Studio Launch Blueprint

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Business Understanding

To support the launch of a new movie studio, this project aims to deliver data-driven insights into what makes films successful by analyzing trends in budgets, profitability, film length, director performance, and genre ratings. Using CRISP-DM methodology, we will gather and clean data from various film databases, address inconsistencies, and apply statistical analysis to uncover patterns that can guide strategic decisions. The findings will help the company select the right genres, directors, and production strategies to produce competitive, high-performing content in a rapidly evolving entertainment industry.The following are our objectives

1:Evaluating the Relationship Between production Budget and Profitability

2.Determine if there is a difference in audience ratings between the shorter and longer films

3.Identify the Best Directors to Work With

4.To identify the genres that are linked to high average rating

Data Understanding

In the data understanding phase, we explored two datasets—The Numbers, which includes financial details like production budgets and box office revenue, and IMDb, which provides movie metadata such as ratings, genres, runtime, and director information. We examined key columns from both datasets and performed essential data quality checks, including identifying missing values (e.g., in runtime_minutes and averagerating), detecting outliers in budget and rating fields, ensuring uniform formatting, and addressing duplicate entries in the IMDb data. We also verified proper merging across tables using unique identifiers like movie_id and person_id to maintain data integrity.

Data Preparation

In the Data Preparation section, we will outline the steps taken to clean, transform, and organize the datasets from The Numbers and IMDb to ensure they are suitable for analysis. This includes handling missing values, removing duplicates, converting data types, merging datasets, and creating new variables such as movie runtime categories for comparative analysis.

Data Cleaning

In [1]:

```
# Import the necessary libraries
import pandas as pd
pd.options.mode.chained_assignment = None          # prevent warnings from
import sqlite3
```

1. The Numbers dataset

In [2]:

```
# Load the dataframe
tn_df = pd.read_csv('./zippedData/tn.movie_budgets.csv.gz')
tn_df.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]:

```
# Gives us a concise summary of our dataframe by giving us basic informati
tn_df.info()
```

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

From our findings above, we can see that our dataframe has 5782 entries and 6 columns in total. We have 5 columns in the string format and one other column in the integer format(int64).

In [4]:
```
# Check the summary statistics of our dataframe
tn_df.describe()
```

Out[4]:

	id
count	5782.000000
mean	50.372363
std	28.821076
min	1.000000
25%	25.000000
50%	50.000000
75%	75.000000
max	100.000000

In [5]:
```
# Shows us the number of rows and columns in our dataframe
print('The dataframe contains:', tn_df.shape[0],'rows')
print('The dataframe contains:', tn_df.shape[1],'columns')
```

```
The dataframe contains: 5782 rows
The dataframe contains: 6 columns
```

Handling missing values and duplicate values

In [6]:
```
#First check for null values
tn_df.isnull().sum()
```

Out[6]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

There are no missing values in our dataframe.

In [7]:
```
#Check for duplicates
tn_df.duplicated().sum()
```

Out[7]:
```
0
```

We can also see that our dataframe has no duplicates.We also have no need for the release date column in our dataframe so we will drop it.

In [8]:
```
# Dropping the release_date column
tn_df= tn_df.drop('release_date', axis=1)
tn_df
```

Out[8]:

	id	movie	production_budget	domestic_gross	worldwide_gross
0	1	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...
5777	78	Red 11	$7,000	$0	$0
5778	79	Following	$6,000	$48,482	$240,495
5779	80	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	A Plague So Pleasant	$1,400	$0	$0
5781	82	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 5 columns

Cleaning the production_budget, domestic_gross and worldwide_gross columns

In [9]:
```
# Checking the datatypes
tn_df.dtypes
```

Out[9]:
```
id                    int64
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
```

Our columns represent financial information so its important for us to work with them in integer or float form so that we are able to perform mathematical operations on them. Since the three columns have object data types, we will convert them into integers.

In [10]:
```
# Removing the dollar signs and commas from the columns
tn_df['worldwide_gross']= tn_df['worldwide_gross'].replace('[\$,]', '', re
tn_df['production_budget']= tn_df['production_budget'].replace('[\$,]', ''
tn_df['domestic_gross']= tn_df['domestic_gross'].replace('[\$,]', '', rege

# Converting the columns into integers
tn_df['worldwide_gross']= tn_df['worldwide_gross'].astype('int64')
tn_df['production_budget']= tn_df['production_budget'].astype('int64')
tn_df['domestic_gross']= tn_df['domestic_gross'].astype('int64')

# Previewing the first five results
tn_df.head()
```

Out[10]:

	id	movie	production_budget	domestic_gross	worldwide_gross
0	1	Avatar	425000000	760507625	2776345279
1	2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Dark Phoenix	350000000	42762350	149762350
3	4	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [11]:
```
# Checking to see if there are any 0 values in our worldwide_gross column
(tn_df['worldwide_gross'] == 0).sum()
```

Out[11]: 367

We have 367 zero values in our column, we will drop these records and retain the rest.

In [12]:
```
# Retaining the rows where the values in the worldwide_gross is greater th
tn_df = tn_df[tn_df['worldwide_gross'] > 0]

# Checking that the zero values have been dropped
assert (tn_df['worldwide_gross']== 0).sum() == 0
```

Checking for outliers in the production_budget column

In [13]:

```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = tn_df['production_budget'].quantile(0.25)
Q3 = tn_df['production_budget'].quantile(0.75)

# Calculate IQR
IQR = Q3 - Q1

# Define lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Find outliers
outliers = tn_df[(tn_df['production_budget'] < lower_bound) | (tn_df['prod

print(f"Number of outliers: {len(outliers)}")
print(outliers[['production_budget']])
```

```
Number of outliers: 411
     production_budget
0            425000000
1            410600000
2            350000000
3            330600000
4            317000000
..                 ...
407           99000000
408           99000000
409           98000000
410           97000000
411           97000000

[411 rows x 1 columns]
```

We keep the outliers since these are true values.

Checking for outliers in the worldwide_gross column

In [14]:
```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = tn_df['worldwide_gross'].quantile(0.25)
Q3 = tn_df['worldwide_gross'].quantile(0.75)

# Calculate IQR
IQR = Q3 - Q1

# Define lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Find outliers
outliers = tn_df[(tn_df['worldwide_gross'] < lower_bound) | (tn_df['worldw

print(f"Number of outliers: {len(outliers)}")
print(outliers[['worldwide_gross']])
```

```
Number of outliers: 564
      worldwide_gross
0          2776345279
1          1045663875
3          1403013963
4          1316721747
5          2053311220
...               ...
4249        278964806
4567        390525192
4589        261249383
4775        263591415
5346        268000000

[564 rows x 1 columns]
```

We also keep the outliers in the worldwide_gross column.

Now we will create a profit column that will allow us to see the profitability of each movie.

In [15]:
```
# Subtracting the production_budget from the worldwide_gross to calculate
tn_df['profit'] = tn_df['worldwide_gross'] - tn_df['production_budget']

# Previewing the first five rows
tn_df.head()
```

Out[15]:

	id	movie	production_budget	domestic_gross	worldwide_gross	profit
0	1	Avatar	425000000	760507625	2776345279	2351345279
1	2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063875
2	3	Dark Phoenix	350000000	42762350	149762350	-200237650
3	4	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963
4	5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999721747

2.im.db

In [16]:

```
# Load the data
import zipfile

# Extract the database file from the ZIP archive
with zipfile.ZipFile('zippedData\im.db.zip', 'r') as zip_ref:
    zip_ref.extractall('zippedData')

# Connect to the extracted SQLite database
conn = sqlite3.connect('zippedData/im.db')

query = "SELECT name FROM sqlite_master WHERE type='table';"

tables = pd.read_sql_query(query, conn)

print("Tables in the database:")
print(tables)
```

```
Tables in the database:
            name
0   movie_basics
1      directors
2      known_for
3     movie_akas
4  movie_ratings
5        persons
6     principals
7        writers
```

Join the relevant columns

In [17]:

```
#Join the persons.directors,movie basics and movie ratings tables
query = """
    SELECT *
    FROM (
        SELECT *
        FROM persons
        JOIN directors USING (person_id)
        JOIN movie_basics USING (movie_id)
        JOIN movie_ratings USING (movie_id)
    ) AS subquery;
"""
imdb_df = pd.read_sql(query, conn)
imdb_df.head()
```

Out[17]:

	person_id	primary_name	birth_year	death_year	primary_professior
0	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manager,miscellaneous
1	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manager,miscellaneous
2	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manager,miscellaneous
3	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manager,miscellaneous
4	nm0062879	Ruel S. Bayani	NaN	NaN	director,production_manager,miscellaneous

In [18]:

```
#Drop the irrelevant columns
imdb_df = imdb_df.drop(['birth_year', 'primary_profession', 'start_year',
imdb_df.head()
```

Out[18]:

	person_id	primary_name	death_year	movie_id	runtime_minutes	genre:
0	nm0062879	Ruel S. Bayani	NaN	tt1592569	110.0	Drama,Romanc
1	nm0062879	Ruel S. Bayani	NaN	tt1592569	110.0	Drama,Romanc
2	nm0062879	Ruel S. Bayani	NaN	tt1592569	110.0	Drama,Romanc
3	nm0062879	Ruel S. Bayani	NaN	tt1592569	110.0	Drama,Romanc
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101.0	Drama,Romance,Thrille

In [19]:
```
#Check the information of the  dataframe
imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181387 entries, 0 to 181386
Data columns (total 7 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   person_id        181387 non-null  object 
 1   primary_name     181387 non-null  object 
 2   death_year       1342 non-null    float64
 3   movie_id         181387 non-null  object 
 4   runtime_minutes  163584 non-null  float64
 5   genres           180047 non-null  object 
 6   averagerating    181387 non-null  float64
dtypes: float64(3), object(4)
memory usage: 9.7+ MB
```

In [20]:
```
# Check the summary statistics
imdb_df.describe()
```

Out[20]:

	death_year	runtime_minutes	averagerating
count	1342.000000	163584.000000	181387.000000
mean	2014.908346	97.789484	6.217683
std	4.866581	194.434689	1.388026
min	1944.000000	3.000000	1.000000
25%	2014.000000	84.000000	5.400000
50%	2016.000000	94.000000	6.300000
75%	2018.000000	107.000000	7.200000
max	2019.000000	51420.000000	10.000000

In [21]:
```
# Display the number of rows and columns im the dataframe
print('The dataframe contains:', imdb_df.shape[0],'rows')
print('The dataframe contains:', imdb_df.shape[1],'columns')
```

```
The dataframe contains: 181387 rows
The dataframe contains: 7 columns
```

Handling the missing values

In [22]:
```
# Check for the null values in the dataframe
imdb_df.isnull().sum()
```

Out[22]:
```
person_id               0
primary_name            0
death_year         180045
movie_id                0
runtime_minutes     17803
genres               1340
averagerating           0
dtype: int64
```

In [23]:
```
# Drop the records with missing values
imdb_df.dropna(subset=['runtime_minutes', 'genres'], inplace= True)
```

In [24]:
```
# Change the runtime_minutes to the integer format
imdb_df['runtime_minutes']= imdb_df['runtime_minutes'].astype('int64')
```

In [25]:
```
# Verifying the column for runtime_minutes is changed
assert imdb_df['runtime_minutes'].dtype == 'int64', "Conversion to int64 f
```

Exploratory Data Analysis

In this section, we perform Exploratory Data Analysis (EDA) to summarize and visualize the main characteristics of our datasets which will be useful for addressing the objectives

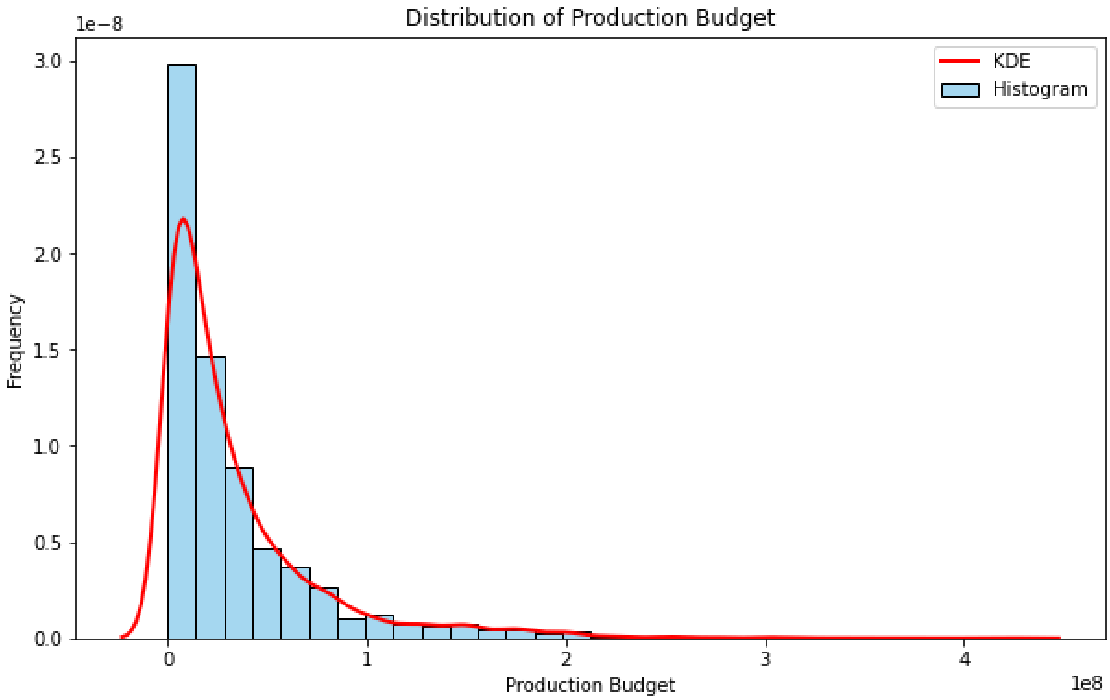
Objective 1:Evaluating the Relationship Between production Budget and Profitability

Univariate Analysis

In this section, we examine the distribution of the production budget variable using a combination of a histogram and a Kernel Density Estimate (KDE) plot. This helps visualize how production budgets are spread across different movies, highlighting patterns such as skewness and the presence of extreme values. By understanding this distribution, we can make informed decisions about how to handle the data in later stages of analysis.

In [26]:

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

# Plotting Histogram and KDE together
plt.figure(figsize=(10, 6))
sns.histplot(tn_df['production_budget'], bins=30, color='skyblue', edgecol
sns.kdeplot(tn_df['production_budget'], color='red', linewidth=2, label='K
plt.title('Distribution of Production Budget')
plt.xlabel('Production Budget')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



Distribution of Production Budgets in Relation to Movie Frequency

- Most films are produced with relatively low budgets, as shown by the concentration of entries on the lower end of the budget range.
- There is a noticeable decline in the number of movies as production budgets rise, indicating that high-budget films are less common.

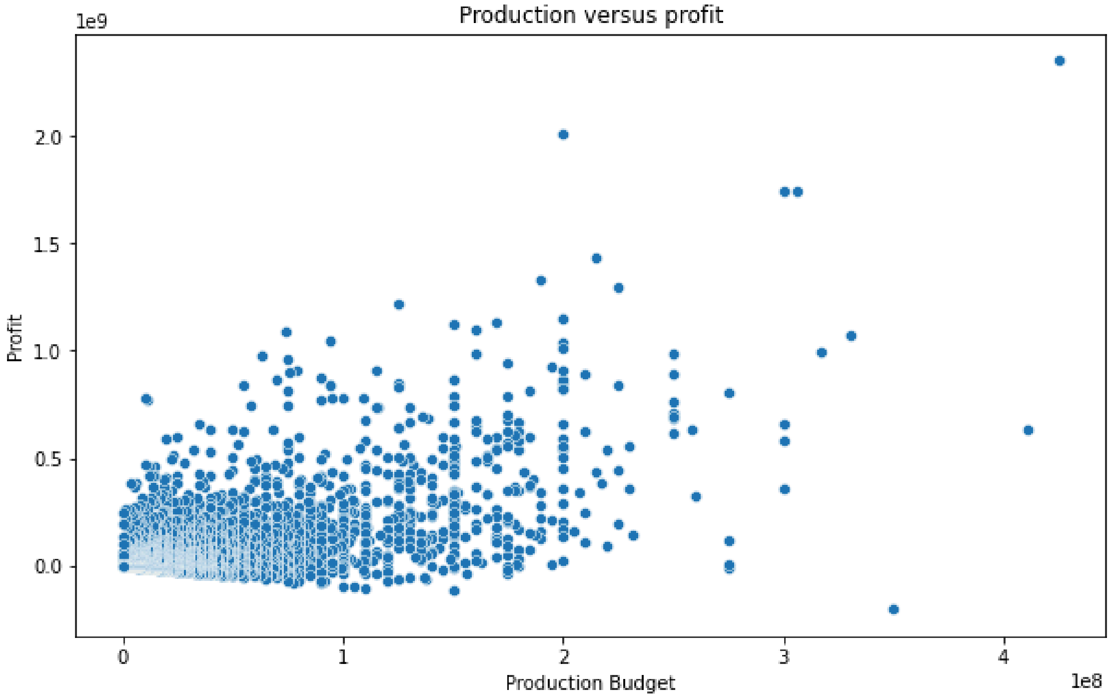
Bivariate Analysis

Relationship Between Production Budgets and Profits for Movies

Bivariate analysis examines the relationship between two variables. It helps you understand how one variable changes in relation to another—whether there's a correlation, trend, or association between them. So we are going to be comparing production budget and profit to see if higher budgets lead to more profit.

In [27]:

```
# Calculate the profit column
tn_df['profit'] = tn_df['worldwide_gross'] - tn_df['production_budget']

# Creating the plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='production_budget', y='profit', data = tn_df)
plt.xlabel('Production Budget')
plt.ylabel('Profit')
plt.title('Production versus profit')
plt.show();
```

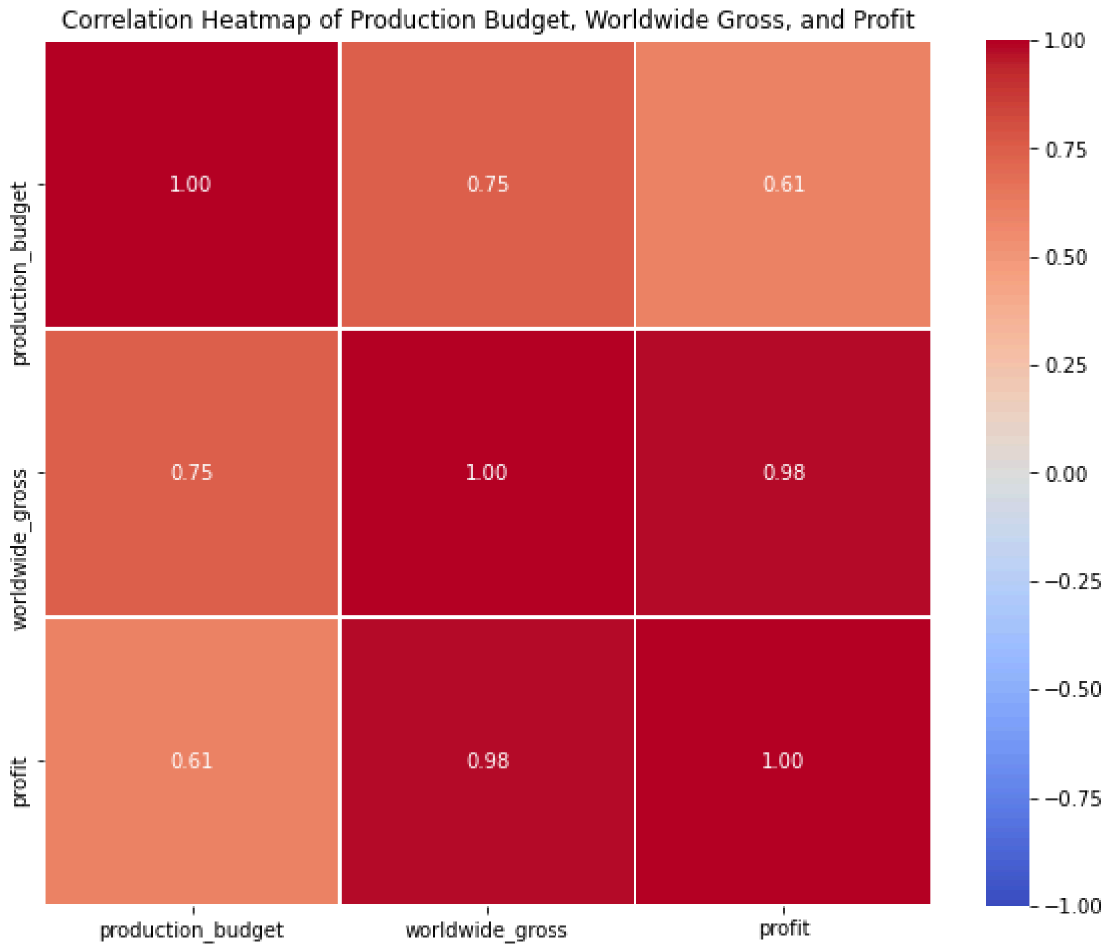


The scatter plot shows that movies with larger production budgets tend to generate higher profits, as indicated by the greater concentration of high-profit points at the upper end of the budget scale.

Multivariate analysis

In the Multivariate Analysis section, we explore the relationships among more than two variables at once. This broader perspective allows for a more thorough understanding of the data's complexity, revealing patterns, associations, and key factors essential for developing strong and precise predictive models.

In [28]:
```
# Select the columns to use
columns = ['production_budget', 'worldwide_gross', 'profit']
# Creating a subset of the DataFrame with the specified columns
Heatmap_df = tn_df[columns]
# Computing the correlation matrix
corr_matrix = Heatmap_df.corr()
# Plotting the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidth
plt.title('Correlation Heatmap of Production Budget, Worldwide Gross, and
plt.show()
```



Production Budget versus. Worldwide Gross: There is a strong positive correlation of 0.75 indicating that movies with larger production budgets typically achieve higher worldwide gross revenues.

Production Budget versus. Profit: A moderate positive correlation of 0.61 suggests that increasing the production budget often leads to higher profits, though this link is not as strong as with worldwide gross.

Worldwide Gross versus Profit: Although the specific correlation value isn't provided, the relationship is expected to be strong, given the positive ties both metrics have with production budget.

Hypothesis Testing

Evaluating the Relationship Between production Budget and Profitability

To better understand how financial inputs and outcomes are interconnected in the film industry, we aim to assess whether a movie's production budget significantly influence its profitability. This exploration is grounded in the following hypotheses:

H_0:There is no significant linear relationship between production budget and profitability.

H_1:There is a significant linear relationship between production budget and profitability.

The Pearson correlation coefficient was computed to determine the linear association between production budget and profit.

In [29]:
```
from scipy.stats import pearsonr

# set the alpha to 0.05
alpha = 0.05
# Calculate both the Pearson correlation coefficient and p-value
correlation, p_value = pearsonr(tn_df['production_budget'], tn_df['profit'
print(f"The P-value is : {p_value}")
print(f"The Pearson Correlation Coefficient is: {correlation}")

if p_value < alpha:
    print("Reject the null hypothesis.There is a significant linear relati
else:
    print("Fail to reject the null hypothesis. There is no sufficient evid
```

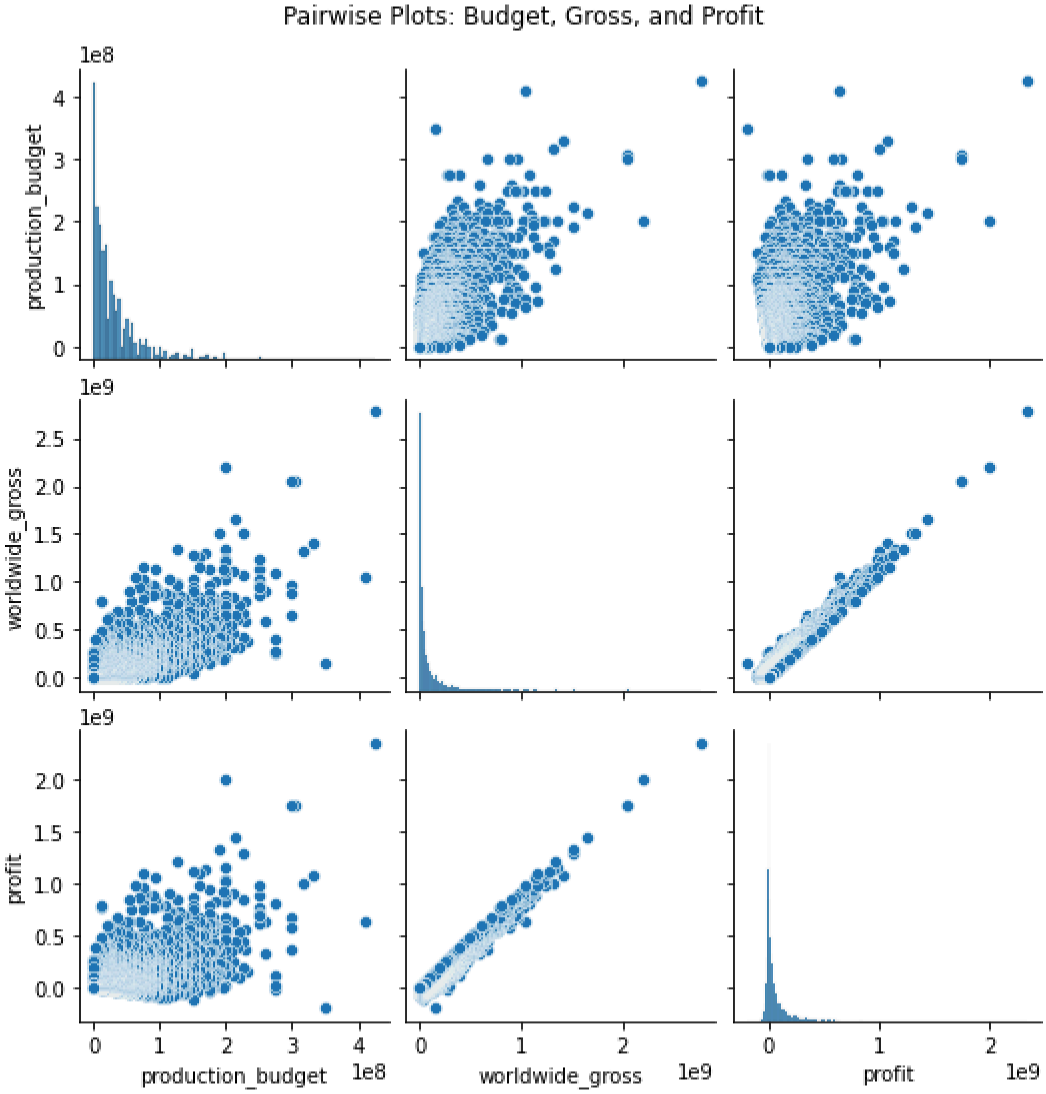
```
The P-value is : 0.0
The Pearson Correlation Coefficient is: 0.6068652923681527
Reject the null hypothesis.There is a significant linear relationship bet
ween the profit and production budget
```

From the output above we can clearly see that A moderate positive correlation of 0.61 suggests that increasing the production budget often leads to higher profits, though this link is not as strong as with worldwide gross. Moreover from our correlation matrix we can see that there is a strong positive correlation of 0.75 indicating that movies with larger production budgets typically achieve higher worldwide gross revenues.

This could further be shown visually as shown in the figure below

In [30]:

```
# Pairplot for visualization
sns.pairplot(tn_df[['production_budget', 'worldwide_gross', 'profit']])
plt.suptitle('Pairwise Plots: Budget, Gross, and Profit', y=1.02)
plt.show()
```



Performing a linear regression model based on the production_budget and profitability

In [31]:

```
#Testing for the equality of variances using the levene's test
from scipy.stats import levene

stat, p = levene(tn_df['production_budget'], tn_df['profit'])
if p <= 0.05:
    print("The variances are not equal")
else:
    print("The variances are equal")
```

```
The variances are not equal
```

To avoid biased standard errors,Inefficient Estimates and invalid standard errors we transform the data since the data has unequal variances

In [32]:
```
# Ensure the columns 'log_production_budget' and 'log_profit' are created
import numpy as np

# Apply log transformation to stabilize variance
tn_df['log_production_budget'] = np.log1p(tn_df['production_budget'])  # L
tn_df['log_profit'] = np.log1p(tn_df['profit'])

# Drop the few rows with NaN values in the relevant columns
tn_df.dropna(subset=['log_production_budget', 'log_profit'], inplace=True)
```

```
c:\Users\Davey\anaconda3\envs\learn-env\lib\site-packages\pandas\core\ser
ies.py:726: RuntimeWarning: invalid value encountered in log1p
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [33]:
```
log_production_budget = tn_df['log_production_budget']
log_profit = tn_df['log_profit']
```

Model Information: The target variable is the log_profit and the independent Feature (X) used for prediction is the log_production_budget.

In [34]:
```

# Import the necessary library
import statsmodels.api as sm

# Defining the feature and target
X = tn_df['log_production_budget'] # feature
y = tn_df['log_profit'] # target
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
predictions = model.predict(X)
```

In [35]:
```
# Statistical Modeling: Linear Regression Summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
=====
Dep. Variable:             log_profit   R-squared:
0.417
Model:                            OLS   Adj. R-squared:
0.417
Method:                 Least Squares   F-statistic:
2612.
Date:                Fri, 02 May 2025   Prob (F-statistic):
0.00
Time:                        22:53:22   Log-Likelihood:                    -6
449.2
No. Observations:                3657   AIC:                             1.29
0e+04
Df Residuals:                    3655   BIC:                             1.29
1e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
================
                            coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
----------------
const                     4.9877      0.241     20.685      0.000
4.515       5.460
log_production_budget     0.7383      0.014     51.106      0.000
0.710       0.767
==============================================================================
=====
Omnibus:                      602.911   Durbin-Watson:
1.096
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                  161
8.962
Skew:                          -0.889   Prob(JB):
0.00
Kurtosis:                       5.732   Cond. No.
173.
==============================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

Regression Coefficients:

- The model estimates the relationship between production_budget and profit.

Intercept (Constant):

- Our 95% confidence level for the intercept is about 4.51 and 5.46

R-squared (R^2):

- The R-squared value is 0.41 - This indicates that only about 41% of the variation in profit can be explained by production_budget.

F-statistic:

- The F-statistic is 2611.833. It assesses the overall significance of the model.
- The F-statistic's p-value (0.0) suggests that the model is statistically significant.

p-values:

- The p-value for 'runtime_minutes' is 0.00, indicating its significance.
- The p-value for the intercept is also 0.00 suggesting its importance.

Model Fit:

- The model's goodness of fit is modest (R-squared = 0.41).

Evaluating and interpreting the model

H_0:The intercept-only model fits the data just as well as our model

H_1:Our model fits the data better than the intercept-only model

In [36]:
```
model.fvalue,model.f_pvalue
```

Out[36]:
```
(2611.8338209104804, 0.0)
```

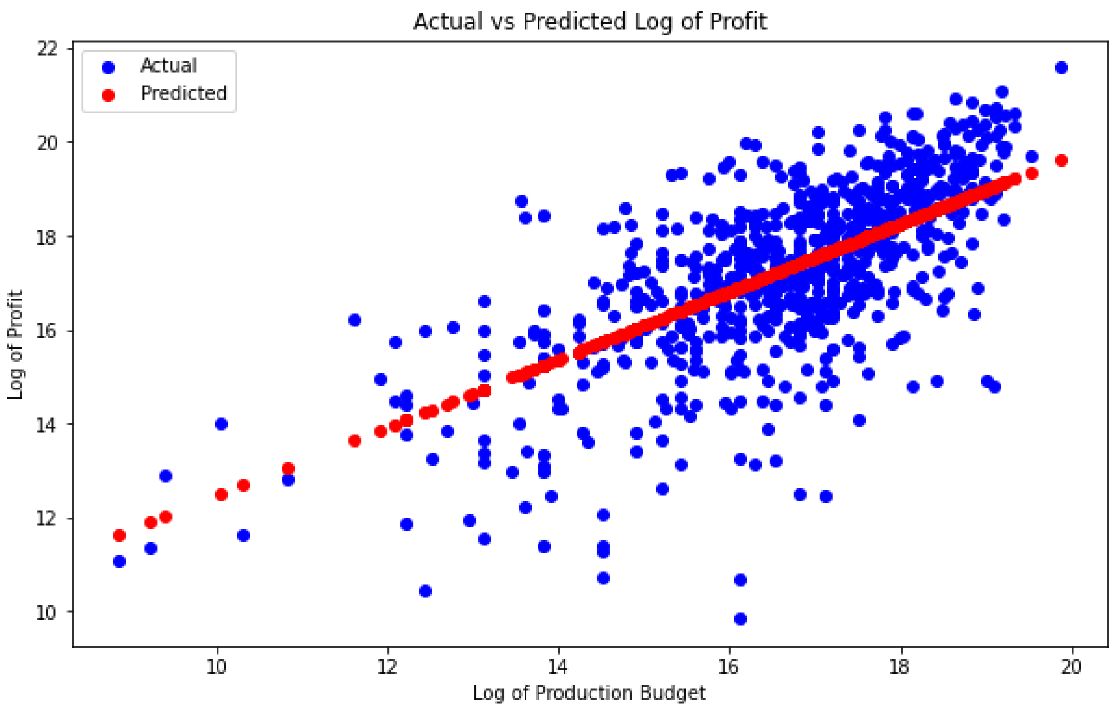
We choose alpha to be 0.05.

So f_pvalue<0.05 so we reject the null hypothesis and conclude that our model fits the data better than the intercept-only model.

In [37]:

```
# Split the data into training and testing sets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    tn_df[['log_production_budget']], tn_df['log_profit'], test_size=0.2,
)

# Fit the model on the training data
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

regressor = LinearRegression()
# Fit the model on the training data
regressor.fit(X_train, y_train)

# Make predictions on the test data
y_pred = regressor.predict(X_test)

# Calculate Mean Squared Error (MSE) on the test data

mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error (MSE): {mse}")


# Visualize
plt.figure(figsize=(10, 6))
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test['log_production_budget'], y_pred, color='red', label='P
plt.xlabel('Log of Production Budget')
plt.ylabel('Log of Profit')
plt.title('Actual vs Predicted Log of Profit')
plt.legend()
plt.show()
```

```
Mean Squared Error (MSE): 1.9152543708775553
```



The figure above is a scatter plot comparing the **actual** and **predicted log of profit** values for the test dataset. Here's the interpretation:

1. **Blue Points (Actual Values):**
   - These represent the actual log of profit values from the test dataset.
   - They show the true relationship between the log of production budget and log of profit.
2. **Red Points (Predicted Values):**
   - These represent the predicted log of profit values generated by the linear regression model.
   - They indicate how well the model approximates the actual values.
   - They closely align with the blue points (actual).

The visualization helps assess how well the model predicts the profits from production budgets.

The spread of points suggests that the model is reasonably accurate

Objective 2: Determine if there is a difference in audience ratings between the shorter and longer films

We restrict the imdb_df DataFrame to include only movies with runtimes between 30 and 200 minutes, ensuring the analysis focuses on films with typical and realistic durations.

In [38]:

```
#Filter to keep movies with runtime between 30 and 200 minutes
relevant_movies_df = imdb_df[(imdb_df['runtime_minutes'] >= 30) & (imdb_df
relevant_movies_df.head()
```

Out[38]:

	person_id	primary_name	death_year	movie_id	runtime_minutes	genre
0	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama,Romanc
1	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama,Romanc
2	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama,Romanc
3	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama,Romanc
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101	Drama,Romance,Thrille

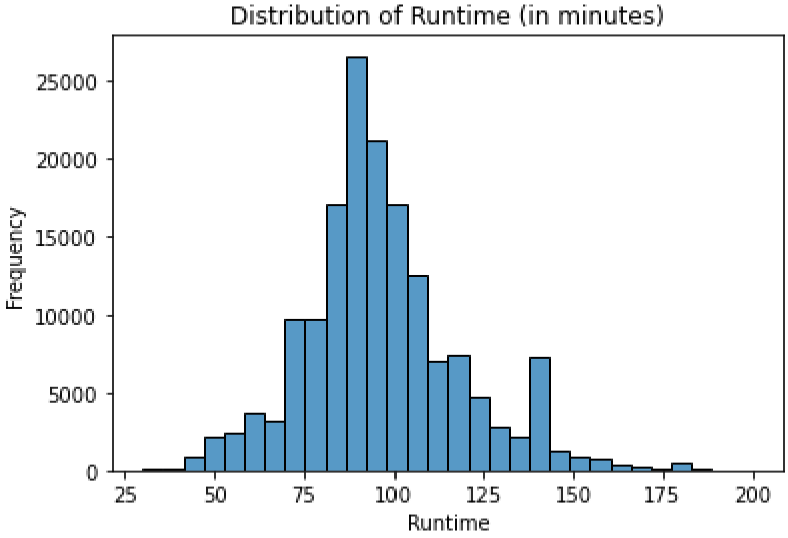
Univariate Analysis

**Distribution of Average rating*

The distribution of average ratings shows how movies are rated by viewers.

In [39]:

```
sns.histplot(relevant_movies_df['runtime_minutes'], bins=30, kde=False)
plt.title('Distribution of Runtime (in minutes)')
plt.xlabel('Runtime')
plt.ylabel('Frequency')
plt.show()
```



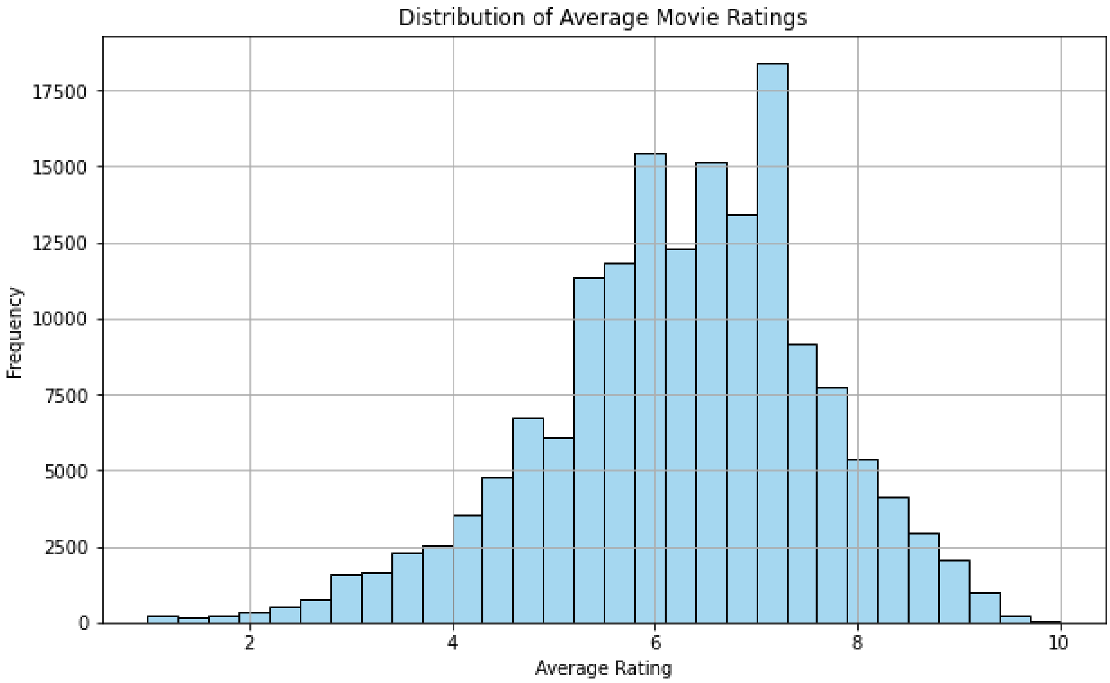
The distribution of movie runtimes is roughly bell-shaped, resembling a normal distribution, but with a slight right skew. The highest concentration of movies is between 90 and 100 minutes, suggesting that this is the most common length for films in the dataset.

Plotting the distribution of Average rating

The Distribution of average ratings illustrates how viewers evaluate movies, offering insight into audience perceptions of movie quality within the dataset.

In [40]:

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

plt.figure(figsize=(10, 6))
sns.histplot(relevant_movies_df['averagerating'], bins=30, color='skyblue'
plt.title('Distribution of Average Movie Ratings')
plt.xlabel('Average Rating')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



From the above we can see that the highest concentration of the average movie ratings is between around 5.9 and 7.5

Bivariate Analysis

In this section, we examine the relationship between a movie's runtime and its average rating.This will help us explore how two continuous variables relate to one another—in this case, whether longer or shorter films tend to receive higher or lower audience ratings. Understanding this relationship can offer valuable insights for content planning and production decisions.

In [41]:

```
#create a copy of the imdb
filt_imdb = relevant_movies_df.copy()
```

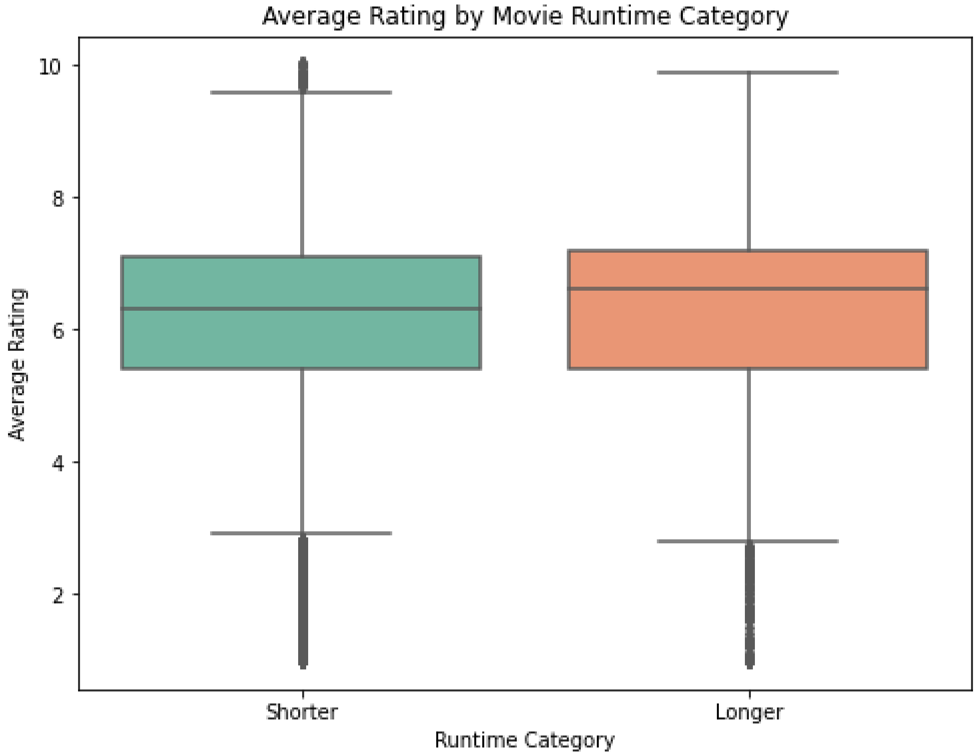
In [42]:

```
#Create a new column categorizing movies as 'Shorter' or 'Longer'
filt_imdb['runtime_group'] = filt_imdb['runtime_minutes'].apply(
    lambda x: 'Longer' if x > 120 else 'Shorter')

# Display the first 20 rows of the new column
filt_imdb['runtime_group'].head(20)
```

Out[42]:

```
0     Shorter
1     Shorter
2     Shorter
3     Shorter
4     Shorter
5     Shorter
6     Shorter
7     Shorter
10    Shorter
11    Shorter
12    Shorter
13    Shorter
14     Longer
15    Shorter
16    Shorter
17    Shorter
18    Shorter
19    Shorter
24    Shorter
25    Shorter
Name: runtime_group, dtype: object
```

In [43]:
```
#Box plot for the runtime_group by movie average rating
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
sns.boxplot(x='runtime_group', y='averagerating', data=filt_imdb, palette=
plt.title('Average Rating by Movie Runtime Category')
plt.xlabel('Runtime Category')
plt.ylabel('Average Rating')
plt.show()
```



Overall, the plot suggests that longer movies might generally receive higher average ratings.

The box plot compares average ratings of movies based on their runtime categories—'Shorter' (≤120 minutes) and 'Longer' (>120 minutes). It reveals that longer movies tend to have a slightly higher median rating than shorter ones.

The rating distribution for longer movies shows greater variability, as indicated by a wider interquartile range.

Hypothesis Testing

H_0: There is no difference in audience ratings between the shorter and the longer films.

H_1: There is a difference in audience ratings between the shorter and the longer films.

In [44]:
```
#Group the data into 'Shorter' and 'Longer' based on the runtime_group col
Shorter = filt_imdb[filt_imdb['runtime_group'] == 'Shorter']['averageratin
Longer = filt_imdb[filt_imdb['runtime_group'] == 'Longer']['averagerating'
```

In [45]:
```
#Testing for the equality of variances using the levene's test
from scipy.stats import levene

stat, p = levene(Shorter, Longer)
if p_value <= 0.05:
    print("The variances are not equal")
else:
    print("The variances are equal")
```

```
The variances are not equal
```

In [46]:
```

#Perform the t-test
from scipy.stats import ttest_ind
t_stat, p_value = ttest_ind(Shorter, Longer, equal_var=True)
print(f't-stat:{t_stat}, p_value: {p_value}')
```

```
t-stat:-18.1935941280581, p_value: 6.874392240583262e-74
```

Decision

Alpha = 0.05

So at 95% level of confidence we reject the null hypothesis and conclude that there is a statistically significant difference in the audience ratings between the shorter and the Longer films

Objetive 3: Identify the Best Directors to Work With

To find the best directors to work with, we simply check for the average movie ratings of the movies they directed. The directors most associated with high ratings should be our target. However, as seen below, the highest rated directors and most experienced ones are different. Hence to determine the best directors, we need to take into account both of these factors.

We assume a director's experience to be the number of movies they have worked on. The more the movies, the higher the experience.

In [47]:

```
# Take the director name and the ratings of their movies from the imdb dat
directors_df = imdb_df[['primary_name', 'averagerating', 'death_year']]
directors_df
```

Out[47]:

	primary_name	averagerating	death_year
0	Ruel S. Bayani	6.4	NaN
1	Ruel S. Bayani	6.4	NaN
2	Ruel S. Bayani	6.4	NaN
3	Ruel S. Bayani	6.4	NaN
4	Ruel S. Bayani	6.4	NaN
...	...	...	...
181381	Benjamin Ovesen	7.4	NaN
181382	Frank W Chen	5.8	NaN
181383	Frank W Chen	5.8	NaN
181384	Prasobh Vijayan	5.7	NaN
181385	Grzegorz Jankowski	5.2	NaN

162708 rows × 3 columns

In [48]:

```
# drop the rows containing actual values in the death_year column so we re
directors_df = directors_df[directors_df['death_year'].isnull()]
```

In [49]:

```
# Group the directors by their name to calculate the average rating of all
directors_df = directors_df.groupby('primary_name').agg(
    Average_Rating=('averagerating', 'mean'),
    Movie_Count=('averagerating', 'count')
).reset_index()

directors_df
```

Out[49]:

	primary_name	Average_Rating	Movie_Count
0	A Normale Jef	7.20	46
1	A'Ali de Sousa	4.20	1
2	A. Blaine Miller	7.00	1
3	A. Cengiz Mert	3.20	1
4	A. Fishman	7.80	1
...	...	...	...
51216	Ümit Kivanç	7.90	2
51217	Ümit Köreken	6.40	3
51218	Ümit Uludag	9.20	1
51219	Ümit Ünal	5.95	4
51220	Þórdur Bragi Jónsson	6.30	1

51221 rows × 3 columns

Since there are no ratings for directors in the dataset, we can use the average rating of their movies as a proxy for the director ratings

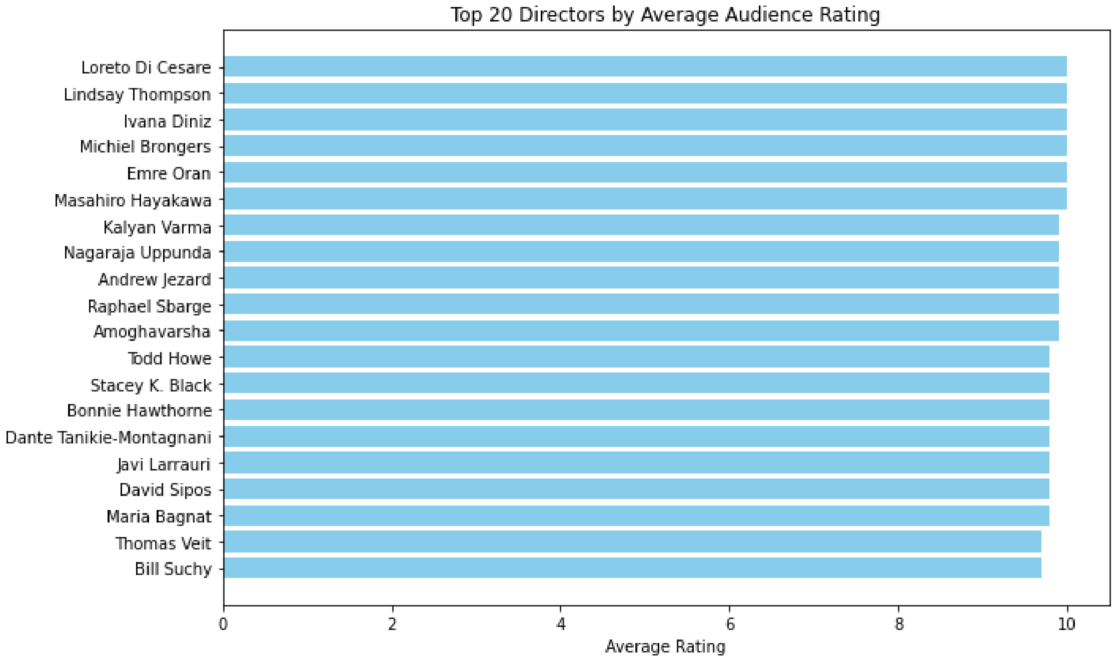
In [50]:

```
# Sort the directors by the average rating of their movies starting from t
top_rated = directors_df.sort_values(by='Average_Rating', ascending=False)
top_rated
```

Out[50]:

	primary_name	Average_Rating	Movie_Count
28580	Loreto Di Cesare	10.0	2
28318	Lindsay Thompson	10.0	1
19546	Ivana Diniz	10.0	2
33269	Michiel Brongers	10.0	1
13985	Emre Oran	10.0	1
31270	Masahiro Hayakawa	10.0	1
25452	Kalyan Varma	9.9	1
34517	Nagaraja Uppunda	9.9	1
2898	Andrew Jezard	9.9	1
39322	Raphael Sbarge	9.9	1
2387	Amoghavarsha	9.9	1
47498	Todd Howe	9.8	1
44821	Stacey K. Black	9.8	1
6066	Bonnie Hawthorne	9.8	1
10750	Dante Tanikie-Montagnani	9.8	1
21060	Javi Larrauri	9.8	1
11567	David Sipos	9.8	1
30235	Maria Bagnat	9.8	1
47037	Thomas Veit	9.7	1
5788	Bill Suchy	9.7	1

In [51]:
```
# visualize the top rated directors
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.barh(top_rated['primary_name'], top_rated['Average_Rating'], color='sk
plt.xlabel('Average Rating')
plt.title('Top 20 Directors by Average Audience Rating')
plt.gca().invert_yaxis()  # Highest rating at the top
plt.tight_layout()
plt.show()
```



As mentioned before, the highest rated directors tend to have worked on very few movies. We need to find the ones with some experience (high movie count) in the industry

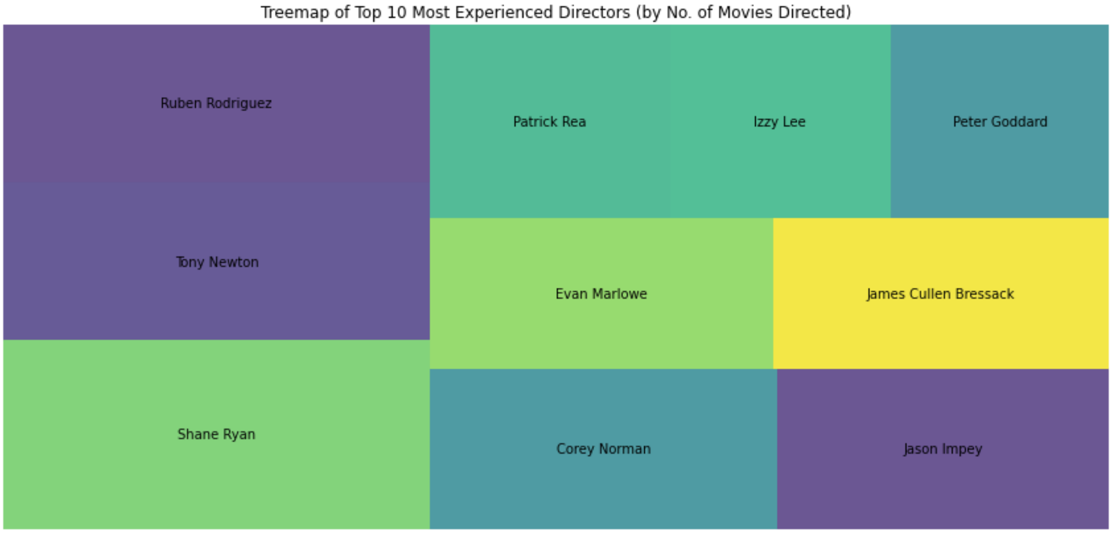
In [52]:
```
# Sort the directors by the number of movies directed to gauge their exper
experienced_df = directors_df.sort_values(by='Movie_Count', ascending=Fals
experienced_df
```

Out[52]:

	primary_name	Average_Rating	Movie_Count
43658	Shane Ryan	5.626452	155
47953	Tony Newton	4.785385	130
41360	Ruben Rodriguez	6.079845	129
9523	Corey Norman	6.017757	107
20890	Jason Impey	5.158824	102
14680	Evan Marlowe	6.403000	100
20202	James Cullen Bressack	4.601020	98
37034	Patrick Rea	6.153933	89
19608	Izzy Lee	5.518293	82
37789	Peter Goddard	5.372840	81

In [53]:

```
# visualize the most experienced directors
import squarify

plt.figure(figsize=(15, 7))
squarify.plot(sizes= experienced_df['Movie_Count'], label=experienced_df['
plt.axis('off')
plt.title('Treemap of Top 10 Most Experienced Directors (by No. of Movies
plt.show()
```



To find the best directors to recommend, we need to take into account both experience level and ratings. So we have to sort by movie count then pick the best rated among these

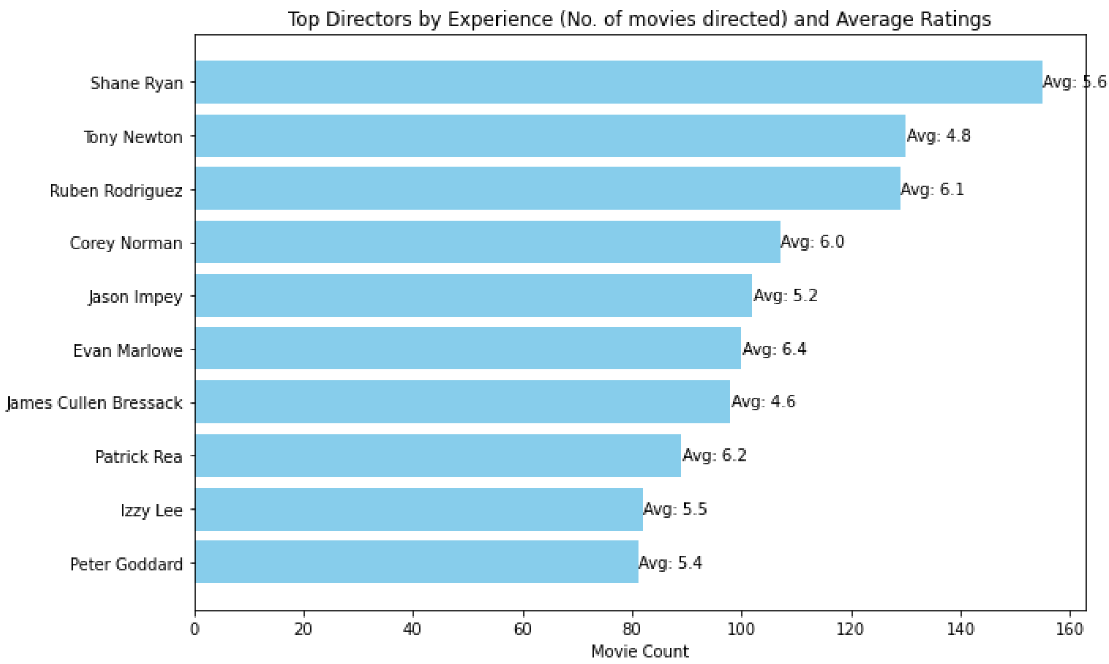
In [54]:

```
# sort directors by movie count then pick the best rated among these exper
best_directors_df = directors_df.sort_values(by='Movie_Count', ascending=F
best_directors_df
```

Out[54]:

	primary_name	Average_Rating	Movie_Count
43658	Shane Ryan	5.626452	155
47953	Tony Newton	4.785385	130
41360	Ruben Rodriguez	6.079845	129
9523	Corey Norman	6.017757	107
20890	Jason Impey	5.158824	102
14680	Evan Marlowe	6.403000	100
20202	James Cullen Bressack	4.601020	98
37034	Patrick Rea	6.153933	89
19608	Izzy Lee	5.518293	82
37789	Peter Goddard	5.372840	81

In [55]:
```
# visualize the data

plt.figure(figsize=(10, 6))
bars = plt.barh(best_directors_df['primary_name'],best_directors_df['Movie

# Annotate each bar with average rating
for bar, rating in zip(bars, best_directors_df['Average_Rating']):
    plt.text(bar.get_width() + 0.1, bar.get_y() + bar.get_height()/2,
             f'Avg: {rating:.1f}', va='center')


plt.gca().invert_yaxis()          # Highest movie count at the top
plt.xlabel('Movie Count')
plt.title('Top Directors by Experience (No. of movies directed) and Averag
plt.tight_layout()
plt.show()
```

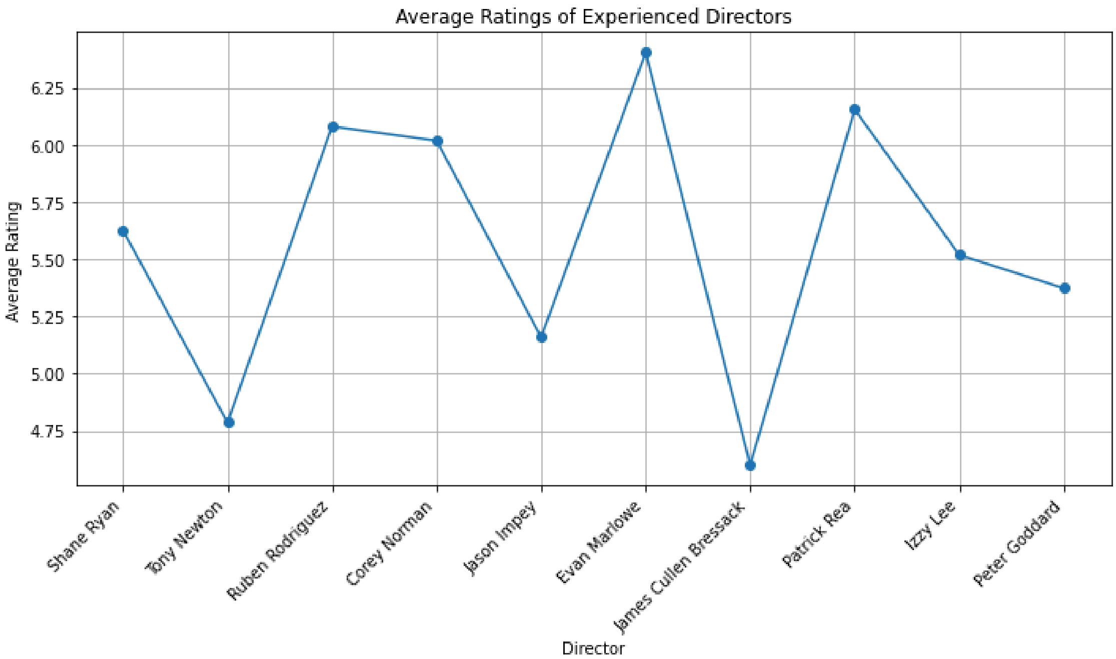


Now we'll plot a line graph to show the ratings of these experienced directors and compare them to find the best among them

Remember, we derived experience from number of movies directed

In [56]:

```
plt.figure(figsize=(10, 6))
plt.plot(best_directors_df['primary_name'], best_directors_df['Average_Rat

# Improve readability
plt.xticks(rotation=45, ha='right')
plt.xlabel('Director')
plt.ylabel('Average Rating')
plt.title('Average Ratings of Experienced Directors')
plt.grid(True)
plt.tight_layout()

plt.show()
```



By picking the highest rated among these directors, we can safely assume they are the best ones to work with and hence recommend them to the executive of the new movie studio

Objective 4: To identify the genres that are linked to high average rating

In [57]:
```
imdb_df = imdb_df.drop_duplicates()
imdb_df
```

Out[57]:

	person_id	primary_name	death_year	movie_id	runtime_minutes	
0	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama,Rc
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101	Drama,Romance
7	nm0062879	Ruel S. Bayani	NaN	tt2590280	100	
10	nm0064023	Bryan Beasley	NaN	tt4512140	53	Docur
11	nm0067234	Hans Beimler	NaN	tt2098699	90	
...	...	...	...	...	...	
181380	nm9541799	Hamed Saleh	NaN	tt7849092	84	C
181381	nm9701687	Benjamin Ovesen	NaN	tt8146836	55	
181382	nm9748617	Frank W Chen	NaN	tt8234502	99	Documenta
181384	nm9769561	Prasobh Vijayan	NaN	tt8273258	91	
181385	nm9781362	Grzegorz Jankowski	NaN	tt4438688	93	Comedy,I

76567 rows × 7 columns

Handling Genre Data

Normalize Genre Data into Individual Rows

Movies with multiple genres are split so each genre appears in its own row. This structure allows accurate per-genre analysis.

In [58]:
```
imdb_df['genres'] = imdb_df['genres'].str.split(',')
imdb_df = imdb_df.explode('genres')

imdb_df
```

Out[58]:

	person_id	primary_name	death_year	movie_id	runtime_minutes	genres	a
0	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Drama	
0	nm0062879	Ruel S. Bayani	NaN	tt1592569	110	Romance	
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101	Drama	
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101	Romance	
4	nm0062879	Ruel S. Bayani	NaN	tt2057445	101	Thriller	
...	...	...	...	...	...	...	
181382	nm9748617	Frank W Chen	NaN	tt8234502	99	Documentary	
181382	nm9748617	Frank W Chen	NaN	tt8234502	99	Sport	
181384	nm9769561	Prasobh Vijayan	NaN	tt8273258	91	Thriller	
181385	nm9781362	Grzegorz Jankowski	NaN	tt4438688	93	Comedy	
181385	nm9781362	Grzegorz Jankowski	NaN	tt4438688	93	Musical	

138591 rows × 7 columns

Calculating Average Rating by Genre *Compute Average Rating for Each Genre* The dataset is grouped by genre, and the mean IMDb rating is calculated for each group. Results are sorted from highest to lowest rated genre.

In [59]:
```
genre_ratings = imdb_df.groupby('genres')['averagerating'].mean().sort_val
genre_ratings
```

Out[59]:
```
genres
Short          8.800000
Documentary    7.300637
Game-Show      7.300000
News           7.263077
Biography      7.153383
Music          7.099956
History        7.053920
Sport          7.000296
War            6.596799
Musical        6.504895
Family         6.411190
Drama          6.397100
Animation      6.281203
Adventure      6.203876
Reality-TV     6.163636
Romance        6.146892
Crime          6.107764
Comedy         6.021834
Fantasy        5.921722
Mystery        5.900030
Western        5.859155
Action         5.786338
Thriller       5.575051
Sci-Fi         5.504845
Horror         4.968743
Adult          3.300000
Name: averagerating, dtype: float64
```

Preparing Genre Ratings DataFrame for Analysis *Finalize Genre Ratings DataFrame* The average ratings are reformatted into a clean DataFrame with clear column names and sorted values. Top 15 and Top 5 genres are selected for visualization.

In [60]:
```
# Group, average, and convert to a DataFrame with named columns
genre_ratings = imdb_df.groupby('genres')['averagerating'].mean().reset_in

# Rename the columns for clarity
genre_ratings.columns = ['genre', 'average_rating']

# Sort the DataFrame by average_rating
genre_ratings = genre_ratings.sort_values(by='average_rating', ascending=F

# Reset the index to remove numbers on the left
genre_ratings = genre_ratings.reset_index(drop=True)


# Create Top 15 and Top 5 DataFrames for plotting
top15 = genre_ratings.head(15).copy()
top5 = genre_ratings.head(5).copy()

# View the result
genre_ratings
```

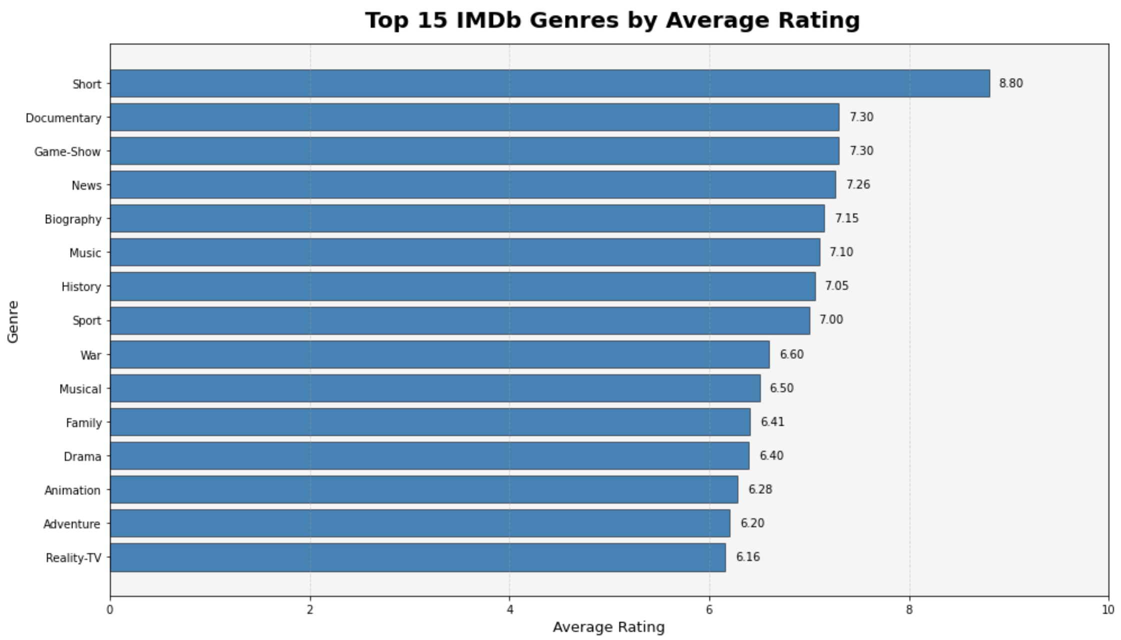
Out[60]:

	genre	average_rating
0	Short	8.800000
1	Documentary	7.300637
2	Game-Show	7.300000
3	News	7.263077
4	Biography	7.153383
5	Music	7.099956
6	History	7.053920
7	Sport	7.000296
8	War	6.596799
9	Musical	6.504895
10	Family	6.411190
11	Drama	6.397100
12	Animation	6.281203
13	Adventure	6.203876
14	Reality-TV	6.163636
15	Romance	6.146892
16	Crime	6.107764
17	Comedy	6.021834
18	Fantasy	5.921722
19	Mystery	5.900030
20	Western	5.859155
21	Action	5.786338
22	Thriller	5.575051
23	Sci-Fi	5.504845
24	Horror	4.968743
25	Adult	3.300000

Visualizing Genre Ratings *Plot Top 15 IMDb Genres (Horizontal Bar Chart)* Displays the 15 highest-rated genres using a horizontal bar chart for readability. Ratings are shown directly on each bar.

In [61]:

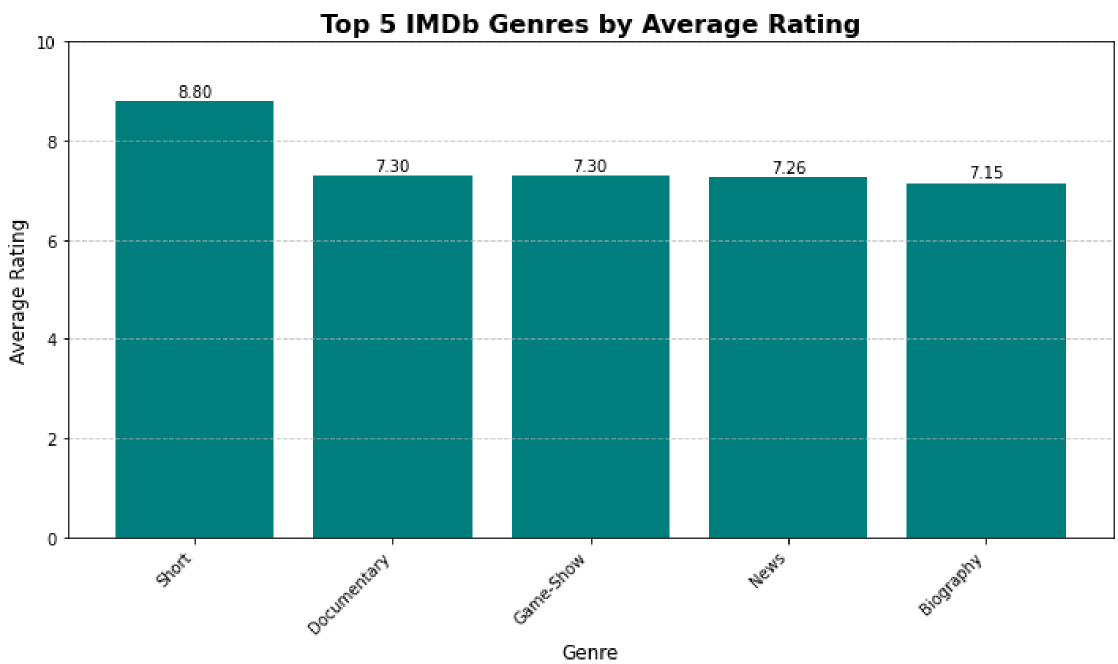
```
plt.figure(figsize=(14, 8))
bars = plt.barh(top15['genre'], top15['average_rating'],
                color='#4682B4', edgecolor='black', linewidth=0.5)

plt.gca().invert_yaxis()

# Add data labels
for bar in bars:
    plt.text(bar.get_width() + 0.1, bar.get_y() + bar.get_height() / 2,
             f"{bar.get_width():.2f}", va='center', fontsize=10)

# Style
plt.title(' Top 15 IMDb Genres by Average Rating', fontsize=20, fontweight
plt.xlabel('Average Rating', fontsize=13)
plt.ylabel('Genre', fontsize=13)
plt.xlim(0, 10)
plt.grid(axis='x', linestyle='--', alpha=0.4)
plt.gca().set_facecolor('#f5f5f5')
plt.tight_layout()
plt.show()
```



Plot Top 5 Genres (Vertical Bar Chart) Highlights the top 5 genres with the highest average IMDb ratings. Includes annotations for clarity.

In [62]:

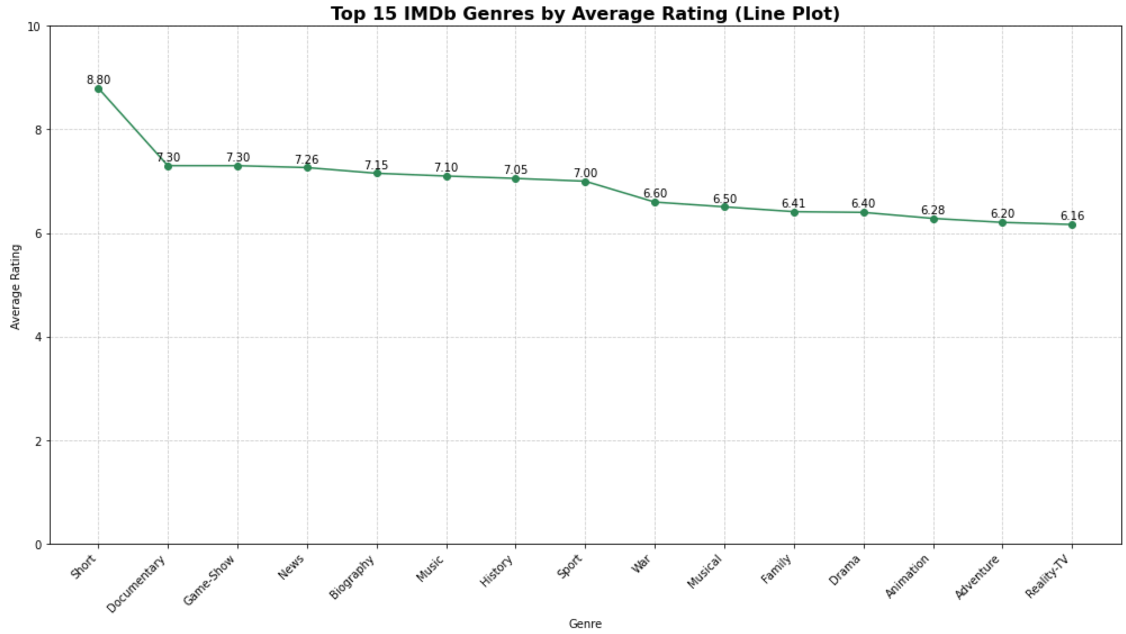
```
plt.figure(figsize=(10, 6))

# Bar plot
bars = plt.bar(top5['genre'], top5['average_rating'], color='teal')

# Add data labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 0.1, f"{height:.2f}

# Titles and labels
plt.title('Top 5 IMDb Genres by Average Rating', fontsize=16, fontweight='
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.ylim(0, 10)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45, ha='right')

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



Line Plot of Top 15 Genre Ratings A line chart is used to show trends in average ratings among the top 15 genres. Data labels are added for clarity.

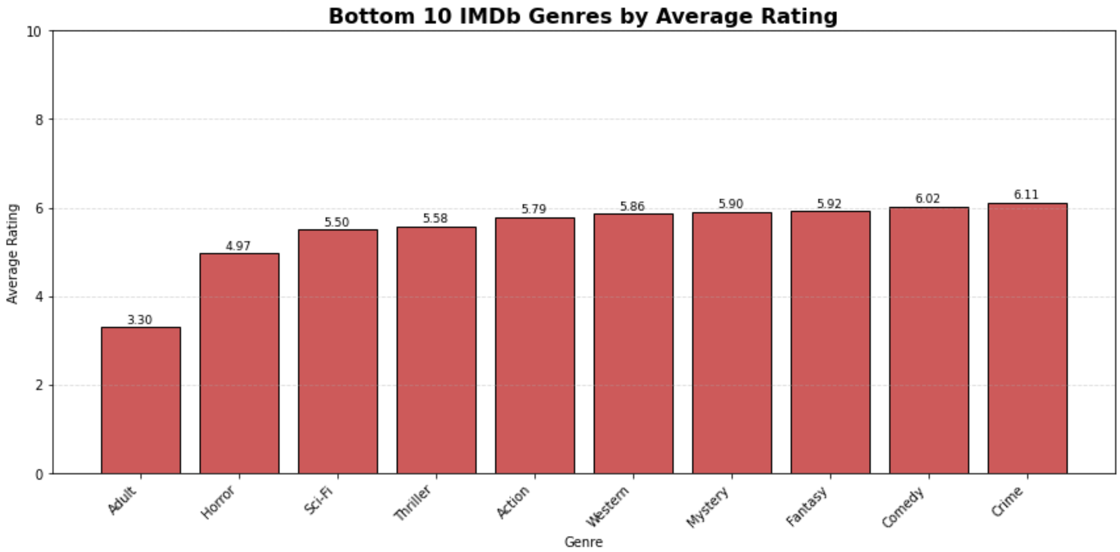
In [63]:

```
plt.figure(figsize=(14, 8))

# Line plot
plt.plot(top15['genre'], top15['average_rating'], marker='o', linestyle='-

# Add data labels
for i, (x, y) in enumerate(zip(top15['genre'], top15['average_rating'])):
    plt.text(i, y + 0.1, f"{y:.2f}", ha='center')

# Titles and labels
plt.title('Top 15 IMDb Genres by Average Rating (Line Plot)', fontsize=16,
plt.xlabel('Genre')
plt.ylabel('Average Rating')
plt.ylim(0, 10)
plt.grid(True, linestyle='--', alpha=0.6)
plt.xticks(rotation=45, ha='right')

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



Bar Chart of Bottom 10 Genres by Rating Plots the 10 lowest-rated genres to highlight underperformers. Annotations provide specific average rating values.

In [64]:
```
bottom10 = genre_ratings.tail(10).sort_values(by='average_rating')

plt.figure(figsize=(12, 6))
bars = plt.bar(bottom10['genre'], bottom10['average_rating'], color='india
plt.xticks(rotation=45, ha='right')
plt.ylim(0, 10)

# Annotate
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 0.1, f"{yval:.2f}", h

plt.title('Bottom 10 IMDb Genres by Average Rating', fontsize=16, weight='
plt.xlabel('Genre')
plt.ylabel('Average Rating')
plt.grid(axis='y', linestyle='--', alpha=0.4)
plt.tight_layout()
plt.show()
```



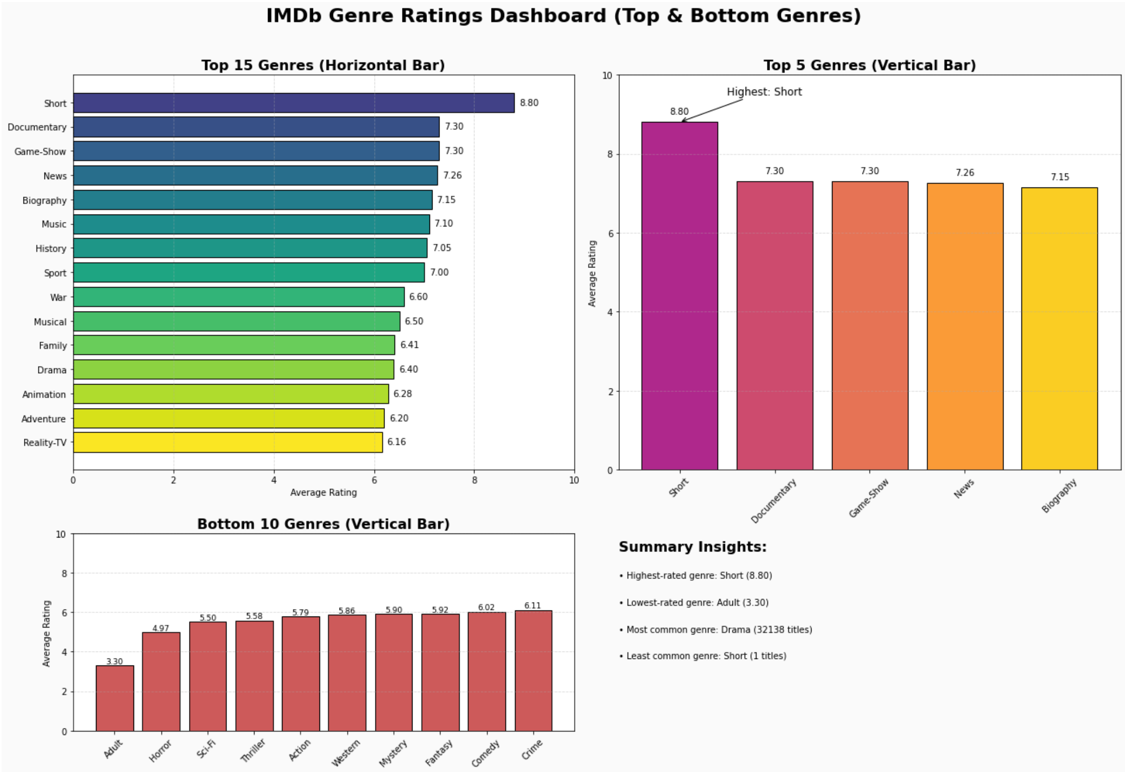
IMDb Genre Ratings Summary Dashboard Combines top and bottom genres into one visual summary. Includes:

- Top 15 horizontal bar chart
- Top 5 vertical chart
- Bottom 10 genres
- Summary insights (highest/lowest-rated and most/least common genres)

In [65]:

```
import matplotlib.cm as cm
import numpy as np


#  Data Preparation
bottom10 = genre_ratings.tail(10).sort_values(by='average_rating')
top_genre = genre_ratings.iloc[0]
low_genre = genre_ratings.iloc[-1]

# Genre frequency for summary
genre_counts = imdb_df['genres'].value_counts()
most_common_genre = genre_counts.idxmax()
least_common_genre = genre_counts.idxmin()

# Plotting Layout
fig, axs = plt.subplots(2, 2, figsize=(18, 12), gridspec_kw={'height_ratio
fig.patch.set_facecolor('#fdfdfd')  # Background color

# Subplot 1: Horizontal Bar Chart (Top 15)
colors = cm.viridis(np.linspace(0.2, 1, len(top15)))
axs[0, 0].barh(top15['genre'], top15['average_rating'], color=colors, edge
axs[0, 0].invert_yaxis()
axs[0, 0].set_title('Top 15 Genres (Horizontal Bar)', fontsize=16, weight=
axs[0, 0].set_xlabel('Average Rating')
axs[0, 0].set_xlim(0, 10)
axs[0, 0].grid(axis='x', linestyle='--', alpha=0.4)
for i, rating in enumerate(top15['average_rating']):
    axs[0, 0].text(rating + 0.1, i, f"{rating:.2f}", va='center', fontsize

# Subplot 2: Vertical Bar Chart (Top 5)
colors5 = cm.plasma(np.linspace(0.4, 0.9, len(top5)))
bars = axs[0, 1].bar(top5['genre'], top5['average_rating'], color=colors5,
axs[0, 1].set_title('Top 5 Genres (Vertical Bar)', fontsize=16, weight='bo
axs[0, 1].set_ylabel('Average Rating')
axs[0, 1].set_ylim(0, 10)
axs[0, 1].tick_params(axis='x', rotation=45)
axs[0, 1].grid(axis='y', linestyle='--', alpha=0.4)
axs[0, 1].annotate(f"Highest: {top_genre['genre']}",
                   xy=(0, top_genre['average_rating']),
                   xytext=(0.5, 9.5),
                   arrowprops=dict(facecolor='black', arrowstyle='->'),
                   fontsize=12)
for bar in bars:
    axs[0, 1].text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.2
                   f"{bar.get_height():.2f}", ha='center', fontsize=10)

# Subplot 3: Bottom 10 Genres
bars = axs[1, 0].bar(bottom10['genre'], bottom10['average_rating'], color=
axs[1, 0].set_title('Bottom 10 Genres (Vertical Bar)', fontsize=16, weight
axs[1, 0].set_ylabel('Average Rating')
axs[1, 0].set_ylim(0, 10)
axs[1, 0].tick_params(axis='x', rotation=45)
axs[1, 0].grid(axis='y', linestyle='--', alpha=0.4)
for bar in bars:
    yval = bar.get_height()
    axs[1, 0].text(bar.get_x() + bar.get_width()/2, yval + 0.1, f"{yval:.2

# Subplot 4: Summary Insights
axs[1, 1].axis('off')
axs[1, 1].text(0, 1.0, 'Summary Insights:', fontsize=16, weight='bold')
axs[1, 1].text(0, 0.85, f"• Highest-rated genre: {top_genre['genre']} ({to
```

```
axs[1, 1].text(0, 0.70, f"• Lowest-rated genre: {low_genre['genre']} ({low
axs[1, 1].text(0, 0.55, f"• Most common genre: {most_common_genre} ({genre
axs[1, 1].text(0, 0.40, f"• Least common genre: {least_common_genre} ({gen
axs[1, 1].set_xlim(0, 1)
axs[1, 1].set_ylim(0, 1.1)

# Final Layout
plt.suptitle('IMDb Genre Ratings Dashboard (Top & Bottom Genres)', fontsiz
plt.tight_layout()
plt.show()
```



Conclusions

1.Increasing the production budget often leads to higher profits

2.Movies with larger production budgets typically achieve higher worldwide gross revenues.

3.There is a difference in the audience ratings between the shorter and the longer films

4.Longer films tend to have a slightly higher median rating than shorter ones.

5.The rating distribution for longer movies shows greater variability, as indicated by a wider interquartile range.

6.As shown the genre Short has high ratings but few titles, it indicates potential low competition and high demand

Recommendations

1.Enhance Profitability Tracking: Implement metrics for profit margin and return on investment (ROI) to better evaluate the success of each project.

2.Refine Budget Allocation Strategies: Invest in production budgets that are high enough to drive profitability, but remain mindful of overspending.

3.Analyze past performance to identify a budget threshold that maximizes returns without crossing into diminishing profit margins.

4.Prioritize Top-Rated Genres for Critical Acclaim: Genres like Short, Documentary, Game Show consistently receive the highest average IMDb ratings.

5.Consider producing at least one high-quality film in one of the above top-rated genre to build studio credibility and recognition.

6.Consider Investing in Longer-Format Films

7.Since longer films tend to receive slightly higher audience ratings, allocating more resources to developing or acquiring quality longer-format content could enhance audience satisfaction and brand reputation.

8.Focus on Quality Storytelling for Long Films

9.The wider variability in ratings for long movies suggests they can either perform very well or poorly.

10.Focus on strong scripts, editing, and pacing to ensure that longer runtimes deliver consistent viewer engagement.

11.Explore Underserved but High-Rated Genres: Some highly-rated genres may also be among the least common. As shown the genre Short has high ratings but few titles, it indicates potential low competition and high demand.Target these niches for original and impactful storytelling that can stand out and attract good ratings.

12.Leverage Popular Genres for Commercial Success:The most common genre, Drama, may not be the highest rated but indicates broad market appeal and a large audience.Add at least one movie in a popular genre like Drama to help draw in more viewers and boost your revenue.

13.From the visualizations, the best three directors alive in the dataset are according to their