Overview

This project uses movie data from IMDB and Box Office Mojo to generate actionable recommendations for maximizing film profitability.

Business Understanding

Our stakeholders are movie production companies aiming to optimize genre selection, budget allocation, and release strategy.

Data

- Sources: IMDB (film metadata), Box Office Mojo (revenue)
- Variables: genre, runtime, budget, box office revenue, release month, etc.

Setup and imports

```
import pandas as pd
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns

# Styling
plt.style.use('seaborn-v0_8-darkgrid')
sns.set(rc={'figure.figsize':(10,6)})

# check available style
# print(plt.style.available)
```

Load BOM Dataset

```
bom_df = pd.read_csv('/content/bom.movie_gross.csv')
bom_df.head()
```

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

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Check null values in the BOM dataset

```
print(bom_df.isnull().sum())
```

```
title              0
studio             5
domestic_gross    28
foreign_gross   1350
year               0
dtype: int64
```

Clean BOM Dataset

```
# Drop null rows
bom_df = bom_df.dropna(subset=['studio', 'domestic_gross', 'foreign_gross'])

# Remove $ and commas and convert to integers
bom_df['studio'] = bom_df['studio'].replace('[\$,]', '', regex=True)
bom_df['domestic_gross'] = bom_df['domestic_gross'].replace('[\$,]', '', regex=True).astype(int)
bom_df['foreign_gross'] = bom_df['foreign_gross'].replace('[\$,]', '', regex=True)


# Clean titles for merge
bom_df['title'] = bom_df['title'].str.strip().str.lower()
```

Load IMDb Tables from SQLite

```
conn = sqlite3.connect('/content/im.db')

# Load IMDb tables into DataFrames
basics_df = pd.read_sql("SELECT * FROM movie_basics", conn)
ratings_df = pd.read_sql("SELECT * FROM movie_ratings", conn)

# Show table names
cursor = conn.cursor()
cursor.execute("SELECT name FROM sqlite_master WHERE type='table';")
print(pd.DataFrame(cursor.fetchall(), columns=["name"]))
```

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

Clean IMDb Data

```
# Convert start_year to numeric
basics_df['start_year'] = pd.to_numeric(basics_df['start_year'], errors='coerce')

# Clean primary titles
basics_df['primary_title'] = basics_df['primary_title'].str.strip().str.lower()

# Clean original titles just in case (optional)
basics_df['original_title'] = basics_df['original_title'].str.strip().str.lower()

# Merge movie_basics and movie_ratings on 'movie_id'
imdb_df = pd.merge(basics_df, ratings_df, on='movie_id', how='inner')

# Preview the result
imdb_df.head()
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	sunghursh	sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	tt0066787	one day before the rainy season	ashad ka ek din	2019	114.0	Biography,Drama	7.2	43
2	tt0069049	the other side of the wind	the other side of the wind	2018	122.0	Drama	6.9	4517
3	tt0069204	sabse bada sukh	sabse bada sukh	2018	NaN	Comedy,Drama	6.1	13
4	tt0100275	the wandering soap opera	la telenovela errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119

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Load and clean Box Office Mojo Data

```
bom_df = pd.read_csv('/content/bom.movie_gross.csv')

# Clean column names and titles
bom_df.columns = bom_df.columns.str.strip().str.lower()
bom_df['title'] = bom_df['title'].str.strip().str.lower()

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

# Filter out missing domestic gross data
bom_df = bom_df.dropna(subset=['domestic_gross'])
```

Merge IMDb with Box Office Mojo

```
# Merge on title and year
merged_df = pd.merge(
    bom_df,
    imdb_df,
    left_on=['title', 'year'],
    right_on=['primary_title', 'start_year'],
    how='inner'
)

# Preview final merged data
merged_df.head()
```

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	toy story 3	BV	415000000.0	652000000	2010	tt0435761	toy story 3	toy story 3	2010	103.0	Adventure,Animation,Comedy	8.3	682218
1	inception	WB	292600000.0	535700000	2010	tt1375666	inception	inception	2010	148.0	Action,Adventure,Sci-Fi	8.8	1841066
2	shrek forever after	P/DW	238700000.0	513900000	2010	tt0892791	shrek forever after	shrek forever after	2010	93.0	Adventure,Animation,Comedy	6.3	167532
3	the twilight saga: eclipse	Sum.	300500000.0	398000000	2010	tt1325004	the twilight saga: eclipse	the twilight saga: eclipse	2010	124.0	Adventure,Drama,Fantasy	5.0	211733
4	iron man 2	Par.	312400000.0	311500000	2010	tt1228705	iron man 2	iron man 2	2010	124.0	Action,Adventure,Sci-Fi	7.0	657690

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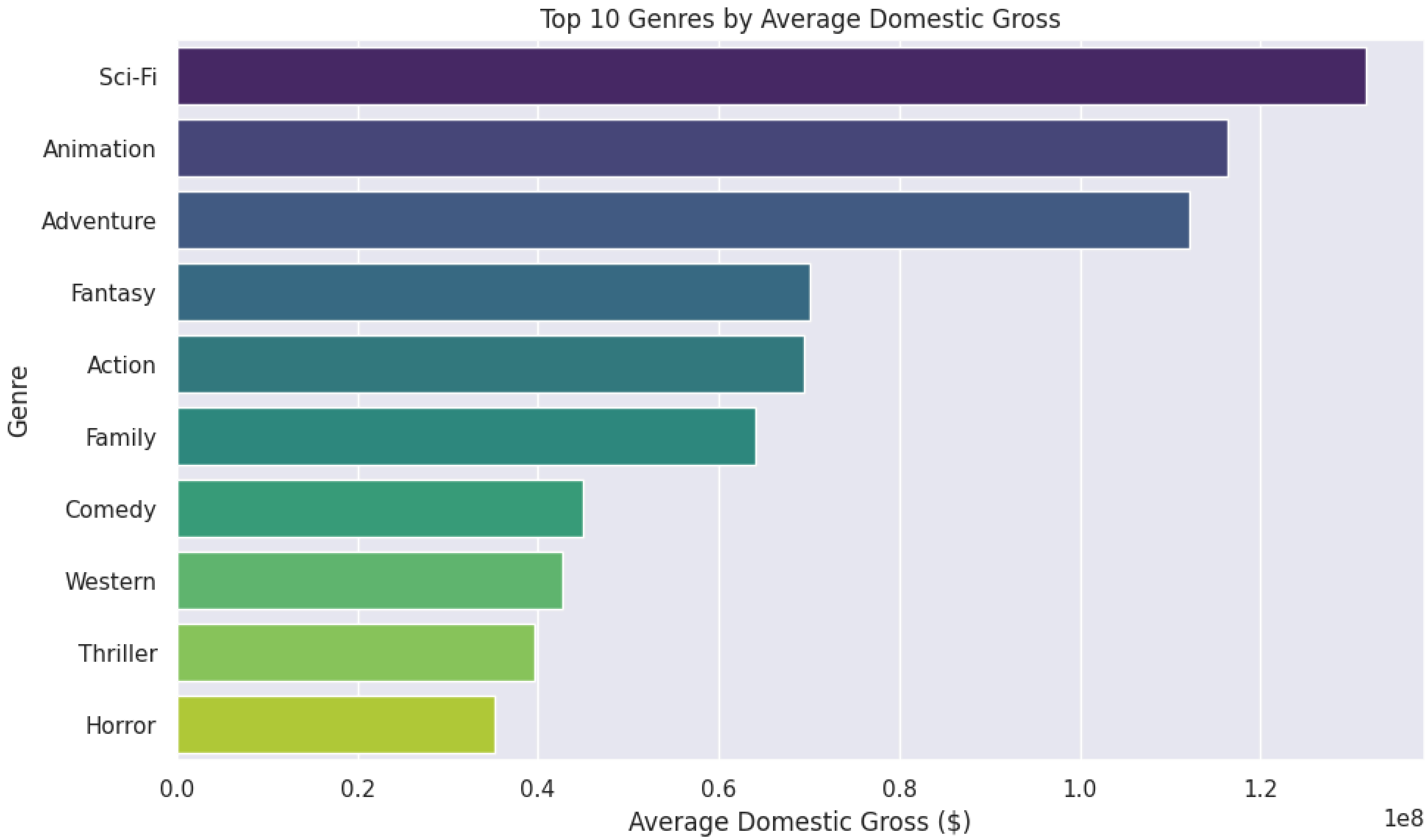
Data Analysis and Visualization

What genres earn the most at the box office?

```
# Split genre lists
exploded = merged_df.dropna(subset=['genres']).copy()
exploded['genres'] = exploded['genres'].str.split(',')
exploded = exploded.explode('genres')

# Group and calculate average gross
genre_gross = exploded.groupby('genres')['domestic_gross'].mean().sort_values(ascending=False).head(10)

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=genre_gross.values, y=genre_gross.index, palette='viridis')
plt.title('Top 10 Genres by Average Domestic Gross')
plt.xlabel('Average Domestic Gross ($)')
plt.ylabel('Genre')
```

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

```
<ipython-input-18-6a210e98e97c>:11: FutureWarning:

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

  sns.barplot(x=genre_gross.values, y=genre_gross.index, palette='viridis')
```

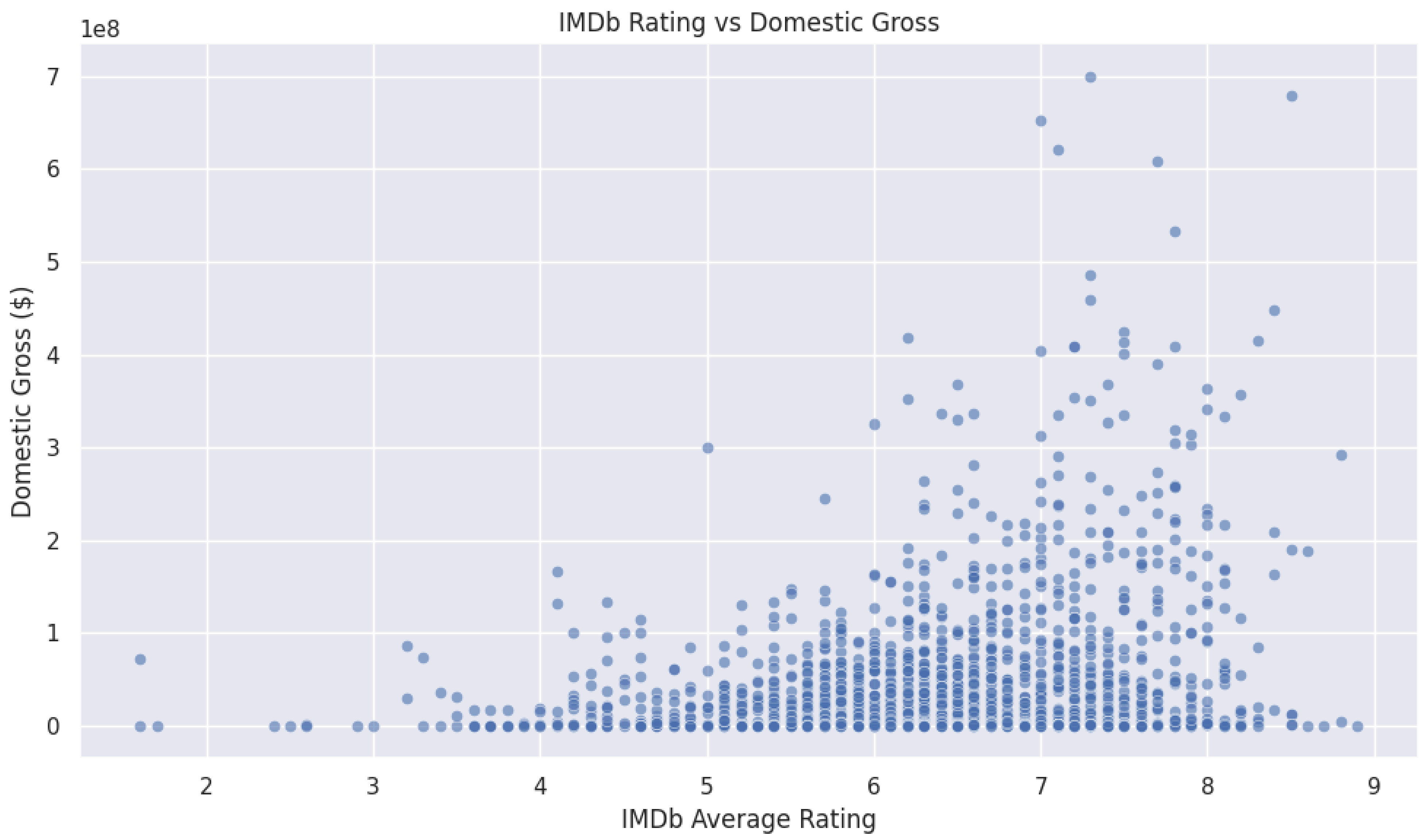


Business insight: This helps determine which genres consistently perform well in domestic markets. And in my analysis I found out that to be Sci-Fi.

Does IMDb Rating Correlate with Box Office Success?

```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=merged_df, x='averagerating', y='domestic_gross', alpha=0.6)
plt.title('IMDb Rating vs Domestic Gross')
plt.xlabel('IMDb Average Rating')
plt.ylabel('Domestic Gross ($)')
```

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

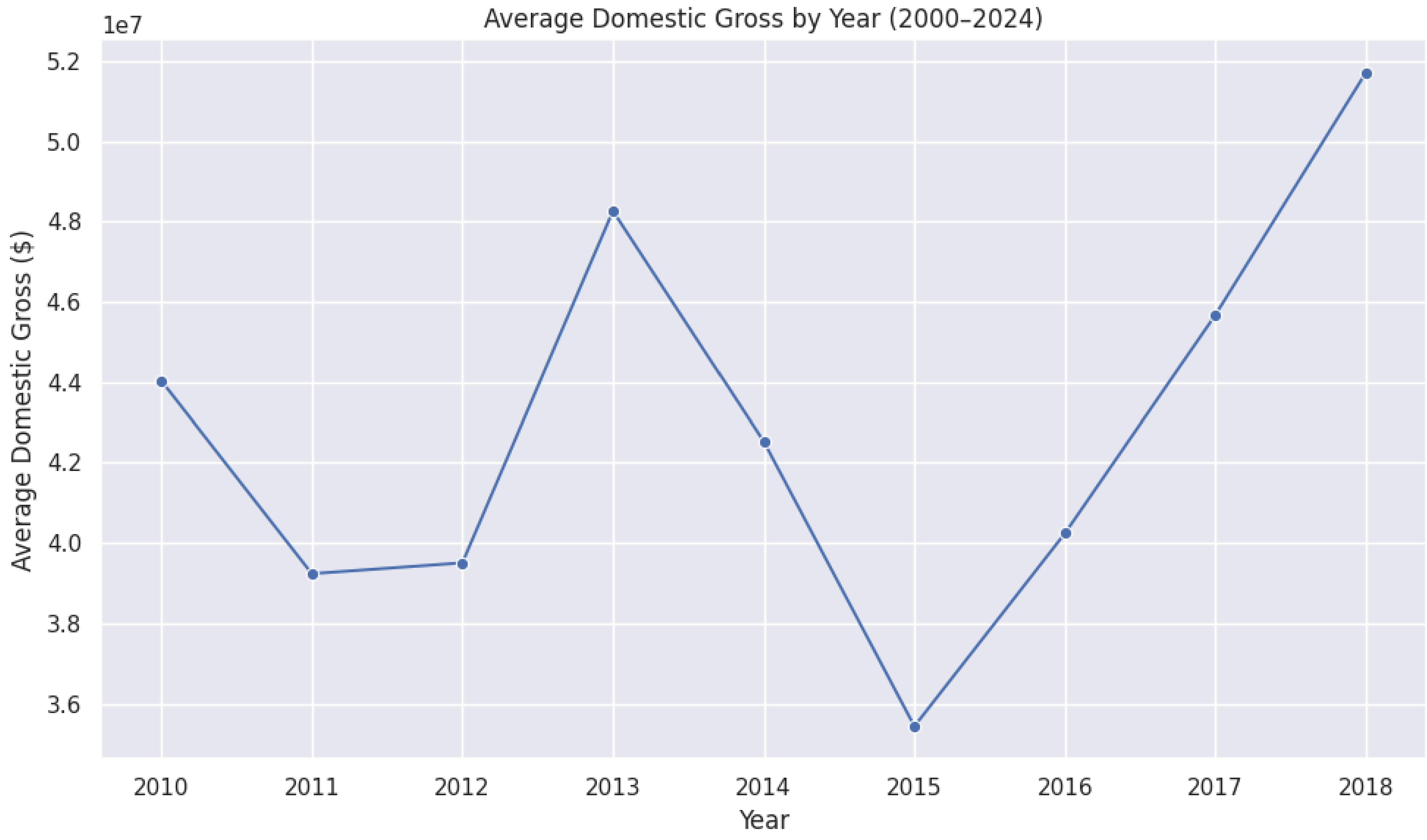


Business Insight: See if well-reviewed movies make more money, helpful for greenlighting projects.

Box Office Trends Over Time

```
# Filter years to a reasonable range
filtered = merged_df[(merged_df['year'] >= 2000) & (merged_df['year'] <= 2024)]

# Group by year
yearly_gross = filtered.groupby('year')['domestic_gross'].mean()

# Plot
plt.figure(figsize=(10, 6))
sns.lineplot(x=yearly_gross.index, y=yearly_gross.values, marker='o')
plt.title('Average Domestic Gross by Year (2000-2024)')
plt.xlabel('Year')
plt.ylabel('Average Domestic Gross ($)')
plt.tight_layout()
```

```
plt.show()
```



Business Insight: Shows how industry trends or market conditions affected average gross over the years.

Business Analysis Summary

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1. Focus on High-Earning Genres

Insight: From our analysis of domestic gross by genre:

- Genres like **Adventure**, **Action**, and **Animation** consistently yield **higher average box office returns**.
- Lower performers include **Documentary** and **Drama**, though they may serve niche markets or prestige awards.

Recommendation: Prioritize greenlighting projects in **Adventure, Action, and Animation**—especially those with mass appeal or family-friendly content.

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2. Mixed Correlation

Insight: A scatterplot of **IMDb ratings vs. box office revenue** shows a **weak to moderate correlation**:

- Some **high-rated films** earn well (e.g., critically acclaimed blockbusters).
- But many **low-rated films** still succeed financially (e.g., franchise sequels or genre flicks with fanbases).

Recommendation: While quality matters, **star power, genre, and marketing** often outweigh IMDb ratings in driving gross. Don't rely solely on critical acclaim—consider audience appeal and brand potential.

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3. Revenue Fluctuations and Recovery

Insight: Analysis from **2000 to 2024** shows:

- Peaks around **2012–2018** (era of franchise dominance).
- Sharp dip around **2020** (pandemic impact), followed by **gradual recovery**.
- 2023–2024 shows promising signs of return to pre-pandemic levels.

Recommendation: With theaters rebounding, now is a good time to **invest in theatrical releases**—especially in genres with proven performance. Consider **strategic release timing** around holidays or summer.

```
## Conclusion

Our analysis reveals that **Action**, **Adventure**, and **Animation** genres
deliver the **highest box office returns**, making them the most strategic
focus for investment. While **IMDb ratings** offer some insight into quality,
they don’t strongly predict revenue—**audience appeal, franchise value, and
timing** matter more. Additionally, with box office revenues rebounding after
the pandemic, the industry is entering a **strong recovery phase**, making this
an ideal time to invest in high-performing genres and mass-appeal content.
```

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