Predicting the Popularity of Movies with Machine Learning Methods

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I. INTRODUCTION

This article is about predicting the popularity of movies. A number of features such as cast, genre, budget, production house, and rating affect a movie's popularity. Twitter, YouTube etc. Social media are the main platforms where people can share their views on movies. Traditional features and social media features are two types of features to be used to estimate the popularity of the movie. The estimate of popularity can be measured in terms of Ratings. (Represented by a positive numeric number less than 10 or a label).

II. DATASET

A. Description

Data Name: CSM (Conventional and Social Media Movies) Dataset 2014 and 2015 Data Set

Data Link:
https://archive.ics.uci.edu/ml/datasets/CSM+%28Conventional+and+Social+Media+Movies%29+Dataset+2014+and+2015

The dataset retrieved information about movies from diverse sources including movies web site, i.e. IMDB, generic web resource i.e. Wikipedia, and social media including YouTube and Twitter. Beyond that, it also used sentiment analysis libraries to get the sentiment score for different movies. The total dataset contains twelve features and can be split in to two sub-dataset, the conventional features and social media features.

1) Conventional Features: Conventional Features contain six features in total and those features are typically available on movie resource websites, such as IMDB.

   • Genre: There are 19 different types of genre in the dataset, such as Action, Adventure and Drama etc. They were already mapped on to integer value from 1-19 and in our project, they are treated as factor variables to represent different genre.
   • Sequel: This variable in integer represents whether the movie is sequel or individual. 1 shows that movie is first release; other n larger than 1 shows that movie is 2nd. e.g. Pirates of Caribbean: Dead Man's Chest is 2nd in sequel, therefore it is assigned the value of 2.
   • Ratings: The value of Ratings ranges between 1 to 10 with 1 being lowest and 10 the highest. These values are collected from IMDB.
   • Gross Income, Budget and Number of Screens: Gross world-wide income and Budget for each movie is collected from IMDB. The unit of gross income and budget is USD and they are already converted into USD if they are represented in other currencies. Number of screens on which movie was initially launched in US is also considered.

2) Social Media Features: Social Media Features also contains six features and those features are collected for each movie.

   • Aggregate Actor Followers: Number of followers of actors in one movie on twitter is used. Only the top 3 in cast are considered.
   • Number of Views and Comments: Those variables represent the number of views and comments of trailer of movies on YouTube.
   • Number of likes and dislikes: Number of Likes and Dislikes of trailers on YouTube are considered.
   • Sentiment Score: A signed integer value is used to represent sentiment score. 0 represents neutral sentiment; "+"sign shows the positive sentiment and the value shows the magnitude; "–"sign shows negative sentiment and the value shows the magnitude. The sentiment score is calculated through analysing the sentiments of tweets about one movie.

B. Plots

A data quality report includes tabular reports that describe the characteristics of each feature in an ABT using standard statistical measures of central tendency and variation.

The tabular reports are accompanied by data visualizations:

- A histogram for each continuous feature in an ABT.
- A bar plot for each categorical feature in an ABT.

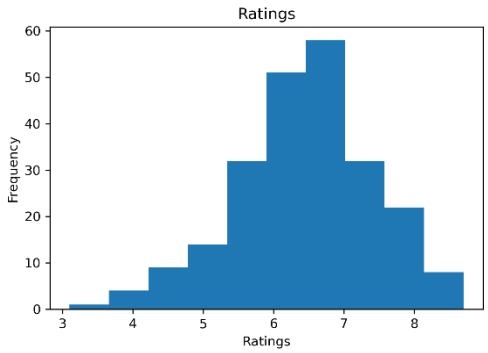
Continuous Features:

	Feature	Count	%Miss	Card	Min	1Qrt	Mean	Median	3Qrt	Max	StdDev
0	Year	231	0.000000	2	2014.0	2014.0	2.014294e+03	2014.0	2015.0	2015.0	4.567498e-01
1	Ratings	231	0.000000	45	3.1	5.8	6.441558e+00	6.5	7.1	8.7	9.887652e-01
2	Genre	231	0.000000	11	1.0	1.0	5.359307e+00	3.0	8.0	15.0	4.141611e+00
3	Gross	231	0.000000	215	2470.0	10300000.0	6.806603e+07	37400000.0	89350000.0	643000000.0	8.890289e+07
4	Budget	230	0.432900	104	70000.0	9000000.0	4.792173e+07	28000000.0	65000000.0	250000000.0	5.428825e+07
5	Screens	221	4.329004	200	2.0	449.0	2.209244e+03	2777.0	3372.0	4324.0	1.463768e+03
6	Sequel	231	0.000000	7	1.0	1.0	1.359307e+00	1.0	1.0	7.0	9.672406e-01
7	Sentiment	231	0.000000	36	-38.0	0.0	2.809524e+00	0.0	5.5	29.0	6.996775e+00
8	Views	231	0.000000	231	698.0	623302.0	3.712851e+06	2409338.0	5217379.5	32626778.0	4.511104e+06
9	Likes	231	0.000000	227	1.0	1776.5	1.273254e+04	6096.0	15247.5	370552.0	2.882548e+04
10	Dislikes	231	0.000000	203	0.0	105.5	6.790519e+02	341.0	697.5	13960.0	1.243929e+03
11	Comments	231	0.000000	213	0.0	248.5	1.825701e+03	837.0	2137.0	38363.0	3.571040e+03
12	Aggregate Followers	196	15.151515	190	1066.0	183025.0	3.038193e+06	1052600.0	3694500.0	31030000.0	4.886278e+06

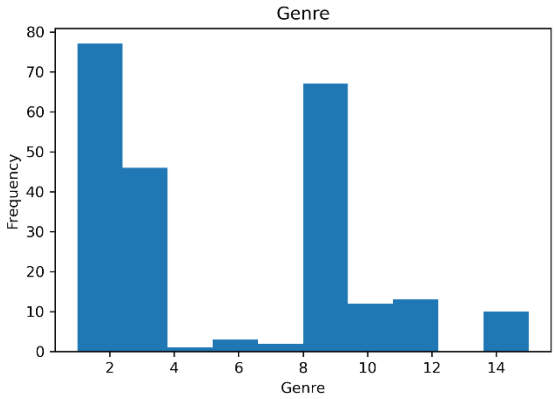
Categorical Features:

	Feature	Count	%Miss	Card	Mode	ModeFreq	%Mode	2ndMode	2ndModeFreq	2nd%Mode
0	Year	231	0.000000	2	2014.0	NaN	NaN	NaN	NaN	NaN
1	Ratings	231	0.000000	45	6.1	NaN	NaN	6.3	NaN	NaN
2	Genre	231	0.000000	11	1.0	NaN	NaN	NaN	NaN	NaN
3	Gross	231	0.000000	215	129000.0	NaN	NaN	1210000.0	NaN	NaN
4	Budget	230	0.432900	104	5000000.0	NaN	NaN	50000000.0	NaN	NaN
5	Screens	221	4.329004	200	2.0	NaN	NaN	4.0	NaN	NaN
6	Sequel	231	0.000000	7	1.0	NaN	NaN	NaN	NaN	NaN
7	Sentiment	231	0.000000	36	0.0	NaN	NaN	NaN	NaN	NaN
8	Views	231	0.000000	231	698.0	NaN	NaN	702.0	NaN	NaN
9	Likes	231	0.000000	227	1.0	NaN	NaN	6.0	NaN	NaN
10	Dislikes	231	0.000000	203	1.0	NaN	NaN	NaN	NaN	NaN
11	Comments	231	0.000000	213	1.0	NaN	NaN	NaN	NaN	NaN
12	Aggregate Followers	196	15.151515	190	130000.0	NaN	NaN	147000.0	NaN	NaN

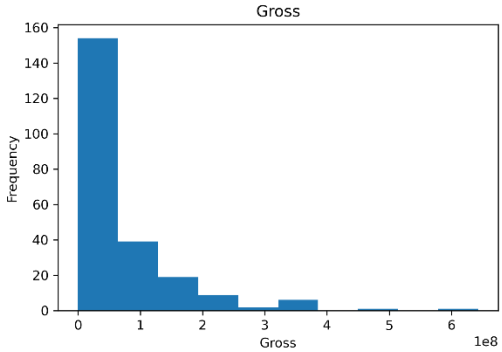
a) Ratings



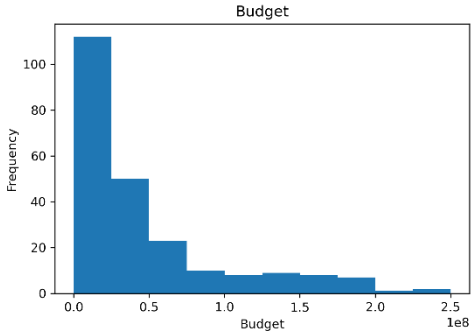
b) Genre



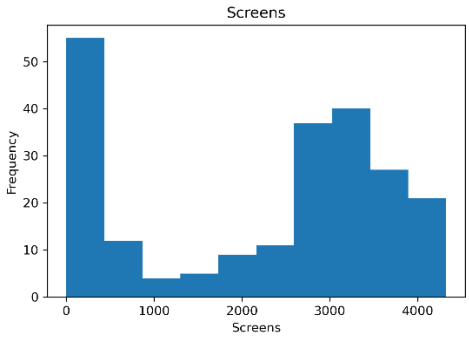
c) Gross



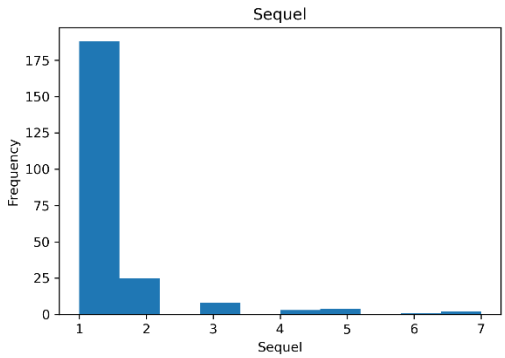
d) Budget



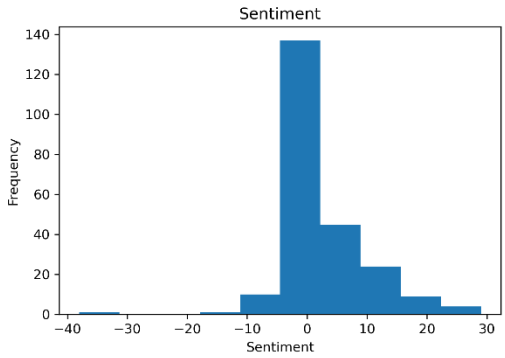
e) Screens



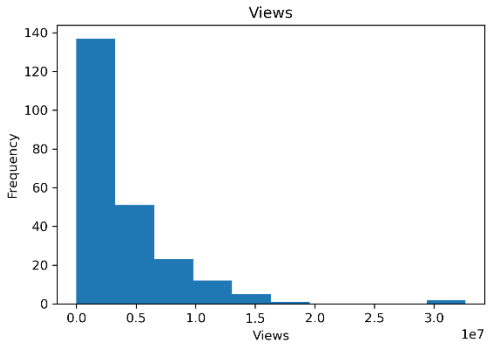
f) Sequel



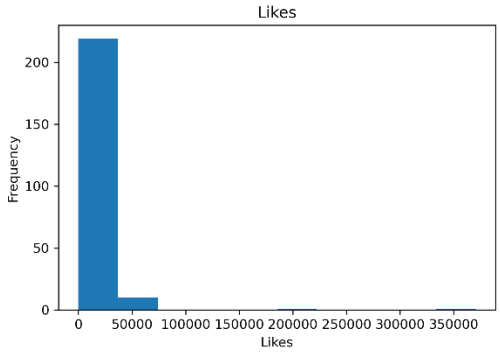
g) Sentiment



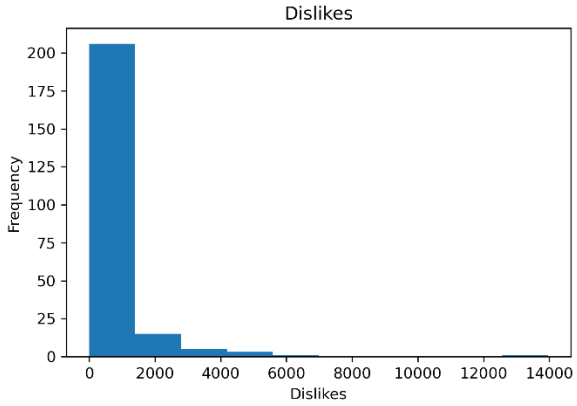
h) Views



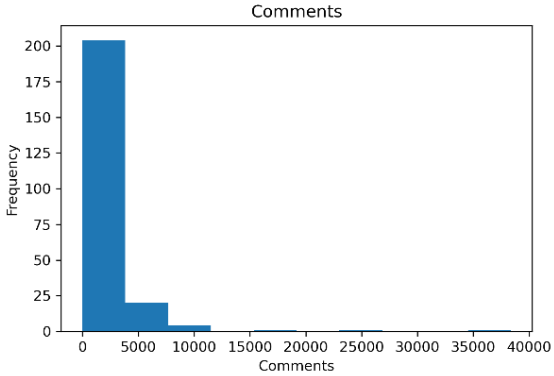
i) Likes



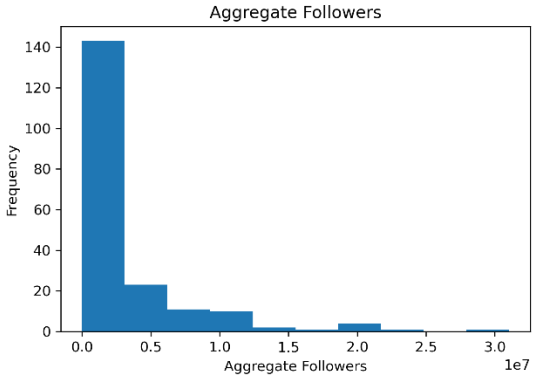
j) Dislikes



k) Comments



l) Aggregate



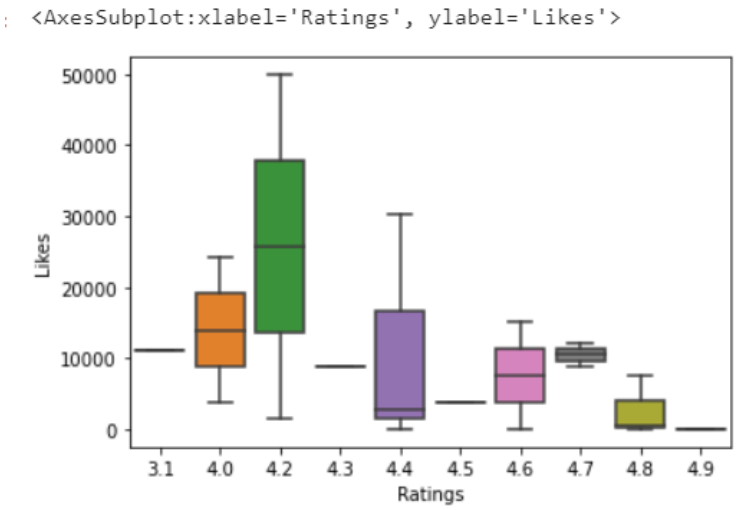
C. Data Preprocess

Table I shows that how we map the Rating to category variable. For methods exclude regression methods, I will use this categorical variable as dependent variable in models and predictions.

Ratings	Assigned Label
0-4.9	Poor
5-6.4	Average
6.5-8	Good
8-10	Excellent

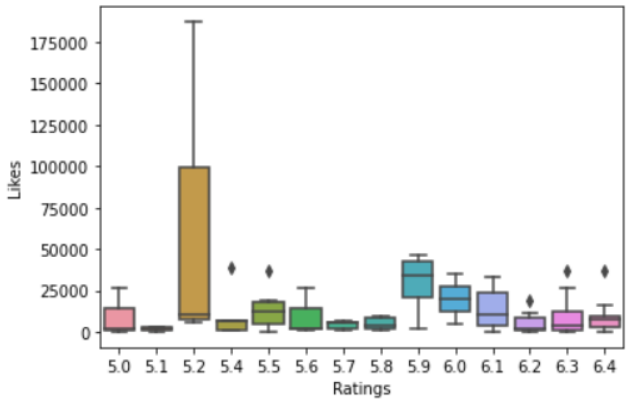
Table I

a) 0 – 4.9 Poor



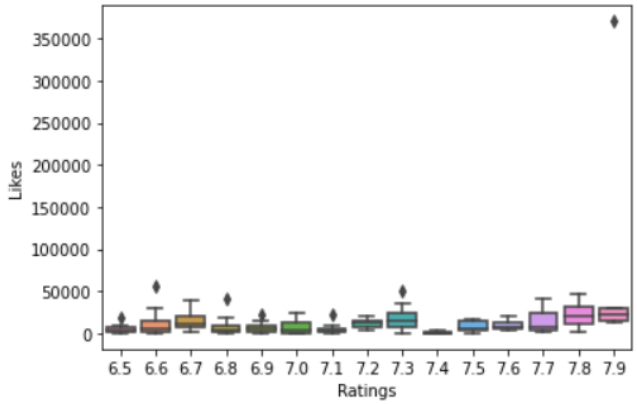
b) 5 - 6.4 Average

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



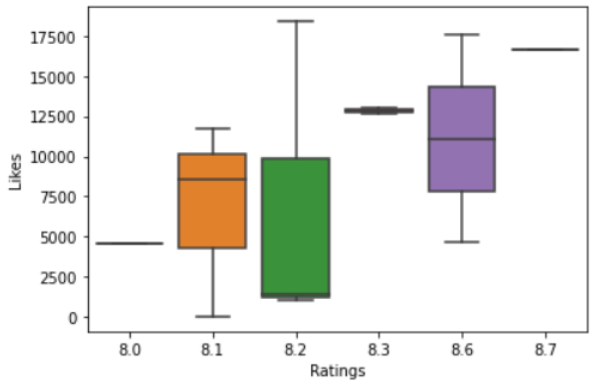
c) 6.5 – 8 Good

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



d) 8 – 10 Excellent

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



From the graphs taken from these numbers, we can learn that the higher the 'Likes' numbers, the higher the likelihood that a movie will be in a higher level, as well as some features can help differentiate rating levels; For other properties, we need to investigate how these properties can be used to estimate the tag of a movie's ratings.

APPENDIX A: Continuous and Categorical Features Code

```
#2014510056- ZEYNEP KOSE

# Libraries
import numpy as np
import numpy.matlib
import matplotlib.pyplot as plt
import pandas as pd
import math
import os #look for directory
%matplotlib inline

# Import database

data = pd.read_csv('data.csv')

data.head(1)
```

```
   Year  Ratings  Genre  Gross     Budget  Screens  Sequel  Sentiment  \
0  2014      6.3      8   9130  4000000.0     45.0       1          0

     Views  Likes  Dislikes  Comments  Aggregate Followers
0  3280543   4632       425       636            1120000.0
```

The structures of the tables included in a data quality report to describe

1) Continuous features

2) Categorical features

```
#It is split into two data frames with different property types:
#Continuous
dataCont=data
```

```
#Categorical
dataCat=data
```

Create "Continuous features" for Quality Report

```
QRcontinue = pd.DataFrame(columns = ['Feature','Count','%Miss','Card','Min','1Qrt','Mean','Median','3Qrt','Max','StdDev'])
QRcontinue
```

```
Empty DataFrame
Columns: [Feature, Count, %Miss, Card, Min, 1Qrt, Mean, Median, 3Qrt, Max, StdDev]
Index: []
```

```
#Feature names
QRcontinue['Feature']=list(dataCont.columns)
#Count Values (data - NaN)
QRcontinue['Count']=list(dataCont.count(axis=0))
# missing values
QRcontinue['%Miss']=list(dataCont.isnull().sum()/len(dataCont)*100)
#Cardinality: number of different values
QRcontinue['Card']=list(dataCont.apply(pd.Series.nunique))
#Minimum value
QRcontinue['Min']=list(dataCont.min(axis=0))
# 1st quartile
QRcontinue['1Qrt']=list(dataCont.quantile(q=0.25,axis=0))  #0<=q<=1 25%percentil=0.25q
#Average
QRcontinue['Mean']= list(dataCont.mean(axis=0))
#Median
QRcontinue['Median']= list(dataCont.median(axis=0))
# 3rd quartile
QRcontinue['3Qrt']=list(dataCont.quantile(q=0.75,axis=0))  #0<=q<=1 25%percentil=0.25q
#Maximum value
QRcontinue['Max']=list(dataCont.max(axis=0))
#Standard deviation
QRcontinue['StdDev']=list(dataCont.std(axis=0))
```

```
QRcontinue
```

	Feature	Count	%Miss	Card	Min	1Qrt	\
0	Year	231	0.000000	2	2014.0	2014.0	
1	Ratings	231	0.000000	45	3.1	5.8	
2	Genre	231	0.000000	11	1.0	1.0	
3	Gross	231	0.000000	215	2470.0	10300000.0	
4	Budget	230	0.432900	104	70000.0	9000000.0	
5	Screens	221	4.329004	200	2.0	449.0	
6	Sequel	231	0.000000	7	1.0	1.0	
7	Sentiment	231	0.000000	36	-38.0	0.0	
8	Views	231	0.000000	231	698.0	623302.0	
9	Likes	231	0.000000	227	1.0	1776.5	
10	Dislikes	231	0.000000	203	0.0	105.5	

```
11           Comments    231   0.000000   213      0.0       248.5
12  Aggregate Followers    196  15.151515   190   1066.0    183025.0
```

```
          Mean      Median        3Qrt         Max        StdDev
0   2.014294e+03      2014.0      2015.0      2015.0  4.567498e-01
1   6.441558e+00         6.5         7.1         8.7  9.887652e-01
2   5.359307e+00         3.0         8.0        15.0  4.141611e+00
3   6.806603e+07  37400000.0  89350000.0  643000000.0  8.890289e+07
4   4.792173e+07  28000000.0  65000000.0  250000000.0  5.428825e+07
5   2.209244e+03      2777.0      3372.0      4324.0  1.463768e+03
6   1.359307e+00         1.0         1.0         7.0  9.672406e-01
7   2.809524e+00         0.0         5.5        29.0  6.996775e+00
8   3.712851e+06   2409338.0   5217379.5   32626778.0  4.511104e+06
9   1.273254e+04      6096.0     15247.5     370552.0  2.882548e+04
10  6.790519e+02       341.0       697.5      13960.0  1.243929e+03
11  1.825701e+03       837.0      2137.0      38363.0  3.571040e+03
12  3.038193e+06   1052600.0   3694500.0   31030000.0  4.886278e+06
```

Create "Categorical features" for Quality Report

```
#"Quality report"
QRcategorical = pd.DataFrame(columns = ['Feature','Count','%Miss','Card','Mode','ModeFreq','%Mode','2ndMode','2ndModeFreq','2nd%Mode'])
QRcategorical
```

```
Empty DataFrame
Columns: [Feature, Count, %Miss, Card, Mode, ModeFreq, %Mode, 2ndMode, 2ndModeFreq, 2nd%Mode]
Index: []
```

```
#Feature names
QRcategorical['Feature']=list(dataCat.columns)
#Count Values (data - NaN)
QRcategorical['Count']=list(dataCat.count(axis=0))
# missing values
QRcategorical['%Miss']=list(dataCat.isnull().sum()/len(dataCat)*100)
#Cardinality: number of different values
QRcategorical['Card']=list(dataCat.apply(pd.Series.nunique))
#Moda
QRcategorical['Mode']=list(dataCat.mode(axis=0).iloc[0])
#Frequency of mode

#Percentage of mode

# 2nd mode
QRcategorical['2ndMode']=list(dataCat.mode(axis=0).iloc[1])
# 2nd mode frequency

#Percentage of 2nd mode
```

QRcategorical

	Feature	Count	%Miss	Card	Mode	ModeFreq	%Mode	\
0	Year	231	0.000000	2	2014.0	NaN	NaN	
1	Ratings	231	0.000000	45	6.1	NaN	NaN	
2	Genre	231	0.000000	11	1.0	NaN	NaN	
3	Gross	231	0.000000	215	129000.0	NaN	NaN	
4	Budget	230	0.432900	104	5000000.0	NaN	NaN	
5	Screens	221	4.329004	200	2.0	NaN	NaN	
6	Sequel	231	0.000000	7	1.0	NaN	NaN	
7	Sentiment	231	0.000000	36	0.0	NaN	NaN	
8	Views	231	0.000000	231	698.0	NaN	NaN	
9	Likes	231	0.000000	227	1.0	NaN	NaN	
10	Dislikes	231	0.000000	203	1.0	NaN	NaN	
11	Comments	231	0.000000	213	1.0	NaN	NaN	
12	Aggregate Followers	196	15.151515	190	130000.0	NaN	NaN	

	2ndMode	2ndModeFreq	2nd%Mode
0	NaN	NaN	NaN
1	6.3	NaN	NaN
2	NaN	NaN	NaN
3	1210000.0	NaN	NaN
4	50000000.0	NaN	NaN
5	4.0	NaN	NaN
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	702.0	NaN	NaN
9	6.0	NaN	NaN
10	NaN	NaN	NaN
11	NaN	NaN	NaN
12	147000.0	NaN	NaN

Easiest way with enough info (for numerical data)

data.describe()

	Year	Ratings	Genre	Gross	Budget	\
count	231.000000	231.000000	231.000000	2.310000e+02	2.300000e+02	
mean	2014.294372	6.441558	5.359307	6.806603e+07	4.792173e+07	
std	0.456750	0.988765	4.141611	8.890289e+07	5.428825e+07	
min	2014.000000	3.100000	1.000000	2.470000e+03	7.000000e+04	
25%	2014.000000	5.800000	1.000000	1.030000e+07	9.000000e+06	
50%	2014.000000	6.500000	3.000000	3.740000e+07	2.800000e+07	
75%	2015.000000	7.100000	8.000000	8.935000e+07	6.500000e+07	
max	2015.000000	8.700000	15.000000	6.430000e+08	2.500000e+08	

	Screens	Sequel	Sentiment	Views	Likes	\
count	221.000000	231.000000	231.000000	2.310000e+02	231.000000	
mean	2209.244344	1.359307	2.809524	3.712851e+06	12732.536797	

```
std    1463.767755    0.967241    6.996775  4.511104e+06   28825.484481
min       2.000000    1.000000  -38.000000  6.980000e+02       1.000000
25%     449.000000    1.000000    0.000000  6.233020e+05    1776.500000
50%    2777.000000    1.000000    0.000000  2.409338e+06    6096.000000
75%    3372.000000    1.000000    5.500000  5.217380e+06   15247.500000
max    4324.000000    7.000000   29.000000  3.262678e+07  370552.000000

         Dislikes      Comments  Aggregate Followers
count    231.000000    231.000000        1.960000e+02
mean     679.051948   1825.701299        3.038193e+06
std     1243.929481   3571.040447        4.886278e+06
min        0.000000      0.000000        1.066000e+03
25%      105.500000    248.500000        1.830250e+05
50%      341.000000    837.000000        1.052600e+06
75%      697.500000   2137.000000        3.694500e+06
max    13960.000000  38363.000000        3.103000e+07
```

APPENDIX B: Histograms and Box-Plot Code

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
```

```
csv_dataset = pd.read_csv('2014_and_2015_CSM_dataset.csv')
csv_dataset.head(5)
```

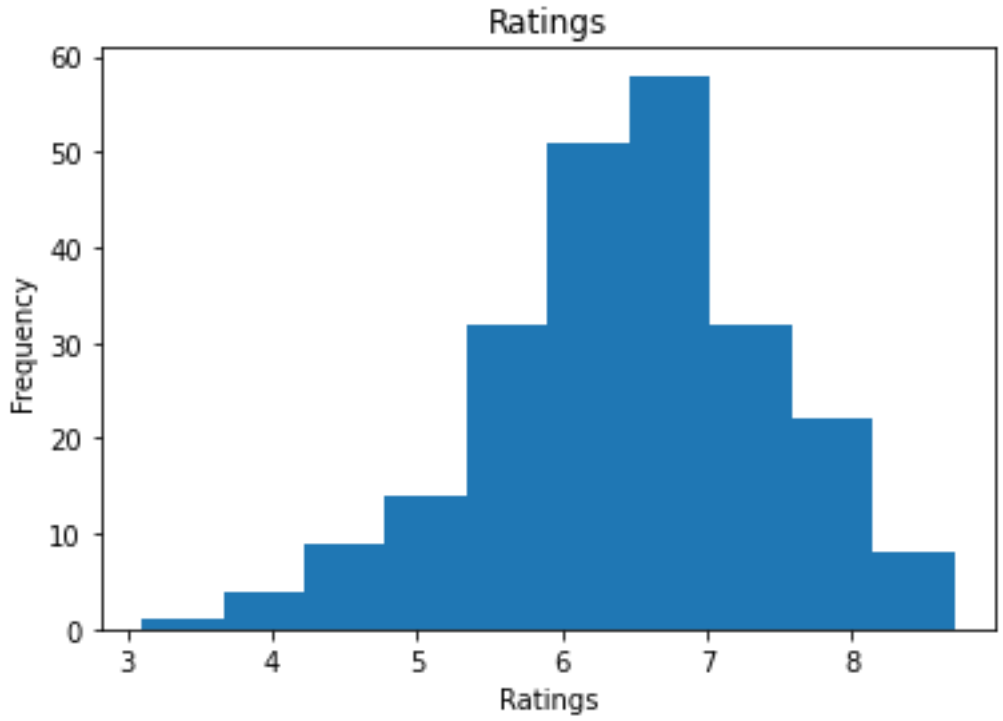
```
                    Movie    Year  Ratings  Genre        Gross       Budget
\
0                  13 Sins  2014.0      6.3    8.0       9130.0    4000000.0
1          22 Jump Street  2014.0      7.1    1.0  192000000.0   50000000.0
2          3 Days to Kill  2014.0      6.2    1.0   30700000.0   28000000.0
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

   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

   Aggregate Followers
0            1120000.0
```

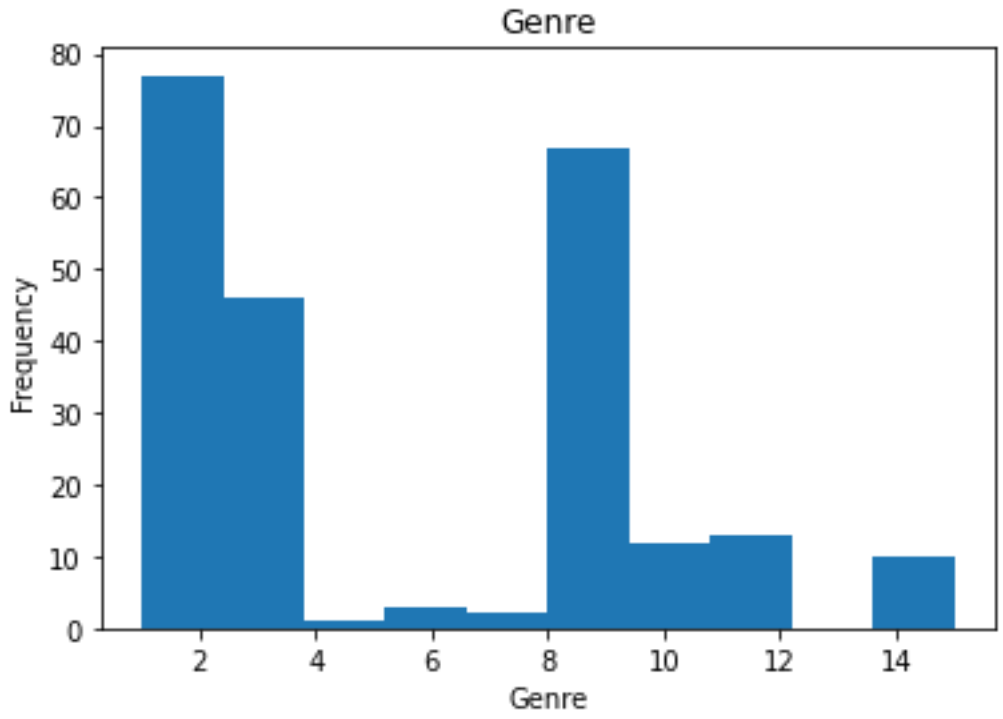
```
1           12350000.0
2             483000.0
3             568000.0
4            1923800.0
```

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Ratings'])
# set title and labels
ax.set_title('Ratings')
ax.set_xlabel('Ratings')
ax.set_ylabel('Frequency')
plt.savefig('histogram_ratings.png', dpi=300)
```

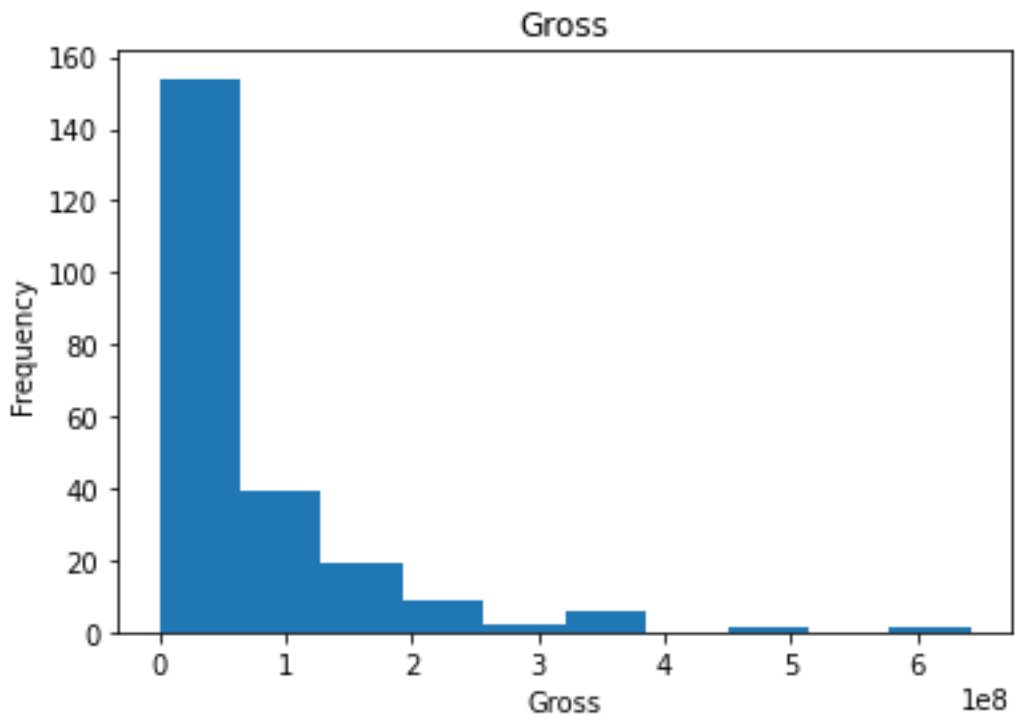



```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Genre'])
# set title and labels
ax.set_title('Genre')
ax.set_xlabel('Genre')
```

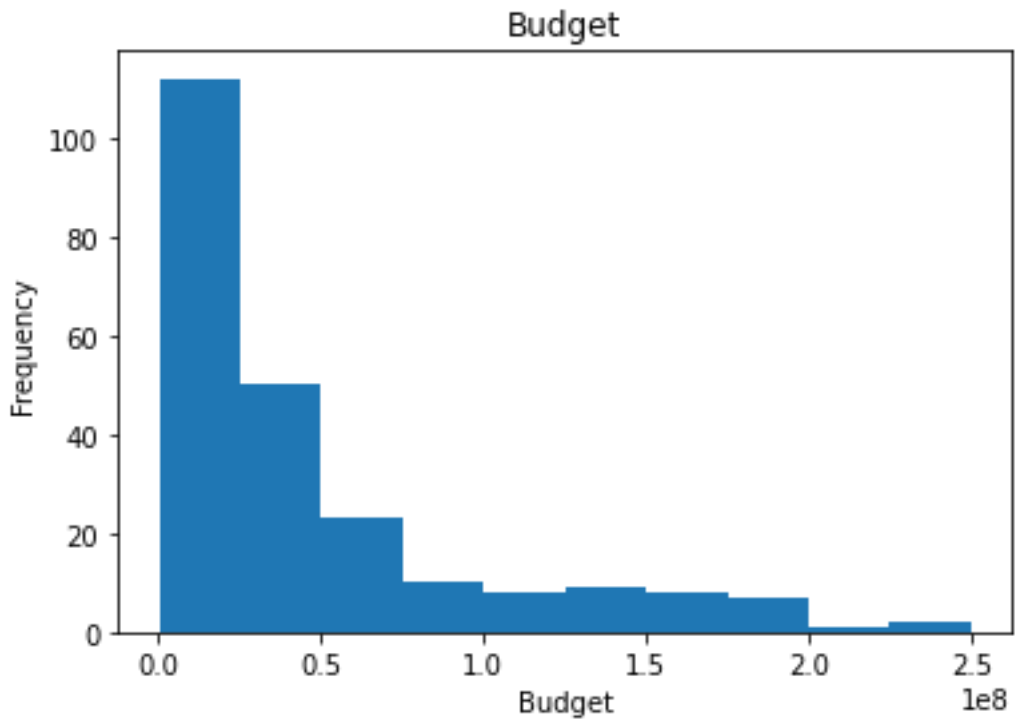
```
ax.set_ylabel('Frequency')
plt.savefig('histogram_genre.png', dpi=300)
```



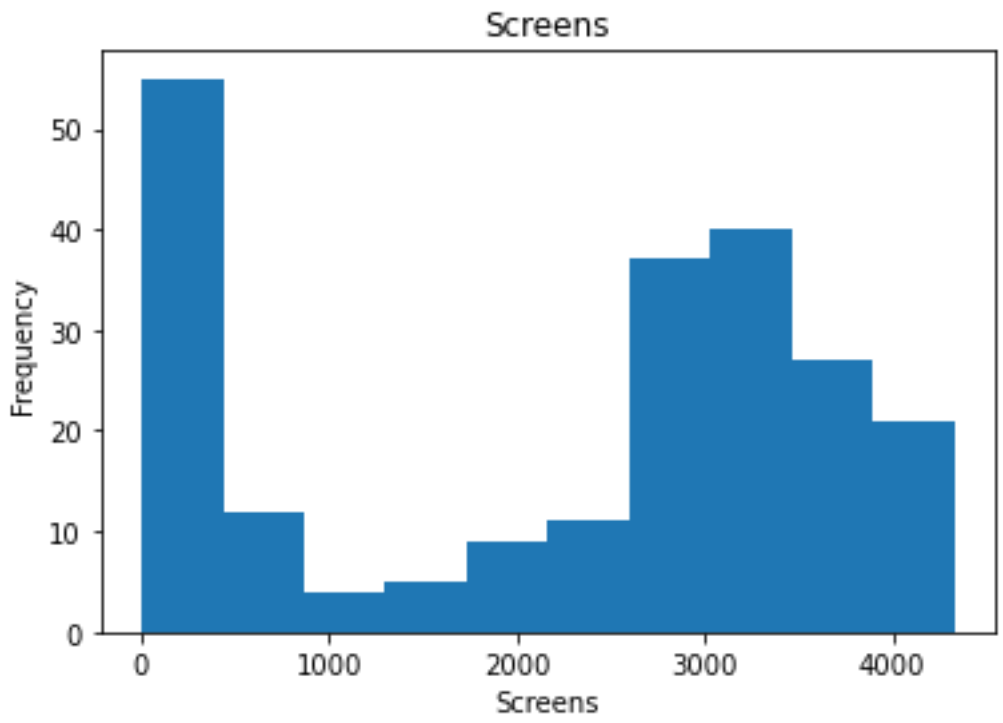

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Gross'])
# set title and labels
ax.set_title('Gross')
ax.set_xlabel('Gross')
ax.set_ylabel('Frequency')
plt.savefig('histogram_gross.png', dpi=300)
```



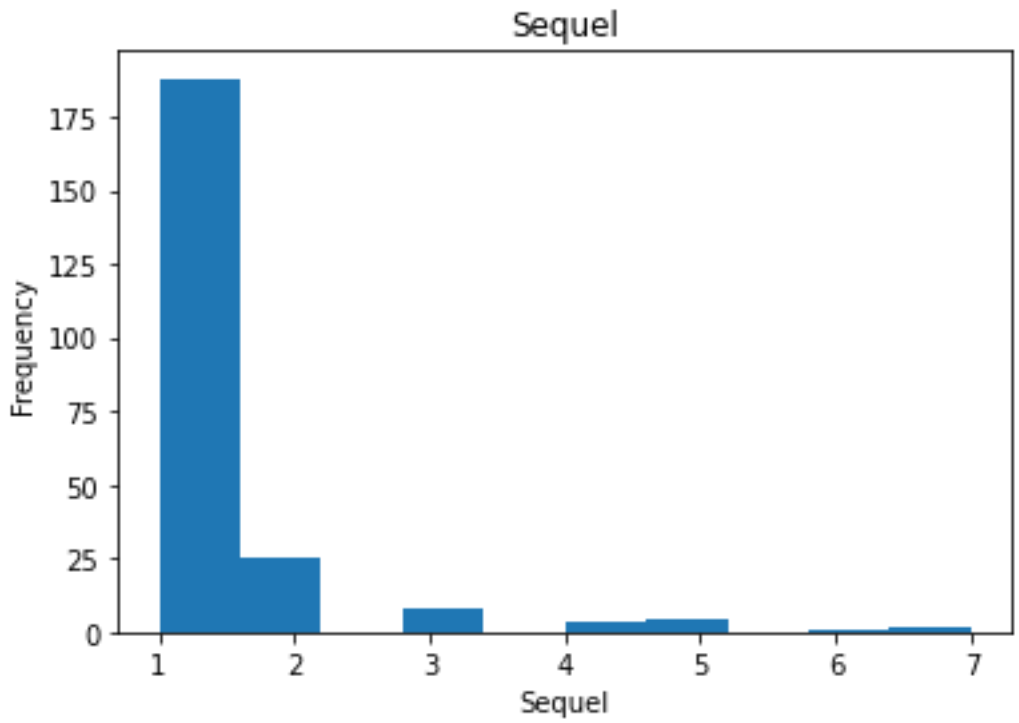

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Budget'])
# set title and labels
ax.set_title('Budget')
ax.set_xlabel('Budget')
ax.set_ylabel('Frequency')
plt.savefig('histogram_budget.png', dpi=300)
```



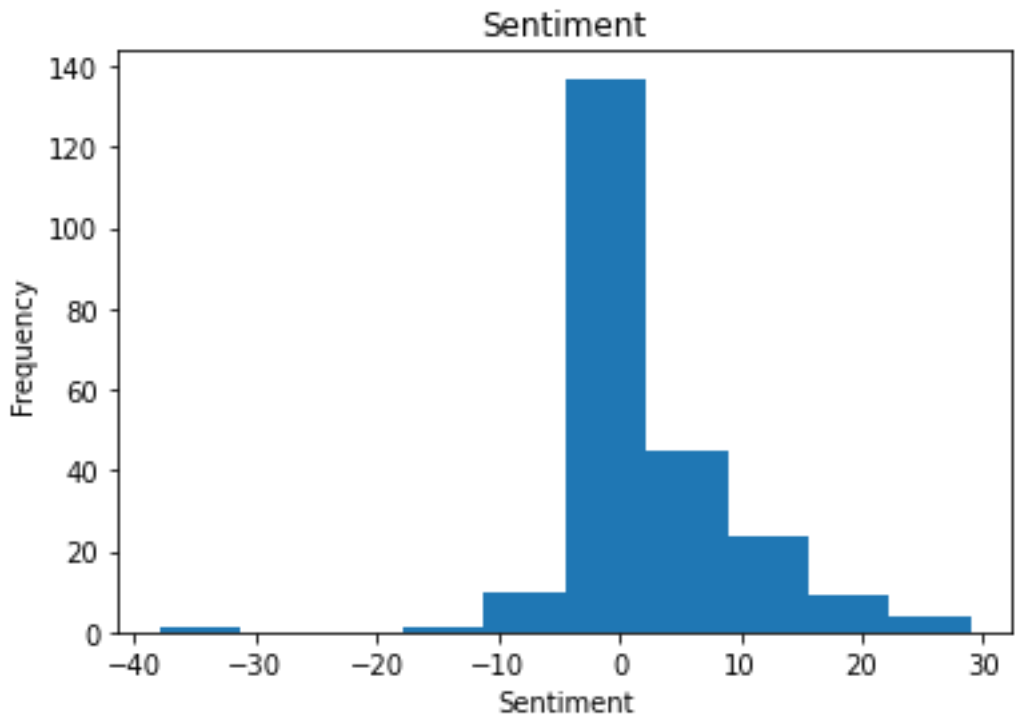

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Screens'])
# set title and labels
ax.set_title('Screens')
ax.set_xlabel('Screens')
ax.set_ylabel('Frequency')
plt.savefig('histogram_screens.png', dpi=300)
```



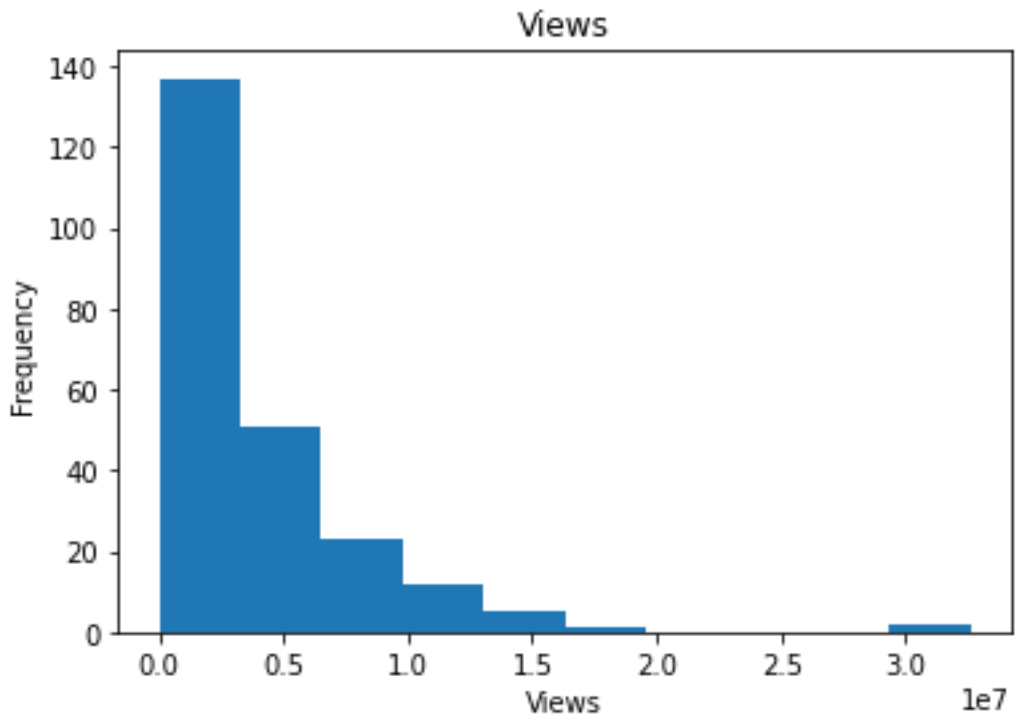

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Sequel'])
# set title and labels
ax.set_title('Sequel')
ax.set_xlabel('Sequel')
ax.set_ylabel('Frequency')
plt.savefig('histogram_sequel.png', dpi=300)
```



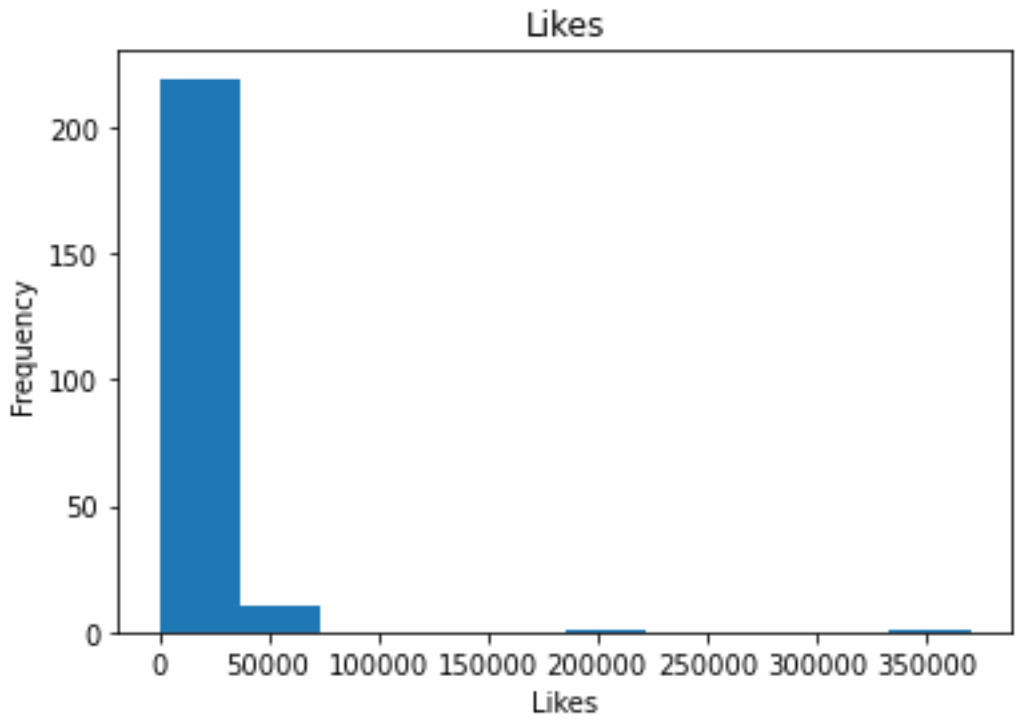

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Sentiment'])
# set title and labels
ax.set_title('Sentiment')
ax.set_xlabel('Sentiment')
ax.set_ylabel('Frequency')
plt.savefig('histogram_sentiment.png', dpi=300)
```



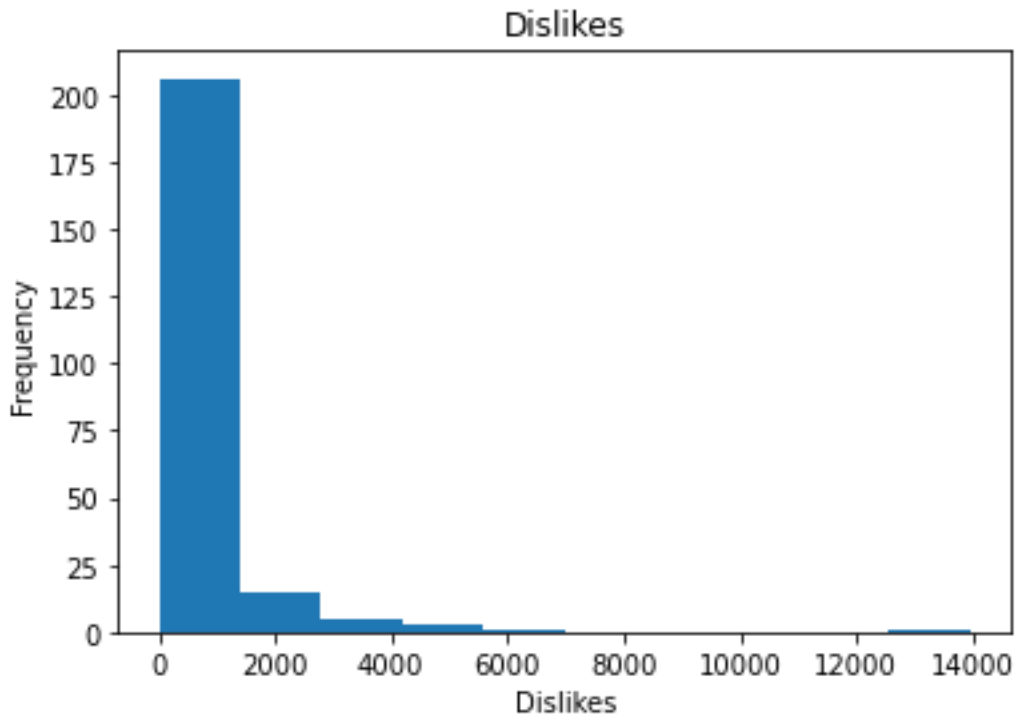

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Views'])
# set title and labels
ax.set_title('Views')
ax.set_xlabel('Views')
ax.set_ylabel('Frequency')
plt.savefig('histogram_views.png', dpi=300)
```



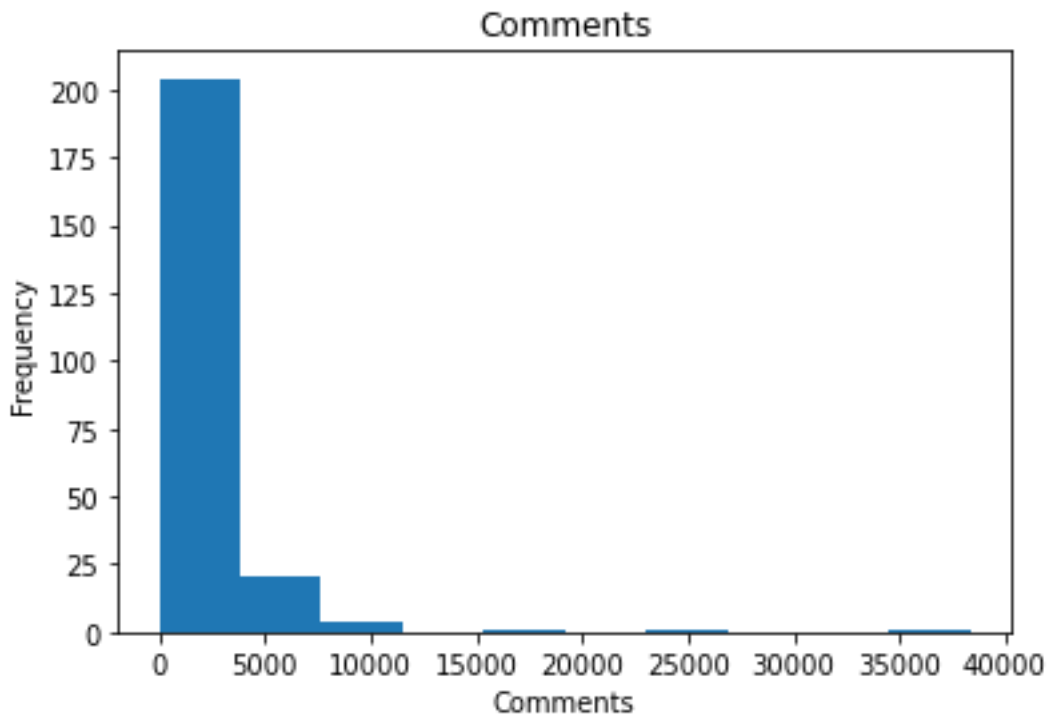

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Likes'])
# set title and labels
ax.set_title('Likes')
ax.set_xlabel('Likes')
ax.set_ylabel('Frequency')
plt.savefig('histogram_likes.png', dpi=300)
```



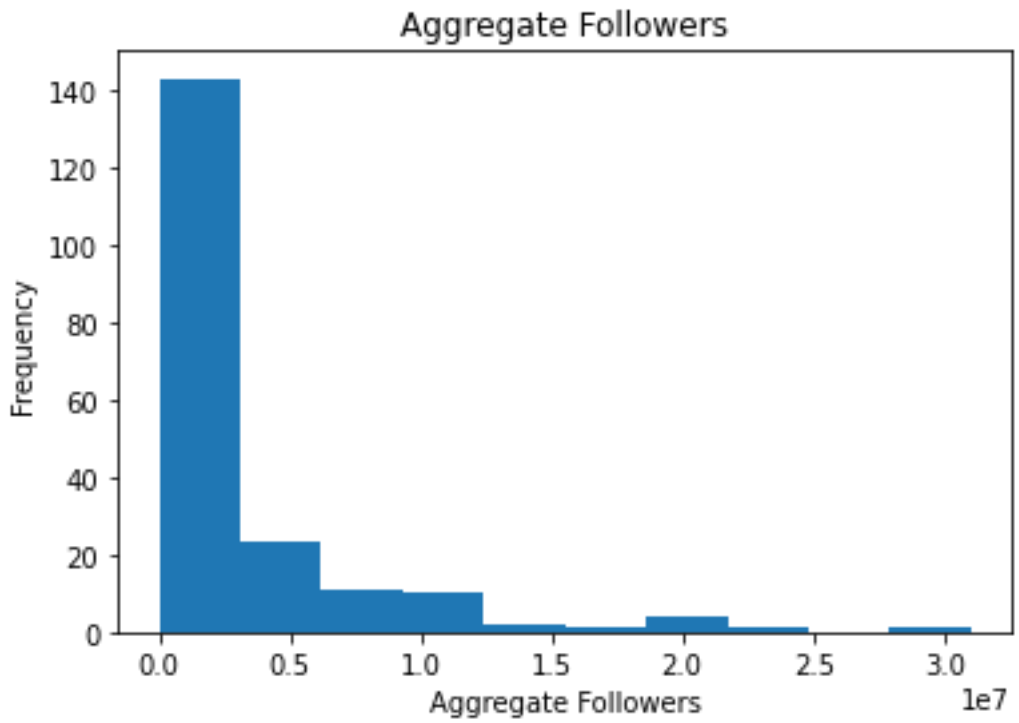

```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Dislikes'])
# set title and labels
ax.set_title('Dislikes')
ax.set_xlabel('Dislikes')
ax.set_ylabel('Frequency')
plt.savefig('histogram_dislikes.png', dpi=300)
```




```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Comments'])
# set title and labels
ax.set_title('Comments')
ax.set_xlabel('Comments')
ax.set_ylabel('Frequency')
plt.savefig('histogram_comments.png', dpi=300)
```




```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset['Aggregate Followers'])
# set title and labels
ax.set_title('Aggregate Followers')
ax.set_xlabel('Aggregate Followers')
ax.set_ylabel('Frequency')
plt.savefig('histogram_aggregate.png', dpi=300)
```

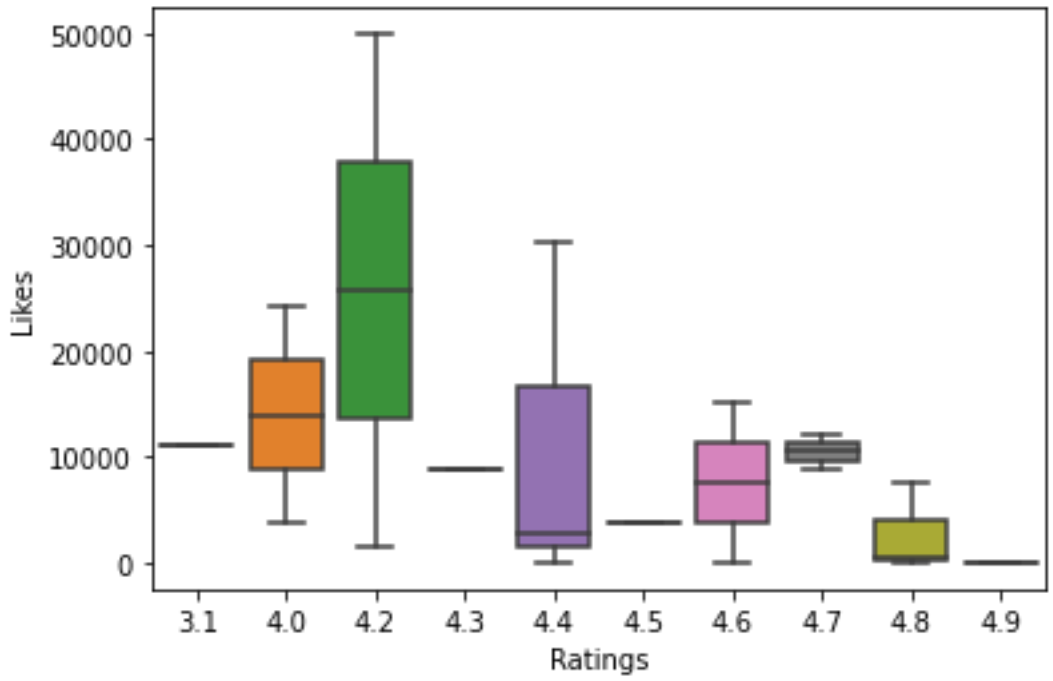



```
# create figure and axis
fig, ax = plt.subplots()
# plot histogram
ax.hist(csv_dataset[''])
# set title and labels
ax.set_title('')
ax.set_xlabel('')
ax.set_ylabel('Frequency')
```

```
df = csv_dataset[(csv_dataset['Ratings']>=0) & (csv_dataset['Ratings']<5)]
sns.boxplot('Ratings', 'Likes', data=df)
```

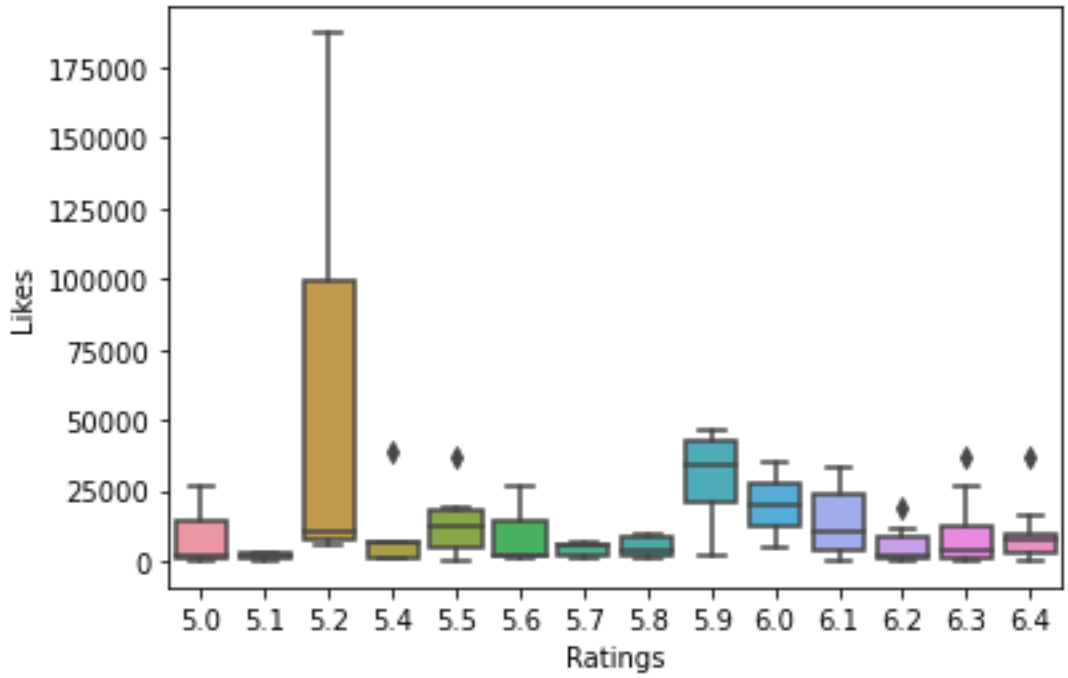
```
C:\Users\zeyne\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureW
arning: Pass the following variables as keyword args: x, y. From version 0.12
, the only valid positional argument will be `data`, and passing other argume
nts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

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



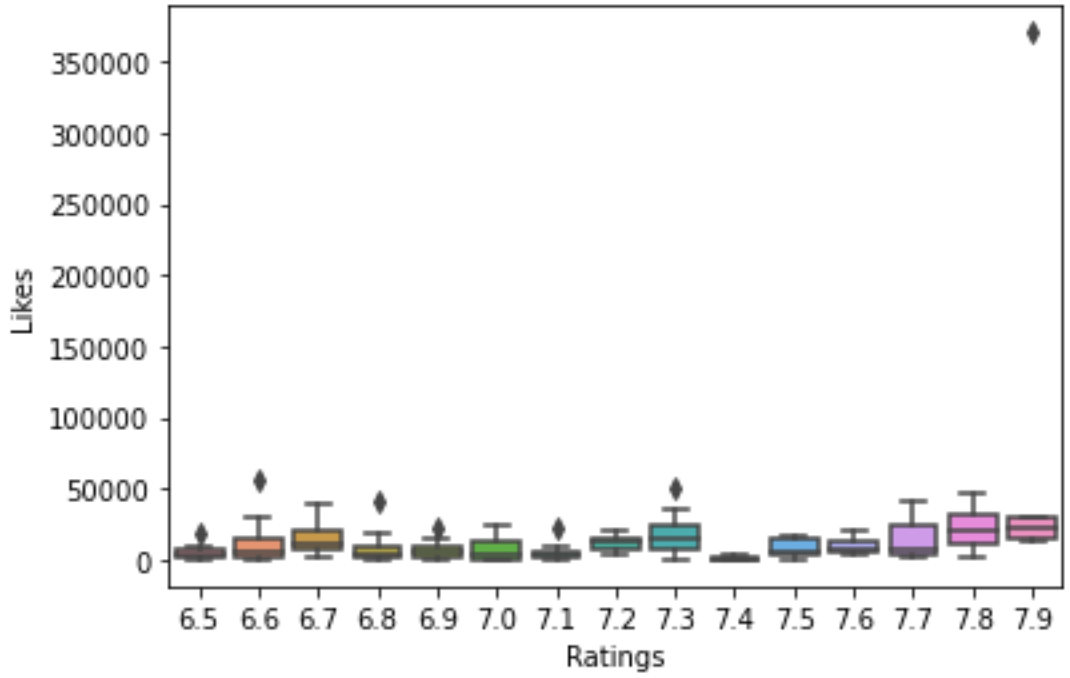

```
df = csv_dataset[(csv_dataset['Ratings']>=5) & (csv_dataset['Ratings']<6.5)]
sns.boxplot('Ratings', 'Likes', data=df)
```

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



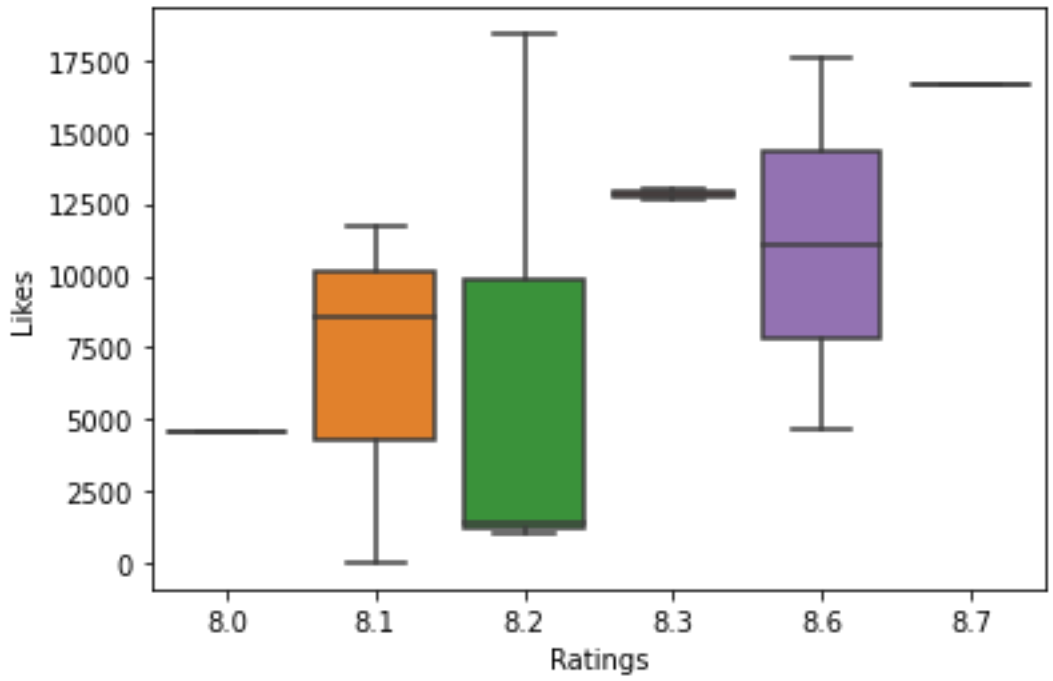

```
df = csv_dataset[(csv_dataset['Ratings']>=6.5) & (csv_dataset['Ratings']<8)]
sns.boxplot('Ratings', 'Likes', data=df)
```

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




```
df = csv_dataset[(csv_dataset['Ratings']>=8) & (csv_dataset['Ratings']<10)]
sns.boxplot('Ratings', 'Likes', data=df)
```

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




```
df = csv_dataset[(csv_dataset['Ratings']>=8) & (csv_dataset['Ratings']<10)]
sns.boxplot('Ratings', 'Gross', data=df)
```

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