# 🎬 Greenlight Analytics — Phase 2 Project

## Executive Summary

This notebook analyzes movie industry data from Box Office Mojo and IMDb (via SQLite) to guide strategic decisions for a new film studio.
The analysis focuses on three key business questions:

1. **Which genres and runtimes are most successful?**
2. **Do ratings correlate with revenue?**
3. **How do domestic vs. foreign markets vary by studio?**

### Key Insights

- Action, Adventure, and Fantasy films consistently generate the highest box office revenues.
- Studios differ significantly in their domestic vs. foreign revenue mix — release strategies matter.
- Runtimes between 95–120 minutes correlate with stronger ratings and solid box office performance.

### Recommendations

1. Prioritize high-performing genres.
2. Balance domestic and international release strategies.
3. Greenlight films with strong audience signals (ratings, genre fit, runtime).

## Data Loading

We combine multiple sources:

- **Box Office Mojo**: CSV with domestic and foreign grosses.
- **IMDb (SQLite)**: movie basics and ratings tables.

The datasets are merged using common keys such as `title` / `primary_title` , `year` / `start_year` , and `movie_id` .

In [23]:
```
import pandas as pd
import sqlite3
import numpy as np

# Load Box Office Mojo data
bom = pd.read_csv('bom.movie_gross.csv.gz')
#bom.head()
```

In [24]:
```
# Load IMDb SQLite tables
path = "im.db"
conn = sqlite3.connect(path)
basics = pd.read_sql("SELECT * FROM movie_basics", conn)
ratings = pd.read_sql("SELECT * FROM movie_ratings", conn)

# Merge Box Office Mojo with IMDb basics
merged_1_2 = pd.merge(bom, basics, left_on=['title','year'], right_on=['primar

# Merge with ratings
df = pd.merge(merged_1_2, ratings, on='movie_id', how='left')
df.tail(5)
```

Out[24]:

| | title | studio | domestic_gross | foreign_gross | year | movie_id | primary_title | original_ |
|---|---|---|---|---|---|---|---|---|
| **1868** | Girls vs Gangsters | WGUSA | 37100.0 | NaN | 2018 | tt7870578 | Girls vs Gangsters | Gui |
| **1869** | The Workshop | Strand | 22100.0 | NaN | 2018 | tt7405478 | The Workshop | Works |
| **1870** | A Paris Education | KL | 21600.0 | NaN | 2018 | tt6593240 | A Paris Education | provinc |
| **1871** | The Quake | Magn. | 6200.0 | NaN | 2018 | tt6523720 | The Quake | Skj |
| **1872** | An Actor Prepares | Grav. | 1700.0 | NaN | 2018 | tt5718046 | An Actor Prepares | An A Prep |

# Data Cleaning

Before analysis, we perform several cleaning steps:

- Remove duplicate rows.
- Handle missing values by dropping rows with critical nulls.
- Convert column types (e.g., `foreign_gross` ).
- Fill missing `foreign_gross` values with 0.
- Create a new `total_gross` column combining domestic and foreign grosses.

In [25]:
```
# Check for duplicates
df.duplicated().sum()

# Drop rows missing essential values
df.dropna(subset=['averagerating','numvotes','studio','runtime_minutes','genre

# Convert foreign_gross to numeric
df['foreign_gross'] = pd.to_numeric(df['foreign_gross'], errors='coerce')

# Replace missing values with 0
df['foreign_gross'].fillna(0, inplace=True)

# Add total_gross column
df['total_gross'] = df['domestic_gross'] + df['foreign_gross']
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1832 entries, 0 to 1872
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   title            1832 non-null   object 
 1   studio           1832 non-null   object 
 2   domestic_gross   1832 non-null   float64
 3   foreign_gross    1832 non-null   float64
 4   year             1832 non-null   int64  
 5   movie_id         1832 non-null   object 
 6   primary_title    1832 non-null   object 
 7   original_title   1832 non-null   object 
 8   start_year       1832 non-null   int64  
 9   runtime_minutes  1832 non-null   float64
 10  genres           1832 non-null   object 
 11  averagerating    1832 non-null   float64
 12  numvotes         1832 non-null   float64
 13  total_gross      1832 non-null   float64
dtypes: float64(6), int64(2), object(6)
memory usage: 214.7+ KB
```

## Question 1: Which Genres and Runtimes Are Most Successful?

We explore revenue trends by genre and runtime.

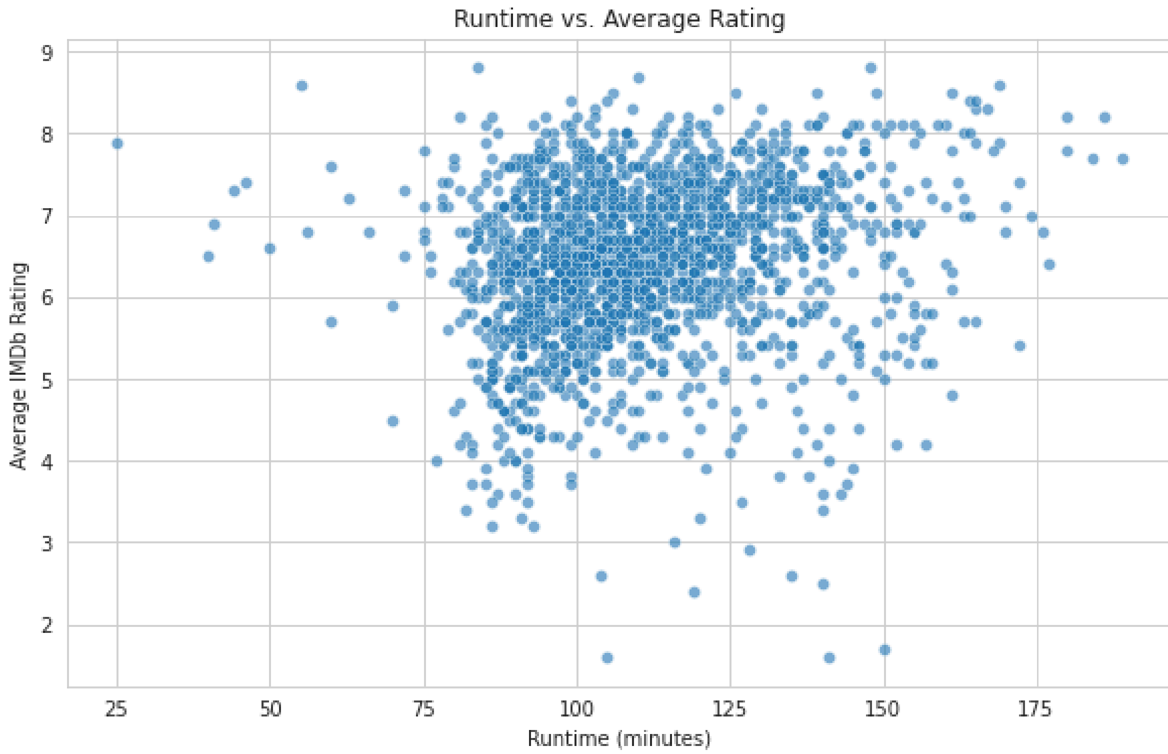
In [26]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')

# Revenue by genre
genre_gross = df.groupby('genres')['total_gross'].agg(['mean','median','count'
genre_gross.head(10)
```

Out[26]:

| genres | mean | median | count |
|---|---|---|---|
| Adventure,Fantasy | 7.040333e+08 | 956000000.0 | 3 |
| Adventure,Drama,Sci-Fi | 6.537500e+08 | 653750000.0 | 2 |
| Action,Adventure,Sci-Fi | 6.120711e+08 | 605499999.0 | 45 |
| Action,Comedy,Mystery | 5.441000e+08 | 544100000.0 | 1 |
| Action,Adventure,Fantasy | 4.565960e+08 | 364700000.0 | 28 |
| Biography,Drama,Musical | 4.350000e+08 | 435000000.0 | 1 |
| Adventure,Mystery,Sci-Fi | 4.034000e+08 | 403400000.0 | 1 |
| Adventure,Animation,Comedy | 4.033133e+08 | 310650000.0 | 68 |
| Action,Adventure,Thriller | 3.923999e+08 | 277200000.0 | 16 |
| Adventure,Family,Fantasy | 3.849875e+08 | 249650000.0 | 8 |

In [27]:
```
# Runtime vs. rating
plt.figure(figsize=(10,6))
sns.scatterplot(data=df, x='runtime_minutes', y='averagerating', alpha=0.6)
plt.title('Runtime vs. Average Rating')
plt.xlabel('Runtime (minutes)')
plt.ylabel('Average IMDb Rating')
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```




## Genres with Mean Gross > $100M (Numbered X-axis)

To improve readability, genres are represented by numbers on the x-axis. A separate mapping dictionary shows the number-to-genre correspondence.

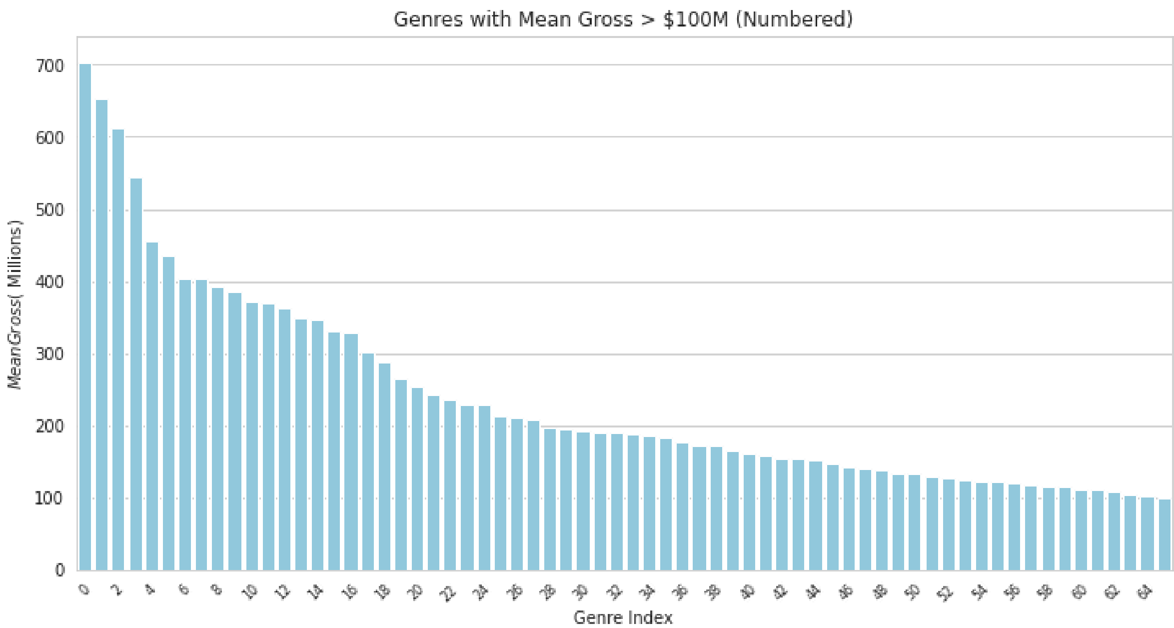
In [28]:
```
# Filtered data for mean gross > $100M
filtered_mean = genre_gross[genre_gross['mean'] > 100_000_000]
genre_mapping_mean = {i: genre for i, genre in enumerate(filtered_mean.index)}

plt.figure(figsize=(12,6))
sns.barplot(x=list(genre_mapping_mean.keys()), y=filtered_mean['mean']/1e6, co

plt.xticks(ticks=range(0, len(genre_mapping_mean), 2), labels=list(genre_mappi
plt.title('Genres with Mean Gross > $100M (Numbered)')
plt.ylabel('$Mean Gross ($ Millions)')
plt.xlabel('Genre Index')
plt.ticklabel_format(style='plain', axis='y')
plt.show()

# print full mapping
# genre_mapping_mean

# Show only top 10 mappings
{k: genre_mapping_mean[k] for k in list(genre_mapping_mean.keys())[:10]}
```




Out[28]:
```
{0: 'Adventure,Fantasy',
 1: 'Adventure,Drama,Sci-Fi',
 2: 'Action,Adventure,Sci-Fi',
 3: 'Action,Comedy,Mystery',
 4: 'Action,Adventure,Fantasy',
 5: 'Biography,Drama,Musical',
 6: 'Adventure,Mystery,Sci-Fi',
 7: 'Adventure,Animation,Comedy',
 8: 'Action,Adventure,Thriller',
 9: 'Adventure,Family,Fantasy'}
```

### Genres with Median Gross > $100M (Numbered X-axis)

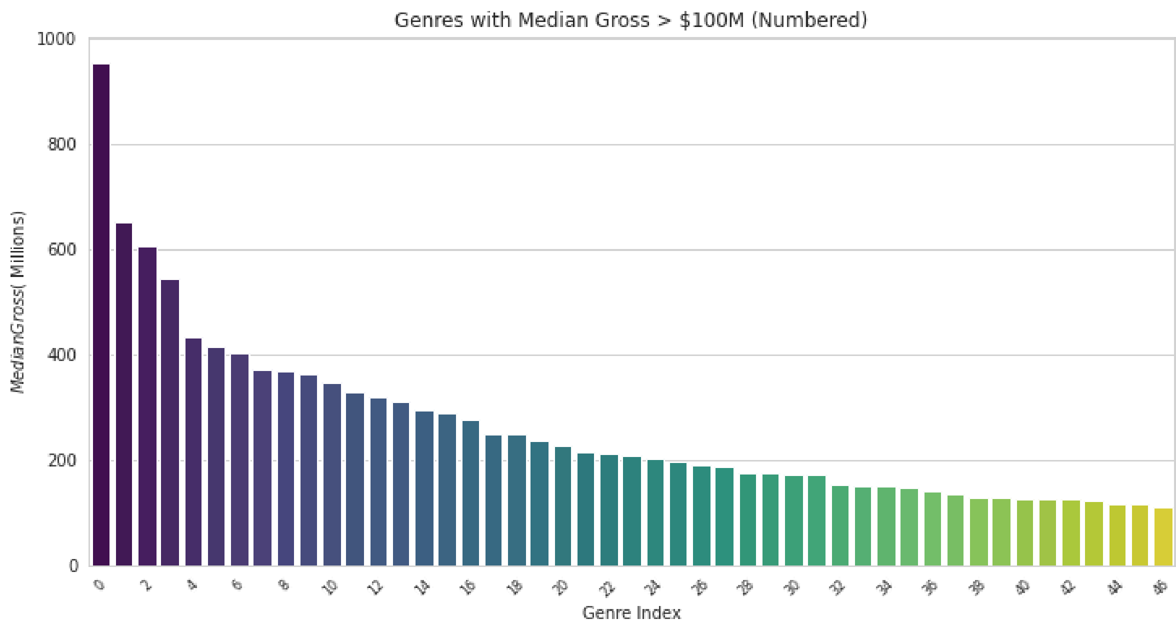
In [29]:
```
# Filtered data for median gross > $100M
filtered_median = genre_gross[genre_gross['median'] > 100_000_000].sort_values
genre_mapping_median = {i: genre for i, genre in enumerate(filtered_median.ind

plt.figure(figsize=(12,6))
sns.barplot(x=list(genre_mapping_median.keys()), y=filtered_median['median']/1

plt.xticks(ticks=range(0, len(genre_mapping_median), 2), labels=list(genre_map
plt.title('Genres with Median Gross > $100M (Numbered)')
plt.ylabel('$Median Gross ($ Millions)')
plt.xlabel('Genre Index')
plt.ticklabel_format(style='plain', axis='y')
plt.show()

# print full mapping
# genre_mapping_median

# Show only top 10 mappings
{k: genre_mapping_median[k] for k in list(genre_mapping_median.keys())[:10]}
```




Out[29]:
```
{0: 'Adventure,Fantasy',
 1: 'Adventure,Drama,Sci-Fi',
 2: 'Action,Adventure,Sci-Fi',
 3: 'Action,Comedy,Mystery',
 4: 'Biography,Drama,Musical',
 5: 'Animation,Comedy,Family',
 6: 'Adventure,Mystery,Sci-Fi',
 7: 'Action,Adventure,Animation',
 8: 'Action,Sci-Fi',
 9: 'Action,Adventure,Fantasy'}
```

## Question 2: Do Ratings Correlate with Revenue?

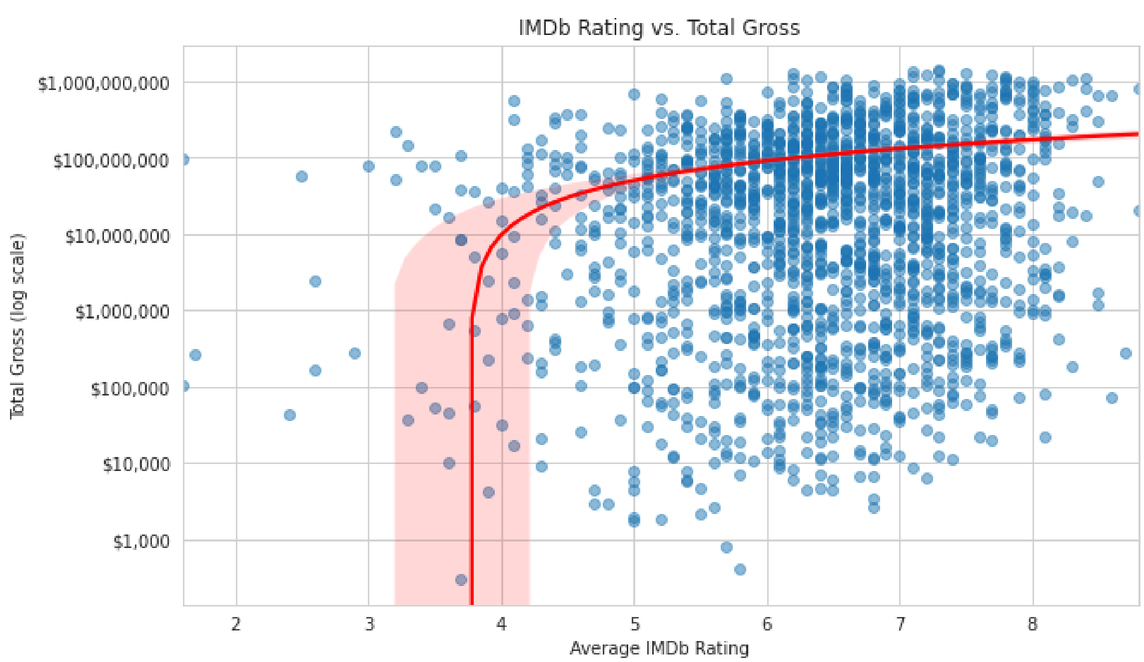
We use scatter plots to examine the relationship between ratings and total revenue.

In [30]:
```
import matplotlib.ticker as mtick

plt.figure(figsize=(10,6))
sns.regplot(
    data=df,
    x='averagerating',
    y='total_gross',
    scatter_kws={'alpha':0.5},
    line_kws={'color':'red'}
)

plt.yscale('log')  # keep log scale
plt.gca().yaxis.set_major_formatter(mtick.StrMethodFormatter('${x:,.0f}'))  #

plt.title('IMDb Rating vs. Total Gross')
plt.xlabel('Average IMDb Rating')
plt.ylabel('Total Gross (log scale)')
plt.show()
```




## Question 3: How Do Domestic vs. Foreign Markets Vary by Studio?

We compare studio-level performance across domestic and foreign revenues.

In [31]:
```
studio_revenue = df.groupby('studio')[['domestic_gross','foreign_gross']].sum(
studio_revenue
```

Out[31]:

| studio | domestic_gross | foreign_gross |
|---|---|---|
| **BV** | 1.464740e+10 | 2.168185e+10 |
| **Uni.** | 1.127364e+10 | 1.470157e+10 |
| **Fox** | 9.397800e+09 | 1.720667e+10 |
| **WB** | 9.251700e+09 | 1.389080e+10 |
| **Sony** | 6.645046e+09 | 1.052080e+10 |
| **Par.** | 6.537913e+09 | 9.735367e+09 |
| **WB (NL)** | 3.739000e+09 | 5.805400e+09 |
| **LGF** | 3.360650e+09 | 4.208225e+09 |
| **P/DW** | 1.682900e+09 | 3.393600e+09 |
| **Wein.** | 1.411008e+09 | 1.820867e+09 |

In [32]:
```
# Stacked bar chart: domestic vs. foreign revenue
studio_revenue[['domestic_gross','foreign_gross']].div(1e6).plot(kind='bar', s
plt.title('Top 10 Studios: Domestic vs. Foreign Gross')
plt.ylabel('$Gross ($ Millions)')
plt.xlabel('Studio')
plt.xticks(rotation=45)
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```