2024

TWITTER SENTIMENT ANALYSIS

Data Analyst Project: Twitter Sentiment Analysis

Project Title: Twitter Sentiment Analysis

Dataset: (https://www.kaggle.com/datasets/kazanova/sentiment140)

Project Overview:

Twitter Sentiment Analysis is a data analytics project that involves analyzing a dataset of tweets to determine the sentiment expressed in each tweet—whether it is positive, negative, or neutral. The project aims to gain insights into public opinions, trends, and sentiments shared on Twitter, utilizing data analytics techniques.

Project Objectives:

1. Data Exploration: - Explore the Sentiment dataset to understand its structure, features, and size. - Identify key variables such as tweet content, timestamp, and sentiment labels.

2. Data Cleaning: - Perform data cleaning tasks to handle missing values, duplicate entries, and irrelevant information. - Ensure data quality by addressing any anomalies or inconsistencies in the dataset.

3. Exploratory Data Analysis (EDA): - Conduct exploratory data analysis to gain initial insights into tweet patterns, sentiment distributions, and temporal trends. - Utilize visualizations (e.g., histograms, word clouds) to represent key aspects of the dataset.

4. Sentiment Distribution: - Visualize the distribution of sentiment labels (positive, negative, neutral) in the dataset. - Analyze the balance of sentiment classes to understand potential biases. INTERN PROJECT PHASE - 2

5. Word Frequency Analysis: - Analyze the frequency of words in tweets to identify common terms and themes. - Create word clouds or bar charts to visualize the most frequent words in positive and negative sentiments.

6. Temporal Analysis: - Explore how sentiment varies over time by analyzing tweet timestamps. - Identify patterns, peaks, or trends in sentiment within specific time frames.

7. Text Preprocessing: - Preprocess tweet text by removing stop words, special characters, and URLs. - Tokenize and lemmatize words to prepare the text for sentiment analysis.

8. Sentiment Prediction Model: - Implement a sentiment prediction model using machine learning or natural language processing techniques. - Train the model on a subset of the dataset and evaluate its performance using metrics like accuracy and F1 score.

9. Feature Importance: - Identify the most important features (words or phrases) contributing to sentiment predictions. - Visualize feature importance using techniques such as bar charts or word clouds.

10. User Interface (Optional): - Develop a simple user interface allowing users to input custom text for sentiment analysis. - Showcase the sentiment prediction results in a user-friendly manner.

11. Documentation: - Create comprehensive documentation covering data preprocessing steps, model implementation, and analysis findings. - Include code snippets, visualizations, and explanations to aid understanding.

12. Insights and Recommendations: - Summarize key insights gained from the analysis. - Provide recommendations or suggestions based on the sentiment trends observed.

Twitter Sentiment Analysis Using Python

A Twitter sentiment analysis determines negative, positive, or neutral emotions within the text of a tweet using NLP and ML models. Sentiment analysis or opinion mining refers to identifying as well as classifying the sentiments that are expressed in the text source.

Tweets are often useful in generating a vast amount of sentiment data upon analysis. These data are useful in understanding the opinion of people on social media for a variety of topics.

Twitter sentiment analysis analyzes the sentiment or emotion of tweets. It uses natural language processing and machine learning algorithms to classify tweets automatically as positive, negative, or neutral based on their content. It can be done for individual tweets or a larger dataset related to a particular topic or event.

Introduction & Techniques

A Twitter sentiment analysis determines negative, positive, or neutral emotions within the text of a tweet using NLP and ML models. Sentiment analysis or opinion mining refers to identifying as well as classifying the sentiments that are expressed in the text source. Tweets are often useful in generating a vast amount of sentiment data upon analysis. These data are useful in understanding the opinion of people on social media for a variety of topics

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- ✔ **Importance of Twitter Sentiment Analysis**

- ❖ **Understanding Customer Feedback**: By analyzing the sentiment of customer feedback, companies can identify areas where they need to improve their products or services.
- ❖ **Reputation Management**: Sentiment analysis can help companies monitor their brand reputation online and quickly respond to negative comments or reviews.
- ❖ **Political Analysis**: Sentiment analysis can help political campaigns understand public opinion and tailor their messaging accordingly.
- ❖ **Crisis Management**: In the event of a crisis, sentiment analysis can help organizations monitor social media and news outlets for negative sentiment and respond appropriately.
- ❖ **Marketing Research**: Sentiment analysis can help marketers understand consumer behavior and preferences, and develop targeted advertising campaigns.

Twitter sentiment analysis using machine learning algorithms, the sentiment of tweets provided from the Sentiment140 dataset by developing a machine learning pipeline involving the use of three classifiers (Logistic Regression, Bernoulli Naive Bayes, and SVM)along with using Term Frequency- Inverse Document Frequency (TF-IDF). The performance of these classifiers is then evaluated using accuracy and F1 Scores.

For data preprocessing, we will be using Natural Language Processing's (NLP) NLTK library.In this project, we try to implement an NLP Twitter sentiment analysis model that helps to overcome the challenges of sentiment classification of tweets. We will be classifying the tweets into positive or negative sentiments. The necessary details regarding the dataset involving the Twitter sentiment analysis project are:

Twitter Sentiment Analysis: Problem Statement

In this project, we try to implement an NLP Twitter sentiment analysis model that helps to overcome the challenges of sentiment classification of tweets. We will be classifying the tweets into positive or negative sentiments. The necessary details regarding the dataset involving the Twitter sentiment analysis project are:

The dataset provided is the Sentiment140 Dataset which consists of 1,600,000 tweets that have been extracted using the Twitter API. The various columns present in this Twitter data are:

- ✓ **Target:** the polarity of the tweet (positive or negative)
- ✓ **Ids:** Unique id of the tweet
- ✓ **Date:** the date of the tweet
- ✓ **Flag:** It refers to the query. If no such query exists, then it is NO QUERY.
- ✓ **User:** It refers to the name of the user that tweeted
- ✓ **Text:** It refers to the text of the tweet
- ✓ **Twitter Sentiment Analysis:** Project Pipeline

The various steps involved in the Machine Learning Pipeline are:

- ✓ Import Necessary Dependencies
- ✓ Read and Load the Dataset
- ✓ Exploratory Data Analysis
- ✓ Data Visualization of Target Variables
- ✓ Data Preprocessing
- ✓ Splitting our data into Train and Test sets.
- ✓ Transforming Dataset using TF-IDF Vectorizer
- ✓ Function for Model Evaluation
- ✓ Model Building
- ✓ Model Evaluation

Source code :

```
# utilities
import re
import numpy as np
import pandas as pd
# plotting
import seaborn as sns
#from wordcloud import WordCloud
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
# nltk
from nltk.stem import WordNetLemmatizer
# sklearn
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import BernoulliNB
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import confusion_matrix, classification_report
import tweepy
from tweepy import OAuthHandler
from textblob import TextBlob
import matplotlib.pyplot as plt
from wordcloud import WordCloud
# Importing the dataset
DATASET_COLUMNS=['Target','Id','Date','Flag','User','Tweets']
DATASET_ENCODING = "ISO-8859-1"
df = pd.read_csv('twittersentiment.csv', encoding=DATASET_ENCODING, names=DATASET_COLUMNS)
```

```
df.sample(3)
df.head()
df.columns
print('Length of data is', len(df))
df. Shape
df.info()
df.describe()
df.dtypes
np.sum(df.isnull().any(axis=1))
print('Count of columns in the data is:  ', len(df.columns))
print('Count of rows in the data is:  ', len(df))
df['Target'].unique()
df['Target'].nunique()
def cleantext(text):
    text = re.sub('@[\w]+',",text)
    text = re.sub('#',  " ,text)
    text = re.sub('RT[\s]+',",text)
    text = re.sub('https? :\/\/\s+',",text)
    return text
df['CleanTweets'] = df['Tweets'].apply(cleantext)
df.head()
from textblob import TextBlob
def getSubjectivity(text):
    return TextBlob(text).sentiment.subjectivity
df['Subjectivity'] = df['CleanTweets'].apply(getSubjectivity)
def getPolarity(text):
    return TextBlob(text).sentiment.polarity
df['Polarity'] = df['CleanTweets'].apply(getPolarity)
df.drop('Tweets',  axis=1).head()
df.sample(15)
df['Target'] = df['Target'].replace(4 , 1)
```

```
df
def getAnalysis(score):
    label=""
    if(score < 0):
        label = 'Negative'
    elif(score == 0):
        label = 'Neutral'
    else:
        label = "Positive"
    return(label)
df['Analysis'] = df['Polarity'].apply(getAnalysis)
df
data=df[['Target','User','Tweets','CleanTweets','Polarity','Analysis']]
data_pos = data[df['Analysis'] == 'Positive']
data_neg = data[df['Analysis'] == 'Negative']
data_neutral = data[df['Analysis'] == 'Neutral']
data
dataset = pd.concat([data_pos, data_neg, data_neutral])
dataset
data_pos = data_pos.iloc[:int(20000)]
data_neg = data_neg.iloc[:int(20000)]
data_neutral = data_neutral.iloc[:int(20000)]
dataset['CleanTweets']=dataset['CleanTweets'].str.lower()
dataset['CleanTweets'].tail()
stopwordlist = ['a', 'about', 'above', 'after', 'again', 'ain', 'all', 'am', 'an',
             'and','any','are', 'as', 'at', 'be', 'because', 'been', 'before',
             'being', 'below', 'between','both', 'by', 'can', 'd', 'did', 'do',
             'does', 'doing', 'down', 'during', 'each','few', 'for', 'from',
             'further', 'had', 'has', 'have', 'having', 'he', 'her', 'here',
             'hers', 'herself', 'him', 'himself', 'his', 'how', 'i', 'if', 'in',
             'into','is', 'it', 'its', 'itself', 'just', 'll', 'm', 'ma',
             'me', 'more', 'most','my', 'myself', 'now', 'o', 'of', 'on', 'once',

             'only', 'or', 'other', 'our', 'ours','ourselves', 'out', 'own', 're','s', 'same', 'she', "shes", 'should',
"shouldve",'so', 'some', 'such',

             't', 'than', 'that', "thatll", 'the', 'their', 'theirs', 'them',

             'themselves', 'then', 'there', 'these', 'they', 'this', 'those',

             'through', 'to', 'too','under', 'until', 'up', 've', 'very', 'was',

             'we', 'were', 'what', 'when', 'where','which','while', 'who', 'whom',

             'why', 'will', 'with', 'won', 'y', 'you', "youd","youll", "youre",

             "youve", 'your', 'yours', 'yourself', 'yourselves']

STOPWORDS = set(stopwordlist)

def cleaning_stopwords(text):

    return " ".join([word for word in str(text).split() if word not in STOPWORDS])

dataset['CleanTweets'] = dataset['CleanTweets'].apply(lambda text: cleaning_stopwords(text))

dataset['CleanTweets'].head()

import string

english_punctuations = string.punctuation

punctuations_list = english_punctuations

def cleaning_punctuations(text):

    translator = str.maketrans(", ", punctuations_list)

    return text.translate(translator)

dataset['CleanTweets']= dataset['CleanTweets'].apply(lambda x: cleaning_punctuations(x))

dataset['CleanTweets'].tail()

def cleaning_repeating_char(text):

    return re.sub(r'(.)1+', r'1', text)

dataset['CleanTweets'] = dataset['CleanTweets'].apply(lambda x: cleaning_repeating_char(x))

dataset['CleanTweets'].tail()

def cleaning_URLs(data):

    return re.sub('((www.[^s]+)|(https? ://[^s]+))',' ',data)

dataset['CleanTweets'] = dataset['CleanTweets'].apply(lambda x: cleaning_URLs(x))

dataset['CleanTweets'].tail()

def cleaning_numbers(data):
    return re.sub('[0-9]+', '', data)
dataset['CleanTweets'] = dataset['CleanTweets'].apply(lambda x: cleaning_numbers(x))
dataset['CleanTweets'].tail()
fig = plt.figure(figsize=(5,5))
sns.countplot(x='Analysis',data=df,hue='Analysis')
fig = plt.figure(figsize=(7,7))
colors=("yellowgreen", "gold","red")
wp={'linewidth':2, 'edgecolor':'black'}
tags=df['Analysis'].value_counts()
explode =(0.1,0.1,0.1)
tags.plot(kind='pie',autopct='%1.1f%%',shadow=True, colors= colors,
        startangle = 90, wedgeprops= wp, explode = explode, label = '' )
plt.title("DISTRIBUTION OF ANALYSIS")
```

Positive , Neutral and Negative Tweets wordcloud

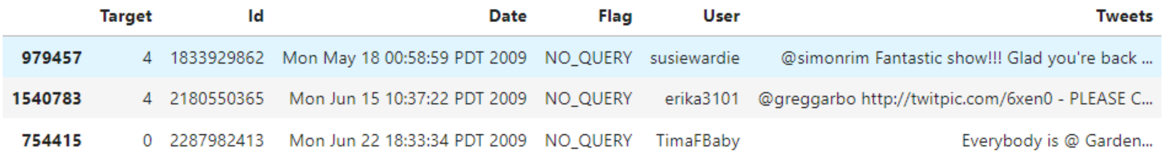
```
postweet = df[df.Analysis == 'Positive']
postweet = postweet.sort_values(['Polarity'],ascending = False)
postweet.head(3)
text = ''.join([word for word in postweet['Tweets']])
plt.figure(figsize=(20,15), facecolor='None')
wordcloud = WordCloud(max_words = 500 , width = 500 , height = 200).generate(text)
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most frequent words in positive tweets", fontsize=20)
plt.show()
negtweet = df[df.Analysis == 'Negative']
negtweet = negtweet.sort_values(['Polarity'],ascending = False)
negtweet.head(3)
text = ''.join([word for word in negtweet['Tweets']])
plt.figure(figsize=(20,15), facecolor='None')
wordcloud = WordCloud(max_words = 500 , width = 500 , height = 200).generate(text)
plt.imshow(wordcloud)
plt.axis("off")

plt.title("Most frequent words in Negative tweets", fontsize=20)

plt.show()

neutraltweet = df[df.Analysis == 'Neutral']

neutraltweet = neutraltweet.sort_values(['Polarity'],ascending = False)

neutraltweet.head(3)

text = ''.join([word for word in neutraltweet['Tweets']])

plt.figure(figsize=(20,15), facecolor='None')

wordcloud = WordCloud(max_words = 500 , width = 500 , height = 200).generate(text)

plt.imshow(wordcloud)

plt.axis("off")

plt.title("Most frequent words in Neutral tweets", fontsize=20)

plt.show()

# Plotting the distribution for dataset.

ax = df.groupby('Target').count().plot(kind='bar', title='Distribution of data',legend=False)

ax.set_xticklabels(['Negative','Positive'], rotation=0)

# Storing data in lists.

text, sentiment = list(df['Tweets']), list(df['Target'])

import seaborn as sns

fig = plt.figure(figsize=(5,5))

sns.countplot(x='Target', data=df, hue='Target')

data['Target'].unique()

import nltk

st = nltk.PorterStemmer()

def stemming_on_text(data):

    text = [st.stem(word) for word in data]

    return data

dataset['CleanTweets']= dataset['CleanTweets'].apply(lambda x: stemming_on_text(x))

dataset['CleanTweets'].head()

lm = nltk.WordNetLemmatizer()

def lemmatizer_on_text(data):
    text = [lm.lemmatize(word) for word in data]
    return data
dataset['CleanTweets'] = dataset['CleanTweets'].apply(lambda x: lemmatizer_on_text(x))
dataset['CleanTweets'].head()
X=data.CleanTweets
Y=data.Target
y
import matplotlib.pyplot as plt
from wordcloud import WordCloud
data_neg = data['Tweets'][:800000]
plt.figure(figsize = (20,20))
wc = WordCloud(max_words = 1000 , width = 500 , height = 200,
              collocations=False).generate(" ".join(data_neg))
plt.imshow(wc)
data_pos = data['Tweets'][800000:]
wc = WordCloud(max_words = 1000 , width = 500 , height = 200,
             collocations=False).generate(" ".join(data_pos))
plt.figure(figsize = (20,20))
plt.title("")
plt.imshow(wc)
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import CountVectorizer
c_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=1000, stop_words='english')
count=c_vectorizer.fit_transform(df['CleanTweets'])
print('success')
count
# Separating the 95% data for training data and 5% for testing data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X , Y, test_size = 0.05, random_state =26105111)
print('finish')
```

```
vectorizer = TfidfVectorizer(ngram_range=(1,2), max_features=500000)

X_train = vectorizer.fit_transform(X_train)

X_test = vectorizer.transform(X_test)

print("yes")

#print(X_train)

print(y_test)

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import f1_score

def model_Evaluate(model):

# Predict values for Test dataset

    y_pred = model.predict(X_test)

    print(classification_report(y_test, y_pred))

    cf_matrix = confusion_matrix(y_test, y_pred)

    categories = ['Negative','Positive']

    group_names = ['True Neg','False Pos', 'False Neg','True Pos']

    group_percentages = ['{0:.2%}'.format(value) for value in cf_matrix.flatten() / np.sum(cf_matrix)]

    labels = [f'{v1}n{v2}' for v1, v2 in zip(group_names,group_percentages)]

    labels = np.asarray(labels).reshape(2,2)

    sns.heatmap(cf_matrix, annot = labels, cmap = 'Blues',fmt = '',

                xticklabels = categories, yticklabels = categories)

    plt.xlabel("Predicted values", fontdict = {'size':14}, labelpad = 10)

    plt.ylabel("Actual values" , fontdict = {'size':14}, labelpad = 10)

    plt.title ("Confusion Matrix", fontdict = {'size':18}, pad = 20)

print("yes")

BNBmodel = BernoulliNB()

BNBmodel.fit(X_train, y_train)

model_Evaluate(BNBmodel)

y_pred1 = BNBmodel.predict(X_test)

from sklearn.svm import LinearSVC

from sklearn.metrics import roc_curve, auc

from sklearn.metrics import roc_curve, auc
```

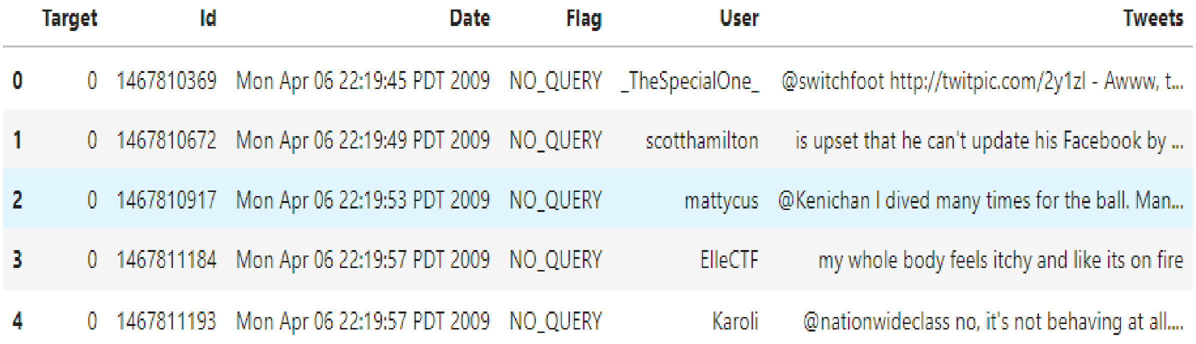
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred1)
roc_auc = auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC CURVE')
#plt.legend(loc="lower right")
plt.show()
SVCmodel = LinearSVC()
SVCmodel.fit(X_train, y_train)
model_Evaluate(SVCmodel)
y_pred2 = SVCmodel.predict(X_test)
from sklearn.metrics import roc_curve, auc
fpr, tpr, thresholds = roc_curve(y_test, y_pred2)
roc_auc = auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC CURVE')
plt.legend(loc="lower right")
plt.show()
LRmodel = LogisticRegression(C = 2, max_iter = 1000, n_jobs=-1)
LRmodel.fit(X_train, y_train)
model_Evaluate(LRmodel)
y_pred3 = LRmodel.predict(X_test)
```

```
from sklearn.metrics import roc_curve, auc

fpr, tpr, thresholds = roc_curve(y_test, y_pred3)

roc_auc = auc(fpr, tpr)

plt.figure()

plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)

plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('ROC CURVE')

plt.legend(loc="lower right")

plt.show()
```

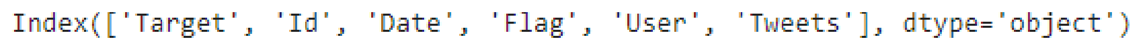
output:



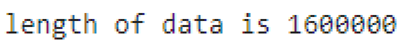
	Target	Id	Date	Flag	User	Tweets
979457	4	1833929862	Mon May 18 00:58:59 PDT 2009	NO_QUERY	susiewardie	@simonrim Fantastic show!!! Glad you're back ...
1540783	4	2180550365	Mon Jun 15 10:37:22 PDT 2009	NO_QUERY	erika3101	@greggarbo http://twitpic.com/6xen0 - PLEASE C...
754415	0	2287982413	Mon Jun 22 18:33:34 PDT 2009	NO_QUERY	TimaFBaby	Everybody is @ Garden...



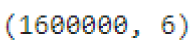
	Target	Id	Date	Flag	User	Tweets
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....



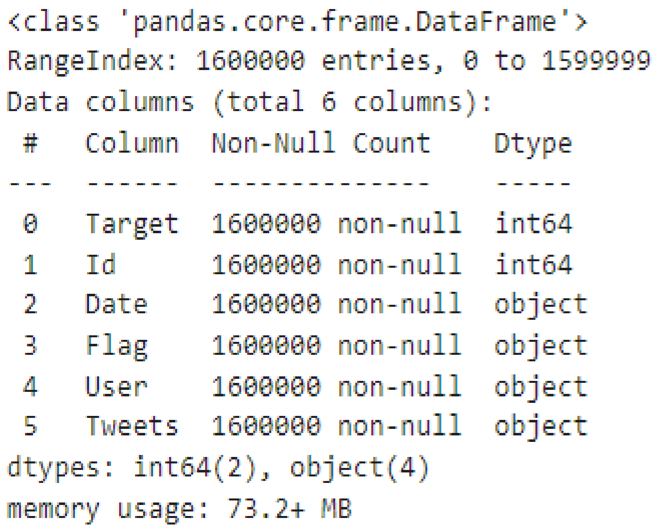
```
Index(['Target', 'Id', 'Date', 'Flag', 'User', 'Tweets'], dtype='object')
```



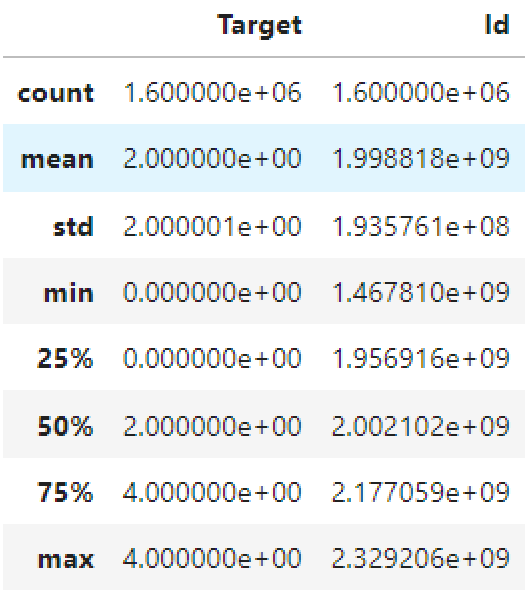
```
length of data is 1600000
```



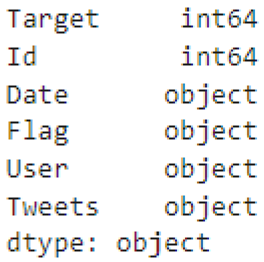
```
(1600000, 6)
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1600000 entries, 0 to 1599999
Data columns (total 6 columns):
 #   Column  Non-Null Count    Dtype 
---  ------  --------------    ----- 
 0   Target  1600000 non-null  int64 
 1   Id      1600000 non-null  int64 
 2   Date    1600000 non-null  object
 3   Flag    1600000 non-null  object
 4   User    1600000 non-null  object
 5   Tweets  1600000 non-null  object
dtypes: int64(2), object(4)
memory usage: 73.2+ MB
```

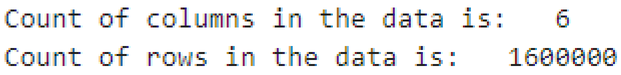


	Target	Id
count	1.600000e+06	1.600000e+06
mean	2.000000e+00	1.998818e+09
std	2.000001e+00	1.935761e+08
min	0.000000e+00	1.467810e+09
25%	0.000000e+00	1.956916e+09
50%	2.000000e+00	2.002102e+09
75%	4.000000e+00	2.177059e+09
max	4.000000e+00	2.329206e+09

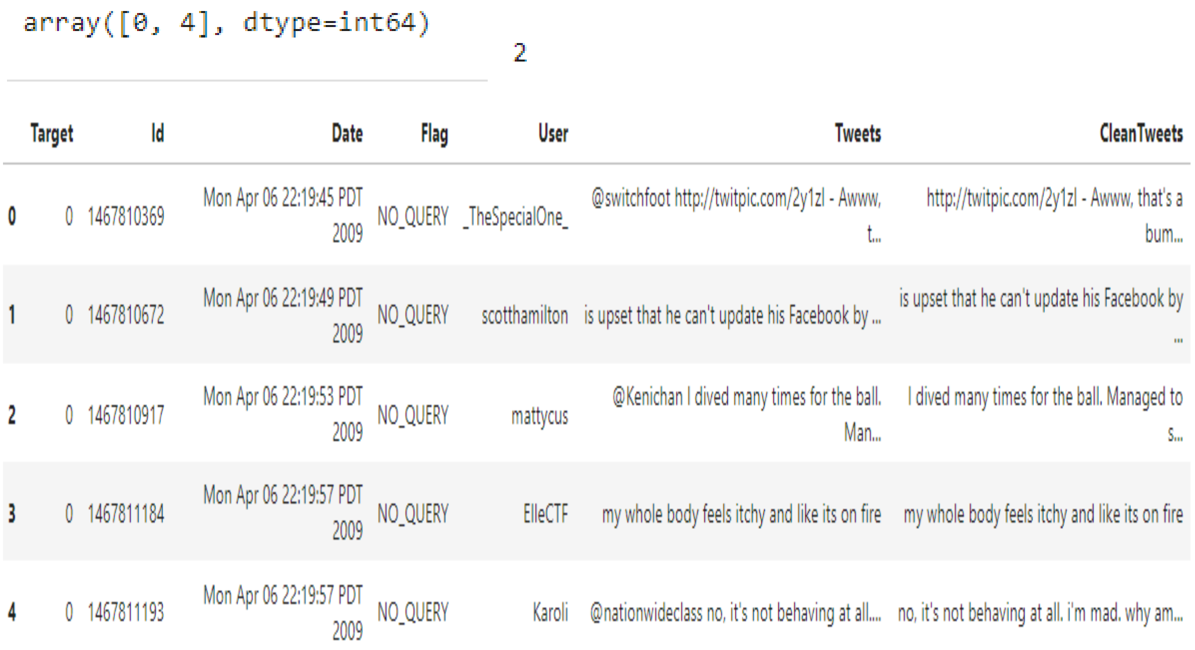


```
Target     int64
Id         int64
Date      object
Flag      object
User      object
Tweets    object
dtype: object
```

```
0
```



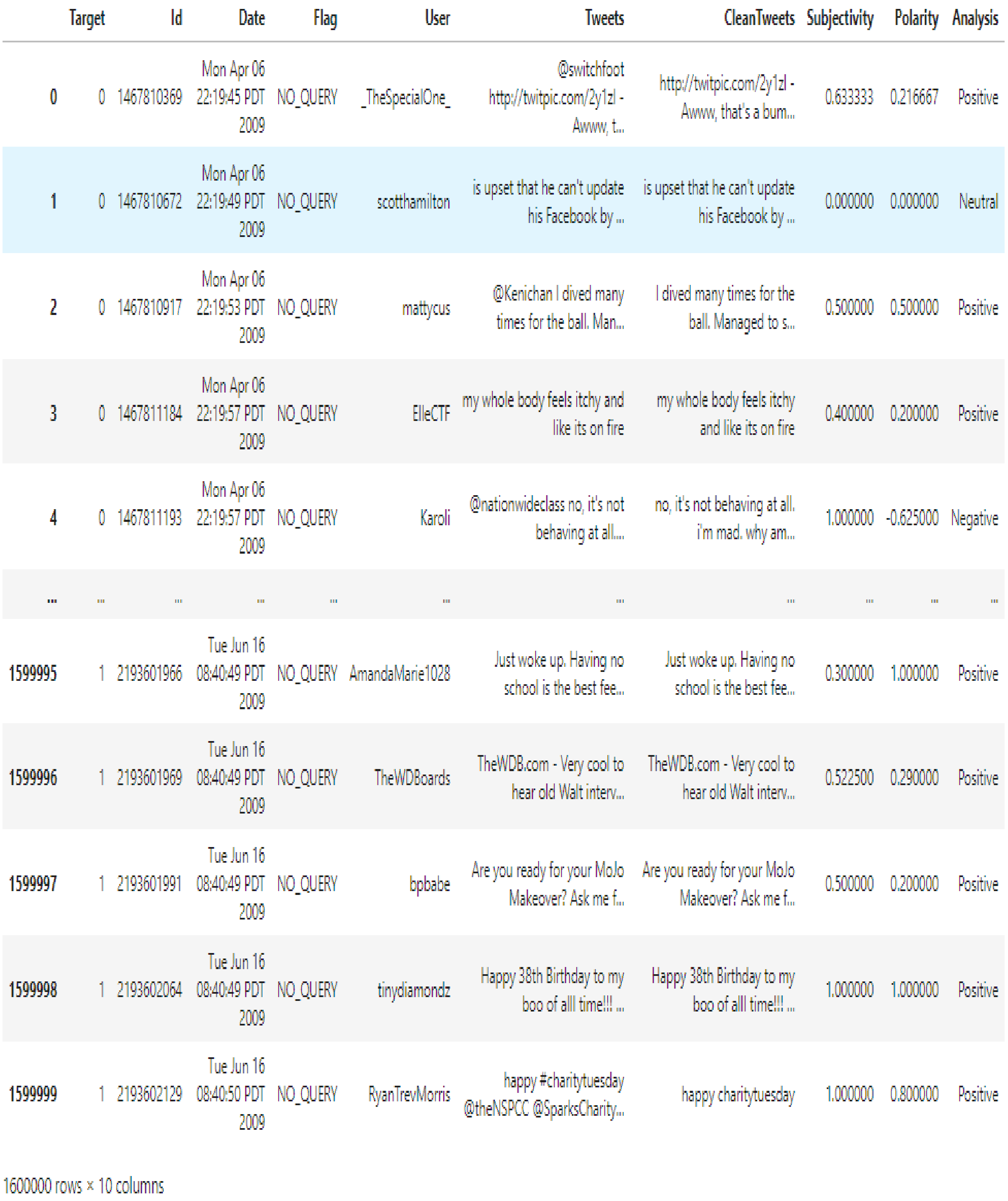
```
Count of columns in the data is:   6
Count of rows in the data is:   1600000
```



```
array([0, 4], dtype=int64)
```

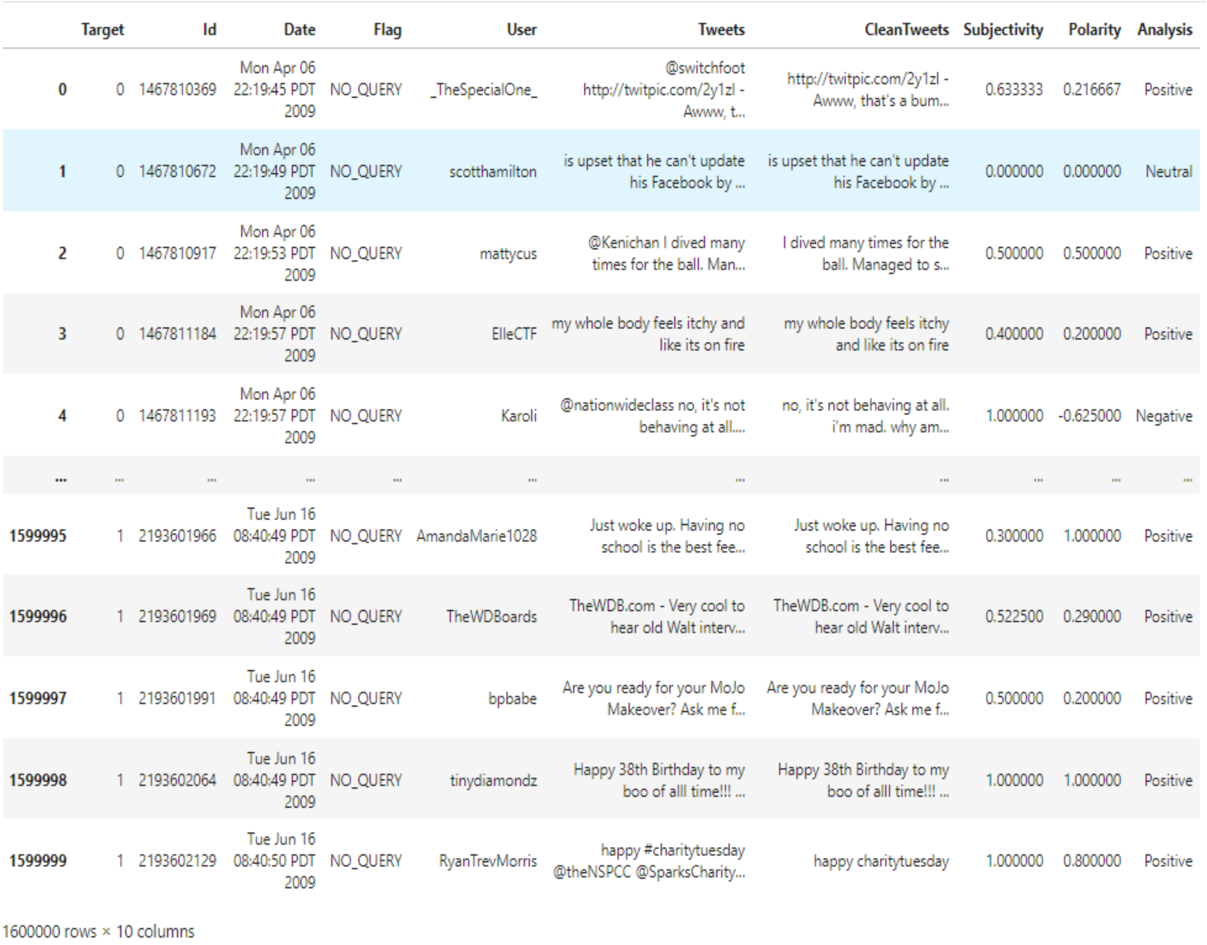
```
2
```

	Target	Id	Date	Flag	User	Tweets	CleanTweets
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	http://twitpic.com/2y1zl - Awww, that's a bum...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...	I dived many times for the ball. Managed to s...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....	no, it's not behaving at all. i'm mad. why am...



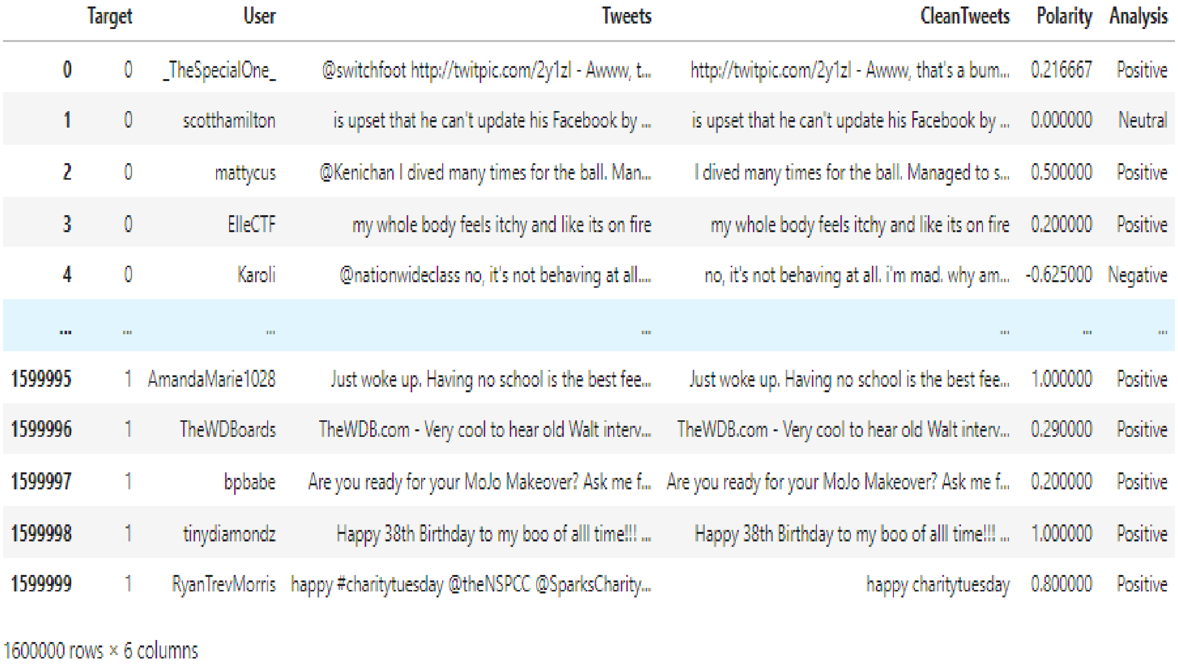
	Target	Id	Date	Flag	User	Tweets	CleanTweets	Subjectivity	Polarity	Analysis
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	http://twitpic.com/2y1zl - Awww, that's a bum...	0.633333	0.216667	Positive
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...	is upset that he can't update his Facebook by ...	0.000000	0.000000	Neutral
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...	I dived many times for the ball. Managed to s...	0.500000	0.500000	Positive
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire	my whole body feels itchy and like its on fire	0.400000	0.200000	Positive
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....	no, it's not behaving at all. i'm mad. why am...	1.000000	-0.625000	Negative
...	...	...	...	...	...	...	...	...	...	...
1599995	1	2193601966	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	AmandaMarie1028	Just woke up. Having no school is the best fee...	Just woke up. Having no school is the best fee...	0.300000	1.000000	Positive
1599996	1	2193601969	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	TheWDBoards	TheWDB.com - Very cool to hear old Walt interv...	TheWDB.com - Very cool to hear old Walt interv...	0.522500	0.290000	Positive
1599997	1	2193601991	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	bpbabe	Are you ready for your MoJo Makeover? Ask me f...	Are you ready for your MoJo Makeover? Ask me f...	0.500000	0.200000	Positive
1599998	1	2193602064	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	tinydiamondz	Happy 38th Birthday to my boo of alll time!!! ...	Happy 38th Birthday to my boo of alll time!!! ...	1.000000	1.000000	Positive
1599999	1	2193602129	Tue Jun 16 08:40:50 PDT 2009	NO_QUERY	RyanTrevMorris	happy #charitytuesday @theNSPCC @SparksCharity...	happy charitytuesday	1.000000	0.800000	Positive

1600000 rows × 10 columns



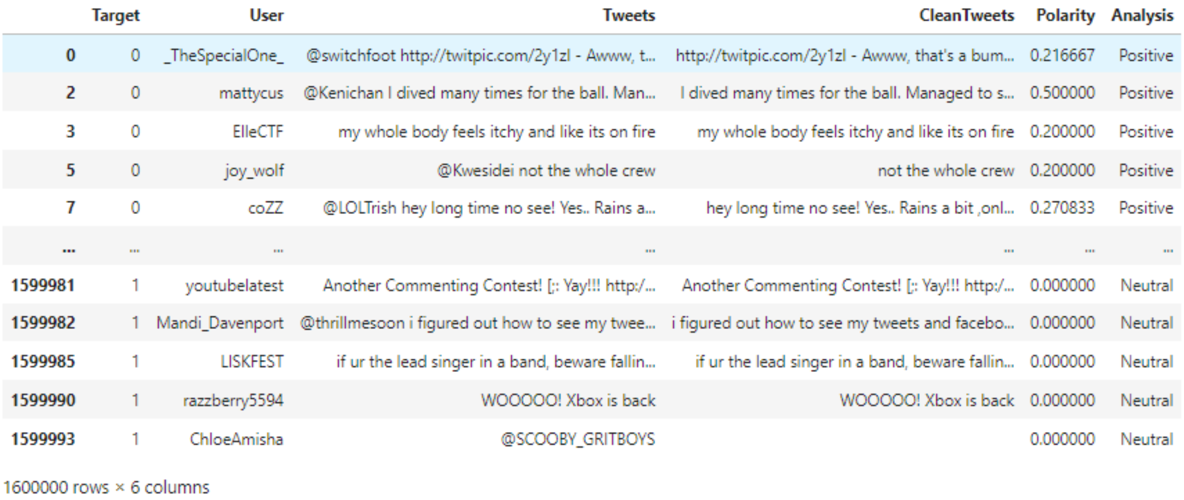
	Target	Id	Date	Flag	User	Tweets	CleanTweets	Subjectivity	Polarity	Analysis
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	http://twitpic.com/2y1zl - Awww, that's a bum...	0.633333	0.216667	Positive
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...	is upset that he can't update his Facebook by ...	0.000000	0.000000	Neutral
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...	I dived many times for the ball. Managed to s...	0.500000	0.500000	Positive
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire	my whole body feels itchy and like its on fire	0.400000	0.200000	Positive
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....	no, it's not behaving at all. i'm mad. why am...	1.000000	-0.625000	Negative
...	...	...	...	...	...	...	...	...	...	...
1599995	1	2193601966	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	AmandaMarie1028	Just woke up. Having no school is the best fee...	Just woke up. Having no school is the best fee...	0.300000	1.000000	Positive
1599996	1	2193601969	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	TheWDBoards	TheWDB.com - Very cool to hear old Walt interv...	TheWDB.com - Very cool to hear old Walt interv...	0.522500	0.290000	Positive
1599997	1	2193601991	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	bpbabe	Are you ready for your MoJo Makeover? Ask me f...	Are you ready for your MoJo Makeover? Ask me f...	0.500000	0.200000	Positive
1599998	1	2193602064	Tue Jun 16 08:40:49 PDT 2009	NO_QUERY	tinydiamondz	Happy 38th Birthday to my boo of alll time!!! ...	Happy 38th Birthday to my boo of alll time!!! ...	1.000000	1.000000	Positive
1599999	1	2193602129	Tue Jun 16 08:40:50 PDT 2009	NO_QUERY	RyanTrevMorris	happy #charitytuesday @theNSPCC @SparksCharity...	happy charitytuesday	1.000000	0.800000	Positive

1600000 rows × 10 columns



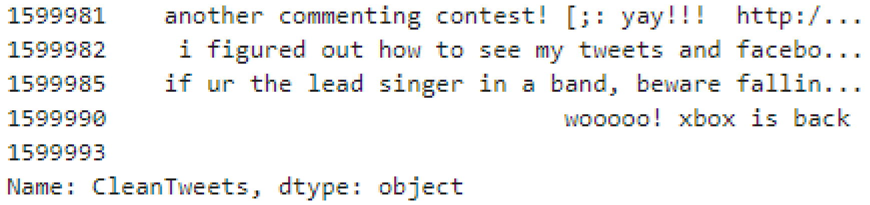
	Target	User	Tweets	CleanTweets	Polarity	Analysis
0	0	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	http://twitpic.com/2y1zl - Awww, that's a bum...	0.216667	Positive
1	0	scotthamilton	is upset that he can't update his Facebook by ...	is upset that he can't update his Facebook by ...	0.000000	Neutral
2	0	mattycus	@Kenichan I dived many times for the ball. Man...	I dived many times for the ball. Managed to s...	0.500000	Positive
3	0	ElleCTF	my whole body feels itchy and like its on fire	my whole body feels itchy and like its on fire	0.200000	Positive
4	0	Karoli	@nationwideclass no, it's not behaving at all....	no, it's not behaving at all. i'm mad. why am...	-0.625000	Negative
...	...	...	...	...	...	...
1599995	1	AmandaMarie1028	Just woke up. Having no school is the best fee...	Just woke up. Having no school is the best fee...	1.000000	Positive
1599996	1	TheWDBoards	TheWDB.com - Very cool to hear old Walt interv...	TheWDB.com - Very cool to hear old Walt interv...	0.290000	Positive
1599997	1	bpbabe	Are you ready for your MoJo Makeover? Ask me f...	Are you ready for your MoJo Makeover? Ask me f...	0.200000	Positive
1599998	1	tinydiamondz	Happy 38th Birthday to my boo of alll time!!! ...	Happy 38th Birthday to my boo of alll time!!! ...	1.000000	Positive
1599999	1	RyanTrevMorris	happy #charitytuesday @theNSPCC @SparksCharity...	happy charitytuesday	0.800000	Positive

1600000 rows × 6 columns

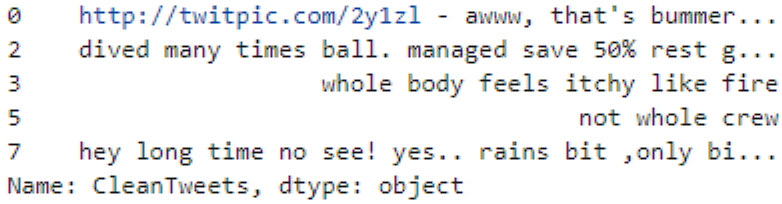


	Target	User	Tweets	CleanTweets	Polarity	Analysis
0	0	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	http://twitpic.com/2y1zl - Awww, that's a bum...	0.216667	Positive
2	0	mattycus	@Kenichan I dived many times for the ball. Man...	I dived many times for the ball. Managed to s...	0.500000	Positive
3	0	ElleCTF	my whole body feels itchy and like its on fire	my whole body feels itchy and like its on fire	0.200000	Positive
5	0	joy_wolf	@Kwesidei not the whole crew	not the whole crew	0.200000	Positive
7	0	coZZ	@LOLTrish hey long time no see! Yes.. Rains a...	hey long time no see! Yes.. Rains a bit ,onl...	0.270833	Positive
...	...	...	...	...	...	...
1599981	1	youtubelatest	Another Commenting Contest! [;: Yay!!! http:/...	Another Commenting Contest! [;: Yay!!! http:/...	0.000000	Neutral
1599982	1	Mandi_Davenport	@thrillmesoon i figured out how to see my twee...	i figured out how to see my tweets and facebo...	0.000000	Neutral
1599985	1	LISKFEST	if ur the lead singer in a band, beware fallin...	if ur the lead singer in a band, beware fallin...	0.000000	Neutral
1599990	1	razzberry5594	WOOOOO! Xbox is back	WOOOOO! Xbox is back	0.000000	Neutral
1599993	1	ChloeAmisha	@SCOOBY_GRITBOYS		0.000000	Neutral

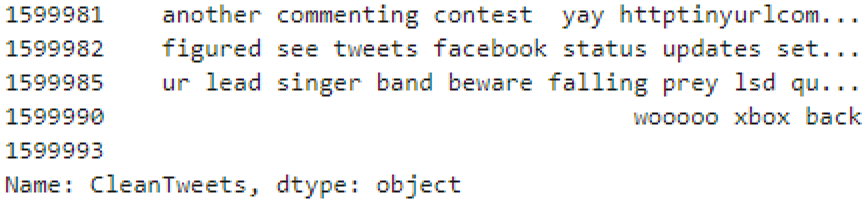
1600000 rows × 6 columns



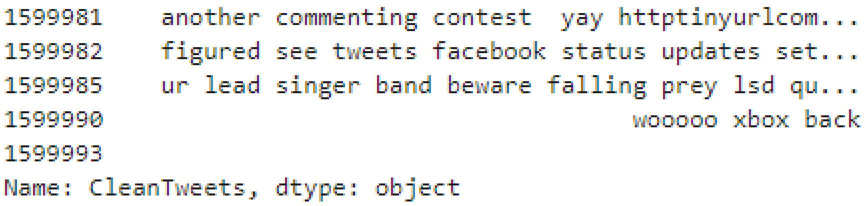
```
1599981    another commenting contest! [;: yay!!!  http:/...
1599982     i figured out how to see my tweets and facebo...
1599985    if ur the lead singer in a band, beware fallin...
1599990                                woooooo! xbox is back
1599993
Name: CleanTweets, dtype: object
```



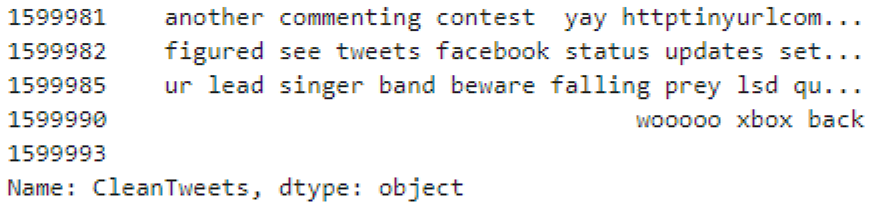
```
0    http://twitpic.com/2y1zl - awww, that's bummer...
2    dived many times ball. managed save 50% rest g...
3                     whole body feels itchy like fire
5                                      not whole crew
7    hey long time no see! yes.. rains bit ,only bi...
Name: CleanTweets, dtype: object
```



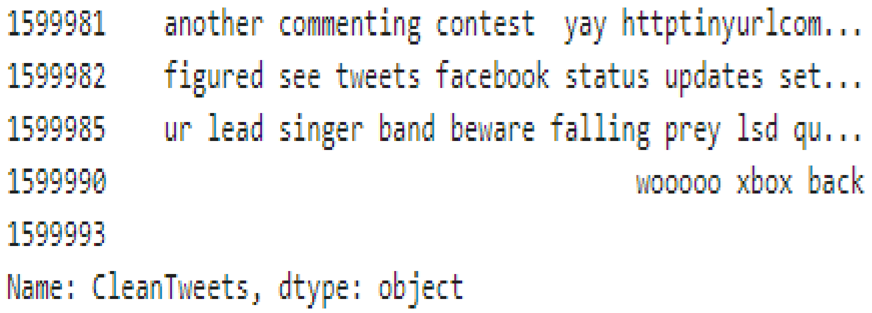
```
1599981    another commenting contest  yay httptinyurlcom...
1599982    figured see tweets facebook status updates set...
1599985    ur lead singer band beware falling prey lsd qu...
1599990                                    wooooo xbox back
1599993
Name: CleanTweets, dtype: object
```



```
1599981    another commenting contest  yay httptinyurlcom...
1599982    figured see tweets facebook status updates set...
1599985    ur lead singer band beware falling prey lsd qu...
1599990                                    wooooo xbox back
1599993
Name: CleanTweets, dtype: object
```

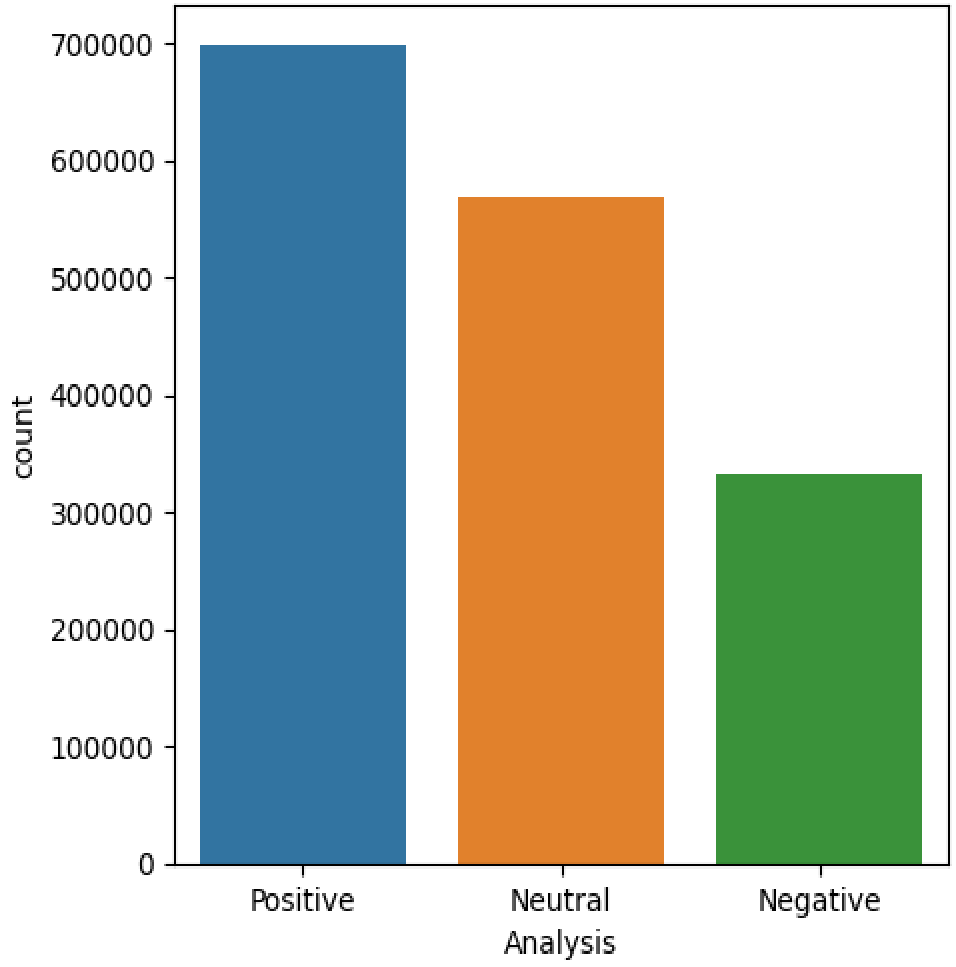


```
1599981    another commenting contest  yay httptinyurlcom...
1599982    figured see tweets facebook status updates set...
1599985    ur lead singer band beware falling prey lsd qu...
1599990                                    wooooo xbox back
1599993
Name: CleanTweets, dtype: object
```

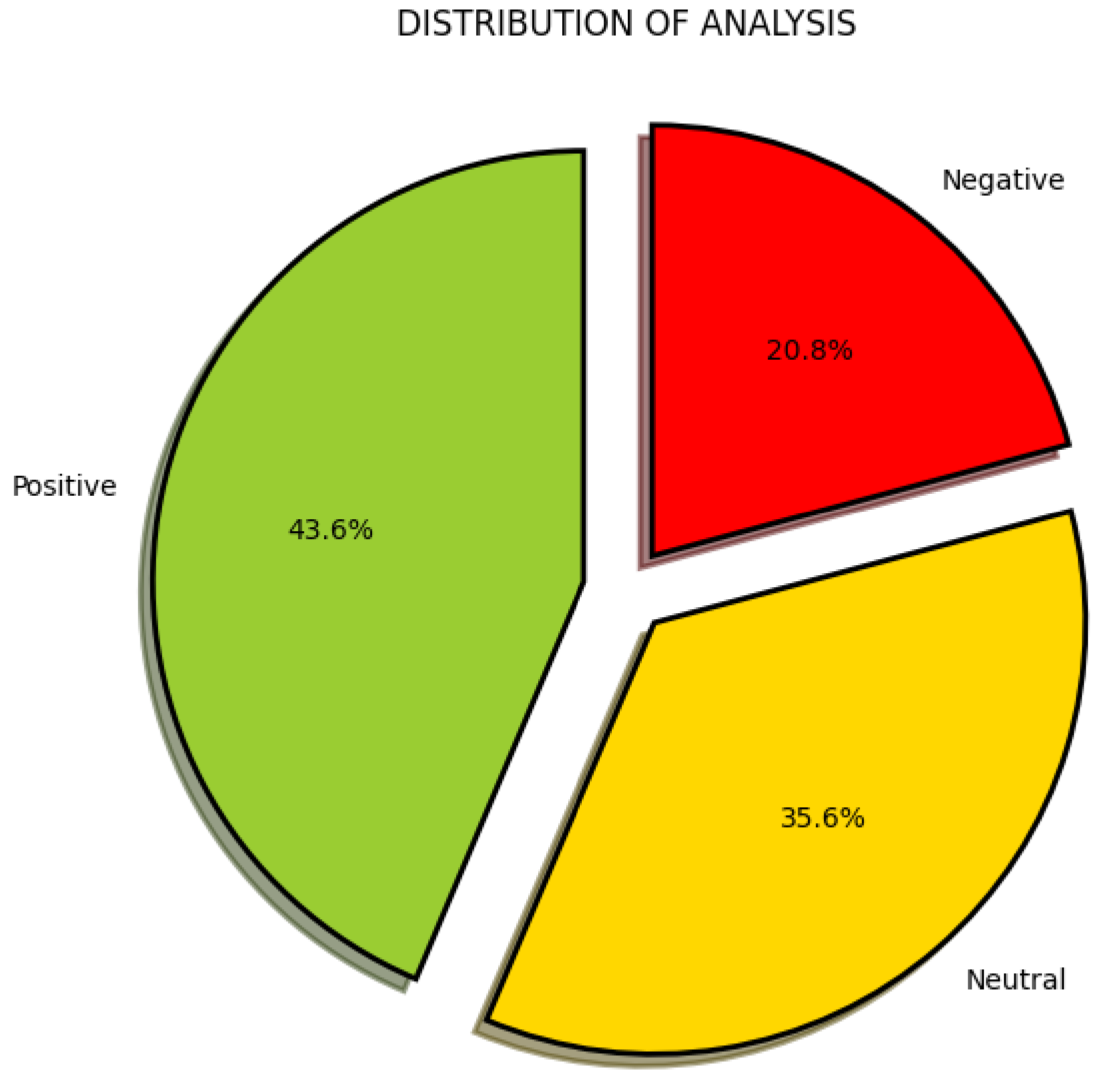


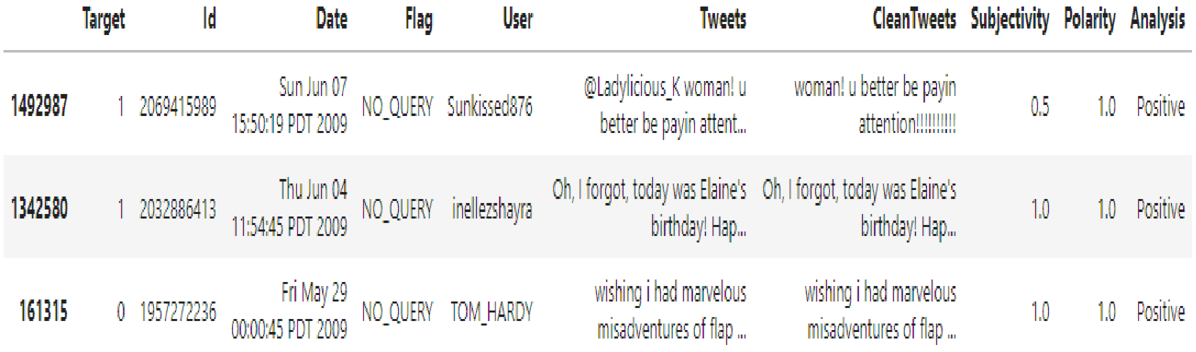
```
1599981    another commenting contest  yay httptinyurlcom...
1599982    figured see tweets facebook status updates set...
1599985    ur lead singer band beware falling prey lsd qu...
1599990                                     wooooo xbox back
1599993                                                     
Name: CleanTweets, dtype: object
```

```
<Axes: xlabel='Analysis', ylabel='count'>
```



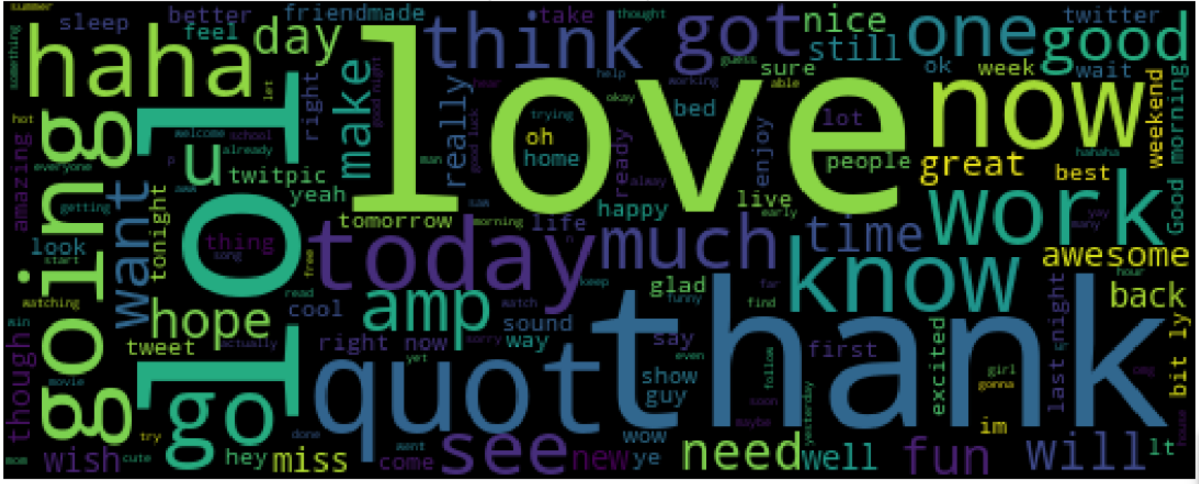
```
Text(0.5, 1.0, 'DISTRIBUTION OF ANALYSIS')
```

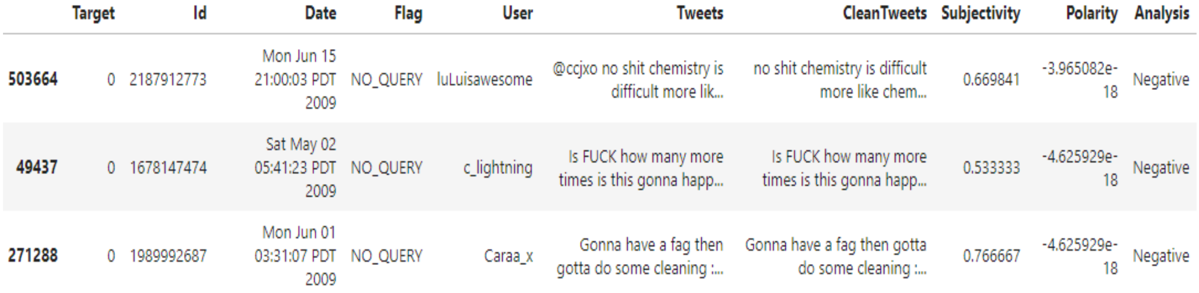




	Target	Id	Date	Flag	User	Tweets	CleanTweets	Subjectivity	Polarity	Analysis
1492987	1	2069415989	Sun Jun 07 15:50:19 PDT 2009	NO_QUERY	Sunkissed876	@Ladylicious_K woman! u better be payin attent...	woman! u better be payin attention!!!!!!!!!!	0.5	1.0	Positive
1342580	1	2032886413	Thu Jun 04 11:54:45 PDT 2009	NO_QUERY	inellezshayra	Oh, I forgot, today was Elaine's birthday! Hap...	Oh, I forgot, today was Elaine's birthday! Hap...	1.0	1.0	Positive
161315	0	1957272236	Fri May 29 00:00:45 PDT 2009	NO_QUERY	TOM_HARDY	wishing i had marvelous misadventures of flap ...	wishing i had marvelous misadventures of flap ...	1.0	1.0	Positive

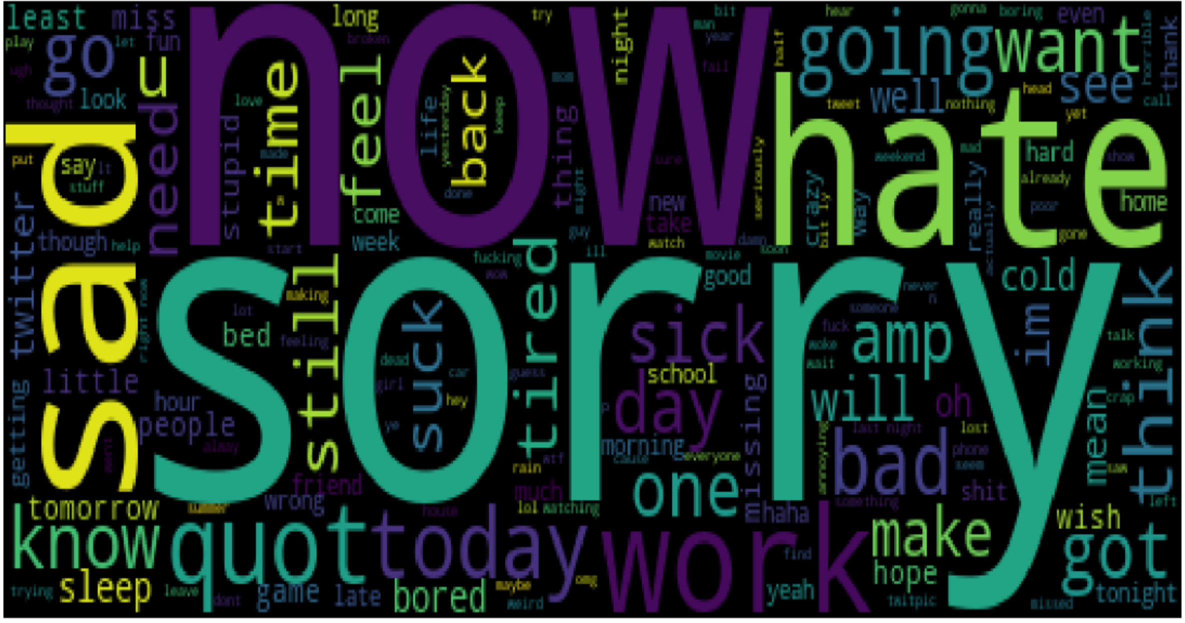
Most frequent words in positive tweets

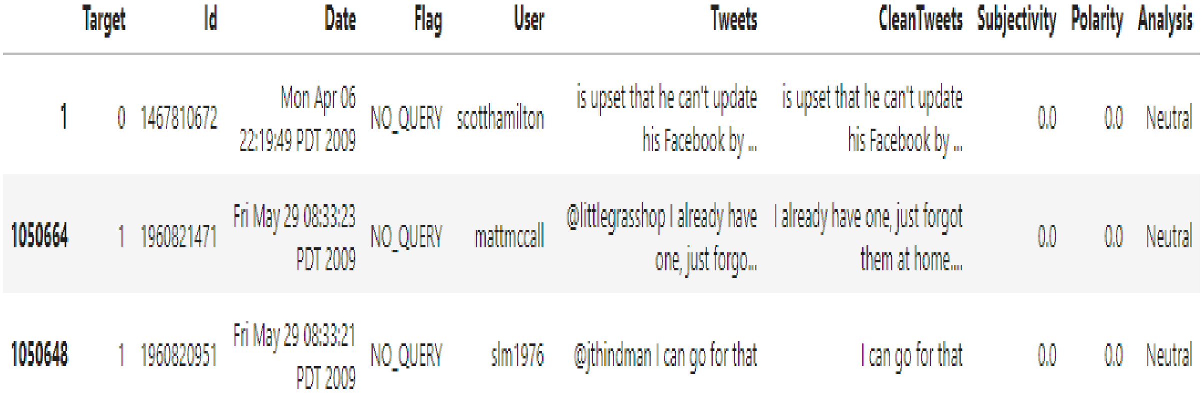




	Target	Id	Date	Flag	User	Tweets	CleanTweets	Subjectivity	Polarity	Analysis
503664	0	2187912773	Mon Jun 15 21:00:03 PDT 2009	NO_QUERY	luLuisawesome	@ccjxo no shit chemistry is difficult more lik...	no shit chemistry is difficult more like chem...	0.669841	-3.965082e-18	Negative
49437	0	1678147474	Sat May 02 05:41:23 PDT 2009	NO_QUERY	c_lightning	Is FUCK how many more times is this gonna happ...	Is FUCK how many more times is this gonna happ...	0.533333	-4.625929e-18	Negative
271288	0	1989992687	Mon Jun 01 03:31:07 PDT 2009	NO_QUERY	Caraa_x	Gonna have a fag then gotta do some cleaning :...	Gonna have a fag then gotta do some cleaning :...	0.766667	-4.625929e-18	Negative

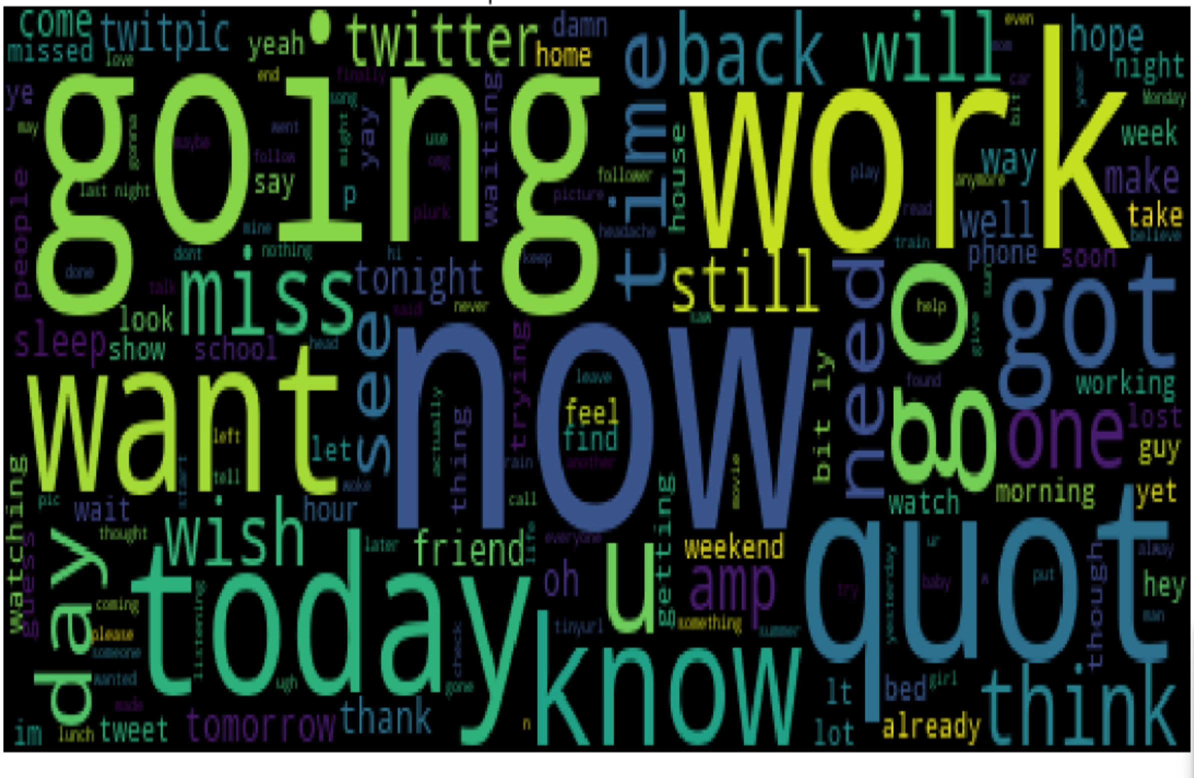
Most frequent words in Negative tweets

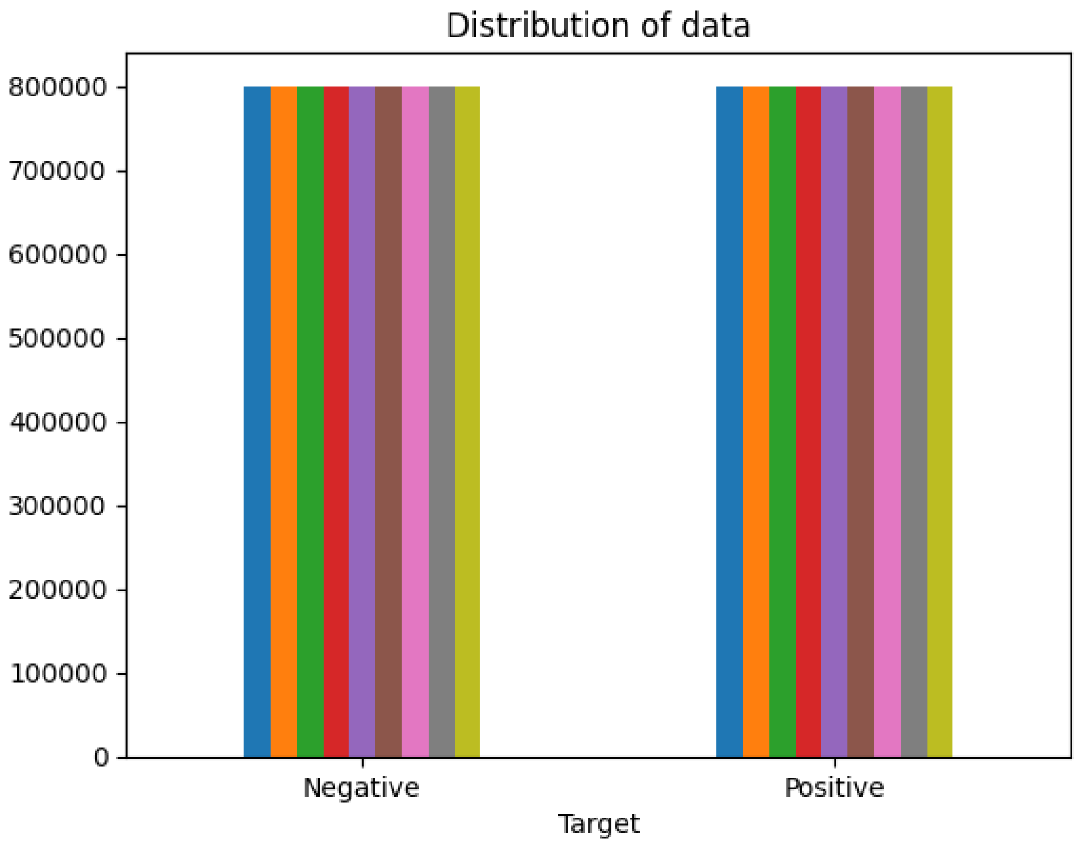




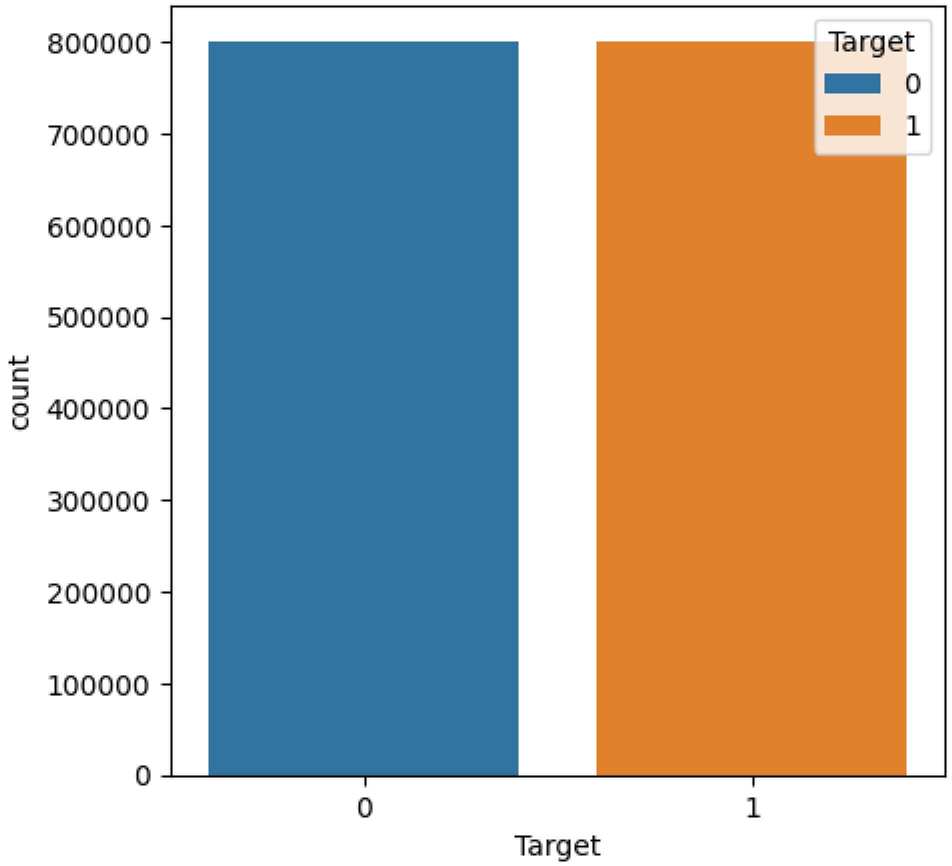
	Target	Id	Date	Flag	User	Tweets	CleanTweets	Subjectivity	Polarity	Analysis
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...	is upset that he can't update his Facebook by ...	0.0	0.0	Neutral
1050664	1	1960821471	Fri May 29 08:33:23 PDT 2009	NO_QUERY	mattmccall	@littlegrasshop I already have one, just forgo...	I already have one, just forgot them at home....	0.0	0.0	Neutral
1050648	1	1960820951	Fri May 29 08:33:21 PDT 2009	NO_QUERY	slm1976	@jthindman I can go for that	I can go for that	0.0	0.0	Neutral

Most frequent words in Neutral tweets



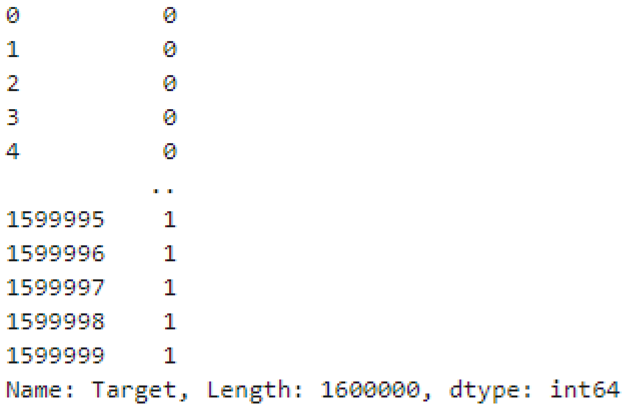

Distribution of data
800000
700000
600000
500000
400000
300000
200000
100000
0
Negative
Positive
Target

```
<Axes: xlabel='Target', ylabel='count'>
```



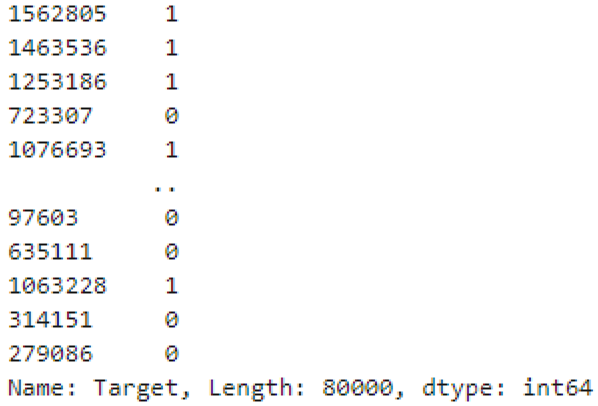
```
array([0, 1], dtype=int64)
```

```
0    httptwitpiccomzl  a s bummer shoulda got david...
2    dived many times ball managed save  rest go bo...
3                         whole body feels itchy like fire
5                                          not whole crew
7    hey long time no see yes rains bit only bit lo...
Name: CleanTweets, dtype: object
```



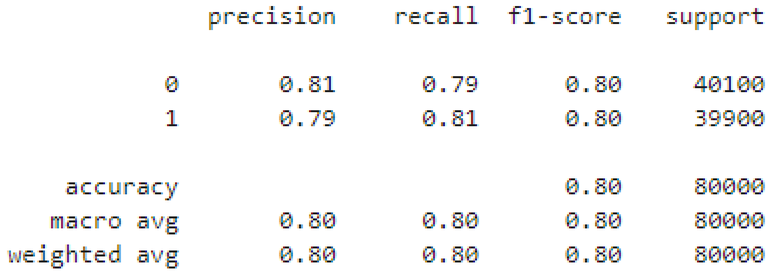
```
0          0
1          0
2          0
3          0
4          0
          ..
1599995    1
1599996    1
1599997    1
1599998    1
1599999    1
Name: Target, Length: 1600000, dtype: int64
```

success   finish   yes

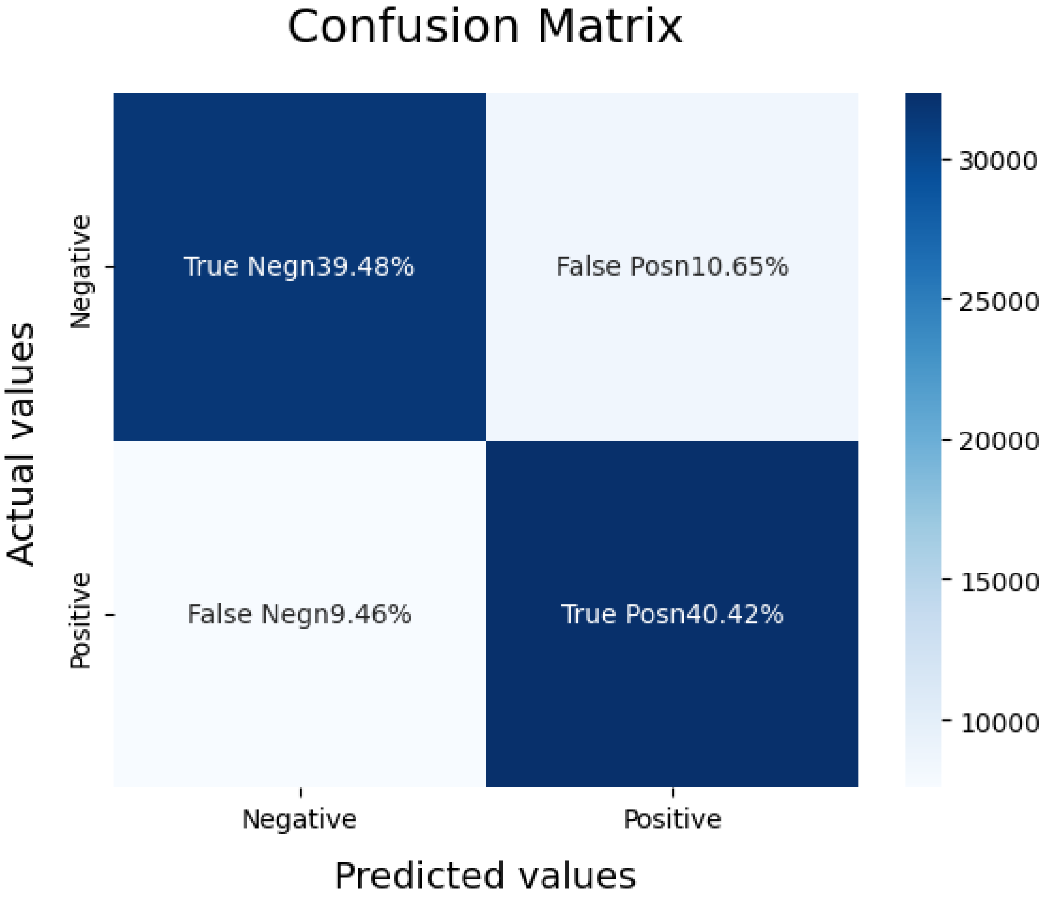


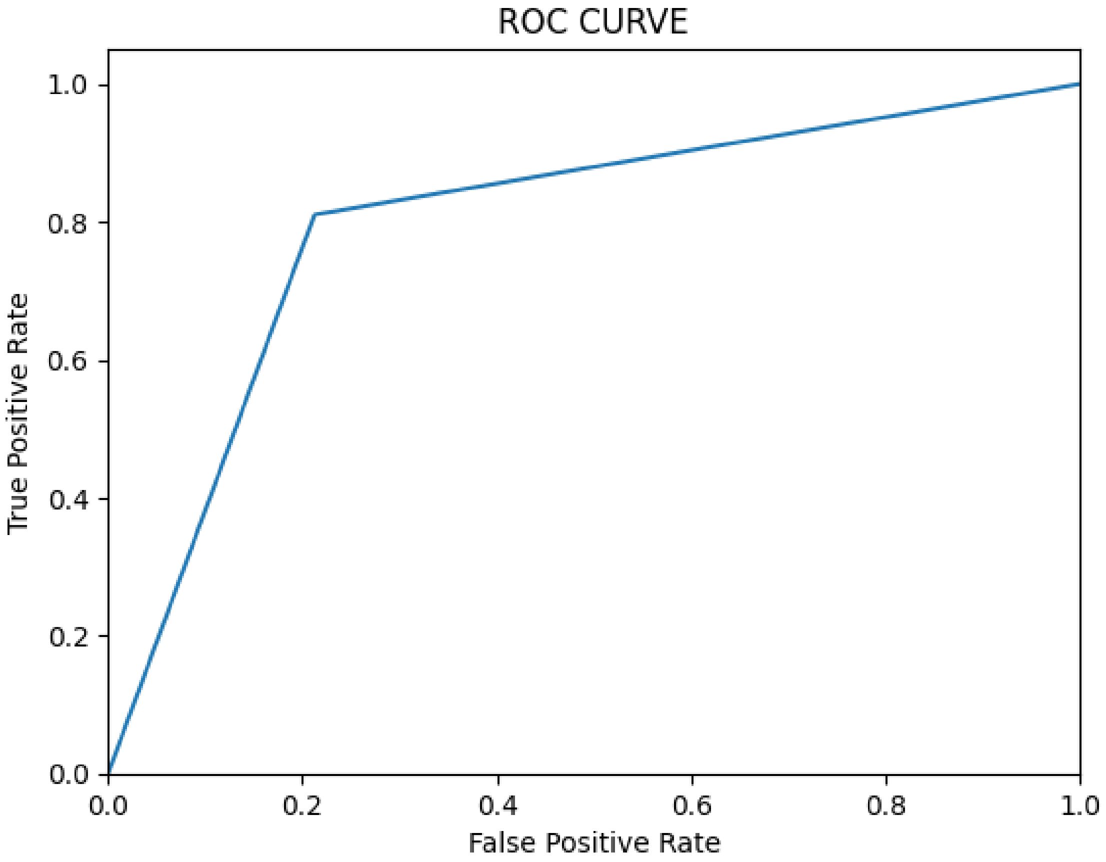
```
1562805    1
1463536    1
1253186    1
723307     0
1076693    1
          ..
97603      0
635111     0
1063228    1
314151     0
279086     0
Name: Target, Length: 80000, dtype: int64
```

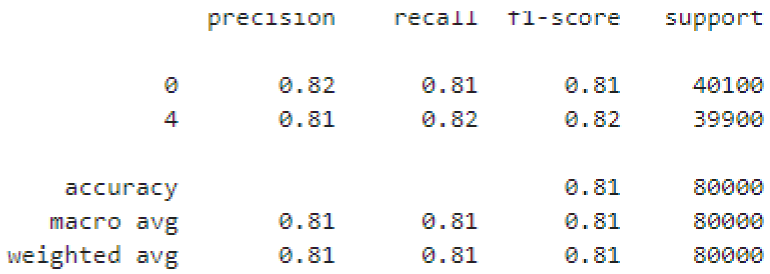
yes



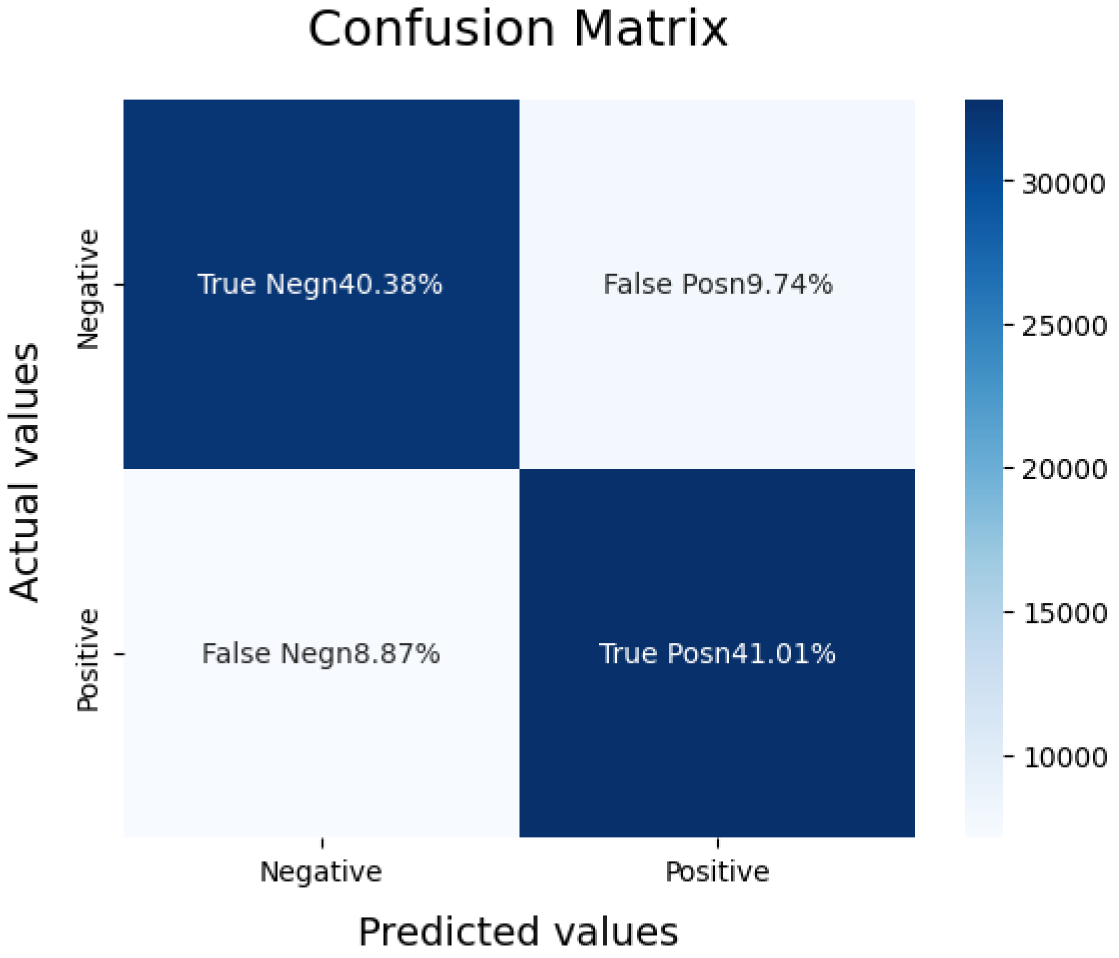
```
              precision    recall  f1-score   support

           0       0.81      0.79      0.80     40100
           1       0.79      0.81      0.80     39900

    accuracy                           0.80     80000
   macro avg       0.80      0.80      0.80     80000
weighted avg       0.80      0.80      0.80     80000
```

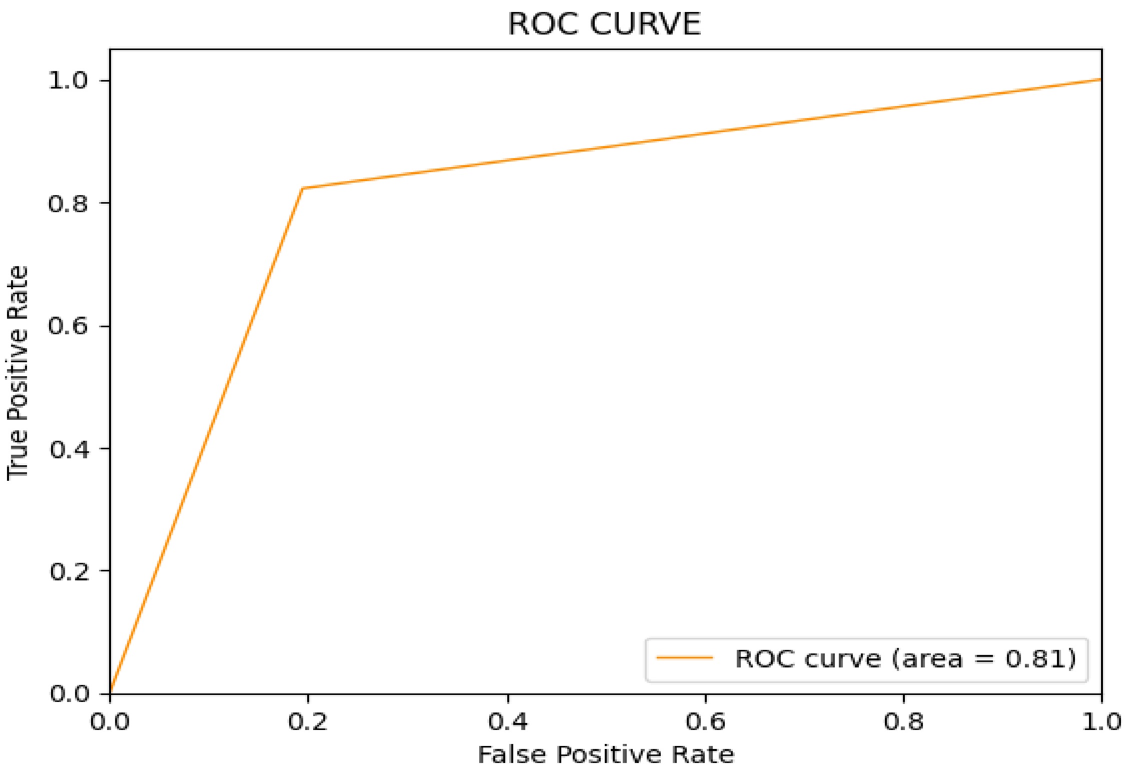

Confusion Matrix
True Negn39.48%
False Posn10.65%
False Negn9.46%
True Posn40.42%
Negative
Positive
Actual values
Negative
Positive
Predicted values
30000
25000
20000
15000
10000

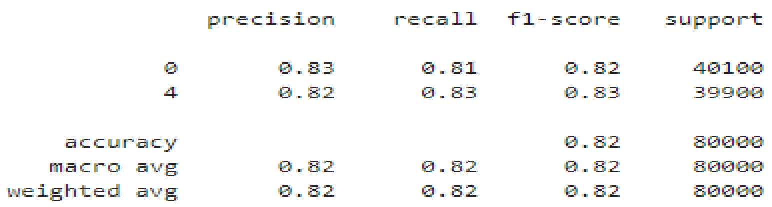

ROC CURVE
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0



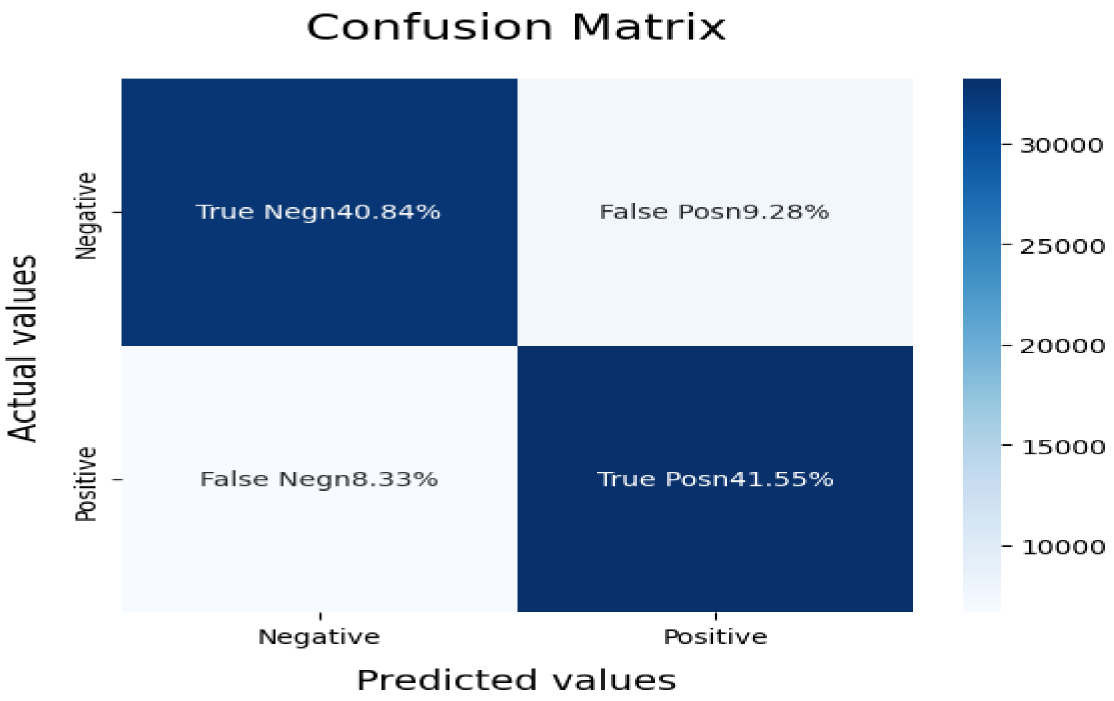
```
              precision    recall  f1-score   support

           0       0.82      0.81      0.81     40100
           4       0.81      0.82      0.82     39900

    accuracy                           0.81     80000
   macro avg       0.81      0.81      0.81     80000
weighted avg       0.81      0.81      0.81     80000
```

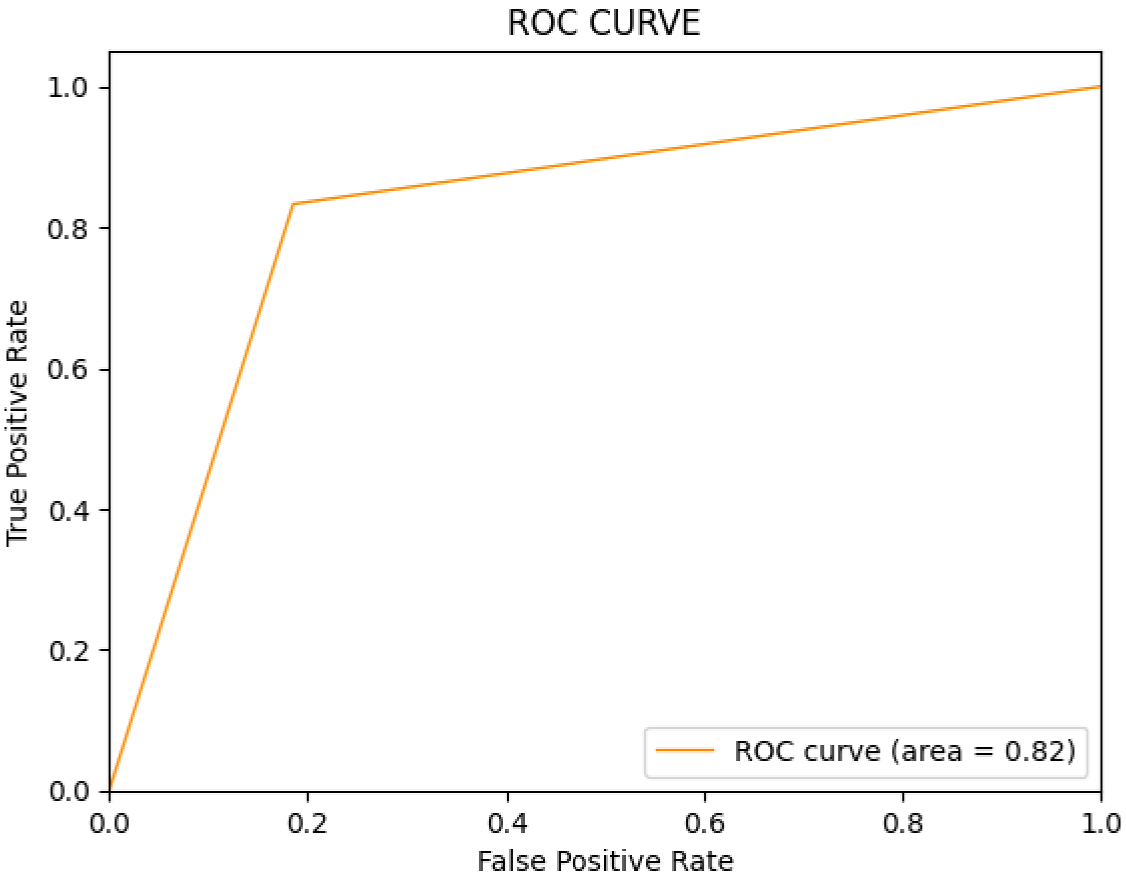






```
              precision    recall  f1-score   support

           0       0.83      0.81      0.82     40100
           4       0.82      0.83      0.83     39900

    accuracy                           0.82     80000
   macro avg       0.82      0.82      0.82     80000
weighted avg       0.82      0.82      0.82     80000
```





Conclusion

We hope through this article, you got a basic of how Sentimental Analysis is used to understand public emotions behind people's tweets. As you've read in this article, Twitter Sentimental Analysis helps us preprocess the data (tweets) using different methods and feed it into ML models to give the best accuracy.

Key Takeaways

Twitter Sentimental Analysis is used to identify as well as classify the sentiments that are expressed in the text source.

Logistic Regression, SVM, and Naive Bayes are some of the ML algorithms that can be used for Twitter Sentimental Analysis.