```
In [1]: # Supress Warnings
        import warnings
        warnings.filterwarnings('ignore')
        #Importing the Libraries
In [2]: # lets import the basic Libraries
        import numpy as np
        import pandas as pd
        # for data visualization
        import matplotlib.pyplot as plt
        import seaborn as sns
        # for jupyter notebook widgets
        #import ipywidgets as widgets
        #from ipywidgets import interact
        #from ipywidgets import interact_manual
        # for Interactive Shells
        from IPython.display import display
        # setting up the chart size and background
        plt.rcParams['figure.figsize'] = (16, 8)
        plt.style.use('fivethirtyeight')
        #Loading the Data Set
In [3]: # Lets read the dataset
        data = pd.read_csv('movie_metadata.csv')
        #Shape of the Data
```

In [4]: # lets check the shape
print(data.shape)

#Information about the Data Set

(5043, 28)

In [5]: # lets check the column wise info data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 5043 entries, 0 to 5042 Data columns (total 28 columns):

#	Column	Non-Null Count	Dtype
0	color	5024 non-null	object
1	director_name	4939 non-null	object
2	num_critic_for_reviews	4993 non-null	float64
3	duration	5028 non-null	float64
4	<pre>director_facebook_likes</pre>	4939 non-null	float64
5	actor_3_facebook_likes	5020 non-null	float64
6	actor_2_name	5030 non-null	object
7	actor_1_facebook_likes	5036 non-null	float64
8	gross	4159 non-null	float64
9	genres	5043 non-null	object
10	actor_1_name	5036 non-null	object
11	<pre>movie_title</pre>	5043 non-null	object
12	num_voted_users	5043 non-null	int64
13	<pre>cast_total_facebook_likes</pre>	5043 non-null	int64
14	actor_3_name	5020 non-null	object
15	<pre>facenumber_in_poster</pre>	5030 non-null	float64
16	plot_keywords	4890 non-null	object
17	<pre>movie_imdb_link</pre>	5043 non-null	object
18	num_user_for_reviews	5022 non-null	float64
19	language	5029 non-null	object
20	country	5038 non-null	object
21	content_rating	4740 non-null	object
22	budget	4551 non-null	float64
23	title_year	4935 non-null	float64
24	actor_2_facebook_likes	5030 non-null	float64
25	imdb_score	5043 non-null	float64
26	aspect_ratio	4714 non-null	float64
27	<pre>movie_facebook_likes</pre>	5043 non-null	int64
dtyp	es: float64(13), int64(3),	object(12)	

memory usage: 1.1+ MB

```
# Use the 'drop()' function to drop the unnecessary columns
        data = data.drop(['color',
                                'director_facebook_likes',
                               'actor_3_facebook_likes',
                                'actor_1_facebook_likes',
                               'cast_total_facebook_likes',
                               'actor 2 facebook likes',
                               'facenumber_in_poster',
                                'content_rating',
                                'country',
                               'movie_imdb_link',
                                'aspect_ratio',
                                'plot_keywords',
                               ],
                                axis = 1)
        data.columns
Out[6]: Index(['director_name', 'num_critic_for_reviews', 'duration', 'actor_2_nam
        e',
                'gross', 'genres', 'actor 1 name', 'movie title', 'num voted user
        s',
                'actor_3_name', 'num_user_for_reviews', 'language', 'budget',
                'title_year', 'imdb_score', 'movie_facebook_likes'],
               dtype='object')
        #Missing Values Imputation
In [7]: # lets check the rows having high percentage of missing values in the datase
        round(100*(data.isnull().sum()/len(data.index)), 2)
Out[7]: director_name
                                    2.06
        num_critic_for_reviews
                                    0.99
                                    0.30
        duration
        actor_2_name
                                    0.26
                                   17.53
        gross
                                    0.00
        genres
        actor_1_name
                                    0.14
        movie_title
                                    0.00
        num_voted_users
                                    0.00
        actor_3_name
                                    0.46
        num_user_for_reviews
                                    0.42
        language
                                    0.28
        budget
                                    9.76
        title_year
                                    2.14
        imdb_score
                                    0.00
        movie facebook likes
                                    0.00
        dtype: float64
```

In [6]: # lets remove unnecassary columns from the dataset

```
In [8]: # Since 'gross' and 'budget' columns have large number of NaN values, drop of
        # 'isnan' function of NumPy alongwith a negation '~'
        data = data[~np.isnan(data['gross'])]
        data = data[~np.isnan(data['budget'])]
        # Now lets again check the Missing Values column wise
        data.isnull().sum()
Out[8]: director name
                                   0
        num_critic_for_reviews
                                   1
                                   1
        duration
                                   5
        actor_2_name
                                   0
        gross
                                   0
        genres
        actor_1_name
                                   3
                                   0
        movie_title
        num_voted_users
                                   0
                                  10
                                 0
        num_user_for_reviews
        language
                                   4
                                   0
        budget
                                   0
        title year
        imdb_score
                                   0
        movie_facebook_likes
                                   0
        dtype: int64
In [9]: # The rows for which the sum of Null is less than two are retained
        data = data[data.isnull().sum(axis=1) <= 2]</pre>
        data.isnull().sum()
Out[9]: director_name
                                  0
        num_critic_for_reviews
                                  1
        duration
                                  1
        actor_2_name
                                  2
                                  0
        gross
                                  0
        genres
                                  0
        actor_1_name
        movie_title
        num_voted_users
                                  0
        actor_3_name
                                  7
                                  0
        num_user_for_reviews
                                  4
        language
        budget
                                  0
        title_year
                                  0
        imdb score
                                  0
        movie_facebook_likes
        dtype: int64
```

```
In [10]: # lets impute the missing values

# using mean for numerical columns
data['num_critic_for_reviews'].fillna(data['num_critic_for_reviews'].mean()
data['duration'].fillna(data['duration'].mean(), inplace = True)

# using mode for categorical column
data['language'].fillna(data['language'].mode()[0], inplace = True)

# As we know that We cannot use statistical values for imputing the missing # actor names with "Unknown Actor"

data['actor_2_name'].fillna('Unknown Actor', inplace = True)
data['actor_3_name'].fillna('Unknown Actor', inplace = True)

# as we imputed all the missing values lets check the no. of total missing values.isnull().sum().sum()
```

Out[10]: 0

#Feature Engineering

```
In [11]: # Lets convert the gross and budget from $ to Million $ to make our analysis

data['gross'] = data['gross']/1000000
data['budget'] = data['budget']/1000000
```

```
In [12]: # lets create a Profit column using the Budget and Gross

data['Profit'] = data['gross'] - data['budget']

# lets also check the name of Top 10 Profitable Movies
data[['Profit','movie_title']].sort_values(by = 'Profit', ascending = False)
```

Out[12]:

	Profit	movie_title
0	523.505847	Avatar
29	502.177271	Jurassic World
26	458.672302	Titanic
3024	449.935665	Star Wars: Episode IV - A New Hope
3080	424.449459	E.T. the Extra-Terrestrial
794	403.279547	The Avengers
17	403.279547	The Avengers
509	377.783777	The Lion King
240	359.544677	Star Wars: Episode I - The Phantom Menace
66	348.316061	The Dark Knight

```
In [13]: # By looking at the above result we can easily analyze that there are some of
# lets print the no. of rows before removing Duplicates
print("No. of Rows Before Removing Duplicates: ",data.shape[0])
# so lets remove all the duplicates from the data
data.drop_duplicates(subset = None, keep = 'first', inplace = True)
# lets print the no. of rows after removing Duplicates
print("No. of Rows After Removing Duplicates: ",data.shape[0])
```

No. of Rows Before Removing Duplicates: 3888 No. of Rows After Removing Duplicates: 3853

#Top 10 Movies with Highest profit

```
In [14]: # Lets check the Top 10 Profitable Movies Again
data[['movie_title','Profit']].sort_values(by = 'Profit', ascending = False)
```

Out[14]:

	movie_title	Profit
0	Avatar	523.505847
29	Jurassic World	502.177271
26	Titanic	458.672302
3024	Star Wars: Episode IV - A New Hope	449.935665
3080	E.T. the Extra-Terrestrial	424.449459
17	The Avengers	403.279547
509	The Lion King	377.783777
240	Star Wars: Episode I - The Phantom Menace	359.544677
66	The Dark Knight	348.316061
439	The Hunger Games	329.999255

#Manupulating the Duration and Language Collumn

In [15]: # lets check the values in the language column data['language'].value_counts()

	-	0 0	-	_
Out[15]:	language			
	English		3674	
	French		37	
	Spanish		26	
	Mandarin		14	
	German		13	
	Japanese		12	
	Hindi		10	
	Cantonese	ة	8	
	Italian		7	
	Portugues	se	5	
	Korean		5	
	Norwegian	1	4	
	Thai		3	
	Hebrew		3	
	Persian		3	
	Danish		3 3 3	
	Dutch			
	Dari		2	
	Indonesia	an	2	
	Aborigina	al	2	
	Arabic		1	
	Russian		1	
	Vietnames	se	1	
	Dzongkha		1	
	Romanian		1	
	Zulu		1	
	Bosnian		1	
	Czech		1	
	Icelandi	2	1	
	Hungarian	1	1	
	Mongoliar	ı	1	
	Aramaic		1	
	Telugu		1	
	Kazakh		1	
	Maya		1	
	Filipino		1	
	Swedish		1	

Name: count, dtype: int64

```
In [16]: # Looking at the above output we can easily observe that out of 3,500 movies
          # so it is better to keep only two languages that is English and Foreign
          def language(x):
              if x == 'English':
                  return 'English'
              else:
                  return 'Foreign'
          # lets apply the function on the language column
          data['language'] = data['language'].apply(language)
          # lets check the values again
          data['language'].value_counts()
Out[16]: language
          English
                     3674
          Foreign
                     179
          Name: count, dtype: int64
In [17]: # The Duration of Movies is not varying a lot but we know that most of the
          # duration movies. we can categorize the movies in two part i.e., short and
          # lets define a function for categorizing Duration of Movies
          def duration(x):
              if x <= 120:
                  return 'Short'
              else:
                  return 'Long'
          # lets apply this function on the duration column
          data['duration'] = data['duration'].apply(duration)
          # lets check the values of Duration column
          data['duration'].value_counts()
Out[17]: duration
          Short
                   2936
          Long
                    917
          Name: count, dtype: int64
In [18]: # lets also check the values in the Genres Column
         data['genres'].value_counts()
Out[18]: genres
          Drama
                                                     153
          Comedy | Drama | Romance
                                                     151
          Comedy Drama
                                                     147
          Comedy
                                                     145
          Comedy | Romance
                                                     135
          Action | Crime | Drama | Thriller | War
                                                       1
          Adventure | Comedy | Family | Musical
                                                       1
          Action | Adventure | Family | Fantasy | Sci-Fi
                                                       1
          Action|Drama|Mystery|Thriller|War
                                                       1
          Comedy | Crime | Horror
          Name: count, Length: 762, dtype: int64
```

```
In [19]: data['genres'].str.split('|')[0]
Out[19]: ['Action', 'Adventure', 'Fantasy', 'Sci-Fi']
In [20]: # we can see from the above output that most of the movies are having a lot # also, a movie can have so many genres so lets keep four genres

data['Moviegenres'] = data['genres'].str.split('|')
    data['Genre1'] = data['Moviegenres'].apply(lambda x: x[0])

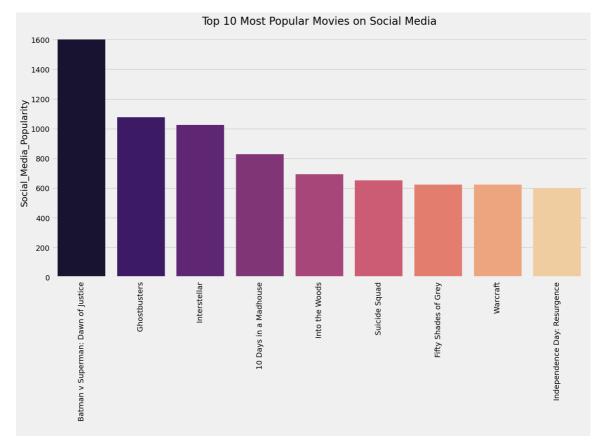
# Some of the movies have only one genre. In such cases, assign the same gendata['Genre2'] = data['Moviegenres'].apply(lambda x: x[1] if len(x) > 1 elsdata['Genre3'] = data['Moviegenres'].apply(lambda x: x[2] if len(x) > 2 elsdata['Genre4'] = data['Moviegenres'].apply(lambda x: x[3] if len(x) > 3 elsdata['genres', 'Genre1', 'Genre2', 'Genre3', 'Genre4']].head(5)
```

Out[20]:

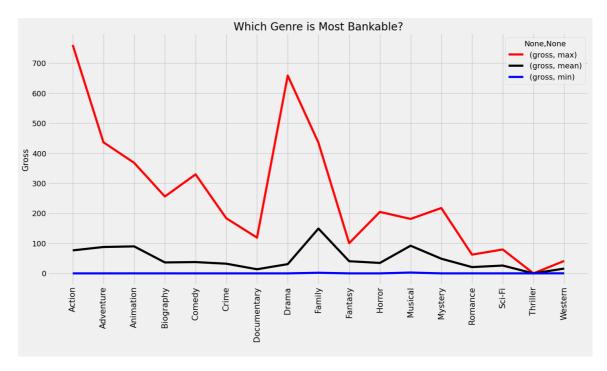
	genres	Genre1	Genre2	Genre3	Genre4
0	Action Adventure Fantasy Sci-Fi	Action	Adventure	Fantasy	Sci-Fi
1	Action Adventure Fantasy	Action	Adventure	Fantasy	Action
2	Action Adventure Thriller	Action	Adventure	Thriller	Action
3	Action Thriller	Action	Thriller	Action	Action
5	Action Adventure Sci-Fi	Action	Adventure	Sci-Fi	Action

#Data Visualisation

	index	<pre>movie_title</pre>	Social_Media_Popularity
0	10	Batman v Superman: Dawn of Justice	1599.794424
1	150	Ghostbusters	1076.336425
2	1582	Ghostbusters	1075.827482
3	96	Interstellar	1024.560802
4	3015	10 Days in a Madhouse	828.025478
5	945	Into the Woods	692.937200
6	73	Suicide Squad	652.816996
7	1190	Fifty Shades of Grey	624.306881
8	108	Warcraft	622.790277
9	92	Independence Day: Resurgence	599.274128



			gross
	max	mean	min
Genre1			
Action	760.505847	76.584686	0.000162
Adventure	436.471036	87.827145	0.004091
Animation	368.049635	89.873480	0.071442
Biography	255.950375	36.431983	0.012836
Comedy	329.691196	37.611935	0.000703
Crime	183.405771	32.223226	0.001111
Documentary	119.078393	13.704278	0.005858
Drama	658.672302	30.778967	0.002580
Family	434.949459	149.160478	2.119994
Fantasy	100.614858	40.483059	0.003478
Horror	204.565000	34.737117	0.005725
Musical	181.360000	92.084000	2.808000
Mystery	217.536138	48.822296	0.016066
Romance	62.453315	20.886339	0.076382
Sci-Fi	79.568000	26.071841	0.018195
Thriller	0.070071	0.040513	0.002468
Western	41.400000	15.914589	0.243768



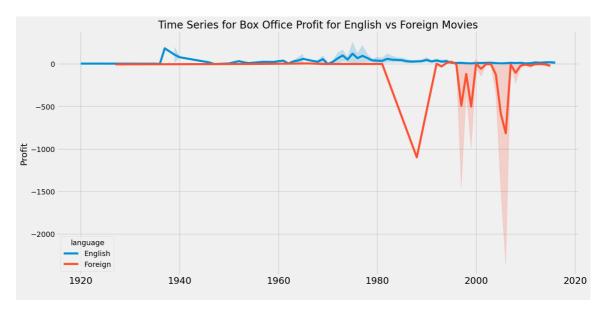
The Most Profitable Movie from each Genre

	Genre1	movie_title	gross
0	Action	Avatar	760.505847
509	Adventure	The Lion King	422.783777
521	Animation	Despicable Me 2	368.049635
1403	Biography	The Blind Side	255.950375
836	Comedy	Forrest Gump	329.691196
3466	Crime	The Godfather	134.821952
3583	Documentary	Fahrenheit 9/11	119.078393
26	Drama	Titanic	658.672302
3080	Family	E.T. the Extra-Terrestrial	434.949459
2485	Fantasy	The Others	96.471845
2916	Horror	The Exorcist	204.565000
3581	Musical	Grease	181.360000
208	Mystery	The Da Vinci Code	217.536138
928	Romance	The Adjustment Bureau	62.453315
2925	Sci-Fi	WarGames	79.568000
5034	Thriller	Cavite	0.070071
3540	Western	Pale Rider	41.400000

Most Profitable Years in Box Office

Profit

language	title_year	
	2014	2729.797944
	2012	2701.504634
	2015	2364.554417
	2002	2268.274235
English	2009	2133.449256
English	2013	2080.782304
	2003	1924.411513
	2007	1754.855579
	2001	1666.984435
	1994	1600.413059



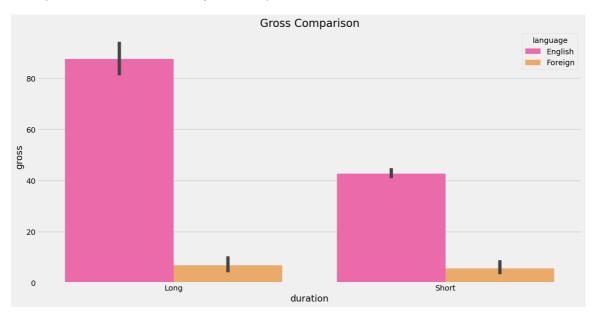
Movies that Made Huge Losses

	movie_title	language	Profit
2323	Princess Mononoke	Foreign	-2397.701809
2334	Steamboy	Foreign	-2127.109510
2988	The Host	Foreign	-12213.298588
3005	Fateless	Foreign	-2499.804112
3859	Lady Vengeance	Foreign	-4199.788333

	movie_title	duration	gross	Profit
0	Avatar	Long	760.505847	523.505847
29	Jurassic World	Long	652.177271	502.177271
26	Titanic	Long	658.672302	458.672302
3024	Star Wars: Episode IV - A New Hope	Long	460.935665	449.935665
17	The Avengers	Long	623.279547	403.279547

	movie_title	duration	gross	Profit
3080	E.T. the Extra-Terrestrial	Short	434.949459	424.449459
509	The Lion King	Short	422.783777	377.783777
812	Deadpool	Short	363.024263	305.024263
521	Despicable Me 2	Short	368.049635	292.049635
338	Finding Nemo	Short	380.838870	286.838870

Out[24]: Text(0.5, 1.0, 'Gross Comparison')



```
In [25]: print("Average IMDB Score for Long Duration Movies is {0:.2f}".format(data[optimit("Average IMDB Score for Short Duration Movies is {0:.2f}".format(data
```

Average IMDB Score for Long Duration Movies is 7.06 Average IMDB Score for Short Duration Movies is 6.28

Highest Rated Long Duration Movie

movie_title imdb_score

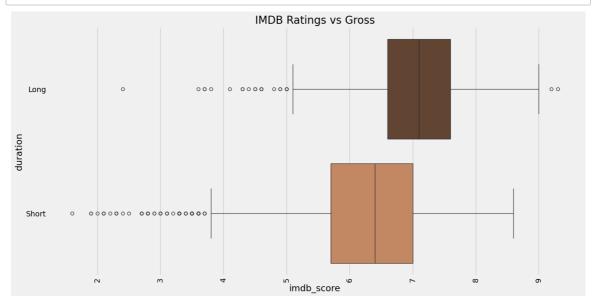
1937 The Shawshank Redemption 9.3

Highest Rated Short Duration Movie

movie_title imdb_score

3592 The Usual Suspects 8.6

In [27]: sns.boxplot(x=data['imdb_score'], y=data['duration'], palette = 'copper')
 plt.title('IMDB Ratings vs Gross', fontsize = 20)
 plt.xticks(rotation = 90)
 plt.show()



```
In [28]: def query_actors(x):
    # Create a boolean mask for each actor's column
    mask_a = data['actor_1_name'] == x
    mask_b = data['actor_2_name'] == x
    mask_c = data['actor_3_name'] == x

# Combine the masks to get rows where any of the three actors match
    combined_mask = mask_a | mask_b | mask_c

# Use the combined mask to filter the data
    result = data[combined_mask]

# Select only the desired columns
    result = result[['movie_title', 'budget', 'gross', 'title_year', 'genresetter'
    return result
```

In [29]: # usage of the function to query actor-specific data
actor_name = "Leonardo DiCaprio" # Replace with the actor's name you want
result = query_actors(actor_name)
print(result)

26					
		udget	gross	title_year	\
$\Gamma \cap$		200.0	658.672302	1997	
50		105.0	144.812796	2013	
97	•	160.0	292.568851	2010	
179		135.0	183.635922	2015	
257		110.0	102.608827	2004	
296	5 5	100.0	162.804648	2012	
307		100.0	57.366262	2006	
308		100.0	116.866727	2013	
326	<u> </u>	100.0	77.679638	2002	
361	The Departed	90.0	132.373442	2006	
452	Shutter Island	80.0	127.968405	2010	
641	Body of Lies	70.0	39.380442	2008	
911	Catch Me If You Can	52.0	164.435221	2002	
990	The Beach	50.0	39.778599	2000	
1114	Revolutionary Road	35.0	22.877808	2008	
1422	The Man in the Iron Mask	35.0	56.876365	1998	
1453	J. Edgar	35.0	37.304950	2011	
1560	The Quick and the Dead	32.0	18.636537	1995	
2067	Marvin's Room	23.0	12.782508	1996	
2757	Romeo + Juliet	14.5	46.338728	1996	
3058	What's Eating Gilbert Grape	11.0	9.170214	1993	
3476	The Great Gatsby 1	105.0	144.812796	2013	
	genres				
26	Drama Romance	_	lish	7.7	
50	Drama Romance				
^ -			glish	7.3	
97	Action Adventure Sci-Fi Thrille	r Eng	lish	8.8	
179	Adventure Drama Thriller Western	r Eng n Eng	lish lish	8.8 8.1	
179 257	Adventure Drama Thriller Western Biography Drama	r Eng n Eng a Eng	lish lish lish	8.8 8.1 7.5	
179 257 296	Adventure Drama Thriller Western Biography Drama Drama Western	r Eng n Eng a Eng n Eng	lish lish lish lish	8.8 8.1 7.5 8.5	
179 257 296 307	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen	r Eng n Eng a Eng n Eng r Eng	lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0	
179 257 296 307 308	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama	r Eng n Eng a Eng n Eng r Eng a Eng	lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2	
179 257 296 307 308 326	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama	r Eng n Eng a Eng n Eng r Eng a Eng a Eng	lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2 7.5	
179 257 296 307 308 326 361	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama	r Eng n Eng a Eng n Eng r Eng a Eng a Eng	lish lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5	
179 257 296 307 308 326 361 452	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Crime Drama Thrillen Mystery Thrillen	r Eng n Eng n Eng n Eng r Eng a Eng r Eng r Eng	lish lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1	
179 257 296 307 308 326 361 452 641	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen	r Eng n Eng n Eng n Eng r Eng a Eng a Eng r Eng r Eng	lish lish lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1	
179 257 296 307 308 326 361 452 641 911	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama	r Eng n Eng a Eng n Eng r Eng a Eng a Eng a Eng r Eng r Eng r Eng	lish lish lish lish lish lish lish lish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1	
179 257 296 307 308 326 361 452 641 911 990	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6	
179 257 296 307 308 326 361 452 641 911 990 1114	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen Drama Romance	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3	
179 257 296 307 308 326 361 452 641 911 990 1114 1422	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen Drama Romance Action Adventure	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4	
179 257 296 307 308 326 361 452 641 911 990 1114 1422 1453	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen Drama Romance Action Adventure Biography Crime Drama Biography Crime Drama Biography Crime Drama Biography Crime Drama Crime Drama Biography Crime Drama Biography Crime Drama Drama	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4 6.6	
179 257 296 307 308 326 361 452 641 911 990 1114 1422 1453 1560	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thriller Biography Comedy Crime Drama Crime Drama Thriller Mystery Thriller Action Drama Thriller Biography Crime Drama Adventure Drama Thriller Drama Romance Action Adventure Biography Crime Drama Romance Action Adventure Drama Adventure Drama Action Thriller Western Action Thriller Western	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4 6.6 6.4	
179 257 296 307 308 326 361 452 641 911 990 1114 1422 1453 1560 2067	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen Drama Romance Action Adventure Biography Crime Drama Action Thrillen Drama Drama	r Enger Enge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4 6.6 6.4 6.7	
179 257 296 307 308 326 361 452 641 911 990 1114 1422 1453 1560 2067 2757	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Romance Action Adventure Biography Crime Drama Action Thrillen Drama Drama Romance Drama	r Engerengengengengengengengengengengengengenge	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4 6.6 6.4 6.7 6.8	
179 257 296 307 308 326 361 452 641 911 990 1114 1422 1453 1560 2067	Adventure Drama Thriller Western Biography Drama Drama Western Adventure Drama Thrillen Biography Comedy Crime Drama Crime Drama Thrillen Mystery Thrillen Action Drama Thrillen Biography Crime Drama Adventure Drama Thrillen Drama Romance Action Adventure Biography Crime Drama Action Thrillen Drama Drama	rn Engeneration En	clish	8.8 8.1 7.5 8.5 8.0 8.2 7.5 8.5 8.1 7.1 8.0 6.6 7.3 6.4 6.6 6.4 6.7	

```
In [30]: def actors_report(x):
             a = data[data['actor_1_name'] == x]
             b = data[data['actor_2_name'] == x]
             c = data[data['actor_3_name'] == x]
             # Concatenate the dataframes vertically
             frames = [a, b, c]
             y = pd.concat(frames, axis=0)
             print("Time:", y['title year'].min(), y['title year'].max())
             print("Max Gross : {0:.2f} Millions".format(y['gross'].max()))
             print("Avg Gross : {0:.2f} Millions".format(y['gross'].mean()))
             print("Min Gross : {0:.2f} Millions".format(y['gross'].min()))
             print("Number of 100 Million Movies :", y[y['gross'] > 100].shape[0])
             print("Avg IMDB Score : {0:.2f}".format(y['imdb_score'].mean()))
             print("Most Common Genres:\n", y['Genre1'].value_counts().head())
         # usage of the function to generate a report for the actor
         actors_report('Leonardo DiCaprio')
```

Time: 1993 2015 Max Gross: 658.67 Millions Avg Gross: 120.44 Millions Min Gross: 9.17 Millions Number of 100 Million Movies : 11 Avg IMDB Score : 7.51 Most Common Genres: Genre1 8 Drama Action 4 4 Biography Adventure 3 Crime 2

Name: count, dtype: int64

```
In [31]: # Lets compare Brad Pitt, Leonardo Caprio and Tom Cruise

def critically_acclaimed_actors(m):
    a = data[data['actor_1_name'] == m]
    b = data[data['actor_2_name'] == m]
    c = data[data['actor_3_name'] == m]

# Concatenate the dataframes vertically
    frames = [a, b, c]
    y = pd.concat(frames, axis=0)

    return y['num_critic_for_reviews'].sum().astype('int')

print("Number of Critics Reviews for Brad Pitt")
print(critically_acclaimed_actors('Brad Pitt'))

print("Number of Critics Reviews for Leonardo DiCaprio")
print(critically_acclaimed_actors('Leonardo DiCaprio'))

print("Number of Critics Reviews for Tom Cruise")
print(critically_acclaimed_actors('Tom Cruise'))
```

```
Number of Critics Reviews for Brad Pitt
7814
Number of Critics Reviews for Leonardo DiCaprio
7014
Number of Critics Reviews for Tom Cruise
6740
```

In [32]: !pip install ipywidgets

```
Requirement already satisfied: ipywidgets in c:\users\ishan\appdata\local \programs\python\python311\lib\site-packages (8.1.1)
```

Requirement already satisfied: comm>=0.1.3 in c:\users\ishan\appdata\local \programs\python\python311\lib\site-packages (from ipywidgets) (0.1.3)

Requirement already satisfied: ipython>=6.1.0 in c:\users\ishan\appdata\lo cal\programs\python\python311\lib\site-packages (from ipywidgets) (8.14.0)
Requirement already satisfied: traitlets>=4.3.1 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from ipywidgets) (5.9.0)

Requirement already satisfied: widgetsnbextension~=4.0.9 in c:\users\ishan \appdata\local\programs\python\python311\lib\site-packages (from ipywidget s) (4.0.9)

Requirement already satisfied: jupyterlab-widgets~=3.0.9 in c:\users\ishan \appdata\local\programs\python\python311\lib\site-packages (from ipywidget s) (3.0.9)

Requirement already satisfied: backcall in c:\users\ishan\appdata\local\pr ograms\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidget s) (0.2.0)

Requirement already satisfied: decorator in c:\users\ishan\appdata\local\p rograms\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidget s) (5.1.1)

Requirement already satisfied: jedi>=0.16 in c:\users\ishan\appdata\local \programs\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidg ets) (0.18.2)

Requirement already satisfied: matplotlib-inline in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from ipython>=6.1.0->i pywidgets) (0.1.6)

Requirement already satisfied: pickleshare in c:\users\ishan\appdata\local \programs\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidg ets) (0.7.5)

Requirement already satisfied: prompt-toolkit!=3.0.37,<3.1.0,>=3.0.30 in c:\users\ishan\appdata\local\programs\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidgets) (3.0.38)

Requirement already satisfied: pygments>=2.4.0 in c:\users\ishan\appdata\l ocal\programs\python\python311\lib\site-packages (from ipython>=6.1.0->ipy widgets) (2.15.1)

Requirement already satisfied: stack-data in c:\users\ishan\appdata\local \programs\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidg ets) (0.6.2)

Requirement already satisfied: colorama in c:\users\ishan\appdata\local\pr ograms\python\python311\lib\site-packages (from ipython>=6.1.0->ipywidget s) (0.4.6)

Requirement already satisfied: parso<0.9.0,>=0.8.0 in c:\users\ishan\appda ta\local\programs\python\python311\lib\site-packages (from jedi>=0.16->ipy thon>=6.1.0->ipywidgets) (0.8.3)

Requirement already satisfied: wcwidth in c:\users\ishan\appdata\local\pro grams\python\python311\lib\site-packages (from prompt-toolkit!=3.0.37,<3. 1.0,>=3.0.30->ipython>=6.1.0->ipywidgets) (0.2.6)

Requirement already satisfied: executing>=1.2.0 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from stack-data->ipyth on>=6.1.0->ipywidgets) (1.2.0)

Requirement already satisfied: asttokens>=2.1.0 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from stack-data->ipyth on>=6.1.0->ipywidgets) (2.2.1)

Requirement already satisfied: pure-eval in c:\users\ishan\appdata\local\p rograms\python\python311\lib\site-packages (from stack-data->ipython>=6.1. 0->ipywidgets) (0.2.2)

Requirement already satisfied: six in c:\users\ishan\appdata\local\program s\python\python311\lib\site-packages (from asttokens>=2.1.0->stack-data->i python>=6.1.0->ipywidgets) (1.16.0)

```
from __future__ import print_function
In [33]:
                           from ipywidgets import interact, interactive, fixed, interact_manual
                           import ipywidgets as widgets
In [34]: @interact
                           def show_movies_more_than(column='imdb_score', score=9.0):
                                      x = data.loc[data[column] > score][['title_year', 'movie_title', 'direc']
                                      x = x.sort_values(by='imdb_score', ascending=False)
                                      x = x.drop_duplicates(keep='first')
                                      return x
                                          column
                                                                imdb score
                                                                                                                           9.00
                                              score
                                              title_year
                                                                      movie_title director_name actor_1_name actor_2_name actor_3_name
                                                                                      The
                                                                                                                       Frank
                                                                                                                                                      Morgan
                                                                                                                                                                                           Jeffrey
                               1937
                                                       1994
                                                                      Shawshank
                                                                                                                                                                                                                   Bob Gunton
                                                                                                                Darabont
                                                                                                                                                   Freeman
                                                                                                                                                                                       DeMunn
                                                                      Redemption
                                                                                                         Francis Ford
                                                                                       The
                               3466
                                                        1972
                                                                                                                                                  Al Pacino
                                                                                                                                                                          Marlon Brando
                                                                                                                                                                                                                Robert Duvall 12
                                                                           Godfather
                                                                                                                 Coppola
In [35]: @interact
                           def show_articles_more_than(column=['budget','gross'], x=1000):
                                      return data.loc[data[column] > x][['movie_title','duration','gross','Province title', 'duration', 'gross', 'Province title', 'gross',
                                         column
                                                                budget
                                                                                                                          1000
                                                       Χ
                                                             movie_title duration
                                                                                                                                                           Profit imdb_score
                                                                                                                        gross
                               2323
                                             Princess Mononoke
                                                                                                  Long 2.298191
                                                                                                                                           -2397.701809
                                                                                                                                                                                              8.4
                               2334
                                                                                                  Short 0.410388
                                                                 Steamboy
                                                                                                                                           -2127.109510
                                                                                                                                                                                              6.9
                               2988
                                                                   The Host
                                                                                                  Short 2.201412 -12213.298588
                                                                                                                                                                                              7.0
                               3005
                                                                    Fateless
                                                                                                  Long 0.195888
                                                                                                                                           -2499.804112
                                                                                                                                                                                              7.1
                               3423
                                                                           Akira
                                                                                                  Long 0.439162
                                                                                                                                          -1099.560838
                                                                                                                                                                                              8.1
                               3859
                                                                                                 Short 0.211667
                                                                                                                                          -4199.788333
                                                                                                                                                                                              7.7
                                                    Lady Vengeance
                           #Recommending Movies based on Languages
In [36]: def recommend_lang(x):
```

y = data[['language','movie_title','imdb_score']][data['language'] == x

y = y.sort_values(by = 'imdb_score', ascending = False)

return y.head(15)

```
In [37]: recommended_movies = recommend_lang('English')
print(recommended_movies)
```

```
language
                                                     movie_title imdb_sco
re
1937
     English
                                       The Shawshank Redemption
9.3
3466 English
                                                  The Godfather
9.2
                                                The Dark Knight
66
     English
9.0
                                         The Godfather: Part II
2837
     English
9.0
339
     English
                The Lord of the Rings: The Return of the King
8.9
1874 English
                                               Schindler's List
8.9
3355
     English
                                                   Pulp Fiction
8.9
97
     English
                                                      Inception
8.8
836
     English
                                                   Forrest Gump
8.8
     English
                Star Wars: Episode V - The Empire Strikes Back
2051
8.8
270
     English The Lord of the Rings: The Fellowship of the R...
8.8
683
     English
                                                     Fight Club
8.8
3867
     English
                                One Flew Over the Cuckoo's Nest
8.7
3024 English
                         Star Wars: Episode IV - A New Hope
8.7
                                                     Goodfellas
1903 English
8.7
```

#Recommending Movies Based on Actors

```
In [38]: import pandas as pd

def recommend_movies_on_actors(x):
    a = data[['movie_title', 'imdb_score']][data['actor_1_name'] == x]
    b = data[['movie_title', 'imdb_score']][data['actor_2_name'] == x]
    c = data[['movie_title', 'imdb_score']][data['actor_3_name'] == x]

# Concatenate the dataframes vertically
frames = [a, b, c]
    a = pd.concat(frames)

a = a.sort_values(by='imdb_score', ascending=False)
    return a.head(15)
```

```
In [39]: recommended_movies = recommend_movies_on_actors('Tom Cruise')
print(recommended_movies)
```

	<pre>movie_title</pre>	imdb_score
1868	Rain Man	8.0
75	Edge of Tomorrow	7.9
284	Minority Report	7.7
158	The Last Samurai	7.7
736	Collateral	7.6
1524	A Few Good Men	7.6
940	Interview with the Vampire: The Vampire Chroni	7.6
155	Mission: Impossible - Ghost Protocol	7.4
135	Mission: Impossible - Rogue Nation	7.4
671	Eyes Wide Shut	7.3
930	Jerry Maguire	7.3
3128	The Outsiders	7.2
2768	Born on the Fourth of July	7.2
370	Valkyrie	7.1
438	Mission: Impossible	7.1

#Recommending similar Genres

2)

Requirement already satisfied: mlxtend in c:\users\ishan\appdata\local\pro grams\python\python311\lib\site-packages (0.23.0)

Requirement already satisfied: scipy>=1.2.1 in c:\users\ishan\appdata\loca l\programs\python\python311\lib\site-packages (from mlxtend) (1.11.0)
Requirement already satisfied: numpy>=1.16.2 in c:\users\ishan\appdata\loc al\programs\python\python311\lib\site-packages (from mlxtend) (1.25.0)
Requirement already satisfied: pandas>=0.24.2 in c:\users\ishan\appdata\loc cal\programs\python\python311\lib\site-packages (from mlxtend) (2.0.2)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\ishan\appdata\local\programs\python\python311\lib\site-packages (from mlxtend) (1.2.

Requirement already satisfied: matplotlib>=3.0.0 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from mlxtend) (3.7.1) Requirement already satisfied: joblib>=0.13.2 in c:\users\ishan\appdata\lo cal\programs\python\python311\lib\site-packages (from mlxtend) (1.2.0) Requirement already satisfied: contourpy>=1.0.1 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0 ->mlxtend) (1.1.0)

Requirement already satisfied: cycler>=0.10 in c:\users\ishan\appdata\loca l\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0->mlx tend) (0.11.0)

Requirement already satisfied: fonttools>=4.22.0 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0 ->mlxtend) (4.40.0)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0 ->mlxtend) (1.4.4)

Requirement already satisfied: packaging>=20.0 in c:\users\ishan\appdata\l ocal\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0-> mlxtend) (23.1)

Requirement already satisfied: pillow>=6.2.0 in c:\users\ishan\appdata\loc al\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0->ml xtend) (9.5.0)

Requirement already satisfied: pyparsing>=2.3.1 in c:\users\ishan\appdata \local\programs\python\python311\lib\site-packages (from matplotlib>=3.0.0 ->mlxtend) (3.1.0)

Requirement already satisfied: python-dateutil>=2.7 in c:\users\ishan\appd ata\local\programs\python\python311\lib\site-packages (from matplotlib>=3. 0.0->mlxtend) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in c:\users\ishan\appdata\loca l\programs\python\python311\lib\site-packages (from pandas>=0.24.2->mlxten d) (2023.3)

Requirement already satisfied: tzdata>=2022.1 in c:\users\ishan\appdata\lo cal\programs\python\python311\lib\site-packages (from pandas>=0.24.2->mlxt end) (2023.3)

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\ishan\appd ata\local\programs\python\python311\lib\site-packages (from scikit-learn>= 1.0.2->mlxtend) (3.1.0)

Requirement already satisfied: six>=1.5 in c:\users\ishan\appdata\local\pr ograms\python\python311\lib\site-packages (from python-dateutil>=2.7->matp lotlib>=3.0.0->mlxtend) (1.16.0)

```
In [41]: from mlxtend.preprocessing import TransactionEncoder

x = data['genres'].str.split('|')
te = TransactionEncoder()
x = te.fit_transform(x)
x = pd.DataFrame(x, columns = te.columns_)

# Lets check the head of x
x.head()
```

Out[41]:

	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Family
0	True	True	False	False	False	False	False	False	False
1	True	True	False	False	False	False	False	False	False
2	True	True	False	False	False	False	False	False	False
3	True	False	False	False	False	False	False	False	False
4	True	True	False	False	False	False	False	False	False

5 rows × 23 columns

genres = x.astype('int')

In [42]: # lets convert this data into boolean so that we can perform calculations

genres.head()

Out[42]:

	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Family
0	1	1	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0

5 rows × 23 columns

```
In [43]: # now, lets insert the movie titles in the first column, so that we can beta
genres.insert(0, 'movie_title', data['movie_title'])
genres.head()
```

Out[43]:

	movie_title	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drar
0	Avatar	1	1	0	0	0	0	0	
1	Pirates of the Caribbean: At World's End	1	1	0	0	0	0	0	
2	Spectre	1	1	0	0	0	0	0	
3	The Dark Knight Rises	1	0	0	0	0	0	0	
4	NaN	1	1	0	0	0	0	0	

5 rows × 24 columns

In [44]: # lets set these movie titles as index of the data
genres = genres.set_index('movie_title')
genres.head()

Out[44]:

nimation	Biography	Comedy	Crime	Documentary	Drama	Family	Fantasy	 Music	Music
0	0	0	0	0	0	0	1	 0	
0	0	0	0	0	0	0	1	 0	
0	0	0	0	0	0	0	0	 0	
0	0	0	0	0	0	0	0	 0	
0	0	0	0	0	0	0	0	 0	

```
In [45]: # making a recommendation engine for getting similar genres

def recommendation_genres(gen):
    gen = genres[gen]
    similar_genres = genres.corrwith(gen)
    similar_genres = similar_genres.sort_values(ascending=False)
    similar_genres = similar_genres.iloc[1:]
    return similar_genres.head(3)
In [46]: recommendation_genres('Action')
Out[46]: Adventure    0.320532
Thriller    0.303708
Sci-Fi    0.295018
dtype: float64
```

#Recommending similar Movies

```
In [47]: # Lets make a sparse matrix to recommend the movies
    x = genres.transpose()
    x.head()
```

Out[47]:

movie_title	Avatar	Pirates of the Caribbean: At World's End	Spectre	The Dark Knight Rises	NaN	John Carter	Spider- Man 3	Tangled	Avengers: Age of Ultron	i F
Action	1	1	1	1	1	1	0	1	0	
Adventure	1	1	1	0	1	1	1	1	1	
Animation	0	0	0	0	0	0	1	0	0	
Biography	0	0	0	0	0	0	0	0	0	
Comedy	0	0	0	0	0	0	1	0	0	

5 rows × 3853 columns

```
In [48]: # making a recommendation engine for getting similar movies

def recommendation_movie(movie):
    movie = x[movie+'\xa0']
    similar_movies = x.corrwith(movie)
    similar_movies = similar_movies.sort_values(ascending=False)
    similar_movies = similar_movies.iloc[1:]
    return similar_movies.head(20)
```

```
In [49]: # lets test on some results
         recommendation_movie('The Avengers')
Out[49]: movie_title
         The Avengers
                                                         1.0
         Transformers: Dark of the Moon
                                                         1.0
         Rapa Nui
                                                         1.0
         American Reunion
                                                         1.0
         Lost in Space
                                                         1.0
         NaN
                                                         1.0
         Risen
                                                         1.0
         The Girl with the Dragon Tattoo
                                                         1.0
         NaN
                                                         1.0
         The Flowers of War
                                                         1.0
         American Sniper
                                                         1.0
         Pirates of the Caribbean: At World's End
                                                         1.0
         Edge of Darkness
                                                         1.0
         The Sorcerer's Apprentice
                                                         1.0
         The Hobbit: The Battle of the Five Armies
                                                         1.0
         Legally Blonde
                                                         1.0
         Quantum of Solace
                                                         1.0
         Australia
                                                         1.0
         X-Men Origins: Wolverine
                                                         1.0
         R.I.P.D.
                                                         1.0
         dtype: float64
 In [ ]:
```