MODULE - 4 (PRACTICAL)

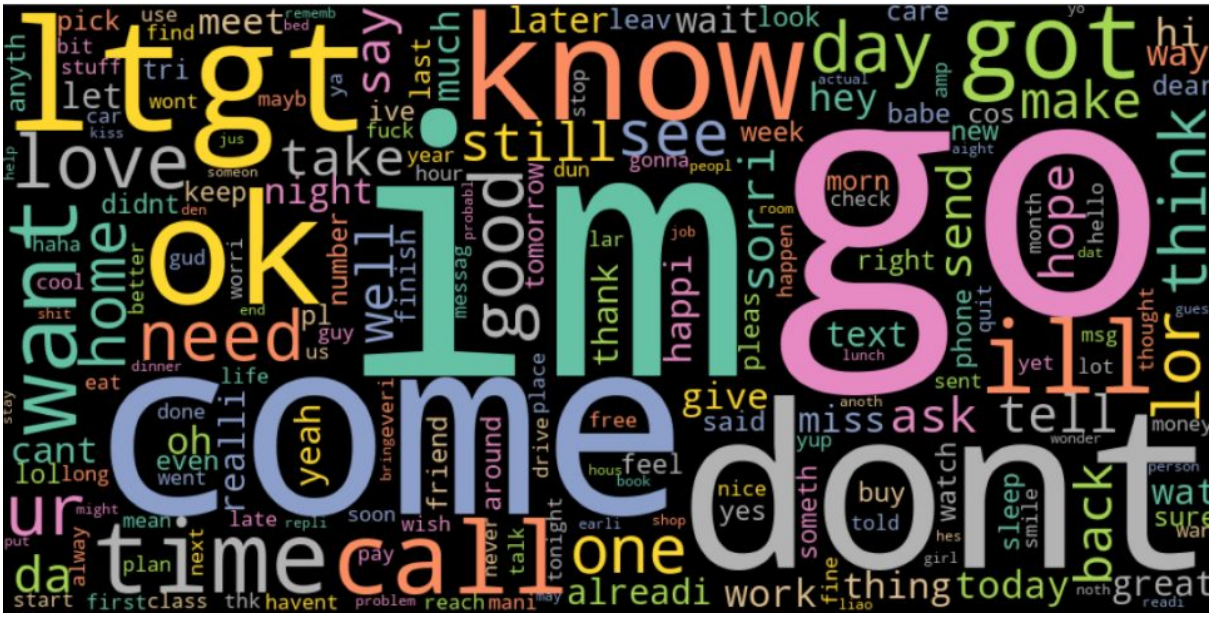
Dataset

SMSSpamCollection Dataset - https://archive.ics.uci.edu/ml/datasets/sms+spam+collection
This dataset contains SMS messages divided into 2 categories ‘ham’ and ‘spam’. There are 5574 rows in total.

Cleaning and EDA

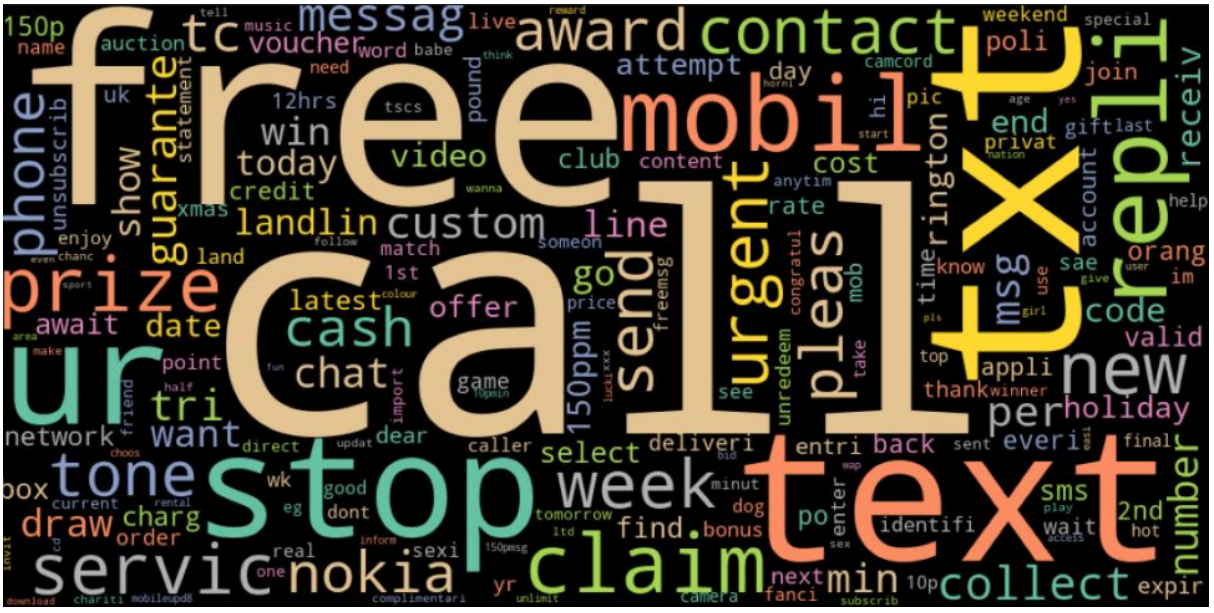
The data contains 444 duplicate values mostly from the ham category. While cleaning the text, we remove all the punctuation,stopwords and apply stemming to the data. We do not remove numbers from the text data as it has been observed that the ‘Spam’ text contains a lot of numbers when compared to the ham data and can be used as a good differentiating factor. The dataset is highly imbalanced even after removing the duplicates, there are 4281 rows in the ‘Ham’ category and 543 rows in the ‘Spam’ category. Therefore to increase the data in the minority class, we use SMOTE, an oversampling technique to balance the data.
The number of unique words in the ‘ham’ are 44 and in ‘spam’ are 39. The mean length of each sentence in ham is 42.129 and the mean length in the ‘spam’ is 98.20994475138122 .

Word Count Visualization ‘ham’ text:



In ‘ham’ messages, we see that the most common words are ‘im’, ‘come’, ‘go’,’dont’ which signify normal text messages and can be easily differentiated between ‘Spam’ messages. The larger the size of the word, the more frequent it is in the category and more weightage it must be given for categorizing.

Word Cloud For Spam :



Here we see that most of the ‘Spam’ messages contain words like ‘free’,’call’,’service’,’win’,’prize’, ‘award' which are the most frequent words that can be found in spam texts. Therefore these words can be given more weightage while classifying ‘spam’ from ‘ham’. We also notice that spam messages tend to be more formal than ham messages.
We use TF-IDF vectorizer to vectorize the feature values.

Modelling Techniques:

SVM(Support Vector Machines):

SVM is one of the approaches I have used for modelling and prediction of the data. The C value in Support Vector Machine indicates to what extent we would tolerate the misclassification of the samples. Larger the C value, smaller the marginal hyperplane. With the C value as 1000, I was able to achieve 95.2 test accuracy and the model misclassified 41 samples.

RNN(Recurrent Neural Network) with LSTM:

In most NLP text classification techniques, RNNs are used to maintain or ‘remember’ the context of the word which is used later in predictions. Each and every word that we input relates to each other. Predictions are made at the end of each data point once the context of each word is stored.
Before we create the RNN, we must map each vector to a number. The number of unique words we took is 600 which gave a perfect fit on many trials. Anything above this number would overfit the model and anything below would underfit it. We also need to make each

encoded input the same length. Therefore we pad zeros to some vectors and we take 25 as the maximum length. The labels must also be encoded from 'ham','spam' to class 1 and class 2. We use the Tokenizer( ) to encode the labels. Once encoded, we must balance the dataset as explained above. We use SMOTE to equalize the classes. After equalizing, we one-hot encode the labels i.e represent the labels in terms of 3 classes since our labels contain 1 and 2. Next, we build our model.
In our model, we add an Embedding layer where words are encoded as high dimensional vectors and closeness of vectors indicate words with similar meanings. We map each word to 8 dimension vectors and the number of words is 600. Next, we initialize the LSTM layer, we pass the dimension as the input. The last Dense layer we have 3 output dimensions with activation 'softmax'. The loss function is 'categorical cross entropy' and metrics accuracy. The optimizer function is 'adam'.

This graph shows the perfect fit which is not overfitting nor underfitting. The train accuracy is 91.1% and test accuracy is 90.14%.

Naive Bayes Algorithm:

The main assumption made by this algorithm is that it assumes all words are independent of each other and each feature makes an equal contribution.
Therefore:

$$P(A,B) = P(A)P(B)$$

This is a fairly strong assumption which does not hold good in most real world applications. Words that heavily depend on the context they are used in and also on surrounding words are not handled by Naive Bayes algorithm due to the independence assumption. Sentiments in more difficult datasets may also include the use of sarcastic contexts that c
Naive Bayes calculates the probability of 'ham' or 'spam' given the word. We use the bayesian formula to calculate this probability. Higher the value, more probable the word or the feature belongs to that class.

$$P(\text{‘ham’}|word) = (P(word|\text{’ham’})P(\text{‘ham’}))/P(word)$$

Naive Bayes algorithm, due to the independence rule assumes that

$$P(word1,word2,word3\ldots.wordN|\text{’ham’}) = P(word1|\text{’ham’})P(word2|\text{’ham’})....P(wordN|\text{’ham’})$$

To account for zero probability or words that the model has not seen before, we apply Laplacian smoothing to cancel out the zero effect on multiplication. We usually take the parameter to be 1. Therefore, we add 1 to the numerator and add a total number of unique words to both classes in the denominator.

Here, we use MultiNomialNB( ) for the classification. In this example Naive Bayes algorithm worked fairly well with 96.21%.