# CS410 – Text Information System

# Final Project Documentation

# Stock Market Tweet Analysis

**Team: Eastern Center**

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**Introduction:**

Numerous factors, including both internal and external factors, can affect and move the stock market. Various data mining techniques are frequently employed to address this problem. Stock prices change instantly due to shifts in supply and demand. On the other hand, machine learning will offer a more precise, accurate, and logical method for addressing stock and market price concerns. A novel approach to creating simulation models that can predict stock market movements and whether they will increase, or decrease has been improved using ML algorithms. Several sentiment analysis studies used Support vector machines (SVM), Naive Bayes regression, Random Forest Classifier, and other techniques. The effectiveness of machine learning algorithms depends on the quantity of training data available. To begin, we train many algorithms using Sentiment 5792 clean Twitter data. We utilized SVM to ascertain the typical sentiment of tweets for each trade day because this was the emotional analysis that performed the best.

**Problem Statement:**

In this project, we attempt to put into practice an NLP Twitter sentiment analysis model that aids in overcoming the difficulties associated with determining the sentiments of the tweets. The following information is necessary for the dataset used in the twitter sentiment analysis project:

The Sentiment Dataset, which was made available (https://www.kaggle.com/datasets/utkarshxy/stockmarkettweets-lexicon-data for Sentiment Analysis), consists of 5972 cleaned tweets that were retrieved using the Twitter API. The dataset's numerous columns include:

1. Text: Twitter data

2. Sentiment: Labeled data corpus for Sentiment Analysis*SentimentIntensityAnalyzer*: library for classifying of sentimentsResults exported in text files. Probability of positive and negative Compound values in a range of -1 to 1, where -1 represents negative for each tweet.

**Tools, System and Dataset**

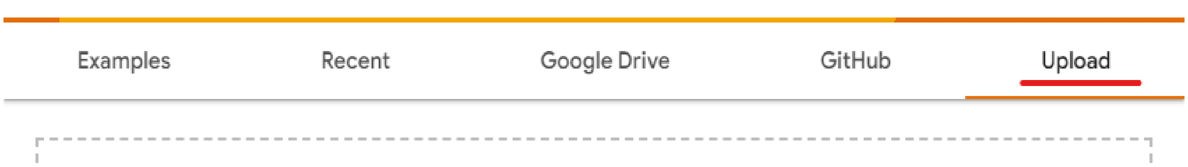
- Google Collab
- http://www.tweepy.org/ - Python Library to access the Twitter API
- http://www.nltk.org/ - Natural Language Toolkit
- Twitter data from Kaggle: https://www.kaggle.com/datasets/utkarshxy/stockmarkettweets-lexicon-data for Sentiment Analysis

**Software Usage**

For this project we have used **Google Collab**. First login to the google account. Create a new account if you don't have already. Download the source code from GitHub

(https://github.com/kasamdh/CourseProject/blob/main/StockMarketSentimentAnalysis.ipynb)

Upload the source code to Collab (http://colab.research.google.com/) From http://colab.research.google.com/. Select: File ->Upload Notebook->Upload->Choose File



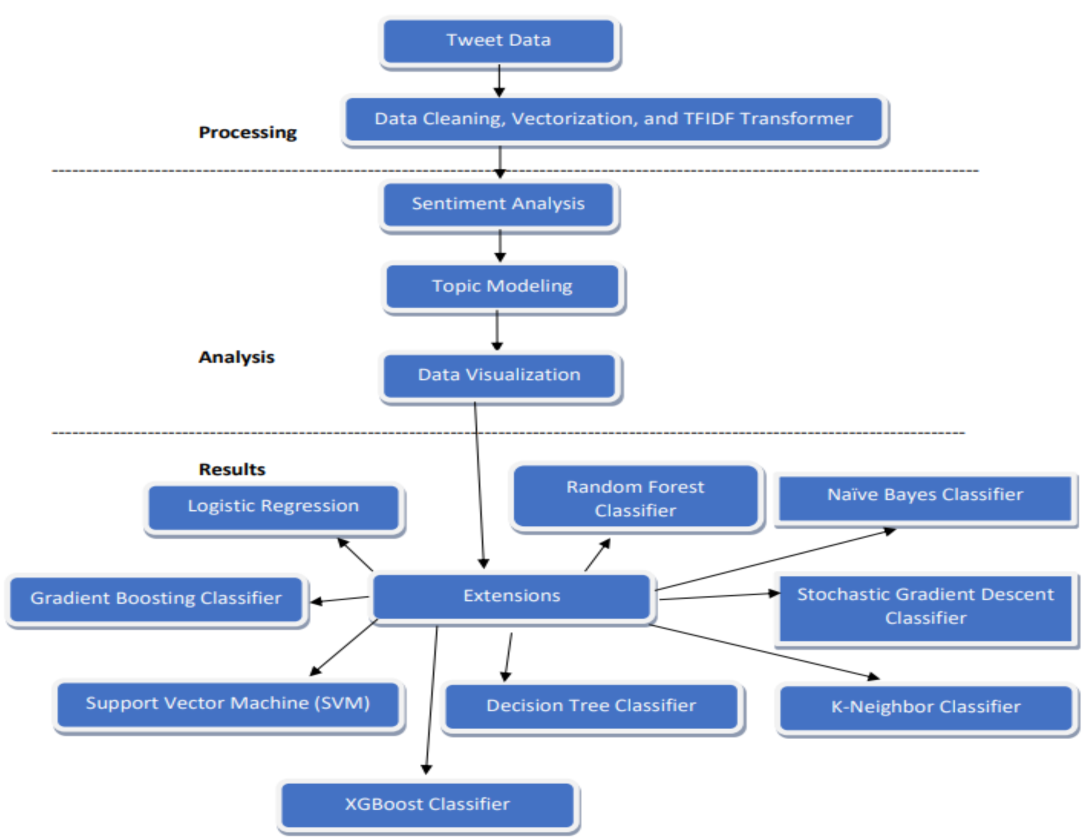
For dataset connection to connect to Google drive:(https://github.com/kasamdh/CourseProject/blob/main/stock_data.csv). Download the **stock_data.csv** from GitHub and upload data set to the Google Drive. Copy the file path from the Google Drive and replace it to **DATA+DIR = mypath + “ ”** in the **Initilized relevant data URI’s** section in Google Collab.

## Initialize relevant data URIs

```
DATA_DIR = mypath + "CS410Project/Datasets/"

STOCK_DATA_CSV_ZIP = "stock_data.csv"
```

**Process flow diagram:**



**Processing:**

**Data Collection:** Tweet data from https://www.kaggle.com/datasets/utkarshxy/stockmarkettweets-lexicon-data for Sentiment Analysis.

### Import required dependencies required for data exploration and data cleaning

In [ ]:

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

### Read CSV data and print first 5 records

In [ ]:

```
data=pd.read_csv(DATA_DIR + STOCK_DATA_CSV_ZIP)
data.head()
```

Out[ ]:

| | Text | Sentiment |
|---|---|---|
| 0 | Kickers on my watchlist XIDE TIT SOQ PNK CPW B... | 1 |
| 1 | user: AAP MOVIE. 55% return for the FEA/GEED i... | 1 |
| 2 | user I'd be afraid to short AMZN - they are lo... | 1 |
| 3 | MNTA Over 12.00 | 1 |
| 4 | OI Over 21.37 | 1 |

### Print the metadata about the data.

In [ ]:

```
data.info()
```

```
RangeIndex: 5791 entries, 0 to 5790
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Text       5791 non-null   object
 1   Sentiment  5791 non-null   int64
dtypes: int64(1), object(1)
memory usage: 90.6+ KB
```

In [ ]:

```
data.describe()
```

Out[ ]:

| | Sentiment |
|---|---|
| count | 5791.000000 |
| mean | 0.272664 |
| std | 0.962192 |
| min | -1.000000 |
| 25% | -1.000000 |
| 50% | 1.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

**Data Cleaning:** Import Stopwords corpus for cleaning the tweets, split data into train, test.

**Vectorization:** There are set of techniques use for extracting meaningful information from text corpus. Which is word vectorization. A word in a vector in the text corpus.

**TF-IDF Transformer:** The vectorization method widely used in text mining to reflect the importance of a term to a document in the corpus.

## Approach

### Data cleaning, vectorization and transformation

Split data into train, test

In [ ]:
```
x_train,x_test,y_train,y_test=train_test_split(data['Text'],data['Sentiment'],test_size=0.3,random_state=101)
```

Count vectorization

In [ ]:
```
cv = CountVectorizer(analyzer=clean)
```

In [ ]:
```
words = cv.fit(x_train)
```

In [ ]:
```
tweets=words.transform(x_train)
print(tweets.shape)
```

```
(4053, 10730)
```

### TFIDF transformer

Perform TFIDF transformation on the vectorized data.

In [ ]:
```
tf=TfidfTransformer()
tf.fit(tweets)
```

Out[ ]:
```
TfidfTransformer()
```

In [ ]:
```
final_transform=tf.transform(tweets)
```

**Analysis**

**Sentiment Analysis and Data Visualization**

Labeled data corpus for Sentiment Analysis *SentimentIntensityAnalyzer*: library for classifying of *sentimentsResults* exported in text files

Outputs: Probability of positive and negative. Compound values in a range of -1 to 1, where -1 represents negative for each tweet. The compound value is comparable to a single measure of polarity.

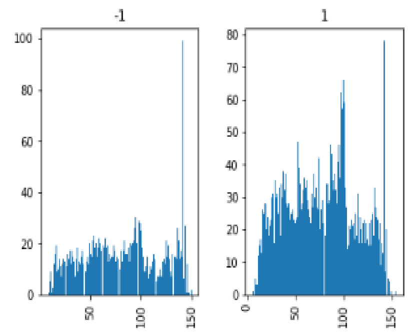
### Data binning by sentiments (Positive/Negative)

In [ ]:

```
plt.figure(figsize=(12,5))
data.hist(column='Length',by='Sentiment',bins=150)
```

Out[ ]:

```
array([,
       ],
      dtype=object)
```




#### Print data distribution between both the categories. Positive and Negative

In [ ]:

```
data['Sentiment'].value_counts()
```

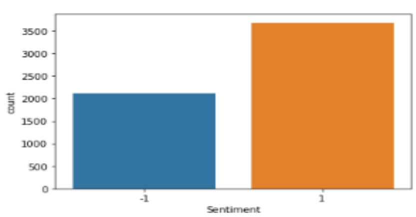
Out[ ]:

```
 1    3685
-1    2106
Name: Sentiment, dtype: int64
```

In [ ]:

```
sns.countplot(x=data['Sentiment'])
```

Out[ ]:




#### Print and describe data distribution based on each category

In [ ]:

```
data.groupby('Sentiment').describe()
```

Out[ ]:

| | Text | | | |
|---|---|---|---|---|
| | count | unique | top | freq |
| Sentiment | | | | |
| -1 | 2106 | 2106 | AAP - user if so then the current downtrend wi... | 1 |
| 1 | 3685 | 3685 | Kickers on my watchlist XIDE TIT SOQ PNK CPW B... | 1 |

## Results

## Logistic Regression:

Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. The nature of target or dependent variable is dichotomous, which means there would be only two possible classes. In simple words, the dependent variable is binary in nature having data coded as either 1 (stands for success/yes) or 0 (stands for failure/no). Logistic regression model predicts P(Y=1) as a function of X.

Build model

```
In [ ]:
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression()
modelfitting = classifier.fit(final_transform, y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("##################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("##################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.42      0.77      0.54       342
           1       0.93      0.73      0.82      1396

    accuracy                           0.74      1738
   macro avg       0.67      0.75      0.68      1738
weighted avg       0.83      0.74      0.77      1738

##################################################
############# Confusion Matrix ##############
[[ 264   78]
 [ 371 1025]]
##################################################
```

**Support Vector Machine:**

Support Vector Machine: An SVM model is basically a representation of different classes in a hyperplane in multidimensional space. The hyperplane will be generated in an iterative manner by SVM so that the error can be minimized. The goal of SVM is to divide the datasets into classes to find a maximum marginal hyperplane (MMH).

The followings are important concepts in SVM −

1. Support Vectors − Datapoints that are closest to the hyperplane is called support vectors. Separating line will be defined with the help of these data points.

2. Hyperplane − As we can see in the above diagram, it is a decision plane or space which is divided between a set of objects having different classes.

3. Margin − It may be defined as the gap between two lines on the closet data points of different classes. It can be calculated as the perpendicular distance from the line to the support vectors. Large margin is considered as a good margin and small margin is considered as a bad margin

Build model

In [ ]:
```
from sklearn.svm import SVC
classifier = SVC()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

In [ ]:
```
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("#####################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("#####################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.42      0.82      0.56       326
           1       0.95      0.74      0.83      1412

    accuracy                           0.75      1738
   macro avg       0.68      0.78      0.69      1738
weighted avg       0.85      0.75      0.78      1738

##################################################
############# Confusion Matrix ##############
[[ 267   59]
 [ 368 1044]]
##################################################
```

## Naive Bayes Classifier

Naïve Bayes algorithms is a classification technique based on applying Bayes' theorem with a strong assumption that all the predictors are independent to each other. In simple words, the assumption is that the presence of a feature in a class is independent to the presence of any other feature in the same class. In Bayesian classification, the main interest is to find the posterior probabilities

Build model

```
In [ ]:
from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("###################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("###################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.27      0.85      0.41       205
           1       0.97      0.70      0.81      1533

    accuracy                           0.72      1738
   macro avg       0.62      0.77      0.61      1738
weighted avg       0.89      0.72      0.77      1738

###################################################
############# Confusion Matrix ##############
[[ 174   31]
 [ 461 1072]]
###################################################
```

## Stochastic Gradient Descent Classifier:

This estimator implements regularized linear models with stochastic gradient descent (SGD) learning: the gradient of the loss is estimated each sample at a time and the model is updated along the way with a decreasing strength schedule (aka learning rate)

Build model

```
In [ ]:
from sklearn.linear_model import SGDClassifier
classifier = SGDClassifier()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("##################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("##################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.61      0.68      0.65       567
           1       0.84      0.79      0.81      1171

    accuracy                           0.75      1738
   macro avg       0.72      0.74      0.73      1738
weighted avg       0.76      0.75      0.76      1738

##################################################
############# Confusion Matrix ##############
[[388 179]
 [247 924]]
##################################################
```

## K Nearest Neighbors Classifier:

The k-nearest neighbors' algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

Build model

```
In [ ]:
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("##################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("##################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.51      0.67      0.58       483
           1       0.86      0.75      0.80      1255

    accuracy                           0.73      1738
   macro avg       0.69      0.71      0.69      1738
weighted avg       0.76      0.73      0.74      1738

##################################################
############# Confusion Matrix ##############
[[326 157]
 [309 946]]
##################################################
```

## Random Forest Classifier:

Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we know that a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

Build model

```
In [ ]:
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("###################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("###################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.53      0.72      0.61       470
           1       0.88      0.77      0.82      1268

    accuracy                           0.75      1738
   macro avg       0.71      0.74      0.72      1738
weighted avg       0.79      0.75      0.76      1738

###################################################
############# Confusion Matrix ##############
[[339 131]
 [296 972]]
###################################################
```

**Gradient Boosting Classifier:**

This algorithm builds an additive model in a forward stage-wise fashion; it allows for the optimization of arbitrary differentiable loss functions. In each stage n_classes_ regression trees are fit on the negative gradient of the loss function, e.g. binary or multiclass log loss. Binary classification is a special case where only a single regression tree is induced.

Build model

```
In [ ]:
from sklearn.ensemble import GradientBoostingClassifier
classifier = GradientBoostingClassifier()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

```
In [ ]:
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("###################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("###################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report #############
              precision    recall  f1-score   support

          -1       0.33      0.76      0.46       276
           1       0.94      0.71      0.81      1462

    accuracy                           0.72      1738
   macro avg       0.64      0.74      0.63      1738
weighted avg       0.84      0.72      0.75      1738

###################################################
############# Confusion Matrix #############
[[ 210   66]
 [ 425 1037]]
###################################################
```

## XGBoost Classifier:

XGBoost, which stands for Extreme Gradient Boosting, is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems.

### XGBoost Classifier

XGBoost, which stands for Extreme Gradient Boosting, is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems.

Build model

In [ ]:
```
from xgboost.sklearn import XGBClassifier
classifier = XGBClassifier()
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction

In [ ]:
```
# Predictions

# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)

print ("############# Classification Report ##############")
print(classification_report(y_predict,y_test))
print ("##################################################")

print ("############# Confusion Matrix ##############")
print(confusion_matrix(y_predict,y_test))
print ("##################################################")
```

```
(1738, 10730)
(1738, 10730)
(1738,)
############# Classification Report ##############
              precision    recall  f1-score   support

          -1       0.38      0.72      0.50       333
           1       0.92      0.72      0.81      1405

    accuracy                           0.72      1738
   macro avg       0.65      0.72      0.65      1738
weighted avg       0.81      0.72      0.75      1738

##################################################
############# Confusion Matrix ##############
[[ 241   92]
 [ 394 1011]]
##################################################
```

**Classifier testing:** Classifier on input. Multinomial Naive Bayes Classifier

In [ ]:
```
# from sklearn.linear_model import LogisticRegression
# classifier = LogisticRegression()

# from sklearn.tree import DecisionTreeClassifier
# classifier = DecisionTreeClassifier()

# from sklearn.svm import SVC
# classifier = SVC()

# from sklearn.naive_bayes import MultinomialNB
# classifier = MultinomialNB()

# from sklearn.linear_model import SGDClassifier
# classifier = SGDClassifier()

# from sklearn.neighbors import KNeighborsClassifier
# classifier = KNeighborsClassifier()

# from sklearn.ensemble import RandomForestClassifier
# classifier = RandomForestClassifier()

# from sklearn.ensemble import GradientBoostingClassifier
# classifier = GradientBoostingClassifier()

from xgboost.sklearn import XGBClassifier
classifier = XGBClassifier()
```

In [ ]:
```
modelfitting=classifier.fit(final_transform,y_train)
```

Prediction on Test data

In [ ]:
```
# Count Vectorization of X_test
tweets_test = words.transform(x_test)
print(tweets_test.shape)

# TFIDF Vectorization
final_transform_test = tf.transform(tweets_test)
print(final_transform_test.shape)

# Classifier predict
y_predict = modelfitting.predict(final_transform_test)
print(y_predict.shape)
```

```
(1738, 10730)
(1738, 10730)
(1738,)
```

In [ ]:
```
# print(classification_report(y_predict,y_test))
```

```
              precision    recall  f1-score   support

          -1       0.38      0.72      0.50       333
           1       0.92      0.72      0.81      1405

    accuracy                           0.72      1738
   macro avg       0.65      0.72      0.65      1738
weighted avg       0.81      0.72      0.75      1738
```

In [ ]:
```
# print(confusion_matrix(y_predict,y_test))
```

```
[[379 252]
 [256 851]]
```

In [ ]:
```
# print(accuracy_score(y_predict,y_test))
```

```
0.716915995397008
```