Spam detection - Customer Retention Project

1. Introduction

 SMS spam collection is a set of SMS tagged that have been used for SS research.It is bifurcated into spam and ham messages. Ham messages are legitimate messages, while others are spam

2. Problem Definition

The objective of creating a spam filter is to filter the ham and spam messages. The file contains one message per line. Each line comprises of 2 columns v1 contains the label (ham or spam) and v2 (contains raw text). We shall be using deep learning and machine learning techniques to filter these SMS messages

3. Experimental Evaluation

3.1 Methodology

- Data cleaning and removing the unwanted columns from the data
- Checking the length and count of the messages
- Used label encoding to add values to spam and ham messages
- Used stop words to clean the data
- Used word cloud to analyse the most common words used in spam
- Convert text into vectors using TF-IDF
- Instantiate MultinomiaLNB classifier
- Split feature and Label
- Train and split on the data set
- Train and predict
- Plot confusion matrix heatmap

3.2 Results

1. Converted to ISO-8859-1 as UTF 8 was creating issues

```
In [12]: df= pd.read_csv("spam.csv", encoding=('ISO-8859-1'))
         df.head()
```

Out[12]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

```
In [13]: df.info
```

2. Labeling the data, finding out the spam and ham message ratio

```
In [15]: # Dataset has extra columns- Remove
         #Renaming v1 and v2
         df.drop (columns=['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], axis=1, inplace=True)
         df.rename(columns={'v1': "label", 'v2': 'message'}, inplace=True)

In [16]: df.head()
         print ('Shape >',df.shape)

         Shape > (5572, 2)

In [17]: print ('ham and spam counts','\n', df.label.value_counts())

         ham and spam counts
          ham     4825
         spam     747
         Name: label, dtype: int64

In [18]: #Ratio
         print ('spam ratio = ', round (len(df[df['label'] == 'spam'])/ len(df.label), 2)*100, '%')
         print ('ham ratio = ', round(len (df[df['label'] == 'ham']) / len(df.label), 2)*100, '%')

         spam ratio =  13.0 %
         ham ratio =  87.0 %
```

3. Used label encoding to bifurcate into ham and spam messages. Also converted the messages to lower case.

```
In [20]: #Label coding 0 and 1
         df['label' ].replace({'ham':0,'spam':1},inplace=True)

In [21]: # Convert all messages to Lower case
         df['message'] = df['message'].str. lower()
         df.head()
```

Out[21]:

	label	message	length
0	0	go until jurong point, crazy.. available only ...	111
1	0	ok lar... joking wif u oni...	29
2	1	free entry in 2 a wkly comp to win fa cup fina...	155
3	0	u dun say so early hor... u c already then say...	49
4	0	nah i don't think he goes to usf, he lives aro...	61

4. Replaced email addresses with 'email'

Replaced the url in the messages with -’webaddress’

Replaced numbers with ‘numbr’

Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber"

```
In [22]: # Replace email addresses with 'email'
df['message'] = df['message'].str.replace(r'^.+@[^\.].*\.[a-z]{2,}$','emailaddress')

In [23]: #Replace URLS with 'webaddress' I
df['message'] = df['message'].str.replace(r'^http\://[a-zA-Z0-9\-\.]+\.[a-zA-Z]{2,3}(/\S*)?$',
'webaddress')

In [24]: # Replace money symbols with 'moneysymb(£ can by typed with ALT key + 156)
df['message'] = df['message'].str.replace(r'£|\$', 'dollers')

In [25]: #Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber"
df['message'] = df['message'].str.replace(r'^\(?P[\d]{3}\)?[\s-]?[\d]{3}[\s-]?[\d]{4}$',
'phonenumber')

In [26]: #Replace numbers with 'numbr
df['message'] = df['message'].str.replace(r'\d+(\.\d+)?', 'numbr')
```

5. Remove stop words with nltk library

```
In [31]: # Remove stopwords
import string
import nltk
from nltk.corpus import stopwords
stop_words=set(stopwords.words('english') + ['u', 'ü', 'ur', '4', '2' 'im', 'dont', 'doin', 'ure'])
df['message'] = df['message'].apply(lambda x: ''.join(
term for term in x.split() if term not in stop_words))

In [32]: # New column (clean_length) after puncuations, stopwords removal
df['clean_length']=df.message.str.len()
df.head()
```

Out[32]:

	label	message	length	clean_length
0	0	gojurongpoint,crazy..availablebugisngreatworld...	111	78
1	0	oklar...jokingwifoni...	29	23
2	1	freeentrynumbrwklycompwinfacupfinaltktsnumbrst...	155	124
3	0	dunsayearlyhor...calreadysay...	49	31
4	0	nahthinkgoesusf,livesaroundthough	61	33

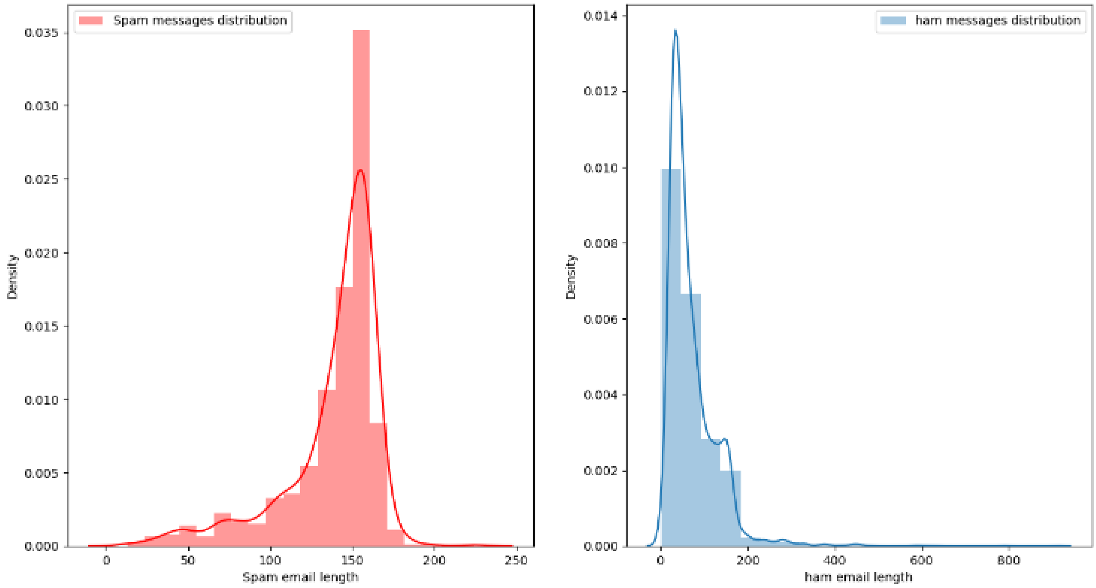
6. Original length vs clean length

```
In [33]: # Total Length removal
print ('Origian Length', df.length. sum())
print ('Clean Length', df.clean_length.sum())

Origian Length 446422
Clean Length 288829
```

In [37]:

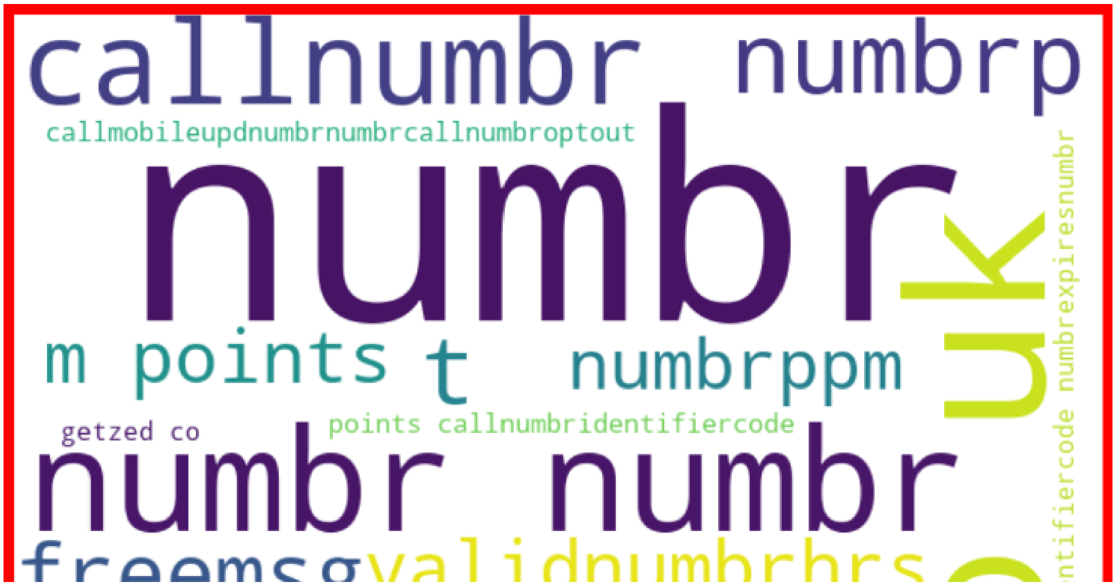
```
# Message distribution BEFORE cleaning
f, ax = plt. subplots(1,2, figsize= (15,8))
sns.distplot(df[df['label']==1]['length'], bins=20, ax=ax[0], label='Spam messages distribution',color='r')
ax[0].set_xlabel('Spam email length')
ax[0].legend()
sns.distplot(df[df['label']==0]['length'],bins=20, ax=ax[1], label='ham messages distribution')
ax[1].set_xlabel('ham email length')
ax[1].legend()
plt.show()
```



7. Used word cloud to find the most company used spam words

In [38]:

```
#Getting sense of word cloud in spam
from wordcloud import WordCloud
spams=df['message'][df['label']==1]
spam_cloud = WordCloud(width=700,height=500, background_color='white', max_words=20).generate(' '.join(spams))
plt.figure(figsize=(10,8), facecolor='r')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



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8. Converting text into vectors into TF-IDF

Splitting feature and label

splitting the data into train and predict

]:

```
#1. Convert text into vectors using TF-IDF
# 2. Instantiate MultinomialNB classifier
#3. Split feature and label
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
tf_vec = TfidfVectorizer()
naive=MultinomialNB()
features=tf_vec.fit_transform(df['message'])
X = features
y = df['label']
```

```
In [42]: # Train and predict
X_train,x_test, Y_train,y_test=train_test_split(X,y,random_state=42)
naive.fit(X_train,Y_train)
y_pred=naive.predict(x_test)
print('Final score = > ', accuracy_score(y_test,y_pred))
```

```
Final score = >  0.91816223977028
```

```
In [43]: print (classification_report(y_test, y_pred))
```

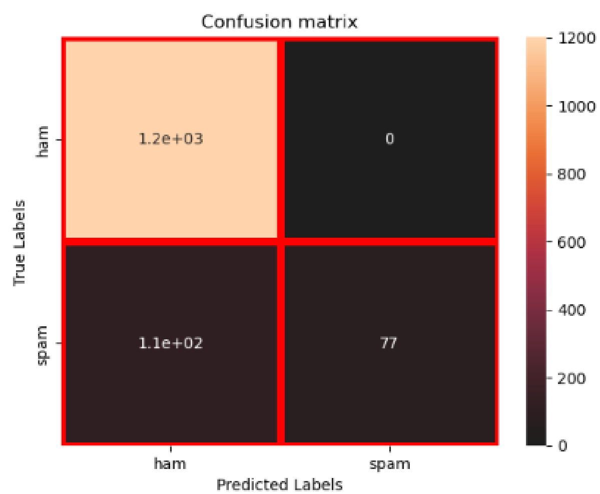
```
              precision    recall  f1-score   support

           0       0.91      1.00      0.95      1202
           1       1.00      0.40      0.57       191

    accuracy                           0.92      1393
   macro avg       0.96      0.70      0.76      1393
weighted avg       0.93      0.92      0.90      1393
```

9. Confusion matrix

```
In [51]: # plot confusion matrix heatmap
conf_mat = confusion_matrix(y_test,y_pred)
ax=plt.subplot()
sns.heatmap(conf_mat, annot=True, ax=ax, linewidths=5,linecolor='r',center=0)
ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels')
ax.set_title('Confusion matrix')
ax.xaxis.set_ticklabels (['ham', 'spam'])
ax.yaxis.set_ticklabels(['ham', 'spam'])
plt.show()
```




```
In [52]: conf_mat
Out[52]: array([[1202,    0],
       [ 114,   77]], dtype=int64)
```

5. Conclusion

Some of the common spam words include: callnumbr, uk, numbr, urgent, co, freemsg, urgent

The final score after prediction is Final score = > 0.91816223977028

The Original Length 446422, whereas Clean Length is 288829