EMAIL SPAM DETECTION

Submitted by:

Shubham Sahu

ACKNOWLEDGMENT

I would like to thank Flip Robo Technologies for providing me with the opportunity to work on this project from which I have learned a lot. I am also grateful to Ms. Khushboo Garg for her constant guidance and support.

Some of the reference sources are as follows:

- Internet
- Coding Ninjas
- Medium.com
- Analytics Vidhya
- Using Naive Bayes Model and Natural Language Processing for Classifying Messages on Online Forum (Research Paper)

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INTRODUCTION

BUSINESS PROBLEM FRAMING

You were recently hired in a Start-up Company and was asked to build a system to identify spam emails. We will explore and understand the process of classifying Emails as Spam or Not Spam by build Machine Learning and NPL model to detect the HAM and SPAM mails. The model will detect the unsolicited and unwanted emails and thus we can prevent them from creeping into user's inbox and therefore, increase the user Experience.

CONCEPTUAL BACKGROUND OF THE DOMAIN PROBLEM

As we know how a machine translates language, or how voice assistants respond to questions, or how mail gets automatically classified into spam or not spam, all these tasks are done through Natural Language Processing (NLP), which processes text into useful insights that can be applied to future data. In the field of artificial intelligence, NLP is one of the most complex areas of research due to the fact that text data is contextual. It needs modification to make it machine-interpretable and requires multiple stages of processing for feature extraction.

Classification problems can be broadly split into two categories: binary classification problems, and multi-class classification problems. Binary classification means there are only two possible label classes, e.g. a patient's condition is cancerous or it isn't, or a financial transaction is fraudulent or it is not. Multi-class classification refers to cases where there are more than two label classes. An example of this is classifying the sentiment of a movie review into positive, negative, or neutral.

There are many types of NLP problems, and one of the most common types is the classification of strings. Examples of this include the classification of movies/news articles into different genres and the automated classification of emails into a spam or not spam. We shall be looking into this last example in more detail for this project.

REVIEW OF LITERATURE

In recent times, unwanted commercial / promotional bulk emails also known as spam has become a huge problem on the internet and for our mail inbox. An individual / organization sending the spam messages are referred to as the spammers. Such a person gathers email addresses from different websites, chatrooms, and other sources to send the mail to bulk audience. Spam prevents the user from making full and good use of time, storage capacity and network bandwidth. The huge volume of spam mails flowing through the computer networks have destructive effects on the memory space of email servers, communication bandwidth, CPU power and user time. The menace of spam email is on the increase on yearly basis and is responsible for over 80% of the whole global email traffic (Source google).

Users who receive spam emails that they did not request find it very irritating. It is also resulted to untold financial loss to many users who have fallen victim of internet scams and other fraudulent practices of spammers who send emails pretending to be from reputable companies with the intention to persuade individuals to disclose sensitive personal information like passwords, Bank Verification Number (BVN) and credit card numbers.

MOTIVATION FOR THE PROBLEM UNDERTAKEN

Motivation for this project has been undertaken because it is a project which is assigned to me during my internship at Flip Robo Technologies. This project will help Start-up companies to detect and filter the SPAM mails in their Email inbox and therefore, increase the user experience and save their server from unwanted mails, phishing mails or other viruses.

ANALYTICAL PROBLEM FRAMING

MATHEMATICAL/ ANALYTICAL MODELING OF THE PROBLEM

Throughout the project multiple mathematical and analytical models have been used, first we have checked the ratio of spam and ham emails in our dataset. The shape of our data set is 2893 rows and 3 columns.

Then we have used regular expressions to clean the message column which contained body of the email. Then we have used TfidfVectorizer, to transforms text to feature vectors that can be used as input to estimator.

In [8]:
```
#Let;s check the detail info of our dataset

email.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2893 entries, 0 to 2892
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   subject  2893 non-null   object
 1   message  2893 non-null   object
 2   label    2893 non-null   int64 
dtypes: int64(1), object(2)
memory usage: 67.9+ KB
```

DATA SOURCES AND THEIR FORMATS

The data was provided to us from the FlipRobo Technologies as a part of our Internship assignment. The data was provided in CSV format and there were 3 attributes and 2893 rows in the data set.

LOADING CSV DATA

In [2]:
```
#Let's load the CSV file

email=pd.read_csv('messages.csv')
email
```

Out[2]:

	subject	message	label
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen...	0
1	NaN	lang classification grimes , joseph e . and ba...	0
2	query : letter frequencies for text identifica...	i am posting this inquiry for sergei atamas (...	0
3	risk	a colleague and i are researching the differin...	0
4	request book information	earlier this morning i was on the phone with a...	0
...	...	...	...
2888	love your profile - ysuolvpv	hello thanks for stopping by ! ! we have taken...	1
2889	you have been asked to join kiddin	the list owner of : " kiddin " has invited you...	1

DATA PREPROCESSING DONE

After loading all the data we will proceeded with the data pre-processing. Following Steps were followed during data pre-processing:

- **Removing unwanted attribute from Dataset :**

It's quite hard to find whether a mail is a spam or not just by looking at the subject. So we started by replacing the null values.

```
In [3]: #Let's check if there are null values in our dataset

        email.isnull().sum()

Out[3]: subject    62
        message     0
        label       0
        dtype: int64

In [4]: #Let's replace the null values in our dataset

        email=email.replace(np.nan,"",regex=True)
        email.head()

Out[4]:
```

	subject	message	label
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen...	0
1		lang classification grimes , joseph e . and ba...	0
2	query : letter frequencies for text identifica...	i am posting this inquiry for sergei atamas (...	0

- **Adding additional attribute :**

In order to analyse the data in a better way while doing pre-processing, we have added an attribute 'Length' which shows length of the message against it. This was done just to compare the length of text before and after preprocessing and to get idea about the memory optimization.

In [13]:
```python
#Let's check the length

email['Subject_length'] = email.subject.str.len()
email['Message_length'] = email.message.str.len()
email.head(5)
```

Out[13]:

	subject	message	label	Subject_length	Message_length
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen...	0	39	2856
1		lang classification grimes , joseph e . and ba...	0	0	1800
2	query : letter frequencies for text identifica...	i am posting this inquiry for sergei atamas (...	0	50	1435
3	risk	a colleague and i are researching the differin...	0	4	324
4	request book information	earlier this morning i was on the phone with a...	0	24	1046

➢ **Converting all the messages to lower case:**

All messages in the 'message' attribute was converted to small case since keeping words in large case does not make sense as same word with small and large case conveys same meaning.

DATA PREPRATION

In [14]:
```python
# Let's convert all the data to lower case for further processing

email['subject'] = email['subject'].str.lower()
email['message'] = email['message'].str.lower()
```

In [15]:
```python
email
```

Out[15]:

	subject	message	label	Subject_length	Message_length
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen...	0	39	2856
1		lang classification grimes , joseph e . and ba...	0	0	1800
2	query : letter frequencies for text identifica...	i am posting this inquiry for sergei atamas (...	0	50	1435
3	risk	a colleague and i are researching the differin...	0	4	324
4	request book information	earlier this morning i was on the phone with a...	0	24	1046
...	...	...	...	...	...
2888	love your profile - ysuolvpv	hello thanks for stopping by ! ! we	1	28	262

➢ Performing Regex operations :

All messages in the 'message' attribute were adjusted to remove unwanted words, characters, numbers etc.

- All mail addresses were replaces by single word 'emailaddress'
- All URL's present in the message were replaced by word 'webaddress'
- All dollars signs ($, £) were replaced by word 'dollers'
- All 10 digit number sequence were replaced by word 'phonenumber'
- All numbers were replaced with word 'numbr'
- Removing punctuations from the message
- Replacing whitespaces between terms with a single space
- Removing leading and trailing whitespaces

DATA CLEANING

In [17]:
```
# Let's replace all the unwanted data from the strings of the subject

# Replace email addresses with 'email'
strings['subject'] = strings['subject'].str.replace(r'^.+@[^\.].*\.[a

# Replace URLs with 'webaddress'
strings['subject'] = strings['subject'].str.replace(r'^http\://[a-zA-

# Replace 10 digit phone numbers (formats include paranthesis, spaces
strings['subject'] = strings['subject'].str.replace(r'^\(?[\d]{3}\)?[

# Replace numbers with 'number'
strings['subject'] = strings['subject'].str.replace(r'\d+(\.\d+)?', '

# Replace money symbols with 'moneysymb' (£ can by typed with ALT key
strings['subject'] = strings['subject'].str.replace(r'£|\$', 'dollers
```

In [18]:
```
# Lets replace all the unwanted data from the strings of the message

# Replace email addresses with 'email'
strings['message'] = strings['message'].str.replace(r'^.+@[^\.].*\.[a

# Replace URLs with 'webaddress'
strings['message'] = strings['message'].str.replace(r'^http\://[a-zA-

# Replace 10 digit phone numbers (formats include paranthesis, spaces
strings['message'] = strings['message'].str.replace(r'^\(?[\d]{3}\)?[

# Replace numbers with 'number'
strings['message'] = strings['message'].str.replace(r'\d+(\.\d+)?', '

# Replace money symbols with 'moneysymb' (£ can by typed with ALT key
strings['message'] = strings['message'].str.replace(r'£|\$', 'dollers
```

In [20]:
```
# Let's remove the punctuation from subject column

# Remove punctuation
strings['subject'] = strings['subject'].str.replace(r'[^\w\d\s]', ' '

# Remove leading and trailing whitespace
strings['subject'] = strings['subject'].str.replace(r'^\s+|\s+?$', ''

# Replace whitespace between terms with a single space
strings['subject'] = strings['subject'].str.replace(r'\s+', ' ')
```

In [21]:
```
# Let's remove the punctuation from messages column

# Remove punctuation
strings['message'] = strings['message'].str.replace(r'[^\w\d\s]', ' '

# Remove leading and trailing whitespace
strings['message'] = strings['message'].str.replace(r'^\s+|\s+?$', ''

# Replace whitespace between terms with a single space
strings['message'] = strings['message'].str.replace(r'\s+', ' ')
```

```
In [22]: # Let's check the top 5 entries from our data set post data processin

strings.head()
```

Out[22]:

	subject	message	label	Subject_length	Message_length
0	job posting apple iss research center	content length number apple iss research cente...	0	39	2856
1		lang classification grimes joseph e and barbar...	0	0	1800
2	query letter frequencies for text identification	i am posting this inquiry for sergei atamas sa...	0	50	1435
3	risk	a colleague and i are researching the differin...	0	4	324
4	request book information	earlier this morning i was on the phone with a...	0	24	1046

➢ **Removal of Stopwords :**

All unwanted words which do not contribute much in model building i.e. stopwords, were removed from dataset.

BUILDING WORD DICTIONARY

```
In [23]: #Let's create a funtion for Stop words

stop_words = set(stopwords.words('english'))
strings['subject'] = strings['subject'].apply(lambda y: ' '.join(term
strings['message'] = strings['message'].apply(lambda x: ' '.join(term
```

```
In [24]: # Let's create a new columns after puncuations, stopwords removal to

strings['Subject_clean_length'] = strings.subject.str.len()
strings['Message_clean_length'] = strings.message.str.len()
strings.head()
```

Out[24]:

	subject	message	label	Subject_length	Message_length	Subject_clean_len
0	job posting apple iss research center	content length number apple iss research cente...	0	39	2856	
1		lang classification grimes joseph e barbara f ...	0	0	1800	

- **Adding additional attribute :**

To compare the length of message before preprocessing and after preprocessing an addition column ‘Cleaned Length’ was added.

After executing all these steps it was found that 2490985 characters were removed from the dataset which were of no use and consuming memory.

```
In [25]: # Let's check the total length of the subject and message pre and pos

         print ('Original Length of Subject column:', strings.Subject_length.s
         print ('Length of Subject column post Cleaning:', strings.Subject_cle
         print ('Original Length of messages column:', strings.Message_length.
         print ('Length of messages column post Cleaning:', strings.Message_cl
```

```
Original Length of Subject column: 91663
Length of Subject column post Cleaning: 79458
Original Length of messages column: 9344743
Length of messages column post Cleaning: 6853758
```

DATA INPUTS- LOGIC- OUTPUT RELATIONSHIPS

We have analysed the words that were present in the spam and ham mails, based on the words present and the data we already have which says if the mail is ham or spam, we are going to train the model to predict the same.

HARDWARE AND SOFTWARE REQUIREMENTS AND TOOLS USED

HARDWARE:

SOFTWARE:

Jupyter Notebook (Anaconda 3) – Python 3.7.6

Microsoft Excel 2010

LIBRARIES:

LOADING LIBRARIES

```
In [1]: # Let's Import all the required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns



import nltk, re
import string
from nltk.corpus import stopwords
from collections import Counter
from nltk.corpus import stopwords
from wordcloud import WordCloud
from nltk.stem.porter import PorterStemmer
from sklearn.feature_extraction.text import CountVectorizer
from nltk.stem import WordNetLemmatizer, SnowballStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import roc_curve,roc_auc_score,auc
from sklearn.metrics import accuracy_score, confusion_matrix,classifi
from sklearn.model_selection import cross_val_score

import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter("ignore")
warnings.warn("deprecated", DeprecationWarning)
```

MODEL/S DEVELOPMENT AND EVALUATION

IDENTIFICATION OF POSSIBLE PROBLEM-SOLVING APPROACHES (METHODS)

As the target column was Bivariant data and the algorithm that we choose depends on this target variable. So, we have chosen classification analysis for this project.

TESTING OF IDENTIFIED APPROACHES (ALGORITHMS)

We have used the following algorithms

- LogisticRegression()
- DecisionTreeClassifier ()
- KneighbourClassifier()
- RandomForestClassifier ()
- AdaBoostClassifier()
- MultinomialNB()

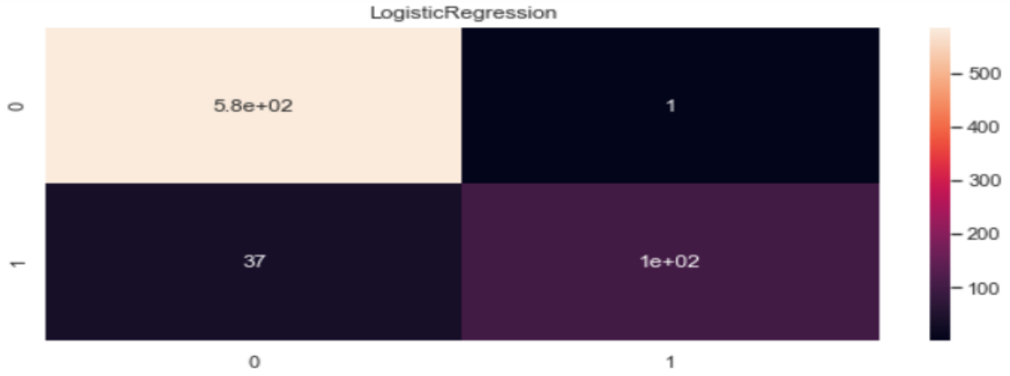
In [39]:
```
# Let's create a for loop function for our model

models=[]
models.append(('LogisticRegression',LR))
models.append(('DecisionTreeClassifier',DT))
models.append(('KneighborsClassifier',KNN))
models.append(('RandomForestClassifier',RF))
models.append(('AdaBoostClassifier',AD))
models.append(('MultinomialNB',MNB))
```

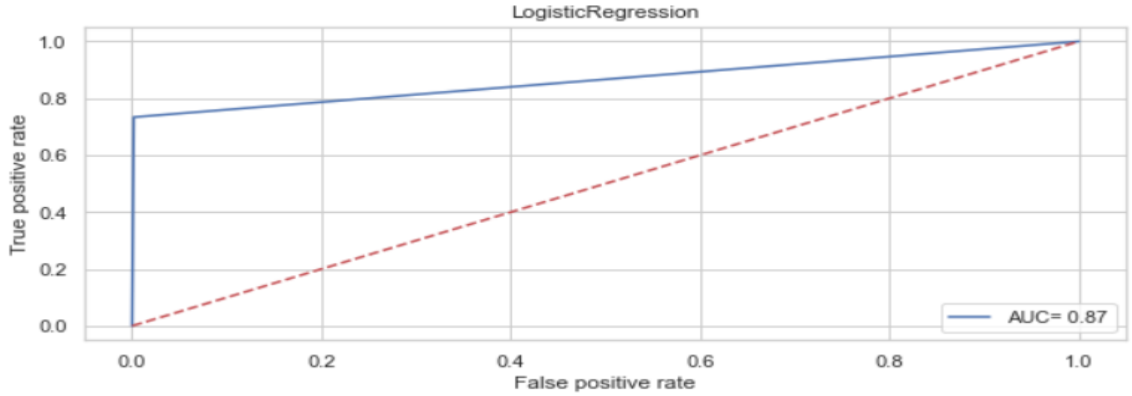
RUN AND EVALUATE SELECTED MODELS

```
In [40]: model_list=[]
         score=[]
         cvs=[]
         rocscore=[]

         for name, model in models:
             print(name,'Model :-',end='\n\n')

             model_list.append(name)
             model.fit(x_train,y_train)
             print(model,end='\n\n')
             pre=model.predict(x_test)
             print('\n')
             AS=accuracy_score(y_test,pre)
             print('Accuracy score =',AS)
             score.append(AS*100)
             print('\n')
             sc=cross_val_score(model,x,y, cv=10, scoring='accuracy').mean()
             print('cross validation score =',sc)
             cvs.append(sc*100)
             print('\n')
             false_positive_rate,true_positive_rate,thresholds=roc_curve(y_test,pre)
             roc_auc=auc(false_positive_rate,true_positive_rate)
             print('roc_auc_score = ', roc_auc)
             rocscore.append(roc_auc*100)
             print('\n')
             print('classification_report\n',classification_report(y_test,pre))
             print('\n')
             cm=confusion_matrix(y_test,pre)
             print(cm)
             print('\n')
             plt.figure(figsize=(10,40))
             plt.subplot(911)
             plt.title(name)
```

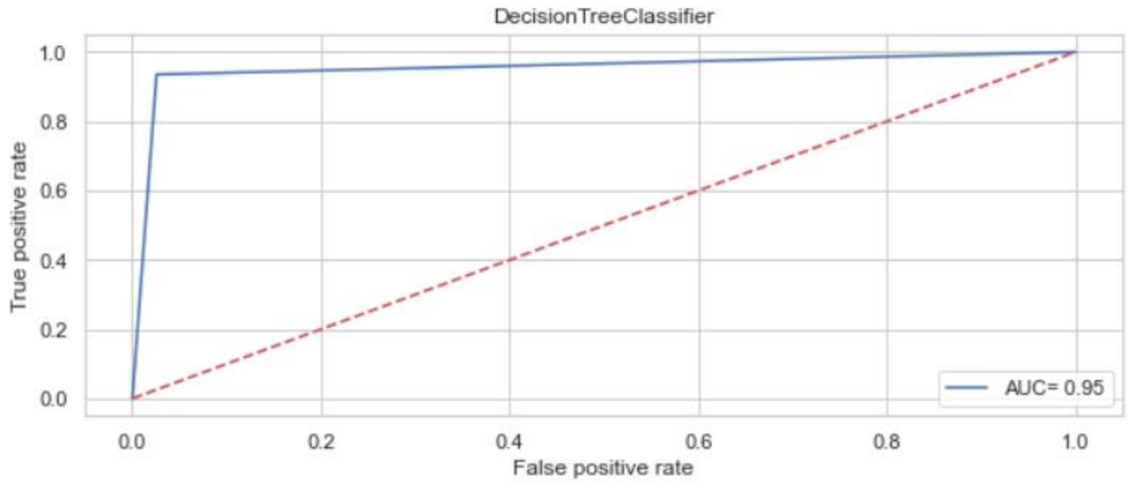
```
    cvs.append(sc*100)
    print('\n')
    false_positive_rate,true_positive_rate,thresholds=roc_curve(y_test,pre)
    roc_auc=auc(false_positive_rate,true_positive_rate)
    print('roc_auc_score = ', roc_auc)
    rocscore.append(roc_auc*100)
    print('\n')
    print('classification_report\n',classification_report(y_test,pre))
    print('\n')
    cm=confusion_matrix(y_test,pre)
    print(cm)
    print('\n')
    plt.figure(figsize=(10,40))
    plt.subplot(911)
    plt.title(name)
    print(sns.heatmap(cm,annot=True))
    plt.subplot(912)
    plt.title(name)
    plt.plot(false_positive_rate,true_positive_rate, label='AUC= %0.2f'%roc_auc)
    plt.plot([0,1],[0,1],'r--')
    plt.legend(loc='lower right')
    plt.ylabel('True positive rate')
    plt.xlabel('False positive rate')
    print('\n\n')
```

```
LogisticRegression Model :-

LogisticRegression()


Accuracy score = 0.9475138121546961


cross validation score = 0.9533301515332298


roc_auc_score =  0.866051773965443


classification_report
               precision    recall  f1-score   support

           0       0.94      1.00      0.97       585
           1       0.99      0.73      0.84       139

    accuracy                           0.95       724
   macro avg       0.97      0.87      0.91       724
weighted avg       0.95      0.95      0.94       724



[[584   1]
 [ 37 102]]


AxesSubplot(0.125,0.808774;0.62x0.0712264)
```

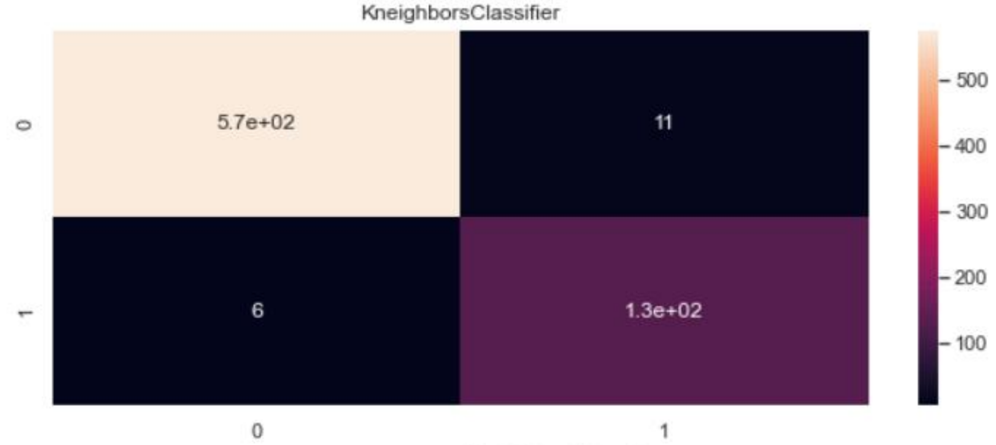


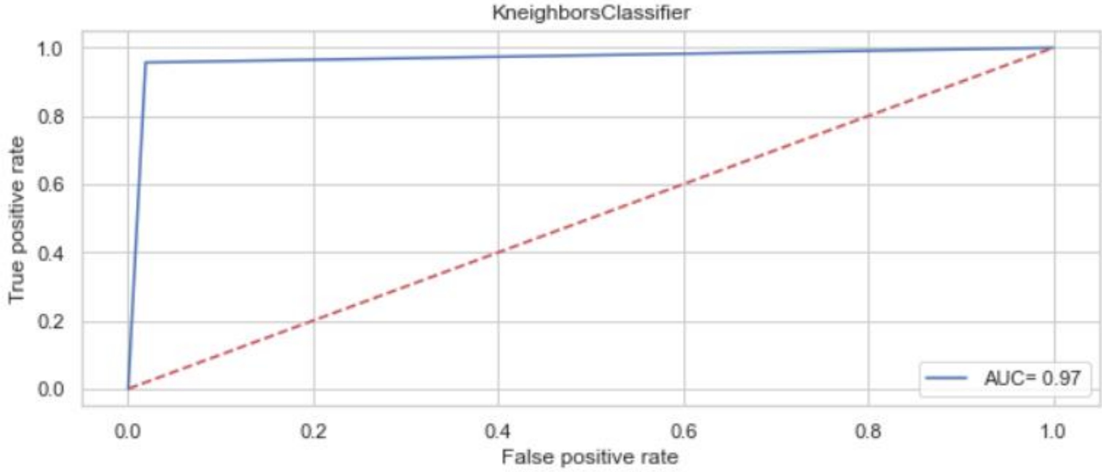


```
DecisionTreeClassifier Model :-

DecisionTreeClassifier(criterion='entropy')


Accuracy score = 0.9668508287292817


cross validation score = 0.9661245674740483


roc_auc_score =  0.9548053864600627


classification_report
               precision    recall  f1-score   support

           0       0.98      0.97      0.98       585
           1       0.90      0.94      0.92       139

    accuracy                           0.97       724
   macro avg       0.94      0.95      0.95       724
weighted avg       0.97      0.97      0.97       724


[[570  15]
 [  9 130]]


AxesSubplot(0.125,0.808774;0.62x0.0712264)
```

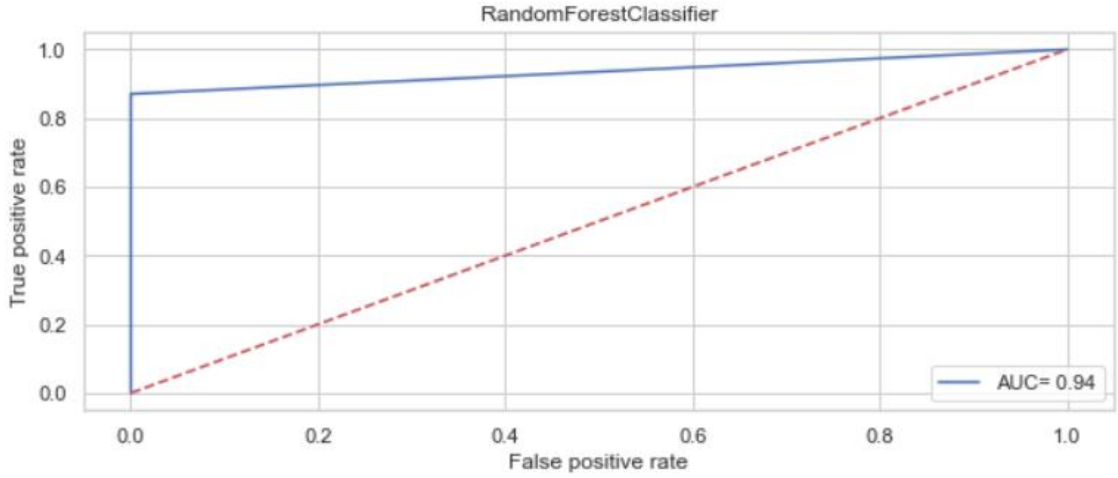


```
KneighborsClassifier Model :-
KNeighborsClassifier(n_neighbors=1)


Accuracy score = 0.9765193370165746

cross validation score = 0.9685431332776518

roc_auc_score =  0.969015556785341

classification_report
              precision    recall  f1-score   support

           0       0.99      0.98      0.99       585
           1       0.92      0.96      0.94       139

    accuracy                           0.98       724
   macro avg       0.96      0.97      0.96       724
weighted avg       0.98      0.98      0.98       724


[[574  11]
 [  6 133]]

AxesSubplot(0.125,0.808774;0.62x0.0712264)
```

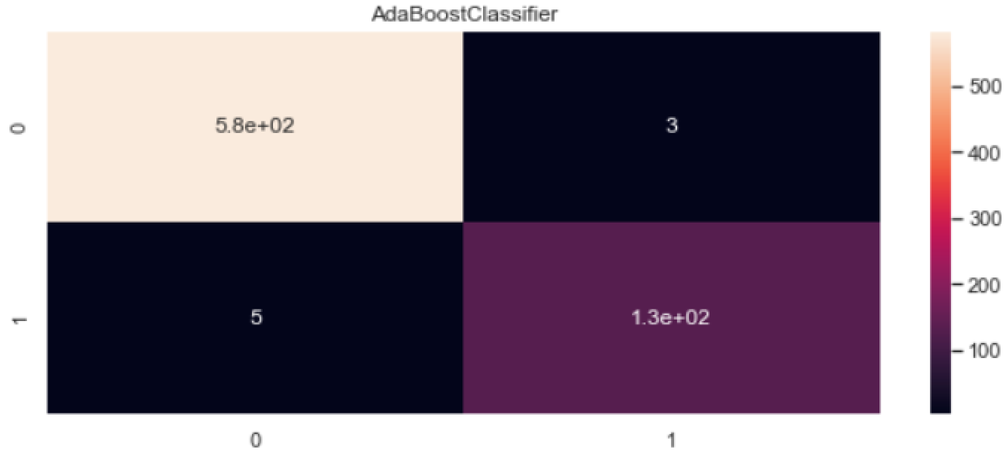


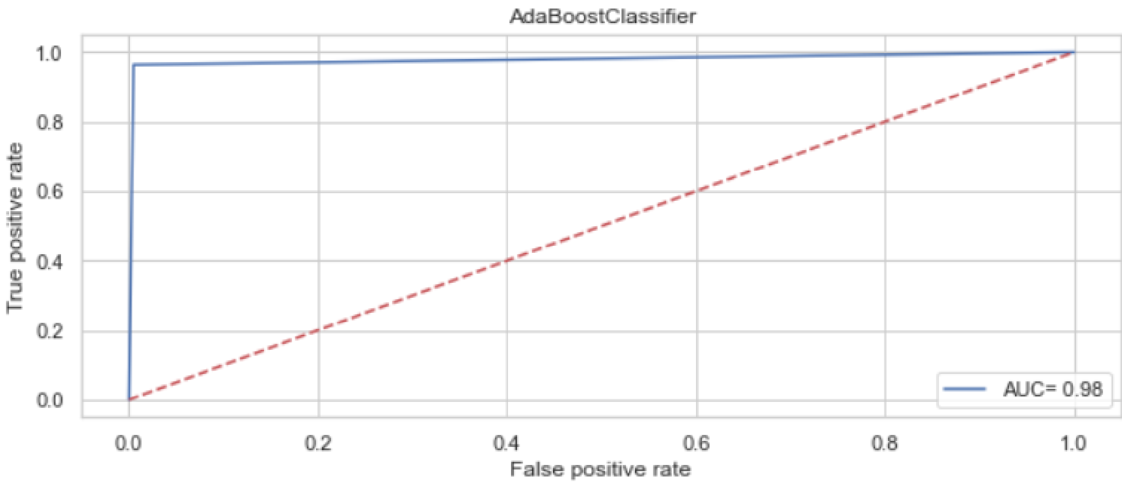


```
RandomForestClassifier Model :-

RandomForestClassifier(random_state=42)


Accuracy score = 0.9751381215469613


cross validation score = 0.9733874239350913


roc_auc_score =  0.935251798561151


classification_report
              precision    recall  f1-score   support

           0       0.97      1.00      0.98       585
           1       1.00      0.87      0.93       139

    accuracy                           0.98       724
   macro avg       0.99      0.94      0.96       724
weighted avg       0.98      0.98      0.97       724



[[585   0]
 [ 18 121]]


AxesSubplot(0.125,0.808774;0.62x0.0712264)
```

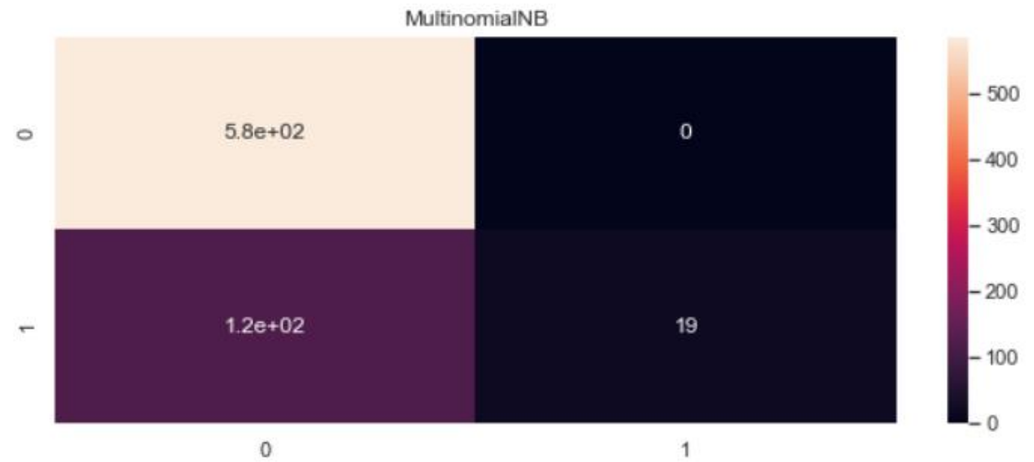


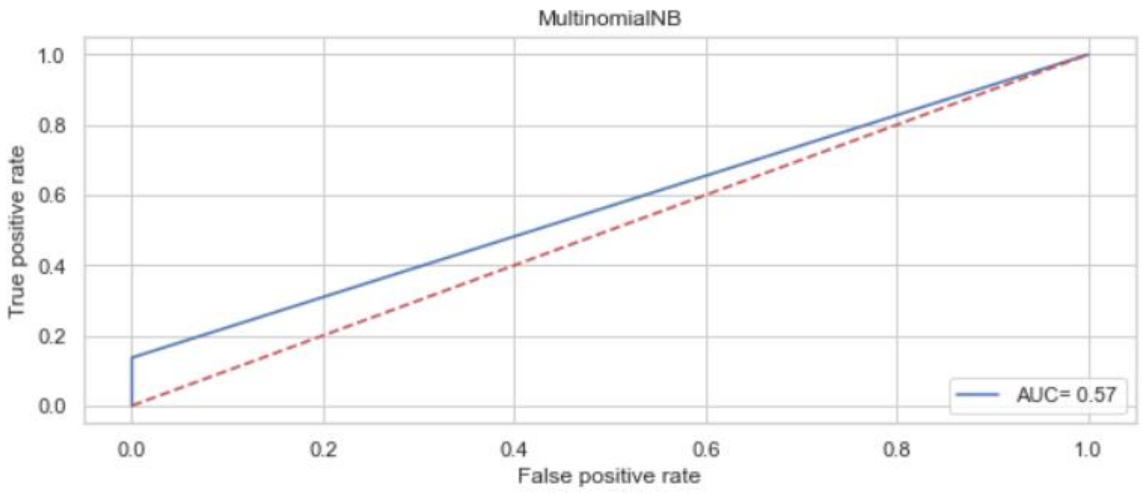
```
AdaBoostClassifier Model :-

AdaBoostClassifier()


Accuracy score = 0.988950276243094


cross validation score = 0.9820200453406513


roc_auc_score =  0.9794502859251061


classification_report
               precision    recall  f1-score   support

           0       0.99      0.99      0.99       585
           1       0.98      0.96      0.97       139

    accuracy                           0.99       724
   macro avg       0.98      0.98      0.98       724
weighted avg       0.99      0.99      0.99       724



[[582   3]
 [  5 134]]

AxesSubplot(0.125,0.808774;0.62x0.0712264)
```





```
MultinomialNB Model :-
MultinomialNB()


Accuracy score = 0.8342541436464088

cross validation score = 0.8606944278725688

roc_auc_score =  0.5683453237410072

classification_report
               precision    recall  f1-score   support

           0       0.83      1.00      0.91       585
           1       1.00      0.14      0.24       139

    accuracy                           0.83       724
   macro avg       0.91      0.57      0.57       724
weighted avg       0.86      0.83      0.78       724


[[585   0]
 [120  19]]

AxesSubplot(0.125,0.808774;0.62x0.0712264)
```





KEY METRICS FOR SUCCESS IN SOLVING PROBLEM UNDER CONSIDERATION

Precision: can be seen as a measure of quality, higher precision means that an algorithm returns more relevant results than irrelevant ones

Recall is used as a measure of quantity and high recall means that an algorithm returns most of the relevant results.

Accuracy score is used when the True Positives and True negatives are more important. Accuracy can be used when the class distribution is similar

F1-score is used when the False Negatives and False Positives are crucial. While F1-score is a better metric when there are imbalanced classes.

Cross_val_score: To run cross-validation on multiple metrics and also to return train scores, fit times and score times. Get predictions from each split of cross-validation for diagnostic purposes. Make a scorer from a performance metric or loss function.

roc _auc _score : ROC curve. It is a plot of the false positive rate (x-axis) versus the true positive rate (y-axis) for a number of different candidate threshold values between 0.0 and 1.0

In [41]:

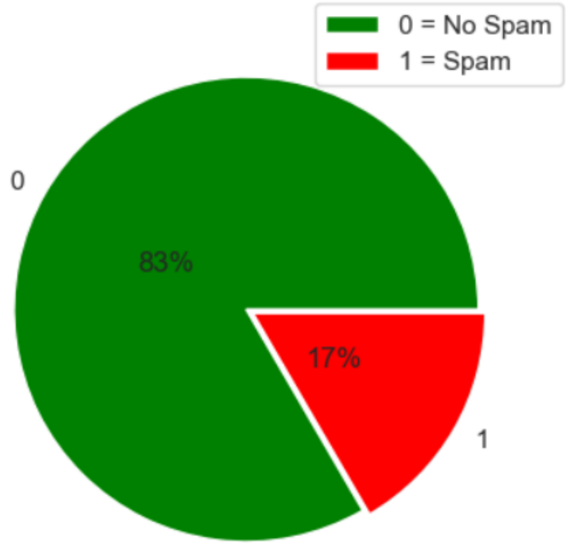
```
# Let's create a Dataframe for our above models

result=pd.DataFrame({'Model': model_list, 'Accuracy_score': score, 'Cross_val_sc
result
```

Out[41]:

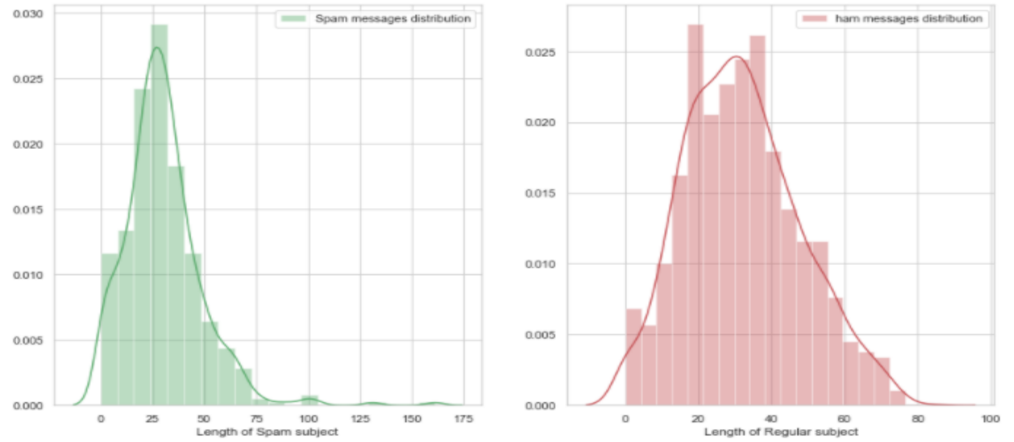
	Model	Accuracy_score	Cross_val_score	Roc_auc_score
0	LogisticRegression	94.751381	95.333015	86.605177
1	DecisionTreeClassifier	96.685083	96.612457	95.480539
2	KneighborsClassifier	97.651934	96.854313	96.901556
3	RandomForestClassifier	97.513812	97.338742	93.525180
4	AdaBoostClassifier	98.895028	98.202005	97.945029
5	MultinomialNB	83.425414	86.069443	56.834532

VISUALIZATIONS

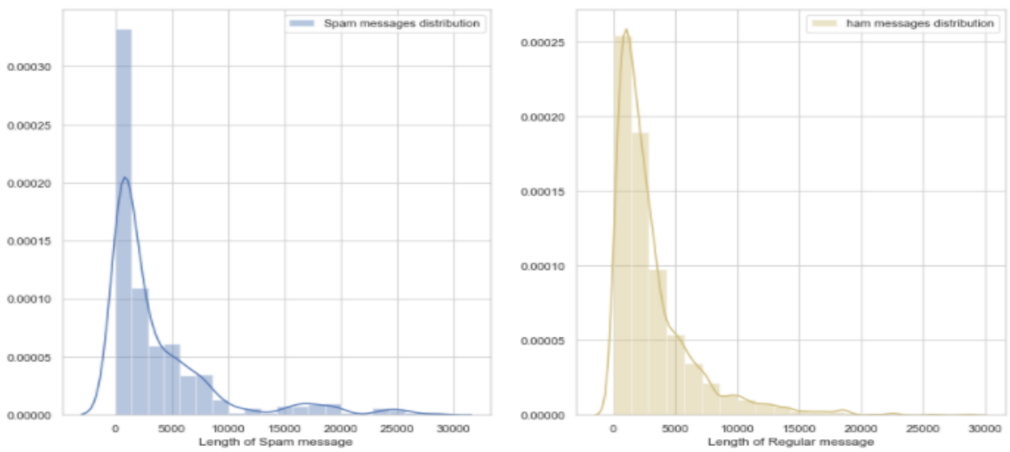
In [9]:
```
#Let's plot a pie chart to visualize the Spam and non spam mails

label=email['label'].value_counts().index.tolist()
value=email['label'].value_counts().values.tolist()
explode=(0.030,0)
clour=('green','red')
plt.figure(figsize=(8,5),dpi=100)
sns.set_context('talk',font_scale=0.2)
sns.set(style='whitegrid')
plt.pie(x=value,explode=explode,labels=label,colors=clour,autopct='%2.0f%%',pctd
plt.legend(["0 = No Spam",'1 = Spam'])
plt.show()
```



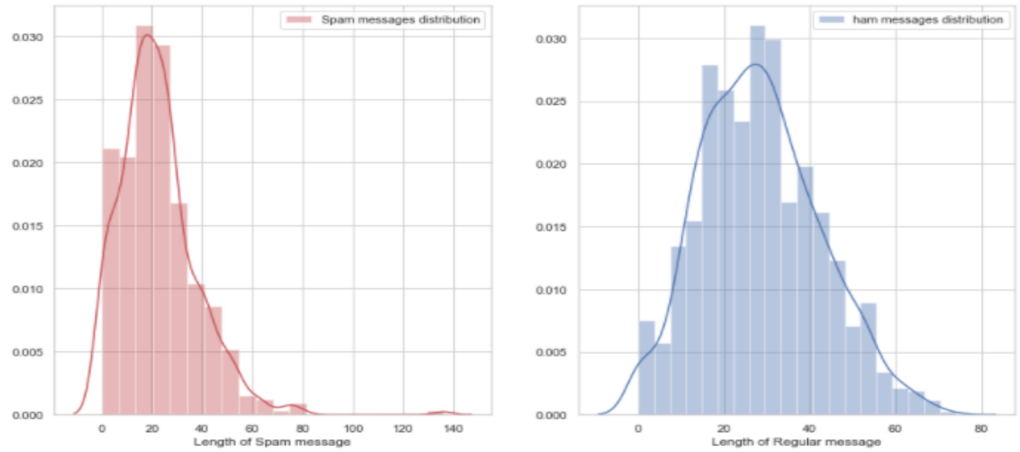
In [26]:
```
# Let's count the distribution of words before cleaning of Subject column

f,ax = plt.subplots(1,2,figsize = (15,8))

sns.distplot(strings[strings['label']==1]['Subject_length'],bins=20,ax=ax[0],lab

ax[0].set_xlabel('Length of Spam subject')
ax[0].legend()

sns.distplot(strings[strings['label']==0]['Subject_length'],bins=20,ax=ax[1],lab
ax[1].set_xlabel('Length of Regular subject')
ax[1].legend()

plt.show()
```



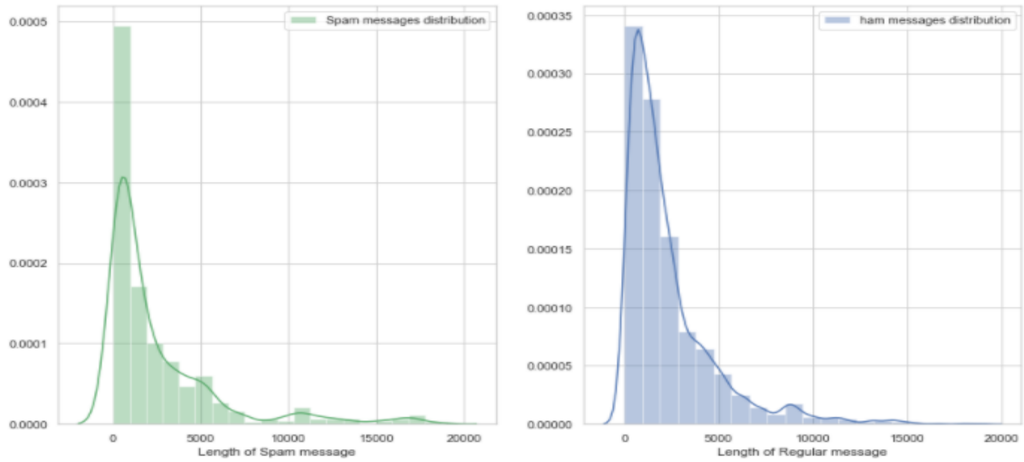
In [27]:
```
# Let's count the distribution of words before cleaning of message column

f,ax = plt.subplots(1,2,figsize = (15,8))

sns.distplot(strings[strings['label']==1]['Message_length'],bins=20,ax=ax[0],lab

ax[0].set_xlabel('Length of Spam message')
ax[0].legend()

sns.distplot(strings[strings['label']==0]['Message_length'],bins=20,ax=ax[1],lab
ax[1].set_xlabel('Length of Regular message')
ax[1].legend()

plt.show()
```



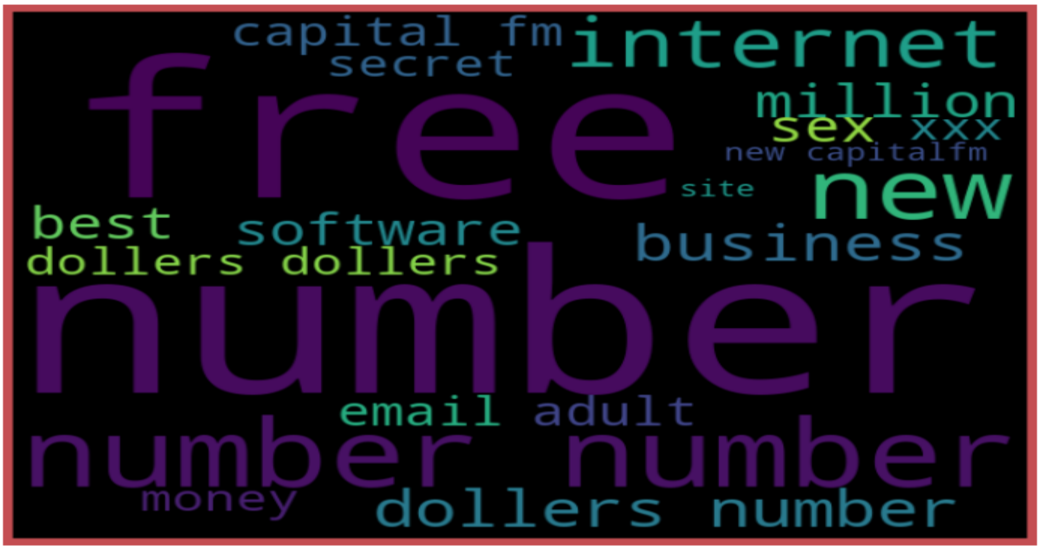
In [28]:
```
# Let's count the distribution of words after cleaning of subject column

f,ax = plt.subplots(1,2,figsize = (15,8))

sns.distplot(strings[strings['label']==1]['Subject_clean_length'],bins=20,ax=ax[
ax[0].set_xlabel('Length of Spam message')
ax[0].legend()

sns.distplot(strings[strings['label']==0]['Subject_clean_length'],bins=20,ax=ax[
ax[1].set_xlabel('Length of Regular message')
ax[1].legend()

plt.show()
```



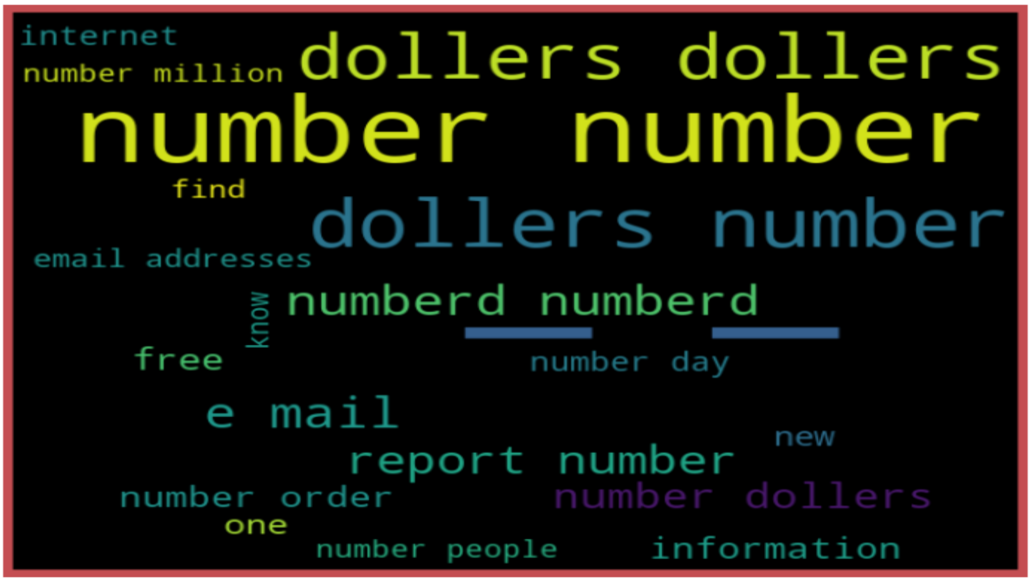
In [29]:
```
# Let's count the distribution of words after cleaning of message column

f,ax = plt.subplots(1,2,figsize = (15,8))

sns.distplot(strings[strings['label']==1]['Message_clean_length'],bins=20,ax=ax[
ax[0].set_xlabel('Length of Spam message')
ax[0].legend()

sns.distplot(strings[strings['label']==0]['Message_clean_length'],bins=20,ax=ax[
ax[1].set_xlabel('Length of Regular message')
ax[1].legend()

plt.show()
```



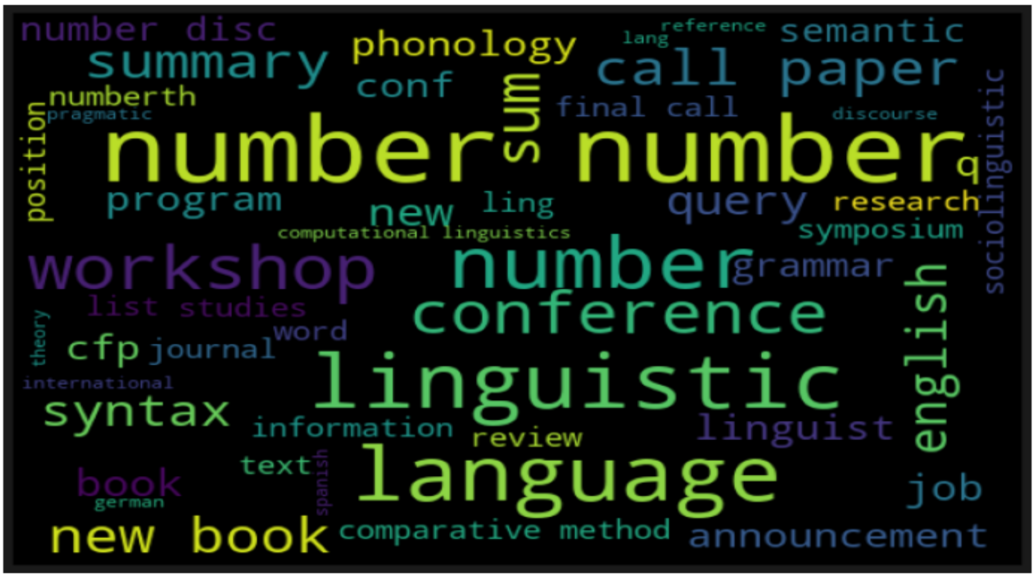
```
In [30]: # Let's plot the loud words in spam for subject column

spams = strings['subject'][strings['label']==1]

spam_cloud = WordCloud(width=700,height=500,background_color='black',max_words=2

plt.figure(figsize=(10,8),facecolor='r')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



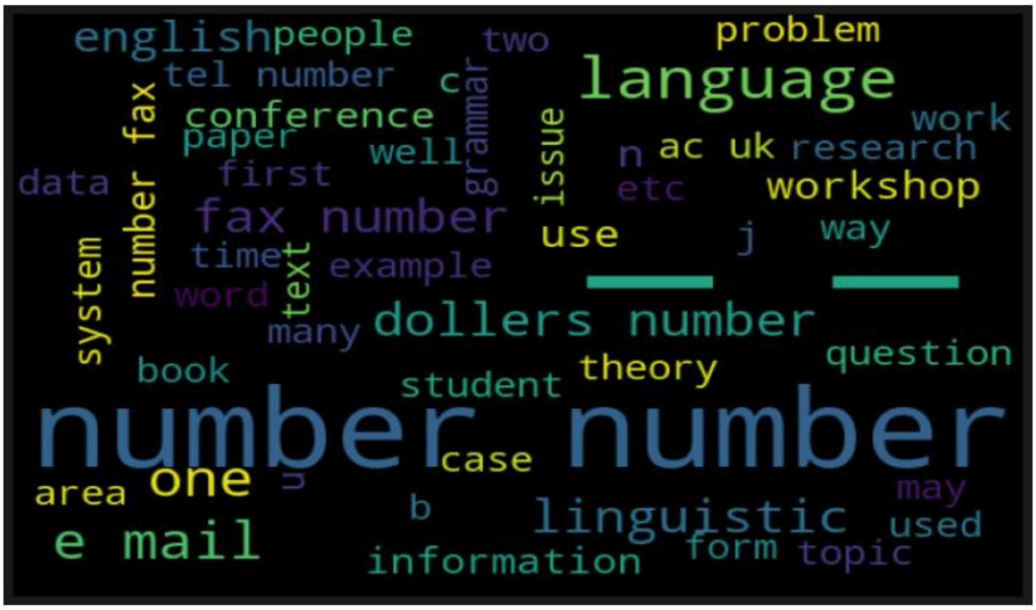

```
In [31]: # Let's plot the loud words in spam for message column

spams = strings['message'][strings['label']==1]

spam_cloud = WordCloud(width=700,height=500,background_color='black',max_words=2

plt.figure(figsize=(10,8),facecolor='r')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



In [32]:
```
# Let's plo the loud words in regular emails for subject column

regular = strings['subject'][strings['label']==0]
regular_cloud = WordCloud(width=600,height=400,background_color='black',max_word
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(regular_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



In [33]:
```
# Let's plot the loud words in regular emails for message column

regular = strings['message'][strings['label']==0]
regular_cloud = WordCloud(width=600,height=400,background_color='black',max_word
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(regular_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



INTERPRETATION OF THE RESULTS

In [41]:
```
# Let's create a Dataframe for our above models

result=pd.DataFrame({'Model': model_list, 'Accuracy_score': score, 'Cross_val_sc
result
```

Out[41]:

	Model	Accuracy_score	Cross_val_score	Roc_auc_score
0	LogisticRegression	94.751381	95.333015	86.605177
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4	AdaBoostClassifier	98.895028	98.202005	97.945029
5	MultinomialNB	83.425414	86.069443	56.834532

PERFORMANCE EVALUATION USING MULTIPLE METRICS ¶

After comparing all the models I have choosen the AdaBoostClassifier because it has the highest scores.

Accuracy score = 98.89%

cross validation score = 98.20%

roc_auc_score = 97.94%

classification_report

	precision	recall	f1-score	support
0	0.99	0.99	0.99	585
1	0.98	0.96	0.97	139
accuracy			0.99	724
macro avg	0.98	0.98	0.98	724

weighted avg

```
            0.99      0.99      0.99       724
```

Confusion matrix:

```
[582    3]
[  5  134]
```

It only classified 8 out of 716 entries incorrectly.

We ran the results for the "Subject" and "Message" columns separately but we got the same results as when they are combined. So, we have included the analysis of both columns combined.

CONCLUSION

KEY FINDINGS AND CONCLUSIONS OF THE STUDY

From the whole evaluation we found out that the spam emails can be classified and can be stopped doing harm to the users.

LEARNING OUTCOMES OF THE STUDY IN RESPECT OF DATA SCIENCE

I found visualisation a very useful technique to infer insights from dataset.

The ROC AUC plot gives large info about the false positive rate and True positive rate at various thresholds.

We are able to classify the emails as spam or non-spam. With high number of emails lots if people using the system it will be difficult to handle all possible mails as our project deals with only limited amount of corpus

LIMITATIONS OF THIS WORK AND SCOPE FOR FUTURE WORK

Since the data contained less number of ‘1’ target labels. The trained model will be limited in scope for this label. More data of spam can definitely improve the model’s performance on identification of Spam mails.