

Movie Data Analysis

For this project, you will use exploratory data analysis to generate insights for a business stakeholder.

```
#Begin by importing all the essential libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# loading the data sets into dataframes

imdb_title_basics = pd.read_csv(r"C:\Users\Mau\Documents\Flatiron\dsc-
data-science-env-config\Movie Review\imdb.title.basics.csv")
imdb_title_ratings = pd.read_csv(r"C:\Users\Mau\Documents\Flatiron\
dsc-data-science-env-config\Movie Review\imdb.title.ratings.csv")
bom_movie_gross = pd.read_csv(r"C:\Users\Mau\Documents\Flatiron\dsc-
data-science-env-config\Movie Review\bom.movie_gross.csv")

# Lets now merge our dataframes based on their unique identifiers

# Merge imdb.title.basics and imdb.title.ratings based on tconst
imdb_merged = pd.merge(imdb_title_basics, imdb_title_ratings,
on='tconst', how='inner')

# Merge the datasets
merged_data = pd.merge(imdb_merged, bom_movie_gross,
left_on='original_title', right_on='title', how='inner')

# Display the merged dataset
df = merged_data
df
```

	tconst	primary_title \
0	tt0315642	Wazir
1	tt0337692	On the Road
2	tt4339118	On the Road
3	tt5647250	On the Road
4	tt0359950	The Secret Life of Walter Mitty
...
2443	tt8097306	Nobody's Fool
2444	tt8108198	Andhadhun
2445	tt8427036	Helicopter Eela
2446	tt8549902	Oolong Courtyard: KungFu School
2447	tt9151704	Burn the Stage: The Movie

	original_title	start_year	runtime_minutes	\
0	Wazir	2016	103.0	
1	On the Road	2012	124.0	
2	On the Road	2014	89.0	
3	On the Road	2016	121.0	
4	The Secret Life of Walter Mitty	2013	114.0	
...	
2443	Nobody's Fool	2018	110.0	
2444	Andhadhun	2018	139.0	
2445	Helicopter Eela	2018	135.0	
2446	Oolong Courtyard	2018	103.0	
2447	Burn the Stage: The Movie	2018	84.0	
	genres	averagerating	numvotes	\
0	Action, Crime, Drama	7.1	15378	
1	Adventure, Drama, Romance	6.1	37886	
2	Drama	6.0	6	
3	Drama	5.7	127	
4	Adventure, Comedy, Drama	7.3	275300	
...	
2443	Comedy, Drama, Romance	4.6	3618	
2444	Crime, Thriller	8.5	43409	
2445	Drama	5.4	673	
2446	Comedy	4.6	61	
2447	Documentary, Music	8.8	2067	
	title	studio	domestic_gross	\
0	Wazir	Relbig.	1100000.0	
1	On the Road	IFC	744000.0	
2	On the Road	IFC	744000.0	
3	On the Road	IFC	744000.0	
4	The Secret Life of Walter Mitty	Fox	58200000.0	
...	
2443	Nobody's Fool	Par.	31700000.0	
2444	Andhadhun	Eros	1200000.0	
2445	Helicopter Eela	Eros	72000.0	
2446	Oolong Courtyard	CL	37700.0	
2447	Burn the Stage: The Movie	Trafalgar	4200000.0	
	foreign_gross	year		
0	NaN	2016		
1	8000000	2012		
2	8000000	2012		
3	8000000	2012		
4	129900000	2013		
...		
2443	1800000	2018		
2444	NaN	2018		
2445	NaN	2018		
2446	NaN	2018		

```
2447      16100000  2018
```

```
[2448 rows x 13 columns]
```

Data Inspection

```
#Display the first 5 and last five rows of the merged data frame  
df.head()
```

```
      tconst      primary_title \  
0  tt0315642      Wazir  
1  tt0337692    On the Road  
2  tt4339118    On the Road  
3  tt5647250    On the Road  
4  tt0359950  The Secret Life of Walter Mitty
```

```
      original_title  start_year  runtime_minutes \  
0      Wazir      2016      103.0  
1    On the Road      2012      124.0  
2    On the Road      2014       89.0  
3    On the Road      2016      121.0  
4  The Secret Life of Walter Mitty      2013      114.0
```

```
      genres  averagerating  numvotes \  
0  Action, Crime, Drama      7.1    15378  
1  Adventure, Drama, Romance      6.1    37886  
2      Drama      6.0      6  
3      Drama      5.7    127  
4  Adventure, Comedy, Drama      7.3   275300
```

```
      title  studio  domestic_gross  
foreign_gross \  
0      Wazir  Relbig.    1100000.0  
NaN  
1    On the Road    IFC    744000.0  
8000000  
2    On the Road    IFC    744000.0  
8000000  
3    On the Road    IFC    744000.0  
8000000  
4  The Secret Life of Walter Mitty    Fox   58200000.0  
129900000
```

```
      year  
0  2016  
1  2012  
2  2012
```

3 2012

4 2013

df.tail()

	tconst	primary_title
original_title \		
2443 tt8097306	Nobody's Fool	Nobody's Fool
2444 tt8108198	Andhadhun	Andhadhun
2445 tt8427036	Helicopter Eela	Helicopter Eela
2446 tt8549902	Oolong Courtyard: KungFu School	Oolong Courtyard
2447 tt9151704	Burn the Stage: The Movie	Burn the Stage: The Movie

	start_year	runtime_minutes	genres	averagerating
2443	2018	110.0	Comedy,Drama,Romance	4.6
2444	2018	139.0	Crime,Thriller	8.5
2445	2018	135.0	Drama	5.4
2446	2018	103.0	Comedy	4.6
2447	2018	84.0	Documentary,Music	8.8

	numvotes	title	studio
domestic_gross \			
2443 3618	Nobody's Fool	Par.	31700000.0
2444 43409	Andhadhun	Eros	1200000.0
2445 673	Helicopter Eela	Eros	72000.0
2446 61	Oolong Courtyard	CL	37700.0
2447 2067	Burn the Stage: The Movie	Trafalgar	4200000.0

	foreign_gross	year
2443	1800000	2018
2444	NaN	2018
2445	NaN	2018
2446	NaN	2018
2447	16100000	2018

```
#Lets derive some basic information regarding our data frame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2448 entries, 0 to 2447
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   tconst                 2448 non-null   object
1   primary_title          2448 non-null   object
2   original_title         2448 non-null   object
3   start_year             2448 non-null   int64
4   runtime_minutes        2403 non-null   float64
5   genres                 2444 non-null   object
6   averagerating          2448 non-null   float64
7   numvotes               2448 non-null   int64
8   title                  2448 non-null   object
9   studio                 2445 non-null   object
10  domestic_gross         2430 non-null   float64
11  foreign_gross          1574 non-null   object
12  year                   2448 non-null   int64
dtypes: float64(3), int64(3), object(7)
memory usage: 248.8+ KB
```

The DataFrame has a total of 2448 entries and 13 columns. It includes various attributes related to movies, such as titles, release years, genres, ratings, box office earnings, and other relevant details. We can see that some data is missing. The columns have ranging data types from float, integers, and object

```
# Check for the missing values
missing_values_sum = df.isnull().sum()
missing_values_sum

tconst          0
primary_title    0
original_title   0
start_year       0
runtime_minutes  45
genres           4
averagerating    0
numvotes         0
title            0
studio           3
domestic_gross   18
foreign_gross    874
year             0
dtype: int64
```

There are a number of missing values such as; runtime_minutes = 45 genres = 4 studio = 3 domestic_gross = 18 foreign_gross = 874 .I am considering dropping some of these column that have no direct impact on our variable

```
# Replace the missing values in runtime_minutes with the median value
median_runtime_value = df['runtime_minutes'].median()

# Replacing
df['runtime_minutes'].fillna(median_runtime_value, inplace = True)

#Replace the genre and studio missing values with a placeholder
df['genres'].fillna('Unknown', inplace = True)
df['studio'].fillna('Unknown', inplace = True)

# Lets check if the missing values have been filled
df.isnull().sum()

tconst          0
primary_title   0
original_title  0
start_year      0
runtime_minutes 0
genres           0
averagerating   0
numvotes        0
title           0
studio          0
domestic_gross  18
foreign_gross   874
year            0
dtype: int64

# Fill the null values in domestic gross column with median
median_domestic_gross_value =
df['domestic_gross'].astype(float).median()

df['domestic_gross'].fillna(median_domestic_gross_value, inplace=True)

# Drop 'foreign_gross' column
df.drop('foreign_gross', axis=1, inplace=True)

# Check the changes
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2448 entries, 0 to 2447
Data columns (total 12 columns):
```

#	Column	Non-Null Count	Dtype
0	tconst	2448 non-null	object
1	primary_title	2448 non-null	object
2	original_title	2448 non-null	object
3	start_year	2448 non-null	int64
4	runtime_minutes	2403 non-null	float64
5	genres	2444 non-null	object
6	averagerating	2448 non-null	float64
7	numvotes	2448 non-null	int64
8	title	2448 non-null	object
9	studio	2445 non-null	object
10	domestic_gross	2448 non-null	float64
11	year	2448 non-null	int64

dtypes: float64(3), int64(3), object(6)

memory usage: 229.6+ KB

#Cleaned dataframe

df

	tconst	primary_title \
0	tt0315642	Wazir
1	tt0337692	On the Road
2	tt4339118	On the Road
3	tt5647250	On the Road
4	tt0359950	The Secret Life of Walter Mitty
...
2443	tt8097306	Nobody's Fool
2444	tt8108198	Andhadhun
2445	tt8427036	Helicopter Eela
2446	tt8549902	Oolong Courtyard: KungFu School
2447	tt9151704	Burn the Stage: The Movie

	original_title	start_year	runtime_minutes \
0	Wazir	2016	103.0
1	On the Road	2012	124.0
2	On the Road	2014	89.0
3	On the Road	2016	121.0
4	The Secret Life of Walter Mitty	2013	114.0
...
2443	Nobody's Fool	2018	110.0
2444	Andhadhun	2018	139.0
2445	Helicopter Eela	2018	135.0
2446	Oolong Courtyard	2018	103.0
2447	Burn the Stage: The Movie	2018	84.0

	genres	averagerating	numvotes \
0	Action, Crime, Drama	7.1	15378
1	Adventure, Drama, Romance	6.1	37886
2	Drama	6.0	6

3		Drama	5.7	127
4	Adventure,Comedy,Drama		7.3	275300
...	
2443	Comedy,Drama,Romance		4.6	3618
2444	Crime,Thriller		8.5	43409
2445	Drama		5.4	673
2446	Comedy		4.6	61
2447	Documentary,Music		8.8	2067

	title	studio	domestic_gross	year
0	Wazir	Relbig.	1100000.0	2016
1	On the Road	IFC	744000.0	2012
2	On the Road	IFC	744000.0	2012
3	On the Road	IFC	744000.0	2012
4	The Secret Life of Walter Mitty	Fox	58200000.0	2013
...
2443	Nobody's Fool	Par.	31700000.0	2018
2444	Andhadhun	Eros	1200000.0	2018
2445	Helicopter Eela	Eros	72000.0	2018
2446	Oolong Courtyard	CL	37700.0	2018
2447	Burn the Stage: The Movie	Trafalgar	4200000.0	2018

[2448 rows x 12 columns]

Exploratory Data Analysis

```
# Dataframe summary
df.describe()
```

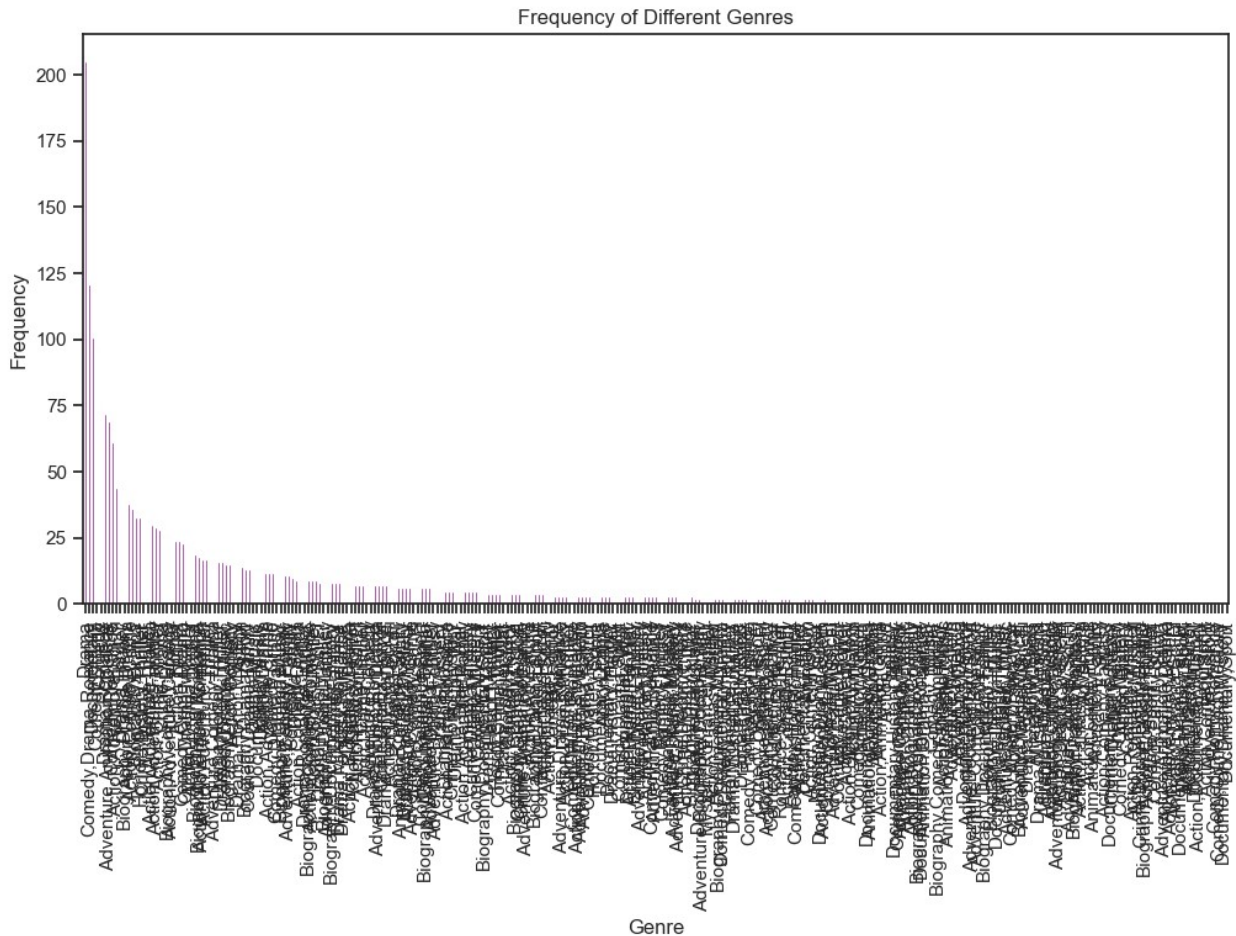
	start_year	runtime_minutes	averagerating	numvotes	\
count	2448.000000	2403.000000	2448.000000	2.448000e+03	
mean	2013.773284	106.799834	6.406454	7.270063e+04	
std	2.496518	20.063935	1.044846	1.345679e+05	
min	2010.000000	3.000000	1.600000	5.000000e+00	
25%	2012.000000	94.000000	5.800000	3.772000e+03	
50%	2014.000000	104.000000	6.500000	2.071850e+04	
75%	2016.000000	118.000000	7.100000	8.058950e+04	

max	2019.000000	186.000000	9.200000	1.841066e+06
-----	-------------	------------	----------	--------------

	domestic_gross	year
count	2.448000e+03	2448.000000
mean	3.588117e+07	2014.000408
std	6.930797e+07	2.465040
min	1.000000e+02	2010.000000
25%	3.040000e+05	2012.000000
50%	5.050000e+06	2014.000000
75%	4.262500e+07	2016.000000
max	7.001000e+08	2018.000000

```
#Count the frequency of different genres  
genre_counts = df['genres'].value_counts()
```

```
# Create bar plot for genre frequency  
plt.figure(figsize=(12, 6))  
genre_counts.plot(kind='bar', color='purple')  
plt.title('Frequency of Different Genres')  
plt.xlabel('Genre')  
plt.ylabel('Frequency')  
  
plt.show()
```



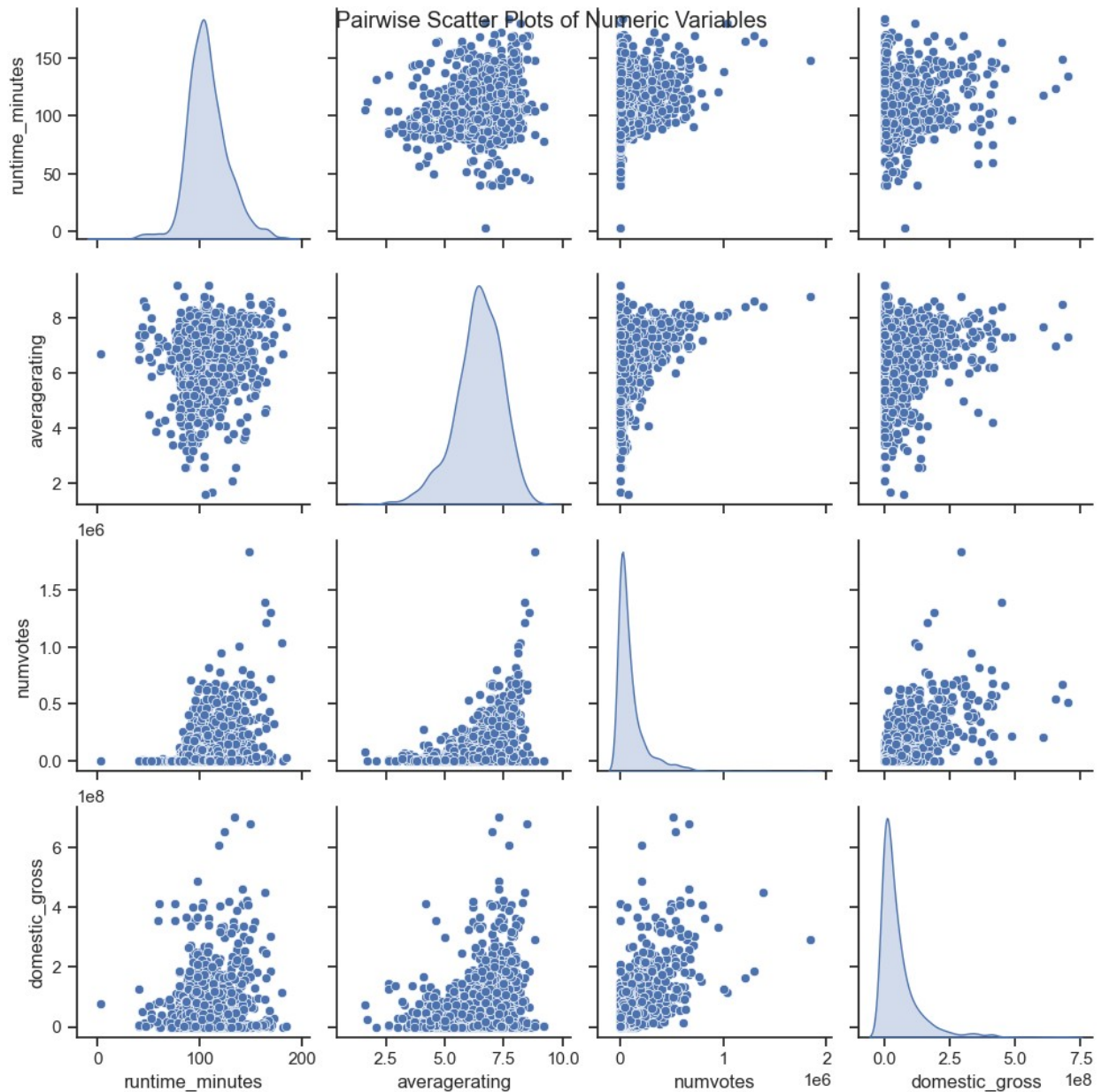
```
# Overview of the numeric variables
```

```
numeric_variables = ['runtime_minutes', 'averagerating', 'numvotes',
                     'domestic_gross']
```

```
# Creating scatter plots for pairs of numeric variables
```

```
sns.set(style="ticks")
sns.pairplot(df[numeric_variables].dropna(), kind='scatter',
             diag_kind='kde')
plt.suptitle('Pairwise Scatter Plots of Numeric Variables')
plt.show()
```

```
C:\Users\Mau\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



```
# Box Office Gross Distribution
```

```
plt.subplot(1, 2, 1)
```

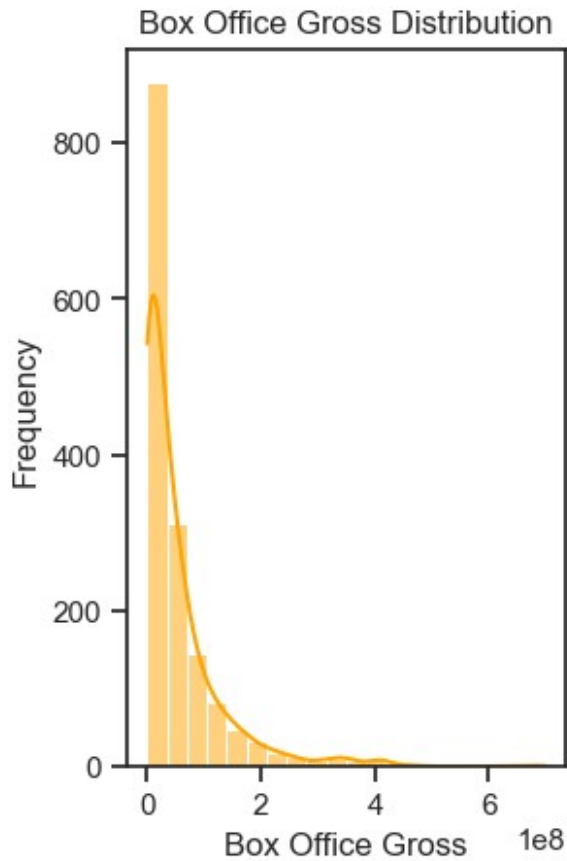
```
sns.histplot(df['domestic_gross'], bins=20, kde=True, color='orange')
```

```
plt.title('Box Office Gross Distribution')
```

```
plt.xlabel('Box Office Gross')
```

```
plt.ylabel('Frequency')
```

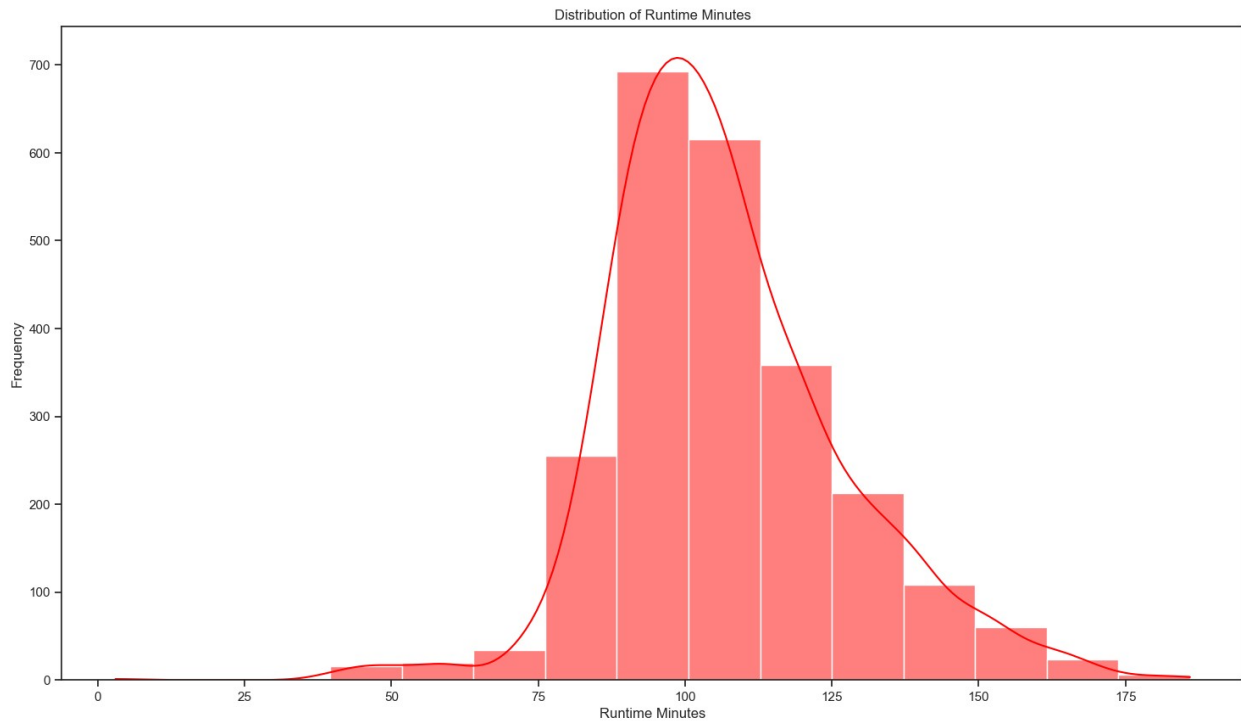
```
Text(0, 0.5, 'Frequency')
```



The distribution of this plot is positively skewed, implying that there are more movies with lower box office gross earnings than with higher earnings.

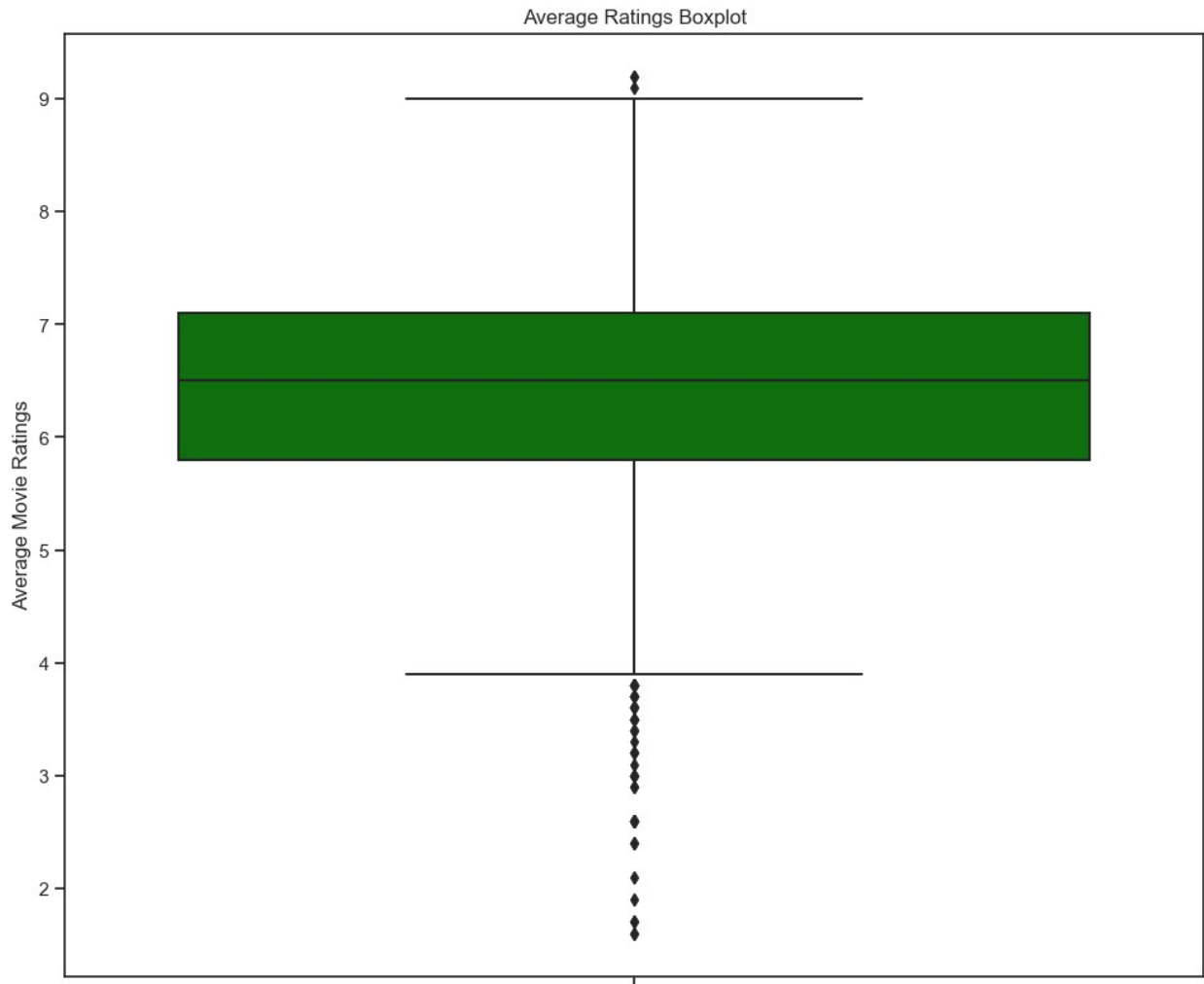
```
# Visualize the runtime minutes in a histogram
```

```
plt.figure(figsize=(18, 10))
sns.histplot(df['runtime_minutes'], bins=15, kde=True, color='red')
plt.title('Distribution of Runtime Minutes')
plt.xlabel('Runtime Minutes')
plt.ylabel('Frequency')
plt.show()
```



Many movies have a runtime ranging between 90-120 minutes. This is a common characteristic of films. This shows a normal distribution. The distribution of the runtime shows that it is positively skewed, meaning that more movies have a shorter runtime, than the ones with a longer runtime.

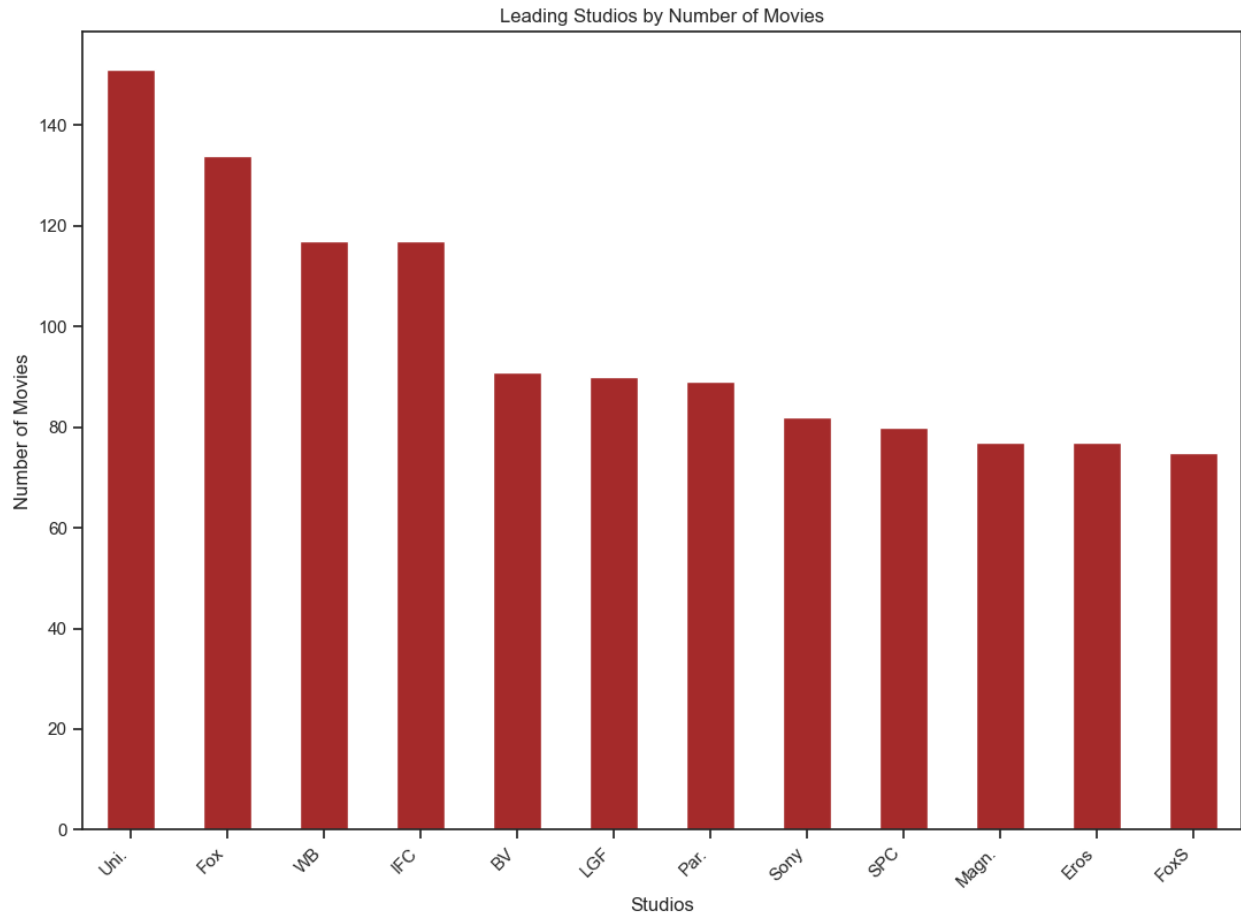
```
# Box plot for average ratings
plt.figure(figsize=(12, 10))
sns.boxplot(y='averagerating', data=df, color = 'green')
plt.title('Average Ratings Boxplot')
plt.ylabel('Average Movie Ratings')
plt.show()
```



There are individual data points outside the whiskers, which denotes the presence of outliers in the data. Movie ratings are evenly distributed across the median.

```
#lets check the leading studios by the number of movies
leading_studios = df['studio'].value_counts().head(12)

plt.figure(figsize=(13, 9))
leading_studios.plot(kind='bar', color='brown')
plt.title('Leading Studios by Number of Movies')
plt.xlabel('Studios')
plt.ylabel('Number of Movies')
plt.xticks(rotation=45, ha='right')
plt.show()
```



From the above bar chart, it is clear that Uni., Fox, IFC and WB are some of the studios with the highest number of movies produced. Factors such as the size of the studio, the marketing strategy, budgets used during production, and resources allocated for production could be the reason behind the high number of movies produced. strategies. Some studios rank small in the studio market, which can actually be a contributing factor to lower production in movies.

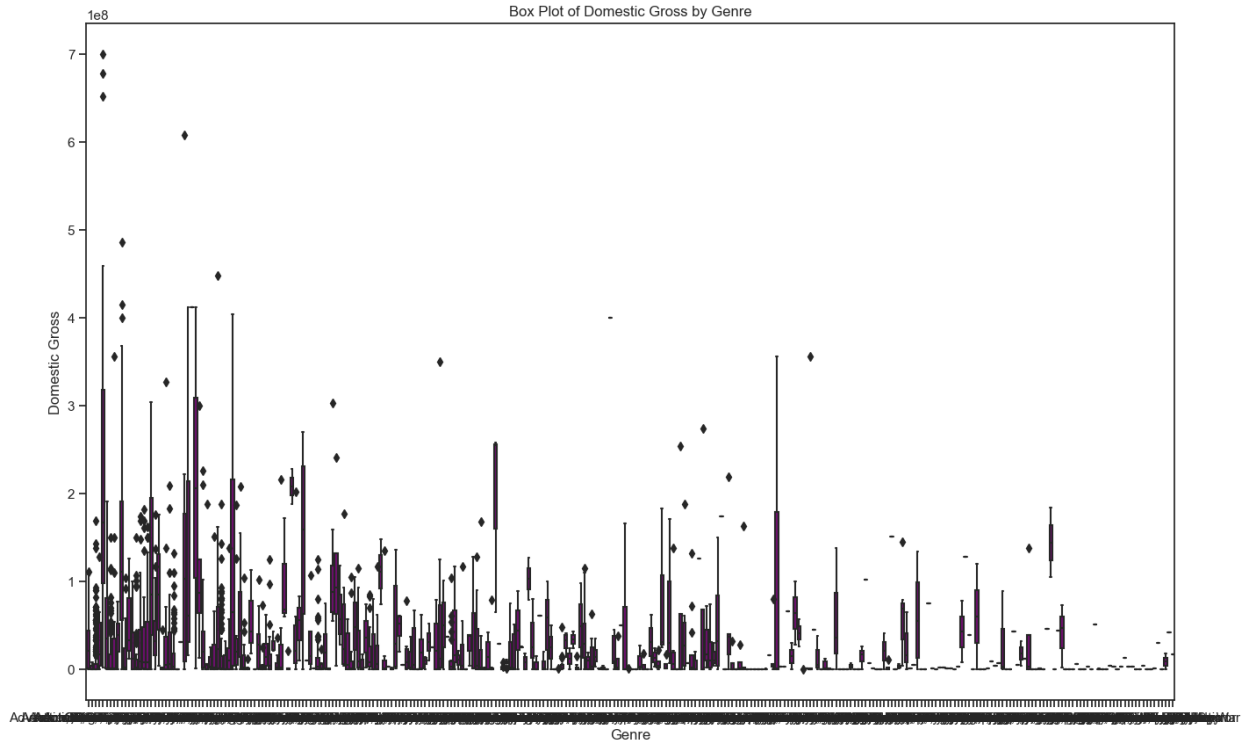
```
# Lets compare, the domestic_gross and genre using a box plot

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(16, 10))
sns.boxplot(x='genres', y='domestic_gross', color = 'purple', data=df)

plt.title('Box Plot of Domestic Gross by Genre')
plt.xlabel('Genre')
plt.ylabel('Domestic Gross')

plt.show()
```



Some genres are exhibiting a wider range of domestic gross earnings, while others have a more concentrated distribution. Genres with higher median domestic gross indicate that, movies within these genres tend to perform better at the box office compared to ones with a lower median domestic gross.

```
df['domestic_gross'] = df['domestic_gross'].astype(str)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2448 entries, 0 to 2447
```

```
Data columns (total 12 columns):
```

#	Column	Non-Null Count	Dtype
0	tconst	2448 non-null	object
1	primary_title	2448 non-null	object
2	original_title	2448 non-null	object
3	start_year	2448 non-null	int64
4	runtime_minutes	2403 non-null	float64
5	genres	2444 non-null	object
6	averagerating	2448 non-null	float64
7	numvotes	2448 non-null	int64
8	title	2448 non-null	object
9	studio	2445 non-null	object
10	domestic_gross	2448 non-null	float64
11	year	2448 non-null	int64

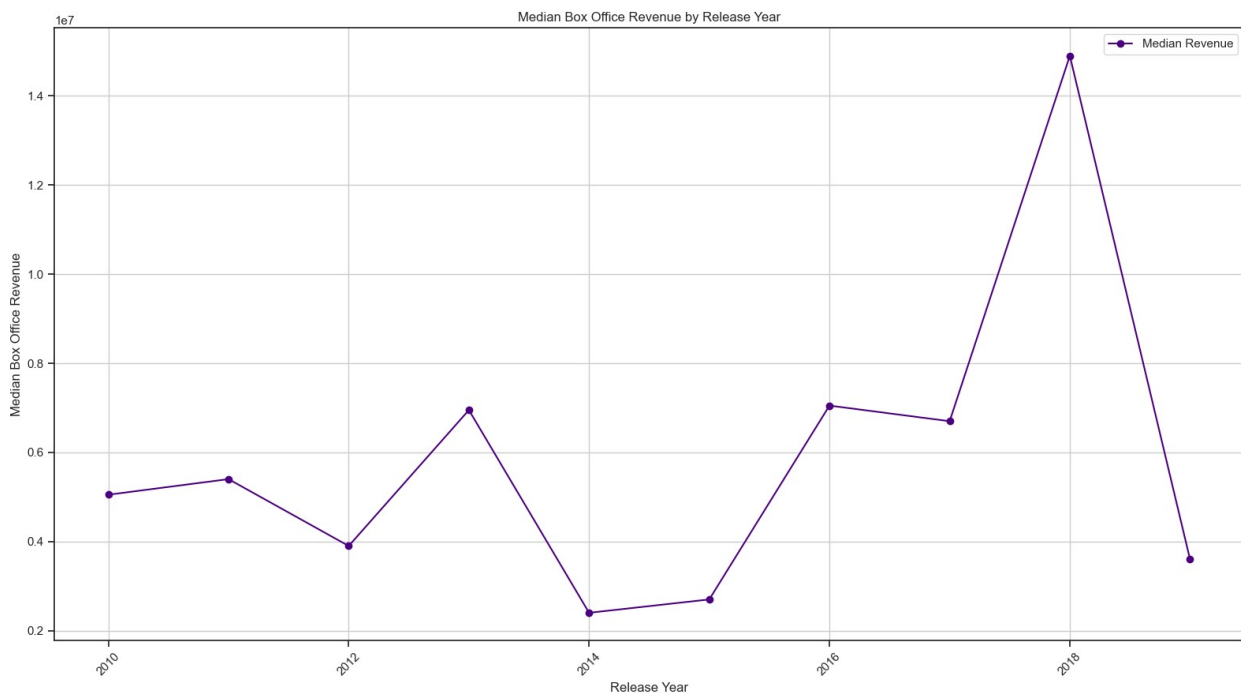

```

dtypes: float64(3), int64(3), object(6)
memory usage: 229.6+ KB

median_revenue_per_year = df.groupby('start_year')
['domestic_gross'].median()

# line plot for median box office revenue per year
plt.figure(figsize=(16, 9))
plt.plot(median_revenue_per_year.index,
median_revenue_per_year.values, marker='o', color='indigo',
label='Median Revenue')
plt.title('Median Box Office Revenue by Release Year')
plt.xlabel('Release Year')
plt.ylabel('Median Box Office Revenue')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

```



The above line plot shows how the median box office revenue for movies has changed over different release years, indicating variability in box office performance over time. The presence of outliers could influence the median and affect the overall trend.

```

movies_per_year = df['start_year'].value_counts().sort_index()

plt.figure(figsize=(12, 6))
sns.barplot(x=movies_per_year.index, y=movies_per_year.values,

```

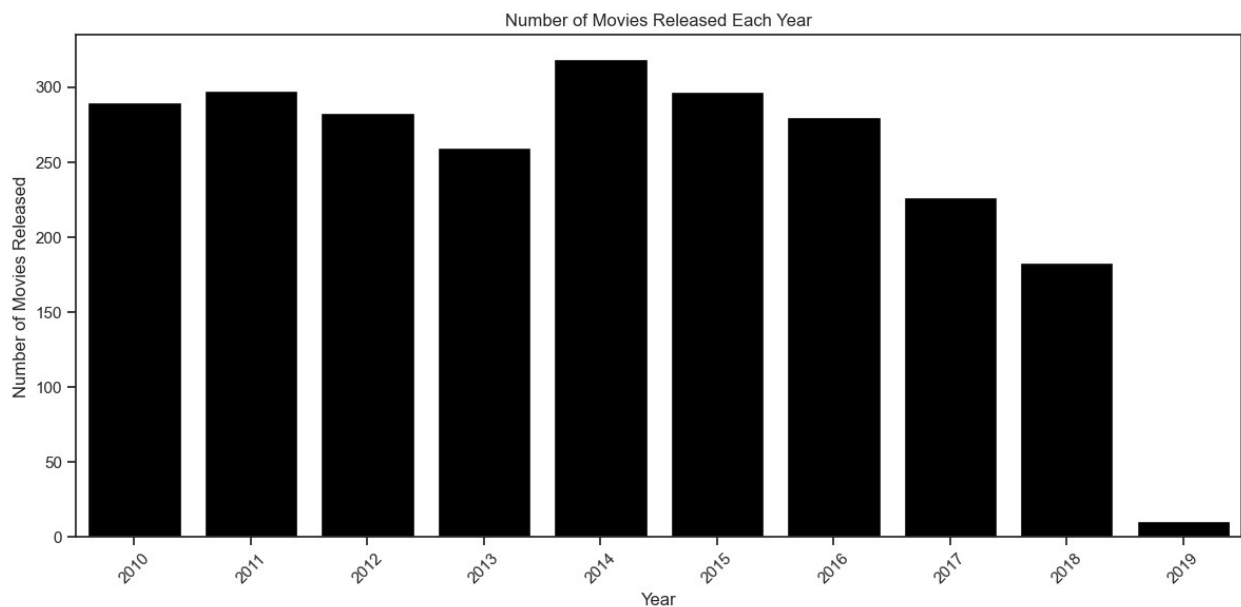
```

color='black')
plt.title('Number of Movies Released Each Year')
plt.xlabel('Year')
plt.ylabel('Number of Movies Released')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Average ratings over time
avg_ratings_per_year = df.groupby('year')['averagerating'].mean()

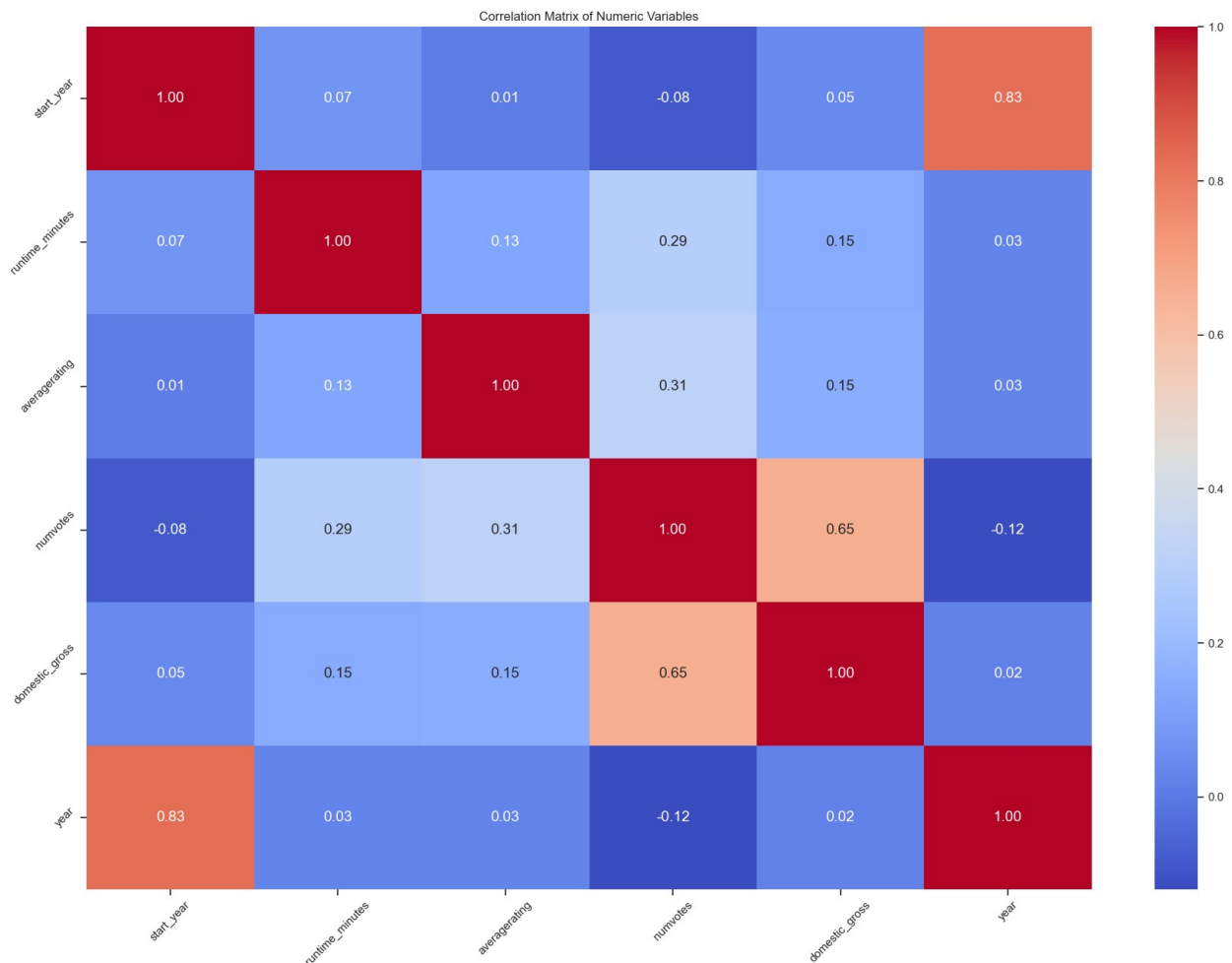
plt.figure(figsize=(12, 6))
sns.lineplot(x=avg_ratings_per_year.index,
y=avg_ratings_per_year.values, color='black')
plt.title('Average Ratings Over Time')
plt.xlabel('Year')
plt.ylabel('Average Rating')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

```




```
# Computing the correlation matrix
correlation_matrix = df[numeric_columns].corr()

# Create a heatmap
plt.figure(figsize=(18, 13))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
            fmt=".2f", annot_kws={"size": 14})
plt.title('Correlation Matrix of Numeric Variables')
plt.xticks(rotation=45)
plt.yticks(rotation=45)
plt.tight_layout()
plt.show()
```



There is a strong positive correlation observed between num_votes and domestic votes, hinting that movies with higher numbers of votes tend to have higher domestic gross earnings, meaning the more the attention a movie gets the more that its likely to perform better at box office. Average rating, the year of release, the runtime, and the start year of the movie may not have a significant impact on its box office performance as they have no strong correlation with domestic gross.

Conclusion

With regards to the analysis above:

Insights into the types of films currently performing well at the box office were derived from correlation analysis, genre distribution, and box office gross trends. Observations indicate that certain genres, such as action, adventure, fantasy, and science fiction, tend to perform better at the box office. Understanding audience preferences and industry dynamics is crucial for establishing a successful movie studio.

Recommendations

Recommendations When making the decision to open a new movie studio,

Consider focusing on genres that are currently popular and have a track record of success at the box office, success in terms of audience interaction. Consider partnerships with established studios, filmmakers, and distribution networks to leverage expertise and resources in the industry. Have some effective marketing and promotional strategies, such as social media, digital platforms to build anticipation and generate word to many when there is a movie releases.