Predicting the news popularity in multiple social media platforms

Data Description ¶

This is a large data set of news items and their respective social feedback on multiple platforms: Facebook, Google+ and LinkedIn.The collected data relates to a period of 8 months, between November 2015 and July 2016, accounting for about 100,000 news items on four different topics: Economy, Microsoft, Obama and Palestine.

File descriptions

- News_Final.csv - the News Final set (contains 93239 News records)

Data fields

- `IDLink` : Unique identifier of news items
- `Title` : Title of the news item according to the official media sources
- `Headline` : Headline of the news item according to the official media sources
- `Source` : Original news outlet that published the news item
- `Topic` : Query topic used to obtain the items in the official media sources
- `PublishDate` : Date and time of the news items' publication
- `SentimentTitle` : Sentiment score of the text in the news items' title
- `SentimentHeadline` : Sentiment score of the text in the news items'headline
- `Facebook` : Final value of the news items' popularity according to the social media source Facebook
- `GooglePlus` : Final value of the news items' popularity according to the social media source Google+
- `LinkedIn` : Final value of the news items' popularity according to the social media source LinkedIn

Import Required Libraries

In [1]:

```
# Import numpy
import numpy as np

# Import pandas
import pandas as pd

# Import Matplotlib
import matplotlib.pyplot as plt

# Import seaborn
import seaborn as sns

# To Avoid warning
from warnings import filterwarnings
filterwarnings('ignore')

# For Scaling
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn import preprocessing

# For Splitting purpose
from sklearn.model_selection import train_test_split

# For Linear regression(OLS)
import statsmodels
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression

# For model performance(OLS)
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error


# For feature selection in OLS
from statsmodels.stats.outliers_influence import variance_inflation_factor

# For DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier

# For Model performance(DT)
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

# For Cross validation
from sklearn.model_selection import GridSearchCV

# For Sampling purpose
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter
```

Read The Data

In [2]:

```
# Load the Data
df_newsone = pd.read_csv("News_Final.csv")

# Print the first 5 record
df_newsone.head()
```

Out[2]:

	IDLink	Title	Headline	Source	Topic	PublishDate	SentimentTitle	Sentime
0	99248.0	Obama Lays Wreath at Arlington National Cemetery	Obama Lays Wreath at Arlington National Cemete...	USA TODAY	obama	2002-04-02 00:00:00	0.000000	
1	10423.0	A Look at the Health of the Chinese Economy	Tim Haywood, investment director business-unit...	Bloomberg	economy	2008-09-20 00:00:00	0.208333	
2	18828.0	Nouriel Roubini: Global Economy Not Back to 2008	Nouriel Roubini, NYU professor and chairman at...	Bloomberg	economy	2012-01-28 00:00:00	-0.425210	
3	27788.0	Finland GDP Expands In Q4	Finland's economy expanded marginally in the t...	RTT News	economy	2015-03-01 00:06:00	0.000000	
4	27789.0	Tourism, govt spending buoys Thai economy in J...	Tourism and public spending continued to boost...	The Nation - Thailand's English news	economy	2015-03-01 00:11:00	0.000000	

Step 1 : Overview of data

1 Shape of the data
2 Check the columns(features)
3 Describe the dataset
4 Check for data types

1. Shape Of The Data

In [3]:

```
df_newsone.shape
```

Out[3]:

```
(93239, 11)
```

There are `93239` observation and `11` features

2. Check the columns

In [4]:

```
df_newsone.columns
```

Out[4]:

```
Index(['IDLink', 'Title', 'Headline', 'Source', 'Topic', 'PublishDate',
       'SentimentTitle', 'SentimentHeadline', 'Facebook', 'GooglePlus',
       'LinkedIn'],
      dtype='object')
```

- `IDLink` (numeric): Unique identifier of news items
- `Title` (string): Title of the news item according to the official media sources
- `Headline` (string): Headline of the news item according to the official media sources
- `Source` (string): Original news outlet that published the news item
- `Topic` (string): Query topic used to obtain the items in the official media sources
- `PublishDate` (timestamp): Date and time of the news items' publication
- `SentimentTitle` (numeric): Sentiment score of the text in the news items' title
- `SentimentHeadline` (numeric): Sentiment score of the text in the news items' headline
- `Facebook` (numeric): Final value of the news items' popularity according to the social media source Facebook
- `GooglePlus` (numeric): Final value of the news items' popularity according to the social media source Google+
- `LinkedIn` (numeric): Final value of the news items' popularity according to the social media source LinkedIn

Describe the dataset

In [5]:

```
df_newsone.describe(include='all').T
```

Out[5]:

	count	unique	top	freq	mean	std	min
IDLink	93239.0	NaN	NaN	NaN	51560.653257	30391.078704	1.0
Title	93239	81259	Business Highlights	37	NaN	NaN	NaN
Headline	93224	86694	Read full story for latest details.	18	NaN	NaN	NaN
Source	92960	5756	Bloomberg	1732	NaN	NaN	NaN
Topic	93239	4	economy	33928	NaN	NaN	NaN
PublishDate	93239	82644	2016-05-19 00:00:00	112	NaN	NaN	NaN
SentimentTitle	93239.0	NaN	NaN	NaN	-0.005411	0.136431	-0.950694
SentimentHeadline	93239.0	NaN	NaN	NaN	-0.027493	0.141964	-0.755433
Facebook	93239.0	NaN	NaN	NaN	113.141336	620.173233	-1.0
GooglePlus	93239.0	NaN	NaN	NaN	3.888362	18.492648	-1.0
LinkedIn	93239.0	NaN	NaN	NaN	16.547957	154.459048	-1.0

- There is no need to apply outlier treatment over the dataframe beacuse there is no mejor diffrence between `mean` column and `50%` column
- There is null values in `Headline` and `Source` columns

Check for data types

In [6]:

```
df_newsone.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 93239 entries, 0 to 93238
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   IDLink             93239 non-null  float64
 1   Title              93239 non-null  object 
 2   Headline           93224 non-null  object 
 3   Source             92960 non-null  object 
 4   Topic              93239 non-null  object 
 5   PublishDate        93239 non-null  object 
 6   SentimentTitle     93239 non-null  float64
 7   SentimentHeadline  93239 non-null  float64
 8   Facebook           93239 non-null  int64  
 9   GooglePlus         93239 non-null  int64  
 10  LinkedIn           93239 non-null  int64  
dtypes: float64(3), int64(3), object(5)
memory usage: 7.8+ MB
```

- we can change datatype for `IDLink` columns

Interpretation

- There are 93239 observation and 11 features
- There is null values in `Headline` and `Source` columns
- we can change datatype for `IDLink` columns

Action

In [7]:

```
df_newsone.IDLink.value_counts()
```

Out[7]:

```
80690.0    2
28854.0    2
81052.0    2
80994.0    2
99248.0    1
          ..
74445.0    1
74382.0    1
19495.0    1
19566.0    1
61870.0    1
Name: IDLink, Length: 93235, dtype: int64
```

In [8]:

```
df_newsone.IDLink= df_newsone.IDLink.astype('int')
```

Step 2 : Null values check

In [9]:

```
(df_newsone.isnull().sum()*100)/len(df_newsone)
```

Out[9]:

```
IDLink              0.000000
Title               0.000000
Headline            0.016088
Source              0.299231
Topic               0.000000
PublishDate         0.000000
SentimentTitle      0.000000
SentimentHeadline   0.000000
Facebook            0.000000
GooglePlus          0.000000
LinkedIn            0.000000
dtype: float64
```

- there is 0.29% null values in `Source` so we drop that rows
- and `Headline` columns 0.016% null values

In [10]:

```
df_newsone=df_newsone.dropna().copy()
```

In [11]:

```
df_newsone.to_csv("remove_null_value.csv",index=False)
```

In [12]:

```
df_news = pd.read_csv("remove_null_value.csv")
df_news.head()
```

Out[12]:

	IDLink	Title	Headline	Source	Topic	PublishDate	SentimentTitle	Sentimen
0	99248	Obama Lays Wreath at Arlington National Cemetery	Obama Lays Wreath at Arlington National Cemete...	USA TODAY	obama	2002-04-02 00:00:00	0.000000	
1	10423	A Look at the Health of the Chinese Economy	Tim Haywood, investment director business-unit...	Bloomberg	economy	2008-09-20 00:00:00	0.208333	
2	18828	Nouriel Roubini: Global Economy Not Back to 2008	Nouriel Roubini, NYU professor and chairman at...	Bloomberg	economy	2012-01-28 00:00:00	-0.425210	
3	27788	Finland GDP Expands In Q4	Finland's economy expanded marginally in the t...	RTT News	economy	2015-03-01 00:06:00	0.000000	
4	27789	Tourism, govt spending buoys Thai economy in J...	Tourism and public spending continued to boost...	The Nation - Thailand's English news	economy	2015-03-01 00:11:00	0.000000	

In [13]:

```
df_news.isnull().sum()
```

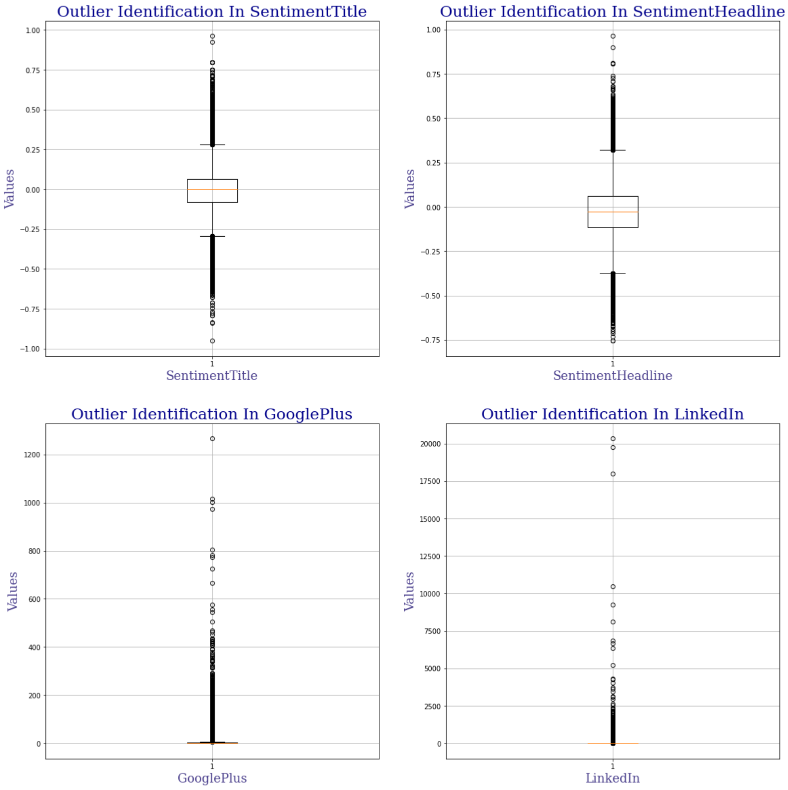
Out[13]:

```
IDLink               0
Title                0
Headline             0
Source               0
Topic                0
PublishDate          0
SentimentTitle       0
SentimentHeadline    0
Facebook             0
GooglePlus           0
LinkedIn             0
dtype: int64
```

Step 3 : Outlier Treatment

In [14]:

```
# Set font style for x_label & y_label
font = {'family':'serif',
        'color':'darkslateblue',
        'weight':'normal',
        'size':18,
        }

# Set font style for title
font_one = {'family':'serif',
        'color':'darkblue',
        'weight':'normal',
        'size':23,
        }

# Set figure size
plt.figure(figsize=(30,20))

# Use the subplots for convinant
# SentimentTitle feature
plt.subplot(2, 3, 1)
plt.boxplot(df_news.SentimentTitle)
plt.xlabel("SentimentTitle",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.grid()
plt.title("Outlier Identification In SentimentTitle",fontdict=font_one,loc='center')

# SentimentHeadline feature
plt.subplot(2, 3, 2)
plt.boxplot(df_news.SentimentHeadline)
plt.xlabel("SentimentHeadline",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.grid()
plt.title("Outlier Identification In SentimentHeadline",fontdict=font_one,loc='center')

# Facebook feature
plt.subplot(2, 3, 3)
plt.boxplot(df_news.Facebook)
plt.xlabel("Facebook",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.grid()
plt.title("Outlier Identification In Facebook",fontdict=font_one,loc='center')

# GooglePlus feature
plt.subplot(2, 3, 4)
plt.boxplot(df_news.GooglePlus)
plt.xlabel("GooglePlus",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.grid()
plt.title("Outlier Identification In GooglePlus",fontdict=font_one,loc='center')

# LinkedIn feature
plt.subplot(2, 3, 5)
plt.boxplot(df_news.LinkedIn)
plt.xlabel("LinkedIn",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.grid()
plt.title("Outlier Identification In LinkedIn",fontdict=font_one,loc='center')

plt.show()
```



- There is no outliers in data

EDA (Exploratory Data Analysis)

In [15]:

```
df_news.head()
```

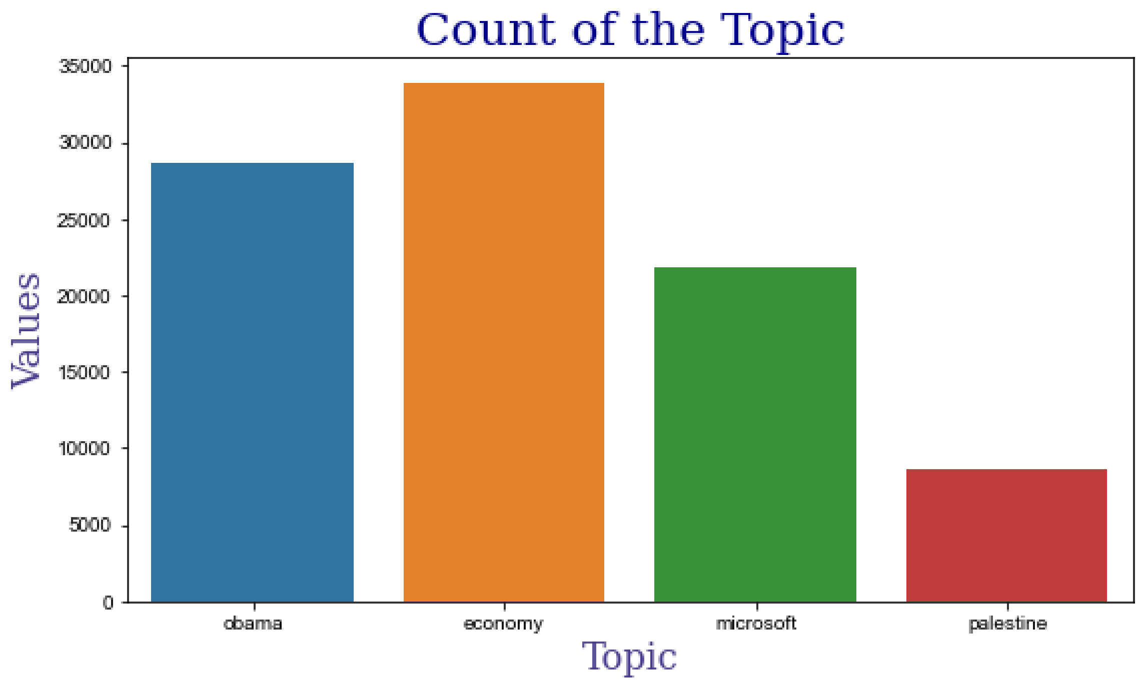
Out[15]:

	IDLink	Title	Headline	Source	Topic	PublishDate	SentimentTitle	Sentimen
0	99248	Obama Lays Wreath at Arlington National Cemetery	Obama Lays Wreath at Arlington National Cemete...	USA TODAY	obama	2002-04-02 00:00:00	0.000000	
1	10423	A Look at the Health of the Chinese Economy	Tim Haywood, investment director business-unit...	Bloomberg	economy	2008-09-20 00:00:00	0.208333	
2	18828	Nouriel Roubini: Global Economy Not Back to 2008	Nouriel Roubini, NYU professor and chairman at...	Bloomberg	economy	2012-01-28 00:00:00	-0.425210	
3	27788	Finland GDP Expands In Q4	Finland's economy expanded marginally in the t...	RTT News	economy	2015-03-01 00:06:00	0.000000	
4	27789	Tourism, govt spending buoys Thai economy in J...	Tourism and public spending continued to boost...	The Nation - Thailand's English news	economy	2015-03-01 00:11:00	0.000000	

1. Univrient Analysis

In [16]:

```
plt.figure(figsize=(9,5))
sns.countplot(df_news.Topic)
sns.set_style("whitegrid")
plt.xlabel("Topic",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.title("Count of the Topic",fontdict=font_one,loc='center')
plt.show()
```

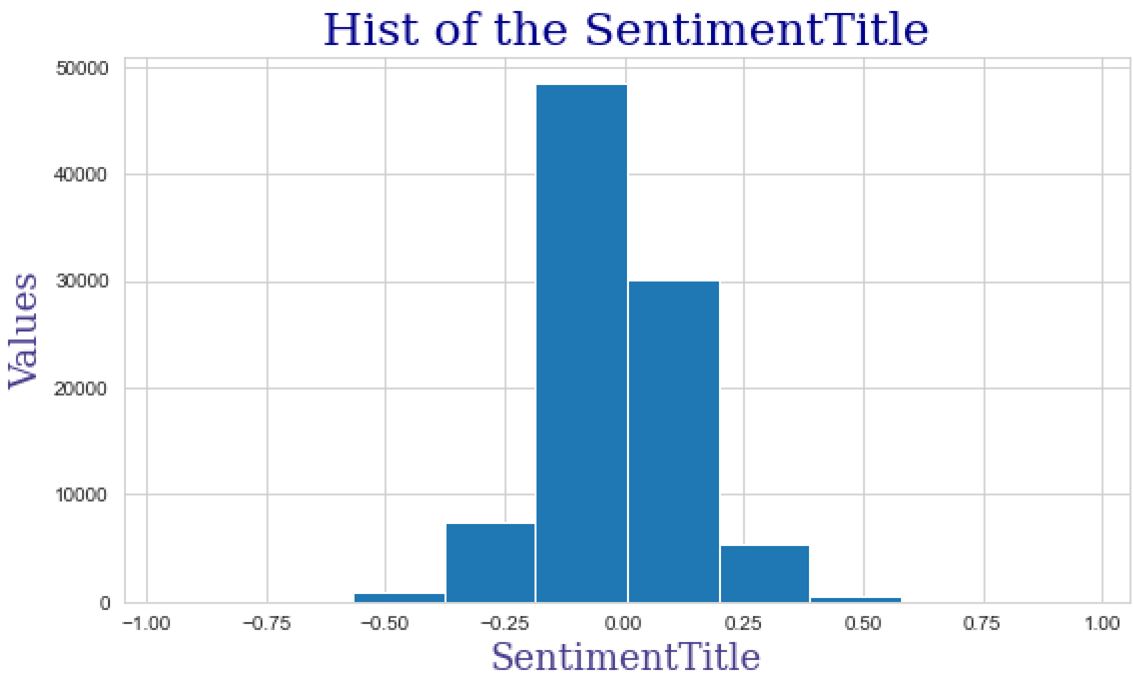


In [17]:

```
df_notText = df_news[["Facebook","GooglePlus","LinkedIn","SentimentTitle","SentimentHeadlin
```

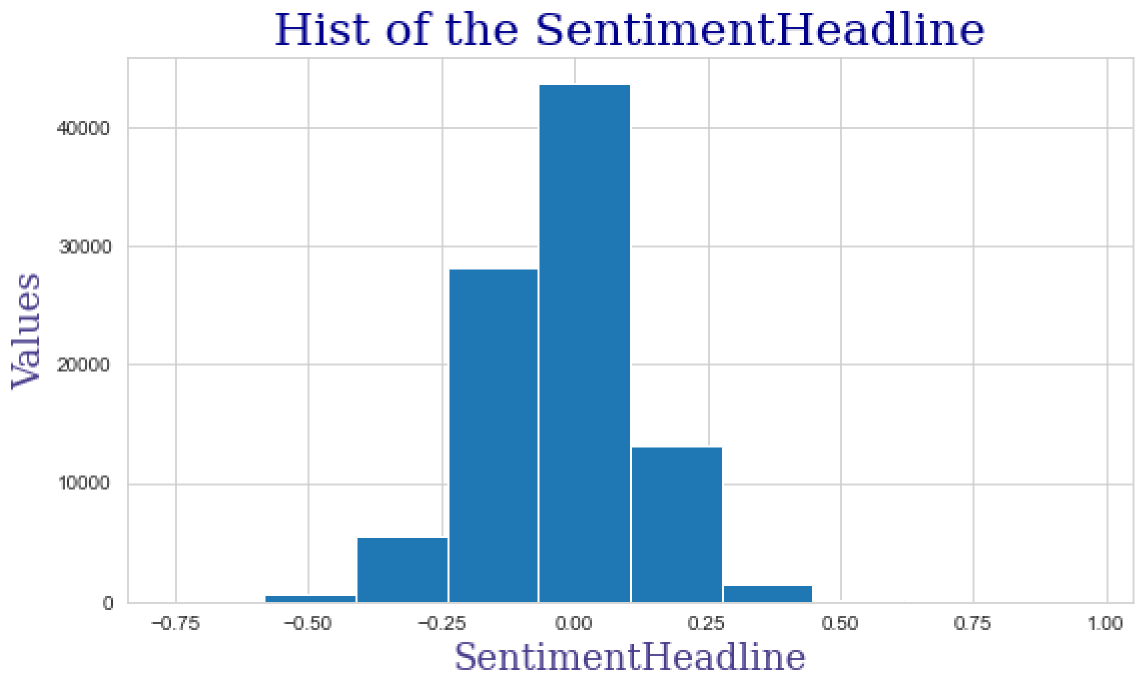
In [18]:

```
plt.figure(figsize=(9,5))
df_notText["SentimentTitle"].hist()
sns.set_style("whitegrid")
plt.xlabel("SentimentTitle",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.title("Hist of the SentimentTitle",fontdict=font_one,loc='center')
plt.show()
```



In [19]:

```
plt.figure(figsize=(9,5))
df_notText["SentimentHeadline"].hist()
sns.set_style("whitegrid")
plt.xlabel("SentimentHeadline",fontdict=font)
plt.ylabel("Values",fontdict=font)
plt.title("Hist of the SentimentHeadline",fontdict=font_one,loc='center')
plt.show()
```



In [20]:

```
df_notText[["Facebook","GooglePlus","LinkedIn"]].describe()
```

Out[20]:

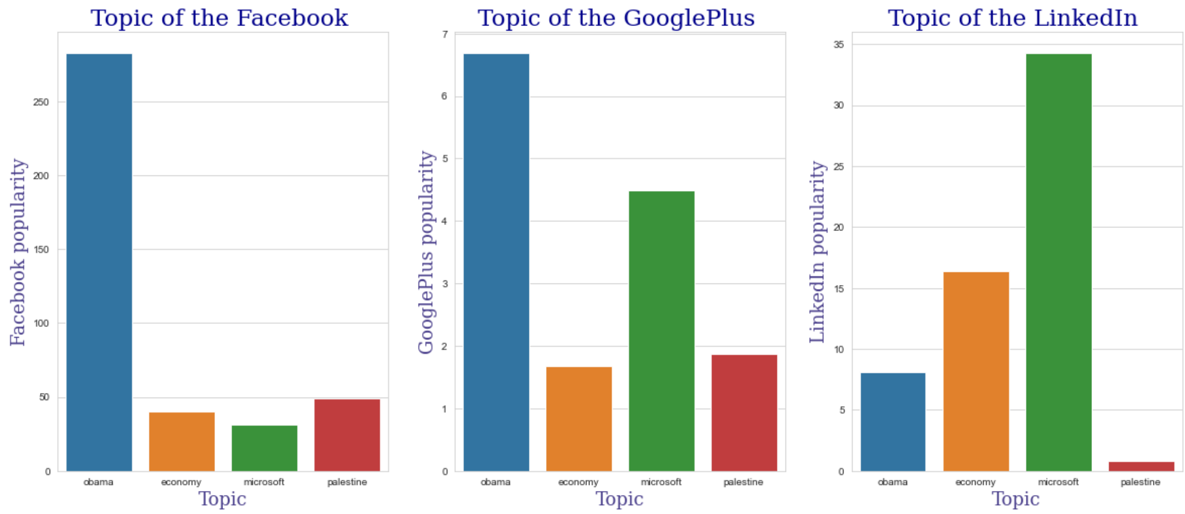
	Facebook	GooglePlus	LinkedIn
count	92945.000000	92945.000000	92945.000000
mean	113.497897	3.901124	16.600882
std	621.120839	18.520443	154.700274
min	-1.000000	-1.000000	-1.000000
25%	0.000000	0.000000	0.000000
50%	5.000000	0.000000	0.000000
75%	33.000000	2.000000	4.000000
max	49211.000000	1267.000000	20341.000000

- The above results and histogram shows that most of the data has neutral comments ,this is confirmed by the SentimentTitle and SentimentHeadline column as the 25 and 75 percentile are around the neutral value i.e. near to zero.
- Also Facebook,GooglePlus,LinkedIn , low-value means, the news was not so engaging and interesting and didn’t reach out to many people in that particular platform as confirmed by the 75% precentile of the data from the three columns are closer to 0 .
- Facebook has the higher reach as compared to GooglePlus and Linkedin.

2. Bivariate Analysis

In [21]:

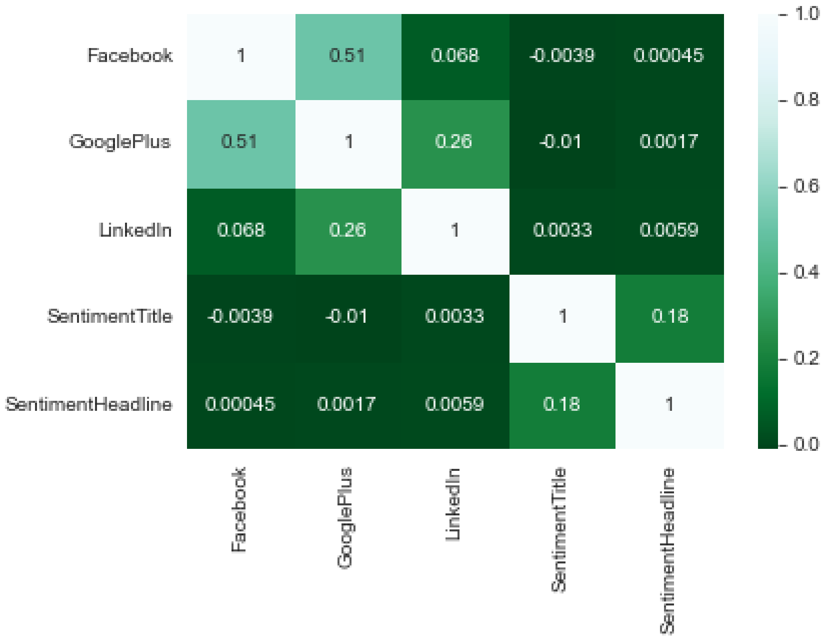
```
sns.set_style("whitegrid")
plt.figure(figsize=(20,8))
plt.subplot(1,3,1)
sns.barplot(x=df_news.Topic,y=df_news.Facebook,ci=None)
plt.xlabel("Topic",fontdict=font)
plt.ylabel("Facebook popularity",fontdict=font)
plt.title("Topic of the Facebook ",fontdict=font_one,loc='center')

plt.subplot(1,3,2)
sns.barplot(x=df_news.Topic,y=df_news.GooglePlus,ci=None)
plt.xlabel("Topic",fontdict=font)
plt.ylabel("GooglePlus popularity",fontdict=font)
plt.title("Topic of the GooglePlus ",fontdict=font_one,loc='center')

plt.subplot(1,3,3)
sns.barplot(x=df_news.Topic,y=df_news.LinkedIn,ci=None)
plt.xlabel("Topic",fontdict=font)
plt.ylabel("LinkedIn popularity",fontdict=font)
plt.title("Topic of the LinkedIn ",fontdict=font_one,loc='center')

plt.show()
```



3.Multivariate analysis

In [22]:

```
sns.heatmap(df_news[["Facebook","GooglePlus","LinkedIn","SentimentTitle","SentimentHeadline
plt.show()
```



- 51% of facebook news are also share in google
- There not much correlation between target variable with independend variable

summary

- In count plot it can be seen that economy related news were most accurate comparing to other news
- In bievarient news topic of obama were popular in time among facebook and googleplus. while microsoft was accurately visible in linkedin
- Through our analysis we could figure that amongst all the four news topics, news items related to Economy were most popular on social media.
- Secondly, we figured that Facebook has higher reach as compared to GooglePlus and LinkedIn.
- Next we found out that the news items related to the topic Obama trended more on Facebook and Google plus. Also, the news items related to Microsoft trended more on LinkedIn.
- In multivariate analysis we could conclude that 51% of Facebook news are also

Feature Engineering

In [23]:

```
# Split the values according to our requirement
# Separate the Time
df_news['Publish_Time']=df_news['PublishDate'].str.split(" ").str[1]
# Separate the date
df_news['Publish_Date']=df_news['PublishDate'].str.split(" ").str[0]
# convert for datatype
df_news['Publish_Date']= pd.to_datetime(df_news['Publish_Date'])

# Separate the month
df_news['Publish_Month']= df_news['Publish_Date'].dt.month
# Separate the day
df_news['Publish_Day']= df_news['Publish_Date'].dt.day
# Map the Month in terms of words
df_news["Season"]=df_news["Publish_Month"].copy()
df_news.Season.replace({1:'Winter',2:'Winter',3:'Spring',4:'Spring',5:'Spring',6:'Summer',7

df_news.Publish_Month.replace({1:'January',2:'February',3:'March',4:'April',5:'May',6:'June

# Print the first 5 record
df_news.head()
```

Out[23]:

	IDLink	Title	Headline	Source	Topic	PublishDate	SentimentTitle	SentimentHeadline	Fa
0	99248	Obama Lays Wreath at Arlington National Cemetery	Obama Lays Wreath at Arlington National Cemete...	USA TODAY	obama	2002-04-02 00:00:00	0.000000	-0.053300	
1	10423	A Look at the Health of the Chinese Economy	Tim Haywood, investment director business-unit...	Bloomberg	economy	2008-09-20 00:00:00	0.208333	-0.156386	
2	18828	Nouriel Roubini: Global Economy	Nouriel Roubini, NYU professor	Bloomberg	economy	2012-01-28 00:00:00	-0.425210	0.139754	

In [24]:

```
df_news.drop('PublishDate',axis=1,inplace=True)
```

In [25]:

```
df_news_copy=df_news.copy()
target_variable =  list(df_news_copy["SentimentTitle"].copy())
df_news_copy.drop("SentimentTitle",axis=1,inplace=True)
```

Encoding

In [26]:

```
# Segregate the data
df_news_copy_object = df_news_copy.select_dtypes('object')
df_news_copy_number = df_news_copy.select_dtypes('number')
```

In [27]:

```
# Do LableEncoding
le = preprocessing.LabelEncoder()
df_news_copy_object_enco = df_news_copy_object.apply(le.fit_transform)
df_news_copy_object_enco.head()
```

Out[27]:

	Title	Headline	Source	Topic	Publish_Time	Publish_Month	Season
0	47119	46352	4995	2	0	0	1
1	1758	76110	518	0	0	11	0
2	45591	45817	518	0	0	4	3
3	18177	21729	3621	0	197	7	1
4	72633	76673	4597	0	282	7	1

In [28]:

```
concat_news_dataframe = pd.concat([df_news_copy_number,df_news_copy_object_enco],axis=1)
```

Scalling

In [29]:

```
# Use StandardScaler for scaling
X_scaler = StandardScaler()
num_scaler = X_scaler.fit_transform(concat_news_dataframe)
X=pd.DataFrame(num_scaler,columns=concat_news_dataframe.columns)
```

Train-Test Split

In [30]:

```
X_train,X_test,Y_train,Y_test = train_test_split(X,target_variable,random_state=1,test_size
```

In [31]:

```
# Convert List into DataFrame Y_train
Y_train = pd.DataFrame(Y_train)
# Convert List into DataFrame Y_test
Y_test = pd.DataFrame(Y_test)

# checking the dimensions of the train & test subset
# print dimension of train set
print("X_train :",X_train.shape)
print("Y_train :",Y_train.shape)

# print dimension of test set
print("X_test :",X_test.shape)
print("Y_test :",Y_test.shape)
```

```
X_train : (55767, 13)
Y_train : (55767, 1)
X_test : (37178, 13)
Y_test : (37178, 1)
```

Base model (LinearRegression)

In [32]:

```
# Use Linear Regression As a base model
base_model = LinearRegression().fit(X_train,Y_train)
```

In [33]:

```
# Check the score for base model
base_model.score(X_train,Y_train)
```

Out[33]:

```
0.03357131449689199
```

In [34]:

```
# Predict using base model
y_pred =  base_model.predict(X_train)

# print the predicted record
y_pred
```

Out[34]:

```
array([[-0.04162616],
       [ 0.01427337],
       [ 0.01484103],
       ...,
       [ 0.01668751],
       [ 0.0154612 ],
       [ 0.01301458]])
```

In [35]:

```
# Check the performance  of the base model using mean_squared_error
mean_squared_error(Y_train, y_pred, squared=False)
```

Out[35]:

```
0.13400613987660245
```

In [36]:

```
# Check the performance  of the base model using mean_absolute_error
mean_absolute_error(Y_train,y_pred)
```

Out[36]:

```
0.09690549758608462
```

In [37]:

```
# Check the performance  of the base model using root_mean_squared_error
np.sqrt(mean_squared_error(Y_train,y_pred))
```

Out[37]:

```
0.13400613987660245
```

Variance Inflation Factor(VIF)

In [38]:

```
# Do the feature selection for base model using VIF
df_news_VIF_number = df_news.select_dtypes('number')
df_news_VIF_number.head()
```

Out[38]:

	IDLink	SentimentTitle	SentimentHeadline	Facebook	GooglePlus	LinkedIn	Publish_Day
0	99248	0.000000	-0.053300	-1	-1	-1	2
1	10423	0.208333	-0.156386	-1	-1	-1	20
2	18828	-0.425210	0.139754	-1	-1	-1	28
3	27788	0.000000	0.026064	-1	-1	-1	1
4	27789	0.000000	0.141084	-1	-1	-1	1

In [39]:

```
for ind in range(len(df_news_VIF_number.columns)):
    vif = pd.DataFrame()
    vif["VIF_Factor"] = [variance_inflation_factor(df_news_VIF_number,i) for i in range(df_
    vif["Features"]=df_news_VIF_number.columns
    multi =  vif[vif['VIF_Factor']>10]


    if (multi.empty == False):
        df_sorted = multi.sort_values(by = 'VIF_Factor',ascending= False)
    else:
        print(vif)
        break


    if (df_sorted.empty == False):
        df_features_vif = df_news_VIF_number.drop(df_sorted.Features.iloc[0], axis=1)
    else:
        print(vif)
        break
```

```
   VIF_Factor           Features
0    2.363040             IDLink
1    1.036659      SentimentTitle
2    1.067113   SentimentHeadline
3    1.416700            Facebook
4    1.515392          GooglePlus
5    1.093871            LinkedIn
6    2.338872         Publish_Day
```

In [40]:

```
# We can see here that all Features contribute for prediction that is why all features are
```

In [41]:

```
# After doing Linear regression we found that regression model is not good fit for this dat
```

Decision Tree

In [42]:

```
df_news["target_sentiment"] = np.round(df_news["SentimentTitle"])
```

In [43]:

```
df_news.target_sentiment.value_counts()
```

Out[43]:

```
 0.0    92640
-1.0      172
 1.0      133
Name: target_sentiment, dtype: int64
```

In [44]:

```
# As we can see here the data is Imbalance(target Varible)
```

In [45]:

```
# We are using oversampling and undersampling concept to balance the data
```

In [46]:

```
avg=df_news[df_news["target_sentiment"]==0]
```

In [47]:

```
high = df_news[df_news["target_sentiment"]==1]
```

In [48]:

```
below_avg=df_news[df_news["target_sentiment"]==-1]
```

In [49]:

```
X1=df_news
Y1= df_news["target_sentiment"]
```

In [50]:

```
df_news.drop("target_sentiment",axis=1,inplace=True)
```

In [51]:

```
# Use Undersampling Concept
```

In [52]:

```
from imblearn.under_sampling import RandomUnderSampler

rus =  RandomUnderSampler(random_state=0)
X_resampled,y_resampled = rus.fit_resample(X1,Y1)
print(sorted(Counter(y_resampled).items()),y_resampled.shape)
```

```
[(-1.0, 133), (0.0, 133), (1.0, 133)] (399,)
```

In [53]:

```
under_sample=pd.concat([X_resampled,y_resampled],axis=1)
```

In [54]:

```
under_sample.drop('target_sentiment', axis=1, inplace=True)
under_sample.drop("SentimentTitle",axis=1,inplace=True)
```

In [55]:

```
under_sample=pd.concat([X_resampled,y_resampled],axis=1)
under_sample.head()
```

Out[55]:

	IDLink	Title	Headline	Source	Topic	SentimentTitle	SentimentHeadline	Facebook	Go
0	72641	Palestinian resolution	Last week, Mumbai witnessed a cultural collabo...	Livemint	palestine	-0.530330	-0.212156	20	
1	98407	Okinawa largely disappointed by Obama's words ...	U.S. President Barack Obama's condolences on M...	Asahi Shimbun	obama	-0.640816	-0.218651	11	
2	20835	Cloud growth? Take a number, Microsoft.	Microsoft's second fiscal quarter showed a com...	The Register	microsoft	-0.515352	-0.164583	4	

In [56]:

```
# change target variable data type into object
under_sample.target_sentiment= under_sample.target_sentiment.astype('object')
target_variable_under = list(under_sample.target_sentiment.copy())
under_sample.drop("target_sentiment",axis=1,inplace=True)
```

In [57]:

```
# change data type of date column
under_sample.Publish_Time = pd.to_timedelta(under_sample.Publish_Time)
```

In [58]:

```
# Segregate the data
under_sample_object = under_sample.select_dtypes('object')
under_sample_number = under_sample.select_dtypes('number')
```

In [59]:

```
# Do LableEncoding
le = preprocessing.LabelEncoder()
under_sample_label_enco = under_sample_object[["Title","Headline","Source"]].apply(le.fit_t
under_sample_dummy_enco = pd.get_dummies(under_sample_object[["Topic","Publish_Month","Seas
concat_under_sample_dataframe = pd.concat([under_sample_label_enco,under_sample_number],axi
concat_under_sample_dataframe.head()
```

Out[59]:

	Title	Headline	Source	IDLink	SentimentTitle	SentimentHeadline	Facebook	GooglePlus	L
0	261	152	108	72641	-0.530330	-0.212156	20	0	
1	243	343	17	98407	-0.640816	-0.218651	11	0	
2	47	181	222	20835	-0.515352	-0.164583	4	4	
3	245	204	123	17201	-0.592927	0.147314	1	0	
4	299	260	91	45381	-0.675000	0.000000	4	0	

In [60]:

```
concat_under_sample_dataframe.drop("Publish_Time",axis=1,inplace=True)
```

In [61]:

```
X_scaler_under = StandardScaler()
num_scaler_under = X_scaler_under.fit_transform(concat_under_sample_dataframe)
X_under=pd.DataFrame(num_scaler_under,columns=concat_under_sample_dataframe.columns)
X_under = pd.concat([X_under,under_sample_dummy_enco],axis=1)
X_under.head()
```

Out[61]:

	Title	Headline	Source	IDLink	SentimentTitle	SentimentHeadline	Facebook	Go
0	0.767970	-0.384435	-0.303280	0.730160	-1.105060	-1.152656	-0.173424	-(
1	0.597363	1.312982	-1.417270	1.597724	-1.331303	-1.187838	-0.223102	-(
2	-1.260361	-0.126712	1.092268	-1.014192	-1.074389	-0.894929	-0.261740	(
3	0.616320	0.077689	-0.119655	-1.136552	-1.233241	0.794775	-0.278300	-(
4	1.128141	0.575361	-0.511388	-0.187707	-1.401303	-0.003298	-0.261740	-(

5 rows × 28 columns

Train-Test Split

In [62]:

```
x_train_under,x_test_under,y_train_under,y_test_under=train_test_split(X_under,target_varia
```

In [63]:

```
# Convert List into DataFrame y_train_under
y_train_under = pd.DataFrame(y_train_under)
# Convert List into DataFrame y_test_under
y_test_under = pd.DataFrame(y_test_under)

# checking the dimensions of the train & test subset
# print dimension of train set
print("x_train_under :",x_train_under.shape)
print("y_train_under :",y_train_under.shape)

# print dimension of test set
print("x_test_under :",x_test_under.shape)
print("y_test_under :",y_test_under.shape)
```

```
x_train_under : (279, 28)
y_train_under : (279, 1)
x_test_under : (120, 28)
y_test_under : (120, 1)
```

Decision tree model

In [64]:

```
# Initialize the decision tree
decision_tree_clasifier=DecisionTreeClassifier(criterion='entropy',random_state=10)
```

In [65]:

```
# Fit the model
decision_tree=decision_tree_clasifier.fit(x_train_under,y_train_under)
```

In [66]:

```
# prediction for training data
predict_train=decision_tree.predict(x_train_under)

# prediction for testing data
predict_test=decision_tree.predict(x_test_under)
```

In [67]:

```
confusion_matrix(y_train_under,predict_train)
```

Out[67]:

```
array([[95,  0,  0],
       [ 0, 96,  0],
       [ 0,  0, 88]], dtype=int64)
```

In [68]:

```
confusion_matrix(y_test_under,predict_test)
```

Out[68]:

```
array([[38,  0,  0],
       [ 0, 36,  1],
       [ 0,  0, 45]], dtype=int64)
```

In [69]:

```
# Classification report for traning data
print(classification_report(y_train_under,predict_train))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00        95
         0.0       1.00      1.00      1.00        96
         1.0       1.00      1.00      1.00        88

    accuracy                           1.00       279
   macro avg       1.00      1.00      1.00       279
weighted avg       1.00      1.00      1.00       279
```

In [70]:

```
# Classification report for testing data
print(classification_report(y_test_under,predict_test))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00        38
        -0.0       1.00      0.97      0.99        37
         1.0       0.98      1.00      0.99        45

    accuracy                           0.99       120
   macro avg       0.99      0.99      0.99       120
weighted avg       0.99      0.99      0.99       120
```

In [71]:

```
# our model is performing well there is no underfiting problem
```

In [72]:

```
# Tune the model using hyperparameter
```

In [73]:

```
# Set the hyperparameter
tuned_params=[{'criterion':['entopy','gini'],'max_depth':[10,20,30],'max_features':['log2',
```

In [74]:

```
# Find the best hyperparameter using grid serch cv
over_tree_grid=GridSearchCV(estimator=decision_tree_clasifier,param_grid=tuned_params,cv=5)
model = over_tree_grid.fit(x_train_under,y_train_under)
print(model.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 10, 'max_features': 'log2', 'max_leaf_nod
es': 50, 'min_samples_leaf': 1, 'min_samples_split': 11}
```

Make a new model with good hyperpatameter

In [75]:

```
# Initialize the dt with good hyperparameter that we found using grid search CV
dt1 =DecisionTreeClassifier(criterion='gini',random_state=10,max_depth=20,max_features='log
                            max_leaf_nodes=70,min_samples_leaf=1,min_samples_split=2)
```

In [76]:

```
# fit the model on the data
final_model = dt1.fit(x_train_under,y_train_under)
```

In [77]:

```
# predict for traning
predicted_train = final_model.predict(x_train_under)

# predict for testing
predicted_test = final_model.predict(x_test_under)
```

In [78]:

```
# Classification report for traing data
print(classification_report(y_train_under,predicted_train))
```

```
              precision    recall  f1-score   support

        -1.0       0.87      0.92      0.89        95
         0.0       0.92      0.94      0.93        96
         1.0       1.00      0.92      0.96        88

    accuracy                           0.92       279
   macro avg       0.93      0.92      0.93       279
weighted avg       0.93      0.92      0.93       279
```

In [79]:

```
#  Classification report for testing data
print(classification_report(y_test_under,predicted_test))
```

```
              precision    recall  f1-score   support

        -1.0       0.62      0.66      0.64        38
        -0.0       0.56      0.65      0.60        37
         1.0       0.78      0.64      0.71        45

    accuracy                           0.65       120
   macro avg       0.66      0.65      0.65       120
weighted avg       0.66      0.65      0.65       120
```

As we can see model is overfitted, the reason is traing accurecy is 92% and testing accurecy 65%

Oversampling concept

In [80]:

```
from imblearn.over_sampling import RandomOverSampler

rus =  RandomOverSampler(random_state=0)
X_resampled_over,y_resampled_over = rus.fit_resample(X1,Y1)
print(sorted(Counter(y_resampled_over).items()),y_resampled_over.shape)
over_sample=pd.concat([X_resampled_over,y_resampled_over],axis=1)
over_sample.head()
```

```
[(-1.0, 92640), (0.0, 92640), (1.0, 92640)] (277920,)
```

In [81]:

```
# change target variable data type into object
over_sample.target_sentiment= over_sample.target_sentiment.astype('object')
target_variable_over = list(over_sample.target_sentiment.copy())
over_sample.drop("target_sentiment",axis=1,inplace=True)
```

In [82]:

```
over_sample_object = over_sample.select_dtypes('object')
over_sample_number = over_sample.select_dtypes('number')
```

In [83]:

```
le = preprocessing.LabelEncoder()
over_sample_label_enco = over_sample_object[["Title","Headline","Source"]].apply(le.fit_tra
over_sample_label_enco.head()
```

Out[83]:

	Title	Headline	Source
0	47119	46352	4995
1	1758	76110	518
2	45591	45817	518
3	18177	21729	3621
4	72633	76673	4597

Encode the each categorical

In [84]:

```
over_sample_dummy_enco = pd.get_dummies(over_sample_object[["Topic","Publish_Month","Season
```

In [85]:

```
concat_over_sample_dataframe = pd.concat([over_sample_label_enco,over_sample_number],axis=1
concat_over_sample_dataframe.head()
```

Out[85]:

	Title	Headline	Source	IDLink	SentimentTitle	SentimentHeadline	Facebook	GooglePlus
0	47119	46352	4995	99248	0.000000	-0.053300	-1	-1
1	1758	76110	518	10423	0.208333	-0.156386	-1	-1
2	45591	45817	518	18828	-0.425210	0.139754	-1	-1
3	18177	21729	3621	27788	0.000000	0.026064	-1	-1
4	72633	76673	4597	27789	0.000000	0.141084	-1	-1

In [86]:

```
X_scaler_over = StandardScaler()
num_scaler_over = X_scaler.fit_transform(concat_over_sample_dataframe)
X_over=pd.DataFrame(num_scaler_over,columns=concat_over_sample_dataframe.columns)
X_over = pd.concat([X_over,over_sample_dummy_enco],axis=1)
X_over.head()
```

Out[86]:

	Title	Headline	Source	IDLink	SentimentTitle	SentimentHeadline	Facebook	Go
0	0.213169	0.082633	1.237859	1.637338	-0.013450	-0.304755	-0.181104	-(
1	-1.715737	1.238428	-1.343713	-1.410554	0.412868	-0.857541	-0.181104	-(
2	0.148194	0.061854	-1.343713	-1.122149	-0.883566	0.730480	-0.181104	-(
3	-1.017545	-0.873720	0.445570	-0.814701	-0.013450	0.120829	-0.181104	-(
4	1.298113	1.260295	1.008361	-0.814667	-0.013450	0.737613	-0.181104	-(

5 rows × 30 columns

Train-Test Split

In [87]:

```
x_train_over,x_test_over,y_train_over,y_test_over=train_test_split(X_over,target_variable_o
```

In [88]:

```
# Convert List into DataFrame y_train_over
y_train_over = pd.DataFrame(y_train_over)
# Convert List into DataFrame y_test_over
y_test_over = pd.DataFrame(y_test_over)

# checking the dimensions of the train & test subset
# print dimension of train set
print("x_train_over :",x_train_over.shape)
print("y_train_over :",y_train_over.shape)

# print dimension of test set
print("x_test_over :",x_test_over.shape)
print("y_test_over :",y_test_over.shape)
```

```
x_train_over : (194544, 30)
y_train_over : (194544, 1)
x_test_over : (83376, 30)
y_test_over : (83376, 1)
```

In [89]:

```
# Initialize the decision tree for oversampling concept
decision_tree_clasifier=DecisionTreeClassifier(criterion='entropy',random_state=10)
```

In [90]:

```
# fit the model
decision_tree=decision_tree_clasifier.fit(x_train_over,y_train_over)
```

In [91]:

```
# predict for traing data
predict_train_over=decision_tree.predict(x_train_over)
predict_train_over

# predict for testing data
predict_test_over=decision_tree.predict(x_test_over)
predict_test_over
```

Out[91]:

```
array([ 1.,  0.,  1., ...,  0., -1.,  1.])
```

In [92]:

```
confusion_matrix(y_train_over,predict_train_over)
```

Out[92]:

```
array([[64997,     0,     0],
       [    0, 64700,     0],
       [    0,     0, 64847]], dtype=int64)
```

In [93]:

```
confusion_matrix(y_test_over,predict_test_over)
```

Out[93]:

```
array([[27643,     0,     0],
       [    0, 27940,     0],
       [    0,     0, 27793]], dtype=int64)
```

In [94]:

```
# Classification report for traning data
print(classification_report(y_train_over,predict_train_over))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00     64997
         0.0       1.00      1.00      1.00     64700
         1.0       1.00      1.00      1.00     64847

    accuracy                           1.00    194544
   macro avg       1.00      1.00      1.00    194544
weighted avg       1.00      1.00      1.00    194544
```

In [95]:

```
# classification report for testing data
print(classification_report(y_test_over,predict_test_over))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00     27643
         0.0       1.00      1.00      1.00     27940
         1.0       1.00      1.00      1.00     27793

    accuracy                           1.00     83376
   macro avg       1.00      1.00      1.00     83376
weighted avg       1.00      1.00      1.00     83376
```

In [96]:

```
# Our model is performing well there is no overfiting problem
```

In [97]:

```
# Tune the model using hyperparameter
```

In [98]:

```
tuned_params=[{'criterion':['entopy','gini'],'max_depth':[10,20,30],'max_features':['log2',
```

In [99]:

```
over_tree_grid=GridSearchCV(estimator=decision_tree_clasifier,param_grid=tuned_params,cv=5)
model = over_tree_grid.fit(x_train_over,y_train_over)
print(model.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 20, 'max_features': 'sqrt', 'max_leaf_nod
es': 70, 'min_samples_leaf': 5, 'min_samples_split': 2}
```

Decision tree model for oversampling concept (Best Hyperpatameter)

In [100]:

```
dt2 =DecisionTreeClassifier(criterion='gini',random_state=10,max_depth=20,max_features='log
                            max_leaf_nodes=70,min_samples_leaf=1,min_samples_split=2)
```

In [101]:

```
# Fit the model on the data
final_model = dt2.fit(x_train_over,y_train_over)

# predict for traing data
predicted_train = final_model.predict(x_train_over)

# predict for testing data
predicted_test = final_model.predict(x_test_over)
```

In [102]:

```
print(classification_report(y_train_over,predict_train_over))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00     64997
         0.0       1.00      1.00      1.00     64700
         1.0       1.00      1.00      1.00     64847

    accuracy                           1.00    194544
   macro avg       1.00      1.00      1.00    194544
weighted avg       1.00      1.00      1.00    194544
```

In [103]:

```
print(classification_report(y_test_over,predict_test_over))
```

```
              precision    recall  f1-score   support

        -1.0       1.00      1.00      1.00     27643
         0.0       1.00      1.00      1.00     27940
         1.0       1.00      1.00      1.00     27793

    accuracy                           1.00     83376
   macro avg       1.00      1.00      1.00     83376
weighted avg       1.00      1.00      1.00     83376
```

In [104]:

```
# As we can see here oversampling concept good fit for the data
# That proven by seen the accuracy of traing and testing
```