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## SENTIMENT ANALYSIS FOR MARKETING

## Phase 4: Development part 2

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# 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.

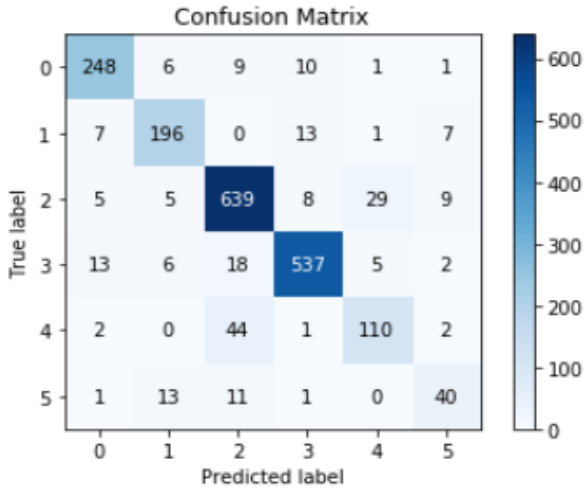
```
#
plt.figure(figsize=(10,5))
plot_confusion_matrix(test_df,predictions)
acc_score = accuracy_score(test_df,predictions)
pre_score = precision_score(test_df,predictions,average='micro')
rec_score = recall_score(test_df,predictions,average='micro')
print('Accuracy_score: ',acc_score)
print('Precision_score: ',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. pytho3
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 stars 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',
'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:

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)
negative_tokens_for_model =
get_tweets_for_model(negative_cleaned_tokens_t)
```

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

This tutorial introduced you to a basic sentiment analysis model using the nltk library in Python 3. First, you performed pre-processing on tweets by tokenizing a tweet, normalizing the words, and removing noise. Next, you visualized frequently occurring items in the data. Finally, you built a model to associate tweets to a particular sentiment.

A supervised learning model is only as good as its training data. To further strengthen the model, you could considering adding more categories like excitement and anger. In this tutorial, you have only scratched the surface by building a rudimentary model. Here's a detailed guide on various considerations that one must take care of while performing sentiment analysis.