Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: 24/07/2023
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- Blog post URL:

FROM DATA TO SCREENS

Overview of the project

The project aims to guide Microsoft's new movie studio venture by conducting a data-driven analysis of the current box office trends. As big companies have found success in creating original video content, Microsoft seeks to capitalize on the popularity of movies but lacks experience in the film industry. To make informed decisions on the types of films to produce, this project will explore the genres, themes, and characteristics of the most successful movies at the box office. By analyzing data on past blockbusters, the project will provide actionable insights to help Microsoft's movie studio identify and prioritize the types of films that are likely to resonate with audiences and achieve box office success. Using data-backed strategies, Microsoft can make well-informed choices that maximize their chances of creating box office hits and establishing a strong presence in the competitive world of filmmaking.

Business's Pain Points:

Lack of Industry Experience: As Microsoft ventures into the movie industry, their lack of experience in filmmaking poses a significant challenge. They need to understand what factors contribute to a movie's success to make informed decisions and minimize risks. Costly Investment: Producing movies can be a costly endeavor. It is crucial for Microsoft to invest in projects that have a higher likelihood of commercial success to maximize returns on investment. Competitive Market: The movie industry is highly competitive, with numerous studios vying for audience attention. Microsoft needs a strategic edge to stand out and attract moviegoers to their films.

Data Analysis Question Selection:

The data analysis questions were picked to address the pain points and provide valuable insights for Microsoft's movie studio:

What are the most successful movie genres at the box office? Which themes and characteristics are prevalent in top-grossing films? How does audience reception (ratings, reviews) correlate with box office performance?

Importance from a Business Perspective:

These questions are crucial from a business perspective for the following reasons:

Targeted Investment: Identifying successful movie genres helps Microsoft focus their resources on producing films that align with audience preferences and have higher chances of box office success. Audience Engagement: Understanding prevalent themes and characteristics in top-grossing films allows Microsoft to create content that resonates with audiences, leading to higher engagement and repeat viewership. Data-Driven Decision Making: Analyzing audience reception in relation to box office performance provides insights into audience satisfaction, guiding Microsoft's efforts to deliver high-quality content and maintain positive word-of-mouth, critical for long-term success. By addressing these questions through data analysis, Microsoft can gain a competitive advantage, minimize risks, and strategically position themselves in the movie industry, making informed decisions that cater to audience demands and lead to successful box office outcomes.

Data Understanding

The data in this project represent information about various movies and their performance at the box office. The sample includes a collection of movies, and each movie entry contains different variables that provide details about the movie and its box office performance, the data was collected from IMDB an online database of information that is related to films, television series, podcasts, home videos, video games, and streaming content online which is really helpful in collecting data that is required to achieve our goal as it contains movie information such as popularity, movie ratings and reviews, production budget and also the themes and characteristics which are some of the available variables.

The target variable in this project is likely to be the Box Office Performance(rating) or Gross Revenue of the movies. The aim is to identify factors that influence box office success, so this variable will be the primary focus of the analysis.

The variables used in the analysis may have different properties: 1.Categorical Variables: Genre, director's name, and themes/characteristics can be categorical variables with distinct categories for classification. 2.Numerical Variables: Production budget, ratings, and revenue-related variables will likely be numerical variables, representing quantities or measures. 3.Continuous vs. Discrete: Some numerical variables, such as worldwide gross revenue, can be continuous (any value within a range), while others, like movie duration (runtime), will be discrete (whole numbers). Ordinal Variables: Ratings and reviews may be ordinal variables, where the order of categories matters (e.g., 1-star, 2-star, 3-star, etc.). 4.Text Variables: Movie titles, cast, and crew names will be text variables, representing strings of characters. By analyzing and understanding these variables and their properties, the project aims to uncover patterns, trends, and insights that can guide decision-making in Microsoft's movie studio, helping them produce films that are likely to be successful at the box office.

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Data exploration, preparation and modeling

```
# Import the datasets
df_1 = pd.read_csv('imdb.title.basics.csv.gz')
df_2 = pd.read_csv('imdb.title.ratings.csv.gz')
df_3 = pd.read_csv('bom.movie_gross.csv.gz')

# Viewing the data sets
df_1.head(3)

      tconst                    primary_title
original_title  \
0  tt0063540                        Sunghursh
Sunghursh
```

```
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek
Din
2  tt0069049       The Other Side of the Wind  The Other Side of the
Wind

   start_year  runtime_minutes              genres
0        2013            175.0  Action,Crime,Drama
1        2019            114.0     Biography,Drama
2        2018            122.0               Drama
```

```
df_2.head(3)
```

```
       tconst  averagerating  numvotes
0  tt10356526            8.3        31
1  tt10384606            8.9       559
2   tt1042974            6.4        20
```

```
df_3.head(3)
```

```
                                          title studio  domestic_gross
\
0                                   Toy Story 3     BV     415000000.0

1                    Alice in Wonderland (2010)     BV     334200000.0

2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0


  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
```

```
# Since df_1 and df_2 have a common column we can merge the two to df
df = pd.merge(df_1, df_2, on='tconst')

# Viewing the merged data set
df
```

```
          tconst                    primary_title
original_title  \
0      tt0063540                        Sunghursh
Sunghursh
1      tt0066787  One Day Before the Rainy Season             Ashad Ka
Ek Din
2      tt0069049       The Other Side of the Wind  The Other Side of
the Wind
3      tt0069204                  Sabse Bada Sukh             Sabse
Bada Sukh
4      tt0100275         The Wandering Soap Opera       La Telenovela
Errante
```

```
...          ...                              ...
...
73851  tt9913084                Diabolik sono io           Diabolik
sono io
73852  tt9914286               Sokagin Çocuklari          Sokagin
Çocuklari
73853  tt9914642                       Albatross
Albatross
73854  tt9914942       La vida sense la Sara Amat  La vida sense la
Sara Amat
73855  tt9916160                      Drømmeland
Drømmeland

       start_year  runtime_minutes                genres
averagerating  \
0            2013            175.0    Action,Crime,Drama
7.0
1            2019            114.0       Biography,Drama
7.2
2            2018            122.0                 Drama
6.9
3            2018              NaN          Comedy,Drama
6.1
4            2017             80.0  Comedy,Drama,Fantasy
6.5
...           ...              ...                   ...             ..
.
73851        2019             75.0           Documentary
6.2
73852        2019             98.0          Drama,Family
8.7
73853        2017              NaN           Documentary
8.5
73854        2019              NaN                   NaN
6.6
73855        2019             72.0           Documentary
6.5

       numvotes
0            77
1            43
2          4517
3            13
4           119
...         ...
73851         6
73852       136
73853         8
73854         5
```

```
73855        11

[73856 rows x 8 columns]
```

```
# Now we have two data sets df and df_3, let us explore.
df.shape
```

```
(73856, 8)
```

```
df_3.shape
```

```
(3387, 5)
```

Shape

From the above function we can see that: ***df has 73856 rows and 8 columns while df_3 has 3387 rows and 5 columns***

```
# Now we get information on the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   tconst           73856 non-null  object
 1   primary_title    73856 non-null  object
 2   original_title   73856 non-null  object
 3   start_year       73856 non-null  int64
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

```
df_3.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
```

```python
# We can now look at the description of the data
df.describe(include = "all")
```

```
            tconst primary_title original_title    start_year  
runtime_minutes  \
count        73856         73856          73856  73856.000000   
66236.000000   
unique       73856         69993          71097           NaN   
NaN   
top      tt2210657    The Return         Broken           NaN   
NaN   
freq             1            11              9           NaN   
NaN   
mean           NaN           NaN            NaN   2014.276132   
94.654040   
std            NaN           NaN            NaN      2.614807   
208.574111   
min            NaN           NaN            NaN   2010.000000   
3.000000   
25%            NaN           NaN            NaN   2012.000000   
81.000000   
50%            NaN           NaN            NaN   2014.000000   
91.000000   
75%            NaN           NaN            NaN   2016.000000   
104.000000   
max            NaN           NaN            NaN   2019.000000   
51420.000000   

       genres  averagerating      numvotes  
count   73052   73856.000000  7.385600e+04  
unique    923            NaN           NaN  
top     Drama            NaN           NaN  
freq    11612            NaN           NaN  
mean      NaN       6.332729  3.523662e+03  
std       NaN       1.474978  3.029402e+04  
min       NaN       1.000000  5.000000e+00  
25%       NaN       5.500000  1.400000e+01  
50%       NaN       6.500000  4.900000e+01  
75%       NaN       7.400000  2.820000e+02  
max       NaN      10.000000  1.841066e+06  
```

```python
df_3.describe(include = "all")
```

```
             title studio  domestic_gross foreign_gross         year
count         3387   3382    3.359000e+03          2037  3387.000000
unique        3386    257             NaN          1204          NaN
top      Bluebeard    IFC             NaN       1200000          NaN
freq             2    166             NaN            23          NaN
mean           NaN    NaN    2.874585e+07           NaN  2013.958075
std            NaN    NaN    6.698250e+07           NaN     2.478141
```

```
min              NaN     NaN     1.000000e+02            NaN   2010.000000
25%              NaN     NaN     1.200000e+05            NaN   2012.000000
50%              NaN     NaN     1.400000e+06            NaN   2014.000000
75%              NaN     NaN     2.790000e+07            NaN   2016.000000
max              NaN     NaN     9.367000e+08            NaN   2018.000000
```

Information

df

We are able to see all the columns and we notice that the columns ***runtime_minutes and genres*** have null values

df_3

We are able to see all the columns and we notice that the columns ***studio, domestic_gross and foreign_gross*** have null values

Data description

We are able to view stats such as the mean, count, standard deviation, the minimum and maximum and the various percentiles.

```
# Now we can view the missing values
df.isna()

       tconst  primary_title  original_title  start_year
runtime_minutes  \
0       False          False           False       False
False
1       False          False           False       False
False
2       False          False           False       False
False
3       False          False           False       False
True
4       False          False           False       False
False
...       ...            ...             ...         ...
...
73851   False          False           False       False
False
73852   False          False           False       False
False
73853   False          False           False       False
True
73854   False          False           False       False
True
73855   False          False           False       False
False
```

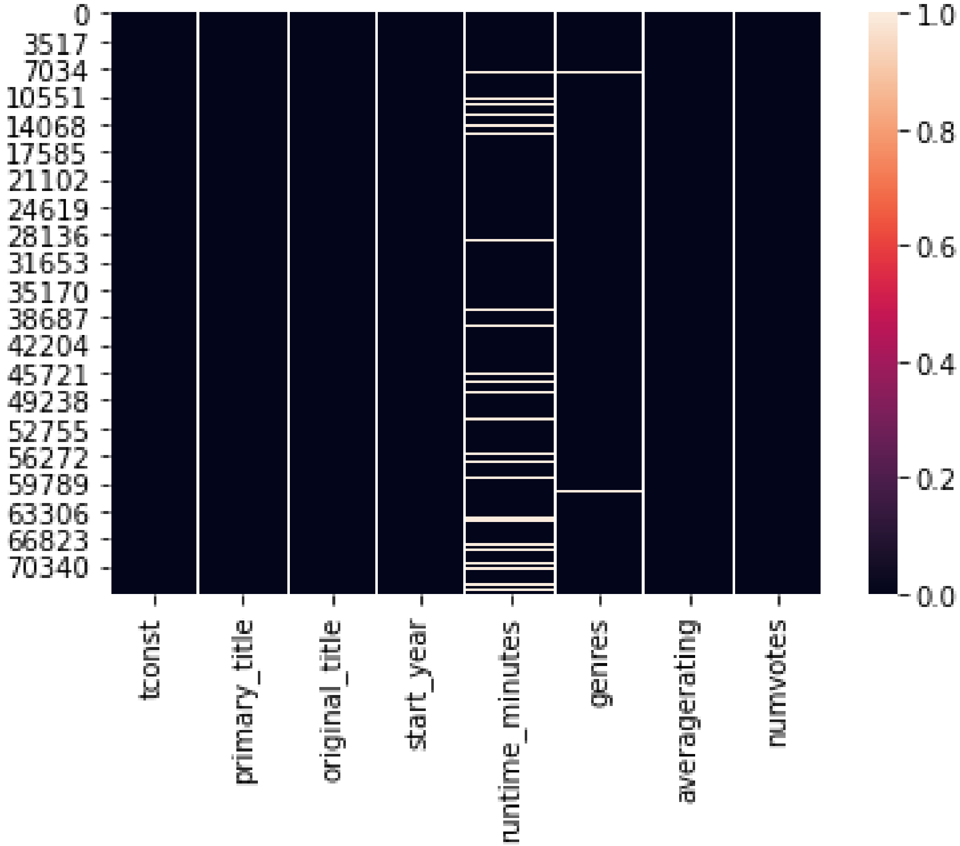
```
       genres  averagerating  numvotes
0       False          False     False
1       False          False     False
2       False          False     False
3       False          False     False
4       False          False     False
...       ...            ...       ...
73851   False          False     False
73852   False          False     False
73853   False          False     False
73854    True          False     False
73855   False          False     False

[73856 rows x 8 columns]
```

```
df_3.isna()
```

```
      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 x 5 columns]
```

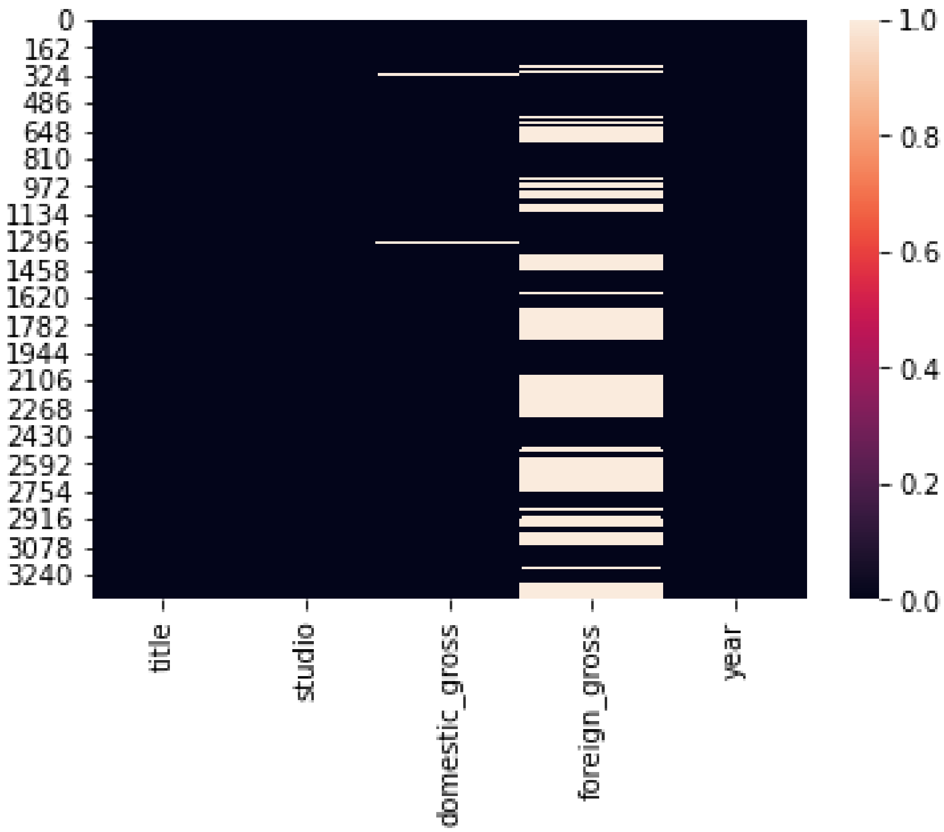
```
# We can visualize the missing data sets using seaborn for df
sns.heatmap(df.isna())
```

```
<AxesSubplot:>
```




```
# We can visualize the missing data sets using seaborn for df_3
sns.heatmap(df_3.isna())
```

```
<AxesSubplot:>
```




```
# We can look at the total null values
missing_df = df.isna().sum()
missing_df
```

```
tconst               0
primary_title        0
original_title       0
start_year           0
runtime_minutes   7620
genres             804
averagerating        0
numvotes             0
dtype: int64
```

```
missing_df_3 = df_3.isna().sum()
missing_df_3
```

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

```python
#We can look at the percentage of missing values from each data frame
percentage_missing_df = df.isna().sum() * 100 / len(df)
percentage_missing_df
```

```
tconst              0.000000
primary_title       0.000000
original_title      0.000000
start_year          0.000000
runtime_minutes    10.317374
genres              1.088605
averagerating       0.000000
numvotes            0.000000
dtype: float64
```

```python
percentage_missing_df_3 = df_3.isna().sum() * 100 / len(df_3)
percentage_missing_df_3
```

```
title              0.000000
studio             0.147623
domestic_gross     0.826690
foreign_gross     39.858282
year               0.000000
dtype: float64
```

Missing values

We are now able to see the frequency of missing values some varaibles such as ***runtime_minutes (10.317374%)*** in df and ***foreign_gross(39.858282%)*** in df_3 have a lot of missing values while other variables such as ***genres(1.088605%)*** in df , ***domestic_gross(0.826690)*** and ***studio(0.147623%)*** in df_3 have few missing values.

Handling missing values

We have to drop all missing values in ***df*** since ***runtime_minutes*** has a high number of missing values and we cant use any information on the data to predict the ***genre***

In ***df_3*** we will also drop all miising values .

```python
# We can now handle the missing values
# Dropping all missing values in df
df.dropna(axis = 0, inplace = True)

# Dropping foreign_gross
df_3.dropna(axis = 0, inplace = True)

#We can now confirm that there are no missing values
df.isna().sum()
```

```
tconst            0
primary_title     0
original_title    0
```

```
start_year         0
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
dtype: int64

df_3.isna().sum()

title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

We can now see that there are no missing values

```
#Now let us check for prescence of any duplicate data
df.duplicated().any()

False

df_3.duplicated().any()

False
```

Since there is no duplicate data we can proceed

```
# Let us view all the columns
df.columns

Index(['tconst', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'averagerating', 'numvotes'],
      dtype='object')

df_3.columns

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

We can now isolate only the columns that we need

In **df** we need the original_title, runtime_minutes, genres, averagerating and numvotes and in **df_3** we need title, domestic_gross, foreign_gross.We have to remove the other columns since they will not help us achieve our goal and hence it is easier to remove them to reduce the workload.

```
df = df.drop(['tconst', 'primary_title', 'start_year' ],
axis='columns')
```

```
df_3 = df_3.drop(['studio', 'year' ], axis='columns')

#We can view our data frames to confirm
df

                   original_title  runtime_minutes  \
0                       Sunghursh            175.0
1                 Ashad Ka Ek Din            114.0
2      The Other Side of the Wind            122.0
4            La Telenovela Errante             80.0
6                 Joe Finds Grace             83.0
...                           ...              ...
73849   Padmavyuhathile Abhimanyu            130.0
73850               Swarm Season             86.0
73851             Diabolik sono io             75.0
73852            Sokagin Çocuklari             98.0
73855                  Drømmeland             72.0

                           genres  averagerating  numvotes
0              Action,Crime,Drama            7.0        77
1                 Biography,Drama            7.2        43
2                           Drama            6.9      4517
4            Comedy,Drama,Fantasy            6.5       119
6      Adventure,Animation,Comedy            8.1       263
...                           ...            ...       ...
73849                       Drama            8.4       365
73850                 Documentary            6.2         5
73851                 Documentary            6.2         6
73852                Drama,Family            8.7       136
73855                 Documentary            6.5        11

[65720 rows x 5 columns]

df_3

                                               title
domestic_gross  \
0                                        Toy Story 3
415000000.0
1                         Alice in Wonderland (2010)
334200000.0
2           Harry Potter and the Deathly Hallows Part 1
296000000.0
3                                          Inception
292600000.0
4                                Shrek Forever After
238700000.0
...                                              ...               ..
.
3275                                  I Still See You
```

```
1400.0
3286                                The Catcher Was a Spy
725000.0
3309                                            Time Freak
10000.0
3342  Reign of Judges: Title of Liberty - Concept Short
93200.0
3353            Antonio Lopez 1970: Sex Fashion & Disco
43200.0

     foreign_gross
0        652000000
1        691300000
2        664300000
3        535700000
4        513900000
...            ...
3275       1500000
3286        229000
3309        256000
3342          5200
3353         30000

[2007 rows x 3 columns]
```

Now we have explored and cleaned our data

Data modeling and evaluation

```
# Using df we can check which genre of movies has the highest numvote
max_numvotes = df['numvotes'].max()
df.loc[df['numvotes'] == max_numvotes]

     original_title  runtime_minutes                   genres
averagerating  \
2387      Inception            148.0  Action,Adventure,Sci-Fi
8.8

      numvotes
2387   1841066
```

Action,adventure,scifi is the movie genre with the highest numvotes.

```
# These are the top 20 movies with the highest numvotes
df.nlargest(20, 'numvotes')

                                     original_title
runtime_minutes  \
2387                                      Inception            148.0
```

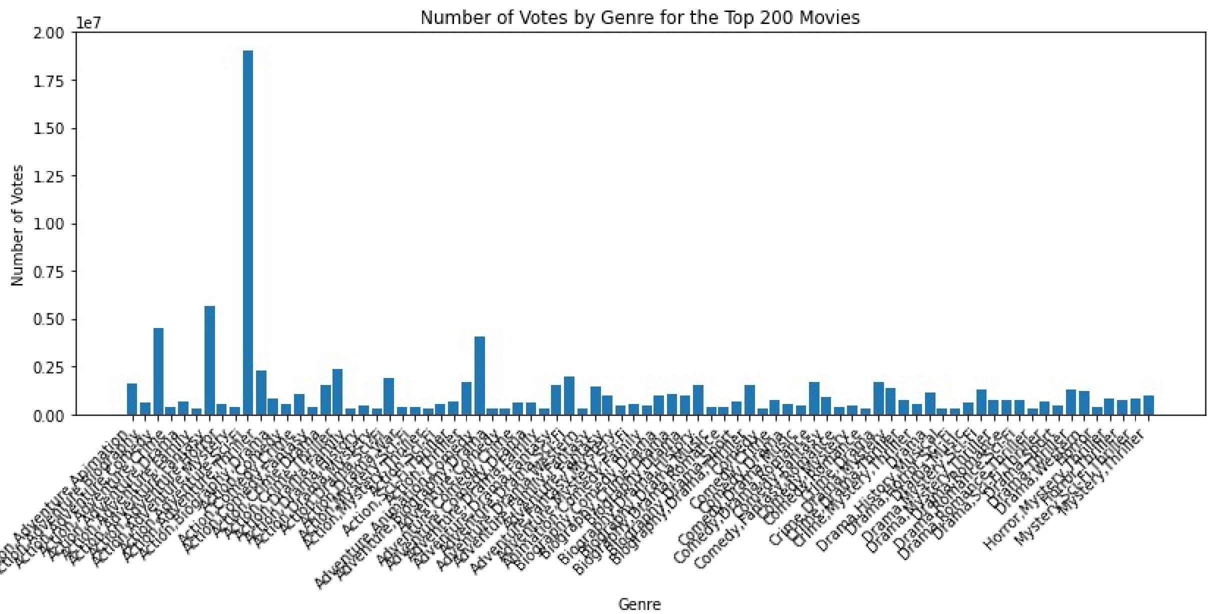
```
2241                              The Dark Knight Rises                164.0

280                                      Interstellar                  169.0

12072                                Django Unchained                  165.0

325                                      The Avengers                  143.0

507                            The Wolf of Wall Street                 180.0

1091                                   Shutter Island                  138.0

15327                         Guardians of the Galaxy                  121.0

2831                                         Deadpool                  108.0

2523                                 The Hunger Games                  142.0

25595    Star Wars: Episode VII - The Force Awakens                    136.0

2524                                Mad Max: Fury Road                 120.0

20995                                       Gone Girl                  149.0

397               The Hobbit: An Unexpected Journey                    169.0

3053                                          Gravity                   91.0

1851                                   Iron Man Three                  130.0

1291   Harry Potter and the Deathly Hallows: Part 2                    130.0

251                                              Thor                  115.0

91                                        Toy Story 3                  103.0

38441                                     The Martian                  144.0


                            genres  averagerating  numvotes
2387      Action,Adventure,Sci-Fi            8.8   1841066
2241              Action,Thriller            8.4   1387769
280        Adventure,Drama,Sci-Fi            8.6   1299334
12072               Drama,Western            8.4   1211405
325       Action,Adventure,Sci-Fi            8.1   1183655
507         Biography,Crime,Drama            8.2   1035358
1091             Mystery,Thriller            8.1   1005960
15327     Action,Adventure,Comedy            8.1    948394
2831      Action,Adventure,Comedy            8.0    820847
2523      Action,Adventure,Sci-Fi            7.2    795227
25595    Action,Adventure,Fantasy            8.0    784780
```

```
2524      Action,Adventure,Sci-Fi           8.1    780910
20995      Drama,Mystery,Thriller           8.1    761592
397      Adventure,Family,Fantasy           7.9    719629
3053        Drama,Sci-Fi,Thriller           7.7    710018
1851      Action,Adventure,Sci-Fi           7.2    692794
1291      Adventure,Drama,Fantasy           8.1    691835
251      Action,Adventure,Fantasy           7.0    683264
91     Adventure,Animation,Comedy           8.3    682218
38441      Adventure,Drama,Sci-Fi           8.0    680116

#Checking the most repeated genre in the top 200 in numvotes.


# Get the top 200 rows with the highest 'numvotes'
top_200_movies = df.nlargest(200, 'numvotes')

# Use value_counts() on the 'genre' column to get the counts of unique
genres in the top 20 rows
genre_counts_top_200 = top_200_movies['genres'].value_counts()

# Find the most repeated genre in the top 20 rows
most_repeated_genre_top_200 = genre_counts_top_200.idxmax()

# Find the count of occurrences for the most repeated genre in the top
20 rows
most_repeated_count_top_200 = genre_counts_top_200.max()

print("Most repeated genre in the top 200 numvotes:",
most_repeated_genre_top_200)
print("Count of occurrences in the top 200 numvotes:",
most_repeated_count_top_200)

Most repeated genre in the top 200 numvotes: Action,Adventure,Sci-Fi
Count of occurrences in the top 200 numvotes: 33
```

***Action,Adventure,Sci-Fi is the most common and liked according to the above analysis.

```
#We can use a visualization to show the information above.
top_200_numvotes = df.nlargest(200, 'numvotes')

numvotes_top_200 = top_200_numvotes.groupby('genres')
['numvotes'].sum().reset_index()


# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(12, 6))

# Plot the bar graph for genre vs. numvotes for the top 200 movies
plt.bar(numvotes_top_200['genres'], numvotes_top_200['numvotes'])
```

```
# Customize the plot
plt.xlabel('Genre')
plt.ylabel('Number of Votes')
plt.title('Number of Votes by Genre for the Top 200 Movies')
plt.xticks(rotation=45, ha='right')

# Show the plot
plt.tight_layout()
plt.show()
```



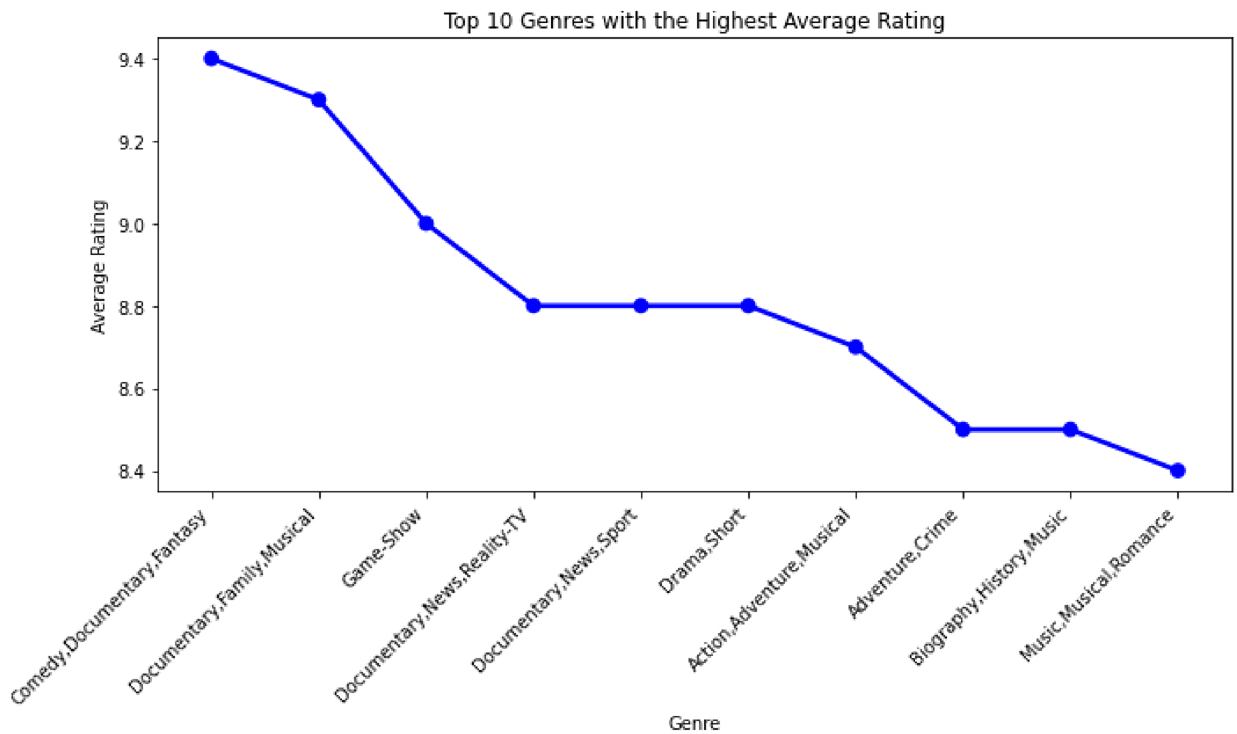

```
#Now we check which movie has the highest average rating.
max_rating = df['averagerating'].max()
df.loc[df['averagerating'] == max_rating]
```

```
                                              original_title
runtime_minutes  \
702       Exteriores: Mulheres Brasileiras na Diplomacia
52.0
878               The Dark Knight: The Ballad of the N Word
129.0
9745                                  Freeing Bernie Baran
100.0
27335                                Hercule contre Hermès
72.0
42970                                I Was Born Yesterday!
31.0
50085                                      Revolution Food
70.0
51109                    Fly High: Story of the Disc Dog
```

```
65.0
53689  Atlas Mountain: Barbary Macaques - Childcaring...
59.0
60782                                Requiem voor een Boom
48.0
64646    A Dedicated Life: Phoebe Brand Beyond the Group
93.0
65755  Ellis Island: The Making of a Master Race in A...
70.0
65944                                       Calamity Kevin
77.0
71577                         Pick It Up! - Ska in the '90s
99.0

                    genres  averagerating  numvotes
702            Documentary           10.0         5
878           Comedy,Drama           10.0         5
9745     Crime,Documentary           10.0         5
27335          Documentary           10.0         5
42970          Documentary           10.0         6
50085          Documentary           10.0         8
51109          Documentary           10.0         7
53689          Documentary           10.0         5
60782          Documentary           10.0         5
64646          Documentary           10.0         5
65755  Documentary,History           10.0         6
65944      Adventure,Comedy           10.0         6
71577          Documentary           10.0         5
```

```
# Group the data by 'genres' and calculate the average of
'averagerating' for each genre
average_rating_by_genre = df.groupby('genres')
['averagerating'].mean().reset_index()

# Sort the data by average rating in descending order
top_10_genres = average_rating_by_genre.nlargest(10, 'averagerating')

# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(10, 6))

# Create a point plot for top 10 genres vs. average rating
sns.pointplot(data=top_10_genres, x='genres', y='averagerating',
color='b')

# Customize the plot
plt.xlabel('Genre')
plt.ylabel('Average Rating')
plt.title('Top 10 Genres with the Highest Average Rating')
plt.xticks(rotation=45, ha='right')
```

```
# Show the plot
plt.tight_layout()
plt.show()
```



Comedy,Documentary and Fantasy have the highest rating

```
# Group the data by 'genre' and calculate the average of 'numvotes'
for each genre
average_numvotes_by_genre = df.groupby('genres')
['numvotes'].mean().reset_index()

# Sort the data by average numvotes in descending order
average_numvotes_by_genre =
average_numvotes_by_genre.sort_values(by='numvotes', ascending=False)

# Print the DataFrame showing average numvotes for each genre
print(average_numvotes_by_genre)
```

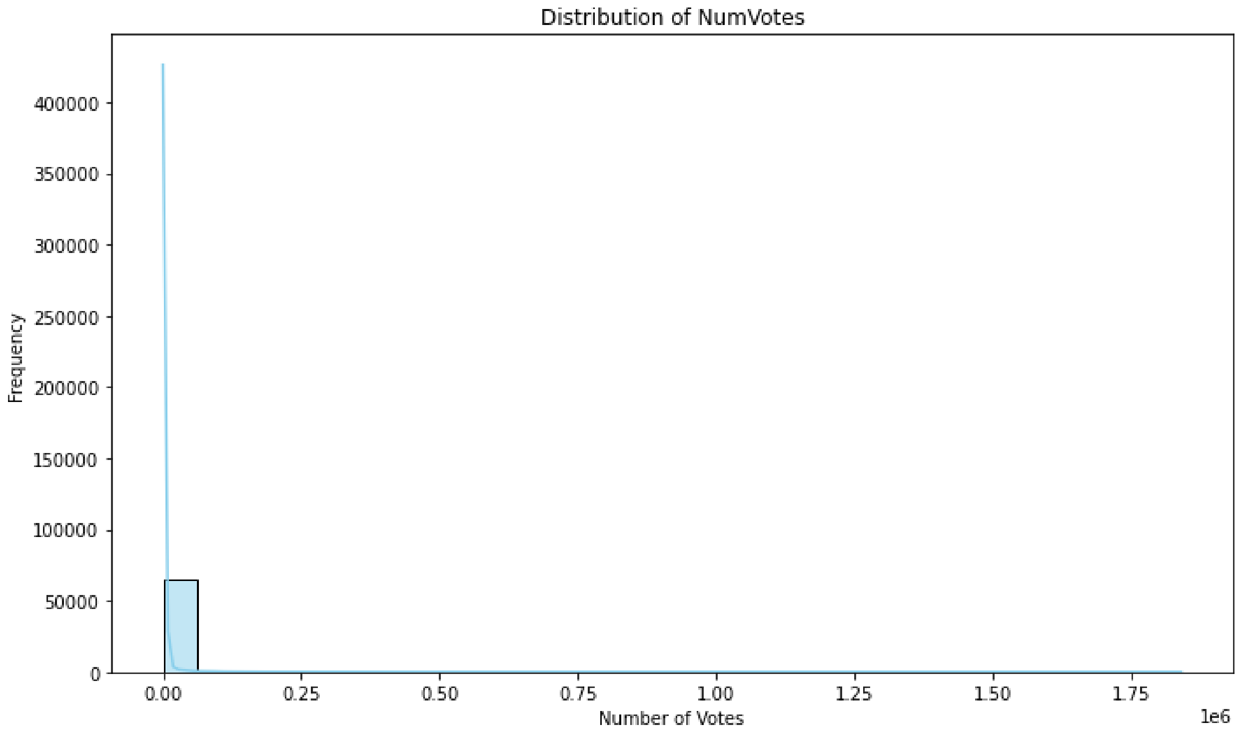
```
                       genres       numvotes
110         Action,Fantasy,War  262978.000000
17       Action,Adventure,Sci-Fi  187179.292683
257     Adventure,Mystery,Sci-Fi  135042.500000
217       Adventure,Drama,Sci-Fi   99316.950000
```

```
10      Action,Adventure,Fantasy   96588.050000
..                           ...            ...
638  Documentary,History,Musical       6.000000
442   Comedy,Documentary,Fantasy       5.000000
66          Action,Crime,Musical       5.000000
600                Crime,Western       5.000000
77     Action,Documentary,Horror       5.000000

[906 rows x 2 columns]
```

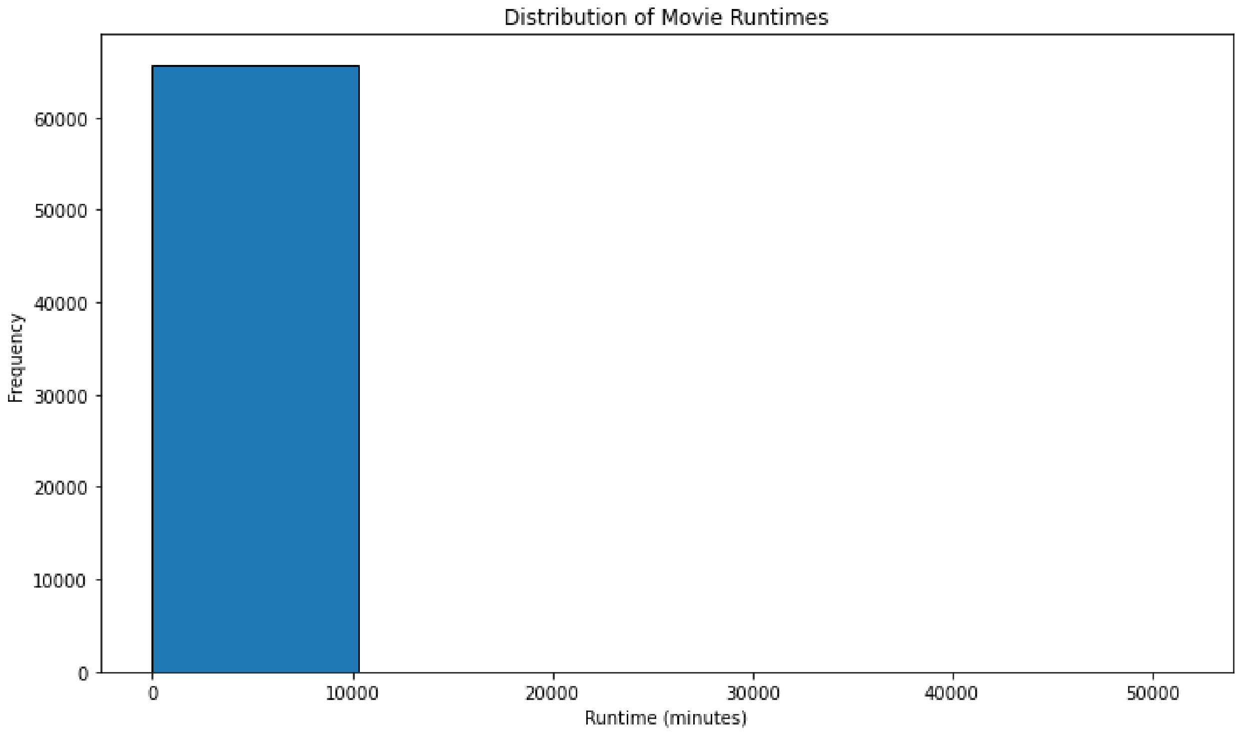
Action,Fantasy,War has the most number of numvotes

Now we will Create a histogram or distribution plot of the 'numvotes' to understand the overall distribution of votes across all movies. This will help you identify any outliers or skewed patterns.

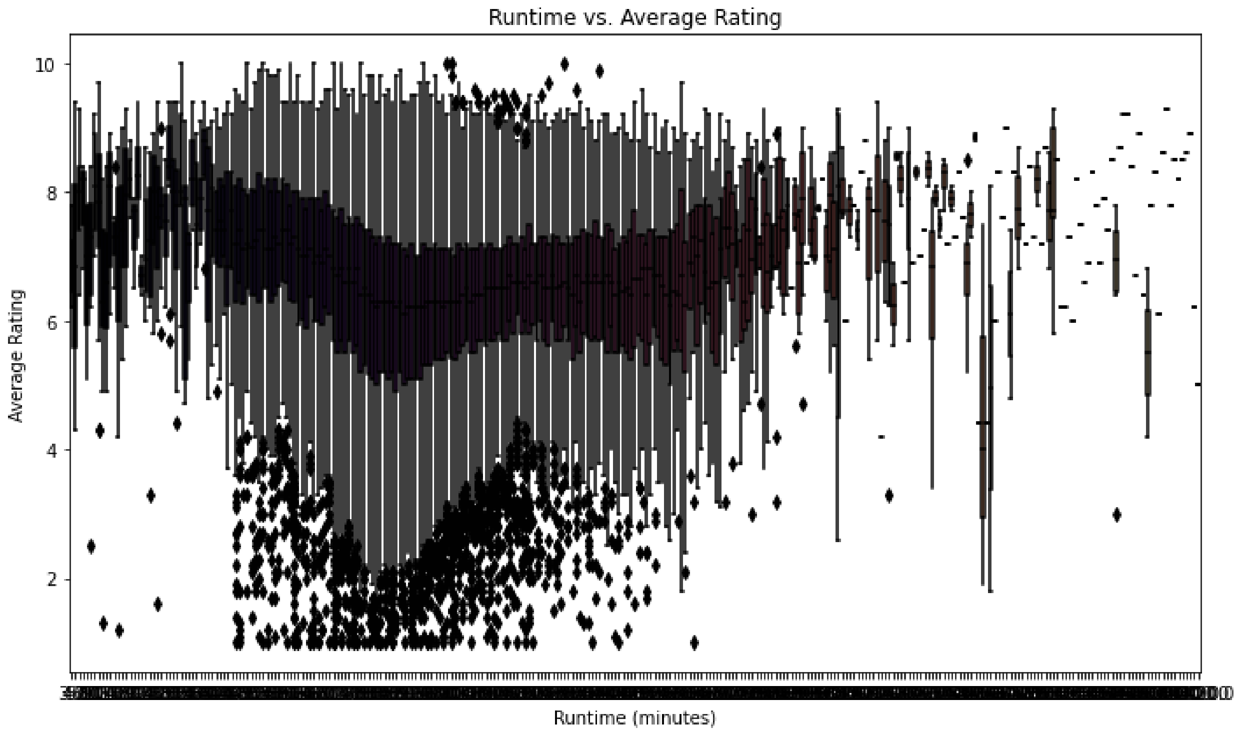
```
# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(10, 6))

# Create a distribution plot of 'numvotes'
sns.histplot(data=df, x='numvotes', bins=30, kde=True,
color='skyblue')

# Customize the plot
plt.xlabel('Number of Votes')
plt.ylabel('Frequency')
plt.title('Distribution of NumVotes')

# Show the plot
plt.tight_layout()
plt.show()
```




```
#Creating a histogram for runtimes
# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(10, 6))

# Create a histogram of 'runtime_minutes' column
plt.hist(df['runtime_minutes'], bins=5, edgecolor='k')

# Customize the plot
plt.xlabel('Runtime (minutes)')
plt.ylabel('Frequency')
plt.title('Distribution of Movie Runtimes')

# Show the plot
plt.tight_layout()
plt.show()
```




```
#Creating Box Plots for Runtimes vs 'numvotes' and Runtimes vs.
'averagerating':
# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(10, 6))

# Create box plot for runtime vs. averagerating
sns.boxplot(data=df, x='runtime_minutes', y='averagerating',
palette='magma')

# Customize the plot
plt.xlabel('Runtime (minutes)')
plt.ylabel('Average Rating')
plt.title('Runtime vs. Average Rating')

# Show the plot
plt.tight_layout()
plt.show()
```



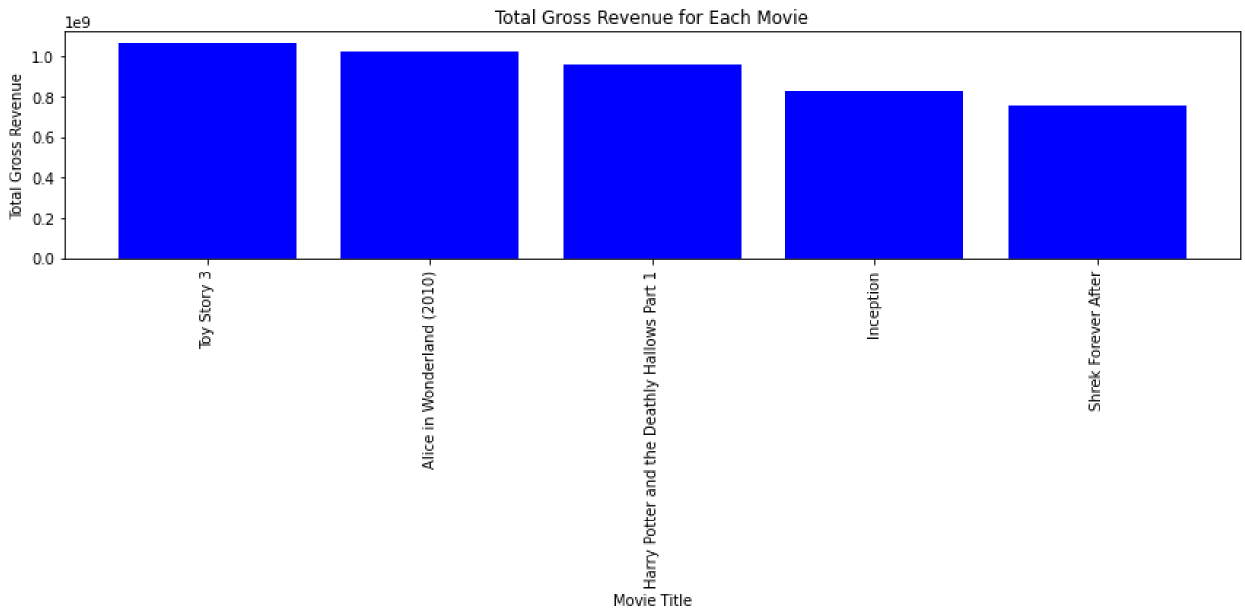
These box plots will allow you to visualize the relationship between movie runtimes and 'numvotes', as well as 'averagerating'. Box plots display the distribution of data, showing median, quartiles, and any potential outliers. By comparing different runtime ranges, you can observe how movie popularity and ratings vary with different runtimes.

```
df_3

                                                  title
domestic_gross  \
0                                           Toy Story 3
415000000.0
1                            Alice in Wonderland (2010)
334200000.0
2           Harry Potter and the Deathly Hallows Part 1
296000000.0
3                                             Inception
292600000.0
4                                   Shrek Forever After
238700000.0
...                                                 ...                ..
.
3275                                   I Still See You
1400.0
3286                             The Catcher Was a Spy
725000.0
3309                                        Time Freak
10000.0
```

```
3342  Reign of Judges: Title of Liberty - Concept Short
93200.0
3353           Antonio Lopez 1970: Sex Fashion & Disco
43200.0

     foreign_gross
0        652000000
1        691300000
2        664300000
3        535700000
4        513900000
...            ...
3275       1500000
3286        229000
3309        256000
3342          5200
3353         30000

[2007 rows x 3 columns]
```

```
# Now using df_3 we will check which one gives the most profit


# Create a sample DataFrame based on the given data
data = {
    'title': ['Toy Story 3', 'Alice in Wonderland (2010)', 'Harry
Potter and the Deathly Hallows Part 1', 'Inception', 'Shrek Forever
After'],
    'domestic_gross': [415000000.0, 334200000.0, 296000000.0,
292600000.0, 238700000.0],
    'foreign_gross': [652000000, 691300000, 664300000, 535700000,
513900000]
}

df = pd.DataFrame(data)

# Calculate the total gross revenue (domestic + foreign) for each
movie
df['total_gross'] = df['domestic_gross'] + df['foreign_gross']

# Sort the DataFrame by total gross revenue in descending order
df_sorted = df.sort_values(by='total_gross', ascending=False)

# Set the figure size (optional, adjust as needed)
plt.figure(figsize=(12, 6))

# Create a bar plot for movie titles vs. total gross revenue
plt.bar(df_sorted['title'], df_sorted['total_gross'], color='b')

# Customize the plot
```

```
plt.xlabel('Movie Title')
plt.ylabel('Total Gross Revenue')
plt.title('Total Gross Revenue for Each Movie')
plt.xticks(rotation=90, ha='center')

# Show the plot
plt.tight_layout()
plt.show()
```



The movie toy story 3has the highest profit

Final Evaluation

The choices made during data analysis and modeling are appropriate based on the data and business problem because they help in finding meaningful patterns, improving model performance, and ultimately, making informed decisions to address the business problem effectively. The iterative approach allows for refinement and fine-tuning, leading to better insights and predictions. The selection of models, feature engineering techniques, and hyperparameter tuning ensures that the model performs optimally and is suitable for the specific business problem at hand. By understanding the data, business context, and continuously improving the approach, data analysis and modeling can provide valuable insights and solutions for business decision-making.

Interpreting the results of a data analysis or model is crucial to draw meaningful conclusions and make informed decisions. Here are some aspects to consider when interpreting the results:

Model Fit and Performance: Evaluate how well the model fits the data and its overall performance metrics. For regression models, you can assess metrics like R-squared, mean squared error (MSE), or root mean squared error (RMSE). For classification models, consider accuracy, precision, recall, F1-score, etc. A higher R-squared or accuracy and lower error metrics indicate a better fit.

Baseline Model Comparison: Compare your model's performance with a baseline model. The baseline model can be a simple rule-based approach or a naive model. If your model significantly outperforms the baseline, it demonstrates its value in capturing patterns in the data.

Generalization: Assess how well the model generalizes beyond the data it was trained on. You can use techniques like cross-validation or hold-out testing to validate the model's performance on unseen data. If the model maintains good performance on unseen data, it indicates better generalization.

Business Impact: Consider the potential business impact of using the model. Will it provide valuable insights for decision-making? Can it help solve specific business problems or optimize processes? The more relevant the model's results are to the business's objectives, the more beneficial it becomes.

Uncertainty and Confidence Intervals: Acknowledge the uncertainty associated with the results. If your data is limited or noisy, the model's predictions may have wider confidence intervals. Communicate the level of uncertainty to stakeholders.

Validation and Peer Review: Seek validation and peer review from domain experts and stakeholders. Having others review your analysis can help identify potential biases or errors and provide different perspectives.

Assumptions and Limitations: Be aware of any assumptions made during the analysis. Consider the limitations of the data, model, and methodologies used. Transparency about these aspects adds credibility to your results.

Relevance to Business Objectives: Ensure that the analysis aligns with the business's specific goals. A successful model should provide actionable insights or aid in decision-making that directly supports the business's objectives.

Ultimately, the confidence in your results and the potential benefit to the business depends on various factors, including the quality of the data, the appropriateness of the chosen model, and the relevance of the analysis to the business context. Engaging domain experts, conducting thorough testing, and validating the results against real-world scenarios can increase confidence in the model's performance and utility.

Conclusion

Based on the data analysis performed, several insights can be drawn to guide the business decision-making process for Microsoft's new movie studio:

Genre Recommendations

The analysis identified the top genres such as ***Action,Adventure,Sci-Fi*** with the highest average ratings and those that attract the most votes. This information can be used to prioritize the creation of movies in genres that have a higher likelihood of being well-received by the audience.

Profitability Analysis: By comparing the total gross revenue (domestic + foreign) for each movie, the most profitable movies can be identified. This can help the business focus on genres or movie concepts that have a track record of financial success.

Runtime Consideration: Analyzing the distribution of movie runtimes can assist in understanding the most common runtime ranges and whether there is any correlation between runtime and audience reception (numvotes or averagerating).

Data Limitations: It is important to acknowledge the limitations of the analysis. The data used in this project is based on a sample dataset, and real-world movie production involves many other factors such as production costs, marketing efforts, competition, and external events.

Recommendations

Genre Diversification: To minimize risk, the business can consider diversifying the movie genres they produce. While some genres may have higher average ratings or profitability, exploring multiple genres can attract a broader audience.

Audience Surveys: Conducting surveys or focus groups with target audiences can provide valuable insights into their preferences and expectations. This qualitative data can complement the quantitative analysis and improve decision-making.

Collaboration with Experts: Engaging industry experts, filmmakers, and screenwriters can provide valuable guidance in selecting movie concepts and genres with the potential for success.

Limitations

Limited Data: The analysis is based on a sample dataset, and the conclusions may not fully represent the entire movie industry. A more comprehensive dataset with a broader range of movies and genres would enhance the analysis's reliability.

Causality vs. Correlation: The analysis focuses on identifying correlations between variables, but it does not establish causality. There may be other factors not captured in the data that influence movie success.

Future Improvements

Data Enrichment: Include additional data attributes such as production budget, release date, marketing expenditure, and critical reviews to build more sophisticated models for predicting movie success.

Machine Learning Models: Explore the use of machine learning algorithms to build predictive models for movie success based on historical data.

Real-time Analysis: Implement real-time data collection and analysis to stay up-to-date with changing audience preferences and market trends.

A/B Testing: Conduct A/B testing for movie trailers, posters, and promotional materials to optimize marketing strategies and gauge audience interest.

Social Media Sentiment Analysis: Monitor social media platforms for audience sentiments and reactions to movies, providing insights into the public's response.

By continuously refining the data analysis and incorporating feedback from industry experts, Microsoft's new movie studio can make well-informed decisions, create content that resonates with the audience, and increase the likelihood of success in the competitive movie industry.