Exploratory Data Analysis (EDA)

Financial Performance Metric

Extracting Datasets from The Numbers dataset

In [1]:
```
# Importing necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
```

In [2]:
```
# Loading the numbers dataset
tn = pd.read_csv(r"C:\Users\A808865\Desktop\moringa\Phase 2\Group Project\Box Offic
tn.head()
```

Out[2]:

	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 [3]:
```
# Understanding the data structure
tn.info()

print("Shape:", tn.shape)
```

```
<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
Shape: (5782, 6)
```

Data Type Conversion and Cleaning

- Converted the release_date column from string format to datetime for proper date handling.

- Cleaned the currency columns (production_budget, domestic_gross, worldwide_gross) by removing dollar signs and commas, then converted them to 64-bit integers for numerical analysis.

In [4]:
```
# Convert release_date to datetime
tn['release_date'] = pd.to_datetime(tn['release_date'])

# Remove $ and , and convert to integers
cols_to_clean = ['production_budget', 'domestic_gross', 'worldwide_gross']
for col in cols_to_clean:
    tn[col] = tn[col].replace('[\$,]', '', regex=True).astype('int64')


# Output
print(tn.dtypes)
tn.head()
```

```
id                            int64
release_date         datetime64[ns]
movie                        object
production_budget             int64
domestic_gross                int64
worldwide_gross               int64
dtype: object
```

Out[4]:

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

Column Restructuring

- Removed the id column from the dataset.
- Created a new column Release year by extracting the year component from the release_date column.

In [5]:
```
# Drop the 'id' column
tn = tn.drop(columns=['id'])

# Extract year from 'release_date' and create a new 'year' column
tn['release_year'] = tn['release_date'].dt.year

# Now print to see the result
tn.head()
```

Out[5]:

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

Summary Statistics

In [6]:

```
# Showing floats with commas and 3 decimal places instead of scientific notation

pd.set_option('display.float_format', '{:,.2f}'.format)

tn.describe()
```

Out[6]:

	release_date	production_budget	domestic_gross	worldwide_gross	release_year
count	5782	5,782.00	5,782.00	5,782.00	5,782.00
mean	2004-07-06 05:20:31.546177792	31,587,757.10	41,873,326.87	91,487,460.91	2,003.97
min	1915-02-08 00:00:00	1,100.00	0.00	0.00	1,915.00
25%	2000-04-22 18:00:00	5,000,000.00	1,429,534.50	4,125,414.75	2,000.00
50%	2007-03-02 00:00:00	17,000,000.00	17,225,945.00	27,984,448.50	2,007.00
75%	2012-12-25 00:00:00	40,000,000.00	52,348,661.50	97,645,836.50	2,012.00
max	2020-12-31 00:00:00	425,000,000.00	936,662,225.00	2,776,345,279.00	2,020.00
std	NaN	41,812,076.83	68,240,597.36	174,719,968.78	12.72

- Our data is spans over 100 years (From 1915 to 2020) Most Movies have smaller budget than average (mean > Median)
- High Standard deviation hence lots of variability
- Some movies perform well globally due to the high mean, we should therefore look at international markets wheb evaluating box office performance

Exploring Incomplete Gross Earnings

In [7]:

```
# Filter movies with 0 domestic gross but non-zero worldwide gross
no_domestic = tn[(tn['domestic_gross'] == 0) & (tn['worldwide_gross'] != 0)]
no_domestic
```

Out[7]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
617	2012-12-31	AstÃ©rix et ObÃ©lix: Au service de Sa MajestÃ©	77600000	0	60680125	2012
619	2019-01-22	Renegades	77500000	0	1521672	2019
820	2018-10-26	Air Strike	65000000	0	516279	2018
1325	2012-12-31	Foodfight!	45000000	0	73706	2012
1367	2006-12-31	Les BronzÃ©s 3: amis pour la vie	42000000	0	83833602	2006
...	...	...	...	...	...	...
5590	2015-03-24	Along the Roadside	250000	0	3234	2015
5652	2015-12-31	Lumea e a mea	168000	0	29678	2015
5661	2013-12-31	Speak No Evil	150000	0	32927	2013
5705	2011-12-31	Absentia	70000	0	8555	2011
5748	2015-09-01	Exeter	25000	0	489792	2015

181 rows × 6 columns

In [8]:

```
# Filter movies with both domestic and worldwide gross equal to 0
no_gross = tn[(tn['domestic_gross'] == 0) & (tn['worldwide_gross'] == 0)]

## Droppings rows with no worldwide or domestic gross
tn = tn.drop(no_gross.index)
tn
```

Out[8]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
0	2009-12-18	Avatar	425000000	760507625	2776345279	2009
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
2	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
3	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017
...	...	...	...	...	...	...
5775	2006-05-26	Cavite	7000	70071	71644	2006
5776	2004-12-31	The Mongol King	7000	900	900	2004
5778	1999-04-02	Following	6000	48482	240495	1999
5779	2005-07-13	Return to the Land of Wonders	5000	1338	1338	2005
5781	2005-08-05	My Date With Drew	1100	181041	181041	2005

5415 rows × 6 columns

In [9]:

```
# Filter movies with non-zero domestic gross but 0 worldwide gross
no_worldwide = tn[(tn['worldwide_gross'] == 0) & (tn['domestic_gross'] != 0)]
no_worldwide
```

Out[9]:

release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year

The best strategy is to produce movies that strike a balance between strong domestic appeal and international potential. Domestic box office earnings are a reliable baseline for worldwide success, movies that earn domestically almost always generate revenue internationally as well. However, while less than 1% of movies earn revenue overseas despite little or no domestic earnings, this minority highlights the importance of considering global market preferences.

Profit & Return on investment

For every $1 that was spent, how much (%) did they get back in profit?

In [10]:

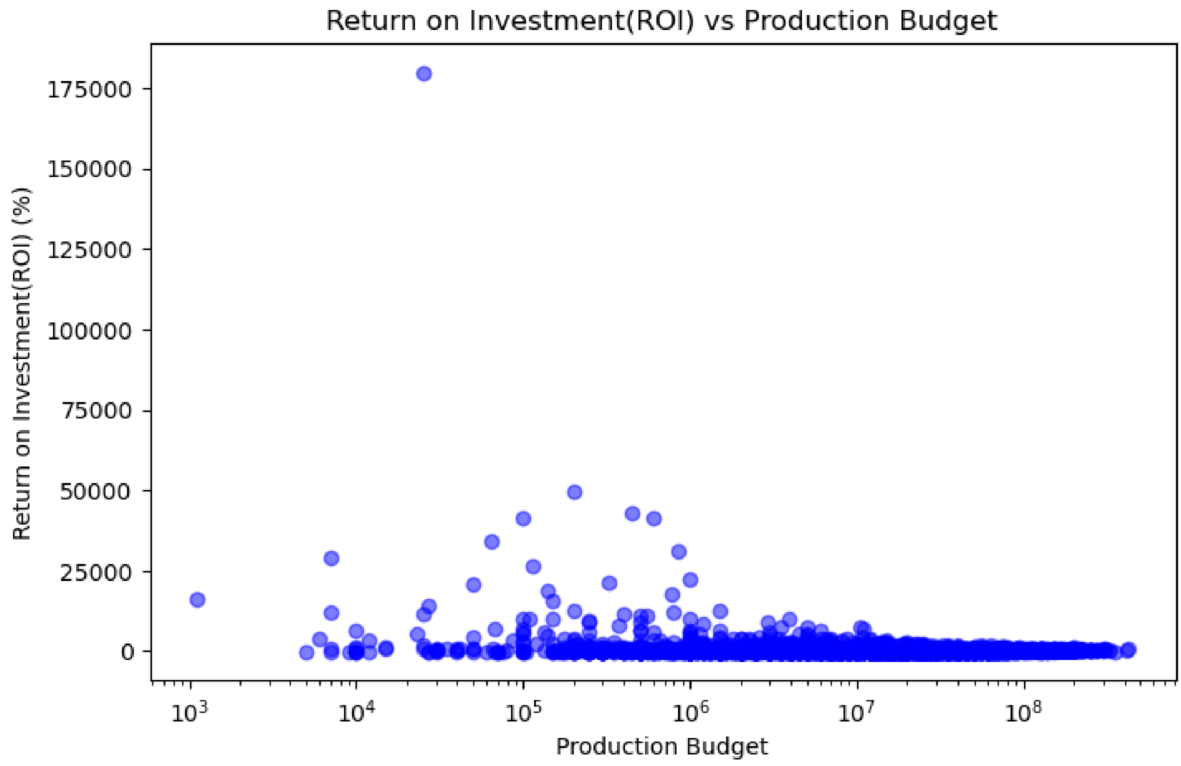
```
# Calculated Profit
tn['profit'] = tn['worldwide_gross'] - tn['production_budget']

# Calculated ROI (as a percentage)
tn['Return on Investment(ROI)'] = (tn['profit'] / tn['production_budget']) * 100

tn.head()
```

Out[10]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	
0	2009-12-18	Avatar	425000000	760507625	2776345279	2009	235
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	63
2	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019	-20
3	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	107
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	99

In [11]:

```
plt.figure(figsize=(8,5))
plt.scatter(tn['production_budget'], tn['Return on Investment(ROI)'], color='blue',
plt.xlabel('Production Budget')
plt.ylabel('Return on Investment(ROI) (%)')
plt.title('Return on Investment(ROI) vs Production Budget')
plt.xscale('log')  # Log scale to better visualize wide range budgets
plt.show()
```



Plot Interpretations:

- We used Scatter plot because it is ideal for visualizing relationships between two continuous variables (Production budget and ROI)
- Each dot = 1 movie.
- We used log scale to better visualize wide range budgets (10^(4) = 10,000)

Observations:

1. High ROI isn't tied to high budget - The movies with the highest ROI are mostly in the low to mid-budget range ($10k–$1M).

2. Big budgets ≠ big ROI - Expensive movies (>$100M or 10^(8)) tend to have lower ROI, even if they make lots of money because their production costs are huge.

3. Diminishing returns at higher budgets - As budgets grow, ROI tends to flatten. Studios make profits, but the percentage return shrinks.

Recomendation

- Consider low to Mid budget movies as they can be highly profitable - These movies are less risky and often perform better per dollar invested. For example $1M movie can return 5000% ROI. Avoid avoid mega budgeted movies early on because they don't guarantee high ROI and they are huge risks because they need global distribution power.

Limitation

Our data doesnt have genres because it would have allowed us to look for genres that thrive on Small Budgets

Grouping movies by release_year and production_budget brackets

Created a new column `budget_bracket` by categorizing `production_budget` into labeled bins: <10M, 10M-50M, 50M-200M, and 200M or more (up to max budget).

In [12]:
```
# Creating budget brackets (bins)
bins = [0, 10_000_000, 50_000_000, 200_000_000, tn['production_budget'].max() + 1]

labels = ['<10M', '10M-50M', '50M-200M', '>200M']

tn['budget_bracket'] = pd.cut(tn['production_budget'], bins=bins, labels=labels, ri
tn
```

Out[12]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
0	2009-12-18	Avatar	425000000	760507625	2776345279	2009
1	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
2	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
3	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
4	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017
...	...	...	...	...	...	...
5775	2006-05-26	Cavite	7000	70071	71644	2006
5776	2004-12-31	The Mongol King	7000	900	900	2004
5778	1999-04-02	Following	6000	48482	240495	1999
5779	2005-07-13	Return to the Land of Wonders	5000	1338	1338	2005
5781	2005-08-05	My Date With Drew	1100	181041	181041	2005

5415 rows × 9 columns

b) Analyzing average ROI and profit for each budget bracket category.

In [13]:
```
budget_summary = tn.groupby('budget_bracket')[['Return on Investment(ROI)', 'profit
budget_summary
```

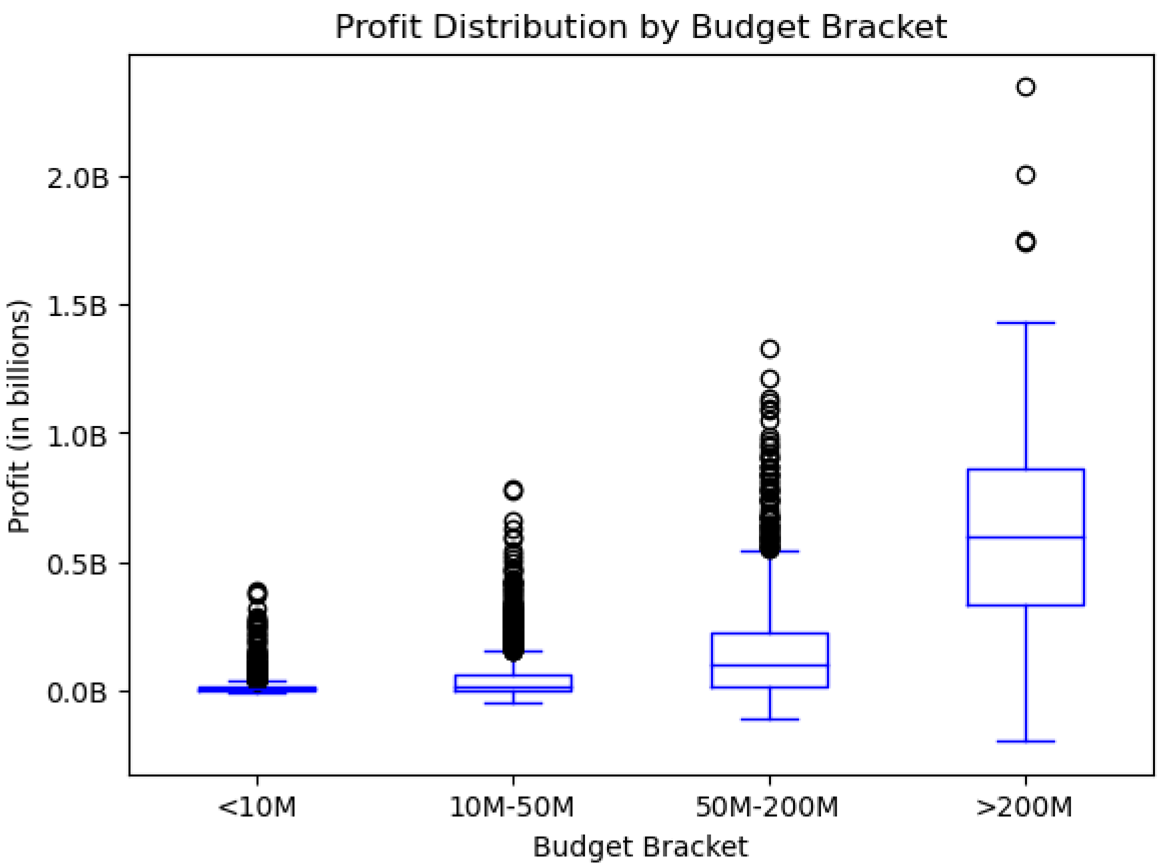
Out[13]:

	budget_bracket	Return on Investment(ROI)	profit
0	<10M	894.37	14,098,381.77
1	10M-50M	193.82	41,407,432.07
2	50M-200M	171.26	158,823,993.18
3	>200M	273.95	648,035,806.38

In [14]:

```
plt.figure(figsize=(8,5))
tn.boxplot(column='profit', by='budget_bracket', grid=False, color='blue')
plt.title('Profit Distribution by Budget Bracket')
plt.suptitle('')
plt.xlabel('Budget Bracket')
plt.ylabel('Profit (in billions)')
plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, _: f'{x*1e-9:.1f
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```



Plot Interpretation:

- Boxplots can be used to compare groups thus shows how profit varies across diffrent movie budget bracket brackets.
- There are many outliers in our data and boxplot shows the outliers clearly which are important for profitability analysis.
- Boxplots show median, spread, and skewnes thus it's easy to feel the spread & risk of our data
- Each Box:
  - Middle line = median profit.
  - Box edges = 25th and 75th percentiles (interquartile range).
  - Whiskers = range of most data.

- Dots = outliers (very high profits).

Observation

1. <10M Budget Bracket - Suggests Low median and tight spread small movies generally earn small profits.
   - Low median profit.
   - Narrow box and whiskers → low variability.
   - A few outliers with decent profit, but most profits are small.

1. 10M–50M Budget Bracket - Slightly better profit, but still not extreme.
   - Slightly higher median than <10M.
   - Moderate spread.
   - A noticeable number of outliers, suggesting a few highly profitable exceptions.

1. 50M–200M Budget Bracket - Suggests a sweet spot where both median profit and upside are attractive, though risk increases (more variability).
   - Higher median profit and wider box (more variability).
   - Many positive outliers (successful movies).

4.>200M Budget Bracket - Indicates high risk, high reward territory (Most profitable bracket) but very wide spread and many outliers (some huge hits, some flops)

- Highest median profit of all brackets.
- Very wide spread and tall box (high variability).
- Many high value outliers (up to 2.3B), but also some low or even negative profits.

Recomendation:

We should target a production budget of possibly between 50-200M range as it balances balances risk and return. Production budget of more than 200M dominates in average profit, it has the highest upside and variability. Smaller budgeted movies are less risky, they have less variability and fewer outliers

ROI trend over release years

In [15]:
```
yearly_summary = tn.groupby('release_year')[['Return on Investment(ROI)', 'profit']
yearly_summary
```

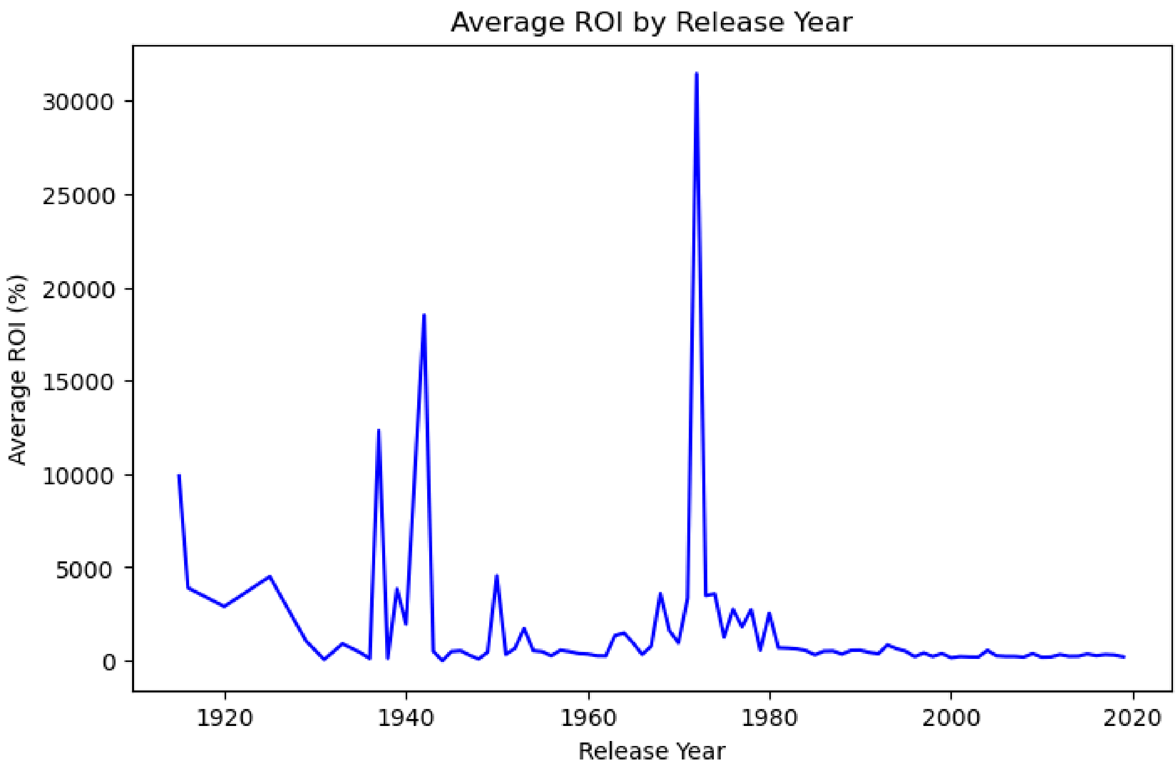
Out[15]:

	release_year	Return on Investment(ROI)	profit
0	1915	9,900.00	10,890,000.00
1	1916	3,900.00	7,800,000.00
2	1920	2,900.00	2,900,000.00
3	1925	4,505.18	13,427,500.00
4	1929	1,049.87	3,979,000.00
...	...	...	...
87	2015	361.69	79,475,952.92
88	2016	267.79	97,451,876.18
89	2017	329.01	124,338,555.59
90	2018	303.05	137,645,677.85
91	2019	206.72	77,823,782.57

92 rows × 3 columns

In [16]:

```
plt.figure(figsize=(8,5))
plt.plot(yearly_summary['release_year'], yearly_summary['Return on Investment(ROI)'
plt.xlabel('Release Year')
plt.ylabel('Average ROI (%)')
plt.title('Average ROI by Release Year')
plt.show()
```



Plot Interpretation:

- To look at how does ROI change over time, and when was investment in movies most efficient? We used time series to track how ROI changes so that it is easy for us to focus on investment performance over the years.

Observation:

- Extremely high ROI spikes occur in older movies (like 1930s–1970s), e.g., a peak above 30,000% around 1972.
- After the 1980s, ROI stabilizes and drops to more realistic levels.
- From 1990 onward, average ROI is consistently much lower, usually below 1,000%.

Conclusion:

Investment in movies was most efficient in the earlier decades as shown by the significantly higher average ROI compared to more recent years though there may also be fewer records for early years, causing data distortion from a few standout movies. ROI has become more conservative over time.To inspire cost effective production strategies today we could study eras of high return movie models (genres, formats, release strategies or potentially produce remakes of 1930s–1970s era of movies with modern twist

Top performers by ROI and profit

In [17]:
```python
# Top 5 movies by ROI
top_roi = tn.sort_values('Return on Investment(ROI)', ascending=False).head(5)[['mo
print("Top 5 movies by ROI:")
top_roi
```

```
Top 5 movies by ROI:
```

Out[17]:

	movie	Return on Investment(ROI)	profit	production_budget
5745	Deep Throat	179,900.00	44975000	25000
5613	Mad Max	49,775.00	99550000	200000
5492	Paranormal Activity	43,051.79	193733034	450000
5679	The Gallows	41,556.47	41556474	100000
5406	The Blair Witch Project	41,283.33	247700000	600000

In [18]:
```python
# Top 5 movies by profit
top_profit = tn.sort_values('profit', ascending=False).head(5)[['movie', 'profit',
print("\nTop 5 movies by Profit:")
top_profit
```

```
Top 5 movies by Profit:
```

Out[18]:

	movie	profit	Return on Investment(ROI)	production_budget
0	Avatar	2351345279	553.26	425000000
42	Titanic	2008208395	1,004.10	200000000
6	Avengers: Infinity War	1748134200	582.71	300000000
5	Star Wars Ep. VII: The Force Awakens	1747311220	571.02	306000000
33	Jurassic World	1433854864	666.91	215000000

Regression Modelling

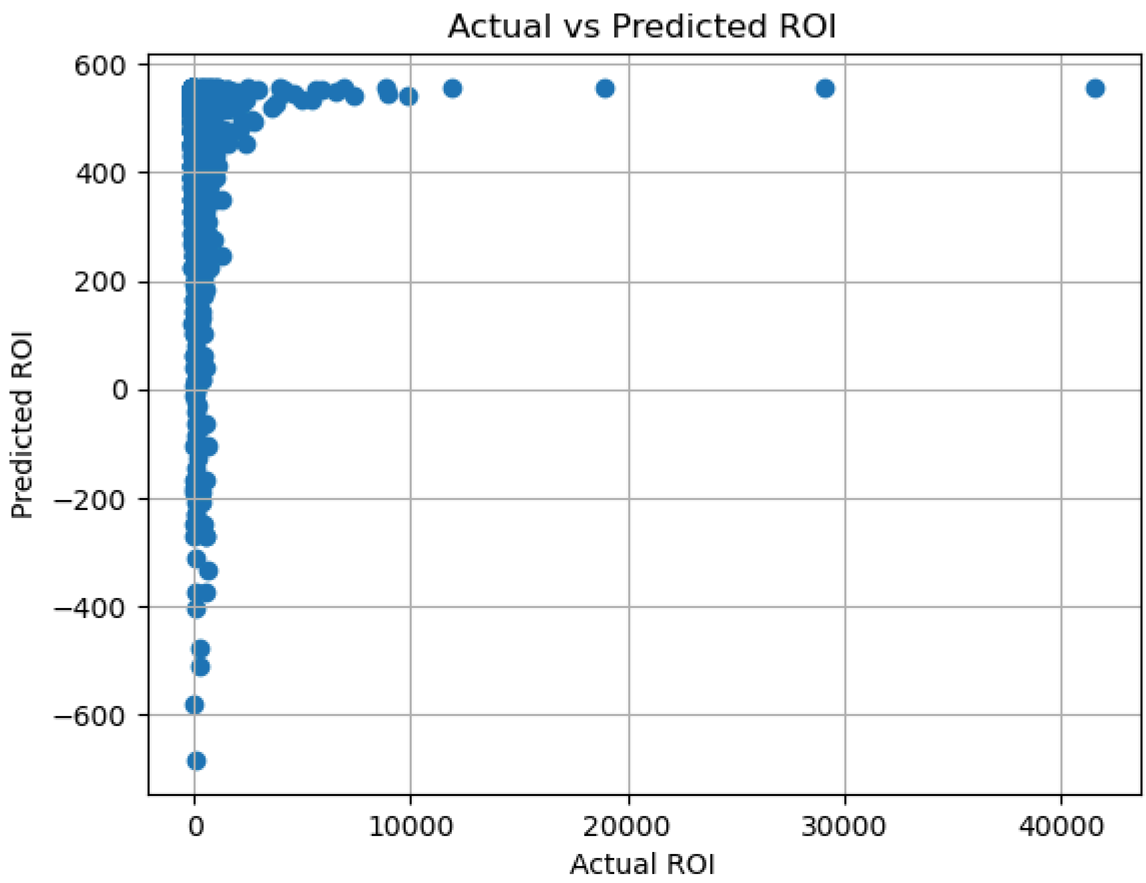
Which production budgets yield the highest return on investment (ROI) in movies?

To explore this, we used ROI as the target variable and production budget as the predictor. We applied a simple linear regression model to examine the relationship and evaluated its performance using R^2 and Mean Squared Error (MSE).

In [19]:
```
# Importing libraries
from sklearn.model_selection import train_test_split   # for splitting data into tr
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Defining features (X) and target (y) variables
#'production_budget' as the feature and 'Return on Investment(ROI)' as the target
X = tn[['production_budget']]
y = tn['Return on Investment(ROI)']

# Splitting data into train and test sets (80% for training the model & 20% for tes
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Training the model
model = LinearRegression()
model.fit(X_train, y_train)

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

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

# metrics to evaluate how well the model performs
print(f"Mean Squared Error: {mse}")    # how far the predictions are from the actu

print(f"R² Score: {r2}")  # how much of the variation in ROI our model can explain
```

```
Mean Squared Error: 3427007.8836275986
R² Score: 0.00691948206586368
```

In [20]:
```
import matplotlib.pyplot as plt

plt.scatter(y_test, y_pred)
plt.xlabel("Actual ROI")
plt.ylabel("Predicted ROI")
plt.title("Actual vs Predicted ROI")
plt.grid(True)
plt.show()
```



The model shows that production budget alone has almost no predictive power for a movie's ROI (R^2 = 0.0069), meaning we can't reliably estimate profitability just from how much was spent on production. This weak relationship highlights a key limitation: production budgets typically exclude other critical financial factors such as marketing expenses, cinema or streaming platform cuts, and backend deals. Simply spending more on production doesn't guarantee higher returns. To make better predictions, we would likely need a broader range of data that captures the full financial picture of a movie's lifecycle.

Market Analysis

In [21]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [22]:
```
data = pd.read_csv(r"C:\Users\A808865\Desktop\moringa\Phase 2\Group Project\Box Off
data
```

Out[22]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415,000,000.00	652000000	2010
1	Alice in Wonderland (2010)	BV	334,200,000.00	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296,000,000.00	664300000	2010
3	Inception	WB	292,600,000.00	535700000	2010
4	Shrek Forever After	P/DW	238,700,000.00	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6,200.00	NaN	2018
3383	Edward II (2018 re-release)	FM	4,800.00	NaN	2018
3384	El Pacto	Sony	2,500.00	NaN	2018
3385	The Swan	Synergetic	2,400.00	NaN	2018
3386	An Actor Prepares	Grav.	1,700.00	NaN	2018

3387 rows × 5 columns

In [23]:

```
data.shape
```

Out[23]:

```
(3387, 5)
```

In [24]:

```
data.info()
```

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

In [25]:

```
data["foreign_gross"]=data["foreign_gross"].fillna(0)
data
```

Out[25]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415,000,000.00	652000000	2010
1	Alice in Wonderland (2010)	BV	334,200,000.00	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296,000,000.00	664300000	2010
3	Inception	WB	292,600,000.00	535700000	2010
4	Shrek Forever After	P/DW	238,700,000.00	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6,200.00	0	2018
3383	Edward II (2018 re-release)	FM	4,800.00	0	2018
3384	El Pacto	Sony	2,500.00	0	2018
3385	The Swan	Synergetic	2,400.00	0	2018
3386	An Actor Prepares	Grav.	1,700.00	0	2018

3387 rows × 5 columns

In [26]:

```
# Remove $ and commas from 'domestic_gross' and 'foreign_gross', then convert to nu
data['foreign_gross'] = (
    data['foreign_gross']
    .replace('[\$,]', '', regex=True)
    .astype(float)
)
```

In [27]:

```
data.info()
```

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

In [28]:

```
# Create total gross column
data['total_gross'] = data['domestic_gross'] + data['foreign_gross']
```

In [29]:

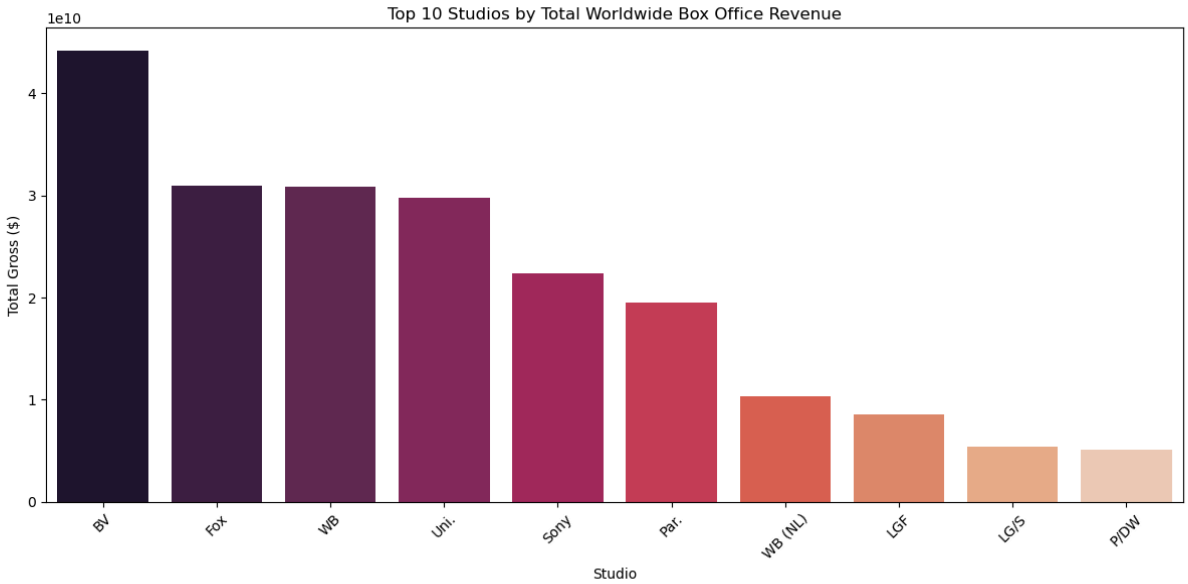
```
#Group by studio and sum total_gross
studio_revenue = (
    data.groupby('studio')['total_gross']
    .sum()
    .sort_values(ascending=False)
    .head(10)
    .reset_index()
)
#studio_revenue['total_gross'] = studio_revenue['total_gross'].apply(lambda x: f"{i
studio_revenue
```

Out[29]:

	studio	total_gross
0	BV	44,212,883,899.10
1	Fox	31,005,366,596.00
2	WB	30,835,948,998.00
3	Uni.	29,757,164,191.40
4	Sony	22,404,919,096.00
5	Par.	19,549,255,697.00
6	WB (NL)	10,334,699,999.00
7	LGF	8,594,582,700.00
8	LG/S	5,431,923,998.00
9	P/DW	5,076,500,000.00

In [30]:

```
plt.figure(figsize=(12,6))
sns.barplot(data=studio_revenue, x='studio', y='total_gross', palette='rocket')
plt.title('Top 10 Studios by Total Worldwide Box Office Revenue')
plt.ylabel('Total Gross ($)')
plt.xlabel('Studio')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [31]:

```
data["year"].unique()
```

Out[31]:

```
array([2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018], dtype=int64)
```

In [32]:

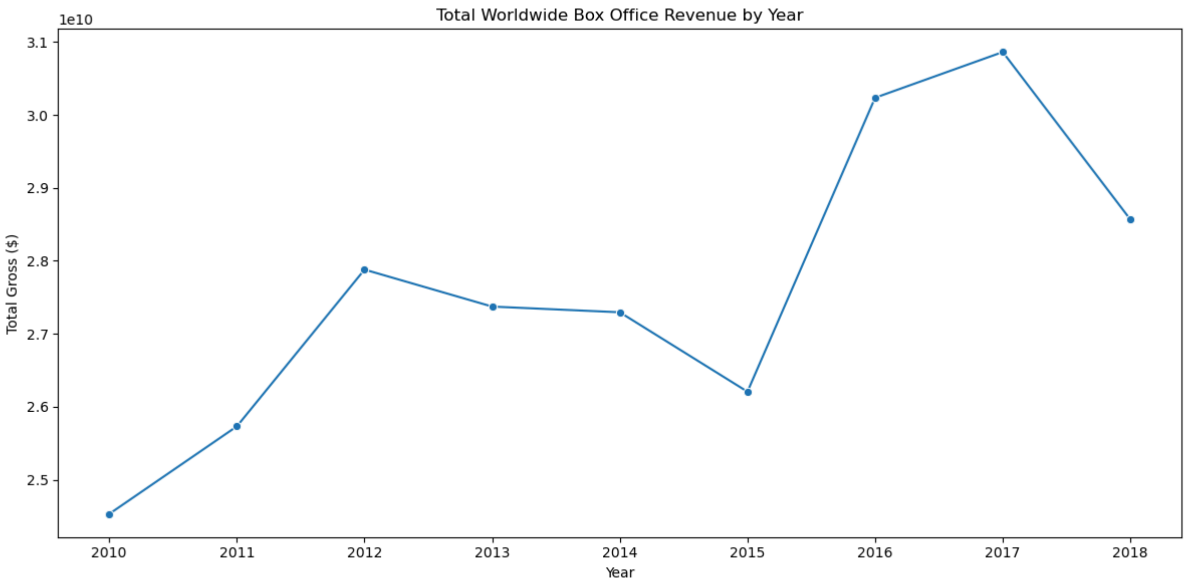
```
gross_by_year = data.groupby('year')['total_gross'].sum().reset_index()
gross_by_year
```

Out[32]:

	year	total_gross
0	2010	24,529,597,497.00
1	2011	25,730,325,196.00
2	2012	27,879,590,994.00
3	2013	27,372,572,195.00
4	2014	27,294,406,197.00
5	2015	26,205,761,807.00
6	2016	30,235,042,397.00
7	2017	30,862,199,205.00
8	2018	28,565,700,468.50

In [33]:

```
plt.figure(figsize=(12, 6))
sns.lineplot(data=gross_by_year, x='year', y='total_gross', marker='o')
plt.title("Total Worldwide Box Office Revenue by Year")
plt.xlabel("Year")
plt.ylabel("Total Gross ($)")
plt.tight_layout()
plt.show()
```



Exploring Movie Success Factors:

- Genre
- Ratings
- Revenue
- Votes

In [34]:

```
dt = pd.read_csv(r"C:\Users\A808865\Desktop\moringa\Phase 2\Group Project\Box Offic
dt.head(2)
```

Out[34]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_c
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 2
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	Ja 2

In [35]:
```
dt.shape
```

Out[35]:
```
(1560, 12)
```

In [36]:
```
dt.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 [37]:
```
# Clean box_office column
dt['box_office'] = pd.to_numeric(dt['box_office'].str.replace('[\$,]', '', regex=Tr

# Convert runtime to integer minutes (assuming format like '120 min')
dt['runtime'] = dt['runtime'].str.extract('(\d+)').astype(float)

# Convert theater_date to datetime and extract year from date
dt['theater_date'] = pd.to_datetime(dt['theater_date'], errors='coerce')
dt['year'] = dt['theater_date'].dt.year
```

In [38]:
```
dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 13 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   datetime64[ns]
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    float64
 10  runtime       1530 non-null   float64
 11  studio        494 non-null    object
 12  year          1201 non-null   float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(8)
memory usage: 158.6+ KB
```

In [39]:

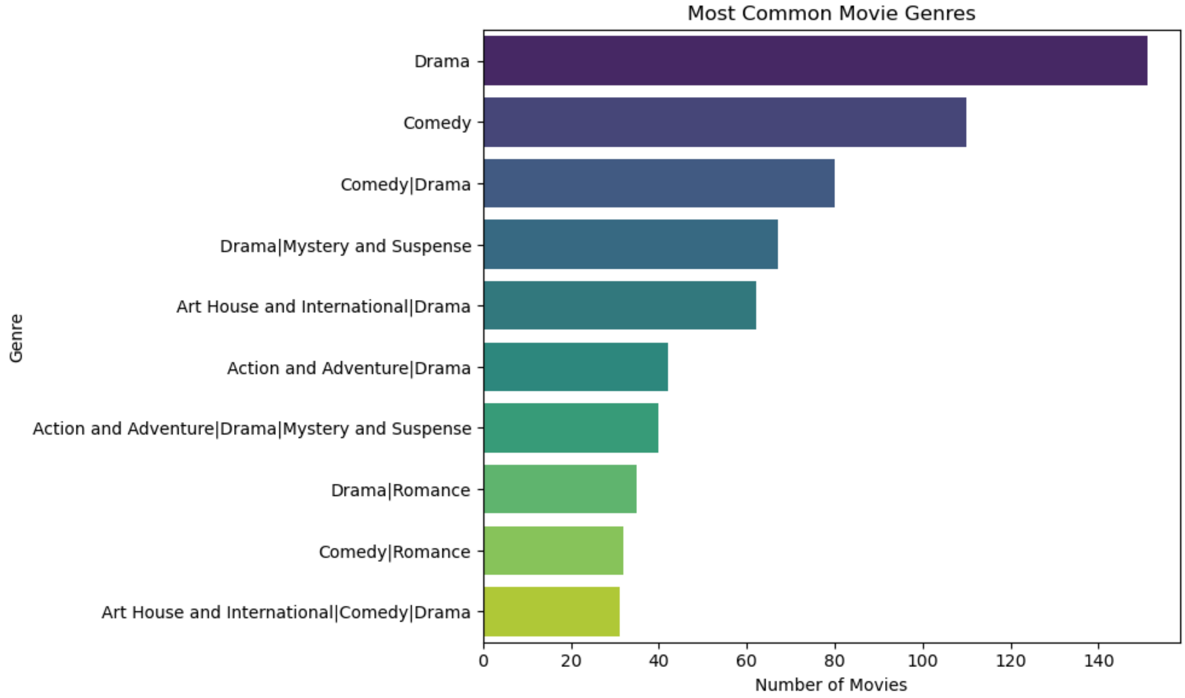
```
#counting the values of genre
genre_counts = dt['genre'].value_counts().head(10)
genre_counts
```

Out[39]:

```
genre
Drama                                                151
Comedy                                               110
Comedy|Drama                                          80
Drama|Mystery and Suspense                            67
Art House and International|Drama                     62
Action and Adventure|Drama                            42
Action and Adventure|Drama|Mystery and Suspense       40
Drama|Romance                                         35
Comedy|Romance                                        32
Art House and International|Comedy|Drama              31
Name: count, dtype: int64
```

In [40]:

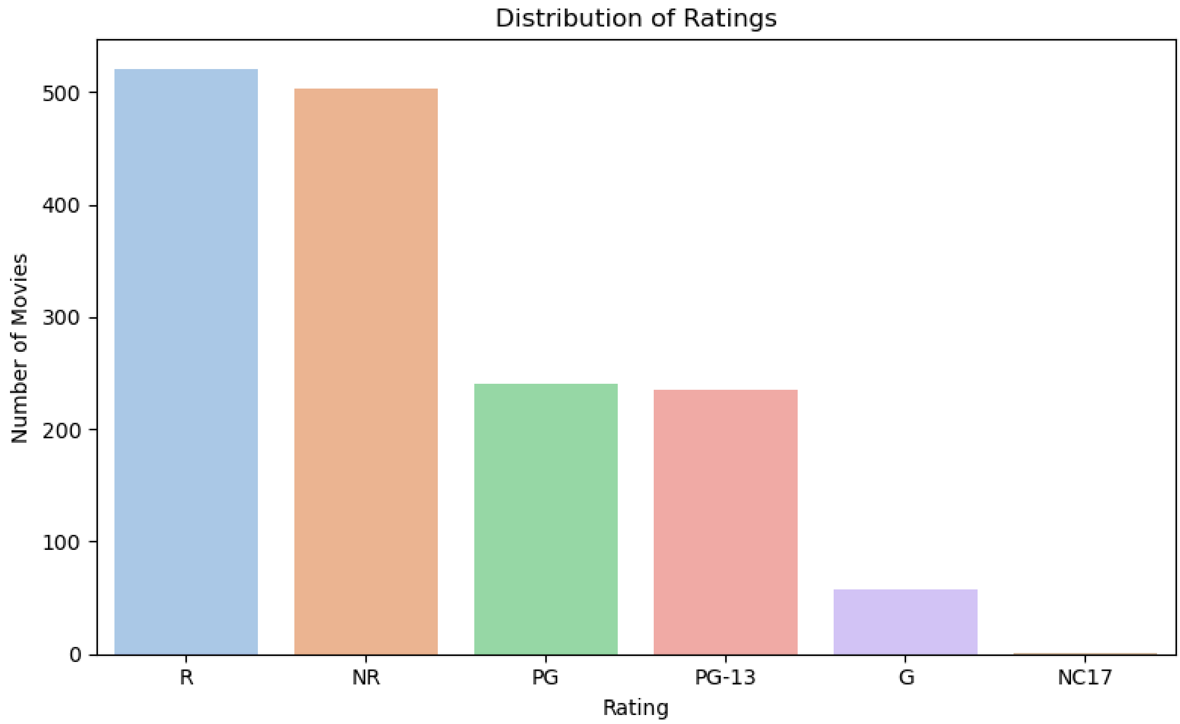
```
#plotting the genre and counts
plt.figure(figsize=(10,6))
sns.barplot(x=genre_counts.values, y=genre_counts.index, palette='viridis')
plt.title('Most Common Movie Genres')
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.tight_layout()
plt.show()
```



In [41]:
```
#counting the ratings
rating_counts = dt['rating'].value_counts()
rating_counts
```

Out[41]:
```
rating
R        521
NR       503
PG       240
PG-13    235
G         57
NC17       1
Name: count, dtype: int64
```

In [42]:
```
#Plotting the ratings with counts
plt.figure(figsize=(8,5))
sns.barplot(x=rating_counts.index, y=rating_counts.values, palette='pastel')
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Number of Movies')
plt.tight_layout()
plt.show()
```



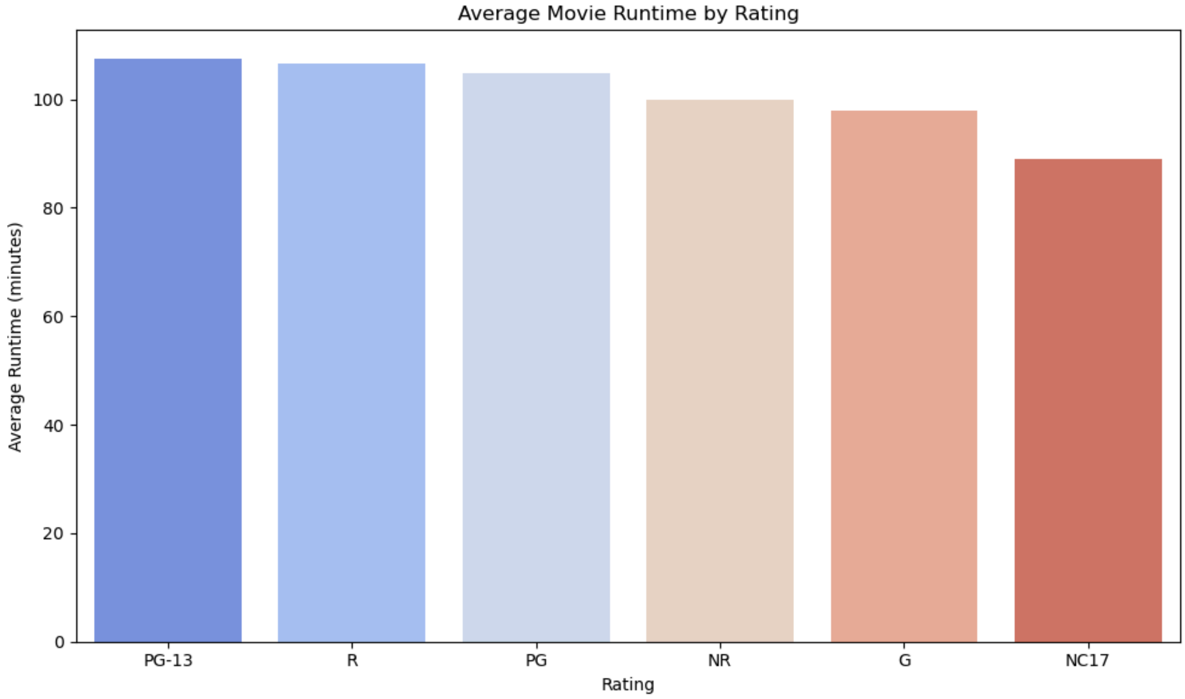
In [43]:
```
# Summary Runtime Stats by Rating
rating_runtime_stats = dt.groupby('rating')['runtime'].agg(['count', 'mean', 'media
rating_runtime_stats
```

Out[43]:

rating	count	mean	median	std
PG-13	232	107.38	106.00	18.47
R	519	106.57	103.00	20.98
PG	239	104.75	100.00	18.30
NR	482	99.89	95.00	31.86
G	57	97.91	95.00	25.74
NC17	1	89.00	89.00	NaN

In [44]:
```
#Compute Mean Runtime per Rating
mean_runtimes = (
    dt.groupby('rating')['runtime']
    .mean()
    .dropna()
    .sort_values(ascending=False)
    .reset_index()
)
```

In [45]:
```
#Plotting Bar Chart of the ratings and mean runtime
plt.figure(figsize=(10,6))
sns.barplot(data=mean_runtimes, x='rating', y='runtime', palette='coolwarm')
plt.title('Average Movie Runtime by Rating')
plt.xlabel('Rating')
plt.ylabel('Average Runtime (minutes)')
plt.tight_layout()
plt.show()
```



In [46]:

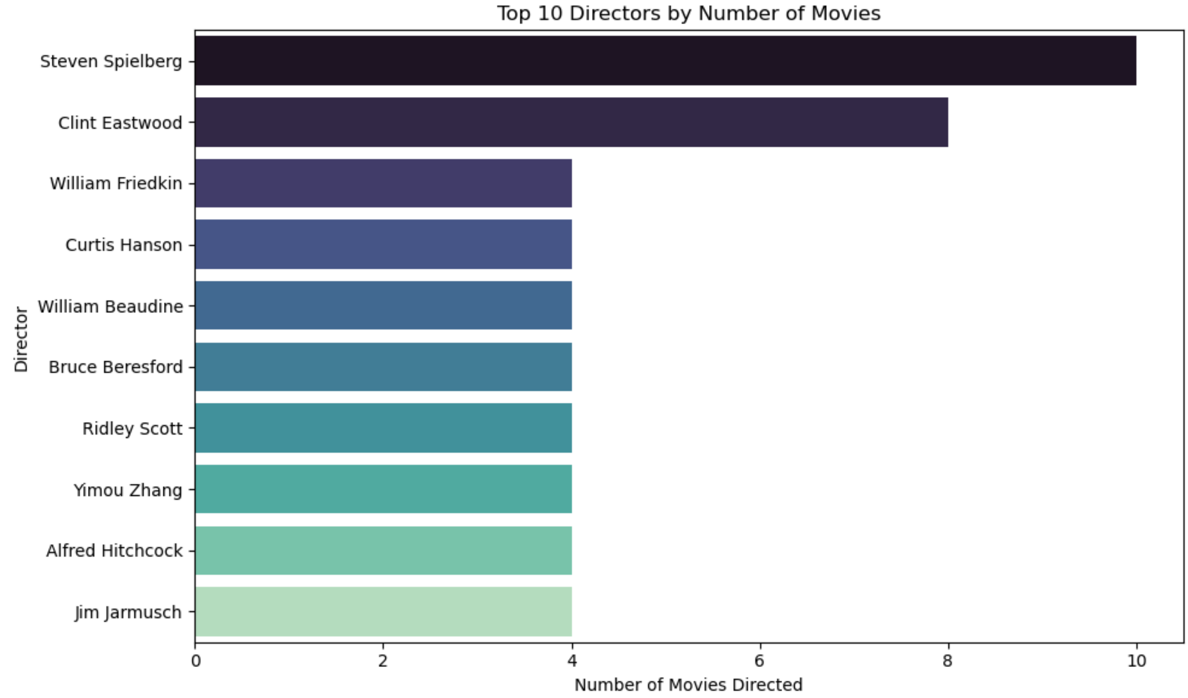
```
# Drop missing directors and do counts
top_directors = (
    dt['director']
    .dropna()
    .value_counts()
    .head(10)
    .reset_index()
)
# Rename columns for clarity
top_directors.columns = ['director', 'movie_count']
top_directors
```

Out[46]:

	director	movie_count
0	Steven Spielberg	10
1	Clint Eastwood	8
2	William Friedkin	4
3	Curtis Hanson	4
4	William Beaudine	4
5	Bruce Beresford	4
6	Ridley Scott	4
7	Yimou Zhang	4
8	Alfred Hitchcock	4
9	Jim Jarmusch	4

In [47]:

```
#plot
plt.figure(figsize=(10,6))
sns.barplot(data=top_directors, x='movie_count', y='director', palette='mako')
plt.title('Top 10 Directors by Number of Movies')
plt.xlabel('Number of Movies Directed')
plt.ylabel('Director')
plt.tight_layout()
plt.show()
```



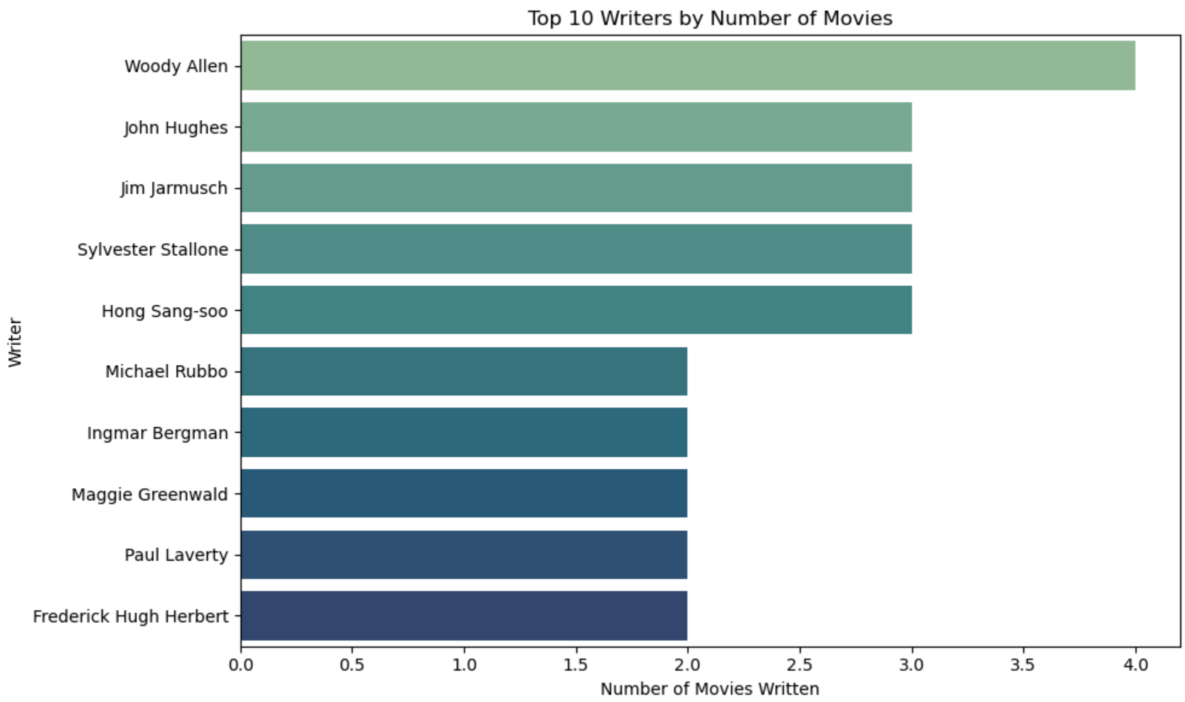
In [48]:
```
# Drop missing writers and count occurrences
top_writers = (
    dt['writer']
    .dropna()
    .value_counts()
    .head(10)
    .reset_index()
)

# Rename columns for clarity
top_writers.columns = ['writer', 'movie_count']
top_writers
```

Out[48]:

	writer	movie_count
0	Woody Allen	4
1	John Hughes	3
2	Jim Jarmusch	3
3	Sylvester Stallone	3
4	Hong Sang-soo	3
5	Michael Rubbo	2
6	Ingmar Bergman	2
7	Maggie Greenwald	2
8	Paul Laverty	2
9	Frederick Hugh Herbert	2

In [49]:
```
#Plot
plt.figure(figsize=(10,6))
sns.barplot(data=top_writers, x='movie_count', y='writer', palette='crest')
plt.title('Top 10 Writers by Number of Movies')
plt.xlabel('Number of Movies Written')
plt.ylabel('Writer')
```

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



What Drives Movie Popularity?

- Ratings
- Genres
- Votes

In [50]:
```
#Import the relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import combinations
```

In [51]:
```
#Load the data set
df = pd.read_csv(r"C:\Users\A808865\Desktop\moringa\Phase 2\Group Project\Box Offic
df.head()
```

Out[51]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	titl
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.53	2010-11-19	Harr Potte and th Deathl Hallows Part
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.73	2010-03-26	How t Trai You Drago
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.52	2010-05-07	Iron Ma
3	3	[16, 35, 10751]	862	en	Toy Story	28.00	1995-11-22	Toy Stor
4	4	[28, 878, 12]	27205	en	Inception	27.92	2010-07-16	Inceptio

In [52]:
```
#Displays the number of rows and columns
print("Dataset shape:", df.shape)
```

```
Dataset shape: (26517, 10)
```

In [53]:
```
# Quick summary of data types and non-null values
df.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 [54]:
```
# Convert release_date to datetime object
#This allows us to analyze trends by year/month and sort by release date.
df["release_date"] = pd.to_datetime(df["release_date"], format="%d-%m-%y", errors='
#errors="coerce" will set invalid dates to NaT (missing) so they don't crash our co
```

In [55]:
```
#Create a genre ID to name map

genre_map = {
    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'
}
```

In [56]:
```
import ast

# Convert genre_ids string to list, then map to genre names
df["genres"] = df["genre_ids"].apply(lambda x: [genre_map.get(i, "Unknown") for i i
```

In [57]:
```
# Check for missing values in each column
print(" Missing values:\n", df.isnull().sum())

# Exclude the 'genres' column (contains unhashable lists) when checking for duplica
df_no_list = df.drop(columns=["genres"])

# Check for duplicate rows (excluding unhashable list columns)
duplicate_count = df_no_list.duplicated().sum()
print(f" Duplicate rows: {duplicate_count}")

# Drop duplicate rows based on id, title, and release_date (common unique identifie
df = df.drop_duplicates(subset=["id", "title", "release_date"])

# Reset index after dropping
df.reset_index(drop=True, inplace=True)
```

```
 Missing values:
 Unnamed: 0                0
genre_ids                0
id                       0
original_language        0
original_title           0
popularity               0
release_date         26517
title                    0
vote_average             0
vote_count               0
genres                   0
dtype: int64
 Duplicate rows: 0
```

In [58]:
```
#Final Check (Print Cleaned Sample)
df_cleaned = df[["title", "genres","id","popularity", "vote_average", "vote_count",

df_cleaned.head()
```

Out[58]:

	title	genres	id	popularity	vote_average	vote_count	release_date
0	Harry Potter and the Deathly Hallows: Part 1	[Adventure, Fantasy, Family]	12444	33.53	7.70	10788	NaT
1	How to Train Your Dragon	[Fantasy, Adventure, Animation, Family]	10191	28.73	7.70	7610	NaT
2	Iron Man 2	[Adventure, Action, Science Fiction]	10138	28.52	6.80	12368	NaT
3	Toy Story	[Animation, Comedy, Family]	862	28.00	7.90	10174	NaT
4	Inception	[Action, Science Fiction, Adventure]	27205	27.92	8.30	22186	NaT

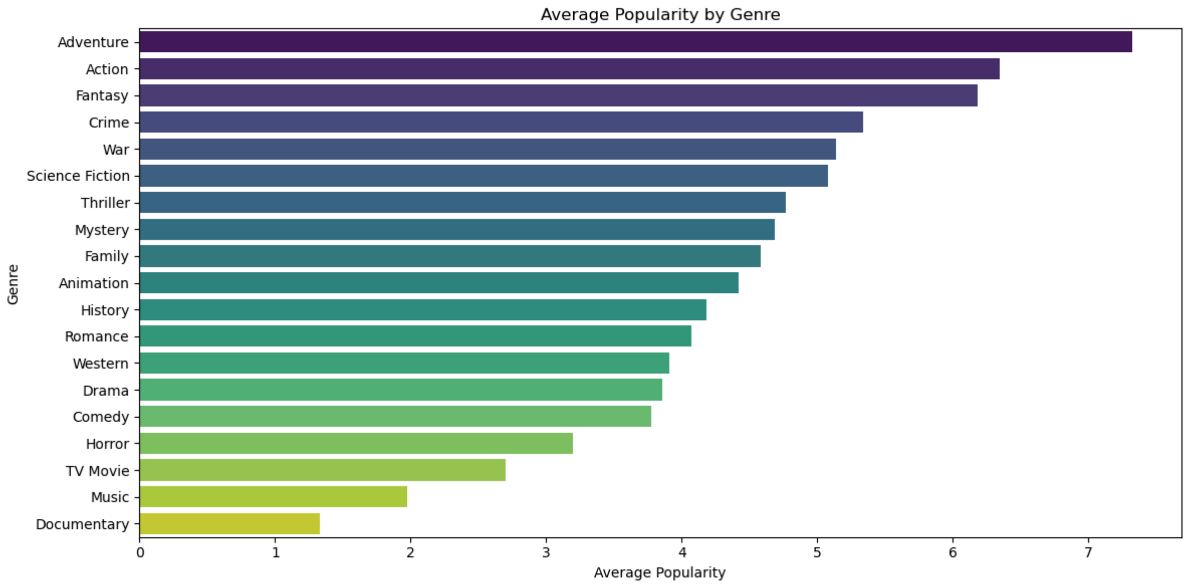
In [59]:

```
#Identify which genres are most commonly associated with high popularity and strong
## Step 1: Explode genres to separate rows
df_exploded = df_cleaned.explode('genres')

# Ensure df_cleaned is a true copy
df_cleaned = df_cleaned.copy()

# Step 2: Group and aggregate
genre_stats = df_exploded.groupby('genres').agg({
    'popularity': 'mean',
    'vote_average': 'mean',
    'title': 'count'  # Movie count per genre
}).rename(columns={'title': 'movie_count'}).reset_index()

# Step 3: Sort by popularity (optional)
genre_stats = genre_stats.sort_values(by='popularity', ascending=False)

# Preview result
print(genre_stats.head())
```

```
       genres  popularity  vote_average  movie_count
1   Adventure        7.32          5.90         1334
0      Action        6.34          5.57         2534
8     Fantasy        6.18          5.91         1082
4       Crime        5.34          5.83         1426
17        War        5.14          6.22          318
```

In [60]:

```
## Barplot: Average popularity per genre
plt.figure(figsize=(12, 6))
sns.barplot(data=genre_stats, x='popularity', y='genres', palette='viridis')
plt.title('Average Popularity by Genre')
plt.xlabel('Average Popularity')
plt.ylabel('Genre')
plt.tight_layout()
plt.show()
```



Top Performing Genres (based on average statistics):

Action: High popularity, moderate ratings (large audience but some mixed reception).

Fantasy: Very high popularity and generally good ratings (attracts both mainstream and dedicated audiences).

Drama: Strong ratings but lower popularity compared to Action/Fantasy.

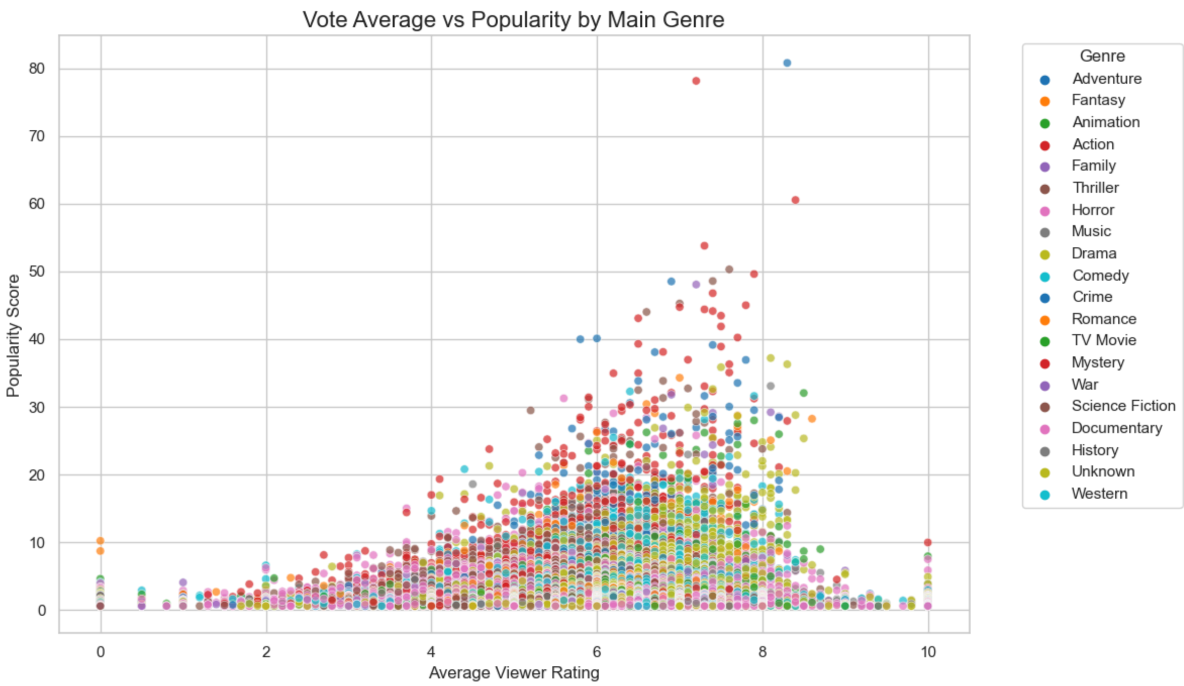
Animation: Very high ratings with moderate popularity — beloved by families and audiences seeking quality storytelling.

By focusing on these top-performing genres, studios can optimize their content portfolio to maximize both audience engagement (popularity) and viewer satisfaction (ratings), ensuring both financial returns and critical acclaim.

In [61]:

```
#The relationship between vote_average (viewer reception) and popularity
# Create a simplified genre column with the first genre only
df_cleaned["main_genre"] = df_cleaned["genres"].apply(lambda x: x[0] if isinstance(

# Ensure df_cleaned is a true copy
df_cleaned = df_cleaned.copy()

# Set plot size and style
plt.figure(figsize=(12, 7))
sns.set(style="whitegrid")

# Scatter plot
sns.scatterplot(
    data=df_cleaned,
    x="vote_average",
    y="popularity",
    hue="main_genre",
    alpha=0.7,
    palette="tab10"
)

# Titles and labels
plt.title("Vote Average vs Popularity by Main Genre", fontsize=16)
plt.xlabel("Average Viewer Rating", fontsize=12)
plt.ylabel("Popularity Score", fontsize=12)
```

```
plt.legend(title="Genre", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



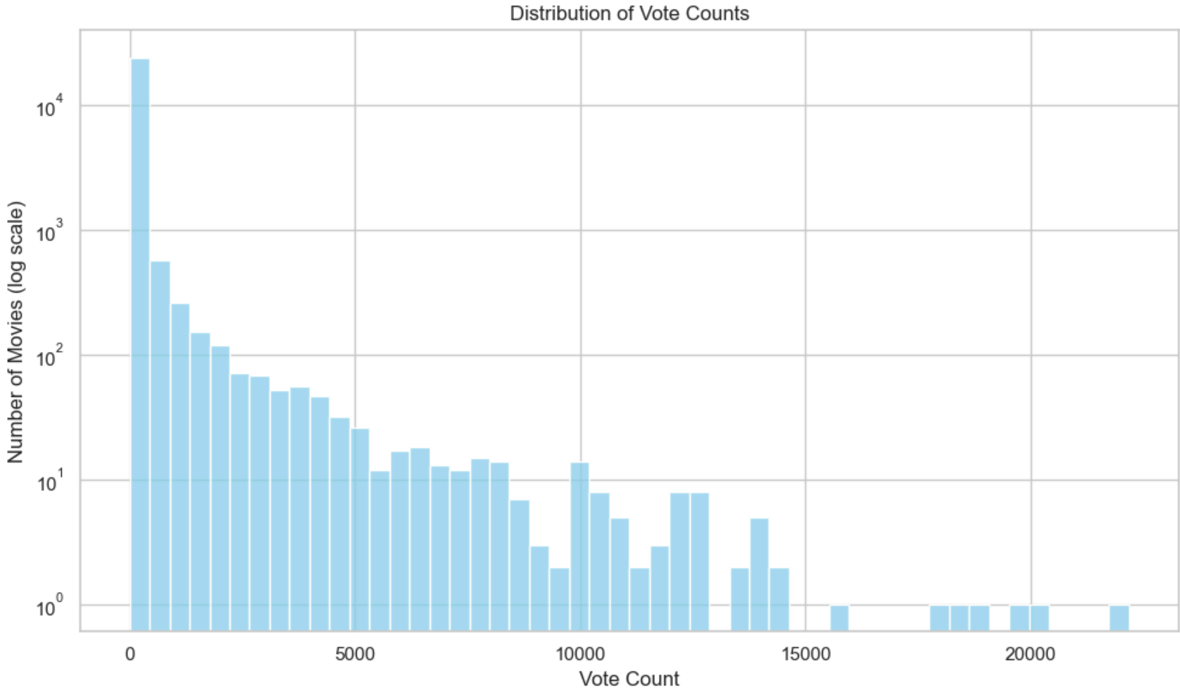
Popularity vs Ratings: From the chart we can seeviewer ratings of 6 and above indicate high popularity in the movies.Popular action movies may bring in a large audience for their flashy effects and colorful explosions, but those movies end up having mixed or average reviews.

Drama, Animation and Family genres have gentler extremes, whereas Action, Sci-Fi, and Adventure tend to be more polarized with their reception. Because of differing audience expectations, some are likely to love them, and some will definitely hate them.

When planning movies, especially for large scale blockbusters versus small scale niche movies, studios must consider the possible popularity level and how the audience will receive it.

In [62]:
```
#Reviewing vote counts to measure audience engagement and interest – higher vote cc
# Basic statistics of vote_count
print("Vote Count Statistics:\n", df_cleaned['vote_count'].describe())

# Visualize distribution of vote counts (log scale to manage skew)
plt.figure(figsize=(10, 6))
sns.histplot(df_cleaned['vote_count'], bins=50, log_scale=(False, True), color='sky
plt.title('Distribution of Vote Counts')
plt.xlabel('Vote Count')
plt.ylabel('Number of Movies (log scale)')
plt.tight_layout()
plt.show()
```

```
Vote Count Statistics:
 count   25,497.00
mean       178.80
std        914.15
min          1.00
25%          1.00
50%          5.00
75%         25.00
max     22,186.00
Name: vote_count, dtype: float64
```



The majority of movies seem to have low-to-moderate engagement (around 100 to 1,000 votes). This could be due to independent or niche movies that don't reach mass audiences.

The long tail of high vote counts is an indicator of a few blockbusters or popular movies that generate significant attention (e.g., Avengers, Harry Potter, etc.).

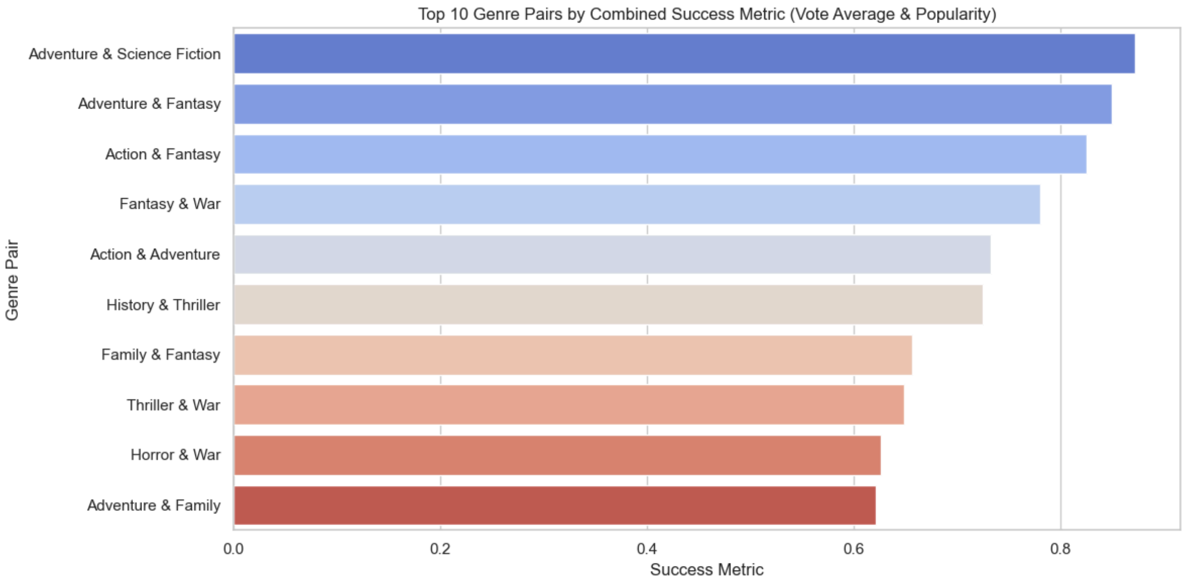
Actionable Insights:

Studios aiming for broader audience engagement might want to focus on genres that have a higher likelihood of generating high vote counts. Typically, action, adventure, and sci-fi genres see more engagement.

Targeting niche genres with consistent moderate engagement may be a way to ensure sustained, smaller but loyal audiences.

In [63]:
```
#Top 10 Genre Pairs by Combined Success Metric (Vote Average & Popularity)
# Generate all unique genre pairs
df_cleaned['genre_pairs'] = df_cleaned['genres'].apply(lambda x: list(combinations(

# Explode rows for each pair (flatten genre pairs)
df_exploded = df_cleaned.explode('genre_pairs')

# Calculate a success metric based on vote_average and popularity
# Normalize the popularity to balance the weight of both metrics
max_popularity = df_exploded['popularity'].max()
df_exploded['success_metric'] = (df_exploded['vote_average'] * df_exploded['popular

# Group by genre pair and aggregate
genre_pair_stats = df_exploded.groupby('genre_pairs').agg({
    'vote_average': 'mean',
    'popularity': 'mean',
    'success_metric': 'mean',
    'title': 'count'
}).rename(columns={'title': 'movie_count'}).reset_index()

# Filter to genre pairs with at least 2 movies (for better reliability)
genre_pair_stats = genre_pair_stats[genre_pair_stats['movie_count'] >= 2]
```

```python
# Sort by success_metric and pick the top 10 pairs
top_pairs = genre_pair_stats.sort_values(by='success_metric', ascending=False).head

# Plotting top 10 genre pairs by success metric
plt.figure(figsize=(12, 6))
sns.barplot(
    x='success_metric',
    y=top_pairs['genre_pairs'].apply(lambda x: f"{x[0]} & {x[1]}"),
    palette='coolwarm',
    data=top_pairs
)
plt.title("Top 10 Genre Pairs by Combined Success Metric (Vote Average & Popularity
plt.xlabel("Success Metric")
plt.ylabel("Genre Pair")
plt.tight_layout()
plt.show()

# Print summary stats
print("🔢 Summary of Top Genre Pairs by Combined Success Metric:\n")
print(top_pairs[['genre_pairs', 'vote_average', 'popularity', 'success_metric', 'mo
```




```
🔢 Summary of Top Genre Pairs by Combined Success Metric:

                    genre_pairs  vote_average  popularity  success_metric  \
30   (Adventure, Science Fiction)          5.87       10.89            0.87
24           (Adventure, Fantasy)          6.01       10.69            0.85
7               (Action, Fantasy)          5.62       10.65            0.83
124                (Fantasy, War)          6.01        9.59            0.78
0             (Action, Adventure)          5.65        9.39            0.73
132           (History, Thriller)          6.50        8.66            0.72
105             (Family, Fantasy)          6.21        8.11            0.66
168               (Thriller, War)          6.10        7.97            0.65
141                 (Horror, War)          5.73        7.96            0.63
23            (Adventure, Family)          6.05        7.84            0.62

     movie_count
30           259
24           304
7            227
124           11
0            570
132           45
105          264
168           44
141            9
23           353
```

- Top Performer: Adventure & Science Fiction is the top combo with a success metric of 8.7
- Adventure & Fantasy (8.5), Strong contender with excellent audience approval and reach.This genre pair works well for epic journeys, mythical stories, or fantasy worlds — think Harry Potter or Lord of the Rings.
- Some genre pairs like Action & Thriller have decent popularity but relatively lower vote_average.

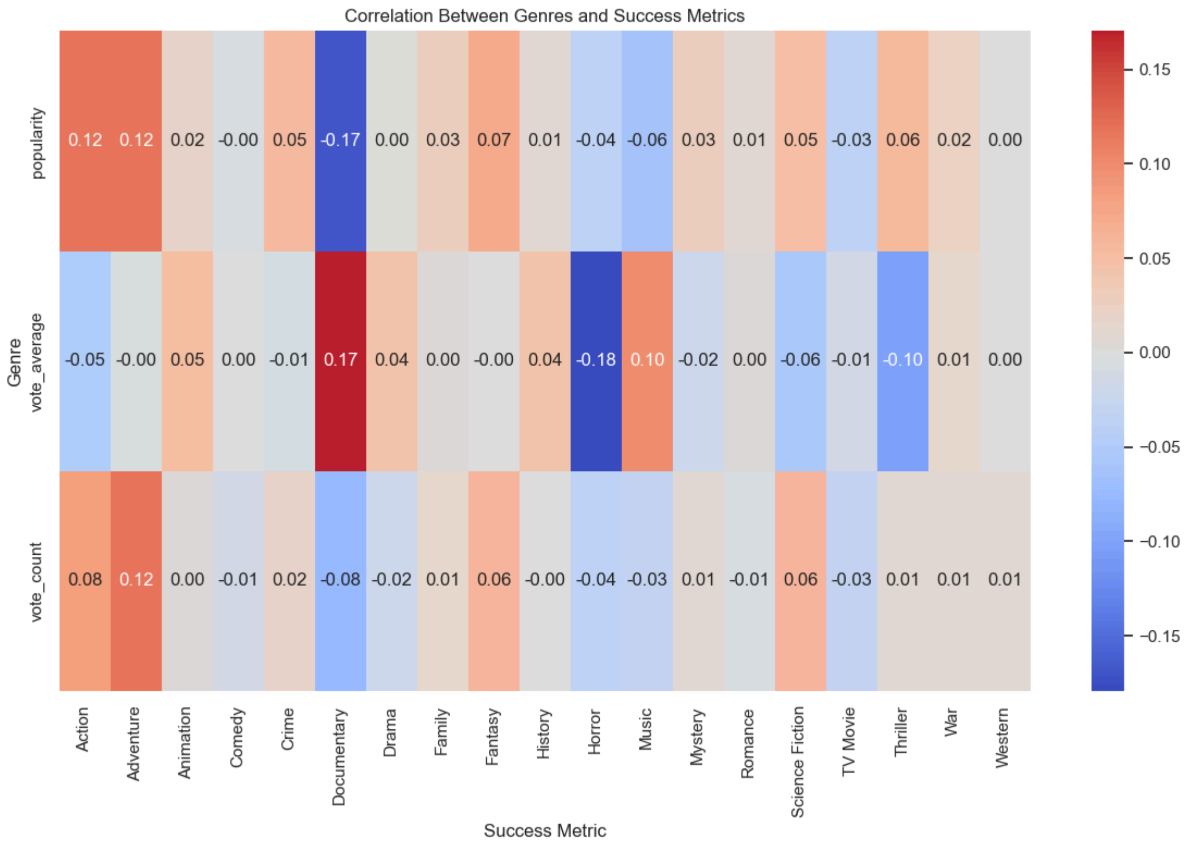
In [64]:
```
#Calculating correlation using popularity,vote_average and vote_count.

# Explode genres so each row has one genre per movie
df_exploded = df.explode('genres')

# One-hot encode genres
genre_dummies = pd.get_dummies(df_exploded['genres'])

# Combine encoded genres with popularity, vote_average, and vote_count
combined = pd.concat([df_exploded[['popularity', 'vote_average', 'vote_count']], ge

# Calculate correlation between each genre and success metrics
correlation_matrix = combined.corr().loc[['popularity', 'vote_average', 'vote_count

# Transpose to make it easier to read
correlation_by_genre = correlation_matrix.T.sort_values(by='popularity', ascending=

# Display top genres most positively correlated with each metric
print(correlation_by_genre.head(10))
```

```
                 popularity  vote_average  vote_count
Action                 0.12         -0.05        0.08
Adventure              0.12         -0.00        0.12
Fantasy                0.07         -0.00        0.06
Thriller               0.06         -0.10        0.01
Crime                  0.05         -0.01        0.02
Science Fiction        0.05         -0.06        0.06
Family                 0.03          0.00        0.01
Mystery                0.03         -0.02        0.01
War                    0.02          0.01        0.01
Animation              0.02          0.05        0.00
```

Insight:

- If the studio wants high popularity and engagement, focus on Action, Adventure, or Sci-Fi.
- If aiming for high ratings, Documentary and History genres show stronger positive correlations.

In [65]:
```
# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, fmt=".2f")
plt.title('Correlation Between Genres and Success Metrics')
plt.xlabel('Success Metric')
plt.ylabel('Genre')
plt.tight_layout()
plt.show()
```



Brighter red cells: Strong positive correlation

Brighter blue cells: Strong negative correlation

How to Interpret Genres with high values in “popularity” column: More likely to attract large audiences.

Genres with high “vote_average”: Likely critically acclaimed.

Genres with high “vote_count”: Receive more viewer engagement or mainstream appeal.

IMDB - Internet Movie Database

In [66]:
```
import sqlite3
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import scipy.stats as stats
```

In [67]:
```
con = sqlite3.connect(r"C:\Users\A808865\Desktop\Visualization Phase 2\im.db")
```

In [68]:
```
cursor = con.cursor()
```

In [69]:
```
schema_df = pd.read_sql("""
SELECT *
FROM sqlite_master
WHERE type='table'
""",con)

schema_df
```

Out[69]:

	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 ...

In [70]:

```
# Movie bascic information

print(schema_df['sql'].iloc[0])
```

```
CREATE TABLE "movie_basics" (
"movie_id" TEXT,
  "primary_title" TEXT,
  "original_title" TEXT,
  "start_year" INTEGER,
  "runtime_minutes" REAL,
  "genres" TEXT
)
```

In [71]:

```
pd.read_sql("""
SELECT *
FROM movie_basics
LIMIT 10
""",con)
```

Out[71]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.00	Comedy
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thriller
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.00	Adventure,Animation,Comedy
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,History
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.00	Biography

In [72]:

```
print(schema_df['sql'].iloc[1])
```

```
CREATE TABLE "directors" (
"movie_id" TEXT,
  "person_id" TEXT
)
```

In [73]:

```
pd.read_sql("""
SELECT *
FROM directors
LIMIT 10
""",con)
```

Out[73]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
3	tt0835418	nm0151540
4	tt0878654	nm0089502
5	tt0878654	nm2291498
6	tt0878654	nm2292011
7	tt0879859	nm2416460
8	tt0996958	nm2286991
9	tt0996958	nm2286991

In [74]:
```
print(schema_df['sql'].iloc[2])
```

```
CREATE TABLE "known_for" (
"person_id" TEXT,
  "movie_id" TEXT
)
```

In [75]:
```
pd.read_sql("""
SELECT *
FROM known_for
LIMIT 10
 """,con)
```

Out[75]:

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241
2	nm0061671	tt0844471
3	nm0061671	tt0118553
4	nm0061865	tt0896534
5	nm0061865	tt6791238
6	nm0061865	tt0287072
7	nm0061865	tt1682940
8	nm0062070	tt1470654
9	nm0062070	tt0363631

In [76]:
```
print(schema_df['sql'].iloc[3])
```

```
CREATE TABLE "movie_akas" (
"movie_id" TEXT,
  "ordering" INTEGER,
  "title" TEXT,
  "region" TEXT,
  "language" TEXT,
  "types" TEXT,
  "attributes" TEXT,
  "is_original_title" REAL
)
```

In [77]:
```
pd.read_sql("""
SELECT *
FROM movie_akas
LIMIT 10
""",con)
```

Out[77]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.00
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.00
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	None	imdbDisplay	None	0.00
3	tt0369610	13	O Mundo dos Dinossauros	BR	None	None	short title	0.00
4	tt0369610	14	Jurassic World	FR	None	imdbDisplay	None	0.00
5	tt0369610	15	Jurassic World	GR	None	imdbDisplay	None	0.00
6	tt0369610	16	Jurassic World	IT	None	imdbDisplay	None	0.00
7	tt0369610	17	Jurski svijet	HR	None	imdbDisplay	None	0.00
8	tt0369610	18	Olam ha'Yura	IL	he	imdbDisplay	None	0.00
9	tt0369610	19	Jurassic World: Mundo Jurásico	MX	None	imdbDisplay	None	0.00

In [78]:

```
print(schema_df['sql'].iloc[4])
```

```
CREATE TABLE "movie_ratings" (
"movie_id" TEXT,
  "averagerating" REAL,
  "numvotes" INTEGER
)
```

In [79]:

```
pd.read_sql("""
SELECT *
FROM movie_ratings
LIMIT 10
""",con)
```

Out[79]:

	movie_id	averagerating	numvotes
0	tt10356526	8.30	31
1	tt10384606	8.90	559
2	tt1042974	6.40	20
3	tt1043726	4.20	50352
4	tt1060240	6.50	21
5	tt1069246	6.20	326
6	tt1094666	7.00	1613
7	tt1130982	6.40	571
8	tt1156528	7.20	265
9	tt1161457	4.20	148

In [80]:

```
print(schema_df['sql'].iloc[5])
```

```
CREATE TABLE "persons" (
"person_id" TEXT,
  "primary_name" TEXT,
  "birth_year" REAL,
  "death_year" REAL,
  "primary_profession" TEXT
)
```

In [81]:

```
pd.read_sql("""
SELECT *
FROM persons
LIMIT 10
""",con)
```

Out[81]:

	person_id	primary_name	birth_year	death_year	primary_profess
0	nm0061671	Mary Ellen Bauder	NaN	None	miscellaneous,production_manager,produ
1	nm0061865	Joseph Bauer	NaN	None	composer,music_department,sound_departm
2	nm0062070	Bruce Baum	NaN	None	miscellaneous,actor,w
3	nm0062195	Axel Baumann	NaN	None	camera_department,cinematographer,art_departm
4	nm0062798	Pete Baxter	NaN	None	production_designer,art_department,set_decor
5	nm0062879	Ruel S. Bayani	NaN	None	director,production_manager,miscellane
6	nm0063198	Bayou	NaN	None	a
7	nm0063432	Stevie Be-Zet	NaN	None	composer,soundt
8	nm0063618	Jeff Beal	1,963.00	None	composer,music_department,soundt
9	nm0063750	Lindsay Beamish	NaN	None	actress,miscellane

In [82]:

```
print(schema_df['sql'].iloc[6])
```

```
CREATE TABLE "principals" (
"movie_id" TEXT,
  "ordering" INTEGER,
  "person_id" TEXT,
  "category" TEXT,
  "job" TEXT,
  "characters" TEXT
)
```

In [83]:
```
pd.read_sql("""
SELECT *
FROM principals
LIMIT 10
""",con)
```

Out[83]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None
4	tt0323808	1	nm3579312	actress	None	["Beth Boothby"]
5	tt0323808	2	nm2694680	actor	None	["Steve Thomson"]
6	tt0323808	3	nm0574615	actor	None	["Sir Lachlan Morrison"]
7	tt0323808	4	nm0502652	actress	None	["Lady Delia Morrison"]
8	tt0323808	5	nm0362736	director	None	None
9	tt0323808	6	nm0811056	producer	producer	None

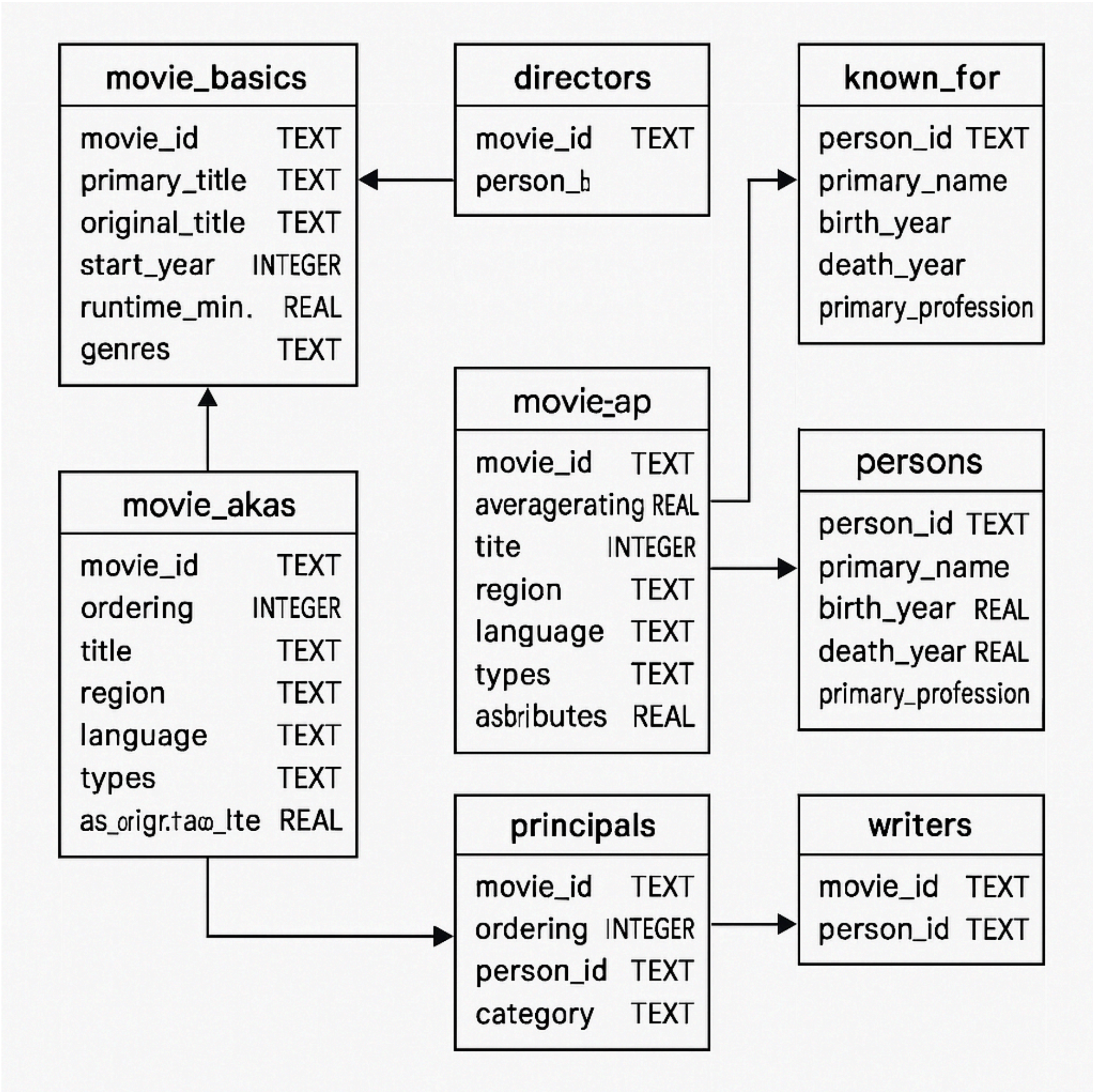
In [84]:
```
print(schema_df['sql'].iloc[7])
```

```
CREATE TABLE "writers" (
"movie_id" TEXT,
  "person_id" TEXT
)
```

In [85]:
```
pd.read_sql("""
SELECT *
FROM writers
LIMIT 10
""",con)
```

Out[85]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726
2	tt0438973	nm1802864
3	tt0462036	nm1940585
4	tt0835418	nm0310087
5	tt0835418	nm0841532
6	tt0878654	nm0284943
7	tt0878654	nm0284943
8	tt0878654	nm0284943
9	tt0996958	nm2286991



Movie Basic

Genre Popularity

In [86]:
```
df = pd.read_sql("""
SELECT *
FROM movie_basics
""",con)
df
```

Out[86]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.00	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.00	None
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

In [87]:
```
pd.read_sql("""
SELECT genres, COUNT(*) AS count
FROM movie_basics
WHERE genres IS NOT NULL
GROUP BY genres
ORDER BY count DESC
""",con)
```

Out[87]:

	genres	count
0	Documentary	32185
1	Drama	21486
2	Comedy	9177
3	Horror	4372
4	Comedy,Drama	3519
...	...	...
1080	Action,Animation,Music	1
1081	Action,Animation,History	1
1082	Action,Animation,Documentary	1
1083	Action,Animation,Biography	1
1084	Action,Adventure,Musical	1

1085 rows × 2 columns

Frequency of each individual genre. (Individual count, comedy alone or adventure alone)

In [88]:

```
# Assuming the DataFrame is named 'df'
# Step 1: Filter out invalid genre entries
valid_genres = df['genres'].dropna()  # Remove NaN
valid_genres = valid_genres[valid_genres != 'None']  # Remove string "None"
valid_genres = valid_genres[valid_genres != '']      # Remove empty strings

# Step 2: Split genres into lists and clean whitespace
split_genres = valid_genres.str.split(',').apply(lambda x: [g.strip() for g in x])

# Step 3: Explode the lists and count frequencies
exploded_genres = split_genres.explode()
genre_counts = exploded_genres.value_counts().reset_index()
genre_counts.columns = ['genre', 'count']

genre_counts
```

Out[88]:

	genre	count
0	Documentary	51640
1	Drama	49883
2	Comedy	25312
3	Thriller	11883
4	Horror	10805
5	Action	10335
6	Romance	9372
7	Biography	8722
8	Crime	6753
9	Adventure	6465
10	Family	6227
11	History	6225
12	Mystery	4659
13	Music	4314
14	Fantasy	3516
15	Sci-Fi	3365
16	Animation	2799
17	Sport	2234
18	News	1551
19	Musical	1430
20	War	1405
21	Western	467
22	Reality-TV	98
23	Talk-Show	50
24	Adult	25
25	Short	11
26	Game-Show	4

Frequency of genre combinations (e.g., Comedy, Drama) just to see if combinations do better than individual genre

In [89]:

```
# Step 1: Filter out both 'None' strings and actual null values
df_clean = df[(df['genres'].notna()) & (df['genres'] != 'None')].copy()

# Step 2: Process genres into sorted tuples
df_clean['genre_tuple'] = df_clean['genres'].apply(
    lambda x: tuple(sorted(g.strip() for g in x.split(',')))
)

# Step 3: Count genre combinations
genre_counts = df_clean['genre_tuple'].value_counts().reset_index()
```

```python
genre_counts.columns = ['genre_combination', 'frequency']

# Convert tuple to readable string
genre_counts['combination_str'] = genre_counts['genre_combination'].apply(
    lambda x: ','.join(x)
)

# Step 4: Analyze single vs. multi-genre performance
genre_counts['genre_count'] = genre_counts['genre_combination'].apply(len)
single_genre_avg = genre_counts[genre_counts['genre_count'] == 1]['frequency'].mear
multi_genre_avg = genre_counts[genre_counts['genre_count'] > 1]['frequency'].mean()

print(f"Average frequency of single genres: {single_genre_avg:.2f}")
print(f"Average frequency of multi-genre combinations: {multi_genre_avg:.2f}")
print(f"Do combinations perform better? {'Yes' if multi_genre_avg > single_genre_av
```

```
Average frequency of single genres: 3254.32
Average frequency of multi-genre combinations: 56.02
Do combinations perform better? No
```

Frequency Insight: The extreme disparity (3254 vs 56) suggests audience preference for clear genre positioning. Multi-genre movies face marketing challenges and niche audience targeting.

Runtime

In [90]:

```python
pd.read_sql("""
SELECT genres, ROUND(AVG(runtime_minutes), 2) AS 'Average runtime'
FROM movie_basics
WHERE genres IS NOT NULL
AND runtime_minutes IS NOT NULL
GROUP BY genres
ORDER BY ROUND(AVG(runtime_minutes), 2) DESC
""",con)
```

Out[90]:

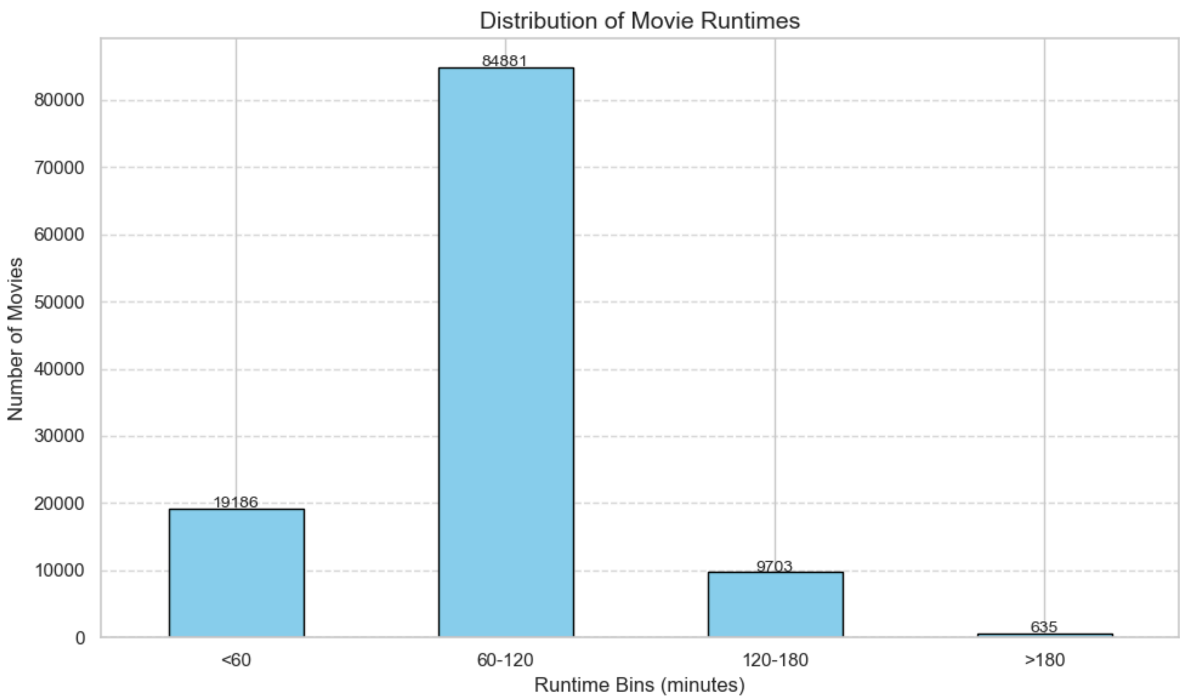
	genres	Average runtime
0	Drama,Western	225.34
1	Biography,Mystery,Sci-Fi	220.00
2	History,Musical,Romance	174.00
3	Action,Musical,Romance	170.00
4	Musical,Romance,Thriller	165.00
...	...	...
1035	Animation,Documentary,Sci-Fi	10.00
1036	Drama,Horror,Short	7.00
1037	Documentary,Mystery,Romance	7.00
1038	Animation,Documentary,Horror	4.00
1039	Comedy,Short	1.00

1040 rows × 2 columns

In [91]:

```python
# Step 1: Filter out missing runtime values
df_clean = df[(df['runtime_minutes'].notna()) & (df['runtime_minutes'] != 'runtime_
```

```
# Step 2: Define bins and labels
bins = [0, 60, 120, 180, float('inf')]
labels = ['<60', '60-120', '120-180', '>180']

# Step 3: Categorize runtimes into bins
df_clean['runtime_bin'] = pd.cut(
    df_clean['runtime_minutes'],
    bins=bins,
    labels=labels,
    right=False  # Ensures [0,60), [60,120), etc.
)

# Step 4: Count movies per bin
bin_counts = df_clean['runtime_bin'].value_counts().reindex(labels, fill_value=0)

# Step 5: Plot histogram
plt.figure(figsize=(10, 6))
bin_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Distribution of Movie Runtimes', fontsize=14)
plt.xlabel('Runtime Bins (minutes)', fontsize=12)
plt.ylabel('Number of Movies', fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Add count labels on top of bars
for i, count in enumerate(bin_counts):
    plt.text(i, count + 100, str(count), ha='center', fontsize=10)

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



Frequency Insight: The predominance of <60 min content suggests dataset includes non-theatrical works. Studio should focus analysis on 70+ min movies for relevant insights.

Movie Ratings

Rating Quality vs Popularity

- What movies are highly rated?

- we can filter out movies with low numvotes to focus on widely seen movies.

In [92]:
```
pd.read_sql("""
SELECT primary_title, averagerating, numvotes
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
WHERE numvotes > 100000
ORDER BY numvotes DESC
LIMIT 10
""",con)
```

Out[92]:

	primary_title	averagerating	numvotes
0	Inception	8.80	1841066
1	The Dark Knight Rises	8.40	1387769
2	Interstellar	8.60	1299334
3	Django Unchained	8.40	1211405
4	The Avengers	8.10	1183655
5	The Wolf of Wall Street	8.20	1035358
6	Shutter Island	8.10	1005960
7	Guardians of the Galaxy	8.10	948394
8	Deadpool	8.00	820847
9	The Hunger Games	7.20	795227

Rank movies by average rating

In [93]:
```
pd.read_sql("""
SELECT primary_title, averagerating
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
ORDER BY averagerating DESC
LIMIT 10
""",con)
```

Out[93]:

	primary_title	averagerating
0	Exteriores: Mulheres Brasileiras na Diplomacia	10.00
1	The Dark Knight: The Ballad of the N Word	10.00
2	Freeing Bernie Baran	10.00
3	Hercule contre Hermès	10.00
4	I Was Born Yesterday!	10.00
5	Dog Days in the Heartland	10.00
6	Revolution Food	10.00
7	Fly High: Story of the Disc Dog	10.00
8	All Around Us	10.00
9	The Paternal Bond: Barbary Macaques	10.00

Rank by both averagerating and numvotes

In [94]:

```
pd.read_sql("""
SELECT primary_title, averagerating, numvotes
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
WHERE numvotes > 100000
ORDER BY averagerating DESC, numvotes DESC
LIMIT 10
""",con)
```

Out[94]:

	primary_title	averagerating	numvotes
0	The Mountain II	9.30	100568
1	Inception	8.80	1841066
2	Avengers: Endgame	8.80	441135
3	Interstellar	8.60	1299334
4	The Intouchables	8.50	677343
5	Avengers: Infinity War	8.50	670926
6	Whiplash	8.50	616916
7	Spider-Man: Into the Spider-Verse	8.50	210869
8	Dangal	8.50	123638
9	The Dark Knight Rises	8.40	1387769

In [95]:

```
pd.read_sql("""
SELECT ROUND(AVG(averagerating))
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
""",con)
```

Out[95]:

	ROUND(AVG(averagerating))
0	6.00

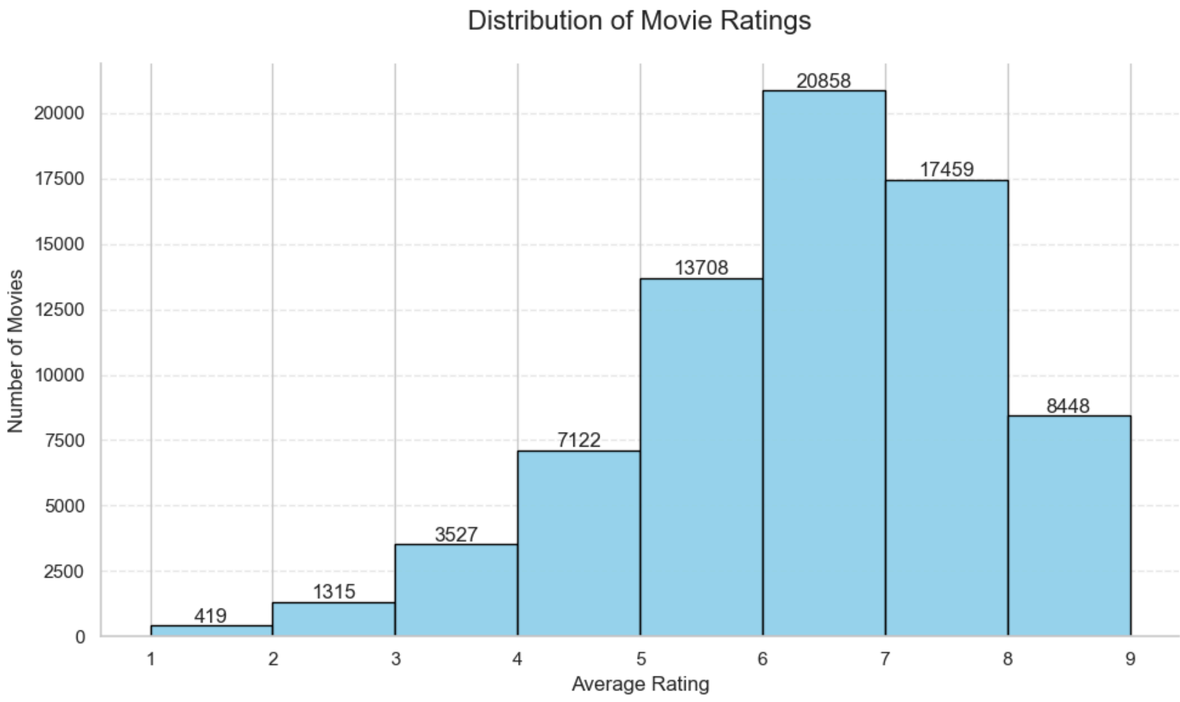
Ratings

- How are the ratings spread across all movies

- A histogram of averagerating to identify what are the most common rating range (Is it 6-7 or 5-8)

In [96]:

```
# Create DataFrame from the ratings table
ratings_df = pd.read_sql("""
SELECT *
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
""",con)

# Create styled histogram
plt.figure(figsize=(10, 6))
ax = sns.histplot(
    data=ratings_df,
    x='averagerating',
    bins=[1, 2, 3, 4, 5, 6, 7, 8, 9],
    kde=False,
    color='skyblue',
    edgecolor='black',
    alpha=0.85,
    stat='count'
)

# Add count labels to bars
for p in ax.patches:
    ax.annotate(
        f'{int(p.get_height())}',
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center', va='center',
        xytext=(0, 5),
        textcoords='offset points'
    )

# Customize plot
plt.title('Distribution of Movie Ratings', fontsize=16, pad=20)
plt.xlabel('Average Rating', fontsize=12)
plt.ylabel('Number of Movies', fontsize=12)
plt.xticks([1, 2, 3, 4, 5, 6, 7, 8, 9])
plt.grid(axis='y', linestyle='--', alpha=0.4)
sns.despine()

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



- After identifying what the average rating is, we then can check per genre to tell us what is considered above average in this industry.

In [97]:
```
# Simulate merged data (since original tables don't share movie IDs)
np.random.seed(42)
movies = pd.read_sql("""
SELECT *
FROM movie_basics
""",con)

ratings = pd.read_sql("""
SELECT *
FROM movie_ratings
""",con)

merged = pd.merge(movies, ratings, on='movie_id')

# Split genres into separate rows
genre_ratings = merged.assign(genres=merged['genres'].str.split(',')).explode('genr
```

In [98]:
```
overall_avg = merged['averagerating'].mean()
print(f"Overall Average Rating: {overall_avg:.2f}")
```

```
Overall Average Rating: 6.33
```

They should strive to have an average rating of 6.33 and above in order to do well in the market

In [99]:
```
genre_stats = (genre_ratings.groupby('genres', as_index=False)
                .agg(
                    avg_rating=('averagerating', 'mean'),
                    movie_count=('movie_id', 'nunique')
                )
                .sort_values('avg_rating', ascending=False))

# Calculate difference from overall average
genre_stats['vs_overall'] = genre_stats['avg_rating'] - overall_avg
```

```
genre_stats
```

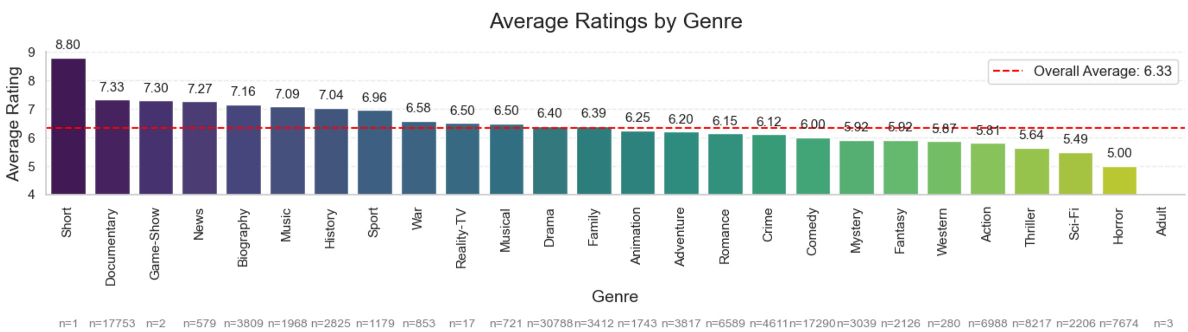
Out[99]:

	genres	avg_rating	movie_count	vs_overall
21	Short	8.80	1	2.47
7	Documentary	7.33	17753	1.00
11	Game-Show	7.30	2	0.97
17	News	7.27	579	0.94
4	Biography	7.16	3809	0.83
14	Music	7.09	1968	0.76
12	History	7.04	2825	0.71
22	Sport	6.96	1179	0.63
24	War	6.58	853	0.25
18	Reality-TV	6.50	17	0.17
15	Musical	6.50	721	0.17
8	Drama	6.40	30788	0.07
9	Family	6.39	3412	0.06
3	Animation	6.25	1743	-0.08
2	Adventure	6.20	3817	-0.14
19	Romance	6.15	6589	-0.19
6	Crime	6.12	4611	-0.22
5	Comedy	6.00	17290	-0.33
16	Mystery	5.92	3039	-0.41
10	Fantasy	5.92	2126	-0.41
25	Western	5.87	280	-0.46
0	Action	5.81	6988	-0.52
23	Thriller	5.64	8217	-0.69
20	Sci-Fi	5.49	2206	-0.84
13	Horror	5.00	7674	-1.33
1	Adult	3.77	3	-2.57

In [100…

```
plt.figure(figsize=(14, 8))
bars = sns.barplot(
    data=genre_stats,
    x='genres',
    y='avg_rating',
    order=genre_stats.sort_values('avg_rating', ascending=False)['genres'],
    palette='viridis'
)

# Add reference line and annotations
plt.axhline(overall_avg, color='red', linestyle='--',
            label=f'Overall Average: {overall_avg:.2f}')
plt.title('Average Ratings by Genre', fontsize=18, pad=20)
```

```python
plt.xlabel('Genre', fontsize=14)
plt.ylabel('Average Rating', fontsize=14)
plt.xticks(rotation=90)  # Vertical x-axis labels
plt.legend(fontsize=12)

# Add value labels
for p in bars.patches:
    bars.annotate(
        f"{p.get_height():.2f}",
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center',
        va='center',
        xytext=(0, 10),
        textcoords='offset points',
        fontsize=11
    )

# Add count labels below x-axis
for i, genre in enumerate(genre_stats['genres']):
    count = genre_stats[genre_stats['genres'] == genre]['movie_count'].values[0]
    plt.text(i, -0.4, f'n={count}',
             ha='center', va='top', fontsize=10, color='gray')

plt.ylim(4, 9)  # Adjust y-axis limits
plt.grid(axis='y', linestyle='--', alpha=0.3)
sns.despine()
plt.tight_layout()
plt.show()
```



They should try and focus on the following genres that have an average rating above the mean average rating of 6.33

In [101…

```python
for genre in genre_stats['genres']:
    genre_vals = genre_ratings[genre_ratings['genres'] == genre]['averagerating']
    t_stat, p_val = stats.ttest_1samp(genre_vals, overall_avg)
    print(f"{genre}: p-value = {p_val:.4f} {'(significant)' if p_val < 0.05 else ''
```

```
Short: p-value = nan
Documentary: p-value = 0.0000 (significant)
Game-Show: p-value = 0.6707
News: p-value = 0.0000 (significant)
Biography: p-value = 0.0000 (significant)
Music: p-value = 0.0000 (significant)
History: p-value = 0.0000 (significant)
Sport: p-value = 0.0000 (significant)
War: p-value = 0.0000 (significant)
Reality-TV: p-value = 0.7030
Musical: p-value = 0.0031 (significant)
Drama: p-value = 0.0000 (significant)
Family: p-value = 0.0089 (significant)
Animation: p-value = 0.0093 (significant)
Adventure: p-value = 0.0000 (significant)
Romance: p-value = 0.0000 (significant)
Crime: p-value = 0.0000 (significant)
Comedy: p-value = 0.0000 (significant)
Mystery: p-value = 0.0000 (significant)
Fantasy: p-value = 0.0000 (significant)
Western: p-value = 0.0000 (significant)
Action: p-value = 0.0000 (significant)
Thriller: p-value = 0.0000 (significant)
Sci-Fi: p-value = 0.0000 (significant)
Horror: p-value = 0.0000 (significant)
Adult: p-value = 0.1534
```

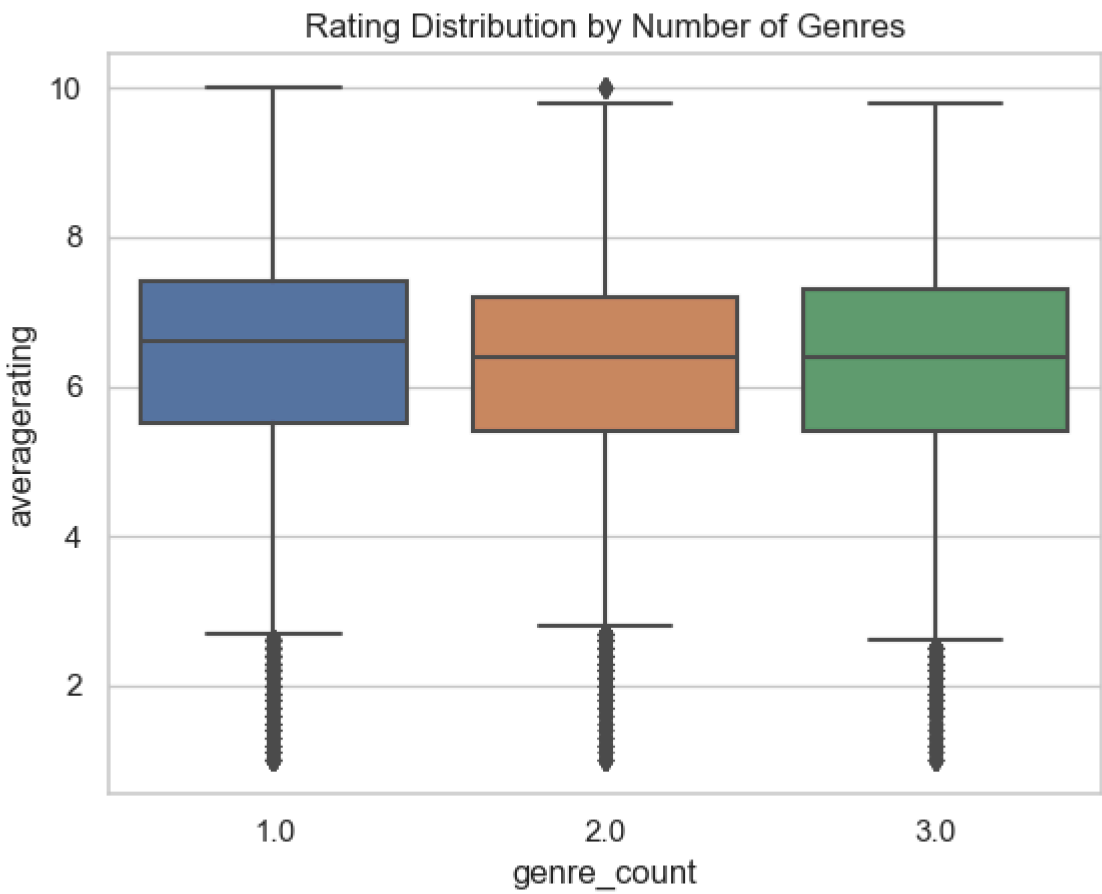
```
c:\Users\A808865\Python\Lib\site-packages\scipy\stats\_stats_py.py:1103: RuntimeWa
rning: divide by zero encountered in divide
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
c:\Users\A808865\Python\Lib\site-packages\scipy\stats\_stats_py.py:1103: RuntimeWa
rning: invalid value encountered in scalar multiply
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
```

In [102…

```python
# Weight ratings by number of votes (if available)
genre_stats['weighted_avg'] = genre_ratings.groupby('genres').apply(
    lambda x: np.average(x['averagerating'], weights=x.get('numvotes', 1))
)
```

In [103…

```python
# Analyze multi-genre combinations
merged['genre_count'] = merged['genres'].str.count(',') + 1
sns.boxplot(data=merged, x='genre_count', y='averagerating')
plt.title('Rating Distribution by Number of Genres');
```



Talent Influence (People Involved)

- What effect does Director, Actor and Producer choice have on movie grossing?

- Are there directors or actors who are consistently associated with successful movies?

In [104…

```
pd.read_sql("""
SELECT primary_name, COUNT(averagerating) as averagerating
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
JOIN directors as d
ON d.movie_id = mb.movie_id
JOIN persons as p
ON p.person_id = d.person_id
WHERE averagerating BETWEEN 5.0 AND 10
GROUP BY primary_name
ORDER BY averagerating DESC
            LIMIT 10
""",con)
```

Out[104]:

	primary_name	averagerating
0	Tony Newton	153
1	Jason Impey	136
2	Shane Ryan	133
3	Ruben Rodriguez	128
4	Martin Sonntag	121
5	Gav Chuckie Steel	116
6	R.J. Wilson	100
7	Sam Mason-Bell	98
8	Evan Marlowe	98
9	Corey Norman	93

- Does having a well-known director or cast significantly influence box office success?

In [105…

```
pd.read_sql("""
SELECT primary_name, Round(Avg(averagerating), 1) AS ratings, COUNT(mb.movie_id) AS
FROM movie_basics AS mb
JOIN movie_ratings AS mr
ON mb.movie_id = mr.movie_id
JOIN directors as d
ON d.movie_id = mb.movie_id
JOIN persons as p
ON p.person_id = d.person_id
JOIN known_for AS kf
ON kf.movie_id = mb.movie_id
JOIN principals AS pr
ON pr.movie_id = mb.movie_id
WHERE category = 'director'
GROUP BY primary_name
ORDER BY ratings DESC, COUNT(mb.movie_id) DESC
LIMIT 10
""",con)
```

Out[105]:

	primary_name	ratings	Number of movies
0	Loreto Di Cesare	10.00	14
1	Chad Carpenter	10.00	13
2	Emre Oran	10.00	11
3	Tristan David Luciotti	10.00	8
4	Masahiro Hayakawa	10.00	6
5	Michael J. Sanderson	10.00	6
6	Lindsay Thompson	10.00	1
7	Michiel Brongers	10.00	1
8	Stephen Peek	10.00	1
9	Raphael Sbarge	9.90	7

In [106…

```
# we have a SQLite connection open in Python:
# Close any active connections
con = sqlite3.connect('im.db')
con.close()  # Important! This releases the file lock
```