Natural Language Processing

CSCE 5290, Fall 2022

UNT™

UNIVERSITY OF NORTH TEXAS

Group 14:

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Project Proposal

Project Title: Sentimental Analysis for Monarchy in UK

1. Motivation

Sentiment analysis is a study of subjective information present in any form of data which will give out different expressions used in any particular statement. Automating such a process gives out deep hidden insights on the data which is possible only with Natural Language Processing.

Our main goal is to find out sentiment analysis on how people reacted to the recent event 'Queen Elizabeth II death' and if possible find the most probable issues that might rise in the future.

2. Significance

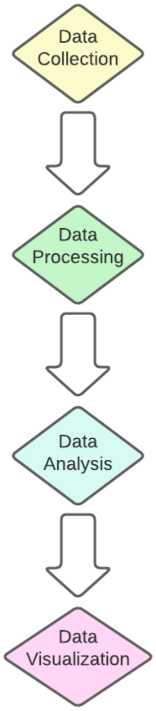
This project can be used for any particular event that occurs around the world and see how people are reacting to it. The expressions of people can be evaluated to see how the country/company is going to progress further in the future. The benefit of knowing things early can be taken as a precaution and avoid it totally which can turn over a catastrophe. This project can be contributed towards Artificial intelligence and further improve

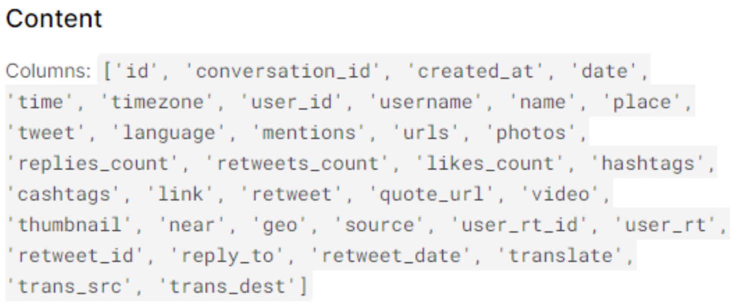
3. Objectives

The main objective of our project is to know about the expressions of people in the UK and around the world on how they feel about the Monarchy in the UK. The following project will help to get a score of expressions and also see how many people are unaffected by it. This score can be used by the officials to see what can be done to increase rating in any particular index. The project may also reveal the emotions of the people and lifestyle changes(in a positive or negative manner) they make after the Queen's death. The reign of the King can be predicted with the tweets of the people and how long it can go without breaking the Country / Government.

4. Features

- This project evaluates any kind of tweet dataset presented and gives a score based on the data.
- Visualization -- that includes charts generated from the data using Google Charts API.





Content

Columns: `['id', 'conversation_id', 'created_at', 'date', 'time', 'timezone', 'user_id', 'username', 'name', 'place', 'tweet', 'language', 'mentions', 'urls', 'photos', 'replies_count', 'retweets_count', 'likes_count', 'hashtags', 'cashtags', 'link', 'retweet', 'quote_url', 'video', 'thumbnail', 'near', 'geo', 'source', 'user_rt_id', 'user_rt', 'retweet_id', 'reply_to', 'retweet_date', 'translate', 'trans_src', 'trans_dest']`

5. Related Work (Background)

<u>**Sentiment Analysis**</u>

Sentimental analysis is a technique, which is used in determination of positivity or negativity of the data. It is used in real life segments like product reviews, spam email filtering, emotions and much more.

Types of sentimental analysis:

1. Graded Sentiment Analysis: It categories the text into 5 levels like very negative, negative, neutral, positive or very positive.

2. Emotion Detection: It determines emotions like happiness, anger and frustration.

3. Aspect-based: If there is a need to find the positivity or negativity in terms of opinion, then it comes under this category.

4. Multilingual: Compared to other types, this is a complex model. In the case of multilingual sentences or idioms, it is hard to find meaning and perform analysis.

Algorithms used:

1. Linear Regression: It is a supervised learning used to perform regression tasks. It implements the model that finds a linear relationship between all the variables.

2. Naive Bayes: It is also a supervised learning which uses Bayes theorem for classification. Sentimental analysis is done considering the probability of the words.

3. Support Vector Machine: This algorithm is supervised learning that is implemented by finding a best fit line in a n-dimensional space to classify the data.

Previous work:

There are many projects that implement sentiment analysis like product reviews, movie reviews, paper reviews, customer feedback and much more.

There is a project that implements the sentimental analysis model on the twitter data.

Overview of the project: In this project is builded to classify the positivity or negativity of the tweets. The data is collected from the Twitter API and uses Naive Bayes classifier.

In this project firstly the preprocessing of the text is done by removing all the stop words, repeated words and punctuations, lower casing all the text and stemming. Next the train and test dataset are formed and the TF-IDF vectorizer is used in transforming the dataset. Finally the prediction is performed. The model is built using Naive Bayes and Support Vector Machine separately and accuracy of both models are compared.

Question Answering:

Question Answering is a technique that answers to any question that is asked from a given text by searching the answer to it in the document.

Questions are of two types in the modern systems:

Factoid Questions:

The answer to any question is simple and can be directly found in an existing document is considered as factoid questions. As the name suggests it totally depends on facts. These will have universal answers.

Example: When is Thanksgiving?

Complex or Narrative Questions:

The answer to any questions is not a simple or one word answer, it will be an explanation or opinion. When a question is asked on an opinion in a document, to answer that question, the answer may vary from model to model. This can be done by categorizing the text.

Example: Questions based on philosophy or opinions.

Text Classification:

The process of categorizing the text into a group is text classification. Sentiment analysis is used to implement text classification.

There are three approaches in the text classification:

1. Rule-based Systems: The text is categorized based on linguistic rules, i.e., list of certain words are categorized into one group.
2. Machine-based: This type uses the bag of words for classification. The text is classified into classes based on the previous observations on the dataset.

3. Hybrid: It is the combination of the rule-based and machine-based approaches. It uses tags and trains the model to create the rules. Among all the approaches this is the best method in text classification.

- ❖ The algorithms used for the text classification are naive bayes, support vector machines and deep learning.

Previous Work:

There are many projects that implement text classification, ‘big multimedia’ and ‘state of are elements’ are among them.

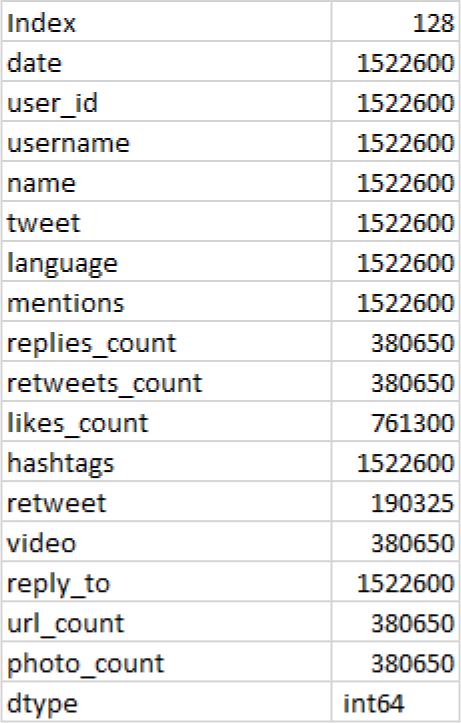
Overview of the big multimedia project: In this project the data is a mixture of audio, images and text. The text classification is done using the feature selection. The review of the text classifiers is carried out which include Decision Tree, Naive Bayes, SVM, Nearest Neighbor and Neural network. By comparing all the models, the model which gives the best feature selection is found.

Overview of the state of arts elements: This is the study of the baseline elements like text classification, data analysis, feature construction and selection, training and evaluation that takes place. The main goal is to develop the best techniques that are used to implement these elements which will be used for future studies.

6. Dataset

In this project we are using the tweets that have been generated on the Queen Elizabeth 2 death. Using this we are going to perform the sentimental analysis.

The dataset comprises of around 200000 tweets. The details of each tweets are recorded and are categorised into 36 columns. These columns gives the details such as the timestamp of the tweet, the name of the user posted, names of the user, like count, retweet count, source, user ID, translate, 'id', 'conversation_id', 'created_at', 'date', 'timezone', 'user_id', 'username', 'place', 'tweet', 'language', 'mentions', 'urls', 'photos', 'replies_count', 'hashtags', 'cashtags', 'link', 'retweet', 'quote_url', 'video', 'thumbnail', 'near', 'geo', 'user_rt_id', 'user_rt', 'retweet_id', 'reply_to', 'retweet_date', 'trans_src', and 'trans_dest'. The size of the data is about 98.72 MB.



Index	128
date	1522600
user_id	1522600
username	1522600
name	1522600
tweet	1522600
language	1522600
mentions	1522600
replies_count	380650
retweets_count	380650
likes_count	761300
hashtags	1522600
retweet	190325
video	380650
reply_to	1522600
url_count	380650
photo_count	380650
dtype	int64

The dataset has a unique hashtags of 26857 and proportion of empty hashtags is 62.558%. It has a unique cashtags of 55 and the proportion of empty cashtags is 99.958%. It also has a unique Mentions Count of 7482 and the proportion of empty Mentions is 91.14999%. It has a unique Urls Count of 37070 and the proportion of empty Urls is 71.594%. It has a unique Photos count of 68241 and the proportion of empty Photos is 63.8839%. It also has a unique Reply_to Count is 8764 and proportion of empty Reply_to is 92.683%. It has 530 unique timezones. The maximum user-id value is 1568164808561950720. Maximum replies count of a tweet is 8102. Maximum retweets count is 16910. The maximum likes count is 151799. The total number of videos is 1 and the maximum uro count is 766 and the maximum photo count of 204.

Among the tweets 83.8% are from the en region. The regions where most of the tweets have been observed are - 4.5% from cy region. 1.7%, 1.6%, 1.4%, belongs to es, und, and qme regions.

7. Detail design of Features

Architecture:

A. Data pre-processing

1) Removal of Punctuations: Sentimental Analysis is sometimes difficult to implement because of the presence of non-useful data(referred as noise) with the useful data. The Non-useful data in our dataset includes Punctuations, emojis, stopwords, etc. We are removing the punctuations, emojis etc, using the Regular Expressions.
2) Removal of Stopwords: Stopwords are words that are present in a high volume in most of the documents and contribute very little to the meaning of the text. These words usually harm the accuracy of the model and it's better to remove them before training. Stopwords are generally filtered out for processing in any natural language processing context. Examples of Stopwords are ‘the’, ‘are’,etc.
3) Removing Repeating Characters: Characters which are appearing repeatedly are removed.
4) Cleaning HTML Data: HTML Data is Cleaned.
5) Removing Numbers: Numbers have been removed using Regular Expressions.
6) Tokenization: Tokenization is the process of breaking a stream of text data into words. This is usually the first step of the NLP Pipeline. After Tokenization we can perform other NLP Processes like Lemmatization.
7) Lemmatization: Lemmatization is the process to get the base form for all the tokens we got after Tokenization. We have used WordNetLemmatizer from the NLTK library.

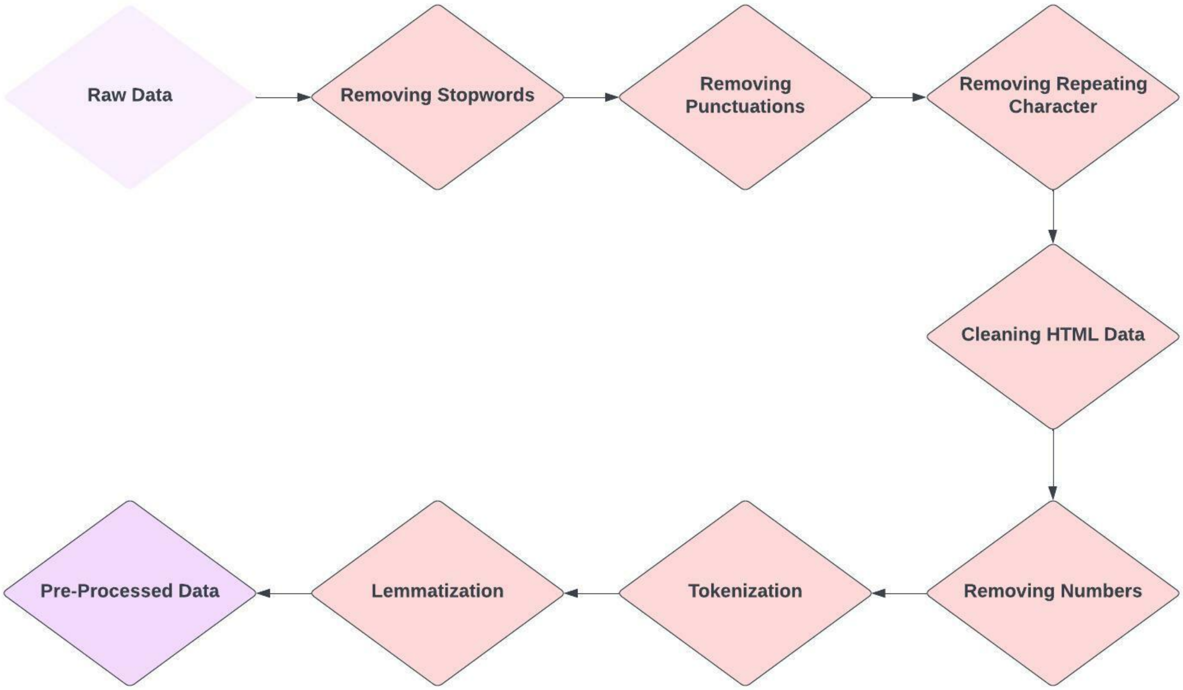


Fig: Workflow diagram

B. Positive and Negative / True Positive and True Negative score

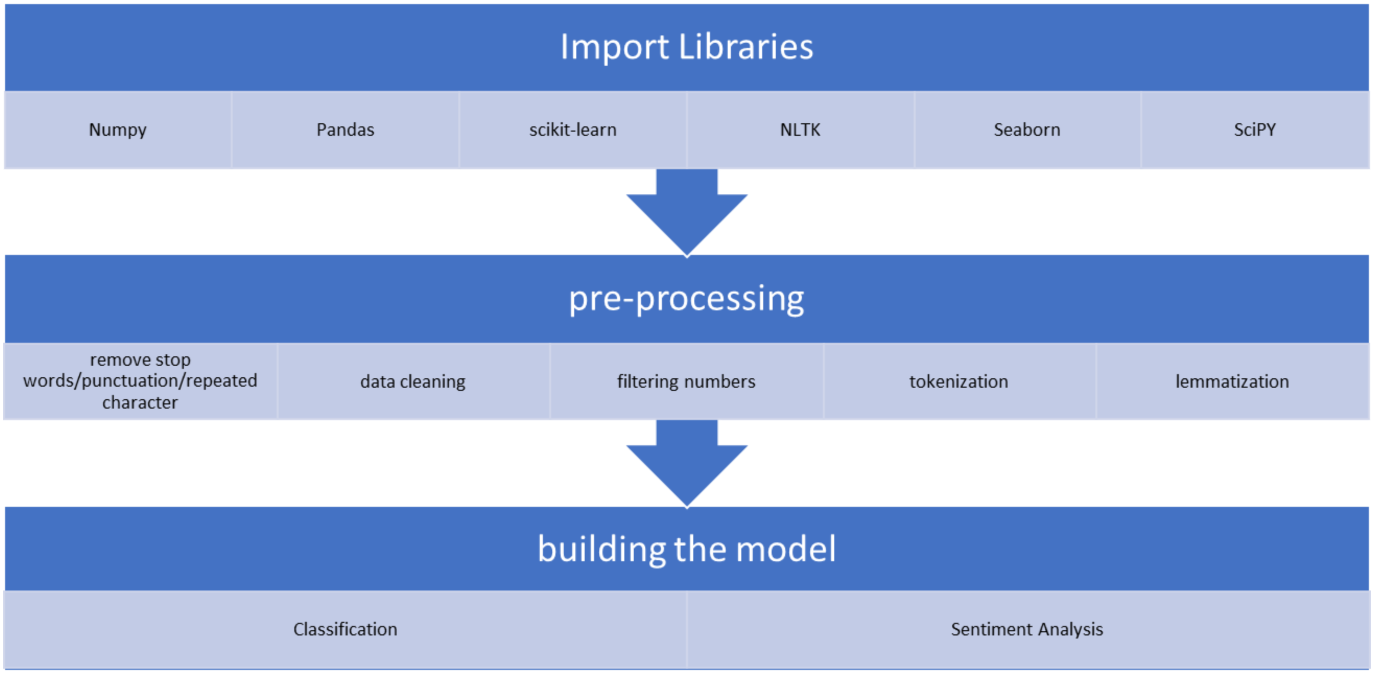
Positive Score refers to the score we get that the tweet is positive(or sentimental/empathetic) towards the queen's death. Negative Score is the score we get that the tweet is negative(or showing anger towards the monarchy). True Positive Score is the score we get when the score is greater than 0.15. True Negative Score is the score we get when the score is less than (-0.15).

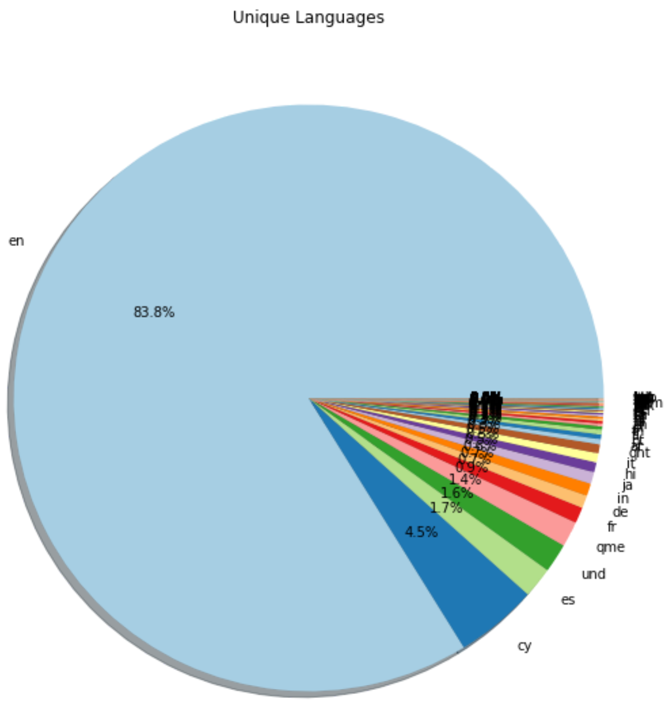
C. Classification of statement

We ask users to enter a tweet(text input), we can classify if the tweet is positive or negative using our model.

8. Analysis

Visualizing the data is important before building a model. There are many ways to visualize. Examples are a flow chart, a histogram, a word cloud, a pie chart, or more. These are all ways to perform exploratory data analysis on the dataset. We have shown a flowchart with the flowchart of the data model. We also have visualized the data by showing the different languages that are present in the tweets. This pie chart helps to see the amount of tweets per language in the dataset.

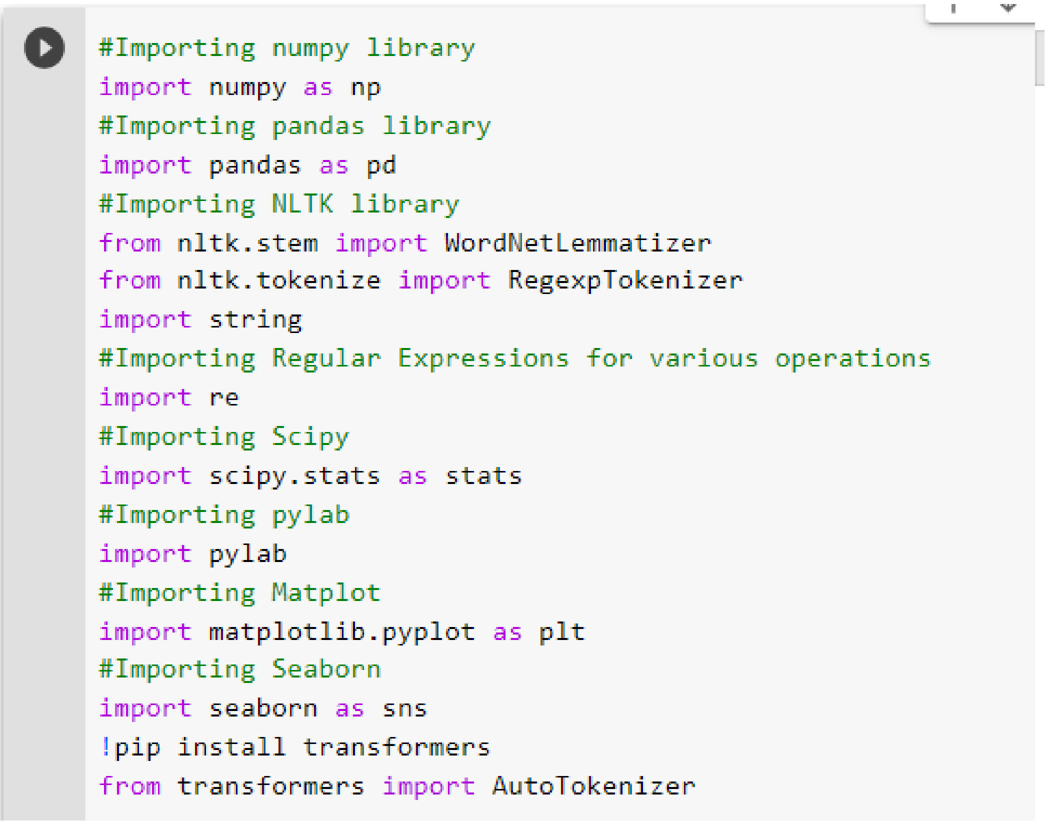




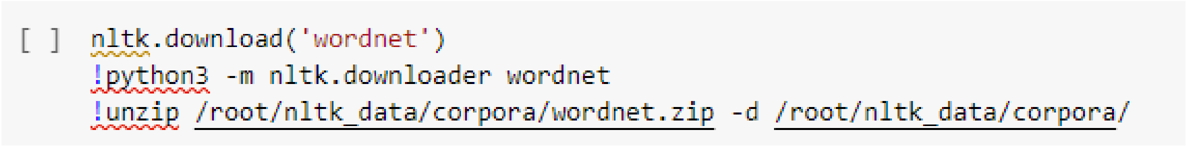
The above pie chart is displaying the portion of languages in the dataset.

9. Implementation / Work completed

Here is the implementation of our code:

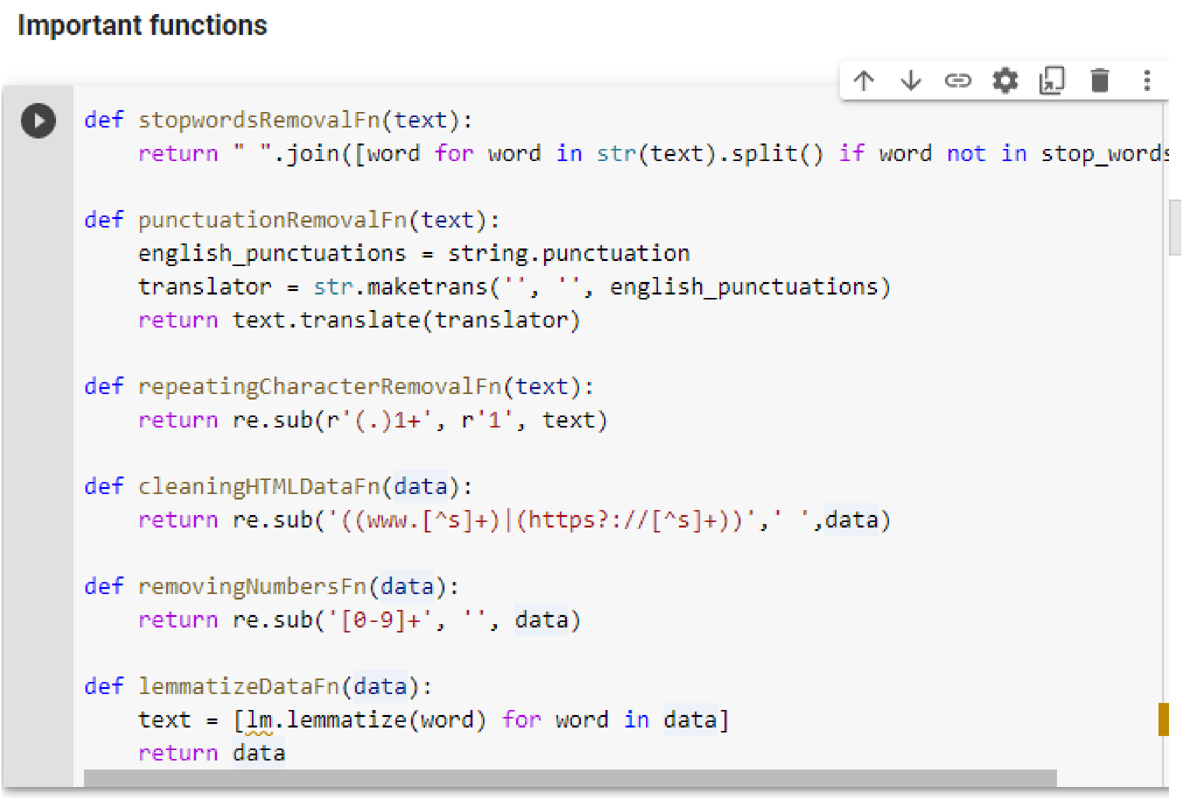


```
#Importing numpy library
import numpy as np
#Importing pandas library
import pandas as pd
#Importing NLTK library
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import RegexpTokenizer
import string
#Importing Regular Expressions for various operations
import re
#Importing Scipy
import scipy.stats as stats
#Importing pylab
import pylab
#Importing Matplot
import matplotlib.pyplot as plt
#Importing Seaborn
import seaborn as sns
!pip install transformers
from transformers import AutoTokenizer
```



```
[ ]  nltk.download('wordnet')
     !python3 -m nltk.downloader wordnet
     !unzip /root/nltk_data/corpora/wordnet.zip -d /root/nltk_data/corpora/
```

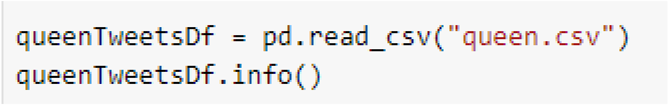
Step 1: First the code starts by importing all the libraries and packages needed to perform the code. We are going to need a lot of libraries since we will be using different pre-processing models and plots for our code.



Important functions

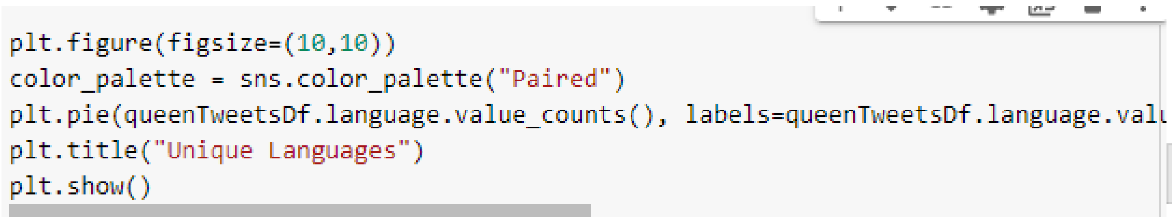
```
def stopwordsRemovalFn(text):
    return " ".join([word for word in str(text).split() if word not in stop_words

def punctuationRemovalFn(text):
    english_punctuations = string.punctuation
    translator = str.maketrans('', '', english_punctuations)
    return text.translate(translator)

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

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

def removingNumbersFn(data):
    return re.sub('[0-9]+', '', data)

def lemmatizeDataFn(data):
    text = [lm.lemmatize(word) for word in data]
    return data
```

Step 2: The code is detailed and will need functions to perform properly. Each function will have a definition to define the properties of the function to tell the computer what to do.



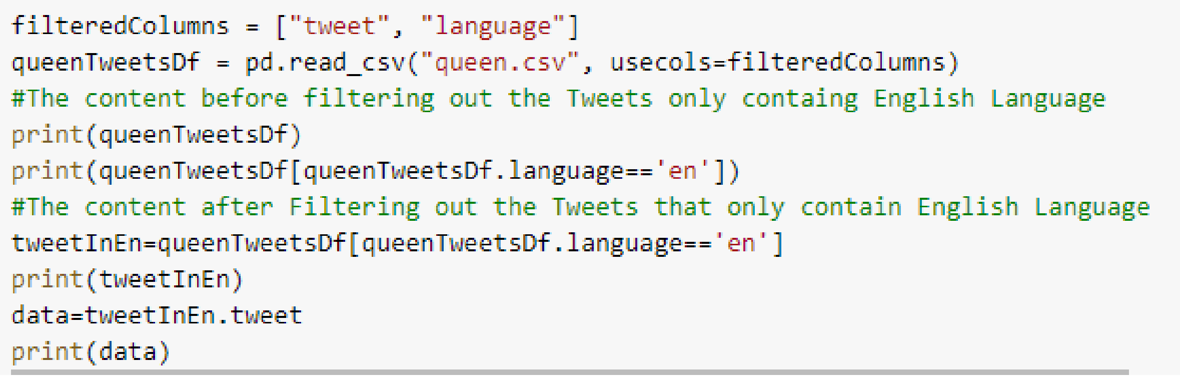
```
queenTweetsDf = pd.read_csv("queen.csv")
queenTweetsDf.info()
```

Step 3: This is the upload of the dataset that we are using. The dataset we are using is tweets about the queen.



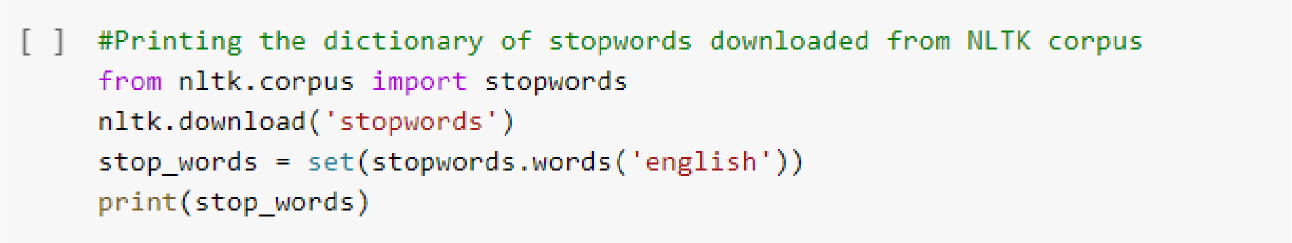
```
plt.figure(figsize=(10,10))
color_palette = sns.color_palette("Paired")
plt.pie(queenTweetsDf.language.value_counts(), labels=queenTweetsDf.language.valu
plt.title("Unique Languages")
plt.show()
```

Step 4: The code then plots the pie chart figure with the color palettes. The labels and titles are also given.

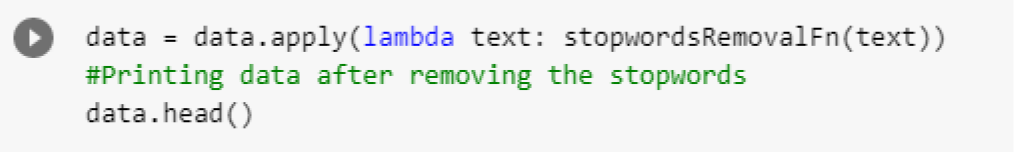


```
filteredColumns = ["tweet", "language"]
queenTweetsDf = pd.read_csv("queen.csv", usecols=filteredColumns)
#The content before filtering out the Tweets only containg English Language
print(queenTweetsDf)
print(queenTweetsDf[queenTweetsDf.language=='en'])
#The content after Filtering out the Tweets that only contain English Language
tweetInEn=queenTweetsDf[queenTweetsDf.language=='en']
print(tweetInEn)
data=tweetInEn.tweet
print(data)
```

Step 5: The code then reads the dataset and filters the tweets in the english language. It then outputs the results for the data in the english language.

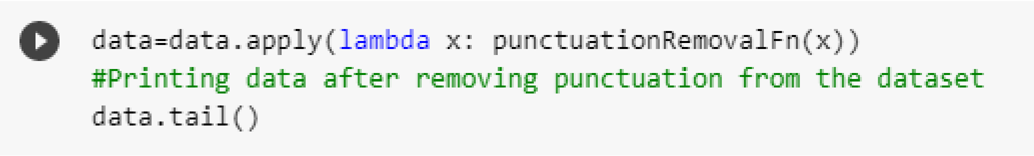


```
#Printing the dictionary of stopwords downloaded from NLTK corpus
from nltk.corpus import stopwords
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
print(stop_words)
```



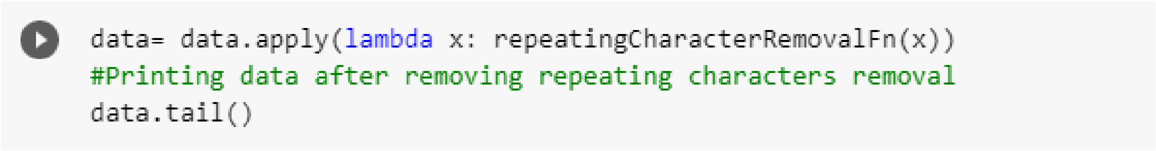
```
data = data.apply(lambda text: stopwordsRemovalFn(text))
#Printing data after removing the stopwords
data.head()
```

Step 6: This is the stop words removal from the dataset. The code then reads the function and removes the stop words from the dataset.



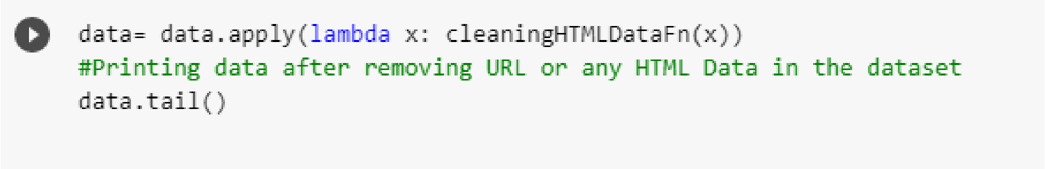
```
data=data.apply(lambda x: punctuationRemovalFn(x))
#Printing data after removing punctuation from the dataset
data.tail()
```

Step 7: This is the punctuation removal from the dataset. The code then reads the function and removes all punctuation from the dataset.



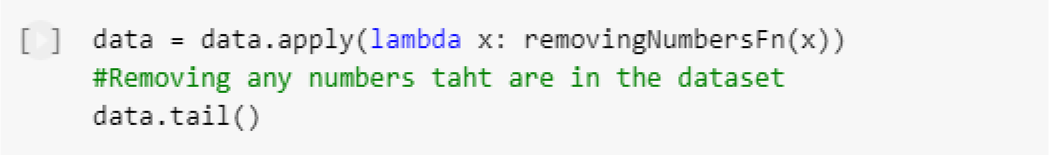
```
data= data.apply(lambda x: repeatingCharacterRemovalFn(x))
#Printing data after removing repeating characters removal
data.tail()
```

Step 8: The code then removes all repeating characters from the dataset.



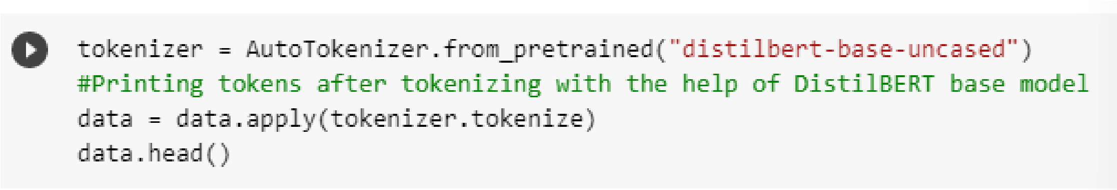
```
data= data.apply(lambda x: cleaningHTMLDataFn(x))
#Printing data after removing URL or any HTML Data in the dataset
data.tail()
```

Step 9: This is the cleaning of the dataset by removing all html and urls



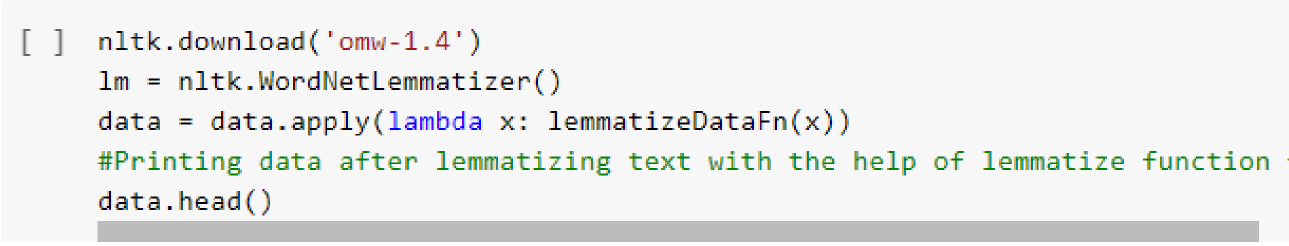
```
data = data.apply(lambda x: removingNumbersFn(x))
#Removing any numbers taht are in the dataset
data.tail()
```

Step 10: This is the removal of all numbers from the dataset.



```
tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased")
#Printing tokens after tokenizing with the help of DistilBERT base model
data = data.apply(tokenizer.tokenize)
data.head()
```

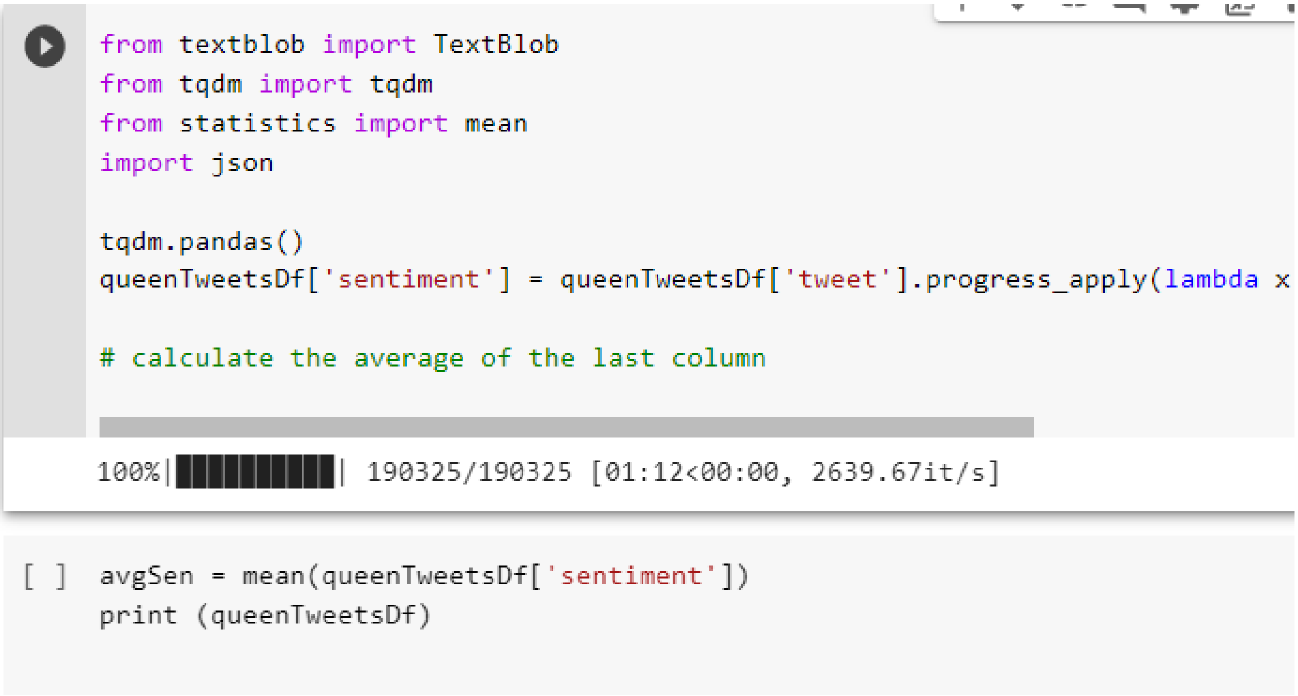
Step 11: This is the tokenization of the dataset. It will lowercase all of the words in the dataset to help the code run smoothly.



```
nltk.download('omw-1.4')
lm = nltk.WordNetLemmatizer()
data = data.apply(lambda x: lemmatizeDataFn(x))
#Printing data after lemmatizing text with the help of lemmatize function
data.head()
```

Step 12: This is the lemmatization of the data. This will help group the words together without knowing their context for the sentiment analysis of the dataset.

Now to the Machine learning:

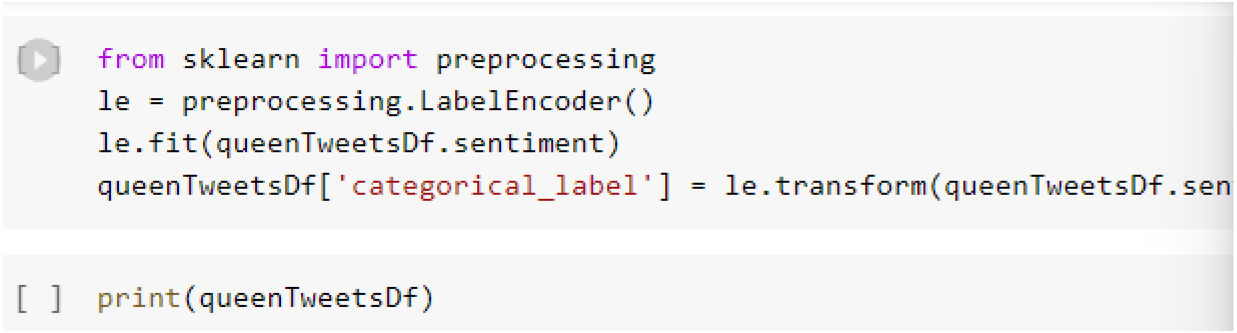


```
from textblob import TextBlob
from tqdm import tqdm
from statistics import mean
import json

tqdm.pandas()
queenTweetsDf['sentiment'] = queenTweetsDf['tweet'].progress_apply(lambda x

# calculate the average of the last column
```

```
100%|██████████| 190325/190325 [01:12<00:00, 2639.67it/s]
```

```
[ ] avgSen = mean(queenTweetsDf['sentiment'])
    print (queenTweetsDf)
```

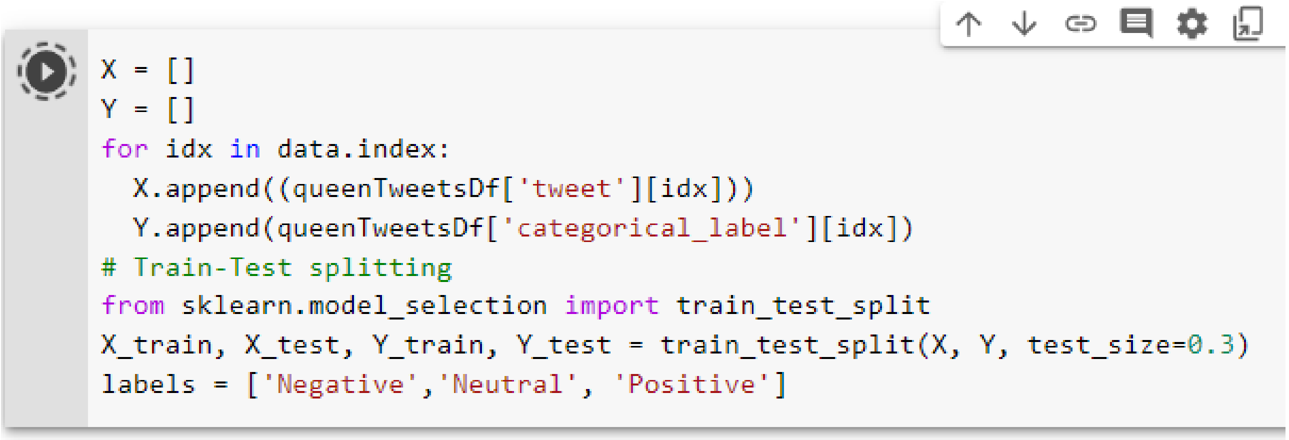
Step 13: This is where the code starts to classify the dataset. It categorizes the dataset on the sentiment of the tweet. It then calculates the average sentiments or emotions out of the tweets.Then print to get the list of emotions and their averages of appearing in the dataset for the english language.



```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(queenTweetsDf.sentiment)
queenTweetsDf['categorical_label'] = le.transform(queenTweetsDf.sen
```

```
[ ]  print(queenTweetsDf)
```

Step 14: This part of the code also creates a category label for the tweets. This transforms the tweets into a new label that will be easier for the code to process.



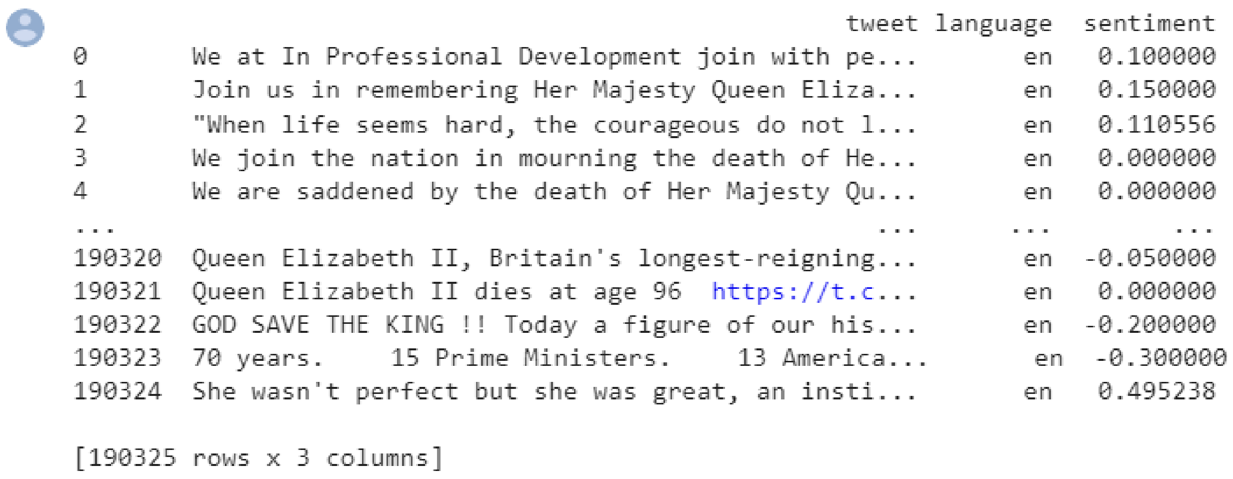
```
X = []
Y = []
for idx in data.index:
  X.append((queenTweetsDf['tweet'][idx]))
  Y.append(queenTweetsDf['categorical_label'][idx])
# Train-Test splitting
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3)
labels = ['Negative','Neutral', 'Positive']
```

Step 15: This is where the code splits the data into its different categories based on their emotion labels. It splits it into test and train data sets for both X and Y for the tweets and category labels.

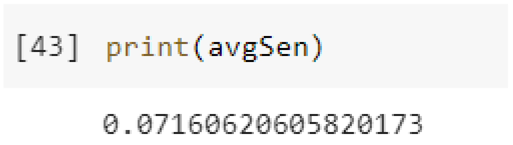
10. Preliminary Results

Our preliminary results show that a large percentage of the data is going to be categorized as bad. The data is from tweets that have been tweeted after the recent passing of the Queen, so a large percentage of tweets will be categorized as bad. The tweets containing information about the death have a sad or shocked emotion that will be categorized into the bad category.

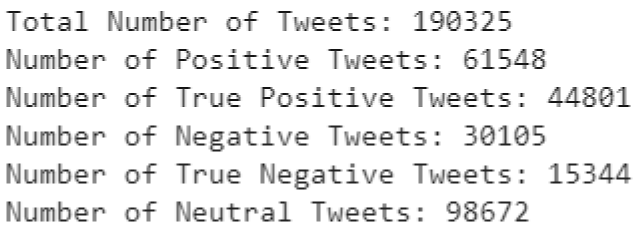
11. Final Results



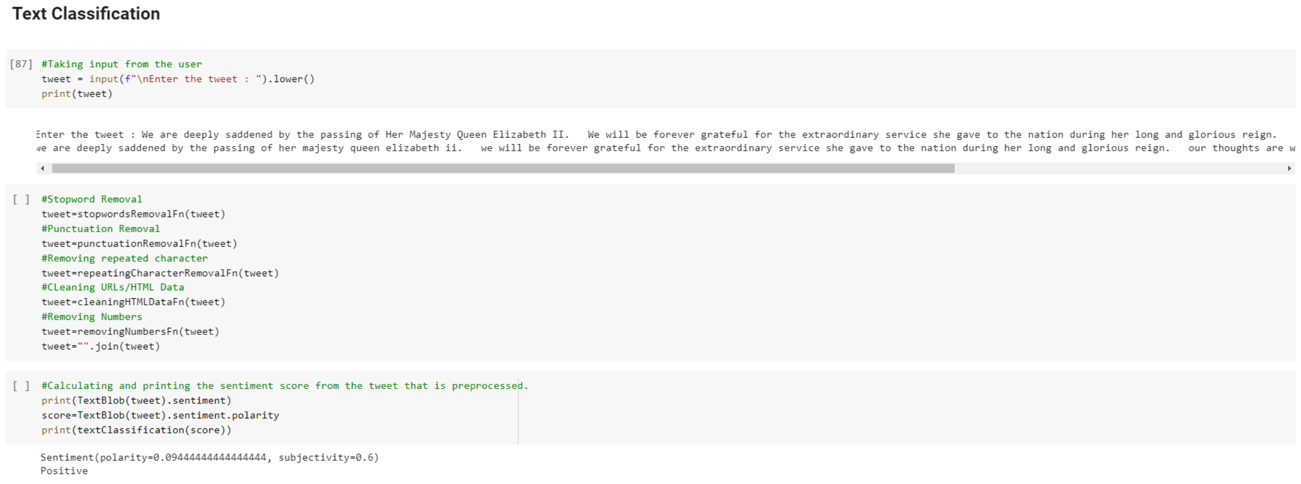
```
                                                    tweet language  sentiment
0       We at In Professional Development join with pe...       en   0.100000
1       Join us in remembering Her Majesty Queen Eliza...       en   0.150000
2       "When life seems hard, the courageous do not l...       en   0.110556
3       We join the nation in mourning the death of He...       en   0.000000
4       We are saddened by the death of Her Majesty Qu...       en   0.000000
...                                                   ...      ...        ...
190320  Queen Elizabeth II, Britain's longest-reigning...       en  -0.050000
190321  Queen Elizabeth II dies at age 96  https://t.c...       en   0.000000
190322  GOD SAVE THE KING !! Today a figure of our his...       en  -0.200000
190323  70 years.     15 Prime Ministers.     13 America...       en  -0.300000
190324  She wasn't perfect but she was great, an insti...       en   0.495238

[190325 rows x 3 columns]
```



```
[43] print(avgSen)

     0.07160620605820173
```



```
Total Number of Tweets: 190325
Number of Positive Tweets: 61548
Number of True Positive Tweets: 44801
Number of Negative Tweets: 30105
Number of True Negative Tweets: 15344
Number of Neutral Tweets: 98672
```



Text Classification

```
[87] #Taking input from the user
     tweet = input(f"\nEnter the tweet : ").lower()
     print(tweet)

Enter the tweet : We are deeply saddened by the passing of Her Majesty Queen Elizabeth II.   We will be forever grateful for the extraordinary service she gave to the nation during her long and glorious reign.
we are deeply saddened by the passing of her majesty queen elizabeth ii.   we will be forever grateful for the extraordinary service she gave to the nation during her long and glorious reign.   our thoughts are w
```

```
[ ]  #Stopword Removal
     tweet=stopwordsRemovalFn(tweet)
     #Punctuation Removal
     tweet=punctuationRemovalFn(tweet)
     #Removing repeated character
     tweet=repeatingCharacterRemovalFn(tweet)
     #CLeaning URLs/HTML Data
     tweet=cleaningHTMLDataFn(tweet)
     #Removing Numbers
     tweet=removingNumbersFn(tweet)
     tweet="".join(tweet)
```

```
[ ]  #Calculating and printing the sentiment score from the tweet that is preprocessed.
     print(TextBlob(tweet).sentiment)
     score=TextBlob(tweet).sentiment.polarity
     print(textClassification(score))

     Sentiment(polarity=0.09444444444444444, subjectivity=0.6)
     Positive
```

12.Project Management

Implementation status report

- **Responsibility/ Contributions (members/percentage)**

Member Name	Contribution description	Overall Contribution
Amough Mittal	Detail Design of Features, Objectives, Features, and Code(Dataset Implementation)	25%
Arun Sai Kumar Gutala	Dataset description & implementing code	25%
Neha Gummalla	Related work, project management	25%
Madi Arnold	Analysis, Implementation, Preliminary Results	25%

- **Responsibility (Task, Person)**

Member Name	Contribution description	Overall Contribution
Amough Mittal	Analysis, Details Design of Features, Code(Classification of a statement)	
Arun Sai Kumar Gutala	Implementation of sentiment analysis and calculated the mean avg sentiment scores	
Neha Gummalla	Implementation of true positive / true negative scores, related work	
Madi Arnold	Analysis, Implementation of true positive / true negative scores, Preliminary Results, and Results Analysis	

- **Issues/Concerns**

13.References

- Tweets after Queen Elizabeth II's Death [https://www.kaggle.com/datasets/aneeshtickoo/tweets-after-queen-elizabeth-iis-death]
- Towards Data Science [https://towardsdatascience.com]
- An Evolutionary-Based Sentiment Analysis Approach for Enhancing Government Decisions during COVID-19 Pandemic: The Case of Jordan [https://www.mdpi.com/2076-3417/11/19/9080]
- Text Blob Sentiment Analysis [https://textblob.readthedocs.io/en/dev/quickstart.html]

Attachments:

1. GitHub Link -- https://github.com/akgutala/NLP_Project