FINAL PROJECT SUBMISSION

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FILM PRODUCTION ANALYSIS

INTRO

Data-driven decision-making has become crucial to ensuring successful investments, targeted marketing, and sustained growth in the film production industry.

This analysis focuses on evaluating and comparing the performance of films listed on several key platforms i.e; Box Office Mojo, The Numbers, and The Movie Database (TMDb).

BUSINESS UNDERSTANDING

A production company must understand what factors contribute to a movie's success commercially before investing in new films. This entails revenue and also how movies perform across audience platforms.

Business Questions

Which movie language performs best among different platforms

What trends exist across genres, release periods, and production budgets in relation to success?

What is the ideal runtime minutes for a movie?

Can early popularity forecast long-term success?

Objectives

Identifying the top ranking movie genres over time

Examining trends in average gross revenue of films over time.

Determining the release months with the highest audience engagement

Examining movie production budget over the years

Identifying ROI trends over the years

Ranking the top 10 highest-grossing film studios

Determining the most popular movie languages

DATA UNDERSTANDING

For this analysis, I used 3 datasets.

Box Office Mojo

Providing revenue statistics for movies published in the Website.

The Movie Database(TMDb)

Also provides useful elements for movies published in the Movie database

The Numbers

Provides revenue data from The numbers dataset

DATA PREPARATION

In [6]:
```
#Importing all the necessary libraries

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
from numbers import Number
import sqlite3
from scipy import stats
%matplotlib inline
import os
import zipfile
```

Loading the Box Office Mojo dataset

In [7]:
```
bom_df = pd.read_csv("bom.movie_gross.csv.gz")
```

Reading the first 5 rows

In [8]:
```
bom_df.head()
```

Out[8]:

	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

Viewing the last rows of the df

In [9]:
```
bom_df.tail()
```

Out[9]:

	title	studio	domestic_gross	foreign_gross	year
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

Identifying the number of rows and columns

In [34]:
```
bom_df.shape
```

Out[34]:
```
(3387, 5)
```

The box office dataframe has 3,387 rows and 5 columns.

In [33]:
```
bom_df.columns
```

Out[33]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='object')
```

title Contains the title of the movies

studio column has abbreviated names of the studios producing the respective movie

domestic_gross column shows the amount of revenue generated by the movie through sales, locally

foreign_gross shows the amount of revenue generated by the movie internationally

year shows the year when the movie was premiered

Showing a summary of the df

In [32]:
```
bom_df.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 [31]:
```
#range of the rows of the df
bom_df.index
```

Out[31]:
```
RangeIndex(start=0, stop=3387, step=1)
```

In [37]:
```
bom_df.dtypes
```

Out[37]:
```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
```

Detecting NaN Values

In [39]:
```
#All cells containing NaN are converted to True, and all cells containing valid data are convert
bom_df.isna()
```

Out[39]:

	title	studio	domestic_gross	foreign_gross	year
0	False	False	False	False	False
1	False	False	False	False	False
2	False	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	False
...	...	...	...	...	...
3382	False	False	False	True	False
3383	False	False	False	True	False
3384	False	False	False	True	False
3385	False	False	False	True	False
3386	False	False	False	True	False

3387 rows × 5 columns

Number of NaN values in the dataset by columns

In [40]:
```
bom_df.isna().sum()
```

Out[40]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

Filling NaN with no values

In [41]:
```
bom_df.fillna('')
```

Out[41]:

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0		2018
3383	Edward II (2018 re-release)	FM	4800.0		2018
3384	El Pacto	Sony	2500.0		2018
3385	The Swan	Synergetic	2400.0		2018
3386	An Actor Prepares	Grav.	1700.0		2018

3387 rows × 5 columns

THE MOVIE DATABASE

Loading the tm dataset

In [34]:
```
tmdb_df = pd.read_csv("tmdb.movies.csv.gz")
```

In [35]:
```
#Viewing the first five rows
tmdb_df.head()
```

Out[35]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	

In [36]:
```
#Checking the last five rows
tmdb_df.tail()
```

Out[36]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	v
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.6	2018-10-13	Laboratory Conditions	
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.6	2018-05-01	_EXHIBIT_84xxx_	
26514	26514	[14, 28, 12]	381231	en	The Last One	0.6	2018-10-01	The Last One	
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.6	2018-06-22	Trailer Made	
26516	26516	[53, 27]	309885	en	The Church	0.6	2018-10-05	The Church	

In [37]:
```
#Identifying the number of rows ad columns
tmdb_df.shape
```

Out[37]:
```
(26517, 10)
```

The movie database has 26,517 rows and 10 columns

In [38]:
```
#Showing the columns
tmdb_df.columns
```

Out[38]:
```
Index(['Unnamed: 0', 'genre_ids', 'id', 'original_language', 'original_title',
       'popularity', 'release_date', 'title', 'vote_average', 'vote_count'],
      dtype='object')
```

In [39]:
```
#Showing a summary of the tmdb df
tmdb_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 [ ]:
```
Detecting the NaN values
```

Number of NaN values in the dataset by columns

In [40]:
```
tmdb_df.isna().sum()
```

Out[40]:
```
Unnamed: 0           0
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

Now it is evident there are no NaN values in the movies database thus the data is clean.

Checking for missing/null values in the dataset

In [41]:
```
tmdb_df.isnull()
```

Out[41]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote
0	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	
26512	False	False	False	False	False	False	False	False	False	
26513	False	False	False	False	False	False	False	False	False	
26514	False	False	False	False	False	False	False	False	False	
26515	False	False	False	False	False	False	False	False	False	
26516	False	False	False	False	False	False	False	False	False	

26517 rows × 10 columns

Counting missing values per column

In [42]:
```
tmdb_df.isnull().sum()
```

Out[42]:
```
Unnamed: 0           0
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

As you can see,this dataset has not a single missing value and is intact

THE NUMBERS DATASET

In [17]:
```
#Loading the dataset
tn_budget = pd.read_csv("tn.movie_budgets.csv.gz")
```

In [18]:
```
#Viewing the first five rows
tn_budget.head()
```

Out[18]:

	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 [19]:
```
#Viewing the last five rows
tn_budget.tail()
```

Out[19]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

DATA CLEANING

Box Office Mojo

Detecting NaN values

In [93]:
```
bom_df.isna()
```

Out[93]:

	title	studio	domestic_gross	foreign_gross	year
0	False	False	False	False	False
1	False	False	False	False	False
2	False	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	False
...	...	...	...	...	...
3382	False	False	False	True	False
3383	False	False	False	True	False
3384	False	False	False	True	False
3385	False	False	False	True	False
3386	False	False	False	True	False

3387 rows × 5 columns

All cells containing NaN are converted to True, and all cells containing valid data are converted to False

In [92]:
```
#Counting missing values per column

round((bom_df.isnull().sum()/ len(bom_df))*100,2)
```

Out[92]:
```
title              0.00
studio             0.15
domestic_gross     0.83
foreign_gross     39.86
year               0.00
dtype: float64
```

foreign_gross holds the highest number of missing values, with 39.86% of its data missing. This can be calculated using other columns like domestic_gross and creating another column called total_gross then computing using the mean of the total gross column.

In [94]:
```
# Convert the two numeric number columns from strings to float datatypes

bom_df['foreign_gross'] = pd.to_numeric(bom_df['foreign_gross'], errors='coerce')

# Calculate another column Total_gross for total gross generated both locally and internationaly

bom_df['Total_gross'] = bom_df['domestic_gross'] + bom_df['foreign_gross']
bom_df.head()
```

Out[94]:

	title	studio	domestic_gross	foreign_gross	year	Total_gross
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08

In [96]:
```
# Use the mean total gross to fill missing values for foreign gross

mean_total = bom_df['Total_gross'].mean()
bom_df.loc[bom_df['foreign_gross'].isna(), 'foreign_gross'] = (
    mean_total - bom_df.loc[bom_df['foreign_gross'].isna(), 'domestic_gross']
)
```

In [110]:
```
#Count for the remaining missing values
round((bom_df.isnull().sum()/ len(bom_df))*100,2)
```

Out[110]:
```
title             0.0
studio            0.0
domestic_gross    0.0
foreign_gross     0.0
year              0.0
Total_gross       0.0
dtype: float64
```

The remaining data has a few missing values that can be dropped now without having a significant effect on our data

In [99]:
```
bom_df= bom_df.dropna()
```

In [100]:
```
#Checking the last rows to see if the remaining missing values are all dropped
bom_df.tail()
```

Out[100]:

	title	studio	domestic_gross	foreign_gross	year	Total_gross
3275	I Still See You	LGF	1400.0	1500000.0	2018	1501400.0
3286	The Catcher Was a Spy	IFC	725000.0	229000.0	2018	954000.0
3309	Time Freak	Grindstone	10000.0	256000.0	2018	266000.0
3342	Reign of Judges: Title of Liberty - Concept Short	Darin Southa	93200.0	5200.0	2018	98400.0
3353	Antonio Lopez 1970: Sex Fashion & Disco	FM	43200.0	30000.0	2018	73200.0

The Movies DataBase (TMDB)

Checking any null values in the dataset

In [43]:
```
round((tmdb_df.isnull().sum()/ len(tmdb_df))*100,2)
```

Out[43]:
```
Unnamed: 0           0.0
genre_ids            0.0
id                   0.0
original_language    0.0
original_title       0.0
popularity           0.0
release_date         0.0
title                0.0
vote_average         0.0
vote_count           0.0
dtype: float64
```

There are no null values in the dataset above and everything is as it should be.

The Numbers Dataset

In [20]:
```

round((tn_budget.isnull().sum()/ len(tn_budget))*100,2)
```

Out[20]:
```
id                   0.0
release_date         0.0
movie                0.0
production_budget    0.0
domestic_gross       0.0
worldwide_gross      0.0
dtype: float64
```

This dataset has no missing values but we need to check for info and find out if the datasets are in the correct format

In [113]:
```
tn_budget.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
```

Some of these columns need to be floats but they are object type.

In [21]:
```
#Convert the date column into a pandas-recognizable datetime format

tn_budget['release_date'] = pd.to_datetime(tn_budget['release_date'])
```

In [22]:
```
columns = ['domestic_gross', 'production_budget', 'worldwide_gross']

# Remove $ and commas, then convert to float

for col in columns:
    tn_budget[col] = tn_budget[col].replace(r'[\$,]', '', regex=True).astype(float)
```

In [116]:
```
#Checking if the corrections are in place
tn_budget.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   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(1)
memory usage: 271.2+ KB
```

From here we then move to data analysis

DATA ANALYSIS

Box Office Mojo

Calculating the trends of both foreign and domestic gross over the years

In [117]:
```
#Using the Box Office Mojo dataset
bom_df.head()
```

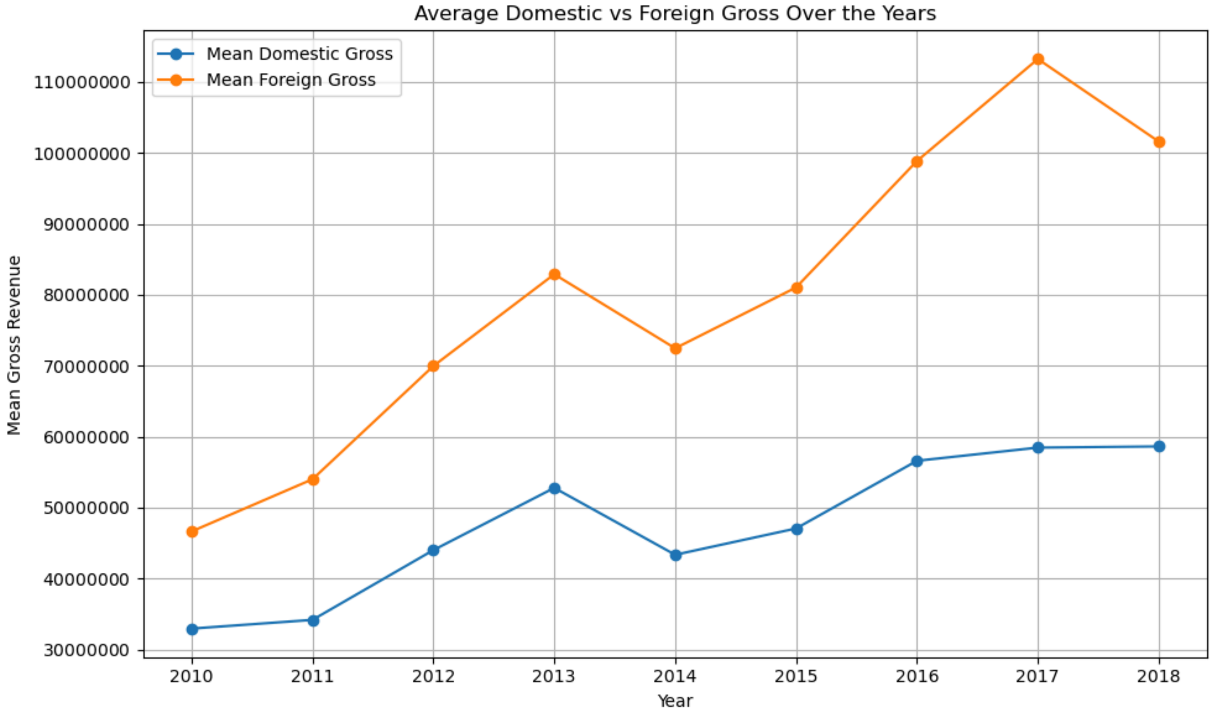
Out[117]:

	title	studio	domestic_gross	foreign_gross	year	Total_gross
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08

In [118]:
```
#Grouping the data
gross_by_year = bom_df.groupby('year')[['domestic_gross', 'foreign_gross', 'Total_gross']].mean(
```

Visualizing comparison between the domestic gross and foreign gross

In [119]:
```
#Create plots.
#Use ticker to ensure visualizations are well labelled

import matplotlib.ticker as ticker
plt.figure(figsize=(10, 6))
plt.plot(gross_by_year['year'], gross_by_year['domestic_gross'], label='Mean Domestic Gross', ma
plt.plot(gross_by_year['year'], gross_by_year['foreign_gross'], label='Mean Foreign Gross', mark
plt.gca().yaxis.set_major_formatter(ticker.ScalarFormatter(useMathText=True))
plt.ticklabel_format(style='plain', axis='y')  # Ensures full number display
plt.xlabel('Year')
plt.ylabel('Mean Gross Revenue')
plt.title('Average Domestic vs Foreign Gross Over the Years')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



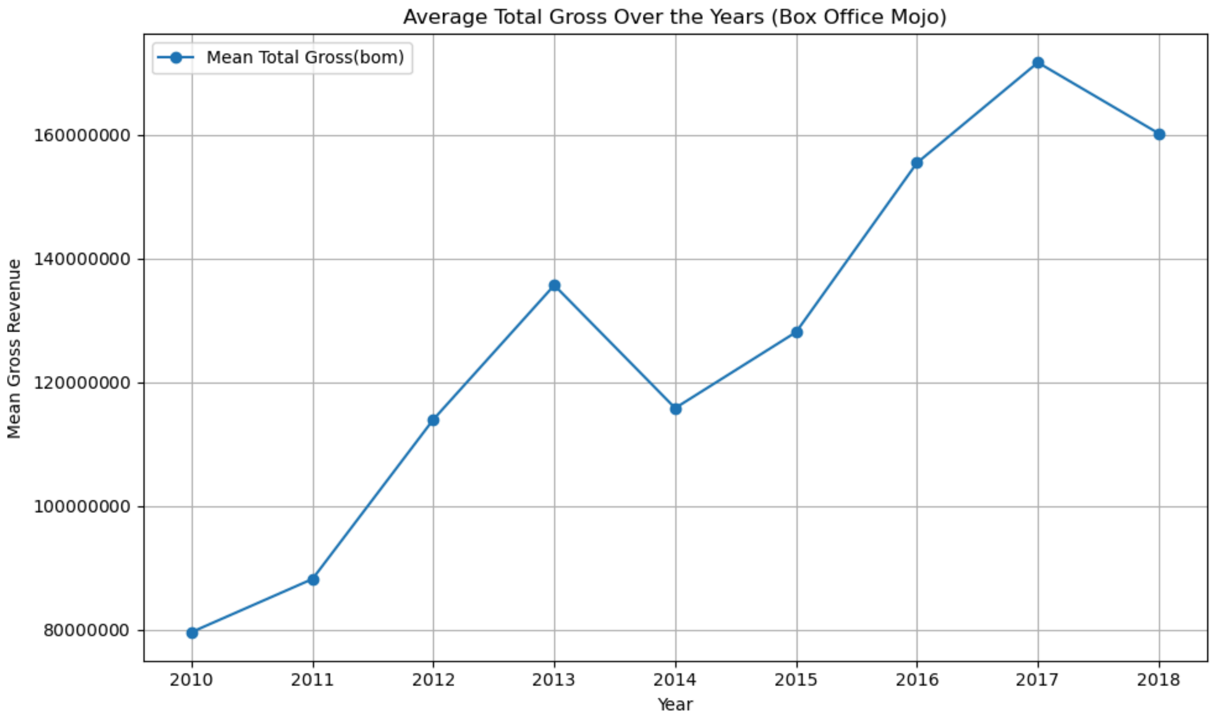
In [120]:
```
gross_by_year.value_counts()
```

Out[120]:
```
year  domestic_gross  foreign_gross  Total_gross
2010  3.296345e+07    4.665380e+07   7.961725e+07    1
2011  3.419203e+07    5.400989e+07   8.820192e+07    1
2012  4.402413e+07    6.997113e+07   1.139953e+08    1
2013  5.279425e+07    8.290121e+07   1.356955e+08    1
2014  4.336745e+07    7.246439e+07   1.158318e+08    1
2015  4.707417e+07    8.103932e+07   1.281135e+08    1
2016  5.661299e+07    9.886140e+07   1.554744e+08    1
2017  5.847027e+07    1.132326e+08   1.717028e+08    1
2018  5.863697e+07    1.015959e+08   1.602328e+08    1
dtype: int64
```

There is a visible increase in the mean foreign gross from 498,986,300 in 2010 to 1,071,536,000 in 2018

Now visualize The total gross of both domestic and foreign gross

In [125]:
```
plt.figure(figsize=(10, 6))
plt.plot(gross_by_year['year'], gross_by_year['Total_gross'], label='Mean Total Gross(bom)', mar
plt.gca().yaxis.set_major_formatter(ticker.ScalarFormatter(useMathText=True))
plt.ticklabel_format(style='plain', axis='y')  # Ensures full number display
plt.xlabel('Year')
plt.ylabel('Mean Gross Revenue')
plt.title('Average Total Gross Over the Years (Box Office Mojo)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



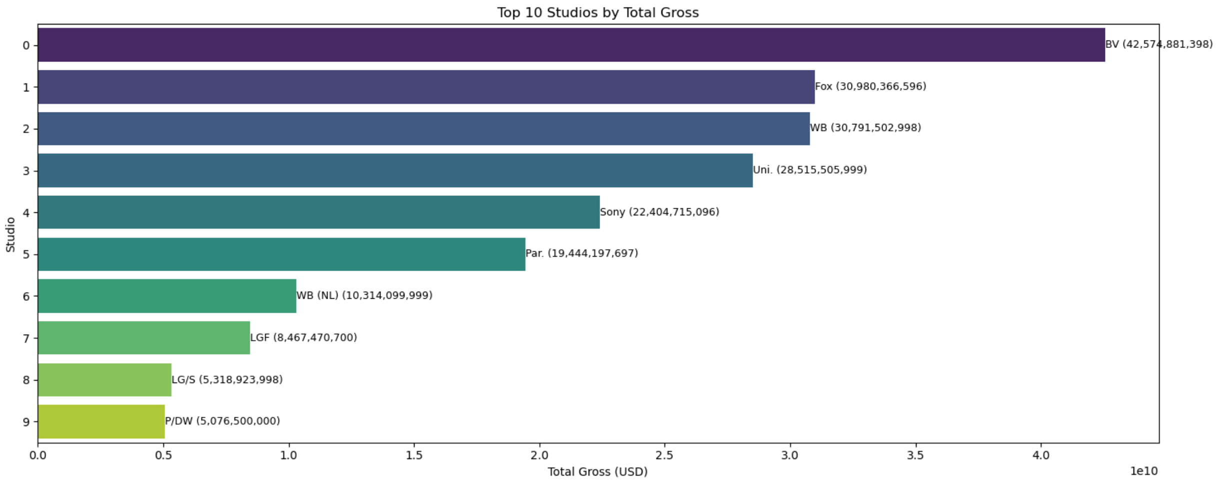
Increase in gross is more visible in the total gross, increasing from 814,415,800 in 2010 to 1,431,640,000 in 2018.

Determining the highest grossing studios

In [135]:
```
bom_df['studio'].value_counts()
```

Out[135]:
```
Uni.            141
Fox             134
WB              130
Sony            105
BV              102
               ...
AGF               1
Icar.             1
MPFT              1
KC                1
Darin Southa      1
Name: studio, Length: 172, dtype: int64
```

In [137]:
```
#Grouping the data first, by studio and calculate the total gross per category

studio_gross = bom_df.groupby('studio')['Total_gross'].sum().sort_values(ascending=False).head(1

#Plot the visualization
plt.figure(figsize=(15,6))
sns.barplot(x=studio_gross.values, y=studio_gross.index, palette='viridis', )
plt.gca().yaxis.set_major_formatter(ticker.ScalarFormatter(useMathText=True))
plt.ticklabel_format(style='plain', axis='y')

# Ensure that it displays the names

for i, (value, name) in enumerate(zip(studio_gross.values, studio_gross.index)):
    plt.text(value + 1e6, i, f'{name} ({value:,.0f})', va='center', fontsize=9)

plt.title("Top 10 Studios by Total Gross")
plt.xlabel("Total Gross (USD)")
plt.ylabel("Studio")
plt.tight_layout()
plt.show()
```



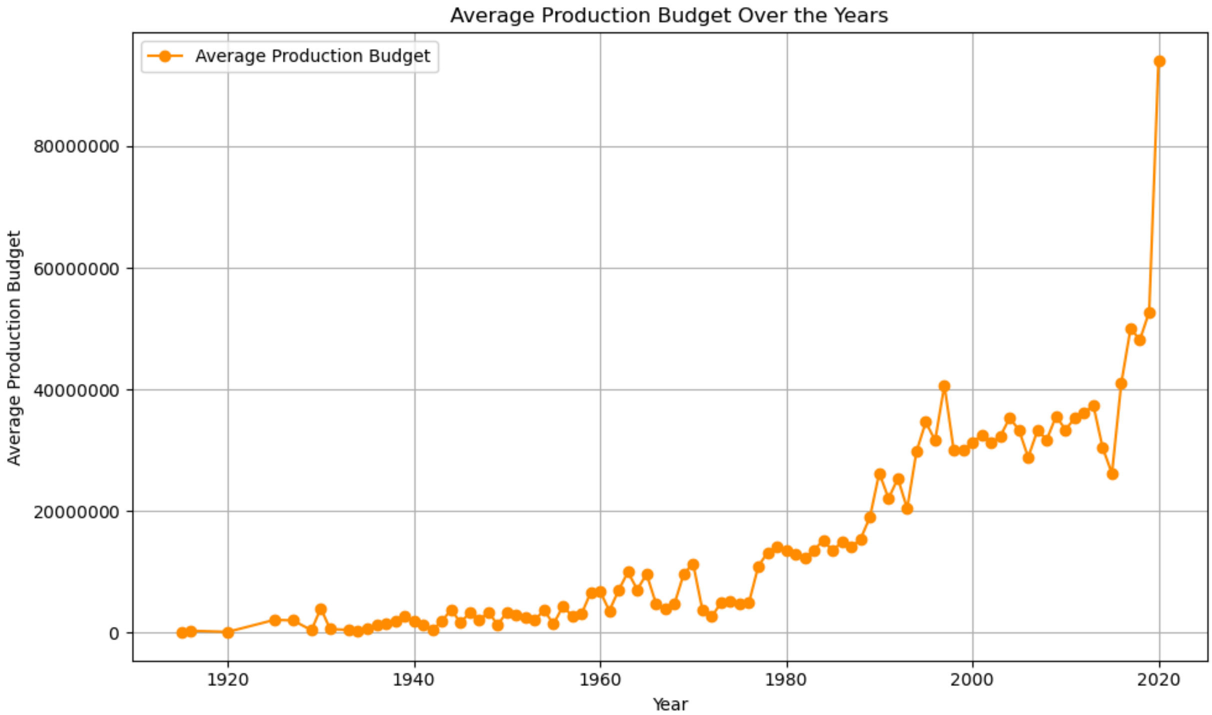
The top ten most grossing studios are BV down to P/DW with their respective total gross alongside each.

The Numbers Dataset

The numbers production budget over the years

In [123]:
```
# Retrieving the year from the date time

tn_budget['year'] = tn_budget['release_date'].dt.year

# Group by year
avg_budget_by_year = tn_budget.groupby('year', as_index=False)['production_budget'].mean()
```

In [126]:
```
# Plotting the production budget

plt.figure(figsize=(10, 6))
plt.plot(avg_budget_by_year['year'], avg_budget_by_year['production_budget'], label='Average Pro
plt.gca().yaxis.set_major_formatter(ticker.ScalarFormatter(useMathText=True))
plt.ticklabel_format(style='plain', axis='y')
plt.xlabel('Year')
plt.ylabel('Average Production Budget')
plt.title('Average Production Budget Over the Years')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



We can see an increase from 1,100,000 in 1915 to 940,000,000 in 2020, thus indicating that the budget increased gradually over time.

In [127]:
```
avg_budget_by_year .value_counts()
```

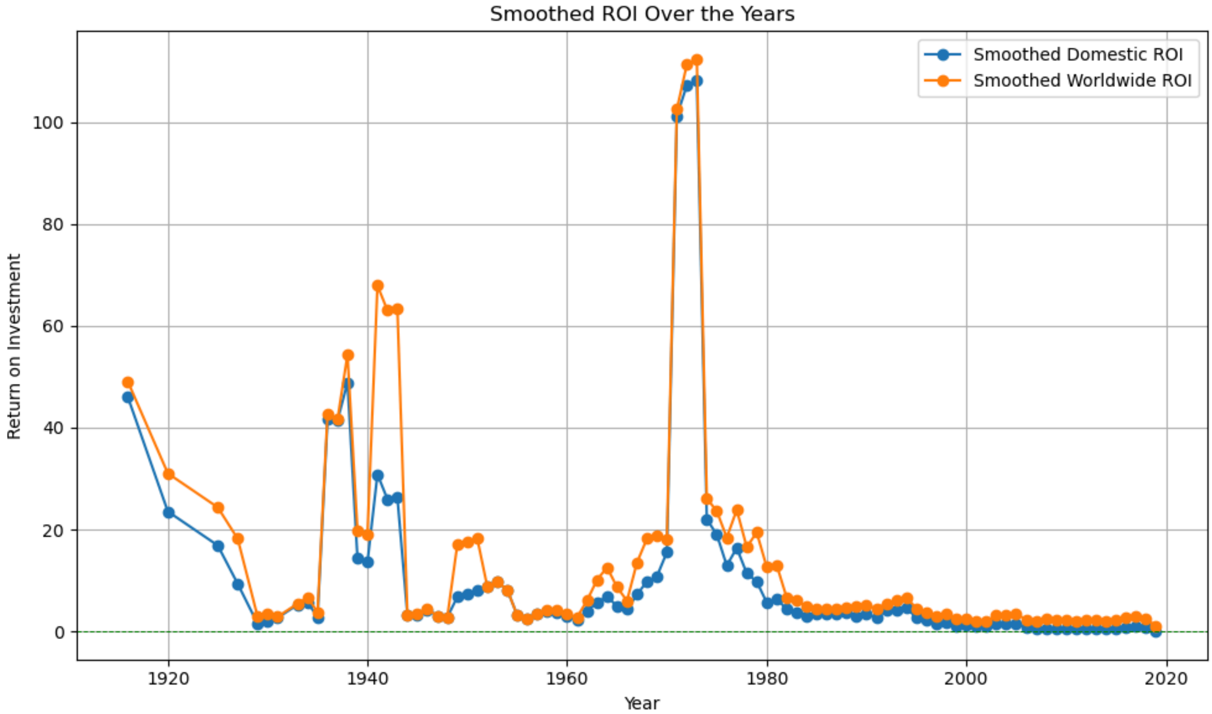
Out[127]:
```
year  production_budget
1915  1.100000e+05         1
1916  2.929535e+05         1
1995  3.463400e+07         1
1994  2.978620e+07         1
1993  2.037973e+07         1
                          ..
1954  3.636667e+06         1
1953  2.128000e+06         1
1952  2.423333e+06         1
1951  2.958333e+06         1
2020  9.400000e+07         1
Length: 96, dtype: int64
```

Identifying trends of ROI over the years

In [128]:
```
tn_budget['domestic_roi'] = (tn_budget['domestic_gross'] - tn_budget['production_budget']) / tn_
tn_budget['worldwide_roi'] = (tn_budget['worldwide_gross'] - tn_budget['production_budget']) / t
```

In [129]:
```
tn_budget['year'] = tn_budget['release_date'].dt.year
roi_by_year = tn_budget.groupby('year', as_index=False)[['domestic_roi', 'worldwide_roi']].mean(
```

In [134]:
```
roi_by_year['domestic_roi_smooth'] = roi_by_year['domestic_roi'].rolling(window=3, center=True).
roi_by_year['worldwide_roi_smooth'] = roi_by_year['worldwide_roi'].rolling(window=3, center=True

# Plotting smoothed curves
plt.figure(figsize=(10, 6))
plt.plot(roi_by_year['year'], roi_by_year['domestic_roi_smooth'], label='Smoothed Domestic ROI',
plt.plot(roi_by_year['year'], roi_by_year['worldwide_roi_smooth'], label='Smoothed Worldwide ROI
plt.axhline(0, color='green', linestyle='--', linewidth=0.7)
plt.xlabel('Year')
plt.ylabel('Return on Investment')
plt.title('Smoothed ROI Over the Years')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



The curve is very unpredictable in both the domestic and worldwide ROI. In the 15s to 70s (years), the ROI was high reaching over 50%, however in the recent years this has gone down to less than 10% annualy.

The Movies Database (TMDB)

Movie language and popularity

In [44]:
```
tmdb_df['original_language'].value_counts()
```

Out[44]:
```
en    23291
fr      507
es      455
ru      298
ja      265
      ...
bo        1
si        1
sl        1
hz        1
dz        1
Name: original_language, Length: 76, dtype: int64
```

At the top is the English movie with 23,291.

RECOMMENDATIONS

Partnering with High-Grossing Studios such as Sony Pictures, Warner Bros, and 20th Century Fox have shown immense-grossing films and Collaborating or buying their ideas of production and distribution strategies could enhance commercial outcomes.

Targeting International Markets; International releases show greater predictability and performance thus expanding production efforts to cater to global audiences can enhance market penetration and revenue stability.

Maximizing Production Budgets Strategically; Investing in quality production, casting, and marketing is essential to securing long-term financial returns.

Investing in High-Demand Language Markets; Strategic investment in languages such as English, French, Spanish, and Russian that consistently demonstrate higher popularity and commercial success is advised to capture broader audience bases.

In [ ]:

```

```