallows: Part 1	7.7	10788	11
1	How to Train Your Dragon	7.7	7610	3
2	Iron Man 2	6.8	12368	5
3	Toy Story	7.9	10174	11
4	Inception	8.3	22186	7

	title	vote_average	vote_count	release_month
...	...	...	...	...
26512	Laboratory Conditions	0.0	1	10
26513	_EXHIBIT_84xxx_	0.0	1	5
26514	The Last One	0.0	1	10
26515	Trailer Made	0.0	1	6
26516	The Church	0.0	1	10

26517 rows × 4 columns

In [48]:

```
df_tn = pd.read_csv("tn.movie_budgets.csv")
df_tn
```

Out[48]:

	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
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

In [49]:

```
df_tn.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 [50]:

```
df_tn['domestic_gross'] = df_tn['domestic_gross'].str.replace('$', '',regex=False)
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].str.replace('$', '',regex=False)
df_tn['production_budget'] = df_tn['production_budget'].str.replace('$', '',regex=False)
```

In [51]:

```
df_tn.head()
```

Out[51]:

Out[51]:

	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

In [52]:

```
df_tn['production_budget'] = df_tn['production_budget'].str.replace('NA', '0',regex=False
)
df_tn['domestic_gross'] = df_tn['domestic_gross'].str.replace('NA', '0',regex=False)
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].str.replace('NA', '0',regex=False)
df_tn['production_budget'] = df_tn['production_budget'].str.replace(',', '',regex=False)
df_tn['domestic_gross'] = df_tn['domestic_gross'].str.replace(',', '',regex=False)
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].str.replace(',', '',regex=False)
```

In [53]:

```
df_tn.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 [54]:

```
df_tn['domestic_gross'] = pd.to_numeric(df_tn['domestic_gross'], errors='coerce').astype
("float64")
df_tn['worldwide_gross'] = pd.to_numeric(df_tn['worldwide_gross'], errors='coerce').asty
pe("float64")
df_tn['production_budget'] = pd.to_numeric(df_tn['production_budget'], errors='coerce').
astype("float64")
```

In [55]:

```
df_tn.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 [56]:

```
df_tn = df_tn.rename(columns={'movie':'title'})
```

In [57]:

```
tndf = ['title','production_budget','domestic_gross','worldwide_gross']
df_tn = df_tn[tndf]
```

In [58]:

```
df_tn
```

Out[58]:

	title	production_budget	domestic_gross	worldwide_gross
0	Avatar	425000000.0	760507625.0	2.776345e+09
1	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
...	...	...	...	...
5777	Red 11	7000.0	0.0	0.000000e+00
5778	Following	6000.0	48482.0	2.404950e+05
5779	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03
5780	A Plague So Pleasant	1400.0	0.0	0.000000e+00
5781	My Date With Drew	1100.0	181041.0	1.810410e+05

5782 rows × 4 columns

In [59]:

```
import sqlite3

conn = sqlite3.connect("im.db")

df2_sql = """
         SELECT name
         FROM SQLITE_MASTER
      """
pd.read_sql_query(df2_sql,conn)
```

Out[59]:

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

In [60]:

```
movie_ratingssql = """ SELECT movie_basics.movie_id,
                     movie_basics.genres,movie_basics.primary_title,movie_ratings.averag
erating,
                     movie_ratings.numvotes,movie_akas.region,movie_akas.language
```

```
                          FROM movie_basics
                          JOIN movie_ratings ON movie_ratings.movie_id = movie_basics.movie_i
d
                          JOIN movie_akas ON movie_akas.movie_id = movie_ratings.movie_id
                          """
movie_ratingssql = pd.read_sql_query(movie_ratingssql,conn)
```

In [61]:

```
movie_ratingssql.to_csv('databasecsv.csv', index=False, encoding='utf-8')
```

In [62]:

```
dfdatabase = pd.read_csv('databasecsv.csv')
dfdatabase
```

Out[62]:

	movie_id	genres	primary_title	averagerating	numvotes	region	language
0	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	NaN	NaN
1	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	IN	NaN
2	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	IN	hi
3	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	IN	hi
4	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	IN	hi
...	...	...	...	...	...	...	...
261801	tt9905462	Drama	Pengalila	8.4	600	IN	NaN
261802	tt9905462	Drama	Pengalila	8.4	600	IN	en
261803	tt9911774	Drama	Padmavyuhathile Abhimanyu	8.4	365	NaN	NaN
261804	tt9911774	Drama	Padmavyuhathile Abhimanyu	8.4	365	IN	ml
261805	tt9911774	Drama	Padmavyuhathile Abhimanyu	8.4	365	IN	ml

261806 rows × 7 columns

In [63]:

```
dfdatabase = dfdatabase.drop_duplicates()
```

In [64]:

```
dfdatabase.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 242723 entries, 0 to 261804
Data columns (total 7 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   movie_id       242723 non-null  object
 1   genres         241653 non-null  object
 2   primary_title  242723 non-null  object
 3   averagerating  242723 non-null  float64
 4   numvotes       242723 non-null  int64
 5   region         205843 non-null  object
 6   language       35124 non-null   object
dtypes: float64(1), int64(1), object(5)
memory usage: 14.8+ MB
```

In [65]:

```
dfdatabase.isna().sum()
```

Out[65]:

```
movie_id              0
genres             1070
primary_title         0
```

```
primary_title          0
averagerating          0
numvotes               0
region             36880
language          207599
dtype: int64
```

In [66]:

```
dfdatabasedrop = dfdatabase.dropna()
```

In [67]:

```
dfdatabasedrop.isna().sum()
```

Out[67]:

```
movie_id         0
genres           0
primary_title    0
averagerating    0
numvotes         0
region           0
language         0
dtype: int64
```

In [68]:

```
dfdatabasedrop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 34992 entries, 2 to 261804
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   movie_id       34992 non-null  object
 1   genres         34992 non-null  object
 2   primary_title  34992 non-null  object
 3   averagerating  34992 non-null  float64
 4   numvotes       34992 non-null  int64
 5   region         34992 non-null  object
 6   language       34992 non-null  object
dtypes: float64(1), int64(1), object(5)
memory usage: 2.1+ MB
```

In [69]:

```
dfdatabasedrop
```

Out[69]:

	movie_id	genres	primary_title	averagerating	numvotes	region	language
2	tt0063540	Action,Crime,Drama	Sunghursh	7.0	77	IN	hi
8	tt0066787	Biography,Drama	One Day Before the Rainy Season	7.2	43	XWW	en
23	tt0069204	Comedy,Drama	Sabse Bada Sukh	6.1	13	IN	bn
24	tt0069204	Comedy,Drama	Sabse Bada Sukh	6.1	13	IN	en
29	tt0100275	Comedy,Drama,Fantasy	The Wandering Soap Opera	6.5	119	XWW	en
...	...	...	...	...	...	...	...
261791	tt9899850	Drama,Thriller	The Agitation	4.9	14	XWW	en
261794	tt9899860	Drama,Thriller	Watching This Movie Is a Crime	8.1	7	XWW	en
261796	tt9899880	Comedy	Columbus	5.8	5	IR	fa
261802	tt9905462	Drama	Pengalila	8.4	600	IN	en
261804	tt9911774	Drama	Padmavyuhathile Abhimanyu	8.4	365	IN	ml

34992 rows × 7 columns

In [70]:

```
dfdatabasedrop = dfdatabasedrop.rename(columns={'primary_title':'title'})
```

In [71]:

```
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3382 entries, 0 to 3386
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3382 non-null   object
 1   domestic_gross  3382 non-null   float64
 2   foreign_gross   3382 non-null   float64
dtypes: float64(2), object(1)
memory usage: 105.7+ KB
```

In [72]:

```
themovie_df = (
    bom
    .merge(df_tmdb, on='title')
    .merge(df_tn, on='title')
    .merge(dfdatabasedrop, on='title')
)
#themovie_df = pd.merge(bom,df_tmdb,df_tn,dfdatabasedrop, on = 'title')
```

In [73]:

```
themovie_df
```

Out[73]:

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gross_
0	**Toy Story 3**	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
1	**Toy Story 3**	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
2	**Toy Story 3**	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
3	**Toy Story 3**	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
4	**Toy Story 3**	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
...	...	...	...	...	...	...	...	.
6005	Gotti	4300000.0	7.505704e+07	5.2	231	6	10000000.0	4286367.
6006	Mandy	1200000.0	7.505704e+07	3.5	2	1	6000000.0	1214525.
6007	Mandy	1200000.0	7.505704e+07	6.2	618	9	6000000.0	1214525.
6008	Lean on Pete	1200000.0	7.505704e+07	6.9	133	4	8000000.0	1163056.
6009	Lean on Pete	1200000.0	7.505704e+07	6.9	133	4	8000000.0	1163056.

6010 rows × 15 columns

In [74]:

```
themovie_df = themovie_df.drop_duplicates()
```

In [75]:

```
themovie_df.value_counts().sum()
```

Out[75]:

5461

In [76]:

```
themovie_df
```

Out[76]:

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gross_
0	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
1	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
2	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
3	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
4	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004880.
...	...	...	...	...	...	...	...	.
6004	Gotti	4300000.0	7.505704e+07	5.2	231	6	10000000.0	4286367.
6005	Gotti	4300000.0	7.505704e+07	5.2	231	6	10000000.0	4286367.
6006	Mandy	1200000.0	7.505704e+07	3.5	2	1	6000000.0	1214525.
6007	Mandy	1200000.0	7.505704e+07	6.2	618	9	6000000.0	1214525.
6008	Lean on Pete	1200000.0	7.505704e+07	6.9	133	4	8000000.0	1163056.

5461 rows × 15 columns

In [77]:

```
themovie_dropcol = themovie_df.drop(columns= ['language', 'region'])
```

In [78]:

```
themovie_df2 = themovie_dropcol.drop_duplicates()
```

In [79]:

```
themovie_df2
```

Out[79]:

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gro
0	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	415004

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gro
8	Inception	292600000.0	5.357000e+08	8.3	22186	7	160000000.0	2925761
17	Shrek Forever After	238700000.0	5.139000e+08	6.1	3843	5	165000000.0	2387367
25	The Twilight Saga: Eclipse	300500000.0	3.980000e+08	6.0	4909	6	68000000.0	3005317
30	Iron Man 2	312400000.0	3.115000e+08	6.8	12368	5	170000000.0	3124333
...	...	...	...	...	...	...	...	
6000	Destroyer	1500000.0	4.000000e+06	5.9	176	12	9000000.0	15333
6004	Gotti	4300000.0	7.505704e+07	5.2	231	6	10000000.0	42863
6006	Mandy	1200000.0	7.505704e+07	3.5	2	1	6000000.0	12145
6007	Mandy	1200000.0	7.505704e+07	6.2	618	9	6000000.0	12145
6008	Lean on Pete	1200000.0	7.505704e+07	6.9	133	4	8000000.0	11630

1335 rows × 13 columns

In [80]:

```
themovie_df2.to_csv('databaseforvisio.csv', index=False, encoding='utf-8')
```

In [81]:

```
themovie_df2['profit'] = themovie_df2['worldwide_gross'] - themovie_df2['production_budget']
themovie_df2['d_profit'] = themovie_df2['domestic_gross_y'] - themovie_df2['production_budget']
```

```
/tmp/ipykernel_21326/1521134713.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  themovie_df2['profit'] = themovie_df2['worldwide_gross'] - themovie_df2['production_budget']
/tmp/ipykernel_21326/1521134713.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  themovie_df2['d_profit'] = themovie_df2['domestic_gross_y'] - themovie_df2['production_budget']
```

In [82]:

```
themovie_df2
```

Out[82]:

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gro
0	Toy Story 3	415000000.0	6.520000e+08	7.7	8340	6	200000000.0	4150048
8	Inception	292600000.0	5.357000e+08	8.3	22186	7	160000000.0	2925761
17	Shrek Forever After	238700000.0	5.139000e+08	6.1	3843	5	165000000.0	2387367
	The							

	title	domestic_gross_x	foreign_gross	vote_average	vote_count	release_month	production_budget	domestic_gro
25	Twilight Saga: Eclipse	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
30	Iron Man 2	312400000.0	3.115000e+08	6.8	12368	5	170000000.0	3124333
...	...	...	...	...	...	...	...	
6000	Destroyer	1500000.0	4.000000e+06	5.9	176	12	9000000.0	15333
6004	Gotti	4300000.0	7.505704e+07	5.2	231	6	10000000.0	42863
6006	Mandy	1200000.0	7.505704e+07	3.5	2	1	6000000.0	12145
6007	Mandy	1200000.0	7.505704e+07	6.2	618	9	6000000.0	12145
6008	Lean on Pete	1200000.0	7.505704e+07	6.9	133	4	8000000.0	11630

1335 rows × 15 columns

Statistical testing, insights extraction, and actionable recommendations.

What Genre of movie receives the highest ratings?

In [83]:

```
# Split and explode genres if not already done
themovie_df2['genres'] = themovie_df2['genres'].str.split(',')
themovie_df2 = themovie_df2.explode('genres')
themovie_df2['genres'] = themovie_df2['genres'].str.strip()

# Average rating by genre
genre_ratings = (
    themovie_df2.groupby('genres')['averagerating']
      .mean()
      .sort_values(ascending=False)
)

genre_ratings.head(10)
```

```
/tmp/ipykernel_21326/3119211118.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  themovie_df2['genres'] = themovie_df2['genres'].str.split(',')
```

Out[83]:

```
genres
Documentary    7.170588
History        7.155556
Biography      7.024031
Sport          6.947619
War            6.857143
Western        6.800000
Drama          6.690831
Animation      6.687912
Musical        6.633333
Sci-Fi         6.604386
Name: averagerating, dtype: float64
```

In [84]:

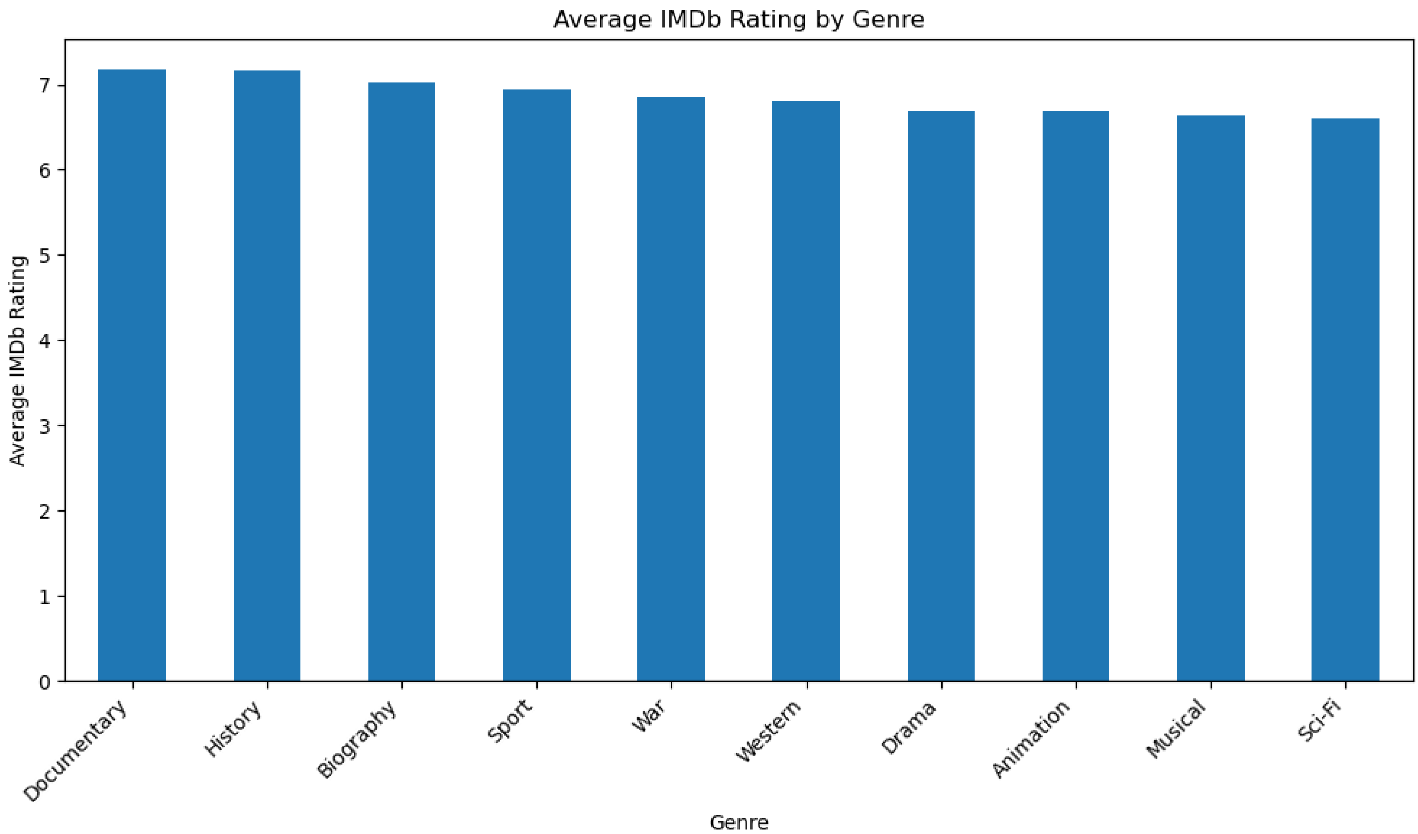
```
themovie_df2['genres'].value_counts(sort="descending")
```

Out[84]:

```
genres
Drama           698
Comedy          450
Action          389
Adventure       321
Thriller        253
Crime           212
Romance         188
Horror          150
Biography       129
Mystery         116
Sci-Fi          114
Fantasy         108
Animation        91
Family           71
History          45
Music            40
Sport            21
Documentary      17
War              14
Western           8
Musical           3
Name: count, dtype: int64
```

In [85]:

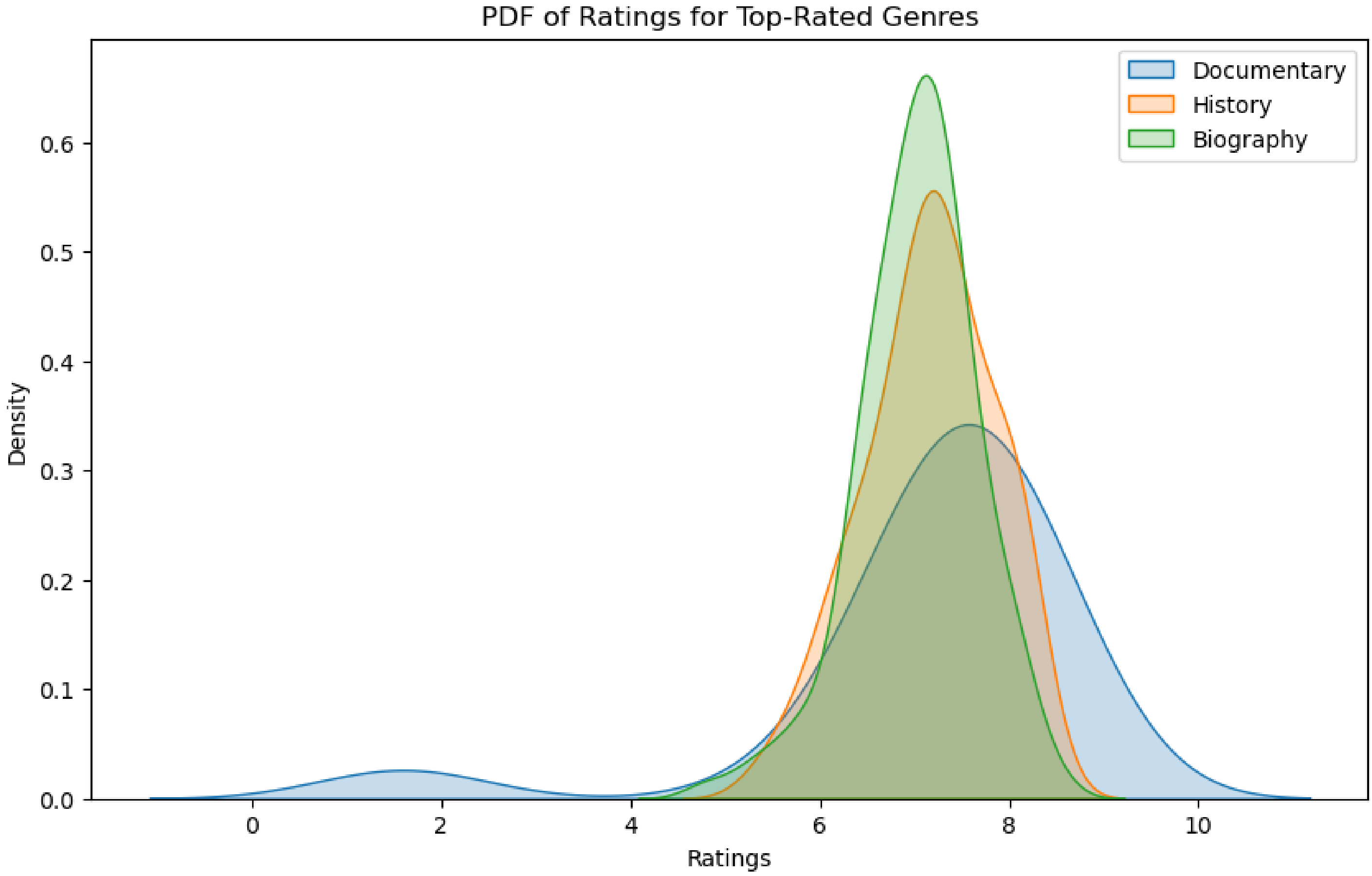
```
import matplotlib.pyplot as plt

top_genre_ratings = genre_ratings.head(10)

plt.figure(figsize=(10,6))
top_genre_ratings.plot(kind='bar')

plt.title("Average IMDb Rating by Genre")
plt.xlabel("Genre")
plt.ylabel("Average IMDb Rating")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



In [86]:

```
# show the distribution of rating
```

```
import seaborn as sns

top_genres = top_genre_ratings.index.tolist()

plt.figure(figsize=(10,6))
for top_g in top_genres[:3]:   # top 3 genres
    sns.kdeplot(
        themovie_df2[themovie_df2['genres'] == top_g]['averagerating'],label=top_g,fill=
True
    )

plt.title("PDF of Ratings for Top-Rated Genres")
plt.xlabel("Ratings")
plt.ylabel("Density")
plt.legend()
plt.show()
```



In [87]:

```
from scipy.stats import f_oneway

samples = [
    themovie_df2[themovie_df2['genres'] == top_g]['averagerating']
    for top_g in top_genres[:5]
]

f_stat, p_value = f_oneway(*samples)

f_stat, p_value
```

Out[87]:

```
(0.6941202654410905, 0.5967399371566486)
```

Conclusion and Recommendation

Documentary, History and Biology movies receive the highest average ratings respectively.

A statistical test (ANOVA) on the genres,gave an F-statistic of 0.6941 and a p-value of 0.5967. Since the p-value

is above 0.05, there's no meaningful difference in average ratings between these genres. This Means good ratings can come from any genre.Hence, the studio should not primarily focus of ratings to measure the success of a movie.

Which genres generated the most profit Wordwide?

In [88]:

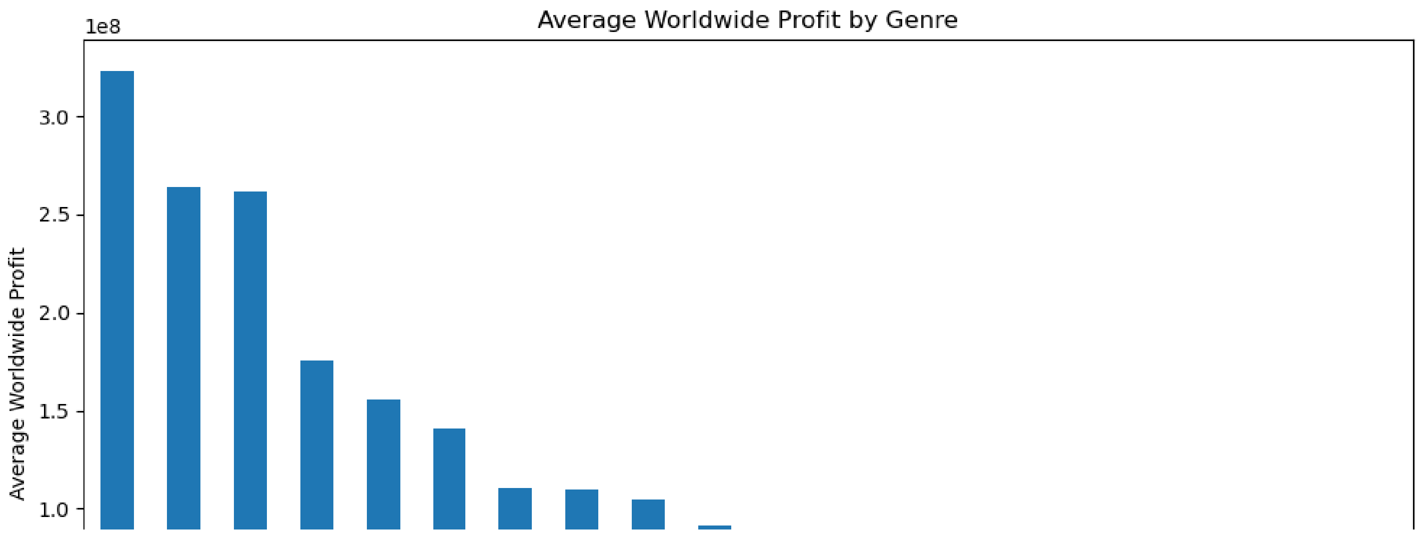
```
genre_revenue = (
    themovie_df2.groupby('genres')['profit'].mean().sort_values(ascending=False))

genre_revenue.head(20)
```

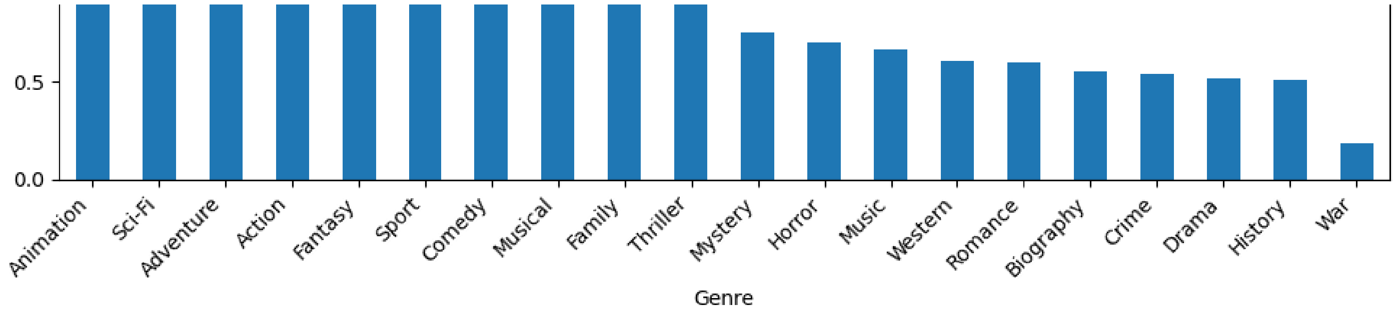
Out[88]:

```
genres
Animation    3.227171e+08
Sci-Fi       2.641798e+08
Adventure    2.619090e+08
Action       1.753462e+08
Fantasy      1.555282e+08
Sport        1.404365e+08
Comedy       1.107014e+08
Musical      1.097501e+08
Family       1.046763e+08
Thriller     9.126921e+07
Mystery      7.510733e+07
Horror       6.993425e+07
Music        6.625840e+07
Western      6.078973e+07
Romance      5.978295e+07
Biography    5.497197e+07
Crime        5.352678e+07
Drama        5.143208e+07
History      5.054726e+07
War          1.806302e+07
Name: profit, dtype: float64
```

In [89]:

```
# Select top 10 genres for readability
top_genre_revenue = genre_revenue.head(20)

plt.figure(figsize=(10,6))
top_genre_revenue.plot(kind='bar')

plt.title("Average Worldwide Profit by Genre")
plt.xlabel("Genre")
plt.ylabel("Average Worldwide Profit")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```





Animation,Sci-Fi and Adventure films generate the highest average worldwide profit, indicating strong global appeal in terms of revenue.The company should prioritize Action and Adventure films when launching its new movie studio.

Does Movie Rating Guarantees high Profits

In [90]:

```
correlation = themovie_df2['averagerating'].corr(themovie_df2['profit'])
correlation
```

Out[90]:

```
0.2567795120039979
```

Conclusion and Recomendation

This is a positive, but not strong. This means,they have a weak relationship. Higher-rated movies tend to make more profit, But ratings alone do not strongly determine profit.Therefore,good ratings help, but they do not guarantee high profit.

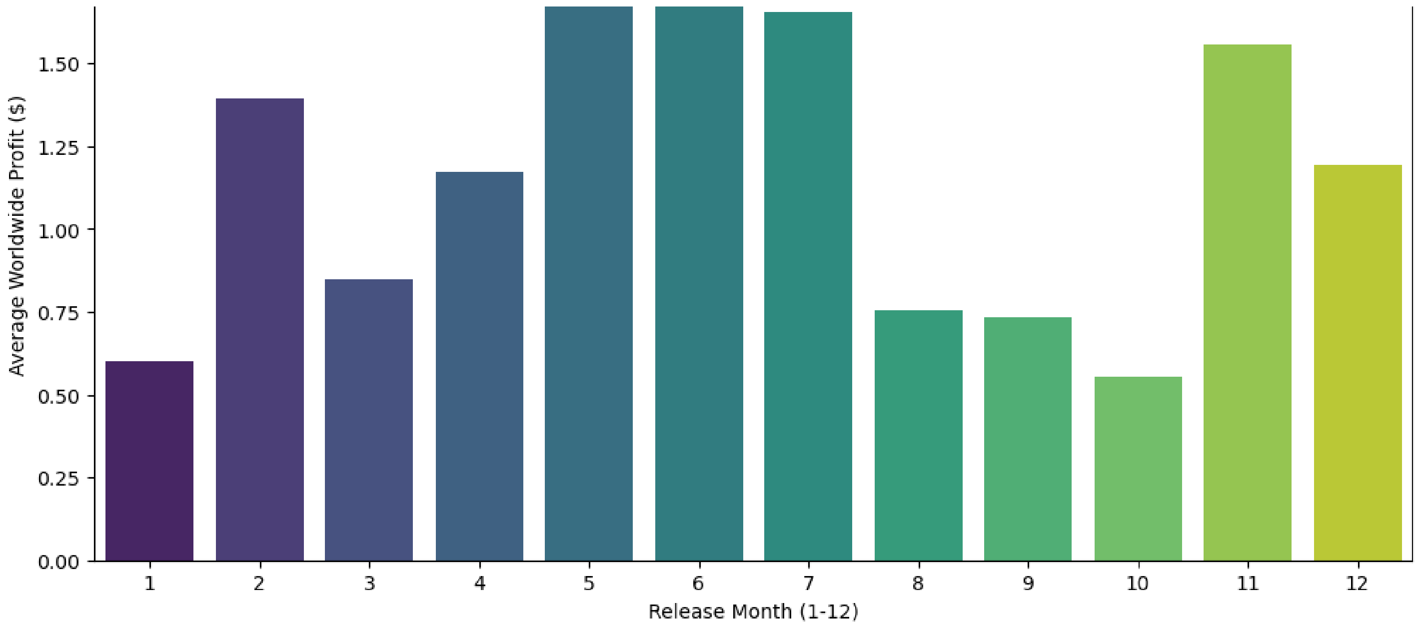
The success of a movie is influenced more by genre and market reach, and not ratings alone.Therefore, the studio should prioritize creating a movie based on genre and market reach but use rating as a secondary metrics.

Does release date (month) affect worldwide profit?

In [91]:

```
import scipy.stats as stats

# group by release month and calculate mean profit
monthly_profit = themovie_df2.groupby('release_month')['profit'].mean().reset_index()
monthly_profit = monthly_profit.sort_values('release_month')

# Visualize
plt.figure(figsize=(12, 6))
sns.barplot(x='release_month', y='profit', data=monthly_profit, palette='viridis')
plt.title('Average Worldwide Profit by Release Month')
plt.xlabel('Release Month (1-12)')
plt.ylabel('Average Worldwide Profit ($)')
plt.show()
```

```
/tmp/ipykernel_21326/2919649226.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='release_month', y='profit', data=monthly_profit, palette='viridis')
```



Hypotheses

Null hypothesis:Worldwide profit is the same for all release months.

Alternative hypothesis:At least one release month has a different worldwide profit.

In [92]:

```
# Prepare data for ANOVA: list of profit arrays for each month
months = themovie_df2['release_month'].unique()
profit_by_month = [themovie_df2[themovie_df2['release_month'] == month]['profit'].values
for month in months]

# Perform ANOVA
f_stat, p_value = stats.f_oneway(*profit_by_month)

print(f"F-statistic: {f_stat}")
print(f"P-value: {p_value}")
```

```
F-statistic: 14.852492410836868
P-value: 1.4629188813546632e-28
```

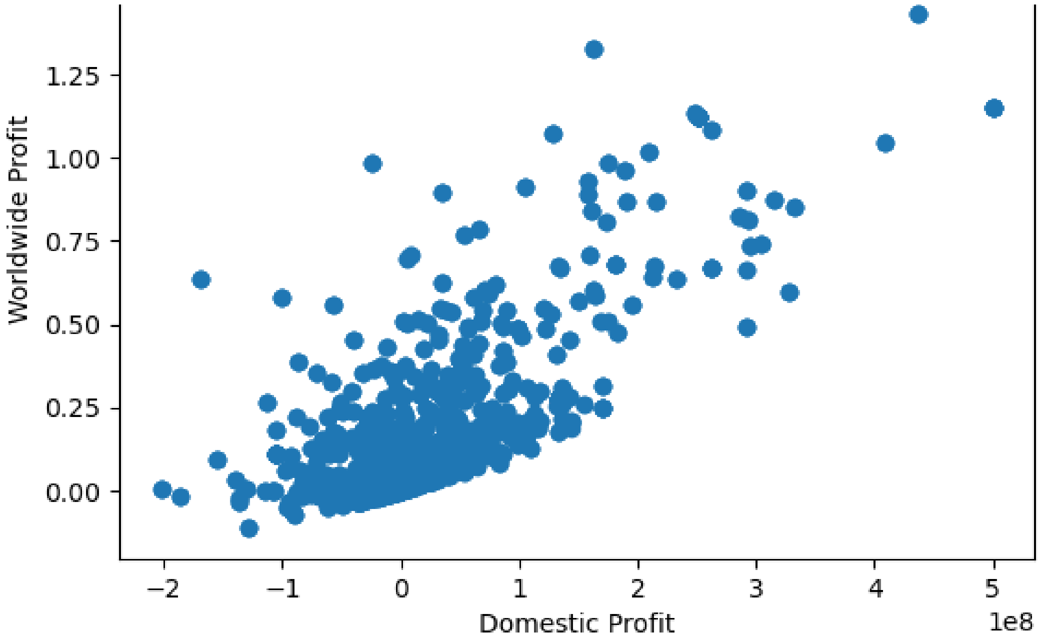
From the observation we will reject the null hypothesis since our pvalue is less than 0.05 This means release month strongly affect movie profit.Time of release is important,So, Where releasing a movie the studio should consider the month which there are releasing the movie. The should release movies on month 2,5,6,7,11 and 12 since this months have the highest profit rate.They should avoid month 1,8,9 and 10.

What is the performance of Worldwide gross vs Domestic gross

Goal: Determine whether movies earn more money internationally than domestically and how strongly the two are related.

In [93]:

```
plt.figure()
plt.scatter(themovie_df2["d_profit"], themovie_df2["profit"])
plt.xlabel("Domestic Profit")
plt.ylabel("Worldwide Profit")
plt.title("Relationship Between Domestic and Worldwide Profit")
plt.show()
```



In [94]:

```
corr, p_value = stats.pearsonr(themovie_df2["d_profit"], themovie_df2["profit"])

print("Correlation:", corr)
print("P-value:", p_value)
```

```
Correlation: 0.7274470666962394
P-value: 0.0
```

Conclusion and Recomendation

The correlation of 0.727447 indicates a very strong positive linear relationship between Domestic gross and worldwide gross p-value of 0 means the relationship is statistically significant so We reject the null hypothesis of no correlation This means if a movie makes more money in the domestic market, it is very likely to make more money worldwide as well.Hence Domestic performance of a movie should be used as a leading indicator for worldwide success of a movie.

Summary of Findings

Ratings vs Genre

Documentary, History, and Biology films receive the highest average ratings. However, an ANOVA test across genres shows no statistically significant difference in average ratings ($F = 0.6941$, $p = 0.5967$). This indicates that high ratings can occur in any genre, and ratings alone are not a reliable measure of a movie's success.

Ratings vs Profit

The relationship between movie ratings and profit is positive but weak. Higher-rated movies tend to earn more, but ratings alone do not strongly determine profitability. This suggests that while good ratings help, they do not guarantee high financial success.

Genre vs Worldwide Profit

Animation, Sci-Fi, and Adventure films generate the highest average worldwide profits, demonstrating strong global appeal. This indicates that genre choice has a greater impact on revenue than ratings. Action and Adventure films, in particular, should be prioritized by the studio.

Release Month vs Profit

Statistical analysis shows that release month has a significant effect on movie profit ($p < 0.05$). Movies released in February, May, June, July, November, and December perform best, while releases in January, August,

September, and October perform poorly. Timing is therefore a critical factor in maximizing profitability.

Domestic vs Worldwide Performance

There is a very strong positive correlation between domestic and worldwide gross ($r \approx 0.73$, $p \approx 0$). This means that movies that perform well domestically are very likely to perform well internationally. Domestic performance can be used as a leading indicator of global success.

Final Conclusion & Recommendation

Movie success is driven primarily by genre selection, release timing, and market reach, rather than ratings alone. While good ratings contribute positively, they should be treated as a secondary metric.

Based on Analysis we Recommend

1.Prioritize Genre for Profitability: Focus on producing Action, Adventure, Animation, and Sci-Fi movies, as these genres consistently generate the highest worldwide profits. Ratings are helpful but should not be the primary measure of expected success.

2.Optimize Release Timing: Schedule movie releases in months with historically high profits: February, May, June, July, November, and December. Avoid releasing in January, August, September, and October, which show lower profit potential.

3.Use Domestic Performance as a Predictor: Monitor domestic box office performance closely, as it is a strong indicator of worldwide success. Strong domestic earnings can help predict and maximize global revenue.

4.Leverage Ratings Strategically: While high ratings do not guarantee profit, they can enhance a movie's marketability. Use ratings as a secondary metric to guide marketing and audience targeting rather than as the primary decision factor for production or release strategy.