News Popularity: Predicting popular news articles.

In [127…

```
pwd
```

Out[127]:

```
'/Users/pratik'
```

In [128…

```
import pandas as pd
```

Collecting Data

In [129…

```
news = pd.read_csv('OnlineNewsPopularity_for_python.csv')
```

In [130…

```
news.head(4)
```

Out[130]:

	url	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens
0	http://mashable.com/2013/01/07/amazon-instant-...	731	12	219	0.663594
1	http://mashable.com/2013/01/07/ap-samsung-spon...	731	9	255	0.604743
2	http://mashable.com/2013/01/07/apple-40-billio...	731	9	211	0.575130
3	http://mashable.com/2013/01/07/astronaut-notre...	731	9	531	0.503788

4 rows × 61 columns

In [131…

```
# handle goal attrubte to binary
popular = news.shares >= 1400
unpopular = news.shares < 1400
news.loc[popular,'shares'] = 1
news.loc[unpopular,'shares'] = 0
```

In [132…

```
news.head(4)
```

Out[132]:

	url	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens
0	http://mashable.com/2013/01/07/amazon-instant-...	731	12	219	0.663594
1	http://mashable.com/2013/01/07/ap-samsung-spon...	731	9	255	0.604743
2	http://mashable.com/2013/01/07/apple-40-billio...	731	9	211	0.575130
3	http://mashable.com/2013/01/07/astronaut-notre...	731	9	531	0.503788

4 rows × 61 columns

Decision Tree

In [133…

```
print(news.columns)
news.info()
```

```
Index(['url', 'timedelta', 'n_tokens_title', 'n_tokens_content',
       'n_unique_tokens', 'n_non_stop_words', 'n_non_stop_unique_tokens',
       'num_hrefs', 'num_self_hrefs', 'num_imgs', 'num_videos',
       'average_token_length', 'num_keywords', 'data_channel_is_lifestyle',
       'data_channel_is_entertainment', 'data_channel_is_bus',
       'data_channel_is_socmed', 'data_channel_is_tech',
       'data_channel_is_world', 'kw_min_min', 'kw_max_min', 'kw_avg_min',
       'kw_min_max', 'kw_max_max', 'kw_avg_max', 'kw_min_avg', 'kw_max_avg',
       'kw_avg_avg', 'self_reference_min_shares', 'self_reference_max_shares',
       'self_reference_avg_sharess', 'weekday_is_monday', 'weekday_is_tuesday',
       'weekday_is_wednesday', 'weekday_is_thursday', 'weekday_is_friday',
       'weekday_is_saturday', 'weekday_is_sunday', 'is_weekend', 'LDA_00',
       'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04', 'global_subjectivity',
       'global_sentiment_polarity', 'global_rate_positive_words',
       'global_rate_negative_words', 'rate_positive_words',
       'rate_negative_words', 'avg_positive_polarity', 'min_positive_polarity',
       'max_positive_polarity', 'avg_negative_polarity',
       'min_negative_polarity', 'max_negative_polarity', 'title_subjectivity',
       'title_sentiment_polarity', 'abs_title_subjectivity',
       'abs_title_sentiment_polarity', 'shares'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39644 entries, 0 to 39643
Data columns (total 61 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   url                            39644 non-null  object
 1   timedelta                      39644 non-null  int64
 2   n_tokens_title                 39644 non-null  int64
 3   n_tokens_content               39644 non-null  int64
 4   n_unique_tokens                39644 non-null  float64
 5   n_non_stop_words               39644 non-null  float64
 6   n_non_stop_unique_tokens       39644 non-null  float64
 7   num_hrefs                      39644 non-null  int64
 8   num_self_hrefs                 39644 non-null  int64
 9   num_imgs                       39644 non-null  int64
 10  num_videos                     39644 non-null  int64
 11  average_token_length           39644 non-null  float64
 12  num_keywords                   39644 non-null  int64
 13  data_channel_is_lifestyle      39644 non-null  int64
 14  data_channel_is_entertainment  39644 non-null  int64
 15  data_channel_is_bus            39644 non-null  int64
 16  data_channel_is_socmed         39644 non-null  int64
 17  data_channel_is_tech           39644 non-null  int64
 18  data_channel_is_world          39644 non-null  int64
 19  kw_min_min                     39644 non-null  int64
 20  kw_max_min                     39644 non-null  float64
 21  kw_avg_min                     39644 non-null  float64
 22  kw_min_max                     39644 non-null  int64
 23  kw_max_max                     39644 non-null  int64
 24  kw_avg_max                     39644 non-null  float64
 25  kw_min_avg                     39644 non-null  float64
 26  kw_max_avg                     39644 non-null  float64
 27  kw_avg_avg                     39644 non-null  float64
 28  self_reference_min_shares      39644 non-null  float64
 29  self_reference_max_shares      39644 non-null  float64
 30  self_reference_avg_sharess     39644 non-null  float64
 31  weekday_is_monday              39644 non-null  int64
 32  weekday_is_tuesday             39644 non-null  int64
 33  weekday_is_wednesday           39644 non-null  int64
 34  weekday_is_thursday            39644 non-null  int64
 35  weekday_is_friday              39644 non-null  int64
 36  weekday_is_saturday            39644 non-null  int64
 37  weekday_is_sunday              39644 non-null  int64
 38  is_weekend                     39644 non-null  int64
 39  LDA_00                         39644 non-null  float64
```

```
 40  LDA_01                         39644 non-null  float64
 41  LDA_02                         39644 non-null  float64
 42  LDA_03                         39644 non-null  float64
 43  LDA_04                         39644 non-null  float64
 44  global_subjectivity            39644 non-null  float64
 45  global_sentiment_polarity      39644 non-null  float64
 46  global_rate_positive_words     39644 non-null  float64
 47  global_rate_negative_words     39644 non-null  float64
 48  rate_positive_words            39644 non-null  float64
 49  rate_negative_words            39644 non-null  float64
 50  avg_positive_polarity          39644 non-null  float64
 51  min_positive_polarity          39644 non-null  float64
 52  max_positive_polarity          39644 non-null  float64
 53  avg_negative_polarity          39644 non-null  float64
 54  min_negative_polarity          39644 non-null  float64
 55  max_negative_polarity          39644 non-null  float64
 56  title_subjectivity             39644 non-null  float64
 57  title_sentiment_polarity       39644 non-null  float64
 58  abs_title_subjectivity         39644 non-null  float64
 59  abs_title_sentiment_polarity   39644 non-null  float64
 60  shares                         39644 non-null  int64
dtypes: float64(34), int64(26), object(1)
memory usage: 18.5+ MB
```

Exploring and Preparing the Data

In [134…

```
target = news['shares']
```

Train, Test data with a aplit of 75% data for training set and 25% data for testing set and seed of 23458. Dropping the "url" column as it is a string type object and just the address of the site, dropping "shares" column from X as "shares" is a response or target variable.

In [135…

```
from sklearn.model_selection import train_test_split
y = target
x = news.drop(['shares','url'], axis=1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=2
```

Design Decision Tree

In [136…

```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
```

In [137…

```
model = tree.DecisionTreeClassifier()
model = model.fit(x_train, y_train)
```

Evaluating the model

In [138…

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
y_predict = model.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[2513 2050]
 [2098 3250]]
```

In [139…

```
print(accuracy_score(y_test, y_predict)*100)
```

```
58.147512864494
```

The results show the accuracy of the model to be 58% for seed of 23458.

Random Forest

In [140…
```
y = target
x = news.drop(['shares','url'], axis=1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=2
```

In [141…
```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier()
clf.fit(x_train, y_train)
```

Out[141]:
```
RandomForestClassifier()
```

In [142…
```
y_predict = clf.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[2794 1769]
 [1520 3828]]
```

In [143…
```
print(accuracy_score(y_test, y_predict)*100)
```

```
66.81465038845728
```

The Results show that using Random Forest the accuracy of predicting popular and unpoularnews based on the model is 67% based on ratio of (True positives and True Negatives) to all predicted observations (TP+FN+FP+TN)

Important Features

In [144…
```
import pandas as pd
feature_importances = pd.DataFrame(clf.feature_importances_, index = news.columns[1:60],
feature_importances
```

Out[144]:

	importance
kw_avg_avg	0.040599
kw_max_avg	0.038371
LDA_02	0.033017
timedelta	0.031161
self_reference_avg_sharess	0.029585
LDA_01	0.028522
LDA_04	0.028398
self_reference_min_shares	0.027897
kw_avg_min	0.027684
LDA_00	0.027673
kw_avg_max	0.027526
global_subjectivity	0.026878
n_unique_tokens	0.026258
n_non_stop_unique_tokens	0.026078
average_token_length	0.025736
kw_max_min	0.025464

n_tokens_content	0.025322
LDA_03	0.025283
global_rate_positive_words	0.024946
avg_positive_polarity	0.024771
kw_min_avg	0.024475
global_sentiment_polarity	0.023800
self_reference_max_shares	0.023728
avg_negative_polarity	0.022924
global_rate_negative_words	0.022820
num_hrefs	0.020784
rate_negative_words	0.019936
rate_positive_words	0.019703
kw_min_max	0.016427
n_tokens_title	0.015610
title_sentiment_polarity	0.014466
min_negative_polarity	0.014348
num_imgs	0.013600
max_negative_polarity	0.013421
num_self_hrefs	0.012824
min_positive_polarity	0.012670
title_subjectivity	0.012334
abs_title_subjectivity	0.011780
abs_title_sentiment_polarity	0.011593
is_weekend	0.011208
max_positive_polarity	0.010282
num_keywords	0.010244
data_channel_is_entertainment	0.009047
num_videos	0.007659
data_channel_is_world	0.006367
kw_max_max	0.005807
data_channel_is_socmed	0.005328
data_channel_is_tech	0.004845
kw_min_min	0.004643
weekday_is_saturday	0.004358
weekday_is_tuesday	0.003403
weekday_is_thursday	0.002950
weekday_is_wednesday	0.002925
weekday_is_friday	0.002870
weekday_is_monday	0.002835

weekday_is_sunday	0.002627
data_channel_is_bus	0.002405
data_channel_is_lifestyle	0.001652
n_non_stop_words	0.000134

We see that the top five most imortant features for the model to predict popular and unpopular news are kw_avg_avg, kw_max_avg, timedelta, LDA_02 and self_reference_min_shares in that order.

Finding Correlation

In [145…
```
import numpy as np
np.corrcoef(y_test, y_predict)
```

Out[145]:
```
array([[1.       , 0.3298427],
       [0.3298427, 1.       ]])
```

We see that the correlation between actual and predicted values is 33%

Finding RMSE

In [146…
```
from sklearn.metrics import mean_squared_error
rmse = mean_squared_error(y_test, y_predict, squared=False)
```

In [147…
```
print(rmse)
```

```
0.5760672670057094
```

The results shows that the root mean squared error is 0.57. It appears that the model isa little less effective than the acceptable range as the difference betweent the the actual and predicted test scores or the errors, account for more than 0.50 or 50%.The lower the rmse value the better the model can be assumed to fit the dataset (rmse values lie in range from 0 to 1).

Part II: Dimensionality Reduction with correlation graph

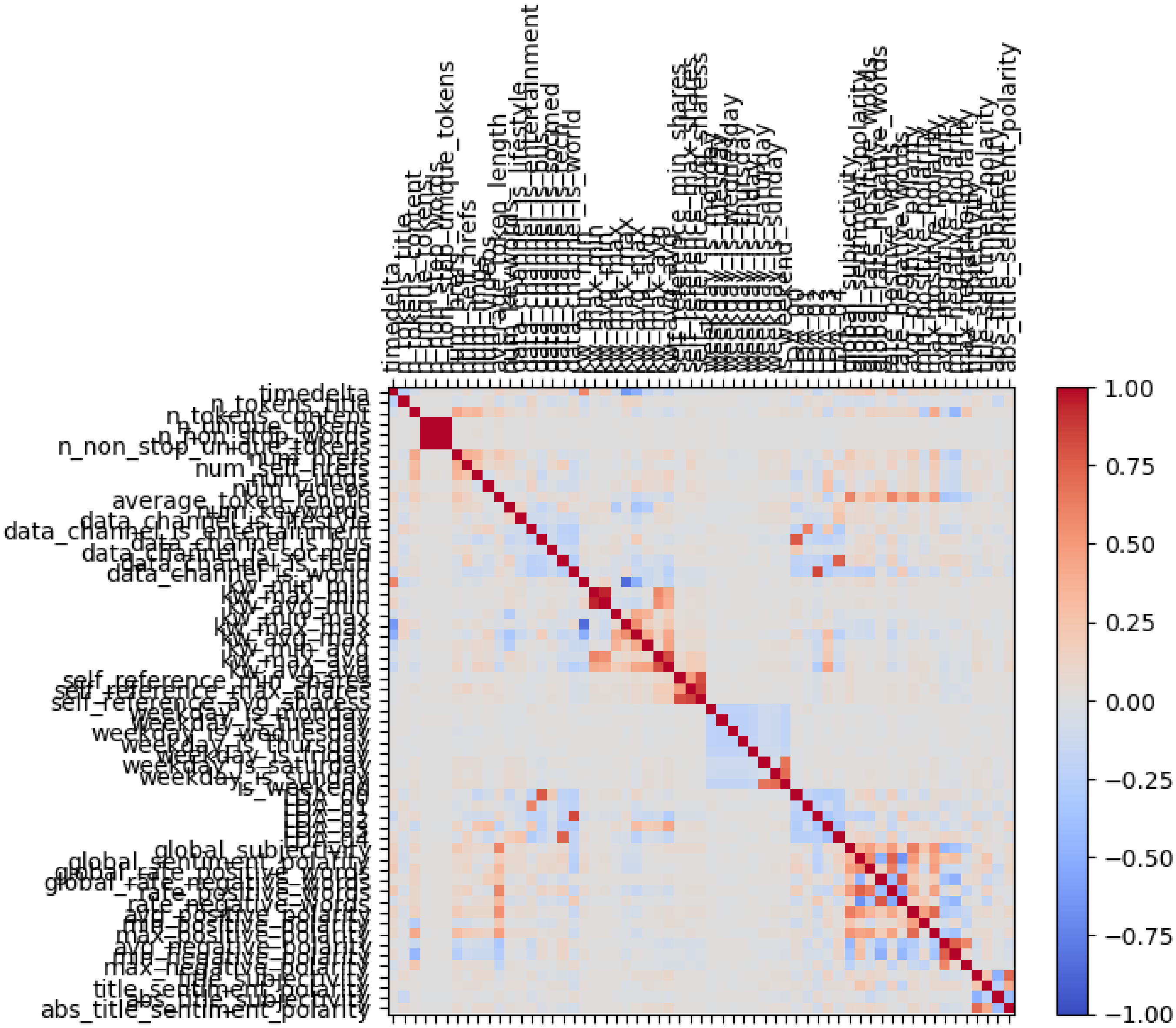
In [148…
```
target = news["shares"]
y = target
x = news.drop(['shares', 'url'], axis = 1)
```

Correlation Graph

In [149…
```
import numpy as np
import matplotlib.pyplot as plt

corr = x.corr()
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
fig.colorbar(cax)
ticks = np.arange(0,len(x.columns),1)
ax.set_xticks(ticks)
plt.xticks(rotation=90)
ax.set_yticks(ticks)
ax.set_xticklabels(x.columns)
```

```
ax.set_yticklabels(x.columns)
plt.show()
```



In [150…

```
corr_matrix = x.corr().abs()
corr_matrix
```

Out[150]:

	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop
timedelta	1.000000	0.240320	0.062867	0.002866	0.
n_tokens_title	0.240320	1.000000	0.018160	0.005318	0
n_tokens_content	0.062867	0.018160	1.000000	0.004737	(
n_unique_tokens	0.002866	0.005318	0.004737	1.000000	0
n_non_stop_words	0.000089	0.004754	0.017512	0.999572	1.
n_non_stop_unique_tokens	0.003805	0.005420	0.000373	0.999852	0.
num_hrefs	0.000832	0.053496	0.423065	0.004352	0
num_self_hrefs	0.064530	0.014856	0.304682	0.006620	0
num_imgs	0.027636	0.008858	0.342600	0.018802	0.
num_videos	0.000936	0.051460	0.103699	0.000597	0.
average_token_length	0.130465	0.071403	0.167789	0.026407	0

num_keywords	0.046884	0.006077	0.072845	0.003679	0
data_channel_is_lifestyle	0.054492	0.070815	0.037548	0.001653	0
data_channel_is_entertainment	0.049109	0.132791	0.060200	0.011016	0
data_channel_is_bus	0.055788	0.023902	0.006105	0.000264	0
data_channel_is_socmed	0.076287	0.090394	0.033424	0.000945	0
data_channel_is_tech	0.083277	0.046716	0.025408	0.002328	0
data_channel_is_world	0.170250	0.049223	0.055989	0.005535	0
kw_min_min	0.591199	0.110672	0.054345	0.001601	0
kw_max_min	0.029503	0.005890	0.000066	0.000552	0.
kw_avg_min	0.133225	0.031400	0.003545	0.000826	0.
kw_min_max	0.076590	0.012926	0.022786	0.000577	0.
kw_max_max	0.637824	0.120841	0.058860	0.001624	0.
kw_avg_max	0.493093	0.115746	0.096460	0.000805	0.
kw_min_avg	0.157204	0.002370	0.022286	0.004563	0.
kw_max_avg	0.051820	0.006918	0.030496	0.002120	0.
kw_avg_avg	0.163164	0.004296	0.079624	0.002083	0
self_reference_min_shares	0.011438	0.004563	0.030686	0.001036	0.
self_reference_max_shares	0.014501	0.000128	0.025657	0.000222	0
self_reference_avg_sharess	0.015655	0.000661	0.013809	0.001992	0
weekday_is_monday	0.006129	0.004274	0.002484	0.002142	0
weekday_is_tuesday	0.005781	0.009322	0.004027	0.010538	0
weekday_is_wednesday	0.009961	0.008935	0.016891	0.002224	0
weekday_is_thursday	0.004042	0.015472	0.007395	0.002248	0.
weekday_is_friday	0.002853	0.002015	0.015949	0.001398	0
weekday_is_saturday	0.004067	0.015013	0.034538	0.002563	0
weekday_is_sunday	0.004226	0.006289	0.036394	0.001803	0
is_weekend	0.000272	0.005996	0.052024	0.003186	0
LDA_00	0.080894	0.070038	0.026218	0.002213	0
LDA_01	0.004423	0.063568	0.009724	0.000827	0.
LDA_02	0.141713	0.038365	0.087266	0.006855	0.
LDA_03	0.030838	0.042208	0.140141	0.003689	0
LDA_04	0.092906	0.065063	0.041265	0.004260	0
global_subjectivity	0.133837	0.056804	0.127879	0.000180	0
global_sentiment_polarity	0.158646	0.072226	0.021937	0.000523	0
global_rate_positive_words	0.207604	0.064951	0.133979	0.000014	0
global_rate_negative_words	0.010266	0.015530	0.125013	0.000877	0
rate_positive_words	0.198654	0.066589	0.098960	0.000667	0
rate_negative_words	0.071968	0.034186	0.101053	0.001657	0
avg_positive_polarity	0.126344	0.049619	0.135123	0.000487	0

min_positive_polarity	0.054772	0.025069	0.261493	0.009193	0.
max_positive_polarity	0.098288	0.021662	0.415706	0.009054	0
avg_negative_polarity	0.000507	0.017096	0.130375	0.001453	C
min_negative_polarity	0.062175	0.029146	0.450603	0.009902	C
max_negative_polarity	0.063239	0.011425	0.225870	0.007315	C
title_subjectivity	0.015919	0.077245	0.004484	0.004678	0.
title_sentiment_polarity	0.038711	0.000240	0.023358	0.002333	0
abs_title_subjectivity	0.011551	0.146954	0.007136	0.009242	C
abs_title_sentiment_polarity	0.002745	0.040550	0.013439	0.004217	0

59 rows × 59 columns

Select Upper triangle of correlation matrix

In [151…

```
import numpy as np
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape) , k=1).astype(np.bool))
```

```
/var/folders/fp/szpx3gxd4ln849f9dbx_lqw00000gn/T/ipykernel_1107/2665990962.py:2: Depreca
tionWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this war
ning, use `bool` by itself. Doing this will not modify any behavior and is safe. If you
specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/relea
se/1.20.0-notes.html#deprecations
  upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape) , k=1).astype(np.bool))
```

Find index of feature columns with correlation greater than 0.95

In [152…

```
to_drop = [column for column in upper.columns if any(upper[column] > 0.6)]
xnew = x.drop(to_drop, axis = 1)
xnew
```

Out[152]:

	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	num_hrefs	num_self_hrefs	num_i
0	731	12	219	0.663594	4	2	
1	731	9	255	0.604743	3	1	
2	731	9	211	0.575130	3	1	
3	731	9	531	0.503788	9	0	
4	731	13	1072	0.415646	19	19	
...	...	...	...	...	...	...	
39639	8	11	346	0.529052	9	7	
39640	8	12	328	0.696296	9	7	
39641	8	10	442	0.516355	24	1	
39642	8	6	682	0.539493	10	1	
39643	8	10	157	0.701987	1	1	

39644 rows × 43 columns

New Accuracy with new Xnew(after dropping highly correlated variables)

Using Xnew(after dropping highly correlated var) for randomising, Splitting, Training model and evaluating

In [153…
```
xnew
```

Out[153]:

	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	num_hrefs	num_self_hrefs	num_i
0	731	12	219	0.663594	4	2	
1	731	9	255	0.604743	3	1	
2	731	9	211	0.575130	3	1	
3	731	9	531	0.503788	9	0	
4	731	13	1072	0.415646	19	19	
...	...	...	...	...	...	...	
39639	8	11	346	0.529052	9	7	
39640	8	12	328	0.696296	9	7	
39641	8	10	442	0.516355	24	1	
39642	8	6	682	0.539493	10	1	
39643	8	10	157	0.701987	1	1	

39644 rows × 43 columns

In [154…
```
to_drop
```

Out[154]:
```
['n_non_stop_words',
 'n_non_stop_unique_tokens',
 'kw_avg_min',
 'kw_max_max',
 'kw_avg_avg',
 'self_reference_avg_sharess',
 'is_weekend',
 'LDA_00',
 'LDA_02',
 'LDA_04',
 'rate_positive_words',
 'rate_negative_words',
 'avg_positive_polarity',
 'max_positive_polarity',
 'min_negative_polarity',
 'abs_title_sentiment_polarity']
```

Dropping to_drop columns

In [155…
```
news_new = news.drop(['n_non_stop_words',
 'n_non_stop_unique_tokens',
 'kw_avg_min',
 'kw_max_max',
 'kw_avg_avg',
 'self_reference_avg_sharess',
 'is_weekend',
 'LDA_00',
 'LDA_02',
 'LDA_04',
 'rate_positive_words',
 'rate_negative_words',
 'avg_positive_polarity',
 'max_positive_polarity',
```

```
    'min_negative_polarity',
    'abs_title_sentiment_polarity'], axis = 1)
```

As above, the to_drop function showed high correlation for 16 columns, which we will remove from our dataset for further analysis. We can see the remainging variables in xnew as below, which we will cond=sider for further analysis

In [156…:
```
xnew
```

Out[156]:

	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	num_hrefs	num_self_hrefs	num_i
0	731	12	219	0.663594	4	2	
1	731	9	255	0.604743	3	1	
2	731	9	211	0.575130	3	1	
3	731	9	531	0.503788	9	0	
4	731	13	1072	0.415646	19	19	
...	...	...	...	...	...	...	
39639	8	11	346	0.529052	9	7	
39640	8	12	328	0.696296	9	7	
39641	8	10	442	0.516355	24	1	
39642	8	6	682	0.539493	10	1	
39643	8	10	157	0.701987	1	1	

39644 rows × 43 columns

In [157…:
```
news_new
```

Out[157]:

	url	timedelta	n_tokens_title	n_tokens_content	n_unique_tok
0	http://mashable.com/2013/01/07/amazon-instant-...	731	12	219	0.663
1	http://mashable.com/2013/01/07/ap-samsung-spon...	731	9	255	0.604
2	http://mashable.com/2013/01/07/apple-40-billio...	731	9	211	0.575
3	http://mashable.com/2013/01/07/astronaut-notre...	731	9	531	0.503
4	http://mashable.com/2013/01/07/att-u-verse-apps/	731	13	1072	0.415
...	...	...	...	...	
39639	http://mashable.com/2014/12/27/samsung-app-aut...	8	11	346	0.529
39640	http://mashable.com/2014/12/27/seth-rogen-jame...	8	12	328	0.696
39641	http://mashable.com/2014/12/27/son-pays-off-mo...	8	10	442	0.516
39642	http://mashable.com/2014/12/27/ukraine-blasts/	8	6	682	0.539
39643	http://mashable.com/2014/12/27/youtube-channel...	8	10	157	0.701

39644 rows × 45 columns

Decision Tree Model: (After dropping the correlated variables)

(Note: It is not necessary to normalize or standardize the data for Decision Tree and Random Forest models)

In [158...
```
y = target
x = xnew
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=2
```

In [159...
```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
model = tree.DecisionTreeClassifier()
model = model.fit(x_train, y_train)
y_predict = model.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[2503 2060]
 [2151 3197]]
```

In [160...
```
print(accuracy_score(y_test, y_predict)*100)
```

```
57.51185551407527
```

Random Forest Model: (After dropping the correlated variables)

In [161...
```
y = target
x = xnew
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=2
```

In [162...
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model = model.fit(x_train, y_train)
y_predict = model.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[2791 1772]
 [1509 3839]]
```

In [163...
```
print(accuracy_score(y_test, y_predict)*100)
```

```
66.89536878216124
```

It is observed that there isn't much difference in the accuracies of Decision Tree and Random Forest models after dropping the correlated variables.

Normalizing the data(Normalization: Use MinMaxScaler from sklearn, Standardization: Use StandardScaler from sklearn)

In [164...
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaled = scaler.fit_transform(xnew)
print(scaled)
```

```
[[1.         0.47619048 0.02584376 ... 0.5        0.40625    0.        ]
 [1.         0.33333333 0.03009205 ... 0.         0.5        1.        ]
 [1.         0.33333333 0.02489969 ... 0.         0.5        1.        ]
 ...
 [0.         0.38095238 0.05215955 ... 0.45454545 0.56818182 0.09090909]
```

```
 [0.         0.19047619 0.08048147 ... 0.         0.5        1.        ]
 [0.         0.38095238 0.01852726 ... 0.33333333 0.625      0.33333333]]
```

Training(90) and Test(10) Split): (Note : Use Normalized x (xnew) when splitting data)

In [165…
```
y = target
x = scaled
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.10, random_state
y_train
```

Out[165]:
```
24329    1
11705    0
1995     1
22132    1
24562    1
        ..
32399    0
17048    1
23924    0
34086    0
27439    0
Name: shares, Length: 35679, dtype: int64
```

In [166…
```
x_train.shape
```

Out[166]:
```
(35679, 43)
```

In [167…
```
x_test.shape
```

Out[167]:
```
(3965, 43)
```

Train the model, Use Linear Separator to design the model

Designing the model

In [168…
```
from sklearn import svm
clf = svm.SVC(kernel = "linear")
clf
```

Out[168]:
```
SVC(kernel='linear')
```

In [169…
```
clf.fit(x_train, y_train)
y_predict = clf.predict(x_test)
```

In [170…
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
print(confusion_matrix(y_test, y_predict))
```

```
[[ 940  927]
 [ 618 1480]]
```

In [171…
```
accuracy_score(y_test, y_predict)*100
```

Out[171]:
```
61.03404791929382
```

Improving the model by changing the kernels

Using the "rbf" kernel

In [172…
```
clf = svm.SVC(kernel='rbf', gamma =0.3)
```

```
#clf = svm.LinearSVC(C=1)
clf.fit(x_train, y_train)
y_predict = clf.predict(x_test)
confusion_matrix(y_test, y_predict)
```

Out[172]:
```
array([[1084,  783],
       [ 617, 1481]])
```

In [173…
```
accuracy_score(y_test, y_predict)*100
```

Out[173]:
```
64.69104665825978
```

Using the 'poly kernel' kernel

In [174…
```
clf = svm.SVC(kernel='poly', degree=8)
#clf = svm.LinearSVC(C=1)
clf.fit(x_train, y_train)
y_predict = clf.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[1217  650]
 [ 754 1344]]
```

In [59]:
```
print(accuracy_score(y_test, y_predict)*100)
```

```
64.59016393442623
```

The highly correlated 16 variabled were removed from before normalizing the data.The input varables(x variables) were normalized using the MinMaxScaler from sklearn. The data was further split into Training (90%) and Test Data set(10%). The LinearSVC Kernel model showed an accuracy of 61.03%. The accuracy increased to 64.69% when using the 'rbf' kernel with gamma =0.3. The Accuracy was seen to be 64.59% by changing the Kernel to 'poly' kernel with degrees = 8.

Part III: Dimensionality Reduction using Principal Component Analysis

In [175…
```
import pandas as pd
news = pd.read_csv('OnlineNewsPopularity_for_python.csv')
news.head()
```

Out[175]:

	url	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens
0	http://mashable.com/2013/01/07/amazon-instant-...	731	12	219	0.663594
1	http://mashable.com/2013/01/07/ap-samsung-spon...	731	9	255	0.604743
2	http://mashable.com/2013/01/07/apple-40-billio...	731	9	211	0.575130
3	http://mashable.com/2013/01/07/astronaut-notre...	731	9	531	0.503788
4	http://mashable.com/2013/01/07/att-u-verse-apps/	731	13	1072	0.415646

5 rows × 61 columns

In [176…
```
news.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 39644 entries, 0 to 39643
Data columns (total 61 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   url                            39644 non-null  object 
 1   timedelta                      39644 non-null  int64  
 2   n_tokens_title                 39644 non-null  int64  
 3   n_tokens_content               39644 non-null  int64  
 4   n_unique_tokens                39644 non-null  float64
 5   n_non_stop_words               39644 non-null  float64
 6   n_non_stop_unique_tokens       39644 non-null  float64
 7   num_hrefs                      39644 non-null  int64  
 8   num_self_hrefs                 39644 non-null  int64  
 9   num_imgs                       39644 non-null  int64  
 10  num_videos                     39644 non-null  int64  
 11  average_token_length           39644 non-null  float64
 12  num_keywords                   39644 non-null  int64  
 13  data_channel_is_lifestyle      39644 non-null  int64  
 14  data_channel_is_entertainment  39644 non-null  int64  
 15  data_channel_is_bus            39644 non-null  int64  
 16  data_channel_is_socmed         39644 non-null  int64  
 17  data_channel_is_tech           39644 non-null  int64  
 18  data_channel_is_world          39644 non-null  int64  
 19  kw_min_min                     39644 non-null  int64  
 20  kw_max_min                     39644 non-null  float64
 21  kw_avg_min                     39644 non-null  float64
 22  kw_min_max                     39644 non-null  int64  
 23  kw_max_max                     39644 non-null  int64  
 24  kw_avg_max                     39644 non-null  float64
 25  kw_min_avg                     39644 non-null  float64
 26  kw_max_avg                     39644 non-null  float64
 27  kw_avg_avg                     39644 non-null  float64
 28  self_reference_min_shares      39644 non-null  float64
 29  self_reference_max_shares      39644 non-null  float64
 30  self_reference_avg_sharess     39644 non-null  float64
 31  weekday_is_monday              39644 non-null  int64  
 32  weekday_is_tuesday             39644 non-null  int64  
 33  weekday_is_wednesday           39644 non-null  int64  
 34  weekday_is_thursday            39644 non-null  int64  
 35  weekday_is_friday              39644 non-null  int64  
 36  weekday_is_saturday            39644 non-null  int64  
 37  weekday_is_sunday              39644 non-null  int64  
 38  is_weekend                     39644 non-null  int64  
 39  LDA_00                         39644 non-null  float64
 40  LDA_01                         39644 non-null  float64
 41  LDA_02                         39644 non-null  float64
 42  LDA_03                         39644 non-null  float64
 43  LDA_04                         39644 non-null  float64
 44  global_subjectivity            39644 non-null  float64
 45  global_sentiment_polarity      39644 non-null  float64
 46  global_rate_positive_words     39644 non-null  float64
 47  global_rate_negative_words     39644 non-null  float64
 48  rate_positive_words            39644 non-null  float64
 49  rate_negative_words            39644 non-null  float64
 50  avg_positive_polarity          39644 non-null  float64
 51  min_positive_polarity          39644 non-null  float64
 52  max_positive_polarity          39644 non-null  float64
 53  avg_negative_polarity          39644 non-null  float64
 54  min_negative_polarity          39644 non-null  float64
 55  max_negative_polarity          39644 non-null  float64
 56  title_subjectivity             39644 non-null  float64
 57  title_sentiment_polarity       39644 non-null  float64
 58  abs_title_subjectivity         39644 non-null  float64
 59  abs_title_sentiment_polarity   39644 non-null  float64
 60  shares                         39644 non-null  int64  
```

```
dtypes: float64(34), int64(26), object(1)
memory usage: 18.5+ MB
```

In [177…
```
# handle goal attrubte to binary
popular = news.shares >= 1400
unpopular = news.shares < 1400
news.loc[popular,'shares'] = 1
news.loc[unpopular,'shares'] = 0
```

In [178…
```
target = news["shares"]
y = target
```

Normalizing the data

In [179…
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled = scaler.fit_transform(news.drop(columns = ["shares", "url"], axis =1))
scaled
```

Out[179]:
```
array([[ 1.75788035,  0.75744723, -0.69521045, ..., -0.97543219,
        -1.81071884,  0.13891975],
       [ 1.75788035, -0.66165665, -0.61879381, ..., -0.26907618,
         0.83774863, -0.68965812],
       [ 1.75788035, -0.66165665, -0.71219192, ..., -0.26907618,
         0.83774863, -0.68965812],
       ...,
       [-1.61808342, -0.18862202, -0.2218518 , ...,  0.24463728,
        -1.56994907, -0.08705603],
       [-1.61808342, -2.08076053,  0.28759248, ..., -0.26907618,
         0.83774863, -0.68965812],
       [-1.61808342, -0.18862202, -0.82681689, ...,  0.67273184,
        -0.92789635,  0.41511238]])
```

Implementing PCA with selecting 30 components from all initial 58 Variables.

In [180…
```
from sklearn.decomposition import PCA
pca = PCA(n_components = 30)
PC = pca.fit(scaled)
PC.components_
```

Out[180]:
```
array([[-0.16132739,  0.0581139 , -0.13404156, ..., -0.08046848,
         0.03406751, -0.07174961],
       [-0.19286504,  0.07672684,  0.09800518, ..., -0.04403546,
        -0.03249026,  0.07886985],
       [-0.06891273,  0.01090471, -0.13706484, ...,  0.12710808,
        -0.0733436 ,  0.09586703],
       ...,
       [ 0.00838535, -0.03247174,  0.10835193, ..., -0.22710656,
         0.11732152,  0.11457629],
       [ 0.09999982, -0.0683428 , -0.0681115 , ...,  0.21921158,
        -0.23191139, -0.17044049],
       [-0.01377077,  0.15246142, -0.19444994, ...,  0.01398225,
         0.58131374,  0.27219535]])
```

Variance in components

In [181…
```
PC.explained_variance_ratio_
```

Out[181]:
```
array([0.08275377, 0.06985565, 0.06110151, 0.0508775 , 0.0476545 ,
       0.04397503, 0.04309095, 0.03886672, 0.03606727, 0.03525317,
       0.03393574, 0.03195266, 0.02806568, 0.02339546, 0.02313932,
       0.02094132, 0.02082307, 0.02053415, 0.02022003, 0.019877  ,
       0.01914186, 0.01839665, 0.01771758, 0.01543414, 0.01476358,
       0.01378672, 0.01224695, 0.0114735 , 0.01112032, 0.01035154])
```

As we see above the 30 principal components together explain a little over 80 % of the variance. So we will select all thirty Principal Components

In [182…
```
new_feats = pca.fit_transform(scaled)
new_feats
```

Out[182]:
```
array([[-1.35785685, -1.88425763, -1.97397881, ..., -0.11094511,
         0.27523182, -0.27541342],
       [ 0.1963981 , -4.30538314, -1.13590248, ..., -0.94971978,
         0.57584067,  0.42601707],
       [-3.7311749 , -3.49820523, -1.735055  , ...,  0.39372428,
        -0.3908806 ,  0.49556552],
       ...,
       [ 0.47529804,  2.6445924 ,  0.06452597, ..., -0.89615935,
         0.70758756, -1.12919284],
       [ 3.57385922,  0.24496315, -3.16682215, ..., -0.84042448,
         0.53751021,  0.10111069],
       [ 0.78548101,  0.61241234,  2.30935024, ...,  0.298666  ,
         1.35605723, -0.161829  ]])
```

Creating dataframe with the new features as the 30 principal components from above.

In [183…
```
new_data = pd.DataFrame(new_feats, columns = ["PCA1", "PCA2", "PCA3", "PC4", "PC5", "PC6
```

In [184…
```
new_data.head()
```

Out[184]:

	PCA1	PCA2	PCA3	PC4	PC5	PC6	PC7	PC8	PCA9
0	-1.357857	-1.884258	-1.973979	-0.000726	0.431248	-3.606503	1.421048	-1.418715	0.462156
1	0.196398	-4.305383	-1.135902	0.082758	-0.351744	-1.565965	3.365590	0.305649	1.896648
2	-3.731175	-3.498205	-1.735055	-0.078569	-0.386974	-0.860576	2.504444	-0.273746	-0.266942
3	-0.670099	-1.695278	-3.436231	-0.106110	1.187241	-2.169244	1.392527	-1.008122	-0.530892
4	-4.169513	-3.718399	-1.441031	-0.131872	0.376862	0.343934	-2.743607	-1.432815	0.532606

5 rows × 30 columns

SVM using "rbf" kernel after dimensionality reduction

In [185…
```
clf = svm.SVC(kernel='rbf', gamma =0.3)
#clf = svm.LinearSVC(C=1)
clf.fit(x_train, y_train)
y_predict = clf.predict(x_test)
confusion_matrix(y_test, y_predict)
```

Out[185]:
```
array([[1084,  783],
       [ 617, 1481]])
```

In [186…
```
print(accuracy_score(y_test, y_predict)*100)
```

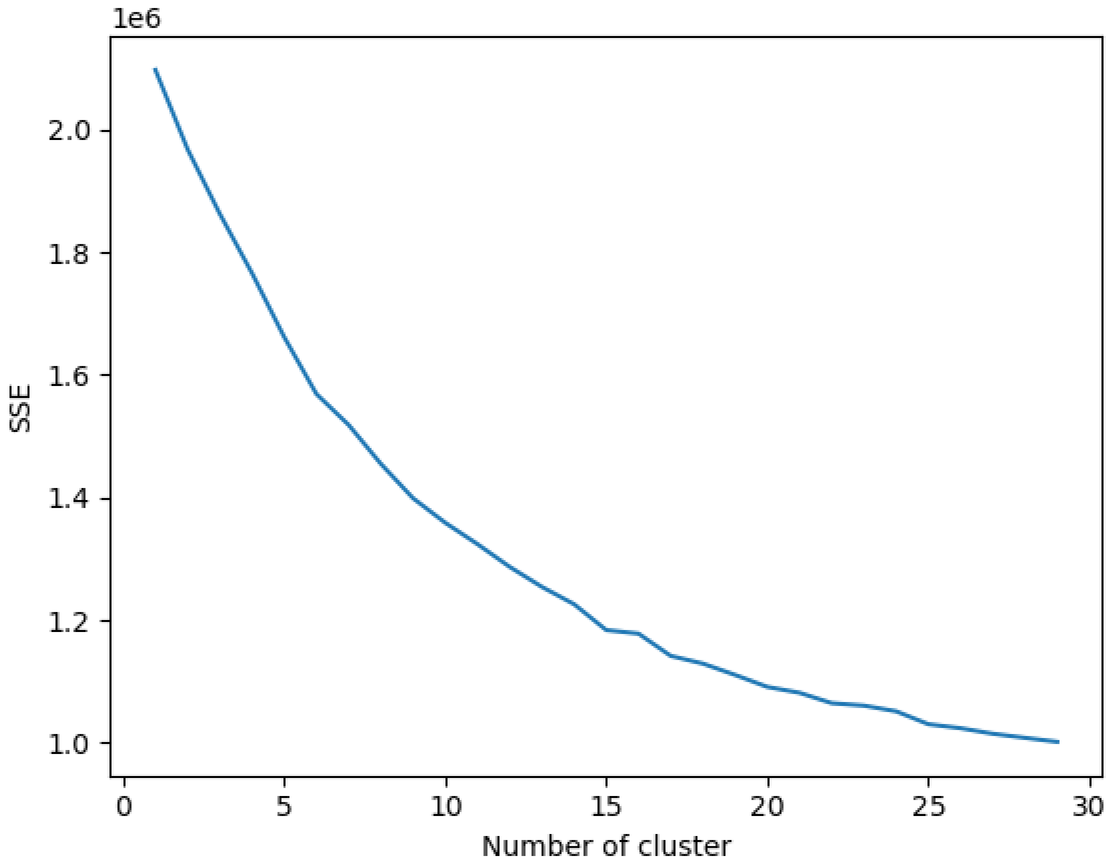
```
64.69104665825978
```

Sunsupervised model: Using Clustering to determine the best value of K using K-means .

In [187…
```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

```python
sse = {}
last_sse = 17592402.70373319
for k in range(1,30):
    kmeans = KMeans(n_clusters=k, random_state=12345, n_init = 25).fit(new_data)
    #print(data["clusters"])
    sse[k] = kmeans.inertia_ # Inertia: Sum of distances of samples to their closest clu
    change_per = (last_sse-kmeans.inertia_)/last_sse*100
    print ('At k= ',k,'The percentage of change in SSE is ',change_per,'%')
    last_sse = kmeans.inertia_
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()))
plt.xlabel("Number of cluster")
plt.ylabel("SSE")
plt.show()
```

```
At k=  1 The percentage of change in SSE is  88.07631058253925 %
At k=  2 The percentage of change in SSE is  6.1770128975934755 %
At k=  3 The percentage of change in SSE is  5.352399147817898 %
At k=  4 The percentage of change in SSE is  5.196874067232386 %
At k=  5 The percentage of change in SSE is  5.907706464446229 %
At k=  6 The percentage of change in SSE is  5.588287251806153 %
At k=  7 The percentage of change in SSE is  3.213208487607857 %
At k=  8 The percentage of change in SSE is  4.181117909254028 %
At k=  9 The percentage of change in SSE is  3.8599610578537344 %
At k=  10 The percentage of change in SSE is  2.8623620777938474 %
At k=  11 The percentage of change in SSE is  2.5649047197786743 %
At k=  12 The percentage of change in SSE is  2.802892920114828 %
At k=  13 The percentage of change in SSE is  2.5372429036207804 %
At k=  14 The percentage of change in SSE is  2.255100568286224 %
At k=  15 The percentage of change in SSE is  3.447060012527133 %
At k=  16 The percentage of change in SSE is  0.4836430128399092 %
At k=  17 The percentage of change in SSE is  3.088310387503831 %
At k=  18 The percentage of change in SSE is  1.1019768357863073 %
At k=  19 The percentage of change in SSE is  1.6371358128957423 %
At k=  20 The percentage of change in SSE is  1.7602885621822693 %
At k=  21 The percentage of change in SSE is  0.8808199240166601 %
At k=  22 The percentage of change in SSE is  1.5642818718455027 %
At k=  23 The percentage of change in SSE is  0.37656337146127855 %
At k=  24 The percentage of change in SSE is  0.8745224075705327 %
At k=  25 The percentage of change in SSE is  2.0028257085055117 %
At k=  26 The percentage of change in SSE is  0.6345199003790533 %
At k=  27 The percentage of change in SSE is  0.8788147395915004 %
At k=  28 The percentage of change in SSE is  0.6613765648575097 %
At k=  29 The percentage of change in SSE is  0.6493573618314269 %
```



From the graph it looks like values of k from 5 to 9 can be a good range.

Using KNN classifier which is a Supervised Learning Algorithm

Using k=2, Randomizing the data with seed 12345

In [188…
```
import random
target = news["shares"]
random.seed(12345)
indx = random.sample(range(0, 1000), 1000)
new_data_rand = new_data.iloc[indx]
target_rand = target.iloc[indx]
```

Splitting into 80% training data and 20% testing data

In [189…
```
from sklearn.model_selection import train_test_split

y = target_rand
x = new_data_rand

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=1
```

Using KNN algorithm for Classification with k=2

In [190…
```
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=2)
model = neigh.fit(x, y)
y_predict = model.predict(x_test)
```

```
/Users/pratik/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
```

```
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [191…

```python
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score

print(confusion_matrix(y_test, y_predict)*100)
```

```
[[9300    0]
 [4100 6600]]
```

In [192…

```python
print(accuracy_score(y_test, y_predict)*100)
```

```
79.5
```

Using K-value of 5

In [193…

```python
import random
target = news["shares"]
random.seed(12345)
indx = random.sample(range(0, 1000), 1000)
new_data_rand = new_data.iloc[indx]
target_rand = target.iloc[indx]


y = target_rand
x = new_data_rand

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=1


neigh = KNeighborsClassifier(n_neighbors=5)
model = neigh.fit(x, y)

y_predict = model.predict(x_test)
```

```
/Users/pratik/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_classification.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [194…

```python
print(confusion_matrix(y_test, y_predict)*100)
print(accuracy_score(y_test, y_predict)*100)
```

```
[[7200 2100]
 [2800 7900]]
75.5
```

Using k-value of 8

In [195…

```python
import random
target = news["shares"]
random.seed(12345)
indx = random.sample(range(0, 1000), 1000)
new_data_rand = new_data.iloc[indx]
target_rand = target.iloc[indx]
```

```
y = target_rand
x = new_data_rand

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=1


neigh = KNeighborsClassifier(n_neighbors=8)
model = neigh.fit(x, y)

y_predict = model.predict(x_test)

print(confusion_matrix(y_test, y_predict)*100)
print(accuracy_score(y_test, y_predict)*100)
```

```
[[7600 1700]
 [4700 6000]]
68.0
```

```
/Users/pratik/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0,
this behavior will change: the default value of `keepdims` will become False, the `axis`
over which the statistic is taken will be eliminated, and the value None will no longer
be accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Using K-20

In [196…

```
import random
target = news["shares"]
random.seed(12345)
indx = random.sample(range(0, 1000), 1000)
new_data_rand = new_data.iloc[indx]
target_rand = target.iloc[indx]


y = target_rand
x = new_data_rand

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=1


neigh = KNeighborsClassifier(n_neighbors=21)
model = neigh.fit(x, y)

y_predict = model.predict(x_test)

print(confusion_matrix(y_test, y_predict)*100)
print(accuracy_score(y_test, y_predict)*100)
```

```
[[6400 2900]
 [4200 6500]]
64.5
```

```
/Users/pratik/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0,
this behavior will change: the default value of `keepdims` will become False, the `axis`
over which the statistic is taken will be eliminated, and the value None will no longer
be accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

As seen above the accuracy for k=2 is 80%, K=5 is 75.5%, k=8 is 69.5% and k=21 is 63.5%. However, from the graph generated above, it looks like k=8 is a better value as the sse is small compared to K=2 and k=5. A slight elbow can be seen from the graph as seen from k= 5 to k=8 with a good percentage change in sse. The percentage in sse after k=9 is very less comparatively. I would like to use value of K= 8.

Conclusion:

Amongst all the algorithms used, the KNN Classifier algorithm after Dimensionality Reduction gave us the maximum accuracy for prediciting the Popular news articles.