In [1]:

```
pip install pillow
```

```
Requirement already satisfied: pillow in c:\users\rani_\anaconda6\lib\site
-packages (9.4.0)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:

```
from IPython.display import Image
```

In [3]:

```
Image('Img/download (2).jpg', width=1000, height=500)
```

Out[3]:

Microsoft Movie Studio Analysis

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Date: 12 August 2023

Overview

In response to the growing trend of big companies investing in movie studios. Microsoft has decided to enter the entertainment arena by establishing a new movie studio. However, lacking experience in the film industry, Microsoft company wants to seek valuable insights before embarking on its cinematic journey. As part of this exploratory phase, I have been given a task to analyze the current state of the box office and identify the most successful film genres. This research aims to provide actionable insights to assist the head of Microsoft's new movie studio in making informed decisions regarding the types of films to create.

I will analyze the data provided to identify what attributes the top-performing films have in common using my data analysis, statistics, and visualizations. Through my analysis, I have been able to identify the top genres, average runtime for a movie, and correlation between domestic gross with variables like runtime, genres, and production budget. Based on these findings, I have made recommendations to consider top genres while also exploring why other genres are not making success in terms of revenue, to stick with average runtime, and aim for the highest production budget to yield high returns because quality matters the most when it comes to success.

Business Problem

As big companies like Universal Pictures, Paramount, Warner Bros, and Disney are investing in original video content and Microsoft company is looking to join this trend by creating its very own "MOVIE STUDIO". But they are currently facing the challenge of navigating an unfamiliar industry. With no prior experience in creating movies, Microsoft seeks insights into the most successful film genres currently dominating the box office.

As part of this exploration, my role is to analyze box office trends and translate these findings into actionable strategies that the head of Microsoft's movie studio can use to make informed decisions on the types of films they want to produce.

Questions to consider:

- What is the top-ranking movie genre?
- What should be the average length of the movie?
- Correlation between domestic gross profit and other variables like runtime, genres, and production budget?

By finding answers to these questions, I believe I can provide valuable insight to Microsoft to identify the gaps they have been looking to produce a successful launch of their movie studio

Data Understanding

For this analysis, I utilized datasets from BoxOffice Mojo, IMDB, and The Numbers to get accurate actionable insights to the head of Microsoft's new movie studio.

Background information on datasets;

IMDB is the Internet Movie Database that provides a wealth of information about movies, television shows, video games, and all aspects of the entertainment industry. However, for this analysis, I used IMDB for gathering information on movies only as this is the main aspect of this project. The most primary categories of information you can find on the IMDB website for most films are;

- Title and Year
- Top 250 Movies
- Most popular movies
- Genres
- Runtime
- Number of votes

- Top Box office

The IMDB datasets used in this project were categorized into two data's

1. Title Basics Dataset - Had 146,144 items focusing on titles, genres, runtime, year. These datasets contained duplicates of titles and missing values for runtime, which were discussed in the data preparation section.
2. Title Rating Dataset - Had 73,856 items focusing on average ratings and number of votes. This dataset had no duplicates or missing values.

Box Office Mojo is an online movie publication and box office reporting service. Its primary function is to track box office revenue in a systematic, algorithmic way. The most common information we can find about movies from this website is;

- Domestic gross
- Foreign gross
- Top 10 domestic/foreign gross
- Distributer or studios
- Box office showdowns

The dataset used for this had 3387 items. For this dataset my main focus was domestic gross for analysis, the data type for this was in float which was converted to integer for better understanding.

The Number is another online platform that provides the financial analysis for each movie in terms of;

- Investor scenarios
- Domestic and international analysis
- Production Budget
- Comparison between different films' financial status

The dataset used for this had 5782 items focusing on the title, release date, production budget, domestic gross, and worldwide gross. My main interest was the production budget and domestic gross, which had a '$' string value in front of the number that was covered to float and then to integer (the full method is explained in data preparation).

Using pieces of information from these datasets, I was able to answer my questions proposed in business problems based on the target variables (Genres, Runtime, Domestic Gross, Production Budget)

Importing packages and datasets

In [4]:

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

In [5]:

```
#Here you run your code to explore the datas
#In this project i decided to use datasets from Internet Movie Database (IMDB), Box offic
```

In [6]:

```
#Read the datasets by importing datas into DataFrames using Panda
#df1 = Box Office Mojo
#df2 = IMDB (title basic )
#df3 = IMDP (title ratings)
#df4 = TN (The Number)
```

In [7]:

```
#Looking at the top five (.head()) and bottom five (.tail()) rows of each datasets for a
#df1
#df2
#df3
#df4
```

DATAFRAME 1

In [8]:

```
#Using pandas library we can import files such as CSV into a DataFrame
#CSV format is a common data storage format in which each line represents a row of data a
df1= pd.read_csv("zippedData/bom.movie_gross.csv")
```

In [9]:

```
df1.head()
```

Out[9]:

	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

In [10]:

```
df1.tail()
```

Out[10]:

	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

In [11]:

```
#using .info() to get quick overviw of the data structure which will give information;
#on the number of entries and coloumn
#the type of each column
#the number of non-null values in each column
#memory usuage of the dataframe.
df1.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
```

DATAFRAME 2

In [12]:

```
df2= pd.read_csv('zippedData/title.basics.csv')
```

In [13]:

```
df2.head()
```

Out[13]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [14]:

```
df2.tail()
```

Out[14]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

In [15]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

DATAFRAME 3

In [16]:

```
df3= pd.read_csv('zippedData/title.ratings.csv')
df3
```

Out[16]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [17]:

```
#Using sort_value() code below will rearrange the df3 DataFrame based on the values in th
#ascending = False parameter sorts the dataframe in descending order based on the values 
df3.sort_values(['numvotes'], ascending=False)
```

Out[17]:

	tconst	averagerating	numvotes
63498	tt1375666	8.8	1841066
8738	tt1345836	8.4	1387769
24920	tt0816692	8.6	1299334
38058	tt1853728	8.4	1211405
48221	tt0848228	8.1	1183655
...	...	...	...
39180	tt8050582	8.0	5
33886	tt6449270	4.0	5
22243	tt3819584	7.6	5
49605	tt2136926	5.8	5
32411	tt2056595	8.8	5

73856 rows × 3 columns

In [18]:

```
df3.head()
```

Out[18]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

In [19]:

```
df3.tail()
```

Out[19]:

	tconst	averagerating	numvotes
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

In [20]:

```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

DATAFRAME 4

In [21]:

```
df4= pd.read_csv('zippedData/tn.movie_budgets.csv')
df4
```

Out[21]:

	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
...	...	...	...	...	...	...
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

5782 rows × 6 columns

In [22]:

```
df4.head()
```

Out[22]:

	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 [23]:

```
df4.tail()
```

Out[23]:

	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

In [24]:

```
df4.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
```

In [25]:

```
#find out what type of data is df1,df2,df3,df4
```

In [26]:

```
type(df1)
type(df2)
type(df3)
type(df4)
```

Out[26]:

```
pandas.core.frame.DataFrame
```

Data Preparation

After importing and reviewing the datasets, I found that there were missing values, duplicates, incorrect data types, outliers for many variable that was interesting for this projects.

- For df1 Dataset, I first converted domestic_gross datatype from float to integer. The reason why I chose to correct the datatype for the targeted variable was because floating numbers can suffer precision issues like rounding errors. By representing money as integer it can avoid this imprecision, therefore it's easier to perform any arthemetic functions.
- For df2 Dataset, I found duplicated titles in the form of primary_title and original_title. By removing the duplicates we can avoid skewing the data analysis and giving misleading results. I also found there were missing values for runtime_minutes, which was replaced with zero (0), by replacing them with zero instead of dropping or deleting them can save us from losing other valuable information from that row for example genres.
- For df3 Dataset, there were no missing values or duplicates were detected.
- For df4 Dataset, I again converted production_budget, domestic_gross and worldwide_gross from string to float to integer. For this data cleaning i used stackerflow platform to figure out how to take remove string element "dollar sign". This mission was acheived first by using 'locale' module in python to convert string representations of numbers into actual float numbers. The 'locale.atof()' function is used to convert string with locale-aware formatting (eg currency symbols) into a float which was then easy to convert into integers.

After cleaning the datasets, i merged df1,df2,df3 datasets together to answer what are the top ranking movie genres, what should be the average runtime for a movie and is there any correlation between domestic gross, runtime, genres?

For this i did limit the number of values in this merged datasets to 2000 in order to collect a meaningful value of reviewed films and expanded genres column into subsets of genres to get better understanding of top ranking genres microsoft company should focus on to get a blockbuster movies and increase in profit. Also did last minute data cleaning for final merged dataset, where i detected duplicate columns for year.

I did further narrow this scope as my analysis progressed to the top 1500 films ranked by number of votes to figure out;

- Top Ranking genres
- Average runtime in minutes
- Correlation between domestic gross and variables like genres, runtime, production budget.

The correlation between the production budget and domestic gross was purely done using df4 dataset.

Data Cleaning

Data cleaning is the process of detecting, correcting or removing any inaccuaries in data to improve its quality.

In [27]:

```
df1
```

Out[27]:

	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	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

3387 rows × 5 columns

In [70]:

```
#handle potentials NaNs in 'domestic_gross' column by dropping them
df1 = df1.copy()
df1 = df1.dropna(subset=['domestic_gross']) #this drop rows where "domestic_gross" is NaN

#changing the data type for 'domestic_gross' from float to integer. As this will give us
df1.loc[:,'domestic_gross']= df1['domestic_gross'].astype(int)
df1.head()
```

Out[70]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000	664300000	2010
3	Inception	WB	292600000	535700000	2010
4	Shrek Forever After	P/DW	238700000	513900000	2010

In [29]:

```
#checking how many rows and the datatype for domestic_gross
#items or entries = 3359, which means the rows which had NaN were deleted of this dataset
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3359 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   title           3359 non-null   object
 1   studio          3356 non-null   object
 2   domestic_gross  3359 non-null   int32 
 3   foreign_gross   2009 non-null   object
 4   year            3359 non-null   int64 
dtypes: int32(1), int64(1), object(3)
memory usage: 144.3+ KB
```

In [30]:

```
df2
```

Out[30]:

	tconst	primary_title	original_title	start_year	runtime_minutes	gen
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dra
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dra
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dra
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Dra
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fant
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Dra
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Document
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Com
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	N
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Document

146144 rows × 6 columns

In [31]:

```
#df2 dataset
#In this dataframe the title is duplicated in the form of 'primary_title' and 'original_t
#Therefore it's better to have one column focusing on 'orignial_title' for simplicity.
#using .drop() function to delete 'primary_title'
```

In [32]:

```
df2 = df2.drop('primary_title', axis=1)
df2.head()
```

Out[32]:

	tconst	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [33]:

```
#Renaming column 'original_title' to 'title' on df2 DataFrame
```

In [34]:

```
#renaming 'original_title' to 'title', as this will make it easier to merge data to df1 [
df2.rename(columns={'original_title':'title'}, inplace=True)
```

In [35]:

```
df2
```

Out[35]:

	tconst	title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 5 columns

In [36]:

```
#filling up NaN with 0 in 'runtime_minutes' using fillna() to give us a better understand
df2['runtime_minutes'].fillna(0, inplace=True)

df2
```

Out[36]:

	tconst	title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	0.0	Comedy,Drama
4	tt0100275	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	0.0	Documentary
146141	tt9916706	Dankyavar Danka	2013	0.0	Comedy
146142	tt9916730	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	2013	0.0	Documentary

146144 rows × 5 columns

In [37]:

```
df3
```

Out[37]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [38]:

```
#no missing values were detected in df3
df3.isna().sum()
```

Out[38]:

```
tconst           0
averagerating    0
numvotes         0
dtype: int64
```

In [39]:

```
df4
```

Out[39]:

	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
...	...	...	...	...	...	...
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

5782 rows × 6 columns

In [40]:

```
#used stackerflow to solve how to convert string (currency symbol) to float for domestic_
#Using 'locale' module in python to convert string representations of numbers into actual
#The 'locale.atof()' function is used to convert string with locale-aware formatting (eg

import locale

locale.setlocale(locale.LC_ALL,'')
df4['domestic_gross']=df4.domestic_gross.map(lambda x: locale.atof(x.strip('$')))
df4
```

Out[40]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	760507625.0	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	241063875.0	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	42762350.0	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	459005868.0	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	620181382.0	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	0.0	$0
5778	79	Apr 2, 1999	Following	$6,000	48482.0	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	1338.0	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	0.0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	181041.0	$181,041

5782 rows × 6 columns

In [41]:

```
#to change string type to float for production_budget
locale.setlocale(locale.LC_ALL,'')
df4['production_budget']=df4.production_budget.map(lambda x: locale.atof(x.strip('$')))
df4
```

Out[41]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	$0
5778	79	Apr 2, 1999	Following	6000.0	48482.0	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	$0
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	$181,041

5782 rows × 6 columns

In [42]:

```
#to change string type to float for worldwide_gross
locale.setlocale(locale.LC_ALL,'')
df4['worldwide_gross']=df4.worldwide_gross.map(lambda x: locale.atof(x.strip('$')))
df4
```

Out[42]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	0.000000e+00
5778	79	Apr 2, 1999	Following	6000.0	48482.0	2.404950e+05
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	0.000000e+00
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	1.810410e+05

5782 rows × 6 columns

In [69]:

```
#converting float to int
# First, round the values in the specified columns
rounded_values = df4[['domestic_gross', 'production_budget', 'worldwide_gross']].round().
#float values will be rounded to the nearest whole number before they ae converted to int

# Convert the rounded values to integers
int_values = rounded_values.astype(int)

# Assign the integer values back to the columns in df4
df4[['domestic_gross', 'production_budget', 'worldwide_gross']] = int_values


df4
```

Out[69]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	-2147483648
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000	0	0
5778	79	Apr 2, 1999	Following	6000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041

5782 rows × 6 columns

Merging DataFrames

Merging datasets in a common operation in data manipulation and analysis. Using the panda library its provides a powerful funtionality to merge, join and concatenate datasets.

Merge 1

In [44]:

```
#Merging df2 (title_basics) and df3 (title_ratings) to get better dataframe to find out s
#What are the top ranking movie genre?
#How long should the film run in minutes for movie genres?
```

In [45]:

```
#merging df2 and df3 DataFrame on a common column 'tconst' and using left join of df2
merged_imdb_df= pd.merge(df2, df3, on='tconst', how='left')
merged_imdb_df
```

Out[45]:

	tconst	title	start_year	runtime_minutes	genres	averagera
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama	
1	tt0066787	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama	
3	tt0069204	Sabse Bada Sukh	2018	0.0	Comedy,Drama	
4	tt0100275	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama	N
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	0.0	Documentary	N
146141	tt9916706	Dankyavar Danka	2013	0.0	Comedy	N
146142	tt9916730	6 Gunn	2017	116.0	NaN	N
146143	tt9916754	Chico Albuquerque - Revelações	2013	0.0	Documentary	N

146144 rows × 7 columns

In [46]:

```
#by merging df2 and df3 by using the left join function, it undisturbs the item numbers
merged_imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 146144 entries, 0 to 146143
Data columns (total 7 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   title            146123 non-null  object 
 2   start_year       146144 non-null  int64  
 3   runtime_minutes  146144 non-null  float64
 4   genres           140736 non-null  object 
 5   averagerating    73856 non-null   float64
 6   numvotes         73856 non-null   float64
dtypes: float64(3), int64(1), object(3)
memory usage: 8.9+ MB
```

Merge 2

In [47]:

```
#merging merged_imdb_df to df1 (bom.movie_gross) at common column 'title' to get better a
#does domestic_gross correlates with genres, runtime or any other variables?
```

In [48]:

```
#creating final_df DataFrame by merging merged_imdb_df to df1 at common column 'title' to
final_df= pd.merge(merged_imdb_df, df1, on='title') #merging at inner to keep it simple c
final_df
```

Out[48]:

	tconst	title	start_year	runtime_minutes	genres	averageratin
0	tt0315642	Wazir	2016	103.0	Action,Crime,Drama	7
1	tt0337692	On the Road	2012	124.0	Adventure,Drama,Romance	6
2	tt2404548	On the Road	2011	90.0	Drama	Na
3	tt3872966	On the Road	2013	87.0	Documentary	Na
4	tt4339118	On the Road	2014	89.0	Drama	6
...	...	...	...	...	...	
2751	tt8549902	Oolong Courtyard	2018	103.0	Comedy	4
2752	tt8802728	The Witch	2018	0.0	Horror	Na
2753	tt8851262	Spring Fever	2019	0.0	Comedy,Horror	Na
2754	tt9151704	Burn the Stage: The Movie	2018	84.0	Documentary,Music	8
2755	tt9805754	Double Trouble	2013	99.0	Comedy,Family	Na

2756 rows × 11 columns

In [49]:

```
#by merging merged_imdb_df and df1, the items is now reduced to 2429
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2756 entries, 0 to 2755
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           2756 non-null   object 
 1   title            2756 non-null   object 
 2   start_year       2756 non-null   int64  
 3   runtime_minutes  2756 non-null   float64
 4   genres           2720 non-null   object 
 5   averagerating    2429 non-null   float64
 6   numvotes         2429 non-null   float64
 7   studio           2755 non-null   object 
 8   domestic_gross   2756 non-null   int32  
 9   foreign_gross    1758 non-null   object 
 10  year             2756 non-null   int64  
dtypes: float64(3), int32(1), int64(2), object(5)
memory usage: 247.6+ KB
```

Summary Statistic for DataFrame: final_df

The 'describe()' method will provide summary statistics that includes count, mean, standard deviation, minimum, 25th percentile(Q1), medium(50th percentile),75th percentile (Q3), and maximum. This function only provides statistic for numeric columns

In [50]:

```
final_df.describe()
```

Out[50]:

	start_year	runtime_minutes	averagerating	numvotes	domestic_gross	ye
count	2756.000000	2756.000000	2429.000000	2.429000e+03	2.756000e+03	2756.0000
mean	2013.994194	97.937591	6.409304	7.319450e+04	3.448273e+07	2013.9916
std	2.566000	35.080314	1.041829	1.349712e+05	6.747451e+07	2.4621
min	2010.000000	0.000000	1.600000	5.000000e+00	1.000000e+02	2010.0000
25%	2012.000000	90.000000	5.800000	3.797000e+03	2.490000e+05	2012.0000
50%	2014.000000	101.000000	6.500000	2.109200e+04	4.350000e+06	2014.0000
75%	2016.000000	115.000000	7.100000	8.128800e+04	4.105000e+07	2016.0000
max	2020.000000	623.000000	9.200000	1.841066e+06	7.001000e+08	2018.0000

Expanding Genres

As in the column 'genres' there are multiple genres per row, therefore to get better understanding of this dataset. I am going to expand each genre

In [51]:

```
#expand each genre into it's own column and drop nulls. Rounding to 2000 results - to get
final_df['genres'].unique()
final_df[['genre_1','genre_2','genre_3']] = final_df['genres'].str.split(',',expand=True)
final_df.dropna(subset=['genres'],inplace =True)
final_df1 = final_df.sort_values('numvotes', ascending=False).head(2000)
final_df1
```

Out[51]:

	tconst	title	start_year	runtime_minutes	genres	average
598	tt1375666	Inception	2010	148.0	Action,Adventure,Sci-Fi	
570	tt1345836	The Dark Knight Rises	2012	164.0	Action,Thriller	
108	tt0816692	Interstellar	2014	169.0	Adventure,Drama,Sci-Fi	
1372	tt1853728	Django Unchained	2012	165.0	Drama,Western	
173	tt0993846	The Wolf of Wall Street	2013	180.0	Biography,Crime,Drama	
...	...	...	...	...	...	
2436	tt4410000	Luis & the Aliens	2018	86.0	Adventure,Animation,Comedy	
1005	tt1757772	Jackie	2010	126.0	Action	
1606	tt2112152	For No Good Reason	2012	89.0	Biography,Documentary,History	
1554	tt2053352	Diana Vreeland: The Eye Has to Travel	2011	86.0	Biography,Documentary	
1295	tt3134422	Gold	2014	88.0	Comedy,Drama,Family	

2000 rows × 14 columns

In [52]:

```
final_df.isna().sum()
#As you can see from the output there is no missing values for the columns that I am inte
#runtime_minutes - i previously filled NaN values with 0 using fillna()
#domestic_gross
#genre_1
```

Out[52]:

```
tconst                0
title                 0
start_year            0
runtime_minutes       0
genres                0
averagerating       295
numvotes            295
studio                1
domestic_gross        0
foreign_gross       986
year                  0
genre_1               0
genre_2             645
genre_3            1328
dtype: int64
```

Highest rated domestic films. took top 1500 voted ranked film based on number of votes, then ordered by highest rank

In [53]:

```
highest_rated_domestic = final_df.copy()
highest_rated_domestic = highest_rated_domestic.sort_values('numvotes',ascending=True).he
highest_rated_domestic = highest_rated_domestic.sort_values('averagerating',ascending=Tru
highest_rated_domestic
```

Out[53]:

	tconst	title	start_year	runtime_minutes	genres	average
2728	tt7607940	Namaste England	2018	141.0	Comedy,Drama,Romance	
70	tt3746918	The Losers	2013	112.0	Drama	
1805	tt2344678	Himmatwala	2013	150.0	Action,Comedy,Drama	
1892	tt3007924	Amy	2013	94.0	Horror	
251	tt3309662	Jackpot	2013	132.0	Comedy,Thriller	
...	...	...	...	...	...	
1228	tt1744662	The Mayor	2011	68.0	Comedy,Documentary,Drama	
732	tt6216234	The Way	2016	85.0	Documentary	
1973	tt2831326	Tomorrow	2015	115.0	Drama	
198	tt6168914	The Runaways	2019	108.0	Adventure	
751	tt1455256	The Wall	2010	78.0	Documentary	

1500 rows × 14 columns

In [54]:

```
#counting total number per genres in top 1500 movies
highest_rated_domestic.genre_1.value_counts()
```

Out[54]:

```
Drama          406
Comedy         333
Action         202
Biography      160
Documentary    137
Adventure       79
Crime           70
Horror          62
Thriller        17
Animation       11
Fantasy          6
Romance          6
Family           4
Mystery          4
Sci-Fi           1
Music            1
Sport            1
Name: genre_1, dtype: int64
```

In [55]:

```
#last min cleaning of the data
#finding out duplicate values 'start_year' and 'year'
highest_rated_domestic = highest_rated_domestic.drop('start_year', axis=1)
highest_rated_domestic.head()
```

Out[55]:

	tconst	title	runtime_minutes	genres	averagerating	numvot
2728	tt7607940	Namaste England	141.0	Comedy,Drama,Romance	1.6	2087
70	tt3746918	The Losers	112.0	Drama	1.7	70
1805	tt2344678	Himmatwala	150.0	Action,Comedy,Drama	1.7	7384
1892	tt3007924	Amy	94.0	Horror	1.9	247
251	tt3309662	Jackpot	132.0	Comedy,Thriller	2.1	647

In [56]:

```
highest_rated_domestic = highest_rated_domestic.sort_values('year',ascending=True).head(1
highest_rated_domestic
```

Out[56]:

	tconst	title	runtime_minutes	genres	averagerati
910	tt1578261	Break Ke Baad	118.0	Comedy,Drama,Romance	5
224	tt1028576	Secretariat	123.0	Biography,Drama,Family	7
1845	tt2387589	The Girl on the Train	80.0	Thriller	4
590	tt1373156	Karthik Calling Karthik	135.0	Drama,Mystery,Thriller	7
525	tt1308165	The Taqwacores	83.0	Drama,Music	6
...	...	...	...	...	
2684	tt6588966	Hichki	116.0	Comedy,Drama	7
2116	tt3041550	Matangi/Maya/M.I.A.	96.0	Biography,Documentary,Music	7
2171	tt3289724	Welcome to Marwen	116.0	Biography,Comedy,Drama	6
2711	tt7137380	Destroyer	121.0	Action,Crime,Drama	6
2728	tt7607940	Namaste England	141.0	Comedy,Drama,Romance	1

1500 rows × 13 columns

In [57]:

```
highest_rated_domestic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1500 entries, 910 to 2728
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           1500 non-null   object 
 1   title            1500 non-null   object 
 2   runtime_minutes  1500 non-null   float64
 3   genres           1500 non-null   object 
 4   averagerating    1500 non-null   float64
 5   numvotes         1500 non-null   float64
 6   studio           1499 non-null   object 
 7   domestic_gross   1500 non-null   int32  
 8   foreign_gross    711 non-null    object 
 9   year             1500 non-null   int64  
 10  genre_1          1500 non-null   object 
 11  genre_2          1109 non-null   object 
 12  genre_3          672 non-null    object 
dtypes: float64(3), int32(1), int64(1), object(8)
memory usage: 158.2+ KB
```

In [58]:

```
#Statistic report
highest_rated_domestic.describe()
#from this we can figure out that the data is collected from 2010 to 2018
```

Out[58]:

	runtime_minutes	averagerating	numvotes	domestic_gross	year
count	1500.000000	1500.000000	1500.000000	1.500000e+03	1500.000000
mean	100.876000	6.223667	10655.476000	1.221634e+07	2014.279333
std	26.875283	1.106144	11477.161398	3.266563e+07	2.427599
min	0.000000	1.600000	5.000000	1.000000e+02	2010.000000
25%	90.000000	5.600000	904.500000	9.900000e+04	2012.000000
50%	100.000000	6.300000	6426.000000	7.775000e+05	2015.000000
75%	113.000000	7.000000	17193.250000	7.050000e+06	2016.000000
max	184.000000	9.200000	41103.000000	4.126000e+08	2018.000000

Data Modeling

As I completed my cleaning steps of the dataframes, I utilised the visualizations below to see the correlation that exists between the variables in the datasets.

GENRES

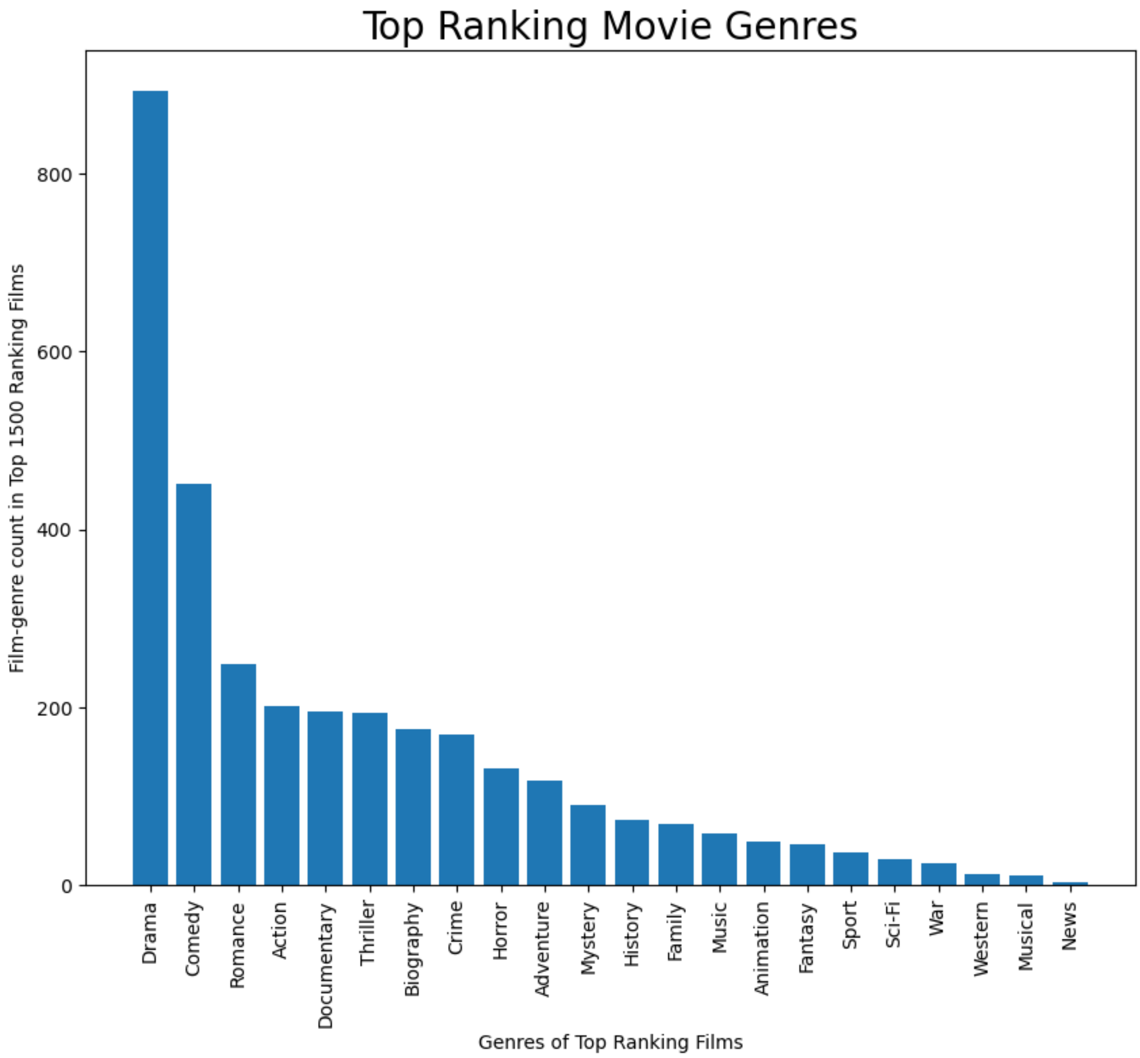
I selected the top 1,500 domestic films based on the number of votes and average rating they received. After ranking them by their ratings/votes (highest_rated_domestic), I was able to determine atleast the top 5 genres that performed the best at the box office from 2010 to 2018.

For analyzing the top genres i prefered using bar plot as this gives the clear visual representation of the data. As barplot are designed to represent categorical data in one axis and quantitative on the other. Below i used x = genre_count_ranks.index which is ploted on the horizontal axis, representing name of genres (Categorical) and y= genre_count_ranks.values represents genres and their total count (quantitative).

- From 2010 to 2018, an examination of movie popularity by genre revealed a clear heirarchy of audience preference. Drama film stood at the forefront, captivating audiences with their compelling narratives and relatable themes. Following closely behing, comedies consistently brought laughter to theaters, securing their place as the second most preferred genre. Romance movie, with their heartwarming and often heart-wrenching tales, clinched the third spot, while action-packed films, thought thrilling and adrenaline fueled, settled in fourth. Documentaries were close to action suggesting that there are population that prefers real based documentaries for example about a celebraty or politcians or even about athletes life. The ranking suggests a significant preference for story driven genres, indicating a potential trend in audience desire to watch.

In [59]:

```
#Top Ranking Movie Genres
top_ranking_movie_genres = highest_rated_domestic.head(1500)
genre_count_ranks = highest_rated_domestic[['genre_1','genre_2','genre_3']].stack().value
x = genre_count_ranks.index
y = genre_count_ranks.values
plt.figure(figsize=(10,8), facecolor='white', edgecolor='black')
plt.bar(x,y)
plt.title("Top Ranking Movie Genres", fontsize =20)
plt.xticks(rotation=90)
plt.xlabel('Genres of Top Ranking Films')
plt.ylabel('Film-genre count in Top 1500 Ranking Films');
```



RUNTIME

If Microsoft company is deciding to open a movie studio and are trying to gauge the ideal movie length, it might be wise to start with standard runtime (100 minutes) to play it safe.

I acheived this by targeting runtimes for each genres and then finding the average runtime required.

Using a bar plot to analyze the relationship between genre and runtime in minutes offer a clear visual presentation of data, allowing for each comparison between different genres.

- Most of the genres like horror, thriller, drama, adventure were ranged from 90-100 minutes, however the action, romance, sport, biography were ranged from 101-116 minutes. There were few genres like

family, sci-fi, documentary ranged from 29-87 minutes.
- However when we look at the average runtime for these genres, it suggested that a movie should run for atleast 100 minutes.

In [60]:

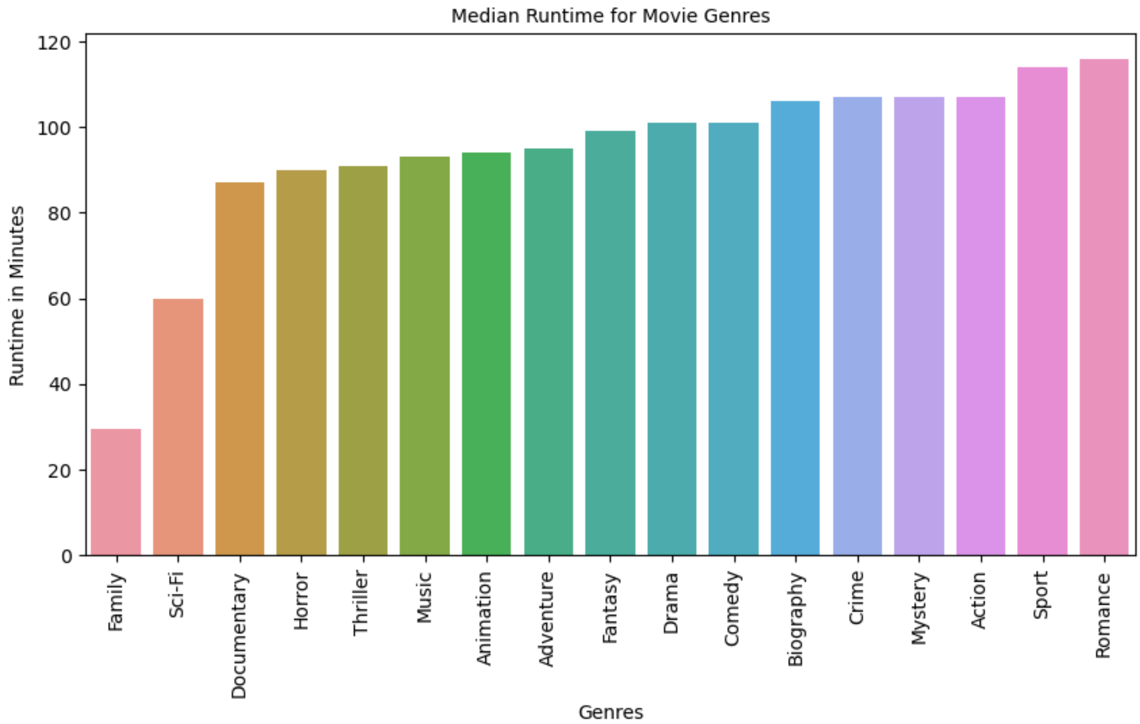
```
#topgenres in genre_1 column from ("highest_rated_domestic")
movie_genre_1 = highest_rated_domestic.groupby('genre_1', as_index=False).median(numeric_
movie_genre_1.loc[:,['genre_1','runtime_minutes']].head(1500)
```

Out[60]:

	genre_1	runtime_minutes
8	Family	29.5
14	Sci-Fi	60.0
6	Documentary	87.0
10	Horror	90.0
16	Thriller	91.0
11	Music	93.0
2	Animation	94.0
1	Adventure	95.0
9	Fantasy	99.0
7	Drama	101.0
4	Comedy	101.0
3	Biography	106.0
5	Crime	107.0
12	Mystery	107.0
0	Action	107.0
15	Sport	114.0
13	Romance	116.0

In [61]:

```
#runtime in minutes per genres
fig, ax = plt.subplots(figsize = (10,5))

sns.barplot(x='genre_1', y='runtime_minutes', data=movie_genre_1.head(1500))

plt.xlabel("Genres")
plt.ylabel("Runtime in Minutes")
plt.title("Median Runtime for Movie Genres", size=10)
plt.xticks(rotation=90)

plt.show()
```



In [62]:

```
#finding out mean for 'runtime_minutes' which is important to find out how much average t
highest_rated_domestic['runtime_minutes'].mean()
```

Out[62]:

```
100.876
```

CORRELATION BETWEEN DOMESTIC GROSS -----> RUNTIME, GENRES, PRODUCTION BUDGET

- First thing to consider was the statistic for domestic_gross, this was acheived by using Box plot visualization. A boxplot shows the median, quartiles, and possible outliers of a dataset (for this i excluded the outliers to get clear output). It gives a visual summary of the central tendancy, spread, and shape of the distribution of the data.
- Looking at the box plot below, we can see that the centre line which represent median IQR (50th percentile) shows that the half of movies have grossed below 7,77,500.0 dollars and half have grossed more. The average domestic gross was 12,216,340.00 dollars.

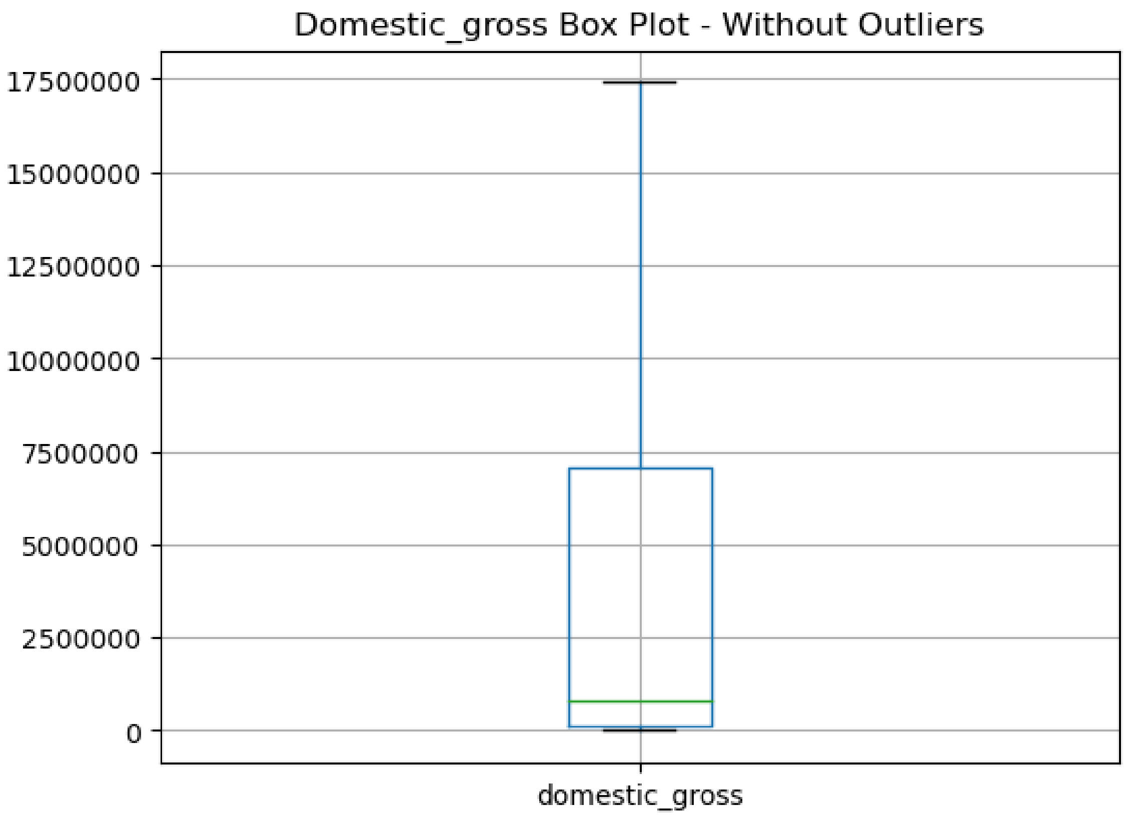
In [63]:

```
#Descriptive statistic of column 'domestic_gross' from DataFrame : highest_rated_domestic
print(highest_rated_domestic[['domestic_gross']].describe())
```

```
       domestic_gross
count    1.500000e+03
mean     1.221634e+07
std      3.266563e+07
min      1.000000e+02
25%      9.900000e+04
50%      7.775000e+05
75%      7.050000e+06
max      4.126000e+08
```

In [64]:

```
#creating a boxplot using 'boxplot' method of the DataFrame
#for domestic_gross from highest_rated_domestic DataFrame
highest_rated_domestic.boxplot(column='domestic_gross', showfliers=False)
plt.ticklabel_format(style='plain',axis='y')
plt.title("Domestic_gross Box Plot - Without Outliers")
plt.show()
```



Correlation between domestic_gross and runtime in minutes profit?

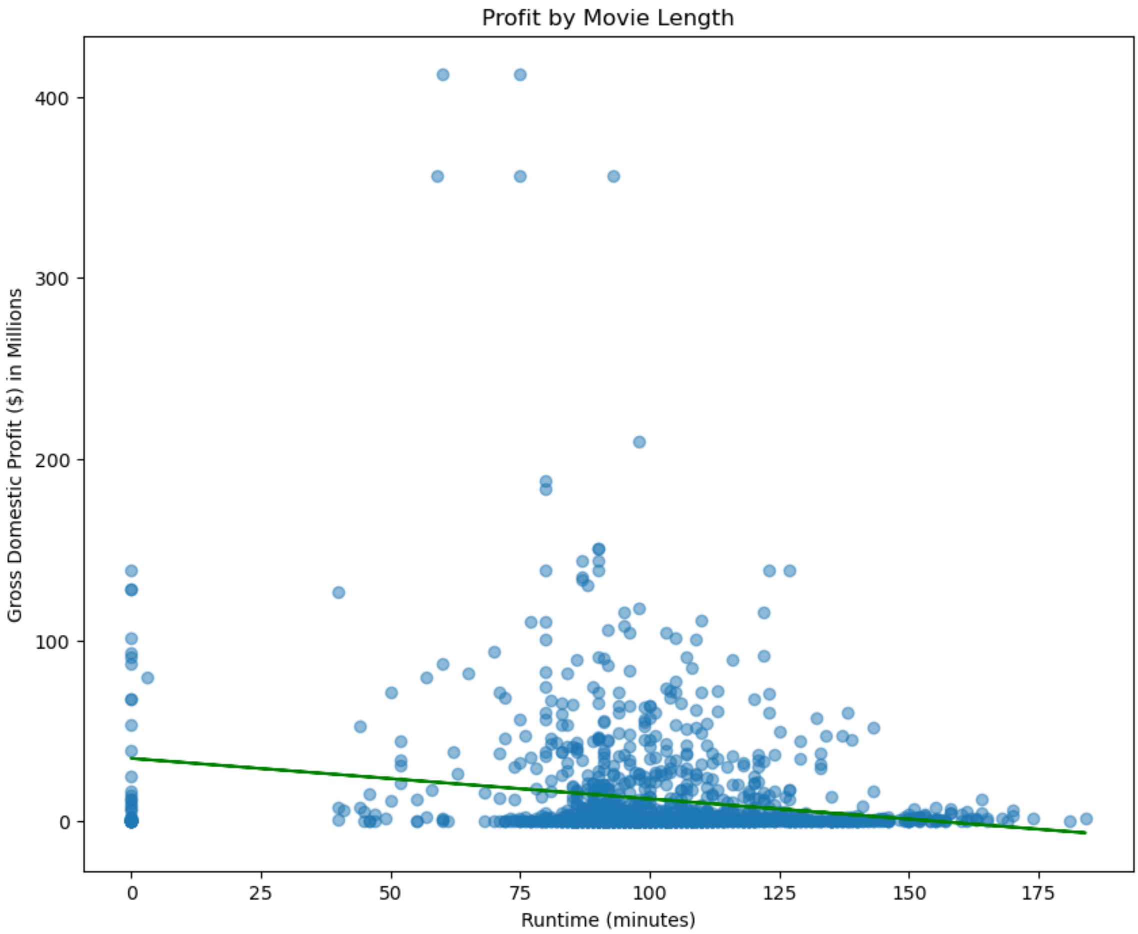
To check the correlation between domestic gross and runtime I prefered using scatter plot. Scatter plot is a best fit for representing correlation between two quantitative values.

- The scatter plot between the domestic gross in millions and the runtime (length in minutes) of movies shows a weak correlation, it means that there isn't a strong linear relationship between these two variables (horizontal line of best fit = weaker correlation).

- There isn't a univerally "perfect" length of a movie. some shorter films (e.g. under 90 minutes) can be incredibly successful while some longer films (e.g. over 120 minutes) can be hit too. Conversebly, movies by length can also be box office flops.
- Therefore some points to consider from here is that if runtime is not the best factor for figuring out the success of a movie then what are other factors to consider for movie's financial success ? Is the quality of story line, is it the genre, the actors involved, the direction, marketing, time of the year?

In [65]:

```
#correlation between runtime and domestic_gross profit? Weak correlation here.
x = highest_rated_domestic['runtime_minutes']
y = (highest_rated_domestic.domestic_gross)/ 1000000
fig,ax = plt.subplots(figsize=(10,8), facecolor = 'white', edgecolor= 'black')
ax.scatter(x,y, alpha = .5)

ax.set_title("Profit by Movie Length")
ax.set_xlabel("Runtime (minutes)")
ax.set_ylabel("Gross Domestic Profit ($) in Millions")

#this calculates the slope 'm' and y-intercept 'b' of the line of best fit for the given
m, b = np.polyfit(x,y,1)
plt.plot(x, m*x +b, color = "green", label="line of best fit")
ax.ticklabel_format(axis = 'y', style='plain');
```



In [66]:

```
#Create a new column in your dataframe with values in millions.
highest_rated_domestic['domestic_gross_millions'] = highest_rated_domestic['domestic_gros
highest_rated_domestic
```

Out[66]:

	tconst	title	runtime_minutes	genres	averagerati
910	tt1578261	Break Ke Baad	118.0	Comedy,Drama,Romance	5
224	tt1028576	Secretariat	123.0	Biography,Drama,Family	7
1845	tt2387589	The Girl on the Train	80.0	Thriller	4
590	tt1373156	Karthik Calling Karthik	135.0	Drama,Mystery,Thriller	7
525	tt1308165	The Taqwacores	83.0	Drama,Music	6
...	...	...	...	...	
2684	tt6588966	Hichki	116.0	Comedy,Drama	7
2116	tt3041550	Matangi/Maya/M.I.A.	96.0	Biography,Documentary,Music	7
2171	tt3289724	Welcome to Marwen	116.0	Biography,Comedy,Drama	6
2711	tt7137380	Destroyer	121.0	Action,Crime,Drama	6
2728	tt7607940	Namaste England	141.0	Comedy,Drama,Romance	1

1500 rows × 14 columns

Correlation between domestic gross and movie genres ?

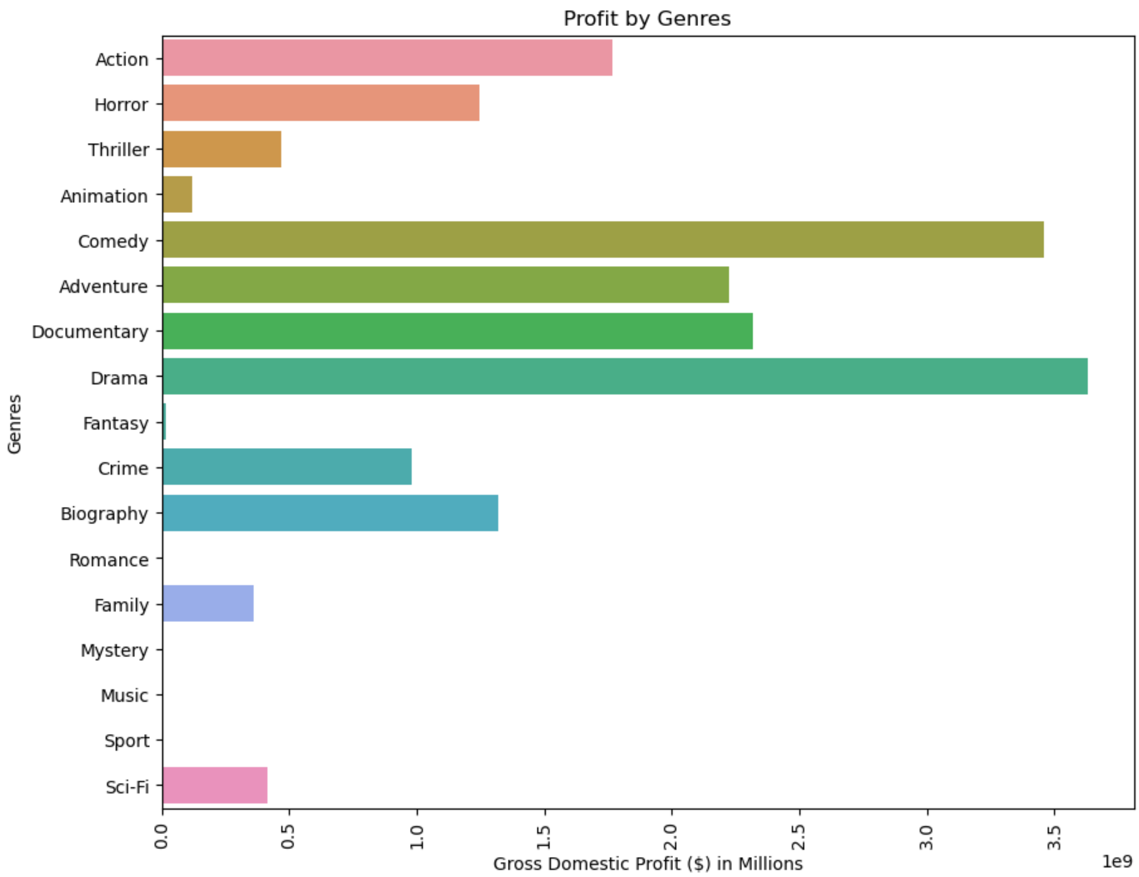
- I used horizontal bar plot to analyze the correlation between domestic gross and movie genres which involved displaying the average domestic gross for each genres.

This plot gave insight into what genres are currently more popular or preferred by the domestic audience.

- The bar plot showed that Drama and Comedy genres generated highest box office revenue of 3.0 to 3.5 million in the given domestic market.
- Genres like adventure, documentary, crime, action , horror, biogarphy showed 0.1 to 2.5 million hit in box office.
- While Sci-fi, family, fantasy, animation and thriller were among the lowest generated box office revenue
- Also some genres like romance, mystery, music and sport shows no box office revenue

In [67]:

```
#sort the data by 'domestic_gross' in descending order

highest_rated_domestic = highest_rated_domestic.sort_values(by='domestic_gross', ascendir

#creating barplot using the 'seaborn' libary as ('sns') to visualize the profit made by a
x= (highest_rated_domestic.domestic_gross)/1000000
y= highest_rated_domestic['genre_1']
fig, ax = plt.subplots(figsize=(10,8), facecolor = 'white', edgecolor= 'black')

sns.barplot(x='domestic_gross', y= 'genre_1', data=highest_rated_domestic,estimator=sum,e


ax.set_title("Profit by Genres")
ax.set_xlabel("Gross Domestic Profit ($) in Millions")
ax.set_ylabel("Genres")
plt.xticks(rotation=90)
plt.show()
```



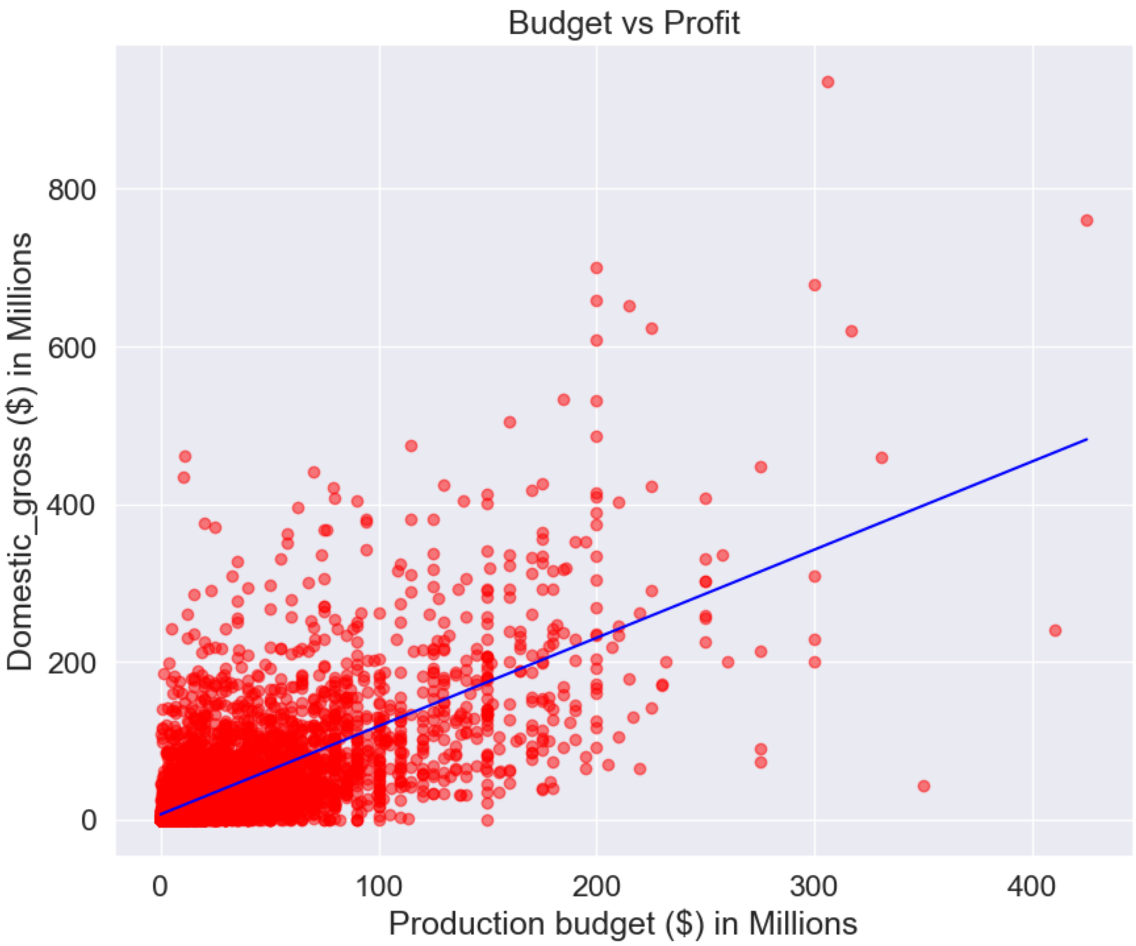
Correlation between Production budget and Domestic gross?

Does this mean the more money that is put into making a movie, the more money that movie will make?

- Using scatter plot we can see from the figure below, there are lot of dot points in the lower left portion of the graph and fewer movies in the top right portion of the graph. Higher budget movies appears to have higher revenue but how much higher and strong is that relationship, is something to consider. This can be acheived by calculating the linear regression anaylsis.

In [68]:

```
#correlation between production budget and domestic_gross
sns.set_style("whitegrid")
sns.set(font_scale = 1.5)

x = df4['production_budget']/1000000
y = df4['domestic_gross']/1000000

#this calculates the slope 'm' and y-intercept 'b' of the line of best fit for the given
m, b = np.polyfit(x,y,1)

fig,ax = plt.subplots(figsize=(10,8), facecolor = 'white', edgecolor= 'black')
ax.scatter(x,y, color = 'red', alpha = .5)

plt.plot(x, m*x +b, color = "blue", label="line of best fit")
ax.set_title("Budget vs Profit")
ax.set_xlabel("Production budget ($) in Millions")
ax.set_ylabel("Domestic_gross ($) in Millions")


ax.ticklabel_format(axis = 'y', style='plain');
```



Evaluation

The analysis offer a comprehensive view of movie preferebces by genre, average runtime, and the box office revenue. Below is the concise evaluation of my findings:

GENRE PREFERENCE

- Drama takes the lead in terms of popularity, suggesting audiences apprciate in-depth storylines and emotions that they can resonate with.
- Comedies are the second most preferred, emphasizing the value of entertainment and laughter.
- Romance and Action films come next, suggesting audiences are diversified in their taste, seeking both emotional connection and adrenaline pumping sequences.
- Some audiences also like Documentaries which indicates an interest in real-life narratives and educational content.

MOVIE RUNTIME

- A mojority of movie genres span between 90-116 minutes. Despite the range, the average runtime for most films is around 100 minutes.

DOMESTIC GROSS

- There is a weak correlation between runtime and domestic gross which signifies that length of a movie doesn't nesscarily predict its financial success.
- Drama and Comedy movies unsupersingly given their popularity, leads in term of revenue. Interestingly, despite action films being fourth in terms of preferences, they aren't among the top grossing genres. This might be due to production cost or market saturation. Genres like romance, mystery, music and sport not generating any revenue is suprising and may warrant further investigation. This could be due to fewer films being produced in these genres or issue with data collection.
- Positive correlation between movie's budget and its revenue suggest that investment in production tends to lead to higher returns.

Conclusions

In examining the movie industry from 2010 to 2018, it's evident that genre plays a pivotal role in a film's success with Drama and Comedy leading in audience preferences and revenure generation. While the average runtime of the film gravitates around 1 hour 40 minute, the length isn't a direct predictor of financial success. Instead the correlation between movie's production budget and its gross indicates that investment in production often results in better returns.

Business Recomendation to Microsoft Company

- **Diversify Portfolio**: While Drama and Comedy have shown strong results, it's important to maintain a diversified portfolio of movie genres to cater to varied audiences preferences and mitigate risks.
- **Budget Allocation**: Allocate budget wisely, focusing on key areas like story quality, casting and post production. A higher budget often correlates with higher returns, but its crucial to ensure the budget is used effectively.
- **Market Research**: Conduct more in-depth market research to understand why genres such as romance, mystery, music arents generating revenue. This will help in making informed decisions for future projects.
- **Movie marketing**: With a movie runtime not being a direct predictor of success in terms of revenue, marketing strategies can play a pivotal role in the movie success.

Some of the reason to consider for analysis might not fully solve the bussiness problems:

- The data only span from 2010 to 2018, which might not capture the most recent trends.

- Factors like quality of storyline, directorial talent, and cast performances which might not be quantified easily but it plays a hugh role in movie's success
- The role of marketing, production, and release strategies is not captured in these datasets but can significantly impact a movie's success

Future improvements for these datasets

- Regularly updating data can give a comprehensive view of current trends.
- Incorporate additional data like critical reviews, audience feedback and competition between movies release in same year to give a holistic view of the factors influencing movie success.

In conclusion while the analysis provides valuable insights, the movie industry's complexity requires a multifaceted approach, considering both quantifiable metrics and qualitative factors to run a successful movie

In [ ]:

```

```