```
!pip install nltk
     Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
     Requirement already satisfied: nltk in /usr/local/lib/python3.8/dist-packages (3.7)
     Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.8/dist-packages (from nltk) (2022.6.2)
     Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages (from nltk) (4.64.1)
    Requirement already satisfied: joblib in /usr/local/lib/python3.8/dist-packages (from nltk) (1.2.0)
     Requirement already satisfied: click in /usr/local/lib/python3.8/dist-packages (from nltk) (7.1.2)
!pip install -q wordcloud
import wordcloud
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('punkt')
nltk.download('averaged perceptron tagger')
     [nltk data] Downloading package stopwords to /root/nltk data...
                  Ungipping corpora/stopwords.zip.
     [nltk data]
     [nltk data] Downloading package wordnet to /root/nltk data...
     [nltk data] Downloading package punkt to /root/nltk_data...
     [nltk_data] Unzipping tokenizers/punkt.zip.
     [nltk_data] Downloading package averaged_perceptron_tagger to
     [nltk_data]
                    /root/nltk_data...
     [nltk data]
                   Unzipping taggers/averaged_perceptron_tagger.zip.
     True
#Importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
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
from sklearn.svm import SVC
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
# Importing the warnings
import warnings
warnings.filterwarnings('ignore')
#Loading the dataset
df = pd.read_csv("messages.csv",encoding='latin-1')
df.head()
                                   subject
                                                                         message label
     0
            job posting - apple-iss research center content - length : 3386 apple-iss research cen...
     1
                                             lang classification grimes , joseph e . and ba...
                                      NaN
                                                                                       0
     2 query: letter frequencies for text identifica...
                                             i am posting this inquiry for sergei atamas ( ...
                                            a colleague and i are researching the differin...
     3
                                       risk
                                                                                       0
     4
                       request book information earlier this morning i was on the phone with a...
#Checking information of dataset
df.info()
     <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 2893 entries. 0 to 2892
    Data columns (total 3 columns):
     #
        Column Non-Null Count Dtype
         subject 2831 non-null
                                    object
     0
         message 2893 non-null
                                    object
         label
                   2893 non-null
     dtypes: int64(1), object(2)
    memory usage: 67.9+ KB
```

#Checking the shape of the dataset
print("Shape of the dataset:", df.shape)

```
#Checking for the null values
df.isnull().values.any()

True

#Checkin for the null values in columns
df.isnull().sum()

subject 62
message 0
label 0
dtype: int64
```

62 row are missing in the subject columns that means 62 emails are without subject heading.

Here, not dropping Nan rows for subject column as it of no use in building model.

```
#Checking total number of mails
print("Count of label:\n",df['label'].value_counts())

Count of label:
    0    2412
    1    481
    Name: label, dtype: int64

# Note:- Here in our dataset 1 stands for Spam mail and 0 stands for not a spam mail.
#Checking the Ratio of labels
print("Not a Spam Email Ratio i.e. 0 label:",round(len(df[df['label']==0])/len(df['label']),2)*100,"%")
print("Spam Email Ratio that is 1 label:",round(len(df[df['label']==1])/len(df['label']),2)*100,"%")
Not a Spam Email Ratio i.e. 0 label: 83.0 %
Spam Email Ratio that is 1 label: 17.0 %
```

▼ so here 17 % of the data is a spam email

```
#Creating the new column for length of message column
df['length'] = df.message.str.len()
df.head()
```

	subject	message	label	length
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen	0	2856
1	NaN	lang classification grimes , joseph e . and ba	0	1800
2	query : letter frequencies for text identifica	i am posting this inquiry for sergei atamas (0	1435
^	• •	a colleague and i are researching the	^	224
	g all messages to lower case e'] = df['message'].str.lowe			

	subject	message	label	length
0	job posting - apple-iss research center	content - length : 3386 apple-iss research cen	0	2856
1	NaN	lang classification grimes , joseph e . and ba	0	1800
2	query : letter frequencies for text identifica	i am posting this inquiry for sergei atamas (0	1435
•	• •	a colleague and i are researching the	^	224

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

```
# Replace URLs with 'webaddress'
df['message'] = df['message'].str.replace(r'^http\://[a-zA-Z]-9\-\.]+\.[a-zA-Z]{2,3}(/\S*)?$','webaddress')
# Replace currency symbols with 'moneysymb' (£ can by typed with ALT key + 156)
df['message'] = df['message'].str.replace(r'f|\$', 'dollers')
# Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber'
 \label{lem:df['message']} $$ df['message'].str.replace(r'^\(?[\d]{3}\)?[\s-]?[\d]{4}$','phonenumber') $$
# Replace numeric characters with 'numbr'
df['message'] = df['message'].str.replace(r'\d+(\.\d+)?', 'numbr')
# Remove punctuation
df['message'] = df['message'].str.replace(r'[^\w\d\s]', '')
# Replace whitespace between terms with a single space
df['message'] = df['message'].str.replace(r'\s+',
# Remove leading and trailing whitespace
df['message'] = df['message'].str.replace(r'^\s+|\s+?$', '')
# now re-checking the data
df.head()
```

	subject	message	label	length
0	job posting - apple-iss research center	content length numbr apple iss research center	0	2856
1	NaN	lang classification grimes joseph e and barbar	0	1800
2	query: letter frequencies for text identifica	i am posting this inquiry for sergei atamas sa	0	1435
^	• •	a colleague and i are researching the	^	224

```
#Removing the stopwords
import string
import nltk
```

from nltk.corpus import stopwords

```
df['message'] = df['message'].apply(lambda x: " ".join(term for term in x.split() if term not in stop_words))
```

stop words = set(stopwords.words('english') + ['u', 'ü', 'ur', '4', '2', 'im', 'dont', 'doin', 'ure'])

New column (clean length) after puncuations, stopwords removal df['clean_length'] = df.message.str.len() df.head()

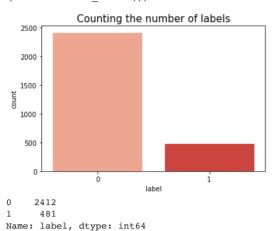
	subject	message	label	length	clean_length
0	job posting - apple-iss research center	content length numbr apple iss research center	0	2856	2179
1	NaN	lang classification grimes joseph e barbara f	0	1800	1454
2	query: letter frequencies for text identifica	posting inquiry sergei atamas satamas umabnet	0	1435	1064
3	risk	colleague researching differing degrees risk p	0	324	210
4	request book information	earlier morning phone friend mine living south	0	1046	629



```
#Total length removal
print("Original Length:",df.length.sum())
print("Cleaned Length:",df.clean_length.sum())
print("Total Words Removed:",(df.length.sum()) - (df.clean_length.sum()))
    Original Length: 9344743
    Cleaned Length: 6767857
    Total Words Removed: 2576886
#Graphical Visualisation for counting number of labels.
plt.figure(figsize=(6,4))
sns.countplot(df['label'],palette= 'Reds')
plt.title("Counting the number of labels", fontsize=15)
```

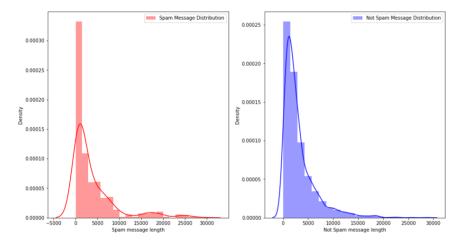
```
plt.xticks(rotation='horizontal')
plt.show()
```

print(df.label.value_counts())

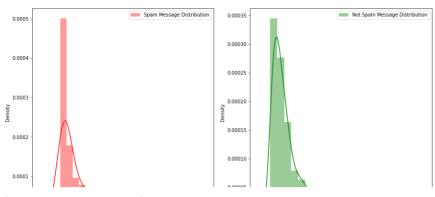


```
#Message distribution before cleaning
f,ax = plt.subplots(1,2,figsize=(15,8))
sns.distplot(df[df['label']==1]['length'],bins=20, ax=ax[0],label='Spam Message Distribution',color='r')
ax[0].set_xlabel('Spam message length')
ax[0].legend()
sns.distplot(df[df['label']==0]['length'],bins=20, ax=ax[1],label='Not Spam Message Distribution',color='b')
ax[1].set_xlabel('Not Spam message length')
ax[1].legend()
```

plt.show()

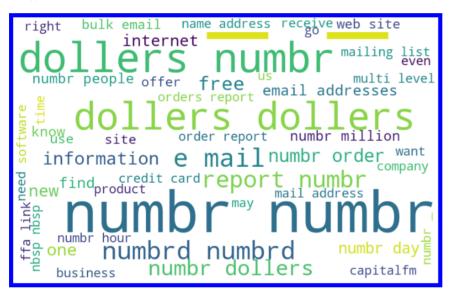


```
#Message distribution after cleaning
f,ax = plt.subplots(1,2,figsize=(15,8))
sns.distplot(df[df['label']==1]['clean_length'],bins=20, ax=ax[0],label='Spam Message Distribution',color='r')
ax[0].set_xlabel('Spam message length')
ax[0].legend()
sns.distplot(df[df['label']==0]['clean_length'],bins=20, ax=ax[1],label='Not Spam Message Distribution',color='g')
ax[1].set_xlabel('Not a Spam message length')
ax[1].legend()
plt.show()
```



#Getting sense of loud words in spam from wordcloud import WordCloud

```
spams = df['message'][df['label']==1]
spam_cloud = WordCloud(width=800,height=500,background_color='white',max_words=50).generate(' '.join(spams))
plt.figure(figsize=(10,8),facecolor='b')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



```
#Getting sense of loud words in not-spam
from wordcloud import WordCloud

not_spams = df['message'][df['label']==0]

spam_cloud = WordCloud(width=800,height=500,background_color='white',max_words=50).generate(' '.join(not_spams))

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

```
research
                       wel
     example
# Converting the text into vectors using TF-IDF, as text cannot be the input in the model
# 1. Convert text into vectors using TF-IDF
# 2. Instantiate MultinomialNB classifier
# 3. Split feature and label
tf vec = TfidfVectorizer()
naive = MultinomialNB()
SVM = SVC(C=1.0, kernel='linear', degree=3 , gamma='auto')
decision = DecisionTreeClassifier()
classifier= RandomForestClassifier(n estimators= 10, criterion="entropy")
clf = LogisticRegression()
features = tf vec.fit transform(df['message'])
X = features
y = df['label']
# Train and predict for naive bayes model
X_train,x_test,Y_train,y_test = train_test_split(X,y,random_state=42)
#test size=0.20 random state=42 test size=0.15
naive.fit(X_train,Y_train)
y_pred= naive.predict(x_test)
print ('Final score = > ', accuracy score(y test,y pred))
    Final score = > 0.8342541436464088
# Train and predict for SVM model
X train,x test,Y train,y test = train test split(X,y,random state=42)
#test_size=0.20 random_state=42 test_size=0.15
SVM.fit(X_train,Y_train)
y_pred = SVM.predict(x_test)
print ('Final score = > ', accuracy_score(y_test,y_pred))
    Final score = > 0.9875690607734806
# train and predict for the Decision tree model
X_train,x_test,Y_train,y_test = train_test_split(X,y,random_state=42)
decision.fit(X_train,Y_train)
#test_size=0.20 random_state=42 test_size=0.15
y_pred = decision.predict(x_test)
print ('Final score = > ', accuracy_score(y_test,y_pred))
    Final score = > 0.9585635359116023
# train and predict uisng random forest classifier
X_train,x_test,Y_train,y_test = train_test_split(X,y,random_state=42)
classifier.fit(X_train, Y_train)
#test_size=0.20 random_state=42 test_size=0.15
```

```
y_pred= classifier.predict(x_test)
printFinedorscore = 0.97,09944779138 propre(y test, y pred))
# train and predict uisng logistic regression
X_train,x_test,Y_train,y_test = train_test_split(X,y,random_state=42)
clf.fit(X train, Y train)
#test_size=0.20 random_state=42 test_size=0.15
y_pred= clf.predict(x_test)
print ('Final score = > ', accuracy_score(y_test,y_pred))
   Final score = > 0.9475138121546961
y pred
   0, 0, 0,
        0, 0, 0, 0, 1, 0, 0, 1, 0,
                               0, 0, 0, 0, 0, 0, 0,
                                               0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,
                                               0, 0, 0,
        0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
          0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1,
           0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1,
           0, 0, 0, 1,
                    0, 0, 0, 0, 0,
                               0, 0, 1, 0, 1, 0, 1,
                                               0, 0, 0, 0,
           0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
                                               0, 0, 0,
           0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
        0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1,
          0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
        1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
        0.
           0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
        1.
           0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
           1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1,
           0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                                               1, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
        0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                                               1, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
           0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 0,\ 1,\ 0,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,
```

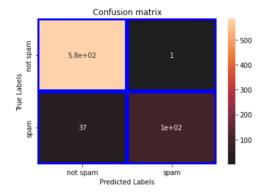
tree.plot_tree(decision)

```
[Text(0.8492647058823529, 0.9827586206896551, 'X[18089] <= 0.015 \\ ngini = 0
0.266 \times = 2169 \times = [1827, 342]'),
     Text(0.7612745098039215, 0.9482758620689655, 'X[41154] <= 0.009\ngini =
0.157\nsamples = 1901\nvalue = [1738, 163]'),
   Text(0.6950980392156862, 0.9137931034482759, 'X[32052] <= 0.076\ngini =
0.12 \times 10^{-12} = 1853 \times 10^
   Text(0.6411764705882353, 0.8793103448275862, 'X[8614] \le 0.053 
0.1\nsamples = 1828\nvalue = [1732, 96]'),
     Text(0.5803921568627451, 0.8448275862068966, 'X[19527] <= 0.068\ngini =
0.08 \times = 1804 \times = [1729, 75]'),
     Text(0.5372549019607843, 0.8103448275862069, 'X[23195] <= 0.019\ngini =
0.065\nsamples = 1780\nvalue = [1720, 60]'),
     Text(0.4980392156862745, 0.7758620689655172, 'X[49044] <= 0.029 ini =
0.057 \times = 1771 \times = [1719, 52]'
    Text(0.466666666666667, 0.7413793103448276, 'X[51790] <= 0.083\ngini =
0.049\nsamples = 1760\nvalue = [1716, 44]'),
   Text(0.45098039215686275, 0.7068965517241379, 'X[7268] \leq 0.044\ngini =
0.043 \times 10^{-10}
    Text(0.4196078431372549, 0.6724137931034483, 'X[11366] <= 0.082\ngini =
0.039 \times = 1750 \times = [1715, 35]'),
     Text(0.403921568627451, 0.6379310344827587, 'X[39836] \le 0.082 
0.036 \times = 1747 \times = [1715, 32]'
    Text(0.3607843137254902, 0.603448275862069, 'X[30114] <= 0.082\ngini =
0.032 \times = 1741 \times = [1713, 28]'),
   Text(0.3215686274509804, 0.5689655172413793, 'X[11408] <= 0.076 
0.027\nsamples = 1735\nvalue = [1711, 24]'),
   Text(0.2901960784313726, 0.5344827586206896, 'X[39107] \le 0.017 \cdot ini = 0.017 \cdot ini =
0.023\nsamples = 1728\nvalue = [1708, 20]'),
Text(0.27450980392156865, 0.5, 'X[52548] <= 0.118\ngini = 0.021\nsamples =
1726\nvalue = [1708, 18]'),
     Text(0.25882352941176473, 0.46551724137931033, 'X[30119] <= 0.152\ngini =
0.018 \times = 1724 \times = [1708, 16]'),
     Text(0.24313725490196078, 0.43103448275862066, 'X[28346] <= 0.135\ngini =
0.016 \times 1722 \times 1722 = [1708, 14]'),
    Text(0.20392156862745098, 0.39655172413793105, 'X[25295] <= 0.09\ngini =
0.014\nsamples = 1719\nvalue = [1707, 12]'),
    Text(0.17254901960784313, 0.3620689655172414, 'X[37433] <= 0.15\ngini =
0.012 \times 1716 \times 1716
     Text(0.1568627450980392, 0.3275862068965517, 'X[46093] \le 0.015 \ngini = 0.015 \
0.01 \times 10^{-10}
    Text(0.1411764705882353, 0.29310344827586204, 'X[10017] \le 0.144 
0.009 \times 1714 \times 1714 = [1706, 8]'
     Text(0.12549019607843137, 0.25862068965517243, 'X[49937] <= 0.102\ngini =
0.008\nsamples = 1713\nvalue = [1706, 7]'),
    Text(0.10980392156862745, 0.22413793103448276, 'X[34059] <= 0.08\ngini =
0.007 \times 1712 \times
   Text(0.09411764705882353, 0.1896551724137931, 'X[488] \le 0.062 \rangle = 0.062
0.006\nsamples = 1711\nvalue = [1706, 5]')
    Text(0.0784313725490196, 0.15517241379310345, 'x[14728] <= 0.177 \ngini =
0.005 \times 1710 \times 1710 = [1706, 4]'
    Text(0.06274509803921569, 0.1206896551724138, 'X[36598] <= 0.068\ngini =
0.004 \times = 1709 \times = [1706, 3]'),
     Text(0.047058823529411764, 0.08620689655172414, 'X[27775] \le 0.22 = 0.22
0.002 \times 1708 \times 1708 \times 1708 = [1706, 2]'),
     Text(0.03137254901960784, 0.05172413793103448, 'X[21822] \le 0.073 
0.001 \times 10^{-100}
    Text(0.01568627450980392, 0.017241379310344827, 'gini = 0.0\nsamples =
```

Checking Classification report
print(classification_report(y_test, y_pred))

	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

```
# 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='b',center=0)
ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels')
ax.set_title('Confusion matrix')
ax.xaxis.set_ticklabels(['not spam','spam'])
ax.yaxis.set_ticklabels(['not spam','spam'])
plt.show()
```



SVM performs best among all the classification models

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