ANALYZING MOVIE INDUSTRY : TRENDS AND INSIGHTS FOR A NEW MOVIE STUDIO

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Overview

The project aims to guide a new movie studio in understanding the key factors that drive box office success, addressing the business problem of identifying profitable genres, optimal budgets, effective release timing, and ideal movie characteristics such as runtime. Using data from IMDB, The Movie Database (TMDb), and The Numbers, we analyzed variables such as production budgets, revenues, genres, release dates, and audience ratings. Statistical analysis and exploratory data visualization were employed to uncover insights on financial performance, audience preferences, and seasonal trends. Results highlight that certain genres like Action and Adventure have the highest net profit, while the ideal movie budget falls within a specific range to balance profitability and risk. Releasing films during high-demand months (e.g., summer or holiday seasons) and aligning runtime with audience expectations also contribute to success. Recommendations include focusing on high profit genres, maintaining realistic budgets, strategically timing releases, and creating engaging films that resonate with target audiences.

Business Problem

Our company is planning to create a new movie studio but lacks experience and insights about the types of movies that perform well at the box office. The goal is to identify the characteristics of successful films and provide actionable insights to guide the company's decisions on the genres, budgets, release strategies, and other factors that maximize box office revenue.

Data Analysis Questions

To address the business problem, the following questions will guide the data analysis:

1. **How does release timing (e.g. month) affect box office success?**

    - Timing the release effectively can capitalize on seasonal trends in audience behavior, to identify the most profitable months to release a movie.
2. **What is the realistic budget cost amount to consider?**

    - Understanding this relationship can inform how much the studio should invest in its films for optimal financial performance.
3. **Which genres have the highest ROI and Profit?**

    - This helps the company to pinpoint genres that deliver the best financial performance..
4. **Which genres have the highest Average Rating?**

    - This enables the company to focus on producing quality films that resonate with audiences based on the specific genres.

5. **What is the appopriate movie length based on Average Rating?**

    - This analysis helps determine the duration of movies that are most likely to achieve better audience reception and critical acclaim.

Pain Points Related to the Project

1. **Uncertainty in Market Preferences:** The company has no prior experience in filmmaking, making it difficult to predict what audiences will respond to.
2. **Financial Risk:** Without proper insights, the studio risks investing heavily in projects that may not perform well.
3. **Highly Competitive Industry:** The studio must differentiate its offerings in a saturated market where established players dominate.
4. **Data-Driven Decision-Making:** The company needs reliable insights to make informed choices about genres, budgets, and marketing strategies.

Approach to Choosing Questions

The questions were selected to address key decision-making areas for a new movie studio: movie release timing, genre selection, budget recommendation & Appropriate movie length. Each question is designed to yield actionable insights by leveraging historical box office and movie industry data.

By focusing on these areas, the company can mitigate risks and make strategic decisions that align with audience preferences and industry trends.

Data Understanding

The data used for this project comes from multiple sources that provide information about movies, their attributes, and box office performance. The sources include IMDB, The Movie Database (TMDb), and The Numbers, each contributing unique and complementary insights. Here's a breakdown of the data and how it relates to the analysis questions:

Data Sources and Relevance

1. **IMDB** (SQLite Database - `im.db`):

    - Contains detailed movie information, including:
        - `movie_basics` : Titles, genres, runtime, and production years.
        - `movie_ratings` : Audience and critic average ratings.
    - It is useful for understanding the popularity of specific genres, trends in ratings and the impact of runtime based on critic ratimg.
2. **The Movie Database (TMDb)**:

    - Provides additional metadata about movies, such as genres, movie title, release date, movie vote-count.
    - It helps to analyze the most appropriate time to release a movie
3. **The Numbers**:

    - Offers box office performance data, including production budget and worldwide gross.
    - It is central to identifying patterns in box office success, such as net profit and financial return on investment.

Data Representation

- The data represents a broad collection of films across multiple decades, including blockbuster hits, independent films, and everything in between.
- **Variables Included:**
    - *From `movie_basics` :* Title, genre(s), runtime, release year.
    - *From `movie_ratings` :* Average rating of critics.
    - *From The Numbers & TMDb:* Production budget, revenue, release date, cast/crew information.

Target Variable

The **target variable** for this analysis is **box office revenue** (international). This metric will measure the success of a film and inform the types of movies to create.

Properties of Key Variables

1. **Categorical Variables:**

    - *Genres*: Multi-label field (e.g., "Action, Adventure").
    - *Release Timing*: Represented by month or season.

2. **Numerical Variables:**

    - *Production Budget*: Continuous variable, reflecting investment levels.
    - *Box Office Revenue*: Continuous variable, representing financial success.

- *Ratings*: Continuous variable, ranging from 1-10, capturing audience and critic reception.

3. **Time Variables:**

   - *Release Year/Month*: Time-related variables to identify trends and seasonality.

Data Challenges

1. **Integration:**

   - Data must be merged across sources using common keys like movie titles or unique identifiers.

2. **Quality Issues:**

   - Missing data in budget, revenue .
   - Inconsistent formats between sources (e.g., genres listed differently).

3. **Normalization:**

   - Variables like budget and revenue may need inflation adjustments for accurate comparisons across years.

Next Steps

1. Explore the structure of the `im.db` database, focusing on `movie_basics` and `movie_ratings` tables.
2. Integrate box office data from The Numbers and TMDb, ensuring consistency and completeness.
3. Clean and preprocess variables, handling missing values and transforming multi-label

In [1]:

```
# Importing the packages we'll be using for this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile
import os
import sqlite3
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Data Preparation

The process for preparing the data for analysis is outlined in detail under each numbered datasets.

1. The Numbers Dataset (TN)

In [2]:
```
# Reading the csv file and coverting the release_date column to datetime

df_tn = pd.read_csv('zippedData/tn.movie_budgets.csv.gz',
                    parse_dates=['release_date'])
df_tn.head()
```

Out[2]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	2009-12-18	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	2019-06-07	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	2015-05-01	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [3]:
```
# Lists column names, data types, and non-null counts.
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   datetime64[ns]
 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: datetime64[ns](1), int64(1), object(4)
memory usage: 271.2+ KB
```

Dropping irrelevant columns

In [4]:
```
# Creating a list of the columns to drop
cols_to_drop = ['id', 'domestic_gross']

df_tn = df_tn.drop(columns=cols_to_drop)
```

Converting numerical columns from objects to integers

In [5]:
```
# Converting numerical columns to integers
for column in ['production_budget', 'worldwide_gross']:
    # Convert to string, replace '$' and ',' with '', then convert to numer
    df_tn[column] = pd.to_numeric(
        df_tn[column].astype(str).replace({'\$': '', ',': ''}, regex=True),
        errors='coerce'  # Replace invalid parsing with NaN
    )

# Verify the changes
df_tn.head()
```

Out[5]:

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

In [6]:
```
# Checking the summary statistics of worldwide gross
df_tn['worldwide_gross'].describe()
```

Out[6]:
```
count    5.782000e+03
mean     9.148746e+07
std      1.747200e+08
min      0.000000e+00
25%      4.125415e+06
50%      2.798445e+07
75%      9.764584e+07
max      2.776345e+09
Name: worldwide_gross, dtype: float64
```

Dropping rows with zero value in worldwide gross through filtering the data

In [7]:
```
#Dropping the rows in world_wide columns that contain the value 0
df_tn_zero = df_tn[df_tn['worldwide_gross'] == 0]
df_tn_zero
```

Out[7]:

	release_date	movie	production_budget	worldwide_gross
194	2020-12-31	Moonfall	150000000	0
479	2017-12-13	Bright	90000000	0
480	2019-12-31	Army of the Dead	90000000	0
535	2020-02-21	Call of the Wild	82000000	0
670	2019-08-30	PLAYMOBIL	75000000	0
...	...	...	...	...
5761	2014-12-31	Stories of Our Lives	15000	0
5764	2007-12-31	Tin Can Man	12000	0
5771	2015-05-19	Family Motocross	10000	0
5777	2018-12-31	Red 11	7000	0
5780	2015-09-29	A Plague So Pleasant	1400	0

In [8]:
```
# Creating a  new variable and drop rows where 'worldwide_gross' equals 0
df_tn_clean = df_tn[df_tn['worldwide_gross'] != 0]

# Verify the changes
df_tn_clean['worldwide_gross'].describe()
```

Out[8]:
```
count    5.415000e+03
mean     9.768800e+07
std      1.788591e+08
min      2.600000e+01
25%      7.004834e+06
50%      3.333987e+07
75%      1.044590e+08
max      2.776345e+09
Name: worldwide_gross, dtype: float64
```

In [9]:
```python
# Checking the changes made
df_tn_clean
```

Out[9]:

	release_date	movie	production_budget	worldwide_gross
0	2009-12-18	Avatar	425000000	2776345279
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875
2	2019-06-07	Dark Phoenix	350000000	149762350
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747
...	...	...	...	...
5775	2006-05-26	Cavite	7000	71644
5776	2004-12-31	The Mongol King	7000	900
5778	1999-04-02	Following	6000	240495
5779	2005-07-13	Return to the Land of Wonders	5000	1338
5781	2005-08-05	My Date With Drew	1100	181041

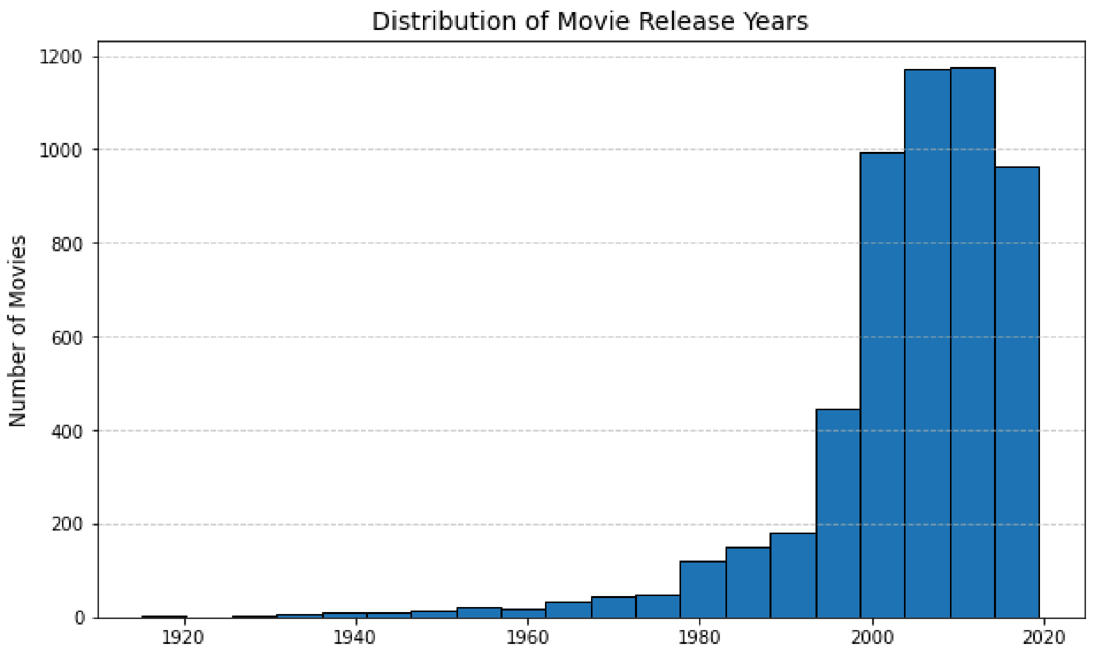
5415 rows × 4 columns

In [10]:
```python
# Plotting to show the release years over the time period
df_tn_clean['release_date'].describe(datetime_is_numeric=True)
```

Out[10]:
```
count                             5415
mean     2004-02-20 12:26:11.634349056
min                1915-02-08 00:00:00
25%                1999-12-13 12:00:00
50%                2006-08-11 00:00:00
75%                2012-05-18 00:00:00
max                2019-06-21 00:00:00
Name: release_date, dtype: object
```

A histogram showing count of movies through out the years

In [11]:
```
# Plot a histogram
plt.figure(figsize=(10, 6))
plt.hist(df_tn_clean['release_date'], bins=20, edgecolor='black')
plt.title('Distribution of Movie Release Years', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Number of Movies', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Focus on movies release from 2010 onwards

- This enable the Numbers data to align well with the Movie data base especially when conducting a join between the two data sets.

In [12]:
```
# Filtering the data to only include movies from the year 2000 onward

df_tn_clean = df_tn_clean[df_tn_clean['release_date'] > pd.Timestamp(2010,

# Verify the changes
df_tn_clean['release_date'].describe(datetime_is_numeric=True) # Check the
```

Out[12]:
```
count                            1922
mean      2014-04-17 05:01:56.129032192
min                2010-01-08 00:00:00
25%                2011-12-16 00:00:00
50%                2014-04-04 00:00:00
75%                2016-05-13 00:00:00
max                2019-06-21 00:00:00
Name: release_date, dtype: object
```

Creating new columns that measure financial success

Profit

- **Formula**: Profit = Worldwide Gross − Production Budget
- It measures the actual monetary gain after covering the production costs and is a direct indicator of how much profit a movie made, which is crucial for understanding its financial success.

In [13]:
```
# Creating a new column that contains profit
df_tn_clean = df_tn_clean.copy()
df_tn_clean['profit'] = df_tn_clean['worldwide_gross'] - df_tn_clean['produ
df_tn_clean
```

Out[13]:

	release_date	movie	production_budget	worldwide_gross	profit
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	635063875
2	2019-06-07	Dark Phoenix	350000000	149762350	-200237650
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963	1072413963
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	999721747
5	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	2053311220	1747311220
...	...	...	...	...	...
5740	2010-10-15	Down Terrace	30000	9812	-20188
5744	2017-01-27	Emily	27000	3547	-23453

Return on Investment (ROI)

- ROI = profit /cost * 100%
- It measures the profitability of investing in a movie relative to its cost.

In [14]:
```python
# Creating a new column that contains ROI
df_tn_clean['ROI'] = df_tn_clean['profit']/df_tn_clean['production_budget']

df_tn_clean
```

Out[14]:

	release_date	movie	production_budget	worldwide_gross	profit	RC
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	635063875	154.66728
2	2019-06-07	Dark Phoenix	350000000	149762350	-200237650	-57.21075
3	2015-05-01	Avengers: Age of Ultron	330600000	1403013963	1072413963	324.38413
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	999721747	315.36963
5	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	2053311220	1747311220	571.01673
...	...	...	...	...	...	.
5740	2010-10-15	Down Terrace	30000	9812	-20188	-67.29333
5744	2017-01-27	Emily	27000	3547	-23453	-86.86296
5748	2015-09-01	Exeter	25000	489792	464792	1859.16800
5760	2010-04-02	Breaking Upwards	15000	115592	100592	670.61333
5772	2012-01-13	Newlyweds	9000	4584	-4416	-49.06666

1922 rows × 6 columns

2. The Movie DB (DB)

In [15]:
```
# Reading the csv file
df_db = pd.read_csv('./zippedData/tmdb.movies.csv.gz', index_col = 0,
                    parse_dates=['release_date'])
df_db
```

Out[15]:

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

26517 rows × 9 columns

In [16]:
```
# Lists column names, data types, and non-null counts.
df_db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   id                 26517 non-null  int64
 2   original_language  26517 non-null  object
 3   original_title     26517 non-null  object
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  datetime64[ns]
 6   title              26517 non-null  object
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 2.0+ MB
```

In [17]:
```python
# Summary statistics of the data
df_db.describe()
```

Out[17]:

	id	popularity	vote_average	vote_count
count	26517.000000	26517.000000	26517.000000	26517.000000
mean	295050.153260	3.130912	5.991281	194.224837
std	153661.615648	4.355229	1.852946	960.961095
min	27.000000	0.600000	0.000000	1.000000
25%	157851.000000	0.600000	5.000000	2.000000
50%	309581.000000	1.374000	6.000000	5.000000
75%	419542.000000	3.694000	7.000000	28.000000
max	608444.000000	80.773000	10.000000	22186.000000

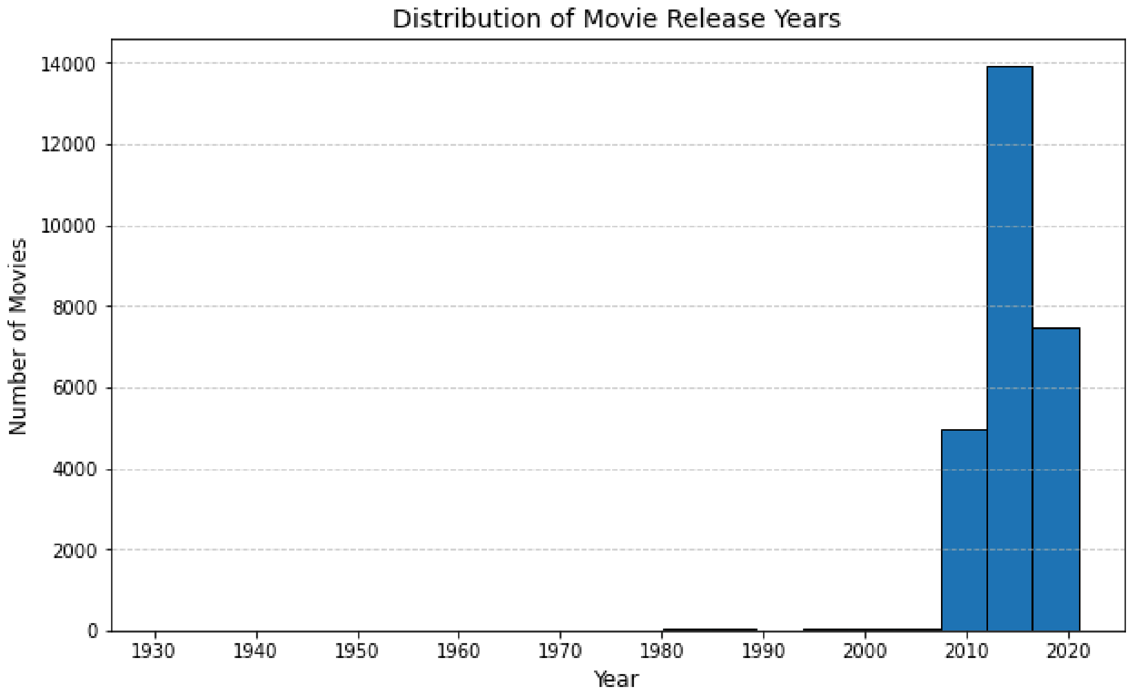
Dropping irrelevant columns

In [18]:
```python
# Creating a list of the columns to drop
columns_to_drop = ['id', 'original_title','popularity']

df_db_clean = df_db.drop(columns=columns_to_drop)

df_db_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   original_language  26517 non-null  object
 2   release_date       26517 non-null  datetime64[ns]
 3   title              26517 non-null  object
 4   vote_average       26517 non-null  float64
 5   vote_count         26517 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(1), object(3)
memory usage: 1.4+ MB
```

A histogram showing count of movies through out the years

In [19]:
```
# Plot a histogram
plt.figure(figsize=(10, 6))
plt.hist(df_db_clean['release_date'], bins=20, edgecolor='black')
plt.title('Distribution of Movie Release Years', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Number of Movies', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In [20]:
```
# Plotting to show the release years over the time period
df_db_clean['release_date'].describe(datetime_is_numeric=True)
```

Out[20]:
```
count                              26517
mean       2014-06-10 02:50:14.730173184
min                  1930-04-29 00:00:00
25%                  2012-06-29 00:00:00
50%                  2014-09-19 00:00:00
75%                  2016-10-01 00:00:00
max                  2020-12-25 00:00:00
Name: release_date, dtype: object
```

Focus on movies release from 2010 onwards

- This enable the Movie data to align well with the Numbers data base especially when conducting a join between the two data sets considering the count of movies released.

In [21]:
```
# Filtering the data to only include movies from the year 2000 onward

df_db_clean = df_db_clean[df_db_clean['release_date'] > pd.Timestamp(2010,
```

In [22]:
```
# Plotting to show the release years over the time period
df_db_clean['release_date'].describe(datetime_is_numeric=True)
```

Out[22]:
```
count                          26022
mean     2014-09-02 02:22:42.969794560
min                2010-01-02 00:00:00
25%                2012-09-01 00:00:00
50%                2014-10-11 00:00:00
75%                2016-10-14 00:00:00
max                2020-12-25 00:00:00
Name: release_date, dtype: object
```

In [23]:
```
# Lists column names, data types, and non-null counts.
df_db_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26022 entries, 0 to 26516
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26022 non-null  object
 1   original_language  26022 non-null  object
 2   release_date       26022 non-null  datetime64[ns]
 3   title              26022 non-null  object
 4   vote_average       26022 non-null  float64
 5   vote_count         26022 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(1), object(3)
memory usage: 1.4+ MB
```

Drop Certain Movies with less votes counts

- Dropping movies with a vote count roughly below the average vote count. i.e 180 votes.

In [24]:
```
# Summary statistics
df_db_clean['vote_count'].describe()
```

Out[24]:
```
count    26022.000000
mean       189.232726
std        943.796552
min          1.000000
25%          2.000000
50%          5.000000
75%         28.000000
max      22186.000000
Name: vote_count, dtype: float64
```

In [25]:
```
# Filtering the vote_count column
df_db_clean =  df_db_clean[df_db_clean['vote_count'] > 180]
```

In [26]:
```python
# Rechecking the summary statistics
df_db_clean['vote_count'].describe()
```

Out[26]:
```
count     2700.000000
mean      1682.864444
std       2467.751359
min        181.000000
25%        332.000000
50%        685.500000
75%       1859.250000
max      22186.000000
Name: vote_count, dtype: float64
```

Focus the original language

- We'll focus on movies with only English as the original language

In [27]:
```python
df_db_clean['original_language'].value_counts()
```

Out[27]:
```
en    2422
fr      93
ja      38
es      34
it      17
de      14
da      12
sv       8
ko       7
no       7
zh       6
cn       6
hi       5
fa       5
pt       4
id       4
pl       3
nl       2
tr       2
```

In [28]:
```
# Filtering the data
df_db_clean = df_db_clean[df_db_clean['original_language'] == 'en']
df_db_clean
```

Out[28]:

	genre_ids	original_language	release_date	title	vote_average	vote_count
0	[12, 14, 10751]	en	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	[14, 12, 16, 10751]	en	2010-03-26	How to Train Your Dragon	7.7	7610
2	[12, 28, 878]	en	2010-05-07	Iron Man 2	6.8	12368
4	[28, 878, 12]	en	2010-07-16	Inception	8.3	22186
5	[12, 14, 10751]	en	2010-02-11	Percy Jackson & the Olympians:	6.1	4229

Creating a new column containg the primary genre to focus on

In [29]:
```python
# Define a function to extract the first genre ID
def extract_primary_id(genre_ids):
    # Remove unwanted characters and extract the first ID
    char_remove = ["'", " ", "[", "]"]
    for char in char_remove:
        genre_ids = genre_ids.replace(char, '')
    return genre_ids.split(',')[0]

# Use .loc to assign the new column
df_db_clean.loc[:, 'primary_id'] = df_db_clean['genre_ids'].apply(extract_p

df_db_clean
```

Out[29]:

	genre_ids	original_language	release_date	title	vote_average	vote_count	prin
0	[12, 14, 10751]	en	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788	
1	[14, 12, 16, 10751]	en	2010-03-26	How to Train Your Dragon	7.7	7610	
2	[12, 28, 878]	en	2010-05-07	Iron Man 2	6.8	12368	
4	[28, 878, 12]	en	2010-07-16	Inception	8.3	22186	
5	[12, 14, 10751]	en	2010-02-11	Percy Jackson & the Olympians: The Lightning T...	6.1	4229	
...	...	...	...	...	...	...	
24383	[27]	en	2018-10-05	Malevolent	5.0	236	
24409	[9648, 53]	en	2017-10-27	All I See Is You	4.9	311	
24422	[35, 18]	en	2018-02-16	The Party	6.4	229	
24454	[27, 53]	en	2017-09-01	The Vault	4.7	187	
24472	[35]	en	2018-07-20	Father of the Year	5.3	235	

2422 rows × 7 columns

Decoding the primary_ids codes

- We found the below movie genre key on The MovieDB website. The key allows us to convert the primary_ids coding into standard English.
- (found at: [https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee (https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)](https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee))

Preparing the data for a Join

In [30]:
```
# Lists column names, data types, and non-null counts.
df_db_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2422 entries, 0 to 24472
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          2422 non-null   object
 1   original_language  2422 non-null   object
 2   release_date       2422 non-null   datetime64[ns]
 3   title              2422 non-null   object
 4   vote_average       2422 non-null   float64
 5   vote_count         2422 non-null   int64
 6   primary_id         2422 non-null   object
dtypes: datetime64[ns](1), float64(1), int64(1), object(4)
memory usage: 151.4+ KB
```

In [31]:
```python
# Create a mapping dictionary
genre_mapping = {
    "28": "Action",
    "12": "Adventure",
    "16": "Animation",
    "35": "Comedy",
    "80": "Crime",
    "99": "Documentary",
    "18": "Drama",
    "10751": "Family",
    "14": "Fantasy",
    "36": "History",
    "27": "Horror",
    "10402": "Music",
    "9648": "Mystery",
    "10749": "Romance",
    "878": "Science Fiction",
    "10770": "TV Movie",
    "53": "Thriller",
    "10752": "War",
    "37": "Western"
}

# Replacing primary_id with corresponding genres
df_db_clean['primary_id'] = df_db_clean['primary_id'].map(genre_mapping)

# Renaming the column to 'primary_genre' for better understanding
df_db_clean.rename(columns={'primary_id': 'primary_genre'}, inplace=True)

# Verifying the changes
df_db_clean
```

Out[31]:

	genre_ids	original_language	release_date	title	vote_average	vote_count	prin
0	[12, 14, 10751]	en	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788	
1	[14, 12, 16, 10751]	en	2010-03-26	How to Train Your Dragon	7.7	7610	
2	[12, 28, 878]	en	2010-05-07	Iron Man 2	6.8	12368	
4	[28, 878, 12]	en	2010-07-16	Inception	8.3	22186	
5	[12, 14, 10751]	en	2010-02-11	Percy Jackson & the Olympians: The Lightning T...	6.1	4229	
...	...	...	...	...	...	...	
24383	[27]	en	2018-10-05	Malevolent	5.0	236	
24409	[9648, 53]	en	2017-10-27	All I See Is You	4.9	311	
24422	[35, 18]	en	2018-02-16	The Party	6.4	229	
24454	[27, 53]	en	2017-09-01	The Vault	4.7	187	
24472	[35]	en	2018-07-20	Father of the Year	5.3	235	

2422 rows × 7 columns

In [32]:
```python
# Create a copy of the DataFrame `df_db_clean` to avoid modifying the origi
df_db_neat = df_db_clean.copy()

# Rename the column 'title' to 'movie' for better clarity or alignment with
df_db_neat.rename(columns={'title': 'movie'}, inplace=True)

# Set the 'movie' column as the index of the DataFrame for easier data acce
df_db_neat.set_index('movie', inplace=True)

# Display the modified DataFrame
df_db_neat
```

Out[32]:

movie	genre_ids	original_language	release_date	vote_average	vote_count	primary_g
Harry Potter and the Deathly Hallows: Part 1	[12, 14, 10751]	en	2010-11-19	7.7	10788	Adver
How to Train Your Dragon	[14, 12, 16, 10751]	en	2010-03-26	7.7	7610	Fan
Iron Man 2	[12, 28, 878]	en	2010-05-07	6.8	12368	Adver
Inception	[28, 878, 12]	en	2010-07-16	8.3	22186	Ac
Percy Jackson & the Olympians: The Lightning Thief	[12, 14, 10751]	en	2010-02-11	6.1	4229	Adver
...	...	...	...	...	...	
Malevolent	[27]	en	2018-10-05	5.0	236	Ho
All I See Is You	[9648, 53]	en	2017-10-27	4.9	311	Mys
The Party	[35, 18]	en	2018-02-16	6.4	229	Con
The Vault	[27, 53]	en	2017-09-01	4.7	187	Ho
Father of the Year	[35]	en	2018-07-20	5.3	235	Con

2422 rows × 6 columns

In [33]:
```
# Lists column names, data types, and non-null counts.
df_tn_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1922 entries, 1 to 5772
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       1922 non-null   datetime64[ns]
 1   movie              1922 non-null   object
 2   production_budget  1922 non-null   int64
 3   worldwide_gross    1922 non-null   int64
 4   profit             1922 non-null   int64
 5   ROI                1922 non-null   float64
dtypes: datetime64[ns](1), float64(1), int64(3), object(1)
memory usage: 105.1+ KB
```

In [34]:
```
# Create a copy of the DataFrame `df_tn_clean` to avoid modifying the origi
df_tn_neat = df_tn_clean.copy()

# Set the 'movie' column as the index of the DataFrame for better data orga
df_tn_neat.set_index('movie', inplace=True)

# Remove the 'release_date' column from the DataFrame as it is no longer ne
df_tn_neat.drop(columns=['release_date'], inplace=True)

# Display the modified DataFrame
df_tn_neat
```

Out[34]:

	production_budget	worldwide_gross	profit	ROI
movie				
Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	635063875	154.667286
Dark Phoenix	350000000	149762350	-200237650	-57.210757
Avengers: Age of Ultron	330600000	1403013963	1072413963	324.384139
Star Wars Ep. VIII: The Last Jedi	317000000	1316721747	999721747	315.369636
Star Wars Ep. VII: The Force Awakens	306000000	2053311220	1747311220	571.016739
...	...	...	...	...
Down Terrace	30000	9812	-20188	-67.293333
Emily	27000	3547	-23453	-86.862963
Exeter	25000	489792	464792	1859.168000

Joining Numbers(TN) and Movie (DB) Data

In [35]:
```
# Perform a join based on the movie index and adding suffixes
combined_df = df_tn_neat.join(df_db_neat, how='inner')
combined_df
```

Out[35]:

movie	production_budget	worldwide_gross	profit	ROI	genre_ids	orig
10 Cloverfield Lane	5000000	108286422	103286422	2065.728440	[53, 878, 18]	
12 Strong	35000000	71118378	36118378	103.195366	[10752, 18, 36, 28]	
12 Years a Slave	20000000	181025343	161025343	805.126715	[18, 36]	
127 Hours	18000000	60217171	42217171	234.539839	[12, 18, 53]	
13 Hours: The Secret Soldiers of Benghazi	50000000	69411370	19411370	38.822740	[28, 18, 36, 53, 10752]	

In [36]:
```
# Scaling the numerical columns by dividing by 1 million for readability
combined_df['production_budget'] = combined_df['production_budget'] / 10000
combined_df['worldwide_gross'] = combined_df['worldwide_gross'] / 1000000
combined_df['profit'] = combined_df['profit'] / 1000000  # In millions

# Showing the updated dataframe
combined_df.head()
```

Out[36]:

movie	production_budget	worldwide_gross	profit	ROI	genre_ids	origina
10 Cloverfield Lane	5.0	108.286422	103.286422	2065.728440	[53, 878, 18]	
12 Strong	35.0	71.118378	36.118378	103.195366	[10752, 18, 36, 28]	
12 Years a Slave	20.0	181.025343	161.025343	805.126715	[18, 36]	
127 Hours	18.0	60.217171	42.217171	234.539839	[12, 18, 53]	
13 Hours: The Secret Soldiers of Benghazi	50.0	69.411370	19.411370	38.822740	[28, 18, 36, 53, 10752]	

In [37]:

```
print(combined_df[['production_budget', 'profit']].describe())
print(combined_df[['production_budget', 'profit']].isnull().sum())
```

```
       production_budget       profit
count        1391.000000  1391.000000
mean           51.040714   116.135429
std            57.457317   204.889569
min             0.100000  -110.450242
25%            12.000000     3.888374
50%            30.000000    40.282881
75%            65.000000   129.748880
max           410.600000  1748.134200
production_budget    0
profit               0
dtype: int64
```

Filter the DataFrame `combined_df` to include only rows where the 'profit' column has positive values

In [38]:

```
# Filter the DataFrame `combined_df` to include only rows where the 'profit
combined_df = combined_df[combined_df['profit'] > 0]

# Print the descriptive statistics for the 'production_budget' and 'profit'
# to understand their distribution, including metrics like mean, standard d
print(combined_df[['production_budget', 'profit']].describe())
```

```
       production_budget       profit
count        1114.000000  1114.000000
mean           56.376825   147.862544
std            60.667416   217.536682
min             0.100000     0.009644
25%            13.000000    21.527604
50%            34.000000    64.383421
75%            77.875000   163.581080
max           410.600000  1748.134200
```

In [39]:
```
# Lists column names, data types, and non-null counts.
combined_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1114 entries, 10 Cloverfield Lane to xXx: Return of Xander Cage
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   production_budget  1114 non-null   float64
 1   worldwide_gross    1114 non-null   float64
 2   profit             1114 non-null   float64
 3   ROI                1114 non-null   float64
 4   genre_ids          1114 non-null   object
 5   original_language  1114 non-null   object
 6   release_date       1114 non-null   datetime64[ns]
 7   vote_average       1114 non-null   float64
 8   vote_count         1114 non-null   int64
 9   primary_genre      1114 non-null   object
dtypes: datetime64[ns](1), float64(5), int64(1), object(3)
memory usage: 95.7+ KB
```

Movie Release Timing

- Here we'll visualize the most profitable months to release a movie

In [40]:
```python
# Creating a new column for the release month
# Copying the dataframe to avoid errors
combined_df = combined_df.copy()

combined_df['release_month'] = combined_df['release_date'].dt.month

# Group by month to calculate average profit, ROI, and worldwide gross
month_analysis = combined_df.groupby('release_month').agg({
    'profit': 'mean'
}).rename(columns={
    'profit': 'avg_profit'
}).reset_index()

# Sort the results for better readability
month_analysis = month_analysis.sort_values(by='release_month')

# Display the results
print("Average performance by release month:")
month_analysis
```

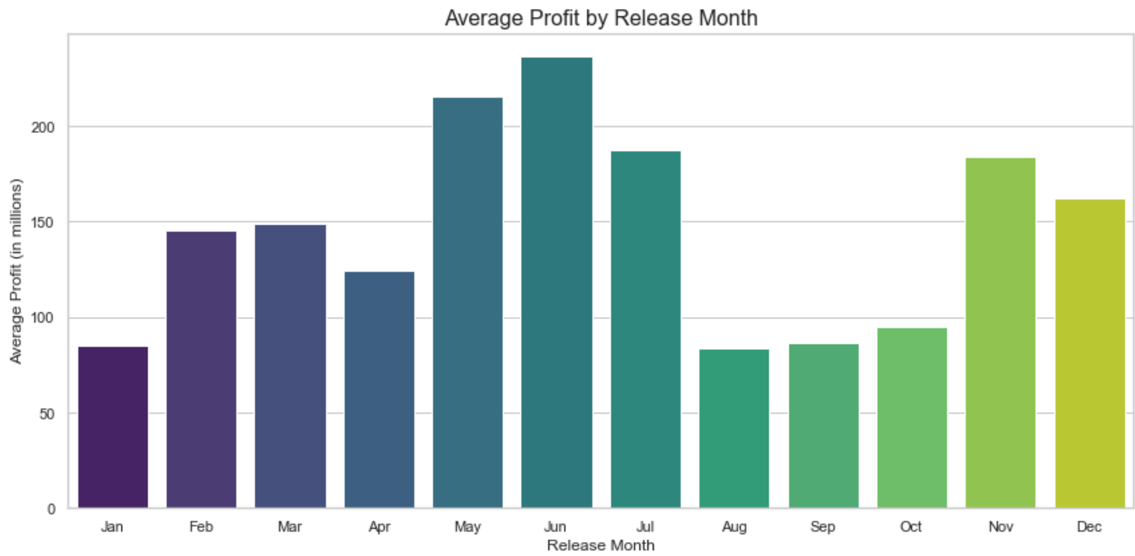
Average performance by release month:

Out[40]:

	release_month	avg_profit
0	1	84.785980
1	2	145.097262
2	3	149.109586
3	4	124.655972
4	5	215.890930
5	6	236.867675
6	7	187.758444
7	8	84.029765
8	9	86.458373
9	10	94.834217

In [41]:

```
# Set plot style
sns.set(style="whitegrid")

# Bar chart for average profit by month
plt.figure(figsize=(12, 6))
sns.barplot(x='release_month', y='avg_profit', data=month_analysis, palette
plt.title('Average Profit by Release Month', fontsize=16)
plt.xlabel('Release Month', fontsize=12)
plt.ylabel('Average Profit (in millions)', fontsize=12)
plt.xticks(ticks=range(0, 12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', '
                                        'Jul', 'Aug', 'Sep', 'Oct', 'Nov',
plt.tight_layout()
plt.show()
```



Grouping the combined data to show genre performance

In [42]:
```
# Group by primary genre and aggregate by mean ROI and profit
genre_performance = combined_df.groupby('primary_genre')[['ROI', 'profit',
genre_performance
```

Out[42]:

primary_genre	ROI	profit	production_budget	worldwide_gross
Action	246.883006	240.217183	98.569333	338.786516
Adventure	234.794563	278.605929	121.910843	400.516772
Animation	313.389362	326.215247	106.956522	433.171769
Comedy	303.097801	72.788430	29.904082	102.692512
Crime	257.324474	83.749472	33.938039	117.687511
Documentary	604.501337	33.483595	5.333333	38.816928
Drama	436.193288	78.555863	26.605276	105.161139
Family	329.761515	276.843604	68.281250	345.124854
Fantasy	199.168408	141.904777	88.696296	230.601073
History	475.598383	104.307712	31.333333	135.641046

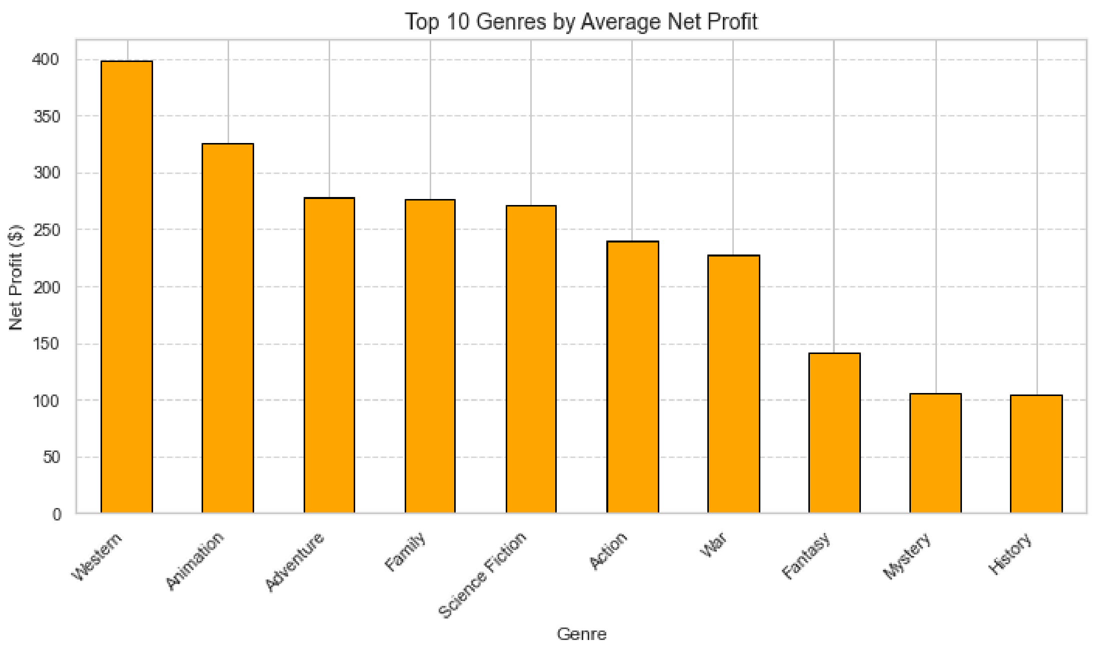
In [43]:
```
# Sort the genres by profit to identify the best performers
genre_performance_sorted_by_profit = genre_performance.sort_values('profit'

genre_performance_sorted_by_profit
```

Out[43]:

primary_genre	ROI	profit	production_budget	worldwide_gross
Western	294.769113	397.938302	135.000000	532.938302
Animation	313.389362	326.215247	106.956522	433.171769
Adventure	234.794563	278.605929	121.910843	400.516772
Family	329.761515	276.843604	68.281250	345.124854
Science Fiction	399.380618	271.007490	96.822222	367.829713
Action	246.883006	240.217183	98.569333	338.786516
War	335.912345	227.454521	67.642857	295.097378
Fantasy	199.168408	141.904777	88.696296	230.601073
Mystery	866.679643	105.145070	29.861538	135.006608
History	475.598383	104.307712	31.333333	135.641046

A Bar plot showing the top 10 genres by Net Profit

In [44]:
```
# Plotting top genres by Net Profit
plt.figure(figsize=(10, 6))
genre_performance_sorted_by_profit['profit'].head(10).plot(kind='bar', colo
plt.title('Top 10 Genres by Average Net Profit', fontsize=14)
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Net Profit ($)', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



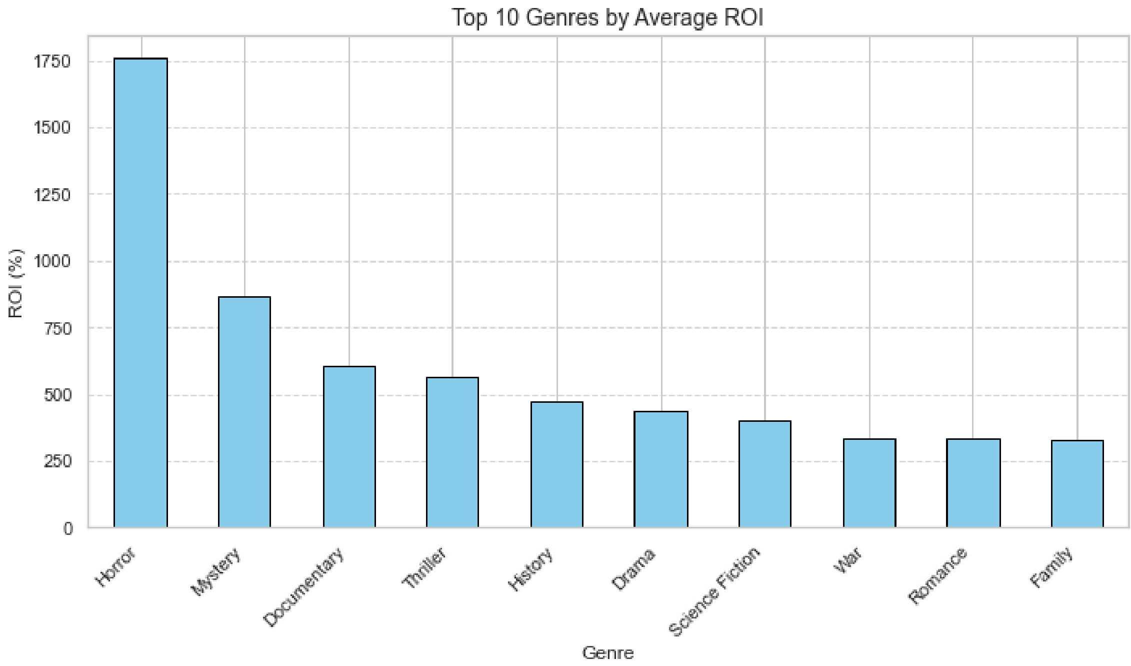
In [45]:
```python
# Sort the genres by ROI to identify the best performers
genre_performance_sorted_by_roi = genre_performance.sort_values('ROI', asce


genre_performance_sorted_by_roi
```

Out[45]:

primary_genre	ROI	profit	production_budget	worldwide_gross
Horror	1757.676050	84.512287	14.679730	99.192016
Mystery	866.679643	105.145070	29.861538	135.006608
Documentary	604.501337	33.483595	5.333333	38.816928
Thriller	565.686747	89.436631	33.466393	122.903025
History	475.598383	104.307712	31.333333	135.641046
Drama	436.193288	78.555863	26.605276	105.161139
Science Fiction	399.380618	271.007490	96.822222	367.829713
War	335.912345	227.454521	67.642857	295.097378
Romance	332.478714	94.304119	27.960000	122.264119
Family	329.761515	276.843604	68.281250	345.124854
Animation	313.389362	326.215247	106.956522	433.171769
Comedy	303.097801	72.788430	29.904082	102.692512
Western	294.769113	397.938302	135.000000	532.938302
Crime	257.324474	83.749472	33.938039	117.687511
Action	246.883006	240.217183	98.569333	338.786516
Adventure	234.794563	278.605929	121.910843	400.516772
Music	232.440218	78.917511	36.500000	115.417511
Fantasy	199.168408	141.904777	88.696296	230.601073

A Bar plot showing the top 10 genres by ROI

In [46]:
```
# Plotting top genres by ROI
plt.figure(figsize=(10, 6))
genre_performance_sorted_by_roi['ROI'].head(10).plot(kind='bar', color='sky
plt.title('Top 10 Genres by Average ROI', fontsize=14)
plt.xlabel('Genre', fontsize=12)
plt.ylabel('ROI (%)', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Type *Markdown* and LaTeX: α^2

Calculating the correlation between numerical columns

In [47]:
```
combined_df[['production_budget', 'worldwide_gross', 'profit']].corr()
```

Out[47]:

	production_budget	worldwide_gross	profit
production_budget	1.000000	0.786251	0.668008
worldwide_gross	0.786251	1.000000	0.985040
profit	0.668008	0.985040	1.000000

The correlation table summarizes the relationships between the variables `production_budget`, `worldwide_gross`, and `profit`:

1. `production_budget and worldwide_gross`:

- Correlation coefficient: **0.786**
- This indicates a strong positive relationship. Higher production budgets are generally associated with higher worldwide gross revenues.

2. **`production_budget and profit`** :

- Correlation coefficient: **0.668**
- This shows a moderate positive relationship. Higher production budgets tend to result in higher profits, although the relationship is weaker compared to that with worldwide gross.

3. **`worldwide_gross and profit`** :

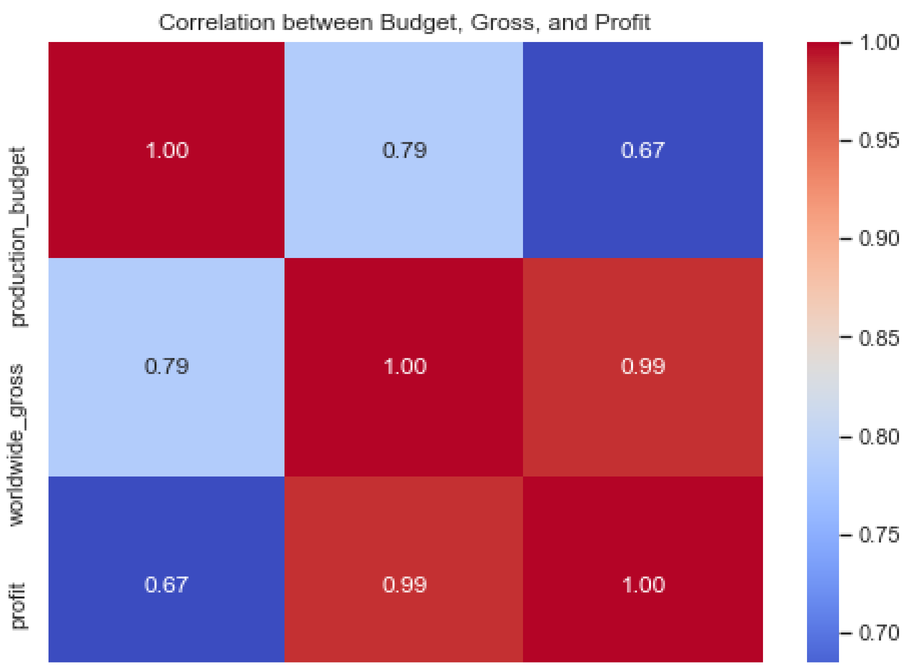
- Correlation coefficient: **0.985**
- This represents a very strong positive relationship. As worldwide gross increases, profit also increases substantially, which is expected since profit is derived from revenue minus production costs.

Key Insights:

- The strongest relationship exists between **`worldwide_gross`** and **`profit`** , highlighting the direct impact of revenue on profitability.
- While production budget correlates positively with both worldwide gross and profit, the relationships are less pronounced, suggesting that other factors (e.g., marketing, audience reception) also play a significant role.

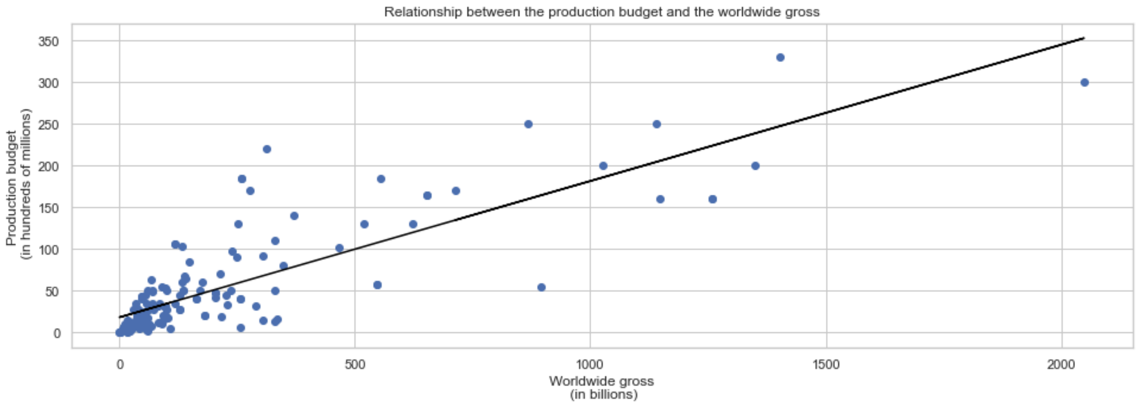
A heatmap showing the correlation

In [48]:
```
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.heatmap(combined_df[['production_budget', 'worldwide_gross', 'profit']]
plt.title('Correlation between Budget, Gross, and Profit')
plt.show()
```



A scatter plot showing the relationship between the production budget and the worldwide gross

In [49]:
```
fig, ax2 = plt.subplots(figsize=(16, 5))
x = combined_df["worldwide_gross"][:150]
y = combined_df["production_budget"][:150]

# Scatter plot
ax2.scatter(x, y)

# Fit a linear regression line
a, b = np.polyfit(x, y, 1)
plt.plot(x, a*x + b, color="black")

# Set title and labels
ax2.set_title("Relationship between the production budget and the worldwide
ax2.set_ylabel("Production budget \n (in hundreds of millions)")
ax2.set_xlabel("Worldwide gross\n (in billions)")

plt.show()
```



- A correlation coefficient of 0.79 indicates a high level of correlation between the worldwide gross and the production budget. Because of this we reccommend a high production budget of the range between 50 - 100 million dollars.

3. IMBD Database

In [50]:
```
# Define the path to the zip file and the extraction folder
zip_file_path = "zippedData/im.db.zip"
extraction_folder = "zippedData"


# Ensure the extraction folder exists
os.makedirs(extraction_folder, exist_ok=True)

# Extract the zip file
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extraction_folder)


print(f"Extracted all files to: {extraction_folder}")
```

```
Extracted all files to: zippedData
```

In [51]:
```
# Establish a connection to the SQLite database stored in the file 'zippedD
conn = sqlite3.connect('zippedData/im.db')

# Define an SQL query to retrieve information about all the tables in the d
q = """  SELECT *
         FROM sqlite_master; """

# Execute the SQL query using pandas' read_sql function and store the resul
tables = pd.read_sql(q, conn)

# Display the DataFrame containing metadata about the tables in the databas
tables
```

Out[51]:

	type	name	tbl_name	rootpage	sql
0	table	movie_basics	movie_basics	2	CREATE TABLE "movie_basics" (\n"movie_id" TEXT...
1	table	directors	directors	3	CREATE TABLE "directors" (\n"movie_id" TEXT,\n...
2	table	known_for	known_for	4	CREATE TABLE "known_for" (\n"person_id" TEXT,\...
3	table	movie_akas	movie_akas	5	CREATE TABLE "movie_akas" (\n"movie_id" TEXT,\...
4	table	movie_ratings	movie_ratings	6	CREATE TABLE "movie_ratings" (\n"movie_id" TEX...
5	table	persons	persons	7	CREATE TABLE "persons" (\n"person_id" TEXT,\n ...
6	table	principals	principals	8	CREATE TABLE "principals" (\n"movie_id" TEXT,\...
7	table	writers	writers	9	CREATE TABLE "writers" (\n"movie_id" TEXT,\n ...

Movie Basics Table

In [52]:
```
# Previewing the table
q = """  SELECT *
         FROM movie_basics; """

movie_basics = pd.read_sql(q , conn)
movie_basics
```

Out[52]:

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

146144 rows × 6 columns

Movie Ratings Table

In [53]:
```
# Previewing the table
q = """  SELECT *
         FROM movie_ratings; """

movie_ratings = pd.read_sql(q , conn)
movie_ratings
```

Out[53]:

	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

Joining the two tables

In [54]:

```
# Previewing the table
q = """
    SELECT
    mb.movie_id AS movie_id,
    mb.primary_title,
    mb.genres,
    mb.start_year,
    mb.runtime_minutes,
    mr.averagerating,
    mr.numvotes
FROM movie_basics mb
LEFT JOIN movie_ratings mr
ON mb.movie_id = mr.movie_id; """

movie_br = pd.read_sql(q , conn)
movie_br
```

Out[54]:

	movie_id	primary_title	genres	start_year	runtime_minutes	avera
0	tt0063540	Sunghursh	Action,Crime,Drama	2013	175.0	
1	tt0066787	One Day Before the Rainy Season	Biography,Drama	2019	114.0	
2	tt0069049	The Other Side of the Wind	Drama	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Comedy,Drama	2018	NaN	
4	tt0100275	The Wandering Soap Opera	Comedy,Drama,Fantasy	2017	80.0	
...	...	...	...	...	...	

In [55]:

```
# Check for missing values
movie_br.isnull().sum()
```

Out[55]:

```
movie_id               0
primary_title          0
genres              5408
start_year             0
runtime_minutes    31739
averagerating      72288
numvotes           72288
dtype: int64
```

In [56]:
```python
# Remove rows from the DataFrame 'movie_br' that have missing values in the
movie_br = movie_br.dropna(subset=['runtime_minutes', 'averagerating', 'num

# Check for remaining missing values in the DataFrame after dropping rows.
movie_br.isnull().sum()
```

Out[56]:
```
movie_id           0
primary_title      0
genres             0
start_year         0
runtime_minutes    0
averagerating      0
numvotes           0
dtype: int64
```

Filtering the runtime column

- This process filters out extreme outliers

In [57]:
```python
# Viweing the max duration of a movie
max_min = movie_br['runtime_minutes'].max()

mean_min = movie_br['runtime_minutes'].mean()

mean_min, max_min
```

Out[57]:
```
(94.7322732805843, 51420.0)
```

In [58]:
```python
# We'll need to exclude such extreme cases.
movie_br[movie_br['runtime_minutes'] == 51420.0]
```

Out[58]:

	movie_id	primary_title	genres	start_year	runtime_minutes	averagerating	nu
132389	tt8273150	Logistics	Documentary	2012	51420.0	5.0	

In [59]:
```python
# Filtering the data to include movies with reasonable runtime i.e 2 hrs 30
movie_br = movie_br[movie_br['runtime_minutes'] < 150 ]  #  Threshold for e

movie_br['runtime_minutes'].max()
```

Out[59]:
```
149.0
```

In [60]:
```python
# Lists column names, data types, and non-null counts.
movie_br.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 64208 entries, 1 to 146134
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         64208 non-null  object 
 1   primary_title    64208 non-null  object 
 2   genres           64208 non-null  object 
 3   start_year       64208 non-null  int64  
 4   runtime_minutes  64208 non-null  float64
 5   averagerating    64208 non-null  float64
 6   numvotes         64208 non-null  float64
dtypes: float64(3), int64(1), object(3)
memory usage: 3.9+ MB
```

In [61]:
```python
# Create a copy of the DataFrame `movie_br` to avoid modifying the original
movie_br = movie_br.copy()

# Create a new column 'primary_genre' by extracting the first genre from th
# The lambda function splits the 'genres' string by commas and selects the
movie_br["primary_genre"] = movie_br["genres"].apply(lambda x: x.split(",")

# Display the modified DataFrame to verify the changes
movie_br
```

Out[61]:

	movie_id	primary_title	genres	start_year	runtime_minute
1	tt0066787	One Day Before the Rainy Season	Biography,Drama	2019	114
2	tt0069049	The Other Side of the Wind	Drama	2018	122
4	tt0100275	The Wandering Soap Opera	Comedy,Drama,Fantasy	2017	80
7	tt0137204	Joe Finds Grace	Adventure,Animation,Comedy	2017	83
10	tt0146592	Pál Adrienn	Drama	2010	136
...	...	...	...	...	
146113	tt9911774	Padmavyuhathile Abhimanyu	Drama	2019	130
146114	tt9913056	Swarm Season	Documentary	2019	86

In [62]:
```
# Checking the value counts
movie_br['primary_genre'].value_counts()
```

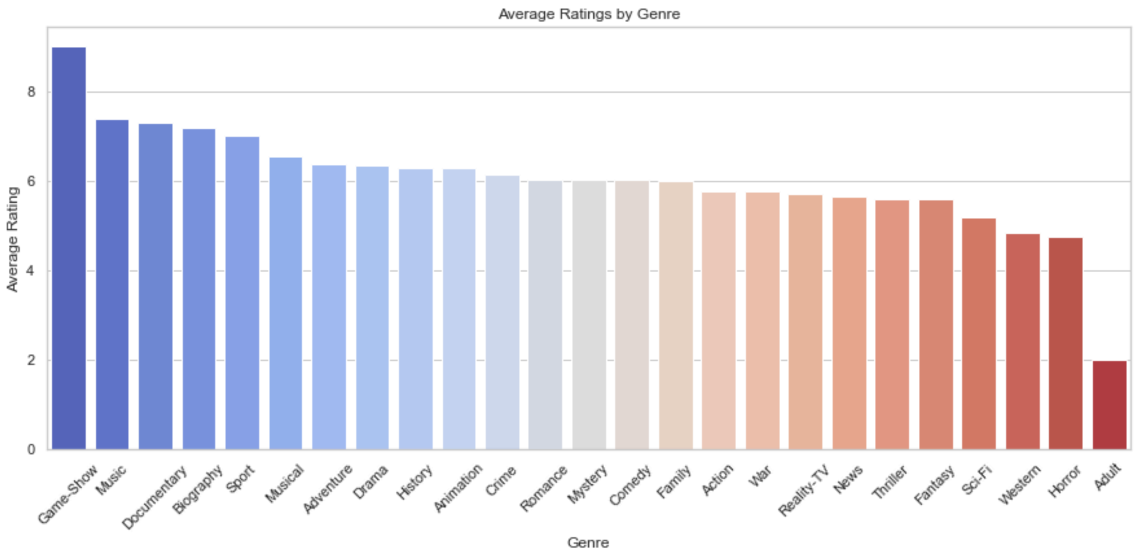
Out[62]:
```
Drama          16383
Comedy         12783
Documentary    12511
Action          5859
Horror          3923
Biography       3266
Adventure       2429
Crime           2297
Thriller        1276
Animation        861
Romance          544
Family           516
Fantasy          377
Mystery          373
Sci-Fi           320
Music            136
Musical          102
History           91
Sport             64
Western           62
War               30
News               2
Adult              1
Reality-TV         1
Game-Show          1
Name: primary_genre, dtype: int64
```

In [63]:
```
# Lists column names, data types, and non-null counts.
movie_br.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 64208 entries, 1 to 146134
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         64208 non-null  object 
 1   primary_title    64208 non-null  object 
 2   genres           64208 non-null  object 
 3   start_year       64208 non-null  int64  
 4   runtime_minutes  64208 non-null  float64
 5   averagerating    64208 non-null  float64
 6   numvotes         64208 non-null  float64
 7   primary_genre    64208 non-null  object 
dtypes: float64(3), int64(1), object(4)
memory usage: 4.4+ MB
```

Genres with Highest Average Ratings

In [64]:
```
# Genres with Highest Average Ratings
plt.figure(figsize=(15, 6))
avg_rating_by_genre = movie_br.groupby('primary_genre')['averagerating'].me
sns.barplot(x=avg_rating_by_genre.index, y=avg_rating_by_genre.values, pale
plt.title('Average Ratings by Genre')
plt.xlabel('Genre')
plt.ylabel('Average Rating')
plt.xticks(rotation=45)
plt.show()
```

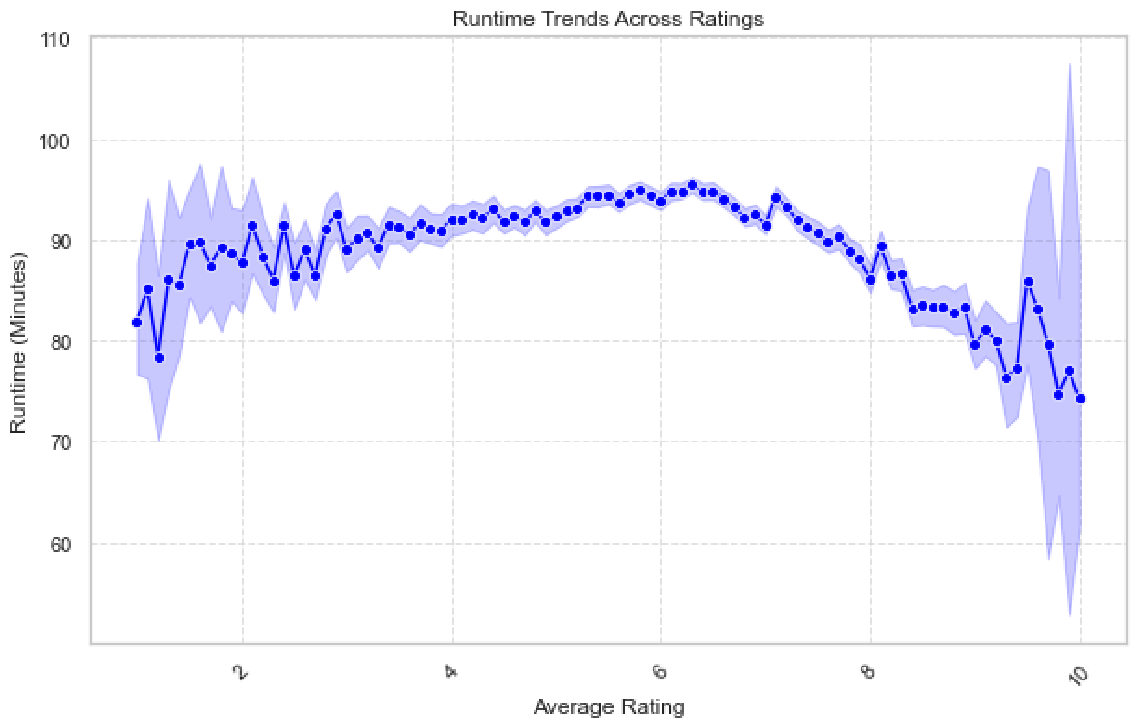


In [65]:
```
# Showing the values
avg_rating_by_genre
```

Out[65]:
```
primary_genre
Game-Show      9.000000
Music          7.377941
Documentary    7.293494
Biography      7.178077
Sport          6.990625
Musical        6.549020
Adventure      6.370441
Drama          6.339321
History        6.279121
Animation      6.266783
Crime          6.139878
Romance        6.027757
Mystery        6.024665
Comedy         6.005515
Family         5.991085
Action         5.762946
War            5.746667
Reality-TV     5.700000
News           5.650000
Thriller       5.590517
Fantasy        5.584881
Sci-Fi         5.168750
Western        4.833871
Horror         4.748968
Adult          2.000000
Name: averagerating, dtype: float64
```

Trends in Movie Runtime

In [66]:
```
plt.figure(figsize=(10, 6))

# Create a line plot for runtime trends across ratings
sns.lineplot(
    x=movie_br['averagerating'],
    y=movie_br['runtime_minutes'],
    color='blue',
    marker='o'
)

plt.title('Runtime Trends Across Ratings')
plt.xlabel('Average Rating')
plt.ylabel('Runtime (Minutes)')
plt.xticks(rotation=45)
plt.grid(visible=True, linestyle='--', alpha=0.5)
plt.show()
```



Data Modeling

In [67]:
```
# Ensure combined_df is a standalone copy to avoid SettingWithCopyWarning
combined_df = combined_df.copy()

# Apply log transformation to relevant features in the dataset
combined_df['log_budget'] = np.log1p(combined_df['production_budget'])
combined_df['log_profit'] = np.log1p(combined_df['profit'])


# Define features (independent variables) and target variable (dependent va
X = combined_df[['log_budget', 'log_profit']]  # Use transformed variables
y = combined_df['ROI']  # Assuming you want to predict ROI

# Split data into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra

# Initialize and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Output results
print(f"Mean Squared Error: {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error: 235680.34
R² Score: 0.43
```

Data Analysis and Modeling Process

1. Analyzing the Data

To solve the problem of understanding factors contributing to movie success at the box office, I conducted the following steps:

- **Exploratory Data Analysis (EDA)**: I analyzed the dataset's structure and summary statistics previously, noting:
  - Presence of zero or negative values in the `profit` column.
  - Significant variation and outliers in the values.
- **Data Cleaning**: I addressed these issues previously:
  - Filtering out negative values in the `profit` column (due to the limitations of log transformation).
  - Removing missing values (NaNs) in essential columns like `production_budget` and `profit`.

2. Data Transformation

- **Log Transformation**: I applied a logarithmic transformation (`np.log1p`) to the `production_budget` and `profit` columns. This reduced the impact of outliers and normalized the distributions, making them more linear for linear regression modeling.

3. Feature Selection

- I selected `log_budget` and `log_profit` as features because they directly relate to movie costs and profitability, making them strong predictors of ROI.

4. Model Selection

- **Linear Regression** was chosen for its simplicity and interpretability. It is suitable for modeling linear relationships and understanding how features (budget, profit) influence the target variable (ROI).

5. Model Evaluation

- I evaluated the model using:
  - **Mean Squared Error (MSE)**: Indicates the accuracy of predictions (lower is better).
  - **R^2 Score**: Shows how much of the variance in ROI is explained by the model (higher is better).

6. Iteration and Improvement

- **Data Transformation**: I ensured the data was transformed appropriately to fit the linear regression model.
- **Addressing Warnings**: Used `.loc[]` to avoid the `SettingWithCopyWarning` during assignments.

7. Results

- The model achieved an **R^2 Score of 0.43**, explaining 43% of the variability in ROI.
- The **MSE** of 235,680.34 suggests room for model improvement.

Relevance of the Modeling process

1. **Business Relevance**: The chosen features (`production_budget` , `profit`) are key factors in movie success, and understanding their impact helps make data-driven decisions.
2. **Linear Regression**: This simple model allows us to interpret how budget and profit influence ROI, making it accessible for business stakeholders.
3. **Log Transformation**: This technique ensures more linear relationships between variables, improving the effectiveness of the regression model.

Conclusions

Based on the analysis, the following recommendations and insights have been derived:

1. **Recommendations for the Business:**

   - Focus on producing movies in high profitable genres like Western, Animation, Adventure, Family and Science Fiction .

- Allocate production budgets strategically within a range that balances profitability and risk i.e. Consider the budget range between 50 to 100 million dollars.
- Time movie releases during peak seasons such as summer and the holiday months to maximize box office success. Summer: June and July Winter: December
- Consider creating films with runtimes aligned with audience preferences (e.g., around 90–120 minutes), ensuring they maintain engagement and align with critical reception trends.
- Leverage insights into audience ratings to produce quality films that resonate with viewers, building long-term loyalty and enhancing the studio’s reputation.

2. **Limitations of the Analysis:**

   - **Data Gaps:** Missing or incomplete data on production budgets, revenues, and other key attributes may limit the accuracy of conclusions.
   - **Historical Bias:** The analysis relies on historical data, which may not account for shifting audience preferences or emerging genres.
   - **Multilabel Genres:** Movies belonging to multiple genres could dilute the financial and audience impact attributed to a specific genre.

3. **Next Steps for Improvement:**

   - **Enhance Data Quality:** Fill in missing data, standardize formats across sources, and adjust for inflation to ensure more accurate comparisons.
   - **Incorporate Marketing Metrics:** Include data on advertising budgets, promotional strategies, and audience engagement to provide a more holistic view of a movie's success.
   - **Analyze Regional Trends:** Study regional performance trends to tailor strategies for different markets.
   - **Explore Streaming Impact:** With the rise of streaming platforms, consider how simultaneous theatrical and online releases affect profitability.
   - **Machine Learning Models:** Build predictive models to forecast box office success based on key variables like budget, genre, and release timing.