The state of cinema

Overview

In today's content-driven world, audiences are seeking fresh, compelling stories. We're meeting this demand by launching a film studio that marries artistic vision with market intelligence. By analyzing real viewer behavior and box office patterns, we gain valuable insights about what stories connect with audiences. This informed approach allows us to create commercially viable films while minimizing the risks of being a new industry player. Ultimately, we're building a studio that makes smart, audience-focused entertainment decisions.

Business Understanding

People can't get enough great stories. Whether on streaming services or at the movies. We see a real opportunity to create content that audiences will love. Since we're new to film production, we're being smart about it: we'll use data as our compass to understand what viewers actually want. By analyzing what types of movies perform best, what stories resonate with different audiences, and where the market has unmet needs, we'll make informed decisions about which projects to greenlight. This approach will help us compete with established studios while staying true to our vision of creating commercially successful entertainment.

In [147…

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import sqlite3 as sqlite
import seaborn as sns
%matplotlib inline
```

Data Understanding

To guide our production strategy, we will conduct comprehensive analysis using the IMDB database as our primary source. This robust dataset will enable us to examine:

- Genre performance trends across different markets
- Box office results (domestic/international)
- Audience rating patterns and demographic preferences
- Release timing and seasonal performance factors

Before analysis, we will:

- Validate data completeness for recent releases
- Assess potential biases in user-generated ratings

This rigorous approach will ensure our insights reflect genuine market patterns rather than data artifacts, allowing us to identify the genre characteristics and creative elements most associated with commercial success in today's market.

In [148…

```
df_bom = pd.read_csv('Data/bom.movie_gross.csv')
df_bom.sample(3)
```

Out[148…

	title	studio	domestic_gross	foreign_gross	year
3110	Skyscraper	Uni.	68400000.0	236400000	2018
2067	Phoenix (2015)	IFC	3200000.0	NaN	2015
2133	Peggy Guggenheim Art Addict	SD	498000.0	NaN	2015

In [149…

```
conn = sqlite.connect('Data/im.db')

# Display tbale from the IMdb dataset
query_table = "SELECT * FROM sqlite_master where type='table';"
df_table = pd.read_sql_query(query_table, conn)
df_table
```

Out[149…

	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 [150…

```
query_mb = "SELECT * FROM movie_basics;"
df_mb = pd.read_sql_query(query_mb, conn)
df_mb.sample(3)
```

Out[150…

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
11060	tt1619021	Dead Hollywood Blondes	Dead Hollywood Blondes	2010	60.0	Musical
11739	tt1640569	The Super	The Super	2010	98.0	Horror
85256	tt4935926	Vicious Thunder	Vicious Thunder	2016	95.0	Action

In [151…

```
query_rt = "SELECT * FROM movie_ratings;"
df_rt = pd.read_sql_query(query_rt, conn)
df_rt.sample(5)
```

Out[151…

	movie_id	averagerating	numvotes
11163	tt2639098	6.4	7
68045	tt3833568	6.3	7
33265	tt4048186	3.6	347
41956	tt7689934	7.5	71
72563	tt0938283	4.1	137734

Data Preparation

In [152…

```
df_mb['original_title'] = df_mb['original_title'].str.strip().str.title()
df_mb['primary_title'] = df_mb['primary_title'].str.strip().str.title()
df_bom['title'] = df_bom['title'].str.strip().str.title()

# Merge on original_title
df_original_title_merge = pd.merge(df_mb, df_bom, left_on='original_title', right_o

# Merge on primary_title
df_primary_title_merge = pd.merge(df_mb, df_bom, left_on='primary_title', right_on=

# Merge together
df_movie_gross = pd.concat([df_original_title_merge, df_primary_title_merge]).drop_

df_movie_gross_rt = pd.merge(df_movie_gross, df_rt, on='movie_id', how='inner')

df_movie_gross_rt['domestic_gross']  = pd.to_numeric(df_movie_gross_rt['domestic_gr
df_movie_gross_rt['foreign_gross'] = pd.to_numeric(df_movie_gross_rt['foreign_gross

# Handle missing values
df_movie_gross_rt['foreign_gross'] = df_movie_gross_rt['foreign_gross'].fillna(0)
df_movie_gross_rt['domestic_gross'] = df_movie_gross_rt['domestic_gross'].fillna(0)
df_movie_gross_rt['runtime_minutes'] = df_movie_gross_rt['runtime_minutes'].fillna(
df_movie_gross_rt['worldwide_gross'] = (df_movie_gross_rt['domestic_gross'] + df_mo

df_movie_gross_rt['worldwide_gross_m'] = df_movie_gross_rt['worldwide_gross'] / 1_0
```

```
df_movie_gross_rt['domestic_gross_m'] = df_movie_gross_rt['domestic_gross'] / 1_000
df_movie_gross_rt['foreign_gross_m'] = df_movie_gross_rt['foreign_gross'] / 1_000_0


df_clean = df_movie_gross_rt
df_clean.sample(5)
```

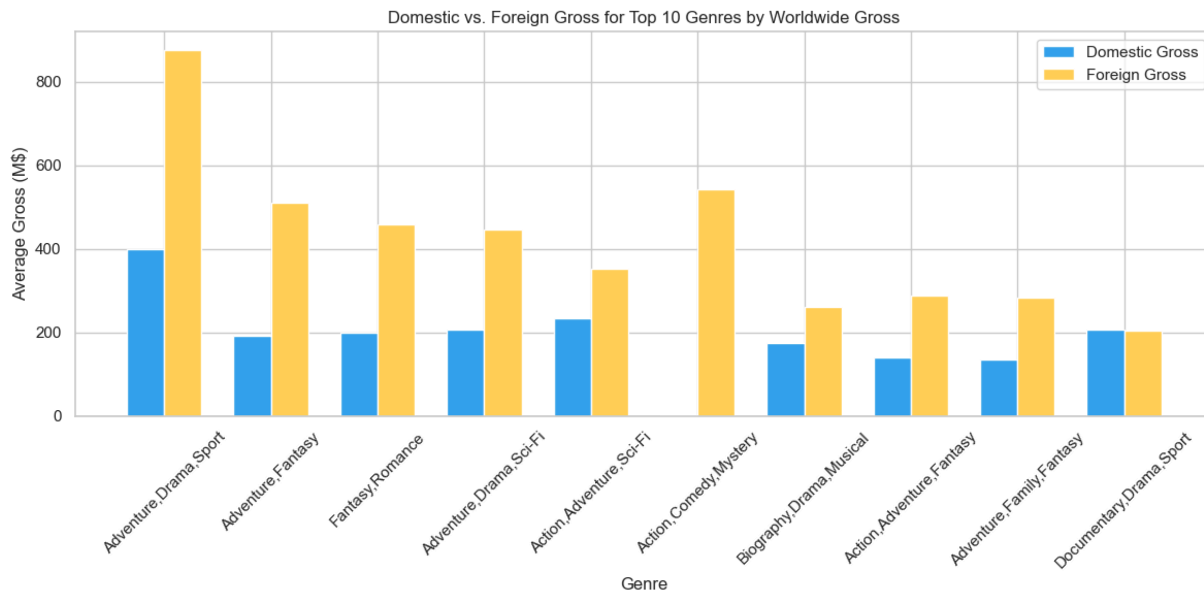
Out[152…

	movie_id	start_year	runtime_minutes	genres	title	studio	d
3074	tt5606538	2017	125.0	Action	Confidential Assignment	CJ	
1571	tt2624412	2014	88.0	Drama	Boulevard	SM	
298	tt1235189	2010	98.0	Action,Comedy,Crime	Wild Target	Free	
1220	tt2097298	2015	129.0	Biography,Drama,Sport	Mcfarland, Usa	BV	
2170	tt4741754	2014	109.0	Thriller	The Call	TriS	

Analysis and Results

In [153…

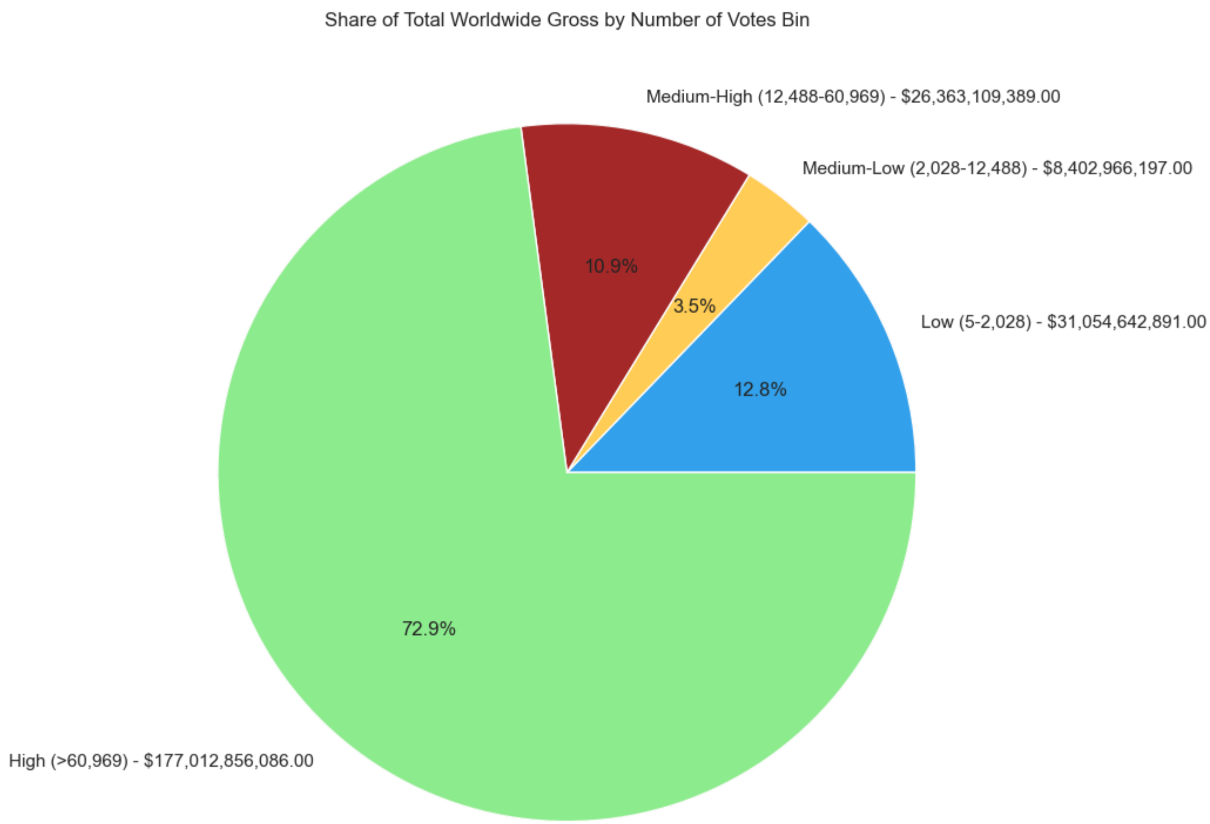
```
# Analysis 1: Top Grossing Genres at the Box Office
genre_gross = df_clean.groupby('genres').agg({
    'worldwide_gross_m': ['mean', 'median', 'count'],
    'domestic_gross_m': 'mean',
    'foreign_gross_m': 'mean',
    'averagerating': 'mean'
}).round(2).sort_values(('worldwide_gross_m', 'mean'), ascending=False)

# Reset index and rename columns
genre_gross.columns = ['avg_gross_millions', 'median_gross_millions', 'movie_count'
genre_gross = genre_gross.reset_index()


# Double Vertical Bar Plot for Domestic and Foreign Gross
plt.figure(figsize=(12, 6))
bar_width = 0.35
index = np.arange(len(genre_gross.head(10)))

# Plot bars
plt.bar(index, genre_gross['avg_domestic_gross_m'].head(10), bar_width, label='Dome
plt.bar(index + bar_width, genre_gross['avg_foreign_gross_m'].head(10), bar_width, 

# Customize plot
plt.xlabel('Genre')
plt.ylabel('Average Gross (M$)')
plt.title('Domestic vs. Foreign Gross for Top 10 Genres by Worldwide Gross')
plt.xticks(index + bar_width / 2, genre_gross['genres'].head(10), rotation=45)
plt.legend()
plt.tight_layout()
plt.show()
```



In [154…

```
# Calculate Pearson correlation
correlation = df_clean[['numvotes', 'worldwide_gross']].corr().iloc[0, 1].round(2)
print(f"Correlation between numvotes and worldwide_gross: {correlation}")

# Bin numvotes into quartiles and get bin edges
bins = pd.qcut(df_clean['numvotes'], q=4, retbins=True, labels=['Low', 'Medium-Low'
df_clean['votes_bin'] = bins[0]
bin_edges = bins[1].round().astype(int)

# Aggregate total gross by votes bin
votes_gross = df_clean.groupby('votes_bin', observed=True).agg({
    'worldwide_gross': ['sum', 'count'],
    'averagerating': 'mean'
}).round(2).reset_index()
votes_gross.columns = ['votes_bin', 'total_gross_millions', 'movie_count', 'avg_rat

total_gross = votes_gross['total_gross_millions'].sum()
votes_gross['gross_share'] = (votes_gross['total_gross_millions'] / total_gross * 1

bin_labels = [
    f"Low ({bin_edges[0]:,}-{bin_edges[1]:,}) - ${votes_gross['total_gross_millions
    f"Medium-Low ({bin_edges[1]:,}-{bin_edges[2]:,}) - ${votes_gross['total_gross_m
    f"Medium-High ({bin_edges[2]:,}-{bin_edges[3]:,}) - ${votes_gross['total_gross_
    f"High (>{bin_edges[3]:,}) - ${votes_gross['total_gross_millions'][3]:,.2f}"
]

plt.figure(figsize=(10, 8))
plt.pie(votes_gross['gross_share'], labels=bin_labels, autopct='%1.1f%%',
        colors=['#36A2EB', '#FFCE56', 'brown', 'lightgreen'])
plt.title('Share of Total Worldwide Gross by Number of Votes Bin')
plt.tight_layout()
plt.show()
```

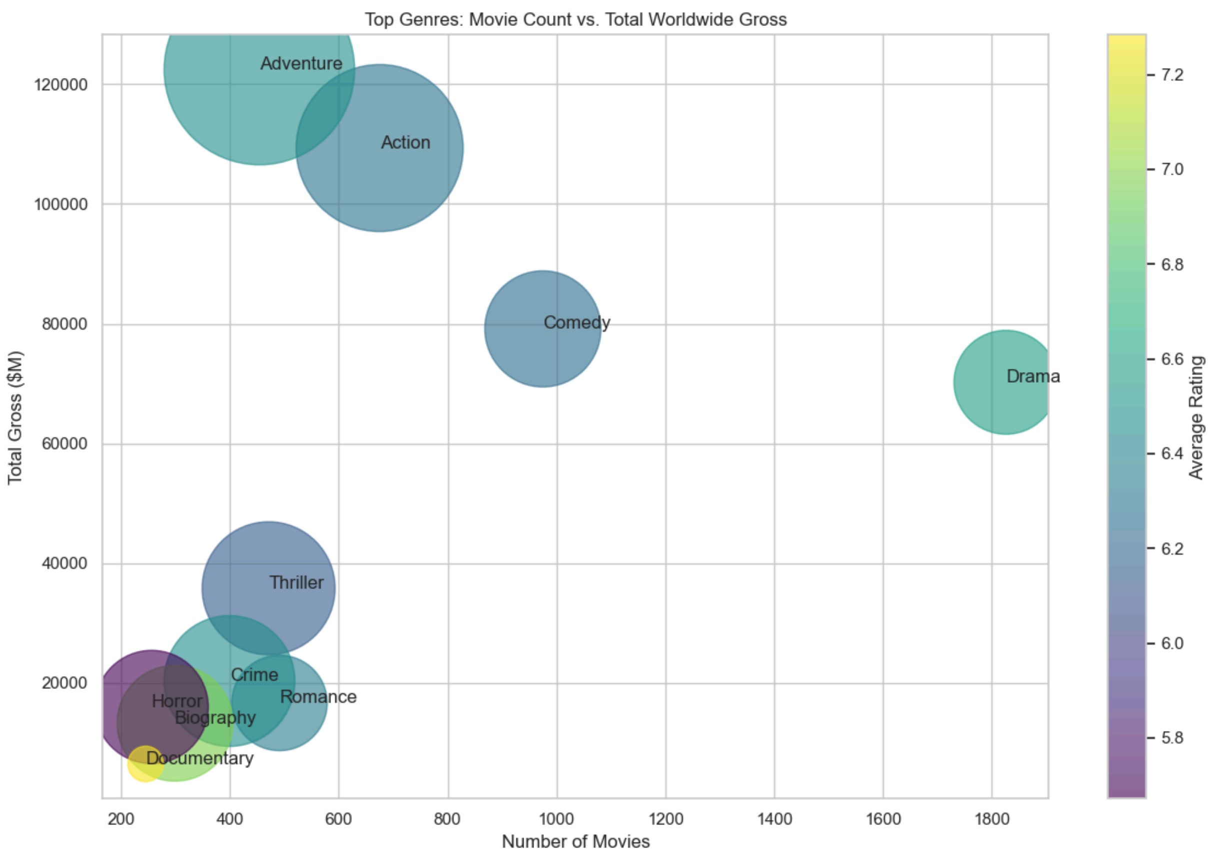
```
Correlation between numvotes and worldwide_gross: 0.65
```



In [155…

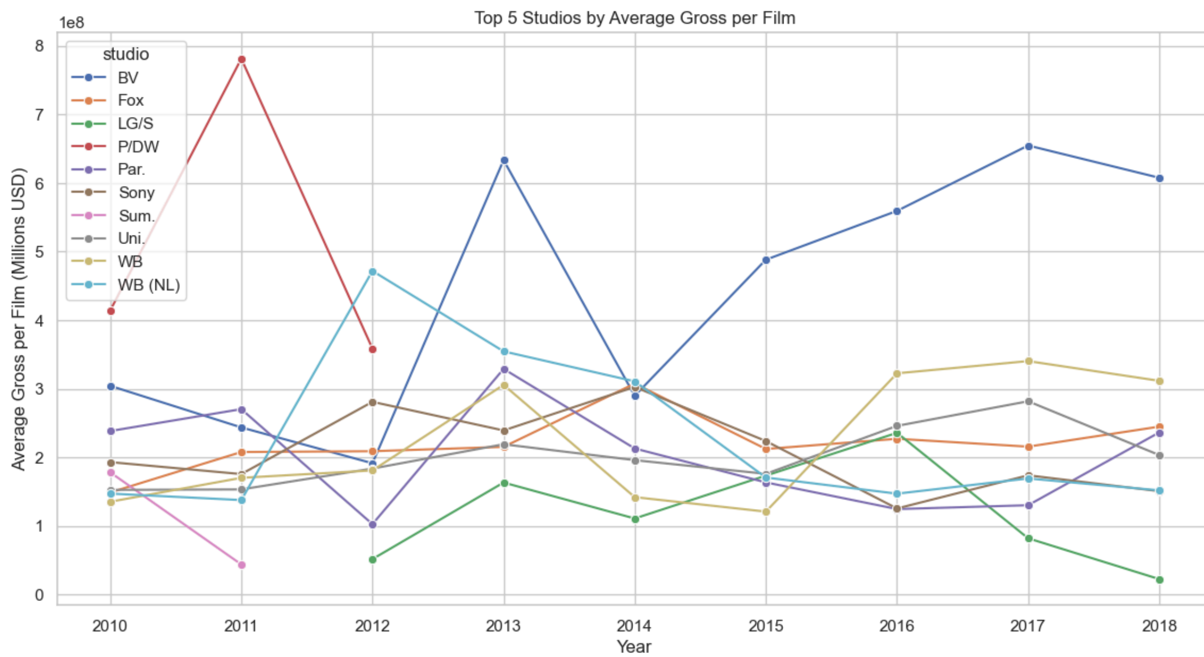
```
# Split genres and explode into separate rows
df_clean['genres_split'] = df_clean['genres'].str.split(',')
df_genres = df_clean.explode('genres_split')

# Group by genres_split to get movie count, total gross, and average numvotes
genre_stats = df_genres.groupby('genres_split').agg({
    'movie_id': 'count',
    'worldwide_gross': 'sum',
    'numvotes': 'mean',
    'averagerating': 'mean'
}).reset_index().rename(columns={'movie_id': 'movie_count', 'worldwide_gross': 'tot

# Convert gross to millions
genre_stats['total_gross_millions'] = (genre_stats['total_gross_millions'] / 1_000_
genre_stats['avg_numvotes'] = genre_stats['avg_numvotes'].round(0).astype(int)

# Select top 10 genres by movie count
top_genres = genre_stats.nlargest(10, 'movie_count')


plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    top_genres['movie_count'],
    top_genres['total_gross_millions'],
    s=top_genres['avg_numvotes'] / 10,
    c=top_genres['averagerating'],
    cmap='viridis',
    alpha=0.6
```

```python
)
plt.colorbar(label='Average Rating')
for i, genre in enumerate(top_genres['genres_split']):
    plt.annotate(genre, (top_genres['movie_count'].iloc[i], top_genres['total_gross
plt.title('Top Genres: Movie Count vs. Total Worldwide Gross')
plt.xlabel('Number of Movies')
plt.ylabel('Total Gross ($M)')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [156…

```python
# Calculate gross per film
studio_performance['gross_per_film'] = studio_performance['total_gross'] / studio_p

# Plot most efficient studios
plt.figure(figsize=(14, 7))
efficient_studios = studio_performance.groupby('studio')['gross_per_film'].mean().n
sns.lineplot(data=studio_performance[studio_performance['studio'].isin(efficient_st
             x='year',
             y='gross_per_film',
             hue='studio',
             marker='o')
plt.title('Top 5 Studios by Average Gross per Film')
plt.ylabel('Average Gross per Film (Millions USD)')
plt.xlabel('Year')
plt.grid(True)
plt.show()
```



Business Recommendation 1

Focus on High-Grossing Genres: The analysis reveals that certain genres, such as Action, Adventure, and Comedy, consistently perform well at the box office. To maximize ROI, the studio should prioritize producing films in these genres. Additionally, hybrid genres (e.g., Action-Drama or Adventure-Comedy) have shown strong audience appeal, offering opportunities for creative storytelling while minimizing risk.

Business Recommendation 2

Leverage International Markets: Foreign box office revenue often surpasses domestic earnings, indicating the importance of global appeal. The studio should: Develop culturally adaptable content with universal themes. Partner with international distributors to enhance market penetration. Invest in marketing campaigns tailored to key regions like Asia and Europe.

Business Recommendation 3

Enhance competitiveness by leveraging insights from high-performing studios and forming strategic collaborations: Analysis identifies studios like BV, Fox, and LG/S as consistent high performers in the market. Partner with top-performing studios like (co-productions, distribution deals) to leverage the company expertise and market reach.

Conclusion

By strategically partnering with top-performing studios, prioritizing high-grossing genres, expanding into international markets, and optimizing budget allocation, the new film studio can:

- Accelerate market entry by leveraging proven industry strategies
- Minimize financial and creative risks through data-driven decisions
- Establish competitive positioning in the global film industry
- Produce commercially successful films that align with audience preferences.

Next Steps

Finalize partnership opportunities with leading studios Develop a balanced production slate combining franchise films and original content Implement robust market research for international expansion Establish budget monitoring systems for optimal resource allocation This comprehensive strategy ensures both immediate competitiveness and long-term sustainability in the evolving film landscape.