



## SENTIMENT ANALYSIS FOR MARKETING

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ECE-III Year -

## SENTIMENT ANALYSIS FOR MARKETING

### **Phase 1: Problem Definition and Design Thinking OBJECTIVE:**

Sentiment analysis can do wonders for any marketer. By understanding what your target audience is thinking on a scale that only sentiment analysis can achieve, you can tweak a product, campaign, and more, to meet their needs and let your customers know you're listening.

Sentiment analysis is an artificial intelligence technique that uses machine learning and natural language processing (NLP) to analyse text for polarity of opinion (positive to negative).

### **DATA COLLECTION:**

Depending on your research goal and scope, you can choose from different data sources and methods for sentiment analysis. Some common data sources are online reviews, social media platforms, blogs, forums, news articles, surveys, and emails. Some common methods are web scraping, APIs, surveys, and online tools.

### **DATA PREPROCESSING:**

- The code begins by importing the necessary libraries, including pandas for data handling, matplotlib and seaborn for visualization, and scikit-learn for machine learning.
- The airline tweet dataset is loaded from a CSV file.

For cleaning the data, we will do the following:

Combine both test and training set so we can preprocess both together

Remove redundant characters- numerics, special characters (not hashtags), short words, usernames(@user)

Tokenise the processed tweet

Stemming- strip suffixes to get the root word.

#### SENTIMENT ANALYSIS TECHNIQUES:

Sentiment analysis is used to analyse raw text to drive objective quantitative results using natural language processing, machine learning, and other data analytics techniques. It is used to detect positive or negative sentiment in text, and often businesses use it to gauge branded reputation among their customers.

There are various types of sentiment analysis where the models focus on feelings and emotions, urgency, even intentions, and polarity. The most popular types of sentiment analysis are:

- A. Fine-grained sentiment analysis
- B. Emotion detection
- C. Aspect based sentiment analysis
- D. Multilingual sentiment analysis

Sentiment analysis is critical because it helps businesses to understand the emotion and sentiments of their customers. Companies analyze customers' sentiment through social media conversations and reviews so they can make better-informed decisions. The Global Sentiment Analysis Software Market is projected to reach US\$4.3 billion by the year 2027. Between 2017 and 2023, the global sentiment analysis market will increase by a CAGR of 14%.

#### FEATURE EXTRACTION:

In sentiment analysis, we detect tweets that have negative sentiment, i.e, racist, sexist or general hate speech. Here, tweets with a label '1' denote a negative tweet, while '0' denotes the absence of hate speech in the tweet.

We extract features using the following:

1. Bag of Words Features
2. TF-IDF features
3. Word Embedding's

#### VISUALIZATION:

- The code creates a histogram to visualize the distribution of airline sentiments.
- It also creates a pie chart to visualize the sentiment distribution using percentages.

We will analyse the text of the tweet and its relation to the sentiment with the following:

Wordcloud: Most used words (have bigger fonts), for positive and negative tweets. Reference.

Hashtags: Analyse the effect of hashtags on the tweet sentiment.

```
all_words=' '.join([text for text in combine['tidy_tweet']])
from wordcloud import WordCloud
word_cloud=WordCloud(width=800, height=500, random_state=21,max_font_size=110,colormap='generate(all_words)
```

```
plt.figure(figsize=(10, 7)) plt.imshow(word_cloud)
plt.axis('off') plt.show()
```

## INSIGHTS GENERATION:

Sentiment Analysis is a natural language processing (NLP) technique used to determine the sentiment of data, i.e. whether the data is positive, negative or neutral. NLP is a branch of artificial intelligence concerning linguistics, more specifically how a computer understands, processes, and analyses large amount of natural language data. It has a vast amount of other use cases such as text classification, speech recognition, chat-bots and more, however the main focus for this project will be Sentiment Analysis. Customer Insights One of the main applications of Sentiment Analysis is for Customer Insights. A customer insight is an interpretation used by businesses to gain a deeper understanding of how their audience feels towards their product or business, allowing them to better understand their consumers needs and improve their product/service accordingly.

```
# Import Libraries import
pandas as pd
import matplotlib.pyplot as plt import
seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression from
sklearn.metrics import roc_auc_score, confusion_matrix from
sklearn.model_selection import train_test_split
```

visualize:

```
# Visualize the distribution of airline sentiments using a pie chart sentiment_counts
= df['airline_sentiment'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(sentiment_counts, labels=sentiment_counts.index, autopct='%.1f%%', startangle=140)
plt.title('Distribution of Airline Sentiments') plt.axis('equal') # Equal aspect ratio ensures that
pie is drawn as a circle.
```

```
# function to collect hashtags def
```

```
hashtag_extract(x):
```

```
    hashtags = []
```

```
    for i in x:
```

```
        ht = re.findall(r"#(\w+)", i)
```

```
        hashtags.append(ht)
```

```
    return hashtags
```

In [22]: linkcode

```
#hashtag list for non negative tweets
```

```
HT_non_negative = hashtag_extract(combine['tidy_tweet'][combine['label'] == 0])
```

```
#hashtag list for negative tweets
```

```
HT_negative = hashtag_extract(combine['tidy_tweet'][combine['label'] == 1])
```

```
#unnest list
```

```
HT_non_negative = sum(HT_non_negative,[])
```

```
HT_negative = sum(HT_negati
```

## MACHINE LEARNING

### INTRODUCTOIN:

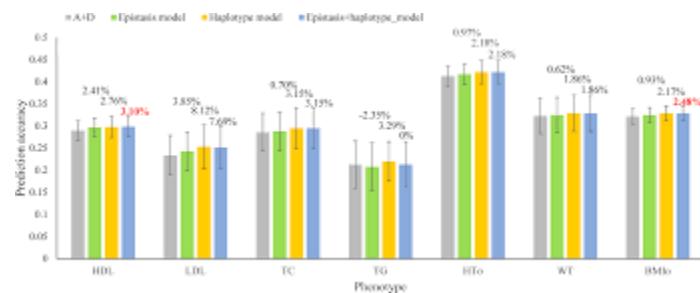
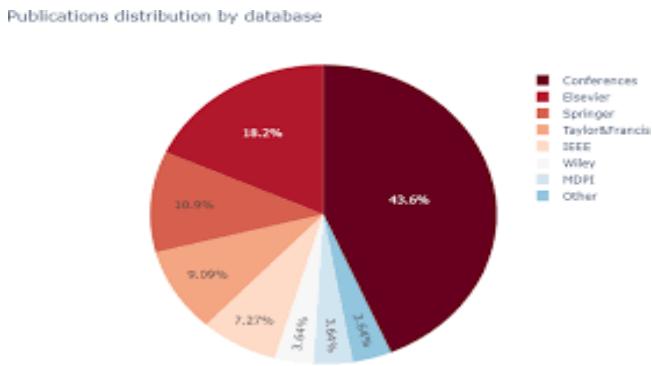
Machine learning is programming computers to optimize a performance criterion using example data or past experience. We have a model defined up to some parameters, and learning is the execution of a computer program to optimize the parameters of the model using the training data or past experience. The model may be predictive to make predictions in the future, or descriptive to gain knowledge from data. The field of study known as machine learning is concerned with the question of how to construct computer programs that automatically improve Comparison

### DEFINITION OF LEARNING:

A computer program is said to learn from experience E with respect to some class of task T and performance measure P, if its performance attasks T, as measured by P, improves with experience E. To answer the question of how hard the two tasks are, we can compare our system's performance against that of humans. We conducted an scaled-down version of the experiment where we had humans attempt the same two classification task as our models. Performance at the human level is often considered the target goal in sentiment analysis. experience.

### HUMAN PREDICTION:

Similar to sales forecasting, are based on datasets from past prices, volatility indices, and fundamental indicators. Beginners can start small with a project like this and use stock-market datasets to create predictions over the next few months. It's a great way to become familiar with creating predictions based on massive datasets. one might ask what is the difficulty of our two task and what level of accuracy would be considered successful. Answer



### Other Attempt:

In addition to what we used in our final model, we had other work that taught us more about extracting emotion from EP. 3 For the max label task, due to the unbalanced distribution of categories we used a balanced human testing set instead of a random subset of the original testing set. Note that this is a harder problem for our SVM classifier since it was trained on an unbalanced training set. As a result the numbers reported here are lower than the ones reported in Results

. Figure 4: Human comparison for max label.

```
params = list(model.named_parameters())
print("The BERT model has {} different named parameters.".format(len(params)))
print("==== Embedding Layer ====")
for p in params[0:5]:
    print("{:12}.".format(p[0], str(tuple(p[1].size()))))
print("==== First Transformers ====")
for p in params[5:21]:
    print("{:12}.".format(p[0], str(tuple(p[1].size()))))
```

```
str(tuple(p[1].size())))) print("==== Output Layer ====") for p in params[-4:]: print("{:12}".format(p[0]),  
str(tuple(p[1].size()))))
```

Furthermore

The user generated information may also contain unnecessary whitespaces at the beginning, in between or at the end of the tweets, special characters like punctuation and repetition of characters. First, all extra white space was removed using the build in function available in Python. Secondly, all the meaningless and unnecessary special characters from the tweets were eliminated (Hemalatha et al. 2012).

These characters include: \ | [ ] ;: {} - + ( ) < > ? ! @ # % \* , and a few more. Neither do these characters have specific and special meaning, nor do they explain if these characters are used for positivity or negativity, hence; removing them is the best option • Non-standard (slang) to standard word mapping • PoS tagging • Tagging Stopword removal • positive/negative word

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```
import numpy as np print('---Train---')

print('input: ', train_input.shape)

print('label: ', train_labels.shape)

print('mask: ', np.array(train_mask).shape)

print('---Validation---')

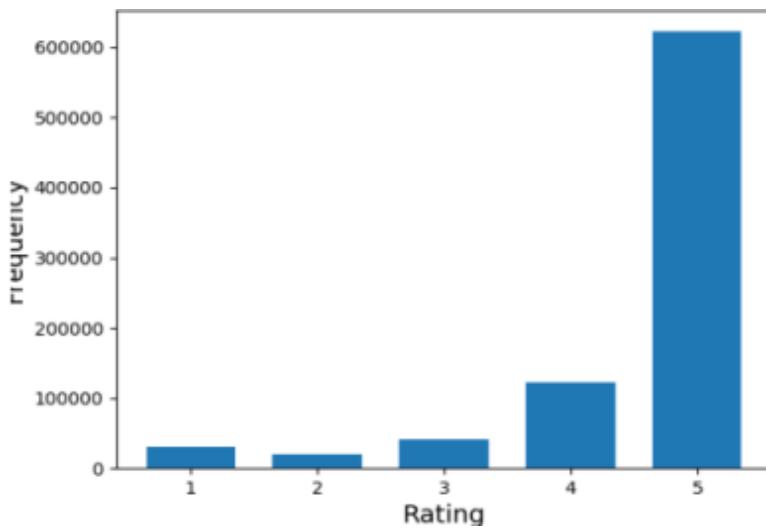
print('input: ', validation_input.shape)

print('label: ', validation_labels.shape)

print('mask: ', np.array(validation_mask).shape)

print('---Test---')

print('input: ', test_input.shape)
```



# AI\_PHASE 3

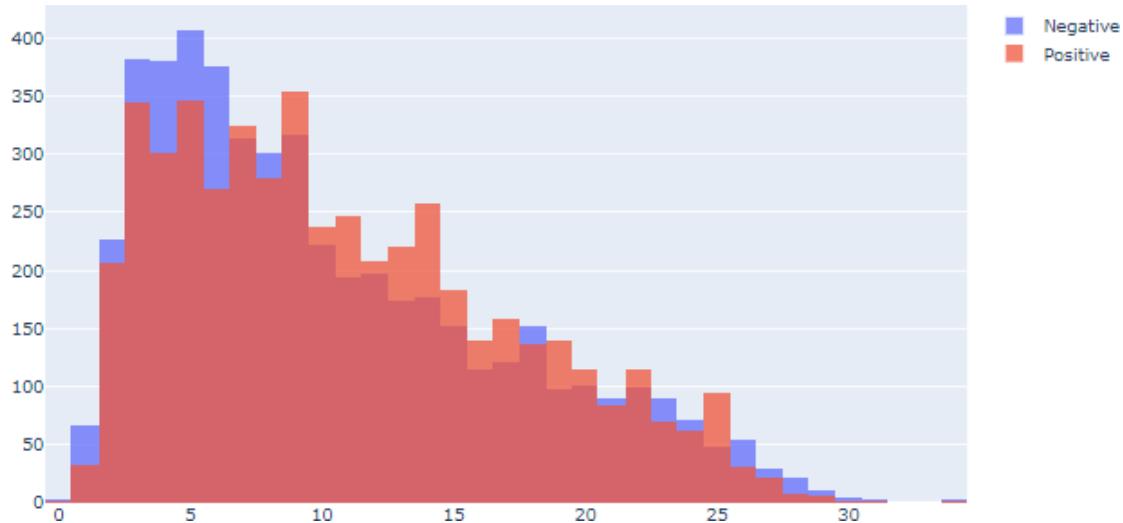
## PREPROCESSING

```
import nltk  
from nltk.corpus import twitter_samples  
import matplotlib.pyplot as plt  
import random
```

## NLTK Twitter Dataset

```
nltk.download('twitter_samples')  
[nltk_data] Downloading package twitter_samples to  
[nltk_data]   /usr/share/nltk_data...  
[nltk_data] Package twitter_samples is already up-to-date!
```

```
all_positive_tweets = twitter_samples.strings('positive_tweets.json')  
all_negative_tweets = twitter_samples.strings('negative_tweets.json')  
  
print('Number of positive tweets: ', len(all_positive_tweets))  
print('Number of negative tweets: ', len(all_negative_tweets))  
  
print('\nThe type of all_positive_tweets is: ', type(all_positive_tweets))  
print('The type of a tweet entry is: ', type(all_negative_tweets[0]))
```

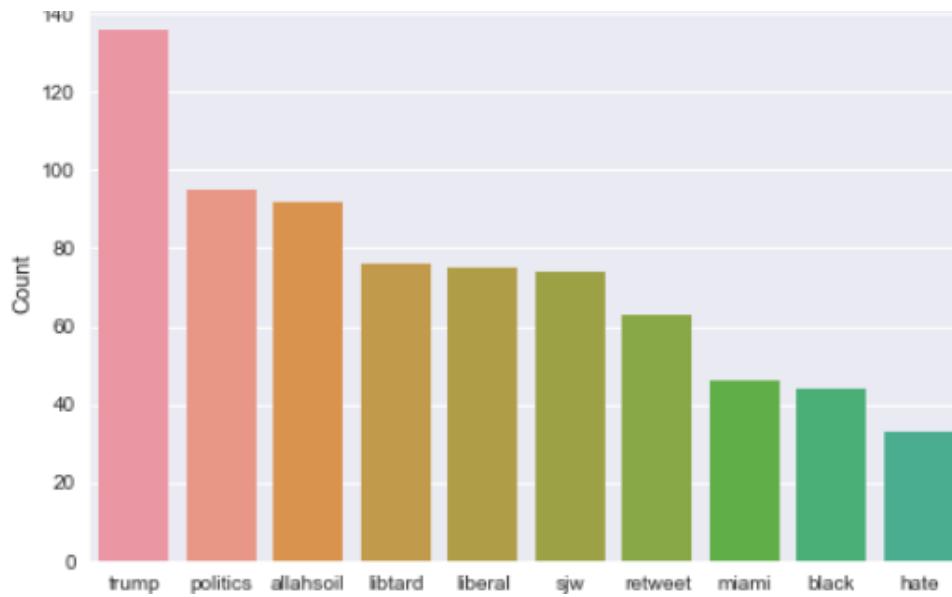


## TWEETS OF DATA

```
train = pd.read_csv('../input/twitter-tweets-data/train_tweet.csv')  
test = pd.read_csv('../input/twitter-tweets-data/test_tweets.csv')
```

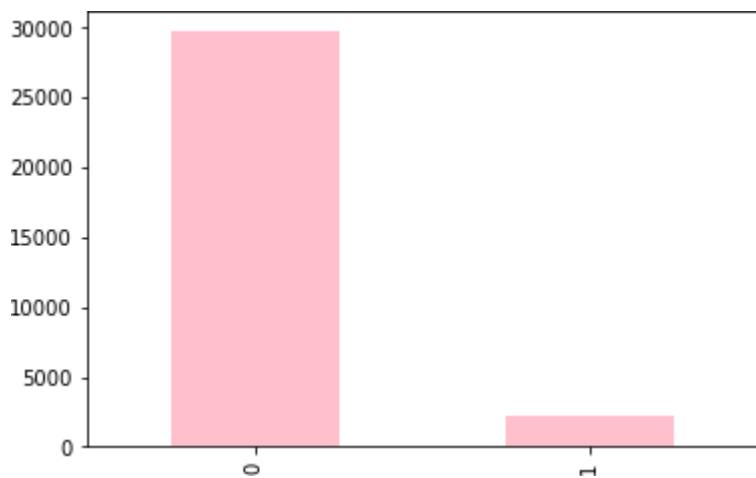
```
print(train.shape)  
print(test.shape)
```

COUNT THE TWEETS



```
train['label'].value_counts().plot.bar(color = 'pink', figsize = (6, 4))
```

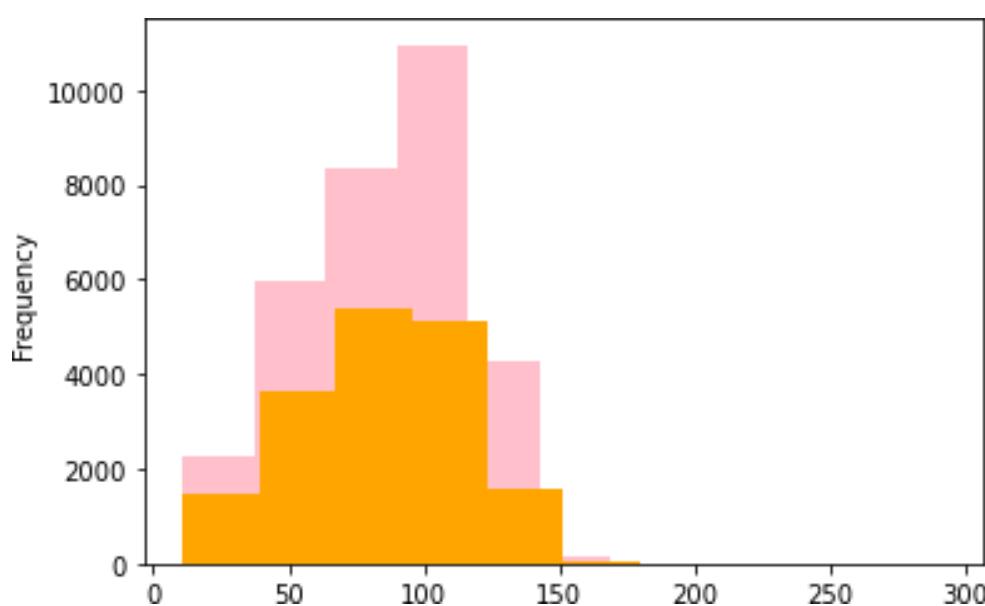
DISTRIBUTION OF TWEETS



```

# checking the distribution of tweets in the data

length_train = train['tweet'].str.len().plot.hist(color = 'pink', figsize = (6, 4))
length_test = test['tweet'].str.len().plot.hist(color = 'orange', figsize = (6, 4))



COUNTS OF TWEETS



from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(stop_words = 'english')
words = cv.fit_transform(train.tweet)

sum_words = words.sum(axis=0)

words_freq = [(word, sum_words[0, i]) for word, i in cv.vocabulary_.items()]
words_freq = sorted(words_freq, key = lambda x: x[1], reverse = True)

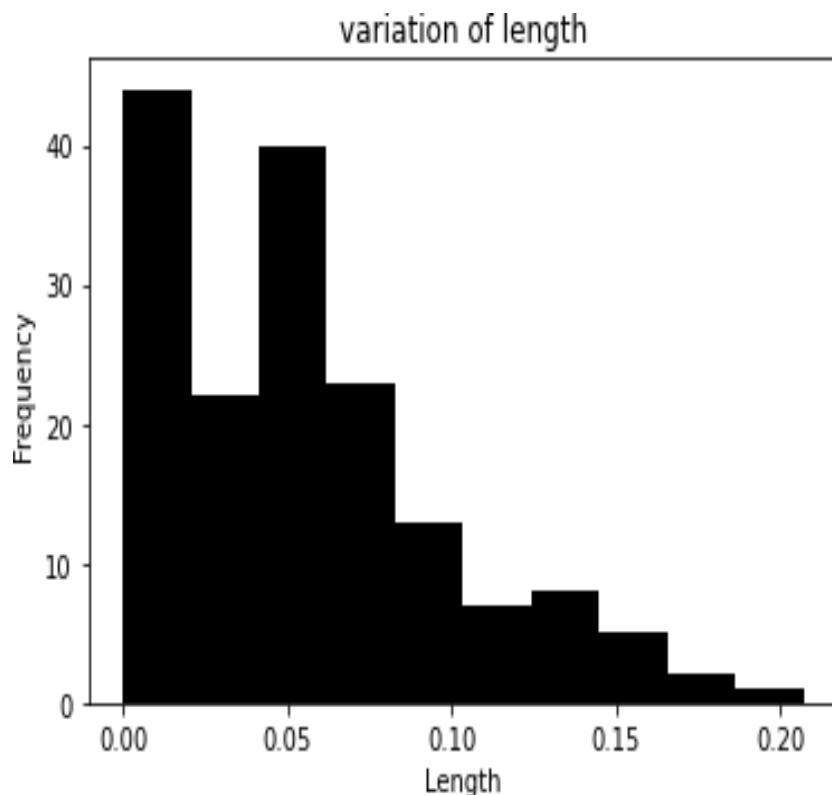
frequency = pd.DataFrame(words_freq, columns=['word', 'freq'])

frequency.head(30).plot(x='word', y='freq', kind='bar', figsize=(15, 7), color = 'blue')
plt.title("Most Frequently Occuring Words - Top 30")

```

## NEGATIVE TWEETS

```
negative_words = ''.join([text for text in train['tweet'][train['label'] == 1]])  
  
wordcloud = WordCloud(background_color = 'red', width=800, height=500, random_state = 0,  
max_font_size = 110).generate(negative_words)  
plt.figure(figsize=(10, 7))  
plt.imshow(wordcloud, interpolation="bilinear")  
plt.axis('off')  
plt.title('The Negative Words')  
plt.show()
```



```
# collecting the hashtags
```

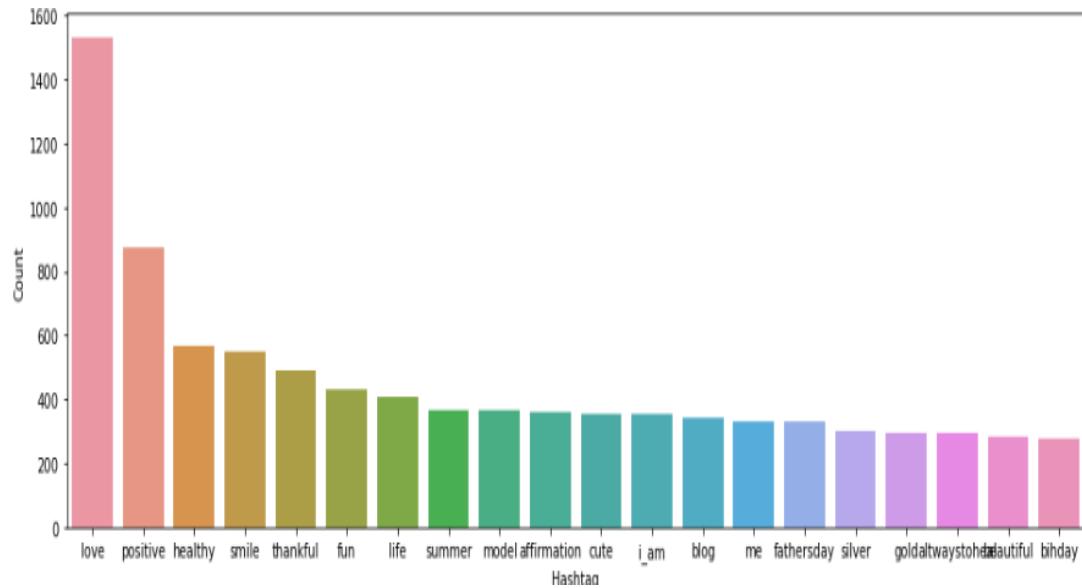
```
def hashtag_extract(x):  
    hashtags = []  
  
    for i in x:  
        ht = re.findall(r"#(\w+)", i)  
        hashtags.append(ht)  
  
    return hashtags
```

```

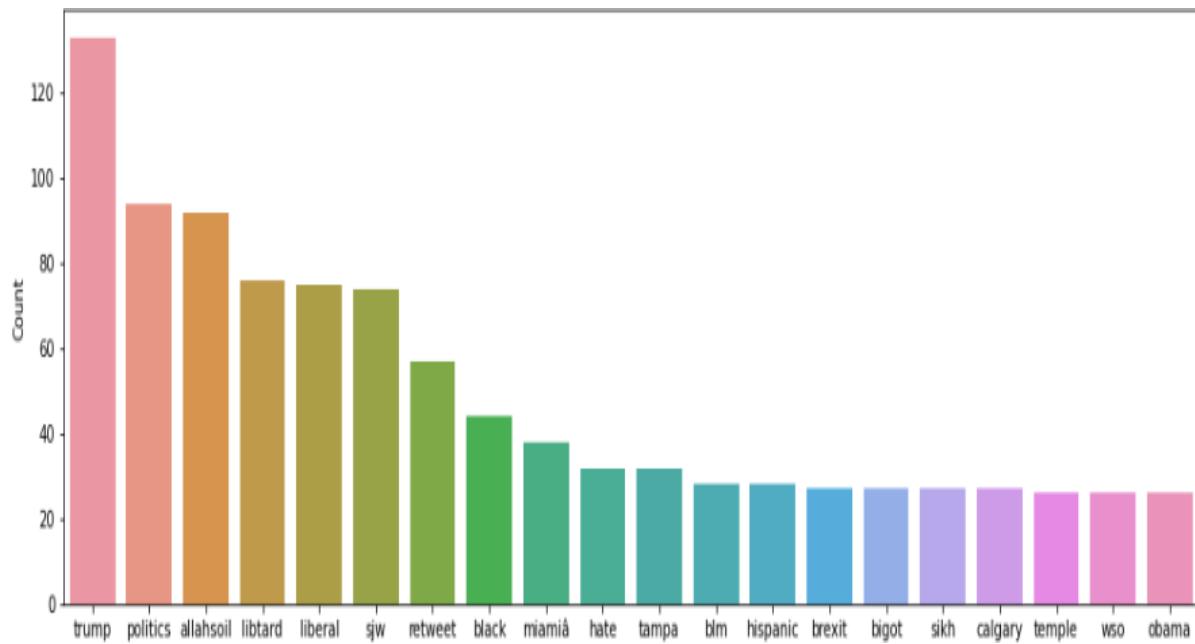
a = nltk.FreqDist(HT_negative)
d = pd.DataFrame({'Hashtag': list(a.keys()),
                  'Count': list(a.values())})

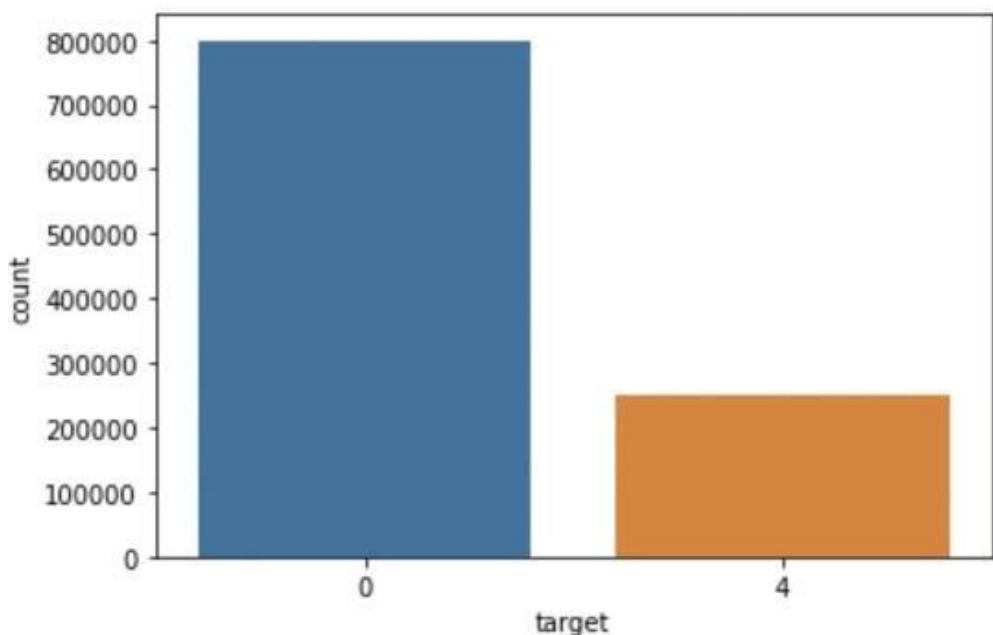
# selecting top 20 most frequent hashtags
d = d.nlargest(columns="Count", n = 20)
plt.figure(figsize=(16,5))
ax = sns.barplot(data=d, x= "Hashtag", y = "Count")
ax.set(ylabel = 'Count')
plt.show()

```



```
model_w2v.wv.most_similar(positive = "dinner")
```





## **AI\_Phase 4: Development part 2**

### **What is NLP for sentiment analysis:**

Sentiment analysis (or opinion mining) is a natural language processing (NLP) technique used to determine whether data is positive, negative or neutral. Sentiment analysis is often performed on textual data to help businesses monitor brand and product sentiment in customer feedback, and understand customer needs.



### **What is generating insights in sentiment analysis:**

Sentiment analysis solutions apply consistent criteria to generate more accurate insights. For example, a machine learning model can be trained to recognise that there are two aspects with two different sentiments. It would average the overall sentiment as neutral, but also keep track of the details.

### **Which algorithm is used for sentiment analysis in NLP**

Overall, Sentiment analysis may involve the following types of classification algorithms: Linear Regression. Naive Bayes. Support Vector Machines.

### **How to use NLP to do sentiment analysis?**



In sentiment analysis, Natural Language Processing (NLP) is essential. NLP uses computational methods to interpret and comprehend human language. It includes several operations, including sentiment analysis, named entity recognition, part-of-speech tagging, and tokenization.

## NLP methods for sentiment analysis

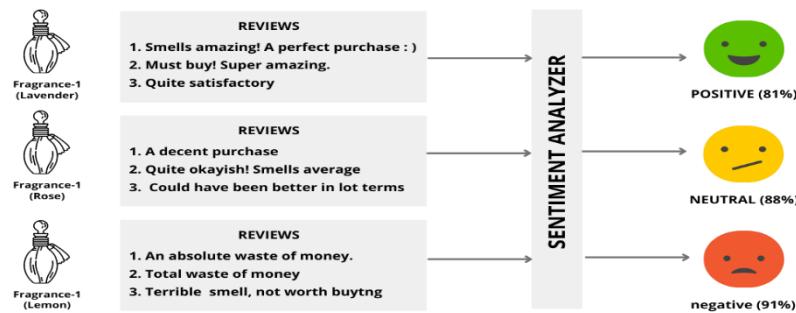
1. using a dictionary of manually defined keywords,
2. creating a 'bag of words',
3. using the TF-IDF strategy.

## Gaining Insights and Making Decisions with Sentiment Analysis

Well, by now I guess we are somewhat accustomed to what sentiment analysis is. But what is its significance and how do organizations benefit from it? Let us try and explore the same with an example. You put up a wide range of fragrances out there and soon customers start flooding in. Now, in order to determine which fragrances are popular, you start going through customer reviews of all the fragrances. But you're stuck! They are just so many that you cannot go through them all in one lifetime. This is where sentiment analysis can rope you out of the pit.

You simply gather all the reviews in one place and apply sentiment analysis to it. The following is a schematic representation of sentiment analysis on the reviews of

three fragrances of perfumes—Lavender, Rose, and Lemon. (Please note that these reviews might have incorrect spellings, grammar, and punctuations as it is in the real-world scenarios)



From these results, we can clearly see that:

- Fragrance-1 (Lavender) has highly positive reviews by the customers which indicates your company can escalate its prices given its popularity.
- Fragrance-2 (Rose) happens to have a neutral outlook amongst the customer which means your company should not change its pricing.
- Fragrance-3 (Lemon) has an overall negative sentiment associated with it—thus, your company should consider offering a discount on it to balance the scales.

This was just a simple example of how sentiment analysis can help you gain insights into your products/services and help your organization make decisions.

## Why is natural language processing important:

Businesses use massive quantities of unstructured, text-heavy data and need a way to efficiently process it. A lot of the information created online and stored in databases is natural human language, and until recently, businesses could not effectively analyze this data. This is where natural language processing is useful.

## Features of NLP:

The advantage of natural language processing can be seen when considering the following two statements: "Cloud computing insurance should be part of every service-level agreement," and, "A good SLA ensures an easier night's sleep -- even in the cloud." If a user relies on natural language processing for search, the program will recognize that *cloud computing* is an entity, that *cloud* is an abbreviated form of cloud computing and that *SLA* is an industry acronym for service-level agreement.

## Model Evaluation

We will evaluate our model using various metrics such as Accuracy Score, Precision Score, Recall Score, Confusion Matrix and create a roc curve to visualize how our model performed.

```
#  
plt.figure(figsize=(10,5))  
plot_confusion_matrix(test_df,predictions)  
acc_score = accuracy_score(test_df,predictions)  
pre_score = precision_score(test_df,predictions,average='micro')  
rec_score = recall_score(test_df,predictions,average='micro')  
print('Accuracy_score: ',acc_score)  
print('Precision_score: ',pre_score)  
print('Recall_score: ',rec_score)  
print("-"*50)  
cr = classification_report(test_df,predictions)  
print(cr)
```

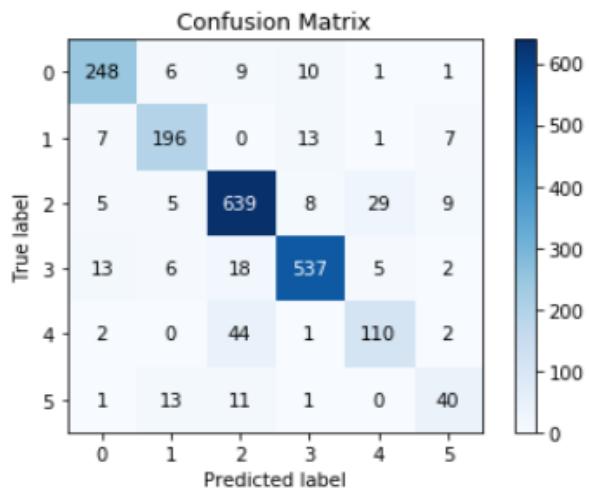
```

Accuracy_score: 0.885
Precision_score: 0.885
Recall_score: 0.885
-----
             precision    recall   f1-score   support
0            0.90      0.90      0.90      275
1            0.87      0.88      0.87      224
2            0.89      0.92      0.90      695
3            0.94      0.92      0.93      581
4            0.75      0.69      0.72      159
5            0.66      0.61      0.63       66

   accuracy          0.89      2000
macro avg          0.83      0.82      0.83      2000
weighted avg       0.88      0.89      0.88      2000

```

<Figure size 1080x720 with 0 Axes>



And, you can get the full code and output from [here](#).

## Step 1 — Installing NLTK and Downloading the Data

You will use the NLTK package in Python for all NLP tasks in this tutorial. In this step you will install NLTK and download the sample tweets that you will use to train and test your model.

First, install the NLTK package with the pip package manager:

**1. pip install nltk==3.3**

This tutorial will use sample tweets that are part of the NLTK package. First, start a Python interactive session by running the following command:

```
1. python3
```

```
2.
```

Then, import the nltk module in the python interpreter.

```
1. import nltk
```

Download the sample tweets from the NLTK package:

```
1. nltk.download('twitter_samples')
```

Running this command from the Python interpreter downloads and stores the tweets locally. If you would like to use your own dataset, you can gather tweets from a specific time period, user, or hashtag by using the Twitter API.

Now that you've imported NLTK and downloaded the sample tweets, exit the interactive session by entering in `exit()`. You are ready to import the tweets and begin processing the data.

## Step 2 — Tokenizing the Data

Language in its original form cannot be accurately processed by a machine, so you need to process the language to make it easier for the machine to understand. The first part of making sense of the data is through a process called *tokenization*, or splitting strings into smaller parts called *tokens*.

To get started, create a new `.py` file to hold your script. This tutorial will use `nlp_test.py`:

```
1. nano nlp_test.py
```

```
2. In this file, you will first import the twitter_samples so you can work with that data:
```

```
nlp_test.py
```

```
from nltk.corpus import twitter_samples
```

This will import three datasets from NLTK that contain various tweets to train and test the model:

- `negative_tweets.json`: 5000 tweets with negative sentiments
- `positive_tweets.json`: 5000 tweets with positive sentiments

- tweets.20150430-223406.json: 20000 tweets with no sentiments

Next, create variables for positive\_tweets, negative\_tweets, and text:

### nlp\_test.py

```
from nltk.corpus import twitter_samples
```

```
positive_tweets = twitter_samples.strings('positive_tweets.json')  
negative_tweets = twitter_samples.strings('negative_tweets.json')  
text = twitter_samples.strings('tweets.20150430-223406.json')
```

The strings() method of twitter\_samples will print all of the tweets within a dataset as strings. Setting the different tweet collections as a variable will make processing and testing easier.

Before using a tokenizer in NLTK, you need to download an additional resource, punkt. For instance, this model knows that a name may contain a period (like “S. Daityari”) and the presence of this period in a sentence does not necessarily end it. First, start a Python interactive session:

- 1.
2. python3

Run the following commands in the session to download the punkt resource:

1. import nltk
- 2.
3. nltk.download('punkt')
- 4.

Once the download is complete, you are ready to use NLTK’s tokenizers. NLTK provides a default tokenizer for tweets with the .tokenized() method. Add a line to create an object that tokenizes the positive\_tweets.json dataset:

### nlp\_test.py

```
from nltk.corpus import twitter_samples
```

```
positive_tweets = twitter_samples.strings('positive_tweets.json')  
negative_tweets = twitter_samples.strings('negative_tweets.json')  
text = twitter_samples.strings('tweets.20150430-223406.json')  
tweet_tokens = twitter_samples.tokenized('positive_tweets.json')
```

If you’d like to test the script to see the .tokenized method in action, add the highlighted content to your nlp\_test.py script. This will tokenize a single tweet from the positive\_tweets.json dataset:

### nlp\_test.py

```
from nltk.corpus import twitter_samples

positive_tweets = twitter_samples.strings('positive_tweets.json')
negative_tweets = twitter_samples.strings('negative_tweets.json')
text = twitter_samples.strings('tweets.20150430-223406.json')
tweet_tokens = twitter_samples.tokenized('positive_tweets.json')[0]

print(tweet_tokens[0])
```

Save and close the file, and run the script:

1. python3 nlp\_test.py
- 2.

The process of tokenization takes some time because it's not a simple split on white space. After a few moments of processing, you'll see the following:

Output

```
['#FollowFriday',
 '@France_Inte',
 '@PKuchly57',
 '@Milipol_Paris',
 'for',
 'being',
 'top',
 'engaged',
 'members',
 'in',
 'my',
 'community',
 'this',
 'week',
 ':')]
```

Here, the `.tokenized()` method returns special characters such as `@` and `_`. These characters will be removed through regular expressions later in this tutorial.

Now that you've seen how the `.tokenized()` method works, make sure to comment out or remove the last line to print the tokenized tweet from the script by adding a `#` to the start of the line:

```
nlp_test.py
from nltk.corpus import twitter_samples

positive_tweets = twitter_samples.strings('positive_tweets.json')
negative_tweets = twitter_samples.strings('negative_tweets.json')
text = twitter_samples.strings('tweets.20150430-223406.json')
tweet_tokens = twitter_samples.tokenized('positive_tweets.json')[0]

#print(tweet_tokens[0])
```

Your script is now configured to tokenize data. In the next step you will update the script to normalize the data.

### Step 3 — Normalizing the Data

Words have different forms—for instance, “ran”, “runs”, and “running” are various forms of the same verb, “run”. Depending on the requirement of your analysis, all of these versions may need to be converted to the same form, “run”. *Normalization* in NLP is the process of converting a word to its canonical form.

The lemmatization algorithm analyzes the structure of the word and its context to convert it to a normalized form. Therefore, it comes at a cost of speed. A comparison of stemming and lemmatization ultimately comes down to a trade off between speed and accuracy.

Before you proceed to use lemmatization, download the necessary resources by entering the following in to a Python interactive session:

```
1..python3
```

```
1.
```

Run the following commands in the session to download the resources:

```
1. import nltk
```

```
2.  
3. nltk.download('wordnet')  
4.  
5. nltk.download('averaged_perceptron_tagger')  
6.
```

wordnet is a lexical database for the English language that helps the script determine the base word. You need the averaged\_perceptron\_tagger resource to determine the context of a word in a sentence.

```
1. from nltk.tag import pos_tag  
2. from nltk.corpus import twitter_samples  
3. ////////////  
4. tweet_tokens = twitter_samples.tokenized('positive_tweets.json')  
5. print(pos_tag(tweet_tokens[0]))
```

Here is the output of the pos\_tag function.

Output

```
[('#FollowFriday', 'JJ'),  
 ('@France_Inte', 'NNP'),  
 ('@PKuchly57', 'NNP'),  
 ('@Milipol_Paris', 'NNP'),  
 ('for', 'IN'),  
 ('being', 'VBG'),  
 ('top', 'JJ'),  
 ('engaged', 'VBN'),  
 ('members', 'NNS'),  
 ('in', 'IN'),  
 ('my', 'PRP$'),  
 ('community', 'NN'),  
 ('this', 'DT'),  
 ('week', 'NN'),  
 (':', 'NN')]
```

From the list of tags, here is the list of the most common items and their meaning:

- NNP: Noun, proper, singular
- NN: Noun, common, singular or mass

- IN: Preposition or conjunction, subordinating
- VBG: Verb, gerund or present participle
- VBN: Verb, past participle

Here is a full list of the dataset.

In general, if a tag starts with NN, the word is a noun and if it starts with VB, the word is a verb. After reviewing the tags, exit the Python session by entering exit(). Update the nlp\_test.py file with the following function that lemmatizes a sentence:

### nlp\_test.py

```
...
from nltk.tag import pos_tag
from nltk.stem.wordnet import WordNetLemmatizer

def lemmatize_sentence(tokens):
    lemmatizer = WordNetLemmatizer()
    lemmatized_sentence = []
    for word, tag in pos_tag(tokens):
        if tag.startswith('NN'):
            pos = 'n'
        elif tag.startswith('VB'):
            pos = 'v'
        else:
            pos = 'a'
        lemmatized_sentence.append(lemmatizer.lemmatize(word, pos))
    return lemmatized_sentence

print(lemmatize_sentence(tweet_tokens[0]))
```

This code imports the WordNetLemmatizer class and initializes it to a variable, lemmatizer.

Save and close the file, and run the script:

```
1.python3 nlp_test.py
```

Here is the output:

### Output

```
['#FollowFriday',  
 '@France_Inte',  
 '@PKuchly57',  
 '@Milipol_Paris',  
 'for',  
 'be',  
 'top',  
 'engage',  
 'member',  
 'in',  
 'my',  
 'community',  
 'this',  
 'week',  
 ':)']
```

You will notice that the verb `being` changes to its root form, `be`, and the noun `members` changes to `member`. Before you proceed, comment out the last line that prints the sample tweet from the script.

#### Step 4 — Removing Noise from the Data

In this step, you will remove noise from the dataset. *Noise* is any part of the text that does not add meaning or information to data.

In this tutorial, you will use regular expressions in Python to search for and remove these items:

- Hyperlinks - All hyperlinks in Twitter are converted to the URL shortener `t.co`. Therefore, keeping them in the text processing would not add any value to the analysis.

```
nlp_test.py  
...  
import re, string  
def remove_noise(tweet_tokens, stop_words =()):  
    cleaned_tokens = []  
    for token, tag in pos_tag(tweet_tokens):  
        token = re.sub('http[s]?://(?:[a-zA-Z][0-9][$_@.&+#!][!*\\(\\),]|"\\"  
        '(?:%[0-9a-fA-F][0-9a-fA-F])+", token)  
        token = re.sub("(@[A-Za-z0-9_]+)", "", token)
```

```

if tag.startswith("NN"):
    pos = 'n'
elif tag.startswith('VB'):
    pos = 'v'
else:
    pos = 'a'

lemmatizer = WordNetLemmatizer()
token = lemmatizer.lemmatize(token, pos)
if len(token) > 0 and token not in string.punctuation and token.lower() not in
stop_words:
    cleaned_tokens.append(token.lower())
return cleaned_tokens

```

This code creates a `remove_noise()` function that removes noise and incorporates the normalization and lemmatization mentioned in the previous section. The code takes two arguments: the tweet tokens and the tuple of stop words.

The code then uses a loop to remove the noise from the dataset.

Execute the following command from a Python interactive session to download this resource:

1. `nltk.download('stopwords')`
- 2.

Once the resource is downloaded, exit the interactive session.

You can use the `.words()` method to get a list of stop words in English. To test the function, let us run it on our sample tweet. Add the following lines to the end of the `nlp_test.py` file:

```

nlp_test.py
...
from nltk.corpus import stopwords
stop_words = stopwords.words('english')

print(remove_noise(tweet_tokens[0], stop_words))

```

After saving and closing the file, run the script again to receive output similar to the following:

### Output

```
['#followfriday', 'top', 'engage', 'member', 'community', 'week', ':)']
```

Notice that the function removes all @ mentions, stop words, and converts the words to lowercase.

Before proceeding to the modeling exercise in the next step, use the `remove_noise()` function to clean the positive and negative tweets. Comment out the line to print the output of `remove_noise()` on the sample tweet and add the following to the `nlp_test.py` script:

### nlp\_test.py

```
... from nltk.corpus import stopwords  
stop_words = stopwords.words('english')  
#print(remove_noise(tweet_tokens[0], stop_words))  
positive_tweet_tokens = twitter_samples.tokenized('positive_tweets.json')  
negative_tweet_tokens = twitter_samples.tokenized('negative_tweets.json')  
positive_cleaned_tokens_list = []  
negative_cleaned_tokens_list = []  
for tokens in positive_tweet_tokens:  
    positive_cleaned_tokens_list.append(remove_noise(tokens, stop_words))  
for tokens in negative_tweet_tokens:  
    negative_cleaned_tokens_list.append(remove_noise(tokens, stop_words))
```

Now that you've added the code to clean the sample tweets, you may want to compare the original tokens to the cleaned tokens for a sample tweet. If you'd like to test this, add the following code to the file to compare both versions of the 500th tweet in the list:

### nlp\_test.py

```
...  
print(positive_tweet_tokens[500])  
print(positive_cleaned_tokens_list[500])
```

Save and close the file and run the script. From the output you will see that the punctuation and links have been removed, and the words have been converted to lowercase.

## Output

```
['Dang', 'that', 'is', 'some', 'rad', '@AbzuGame', '#fanart', '!', ':D', ':D',  
'https://t.co/bI8k8tb9ht']  
['dang', 'rad', '#fanart', ':d']
```

Now that you've seen the `remove_noise()` function in action, be sure to comment out or remove the last two lines from the script so you can add more to it:

```
#print(positive_cleaned_tokens_list[nlp_test.py  
...  
#print(positive_tweet_tokens[500])  
500])
```

In this step you removed noise from the data to make the analysis more effective. In the next step you will analyze the data to find the most common words in your sample dataset.

## Step 5 — Determining Word Density

The most basic form of analysis on textual data is to take out the word frequency. A single tweet is too small of an entity to find out the distribution of words, hence, the analysis of the frequency of words would be done on all positive tweets. Add the following code to your `nlp_test.py` file:

```
nlp_test.py  
...def get_all_words(cleaned_tokens_list):  
    for tokens in cleaned_tokens_list:  
        for token in tokens:  
            yield token  
all_pos_words = get_all_words(positive_cleaned_tokens_list)
```

Now that you have compiled all words in the sample of tweets, you can find out which are the most common words using the `FreqDist` class of NLTK. Adding the following code to the `nlp_test.py` file:

```
nlp_test.py  
from nltk import FreqDist  
freq_dist_pos = FreqDist(all_pos_words)  
print(freq_dist_pos.most_common(10))
```

The `.most_common()` method lists the words which occur most frequently in the data. Save and close the file after making these changes.

When you run the file now, you will find the most common terms in the data:

## Output

```
[(':', 3691),  
(':-)', 701),  
(':d', 658),  
('thanks', 388),  
('follow', 357),  
('love', 333),  
('...', 290),  
('good', 283),  
('get', 263),  
('thank', 253)]
```

To summarize, you extracted the tweets from `nltk`, tokenized, normalized, and cleaned up the tweets for using in the model. Finally, you also looked at the frequencies of tokens in the data and checked the frequencies of the top ten tokens.

In the next step you will prepare data for sentiment analysis.

## Step 6 — Preparing Data for the Model

Sentiment analysis is a process of identifying an attitude of the author on a topic that is being written about. You will create a training data set to train a model. It is a supervised learning machine learning process, which requires you to associate each dataset with a “sentiment” for training. In this tutorial, your model will use the “positive” and “negative” sentiments.

In the data preparation step, you will prepare the data for sentiment analysis by converting tokens to the dictionary form and then split the data for training and testing purposes.

Add the following code to convert the tweets from a list of cleaned tokens to dictionaries with keys as the tokens and `True` as values. The corresponding dictionaries are stored

in `positive_tokens_for_model` and `negative_tokens_for_model`.

```
nlp_test.py
```

```
lis...
```

```
def get_tweets_for_model(cleaned_tokens_list):
```

```
for tweet_tokens in cleaned_tokens_list:  
    yield dict([token, True] for token in tweet_tokens)  
positive_tokens_for_model =  
get_tweets_for_model(positive_cleaned_tokens_list).list()  
negative_tokens_for_model =  
get_tweets_for_model(negative_cleaned_tokens_list).list()
```

### Splitting the Dataset for Training and Testing the Model

Next, you need to prepare the data for training the `NaiveBayesClassifier` class. Add the following code to the file to prepare the data:

```
nlp_test.py  
...  
import random  
  
positive_dataset = [(tweet_dict, "Positive")]  
    for tweet_dict in positive_tokens_for_model:  
negative_dataset = [(tweet_dict, "Negative")]  
    for tweet_dict in negative_tokens_for_model:  
dataset = positive_dataset + negative_dataset  
random.shuffle(dataset)  
train_data = dataset[:7000]  
test_data = dataset[7000:]
```

This code attaches a `Positive` or `Negative` label to each tweet. It then creates a dataset by joining the positive and negative tweets.

Finally, the code splits the shuffled data into a ratio of 70:30 for training and testing, respectively. Since the number of tweets is 10000, you can use the first 7000 tweets from the shuffled dataset for training the model and the final 3000 for testing the model.

In this step, you converted the cleaned tokens to a dictionary form, randomly shuffled the dataset, and split it into training and testing data.

### Step 7 — Building and Testing the Model

Finally, you can use the `NaiveBayesClassifier` class to build the model. Use the `.train()` method to train the model and the `.accuracy()` method to test the model on the testing data.

```
nlp_test.py
```

```

from nltk import classify
from nltk import NaiveBayesClassifier
classifier = NaiveBayesClassifier.train(train_data)
print("Accuracy is:", classify.accuracy(classifier, test_data))
print(classifier.show_most_informative_features(10))

```

Save, close, and execute the file after adding the code. The output of the code will be as follows:

## Output

Accuracy is: 0.9956666666666667

### Most Informative Features

:( :) = True	Negati : Positi = 2085.6 : 1.0
welcome = True	Positi : Negati = 986.0 : 1.0
arrive = True	Positi : Negati = 37.2 : 1.0
sad = True	Positi : Negati = 31.3 : 1.0
follower = True	Negati : Positi = 25.9 : 1.0
bam = True	Positi : Negati = 21.1 : 1.0
glad = True	Positi : Negati = 20.7 : 1.0
x15 = True	Positi : Negati = 18.1 : 1.0
community = True	Negati : Positi = 15.9 : 1.0
	Positi : Negati = 14.1 : 1.0

Accuracy is defined as the percentage of tweets in the testing dataset for which the model was correctly able to predict the sentiment. A 99.5% accuracy on the test set is pretty good.

Next, you can check how the model performs on random tweets from Twitter. Add this code to the file:

```

nlp_test.py
from nltk.tokenize import word_tokenize
custom_tweet = "I ordered just once from TerribleCo, they screwed up, never used the app again."
custom_tokens = remove_noise(word_tokenize(custom_tweet))
print(classifier.classify(dict([token, True] for token in custom_tokens)))

```

This code will allow you to test custom tweets by updating the string associated with the `custom_tweet` variable. Save and close the file after making these changes.

Run the script to analyze the custom text. Here is the output for the custom text in the example:

**Output**

'Negative'

You can also check if it characterizes positive tweets correctly:

nlp\_test.py

...

```
custom_tweet = 'Congrats #SportStar on your 7th best goal from last season winning goal of the year :) #Baller #Topbin #oneofmanyworldies'
```

Here is the output:

**Output**

'Positive'

Now that you've tested both positive and negative sentiments, update the variable to test a more complex sentiment like sarcasm.

nlp\_test.py

...

```
custom_tweet = 'Thank you for sending my baggage to CityX and flying me to CityY at the same time. Brilliant service. #thanksGenericAirline'
```

Here is the output:

**Output**

'Positive'

The model classified this example as positive. This is because the training data wasn't comprehensive enough to classify sarcastic tweets as negative. In this step you built and tested the model. You also explored some of its limitations, such as not detecting sarcasm in particular examples. Your completed code still has artifacts leftover from following the tutorial, so the next step will guide you through aligning the code to Python's best practices.

**Step 8 — Cleaning Up the Code (Optional)**

Though you have completed the tutorial, it is recommended to reorganize the code in the `nlp_test.py` file to follow best programming practices. Per best practice, your code should meet this criteria:

- All imports should be at the top of the file. Imports from the same library should be grouped together in a single statement.
  - All functions should be defined after the imports.
  - All the statements in the file should be housed under an `if __name__ == "__main__":` condition. This ensures that the statements are not executed if
- Here is the cleaned version of `nlp_test.py`:

```
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import twitter_samples, stopwords
from nltk.tag import pos_tag
from nltk.tokenize import word_tokenize
from nltk import FreqDist, classify, NaiveBayesClassifier
import re, string, random
def remove_noise(tweet_tokens, stop_words =())::
    cleaned_tokens = []
    for token, tag in pos_tag(tweet_tokens):
        token = re.sub('http[s]?://(?:[a-zA-Z][0-9][$-_@.&+#!|!*\(\),]|'\
                      '(?:%[0-9a-fA-F][0-9a-fA-F])+'',',', token)
        token = re.sub("(@[A-Za-z0-9_]+)", "", token)
        if tag.startswith("NN"):
            pos = 'n'
        elif tag.startswith('VB'):
            pos = 'v'
        else:
            pos = 'a'
        lemmatizer = WordNetLemmatizer()
        token = lemmatizer.lemmatize(token, pos)
        if len(token) > 0 and token not in string.punctuation and
token.lower() not in stop_words:
            cleaned_tokens.append(token.lower())
    return cleaned_tokens
def get_all_words(cleaned_tokens_list):
    for tokens in cleaned_tokens_list:
        for token in tokens:
            yield token
```

```

def get_tweets_for_model(cleaned_tokens_list):
    for tweet_tokens in cleaned_tokens_list:
        yield dict([token, True] for token in tweet_tokens))

if __name__ == "__main__":
    positive_tweets = twitter_samples.strings('positive_tweets.json')
    negative_tweets = twitter_samples.strings('negative_tweets.json')
    text = twitter_samples.strings('tweets.20150430-223406.json')
    tweet_tokens = twitter_samples.tokenized('positive_tweets.json')[0]
    stop_words = stopwords.words('english')
    positive_tweet_tokens = twitter_samples.tokenized('positive_tweets.json')
    negative_tweet_tokens = twitter_samples.tokenized('negative_tweets.json')
    positive_cleaned_tokens_list = []
    negative_cleaned_tokens_list = []
    for tokens in positive_tweet_tokens:
        positive_cleaned_tokens_list.append(remove_noise(tokens, stop_words))
    for tokens in negative_tweet_tokens:
        negative_cleaned_tokens_list.append(remove_noise(tokens, stop_words))
    all_pos_words = get_all_words(positive_cleaned_tokens_list)
    freq_dist_pos = FreqDist(all_pos_words)
    print(freq_dist_pos.most_common(10))
    positive_tokens_for_model = get_tweets_for_model(positive_cleaned_tokens_list)
    negative_tokens_for_model = get_tweets_for_model(negative_cleaned_tokens_list)
    positive_dataset = [(tweet_dict, "Positive")]
        for tweet_dict in positive_tokens_for_model]
    negative_dataset = [(tweet_dict, "Negative")]
        for tweet_dict in negative_tokens_for_model]
    dataset = positive_dataset + negative_dataset
    random.shuffle(dataset)
    train_data = dataset[:7000]
    test_data = dataset[7000:]
    classifier = NaiveBayesClassifier.train(train_data)
    print("Accuracy is:", classify.accuracy(classifier, test_data))

```

```
print(classifier.show_most_informative_features(10))
custom_tweet = "I ordered just once from TerribleCo, they screwed up, never used the app again."
custom_tokens = remove_noise(word_tokenize(custom_tweet))
print(custom_tweet, classifier.classify(dict([token, True] for token in custom_tokens)))
```

## Conclusion

Sentiment analysis is a technique used to understand the emotional tone of the text. It can be used to identify positive, negative, and neutral sentiments in a piece of writing.

Sentiment analysis focuses on the polarity of a text (positive, negative, neutral), but it also goes beyond polarity to detect specific feelings and emotions (angry, happy, sad, etc.), urgency (urgent, not urgent), and even intentions (interested vs. not interested).

### What is the goal of sentiment analysis:

Sentiment analysis is a technique used to understand the emotional tone of the text. It can be used to identify positive, negative, and neutral sentiments in a piece of writing. Sentiment analysis focuses on the polarity of a text (positive, negative, neutral), but it also goes beyond polarity to detect specific feelings and emotions (angry, happy, sad, etc.), urgency (urgent, not urgent), and even intentions (interested vs. not interested).

### What is future scope of sentiment analysis:

However, sentiment analysis will delve deeper in the future, beyond the concept of positive, negative, or neutral, to reach and comprehend the significance of understanding conversations and what they reveal about consumers.