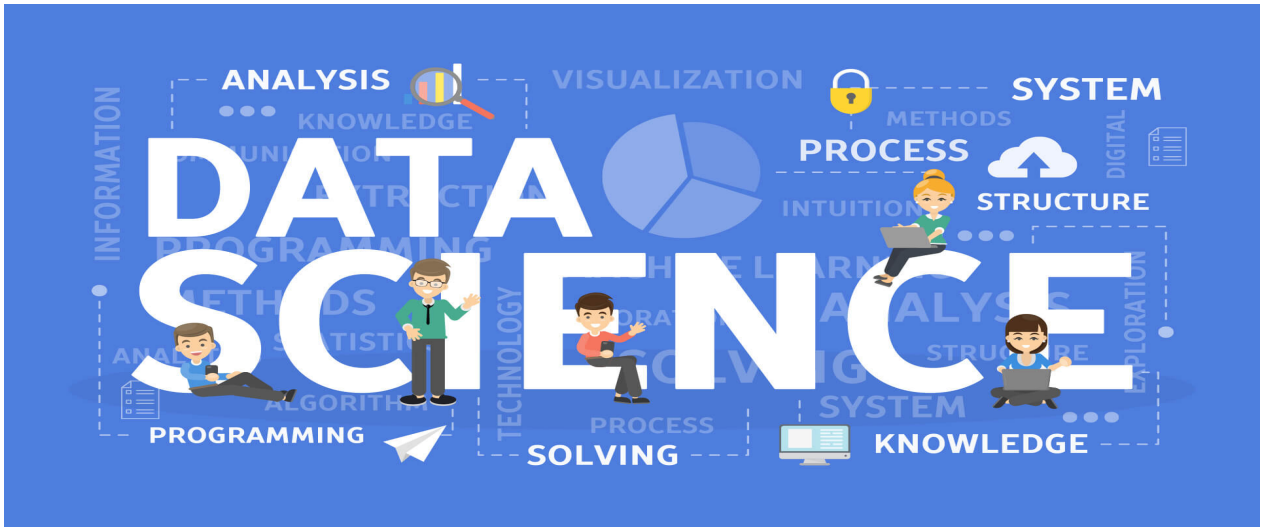
LNMIIT
The LNM Institute of Information Technology

INTRODUCTION TO DATA SCIENCE

MOVIE POPULARITY ANALYSIS

Team Members

- 19ucs038 - Shubham Sharma
- 19ucs201 - Garvit Vijayvargia
- 19ucs203 - Tanush Garg
- 19ucs208 - Divyesh Rajesh Chhabra



INDEX:

PROJECT OVERVIEW:

We have done a popularity analysis on the conventional and social media movies released between 2014-2015. We have picked a dataset which contains information about these movies and studied their popularity.

INTRODUCTION:

A social film is a type of interactive film that is presented through the lens of social media. A social film is distributed digitally and integrates with a social networking service, such as Facebook or Google+. It combines features of web video, social-network games and social media.
So film analysis helps us understand what we're watching and how it affects us. It can help us to understand important themes expressed or encoded by filmmakers that would otherwise be missed.

DATASET:

We have used dataset from the following link:
https://archive.ics.uci.edu/ml/datasets/CSM+%28Conventional+and+Social+Media+Movies%29+Dataset+2014+and+2015#

CODE LINK:

The link of code made by us to accomplish this project:
https://github.com/Divu2611/IDS

OBJECTIVE:

Apply different ML Classification Algorithms on the dataset and derive inferences from data using Python.

SYSTEM REQUIREMENTS:

- Python3 should be installed on the PC.
- Data Science Packages such as matplotlib, pandas, scikit-learn, numpy etc.
- The code can be run in Spyder IDE for better understanding and results, if installed.
- Some of the statistical data was derived using the Jupyter Notebook.

DATA SET DETAILS:

Our data is based on the Hollywood movies released between 2014 and 2015. The various specifications of this dataset are as follows:-

Data Set Characteristics:	Multivariate	**Number of Instances:**	217	**Area:**	Computer
Attribute Characteristics:	Integer	**Number of Attributes:**	12	**Date Donated**	2017-10-11
Associated Tasks:	Classification, Regression	**Missing Values?**	Yes	**Number of Web Hits:**	40892

Attributes of this dataset are:

Year	Ratings
Genre	Gross
Budget	Screens
Sequel	Sentiment
Views	Likes
Dislikes	Comments
Aggregate Followers	Movies

This is a sample description of our dataset:

Movie	Year	Ratings	Genre	Gross	Budget	Screens	Sequel	Sentiment	Views	Likes	Dislikes	Comments	Aggregate Followers
13 Sins	2014	6.3	8	9130	4000000	45	1	0	3280543	4632	425	636	1120000
22 Jump Street	2014	7.1	1	192000000	50000000	3306	2	2	583289	3465	61	186	12350000
3 Days to Kill	2014	6.2	1	30700000	28000000	2872	1	0	304861	328	34	47	483000
300: Rise of an Empire	2014	6.3	1	106000000	110000000	3470	2	0	452917	2429	132	590	568000
A Haunted House 2	2014	4.7	8	17300000	3500000	2310	2	0	3145573	12163	610	1082	1923800
A Long Way Off	2014	4.6	3	29000	500000		1	0	91137	112	7	1	310000
A Million Ways to Die in the West	2014	6.1	8	42600000	40000000	3158	1	0	3013011	9595	419	1020	8153000
A Most Violent Year	2014	7.1	1	5750000	20000000	818	1	2	1854103	2207	197	593	130655
A Walk Among the Tombstones	2014	6.5	10	26000000	28000000	2714	1	3	2213659	2210	419	382	125646
About Last Night	2014	6.1	8	48600000	12500000	2253	1	0	5218079	11709	532	770	21697300
American Sniper	2014	7.3	1	350000000	58800000	3555	1	4	3927600	13143	573	3134	24300
And So It Goes	2014	5.7	8	15200000	30000000	1762	1	0	519327	963	94	70	386400
Annabelle	2014	5.4	15	84300000	6500000	3185	1	0	19032902	38810	4382	4392	19420105
Annie	2014	5.2	8	85900000	65000000	3116	1	0	930006	5150	707	1484	5130800
Atlas Shrugged: Who Is John Galt?	2014	4.4	3	830000	5000000	65	3	0	595194	85	36	39	15112
Barefoot	2014	6.6	8	11800	6000000	18	1	2	3915978	6983	247	460	253000
Better Living Through Chemistry	2014	6.3	8	72300	5000000	25	1	0	1391527	2479	146	182	1658900

IMPORTING DATASET:

While performing data preprocessing, we did the following:-

1. Imported libraries such as matplotlib, pandas, scikit-learn and numpy.
2. Imported our dataset CSM_2014_2015_dataset.csv in our code using read_csv() command of pandas and stored it in a dataframe.
3. In order to perform descriptive data analytics, we first need to import the dataset from our system. Pd.read_csv function in the pandas library is used to import the .csv dataset.

```
In [12]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns

In [13]: data = pd.read_csv('CSM.csv')
```

Printing the dataset to have a look at how our dataset looks.data.head() function by default prints top 5 instances of the dataset.

```
In [14]: data = pd.read_csv('CSM.csv')
         data.head()
```

Out[14]:

	Movie	Year	Ratings	Genre	Gross	Budget	Screens	Sequel	Sentiment	Views	Likes	Dislikes	Comments	Aggregate Followers
0	13 Sins	2014.0	6.3	8.0	9130.0	4000000.0	45.0	1.0	0.0	3280543.0	4632.0	425.0	636.0	1120000.0
1	22 Jump Street	2014.0	7.1	1.0	192000000.0	50000000.0	3306.0	2.0	2.0	583289.0	3465.0	61.0	186.0	12350000.0
2	3 Days to Kill	2014.0	6.2	1.0	30700000.0	28000000.0	2872.0	1.0	0.0	304861.0	328.0	34.0	47.0	483000.0
3	300: Rise of an Empire	2014.0	6.3	1.0	106000000.0	110000000.0	3470.0	2.0	0.0	452917.0	2429.0	132.0	590.0	568000.0
4	A Haunted House 2	2014.0	4.7	8.0	17300000.0	3500000.0	2310.0	2.0	0.0	3145573.0	12163.0	610.0	1082.0	1923800.0

4. To check the no. of data in a column and its datatype df.info() is used.

```
In [15]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 232 entries, 0 to 231
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Movie                 231 non-null    object
 1   Year                  231 non-null    float64
 2   Ratings               231 non-null    float64
 3   Genre                 231 non-null    float64
 4   Gross                 231 non-null    float64
 5   Budget                230 non-null    float64
 6   Screens               221 non-null    float64
 7   Sequel                231 non-null    float64
 8   Sentiment             231 non-null    float64
 9   Views                 231 non-null    float64
 10  Likes                 231 non-null    float64
 11  Dislikes              231 non-null    float64
 12  Comments              231 non-null    float64
 13  Aggregate Followers   196 non-null    float64
dtypes: float64(13), object(1)
memory usage: 25.5+ KB
```

5.Now we will check for null objects.

```
In [17]: data.isna().sum()

Out[17]: Movie                   1
         Year                    1
         Ratings                 1
         Genre                   1
         Gross                   1
         Budget                  2
         Screens                11
         Sequel                  1
         Sentiment               1
         Views                   1
         Likes                   1
         Dislikes                1
         Comments                1
         Aggregate Followers    36
         dtype: int64
```

6. For better results, we filled the null values with some other values using mydataset.interpolate() command. It fills the null value with the mean of the previous non- null value and next non-null value of the same column.

```
In [16]: data.interpolate()
```

Out[16]:

	Movie	Year	Ratings	Genre	Gross	Budget	Screens	Sequel	Sentiment	Views	Likes	Dislikes	Comments	Aggregate Followers
0	13 Sins	2014.0	6.3	8.0	9130.0	4000000.0	45.0	1.0	0.0	3280543.0	4632.0	425.0	636.0	1120000.0
1	22 Jump Street	2014.0	7.1	1.0	192000000.0	50000000.0	3306.0	2.0	2.0	583289.0	3465.0	61.0	186.0	12350000.0
2	3 Days to Kill	2014.0	6.2	1.0	30700000.0	28000000.0	2872.0	1.0	0.0	304861.0	328.0	34.0	47.0	483000.0
3	300: Rise of an Empire	2014.0	6.3	1.0	106000000.0	110000000.0	3470.0	2.0	0.0	452917.0	2429.0	132.0	590.0	568000.0
4	A Haunted House 2	2014.0	4.7	8.0	17300000.0	3500000.0	2310.0	2.0	0.0	3145573.0	12163.0	610.0	1082.0	1923800.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
227	Aloha	2015.0	5.5	15.0	21000000.0	37000000.0	2815.0	1.0	13.0	7119456.0	18803.0	1128.0	2290.0	1188000.0
228	Unfinished Business	2015.0	5.4	8.0	10200000.0	35000000.0	2777.0	1.0	7.0	3450614.0	6823.0	325.0	409.0	1188000.0
229	War Room	2015.0	5.4	1.0	12300000.0	3000000.0	2748.5	1.0	10.0	66872.0	400.0	67.0	201.0	1188000.0
230	The Gallows	2015.0	4.4	15.0	22600000.0	100000.0	2720.0	1.0	-5.0	659772.0	2841.0	431.0	606.0	1188000.0
231	NaN	2015.0	4.4	15.0	22600000.0	100000.0	2720.0	1.0	-5.0	659772.0	2841.0	431.0	606.0	1188000.0

232 rows × 14 columns

7. We then find the values of the central tendencies of the data.

	Year	Ratings	Genre	Gross	Budget	Screens	Sequel	Sentiment	Views	Likes	Dislikes	Comments	Aggregate Followers
count	232.000000	232.000000	232.000000	2.320000e+02	2.320000e+02	232.000000	232.000000	232.000000	2.320000e+02	232.000000	232.000000	232.000000	2.320000e+02
mean	2014.297414	6.432759	5.400862	6.787006e+07	4.758878e+07	2201.495690	1.357759	2.775862	3.699691e+06	12689.900862	677.982759	1820.443966	2.857635e+06
std	0.458109	0.995686	4.180826	8.876046e+07	5.417779e+07	1440.880589	0.965433	7.000416	4.505790e+06	28770.354251	1241.340903	3564.202205	4.571739e+06
min	2014.000000	3.100000	1.000000	2.470000e+03	7.000000e+04	2.000000	1.000000	-38.000000	6.980000e+02	1.000000	0.000000	0.000000	1.066000e+03
25%	2014.000000	5.800000	1.000000	1.035000e+07	8.983195e+06	476.750000	1.000000	0.000000	6.308380e+05	1811.750000	105.750000	249.250000	2.237500e+05
50%	2014.000000	6.500000	3.000000	3.690000e+07	2.750000e+07	2761.500000	1.000000	0.000000	2.401178e+06	6024.500000	344.000000	817.000000	1.188000e+06
75%	2015.000000	7.100000	8.000000	8.932500e+07	6.500000e+07	3323.500000	1.000000	5.250000	5.217030e+06	15195.750000	694.250000	2120.500000	3.191675e+06
max	2015.000000	8.700000	15.000000	6.430000e+08	2.500000e+08	4324.000000	7.000000	29.000000	3.262678e+07	370552.000000	13960.000000	38363.000000	3.103000e+07

EXPLORING THE DATA:

After importing the data, we find the number of rows and columns in our data.

```
In [6]: data.shape
Out[6]: (232, 14)
```

There are 232 rows and 14 columns in our dataset

```
In [18]: print(data)
                        Movie    Year  Ratings  Genre        Gross       Budget  \
0                    13 Sins  2014.0      6.3    8.0       9130.0    4000000.0
1            22 Jump Street   2014.0      7.1    1.0  192000000.0   50000000.0
2            3 Days to Kill   2014.0      6.2    1.0   30700000.0   28000000.0
3    300: Rise of an Empire   2014.0      6.3    1.0  106000000.0  110000000.0
4         A Haunted House 2   2014.0      4.7    8.0   17300000.0    3500000.0
..                       ...     ...      ...    ...          ...          ...
227                   Aloha  2015.0      5.5   15.0   21000000.0   37000000.0
228     Unfinished Business  2015.0      5.4    8.0   10200000.0   35000000.0
229               War Room   2015.0      5.4    1.0   12300000.0    3000000.0
230             The Gallows  2015.0      4.4   15.0   22600000.0     100000.0
231                     NaN     NaN      NaN    NaN          NaN          NaN

     Screens  Sequel  Sentiment      Views    Likes  Dislikes  Comments  \
0       45.0     1.0        0.0  3280543.0   4632.0     425.0     636.0
1     3306.0     2.0        2.0   583289.0   3465.0      61.0     186.0
2     2872.0     1.0        0.0   304861.0    328.0      34.0      47.0
3     3470.0     2.0        0.0   452917.0   2429.0     132.0     590.0
4     2310.0     2.0        0.0  3145573.0  12163.0     610.0    1082.0
..       ...     ...        ...        ...      ...       ...       ...
227   2815.0     1.0       13.0  7119456.0  18803.0    1128.0    2290.0
228   2777.0     1.0        7.0  3450614.0   6823.0     325.0     409.0
229      NaN     1.0       10.0    66872.0    400.0      67.0     201.0
230   2720.0     1.0       -5.0   659772.0   2841.0     431.0     606.0
231      NaN     NaN        NaN        NaN      NaN       NaN       NaN

     Aggregate Followers
0              1120000.0
1             12350000.0
2               483000.0
3               568000.0
4              1923800.0
..                   ...
227                NaN
228                NaN
229                NaN
230                NaN
231                NaN

[232 rows x 14 columns]
```

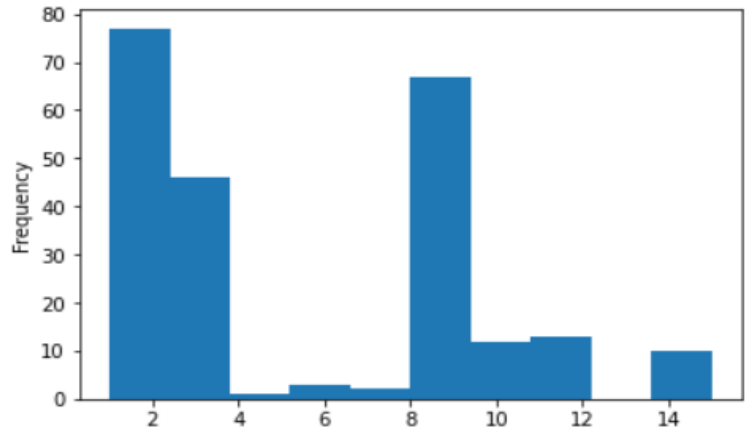
INFERENCES:

Here are some inferences made from our dataset.

➔ Histogram Plot(Frequency vs Genre)

```
data['Genre'].plot(kind='hist')
```

```
<AxesSubplot:ylabel='Frequency'>
```

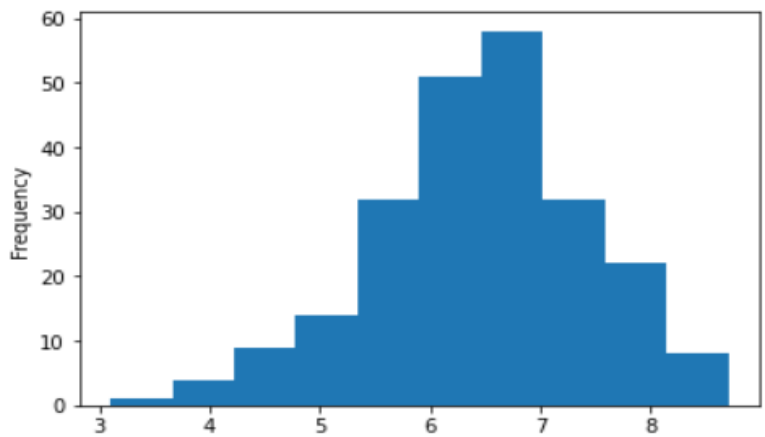


From the above histogram, we can see that the highest number of movies belonged to genre 1 followed by genre 8 and genre 3. Only 2 movies belonged to genre 7, 1 to genre 4 and no movies were released from genre 5, 11, 13 and 14.

➔ Histogram Plot(Frequency vs Rating)

```
data['Ratings'].plot(kind='hist')
```

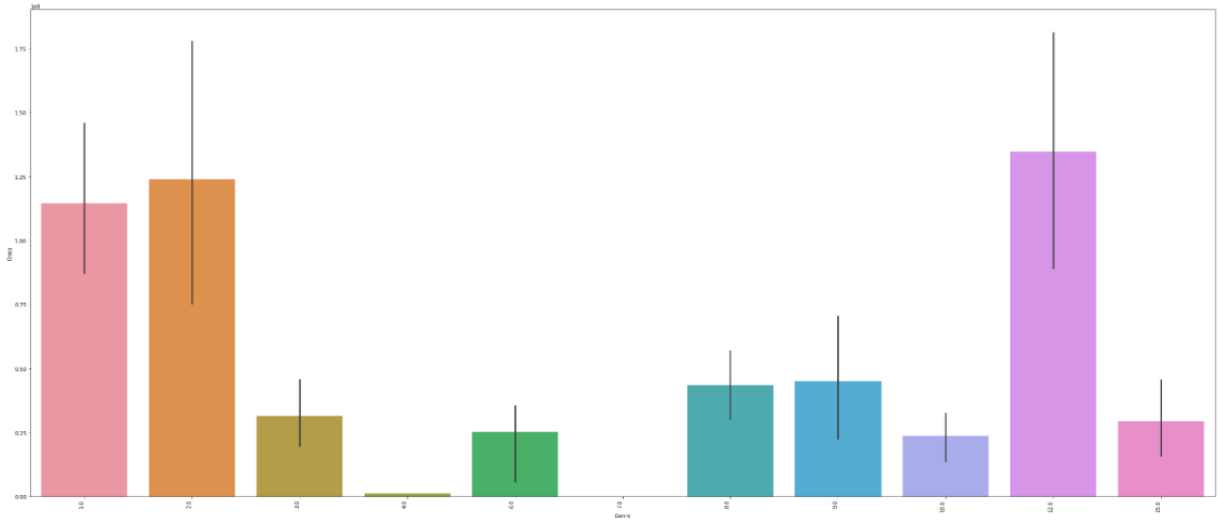
```
<AxesSubplot:ylabel='Frequency'>
```



From the given histogram, we can see that most movies had ratings in the 6-7 range with a gradual decrease in the number of movies on either side of said range. There are hardly any movies rated greater than 9 and less than 4.

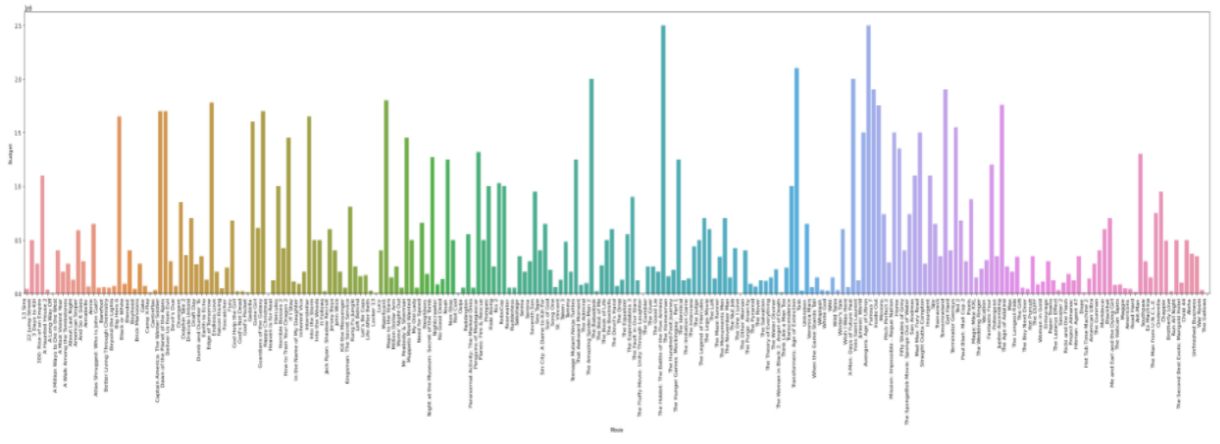
➔ Bar graph plot (Genre vs Gross)

```
movie=list(data['Genre'])
fig=plt.gcf()
fig.set_size_inches(40,20)
ax=sns.barplot(y=data['Gross'],x=data['Genre'])
fig.autofmt_xdate(rotation=90)
```



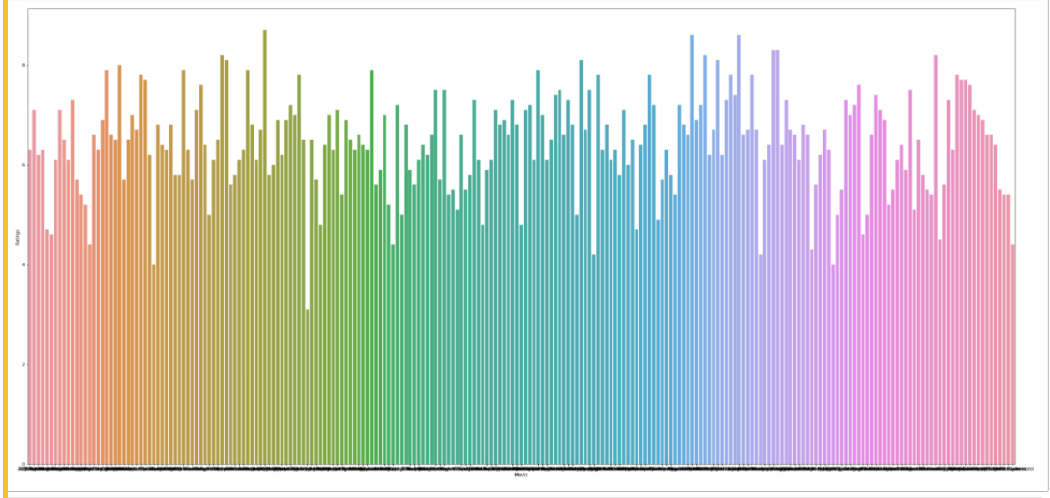
➔ Bar graph plot (Movies vs Budget)

```
movie=list(data['Movie'])
fig=plt.gcf()
fig.set_size_inches(50,10)
ax=sns.barplot(y=data['Budget'],x=data['Movie'])
fig.autofmt_xdate(rotation=90)
```



➔ Bar graph plot (Rating vs Movie)

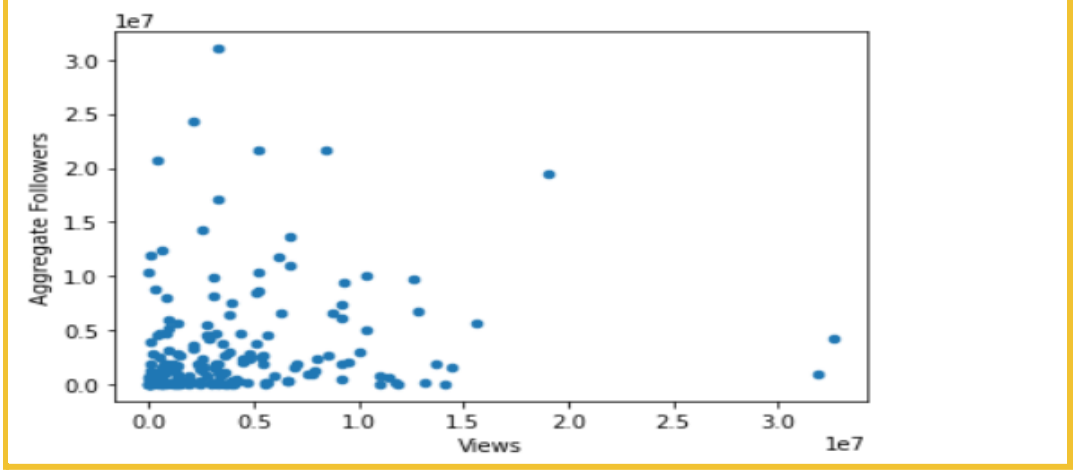
```
movie=list(data['Ratings'])
fig=plt.gcf()
fig.set_size_inches(40,20)
ax=sns.barplot(x=data['Movie'],y=data['Ratings'])
# fig.autofmt_xdate(rotation=90)
```



➔ Scatter plot (Aggregate followers vs Views)

```
data.plot(kind='scatter',y='Aggregate Followers', x='Views')
```

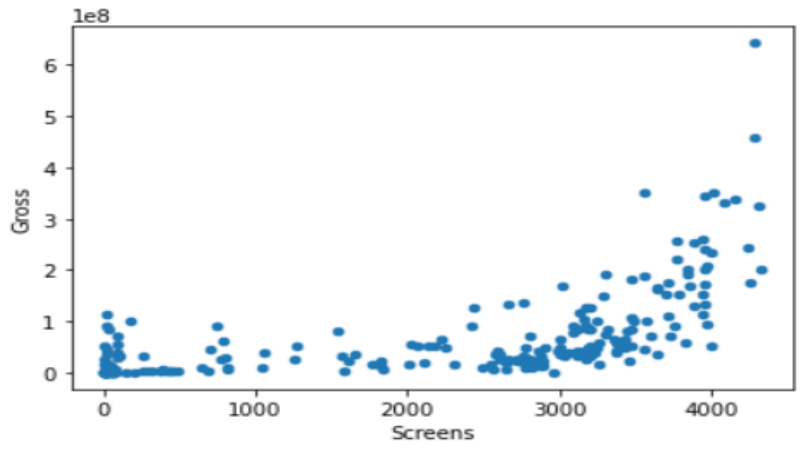
```
<AxesSubplot:xlabel='Views', ylabel='Aggregate Followers'>
```



We had expected to see more or less a linear relationship between views and aggregate followers since if a movie has a larger following, then more people will view it and vice versa. But no such relationship was observed as can be seen from the above scatter plot. Some outliers were also observed where some movies with very few followers had lots of views and some movies with a large following had very less views

➔ Scatter plot (Gross vs Screens)

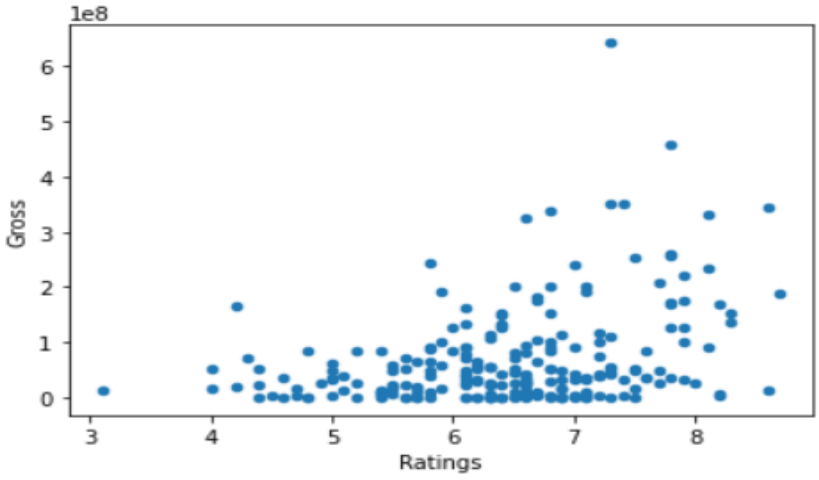
```
data.plot(kind='scatter',y='Gross', x='Screens')
<AxesSubplot:xlabel='Screens', ylabel='Gross'>
```



Generally, it was found that revenue generated by the movies increased with the number of screenings they got, but there were indeed some movies which generated a fair bit of revenue even though they got negligible screening, leading us to believe that movies don't just make money from selling tickets but from other activities like on OTT platforms etc.

➔ Scatter plot (Gross vs Ratings)

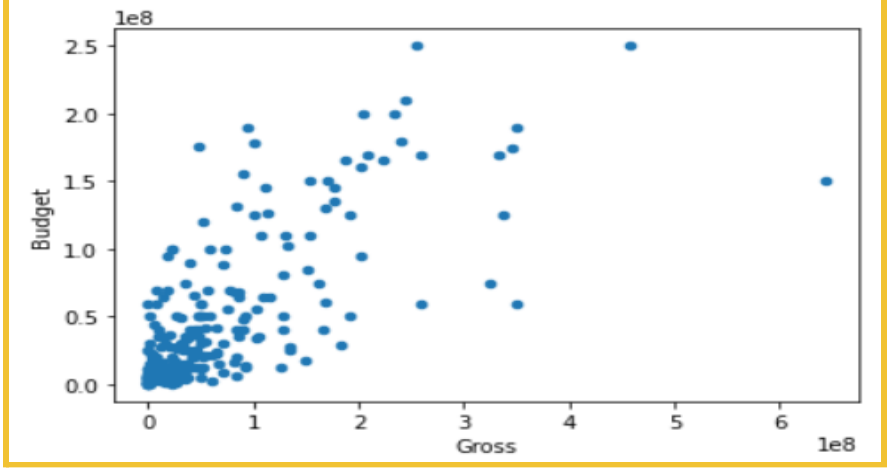
```
data.plot(kind='scatter',y='Gross', x='Ratings')
<AxesSubplot:xlabel='Ratings', ylabel='Gross'>
```



On expected lines, it was found that higher rated movies made more money, generally, than lower rated movies.

➔ Scatter plot (Budget vs Gross)

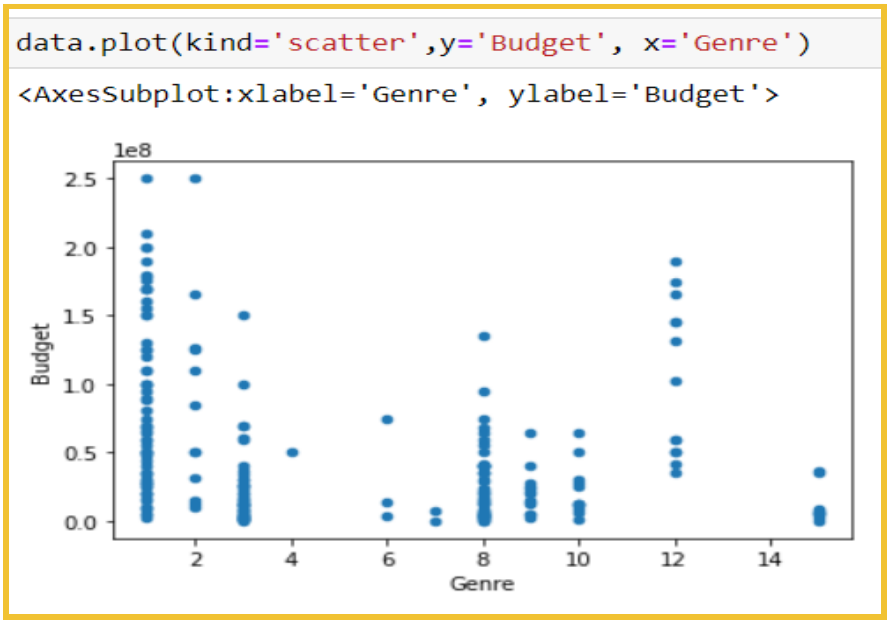
```
data.plot(kind='scatter',y='Budget', x='Gross')
<AxesSubplot:xlabel='Gross', ylabel='Budget'>
```



A comparison of budget and gross shows, barring very few outliers, the budget and gross revenue of movies were mostly comparable with most movies making a profit (gross > budget). Another pattern we found was that none of the high budget movies incurred a loss. It was only some of the low budget movies that incurred losses.

➔ Scatter plot (Budget vs Genre)

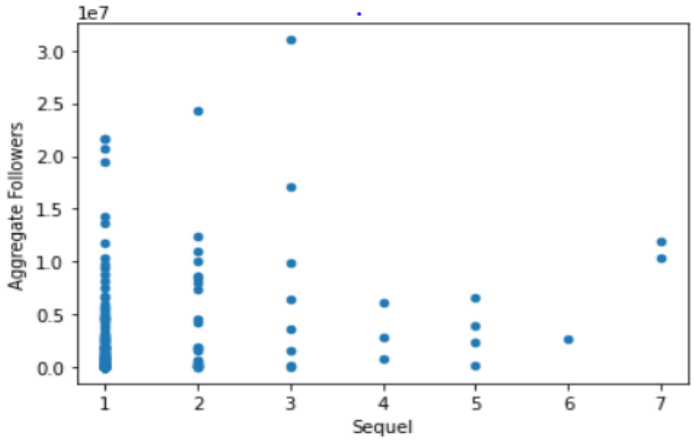
```
data.plot(kind='scatter',y='Budget', x='Genre')
<AxesSubplot:xlabel='Genre', ylabel='Budget'>
```



As we can see, movies with the highest budget belong to genre 1 and 2. But on an average, most big budget movies belong to genre 12 while most movies on a tight budget belong to genre 8.

➔ Scatter plot (Aggregate followers vs Sequel)

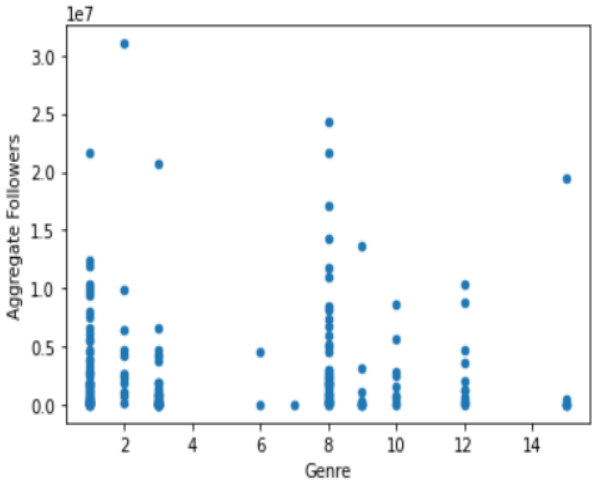
```
data.plot(kind='scatter',y='Aggregate Followers', x='Sequel')
<AxesSubplot:xlabel='Sequel', ylabel='Aggregate Followers'>
```



We were hoping to see whether the public followed more standalone movies or franchise movies and whether the increase in the number of sequels had any effect on the following the franchise had. Unfortunately, no obvious pattern could be found between both.

➔ Scatter plot (Aggregate followers vs Genre)

```
In [21]: data.plot(kind='scatter',y='Aggregate Followers', x='Genre')
Out[21]: <AxesSubplot:xlabel='Genre', ylabel='Aggregate Followers'>
```

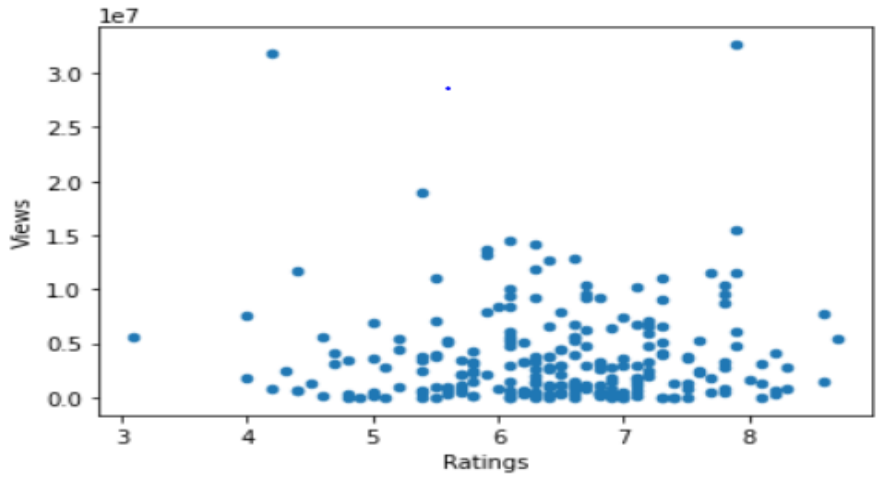


As we can see, the aggregate followers of movies belonging to genre 8 are the highest on an average and that for genre 10 are the least.

➔ Scatter plot (Views vs Rating)

```
data.plot(kind='scatter',y='Views', x='Ratings')
```

```
<AxesSubplot:xlabel='Ratings', ylabel='Views'>
```

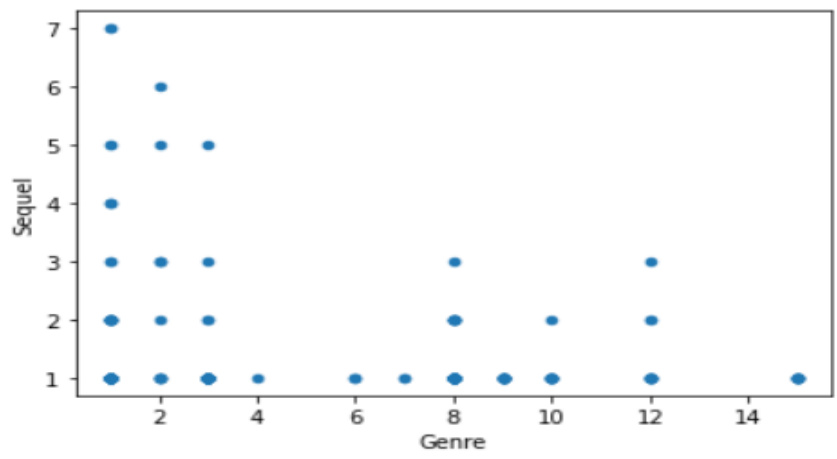


We wanted to see if the rating a movie got affected the viewing habit of people. From the above plot, we found that it had little to no effect and besides a few outliers, people viewed movies from the entire spectrum of ratings with almost equal interest.

➔ Scatter plot (Sequel vs Genre)

```
data.plot(kind='scatter',y='Sequel', x='Genre')
```

```
<AxesSubplot:xlabel='Genre', ylabel='Sequel'>
```

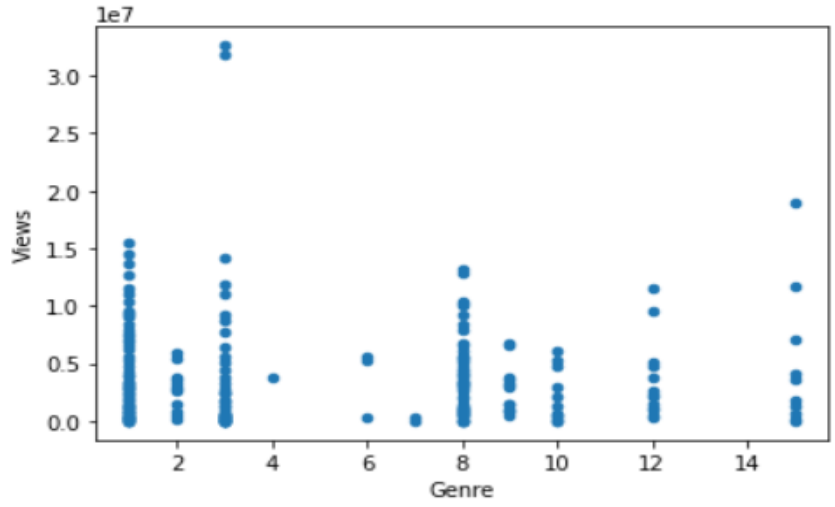


It was found that most franchise films belonged to genre 1 and. Apart from these, genres 3, 8 and 12 had some franchise films. All other genres dealt exclusively with standalone titles.

➔ Scatter plot (Views vs Genre)

```
data.plot(kind='scatter',y='Views', x='Genre')
```

```
<AxesSubplot:xlabel='Genre', ylabel='Views'>
```

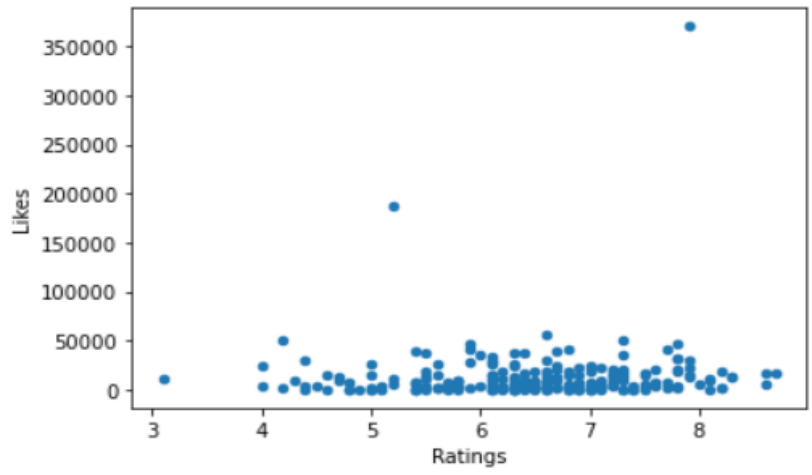


As we can see, movies with the highest number of views belong to genre 8 on an average, followed by genre 3 and 1.

➔ Scatter plot (Likes vs Rating)

```
data.plot(kind='scatter',y='Likes', x='Ratings')
```

```
<AxesSubplot:xlabel='Ratings', ylabel='Likes'>
```



Again, there was no correlation visible between the ratings and likes a movie received with likes uniformly distributed across the entire spectrum of ratings, with the exception of 2 outliers.

MODEL BUILDING:

- **Critical Success:-**

  All movies have a Likes-Dislikes figure. The ratio of Likes and Dislikes determines our Critical Success.

```
Likes = new_df['Likes'].values
Dislikes = new_df['Dislikes'].values
critical_success = [0]*len(Gross)
for i in range(0,len(Likes)) :
    num = Likes[i] / Dislikes[i]
    if num < 15:
        critical_success[i] = "not supported by public"
    else:
        critical_success[i] = "supported by public"
new_df['critical_success'] =  critical_success
```

- **Commercial Success:-**

  All movies have a budget and gross earnings. We summarised Commercial success on the basis of difference of budget and gross earning.

```
Gross = new_df['Gross'].values
Budget = new_df['Budget'].values
commercial_success = [0]*len(Gross)
for i in range(0,len(Gross)) :
    num = (Gross[i] - Budget[i])
    if num < 10000000:
        commercial_success[i] = "flop"
    elif num > 17000000:
        commercial_success[i] ="Super hit"
    else:
        commercial_success[i] = "hit"
new_df['commercial_success'] =  commercial_success
```

- **Review:-**

  All movies have ratings ranging from 1 to 10. We divided these ratings into 3 different categories:
  Bad (<5), Average (5-6) and Good (>6).

```
10  Ratings = new_df["Ratings"].values
11  Review = []
12  for num in Ratings:
13      if num < 5:
14          Review.append("Bad")
15      elif num >=7:
16          Review.append("Good")
17      else:
18          Review.append("Average")
19  new_df['Review'] = Review
```

- **Targeting the Labels:-**

  After creating these new columns, we labelled them with some numericals:
  1.For 'critical_success', 0 is for 'not supported by the public' and 1 is for 'supported by the public'.
  2.For 'commercial_success', 2 is for 'Super hit', 1 is for 'hit', and 0 is for 'flop'.
  3.For 'Review', 2 is 'Good', 1 is 'Average' and 0 is 'Bad'.

```
47  y = new_df['Review']
48  from sklearn.preprocessing import LabelEncoder
49  le=LabelEncoder()
50  labelencoder_y =LabelEncoder()
51  y= labelencoder_y.fit_transform(y)
52
```

TRAINING DATA AND TEST DATA:

- **For critical_success**
  1. Now we will count the number of ‘supported by public’ and ‘not supported by public’ instances in the dataframe

```
In [12]: new_df['critical_success'].value_counts()
Out[12]:
supported by public        145
not supported by public     87
Name: critical_success, dtype: int64
```

  2. As we can see there are more ‘supported by public’ movies than ‘not supported by public’ movies
  3. Now we separate our dataset into two columns x and y where x signifies known attributes and y signifies predicted attributes

```
63   y = new_df['critical_success']
64   x = new_df[['Gross', 'Views' , 'Likes' , 'Aggregate Followers']]
65
```

  4. Now we divide the dataset into two parts, where 75% of our dataset is the training part and the rest is for the testing part.

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state = 0
```

- **For commercial_success**
  1. Now we will count the number of Super hit, hit and flop instances in the dataframe

```
In [10]: new_df['commercial_success'].value_counts()
Out[10]:
flop         125
Super hit     95
hit           12
Name: commercial_success, dtype: int64
```

2. As we can see there are more flop movies than super hit or hit movies
3. Now we separate our dataset into two columns x and y where x signifies known attributes and y signifies predicted attributes

```
57   y = new_df['commercial_success']
58   x = new_df[['Gross', 'Views' , 'Likes' , 'Aggregate Followers']]
```

4. Now we divide the dataset into two parts, where 75% of our dataset is the training part and the rest is for testing part

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state = 0)
```

- **For 'Review'**
  1. Now we will count the number of good,bad and average instances in the dataframe

```
In [7]: new_df['Review'].value_counts()
Out[7]:
Average    144
Good        69
Bad         19
Name: Review, dtype: int64
```

  2. As we can see there are more average movies than good or bad movies
  3. Now we separate our dataset into two columns x and y where x signifies known attributes and y signifies predicted attributes

```
55   y = new_df['Review']
56   x = new_df[['Gross', 'Views' , 'Likes' , 'Aggregate Followers']]
```

  4. Now we divide the dataset into two parts, where 75% of our dataset is the training part and the rest is for testing part

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state = 0)
```

ALGORITHMS APPLIED:

1. Naive Bayes Classification:-

It is a supervised learning classification algorithm based on Bayes Theorem. It is mainly used in text classification that includes a high-dimensional training dataset.

Basic Idea:- Bayes theorem says that P(Y|X) =(P(X|Y)*P(Y)) / P(X). Our given attributes would be mentioned in the X part and we will have to predict the class value which will be Y.

```
71  ##naive bayes
72  from sklearn.naive_bayes import GaussianNB
73  classifier=GaussianNB()
74  classifier.fit(x_train,y_train)
75  predicted=classifier.predict(x_test)
76  from sklearn.metrics import confusion_matrix
77  from sklearn.metrics import accuracy_score
78  from sklearn.metrics import classification_report
79  cm=confusion_matrix(y_test,predicted)
80  print(cm)
81  print("Accuracy is "+str(round(accuracy_score(y_test,predicted),4) *100))
82  print("Classification Report\n"+str(classification_report(y_test, predicted)))
83
```

2. Support Vector Machine:-

It is a supervised learning algorithm consisting of prediction methods based on the statistical learning framework or VC theory proposed by Vapnik and Chervonenkis.

Basic Idea:- Suppose some numeric and linearly separable data is given to us which we plot on a plane. Our main goal would be to select the most optimal hyperplane so as to separate the data.

```
84  ## SVm
85  from sklearn.svm import SVC
86  classifier=SVC(kernel='rbf',random_state=0,gamma='auto')
87  classifier.fit(x_train,y_train)
88  p=classifier.predict(x_test)
89  from sklearn.metrics import confusion_matrix
90  from sklearn.metrics import accuracy_score
91  from sklearn.metrics import classification_report
92  p=classifier.predict(x_test)
93  cm=confusion_matrix(y_test,p)
94  print(cm)
95  print("Accuracy is "+str(round(accuracy_score(y_test,p),4) *100))
96  print("Classification Report\n"+str(classification_report(y_test, p)))
97
```

3. Logical Regression:-

It is a supervised learning classification algorithm, in which the probability of a target variable is predicted. It simply builds a model between X (dependent variable) and Y (Independent Variable).

Basic Idea:- In logical regression, we would build a 2-D plane model, and then use that model to predict the y values for x values given in the testing data.

```
##logical regression
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression()
log_reg.fit(x_train,y_train)
predicted = log_reg.predict(x_test)
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
cm=confusion_matrix(y_test , predicted)
print(cm)
print("Accuracy is "+str(round(accuracy_score(y_test,predicted),4) *100))
print("Classification Report\n"+str(classification_report(y_test, predicted)))
```

4. K-Nearest Neighbour:-

It is a supervised learning algorithm which assumes the similarity between the new case/data and available cases and puts the new case into the category that is most similar to the available categories.

Basic Idea:- We would be given a set of records. If we want to find the class value for a record, then we would find the difference between that record with all the other given records and sort them. After that, we will select the first smallest records on the basis of sorted differences, and then select the class value on the basis of majority voting.

```
## KNN
from sklearn.neighbors import KNeighborsClassifier
classifier=KNeighborsClassifier(n_neighbors=10)
classifier.fit(x_train,y_train)
p=classifier.predict(x_test)
acc=[]
for i in range(1,21):
    classifier1=KNeighborsClassifier(n_neighbors=i)
    classifier1.fit(x_train,y_train)
    predicted1=classifier1.predict(x_test)
    acc.append(accuracy_score(y_test, predicted1)*100)
plt.figure(figsize=(7,7))
plt.plot(acc)
plt.xticks(np.array(range(1,17)))
plt.title("Selection of k")
plt.xlabel("k for Nearest Neighbour")
plt.ylabel("Accuracy")
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
cm=confusion_matrix(y_test,p)
print(cm)
print("Accuracy is "+str(accuracy_score(y_test, p)*100))
print("Classification Report\n"+str(classification_report(y_test, p)))
```

RESULTS:

- **For 'critical_success'**

1. Naive Bayes Classification

```
[[23  9]
 [40 21]]
Accuracy is 47.31
Classification Report
                         precision    recall  f1-score   support

not supported by public       0.37      0.72      0.48        32
    supported by public       0.70      0.34      0.46        61

               accuracy                           0.47        93
              macro avg       0.53      0.53      0.47        93
           weighted avg       0.58      0.47      0.47        93
```

The result is accuracy=47.31%

2. Support Vector Machine

```
[[ 1 31]
 [ 0 61]]
Accuracy is 66.67
Classification Report
                         precision    recall  f1-score   support

not supported by public       1.00      0.03      0.06        32
    supported by public       0.66      1.00      0.80        61

               accuracy                           0.67        93
              macro avg       0.83      0.52      0.43        93
           weighted avg       0.78      0.67      0.54        93
```

The result is accuracy=66.67%

3. Logical Regression

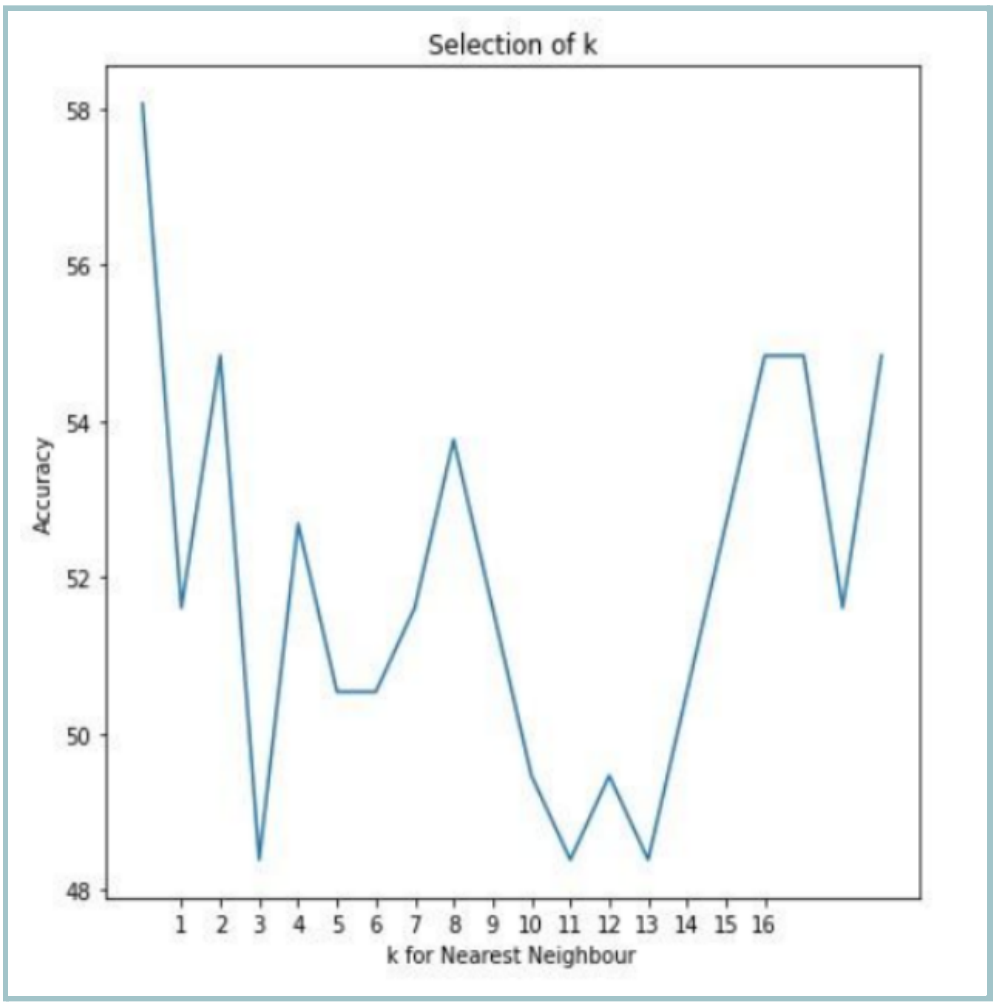
```
[[ 8 24]
 [ 9 52]]
Accuracy is 64.52
Classification Report
                         precision    recall  f1-score   support

not supported by public       0.47      0.25      0.33        32
    supported by public       0.68      0.85      0.76        61

               accuracy                           0.65        93
              macro avg       0.58      0.55      0.54        93
           weighted avg       0.61      0.65      0.61        93
```

The result is accuracy=64.52%

4. K-Nearest Neighbour




```
[[12 20]
 [25 36]]
Accuracy is 51.61290322580645
Classification Report
                        precision    recall  f1-score   support

not supported by public       0.32      0.38      0.35        32
    supported by public       0.64      0.59      0.62        61

              accuracy                           0.52        93
             macro avg       0.48      0.48      0.48        93
          weighted avg       0.53      0.52      0.52        93
```

The result is accuracy=51.61%

- **For ‘commercial_success’**

1. Naive Bayes Classification

```
[[19 15  5]
 [ 5 38  6]
 [ 1  1  3]]
Accuracy is 64.52
Classification Report
              precision    recall  f1-score   support

           0       0.76      0.49      0.59        39
           1       0.70      0.78      0.74        49
           2       0.21      0.60      0.32         5

    accuracy                           0.65        93
   macro avg       0.56      0.62      0.55        93
weighted avg       0.70      0.65      0.65        93
```

The result is accuracy=64.52%

2. Support Vector Machine

```
[[32  0  4]
 [ 6  0  0]
 [10  0  6]]
Accuracy is 65.51724137931035
Classification Report
              precision    recall  f1-score   support

           0       0.67      0.89      0.76        36
           1       0.00      0.00      0.00         6
           2       0.60      0.38      0.46        16

    accuracy                           0.66        58
   macro avg       0.42      0.42      0.41        58
weighted avg       0.58      0.66      0.60        58
```

The result is accuracy=65.51%

3. Logical Regression

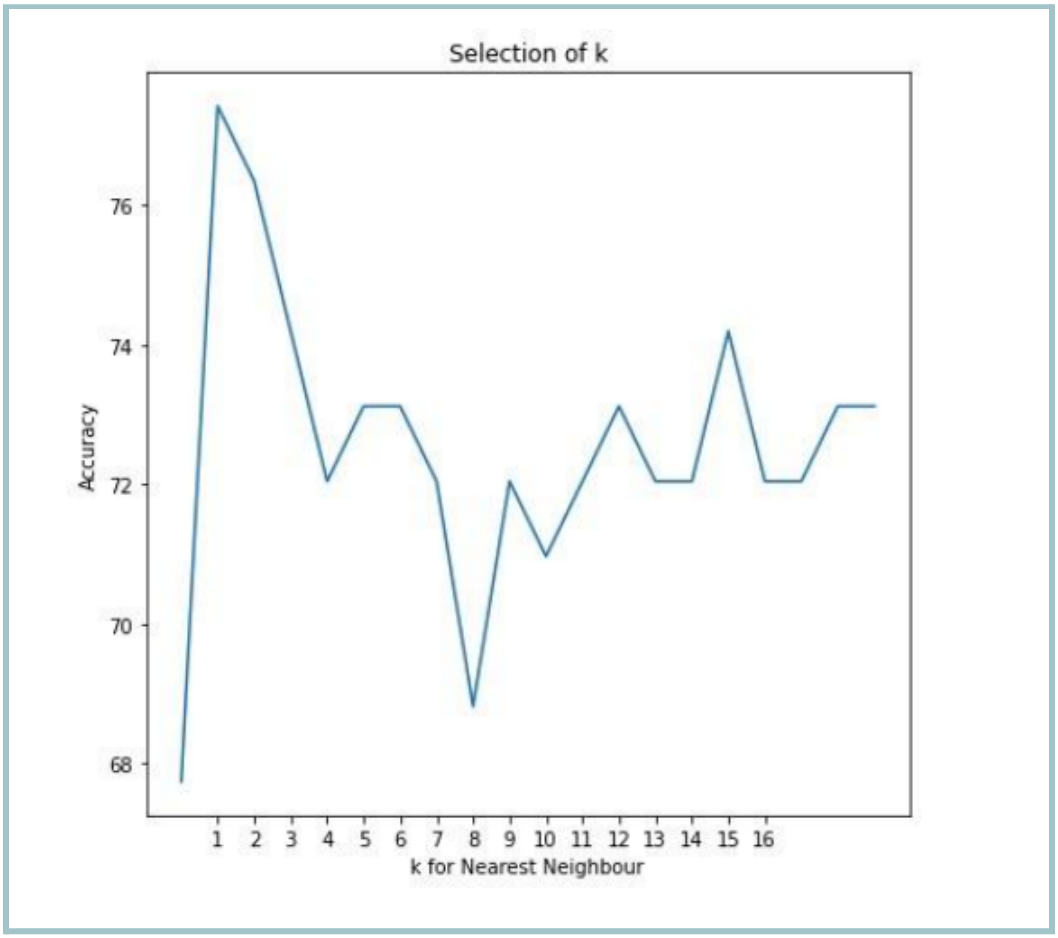
```
Prediction for commercial_success
[[31  8  0]
 [18 31  0]
 [ 4  1  0]]
Accuracy is 66.67
Classification Report
              precision    recall  f1-score   support

           0       0.58      0.79      0.67        39
           1       0.78      0.63      0.70        49
           2       0.00      0.00      0.00         5

    accuracy                           0.67        93
   macro avg       0.45      0.48      0.46        93
weighted avg       0.65      0.67      0.65        93
```

The result is accuracy=66.67%

4. K-Nearest Neighbour




```
[[29 10  0]
 [11 38  0]
 [ 3  2  0]]
Accuracy is 72.04301075268818
Classification Report
              precision    recall  f1-score   support

           0       0.67      0.74      0.71        39
           1       0.76      0.78      0.77        49
           2       0.00      0.00      0.00         5

    accuracy                           0.72        93
   macro avg       0.48      0.51      0.49        93
weighted avg       0.68      0.72      0.70        93
```

The result is accuracy=72.04%

- **For ‘reviews’**

1. Naive Bayes Classification

```
[[14 16  6]
 [ 2  3  1]
 [ 4  8  4]]
Accuracy is 36.21
Classification Report
              precision    recall  f1-score   support

           0       0.70      0.39      0.50        36
           1       0.11      0.50      0.18         6
           2       0.36      0.25      0.30        16

    accuracy                           0.36        58
   macro avg       0.39      0.38      0.33        58
weighted avg       0.55      0.36      0.41        58
```

The result is accuracy=36.21%

2. Support Vector Machine

```
[[36  0  0]
 [ 5  1  0]
 [16  0  0]]
Accuracy is 63.79
Classification Report
              precision    recall  f1-score   support

           0       0.63      1.00      0.77        36
           1       1.00      0.17      0.29         6
           2       0.00      0.00      0.00        16

    accuracy                           0.64        58
   macro avg       0.54      0.39      0.35        58
weighted avg       0.50      0.64      0.51        58
```

The result is accuracy=63.79%

3. Logical Regression

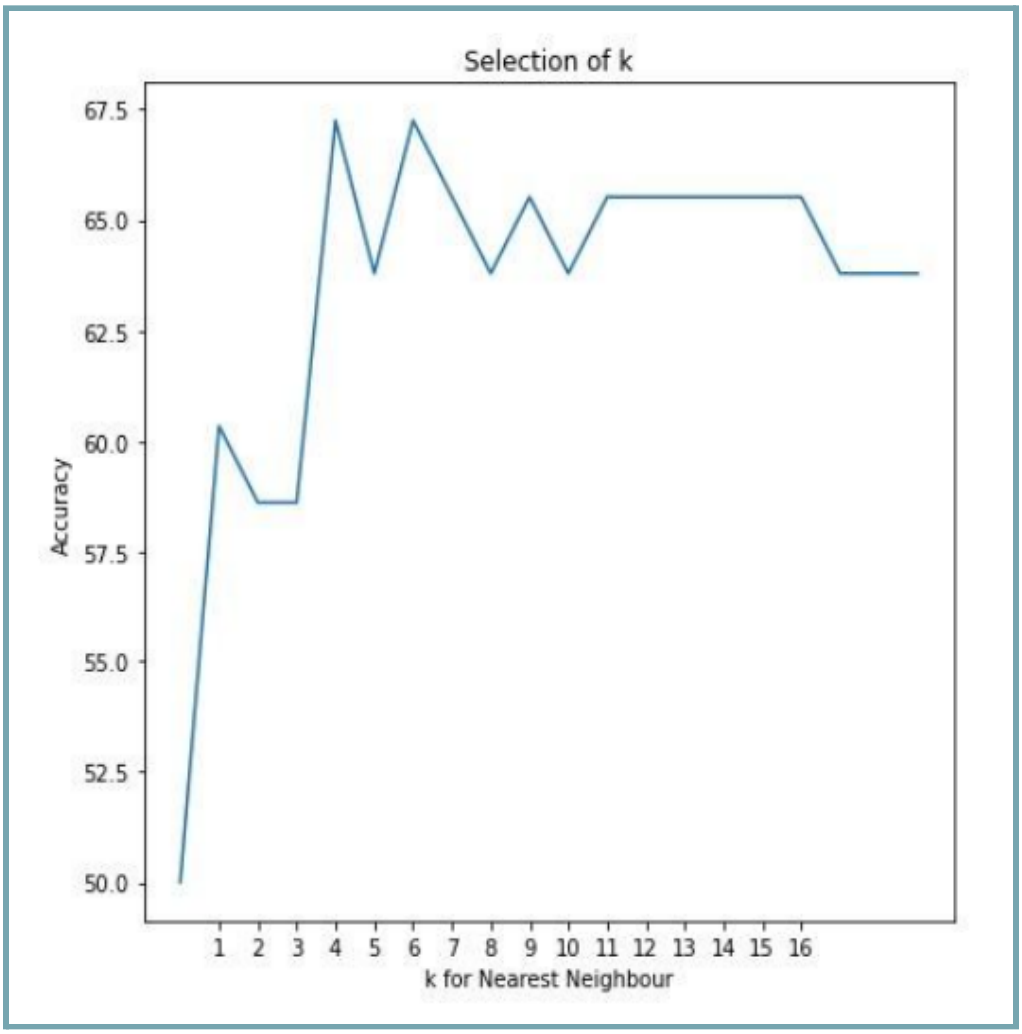
```
[[25  0 11]
 [ 5  0  1]
 [ 9  0  7]]
Accuracy is 55.169999999999995
Classification Report
              precision    recall  f1-score   support

           0       0.64      0.69      0.67        36
           1       0.00      0.00      0.00         6
           2       0.37      0.44      0.40        16

    accuracy                           0.55        58
   macro avg       0.34      0.38      0.36        58
weighted avg       0.50      0.55      0.52        58
```

The result is accuracy=55.17%

4. K-Nearest Neighbour




```
[[32  0  4]
 [ 6  0  0]
 [10  0  6]]
Accuracy is 65.51724137931035
Classification Report
              precision    recall  f1-score   support

           0       0.67      0.89      0.76        36
           1       0.00      0.00      0.00         6
           2       0.60      0.38      0.46        16

    accuracy                           0.66        58
   macro avg       0.42      0.42      0.41        58
weighted avg       0.58      0.66      0.60        58
```

The result is accuracy=65.51%

CONCLUSION:

- **For 'critical_success'**

  As we can see for the 'critical_success' attribute estimation case, KNN Classifier gives the most accurate results of all four classifiers from the given dataset, and Naive Bayes Classifier gives the least accurate results.

ALGORITHMS APPLIED	RESULT
Naive Bayes Classification	47.31%
Support Vector Machine	66.67%
Logical Regression	64.52%
K-Nearest Neighbour	51.61%

Increasing accuracy:- Naive Bayes<KNN:<Logical Regression<SVM

- **For 'commercial_success'**

  As we can see for the commercial_success attribute estimation case, KNN Classifier gives the most accurate results of all four classifiers from the given dataset, and Naive Bayes Classifier gives the least accurate results.

ALGORITHMS APPLIED	RESULT
Naive Bayes Classification	64.52%
Support Vector Machine	65.51%
Logical Regression	66.67%
K-Nearest Neighbour	72.04%

Increasing accuracy:- Naive Bayes<SVM<Logical Regression<KNN

- **For 'reviews'**

  As we can see for the 'Review' attribute estimation case, KNN Classifier gives the most accurate results of all four classifiers from the given dataset, and Naive Bayes Classifier gives the least accurate results.

ALGORITHMS APPLIED	RESULT
Naive Bayes Classification	36.21%
Support Vector Machine	63.79%
Logical Regression	55.17%
K-Nearest Neighbour	65.51%

Increasing accuracy:- Naive Bayes<Logical Regression<SVM<KNN

ACKNOWLEDGEMENT:

We thank Dr. Sudheer Sharma ,Dr. Aloke Datta and Dr. Indra Deep Mastan for giving us this opportunity to have a deeper understanding on the topic “Conventional and Social Media Movies Analysis”.We would extend our regards to all our group members from the LNM Institute of Information Technology who provided insight and expertise that greatly assisted this project.

REFERENCES:

- ☐ An introduction to seaborn — seaborn 0.11.0 documentation (pydata.org)
- ☐ Tutorials — Matplotlib 3.1.2 documentation
- ☐ https://www.youtube.com/watch?v=tVQb1e8Gu94&t=1928s
- ☐ Community tutorials — pandas 1.1.4 documentation (pydata.org)
- ☐ scikit-learn: machine learning in Python — scikit-learn 0.23.2 documentation (scikit-learn.org)