Data processing using pandas library

```
import pandas as pd
```

Importing Dataset

```
from google.colab import drive
drive.mount('/content/drive/')
data = '/content/spam.tsv'
```

Drive already mounted at /content/drive/; to attempt to forcibly remount, call

Loading Dataset

```
dataset=pd.read csv(data,sep='\t',header=None)
```

dataset

•		0	1					
	0	ham	I've been searching for the right words to tha					
	1	spam	Free entry in 2 a wkly comp to win FA Cup fina					
	2	ham	Nah I don't think he goes to usf, he lives aro					
	3	ham	Even my brother is not like to speak with me					
	4	ham	I HAVE A DATE ON SUNDAY WITH WILL!!!					
	5562	spam	This is the 2nd time we have tried 2 contact u					
	5563	ham	Will ü b going to esplanade fr home?					
	5564	ham	Pity, * was in mood for that. Soany other s					
	5565	ham	The guy did some bitching but I acted like i'd					
	5566	ham	Rofl. Its true to its name					
	5567 rows × 2 columns							

Exploratory Data Analysis (EDA)

The better your domain knowledge on the data, the better your ability to engineer more features from it. Feature engineering is a very large part of spam detection in general.

```
dataset.columns=["label", "message"]
```

```
dataset.head()
```

```
label
                                                  message
0
              I've been searching for the right words to tha...
     ham
1
    spam Free entry in 2 a wkly comp to win FA Cup fina...
2
               Nah I don't think he goes to usf, he lives aro...
     ham
3
             Even my brother is not like to speak with me. ...
     ham
                I HAVE A DATE ON SUNDAY WITH WILL!!!
4
     ham
```

```
## Data Cleaning and text preprocessing
import re
import nltk
nltk.download('stopwords')
     [nltk data] Downloading package stopwords to /root/nltk data...
                   Package stopwords is already up-to-date!
     [nltk data]
     True
from nltk.corpus import stopwords
stopwords.words('english')
     ['i',
      'me',
      'my',
      'myself',
      'we',
      'our',
      'ours',
      'ourselves',
      'you',
      "you're",
      "you've",
      "you'll",
      "you'd",
      'your',
      'yours',
      'yourself',
      'yourselves',
      'he',
      'him',
      'his',
      'himself',
      'she',
      "she's",
      'her',
      'hers',
```

'herself',

'it',

```
"it's",
      'its',
      'itself',
      'they',
      'them',
      'their',
      'theirs',
      'themselves',
      'what',
      'which',
      'who',
      'whom',
      'this',
      'that',
      "that'll",
      'these',
      'those',
      'am',
      'is',
      'are',
      'was',
      'were',
      'be',
      'been',
      'being',
      'have',
      'has',
      'had',
      'having',
      'do',
      'does',
stopword list=['i',
 'me',
 'my',
 'myself',
 'we',
 'our',
 'ours',
 'ourselves',
 'you',
 "you're",
 "you've",
 "you'll",
 "you'd",
 'your',
 'yours',
 'yourself',
 'yourselves',
 'he',
 'him',
 'his',
 'himself',
 'she',
 "she's",
 'her',
 'hers',
```

'it',

'herself',

```
"it's",
'its',
'itself',
'they',
'them',
'their',
'theirs',
'themselves',
'what',
'which',
'who',
'whom',
'this',
'that',
"that'll",
'these',
'those',
'am',
'is',
'are',
'was',
'were',
'be',
'been',
'being',
'have',
'has',
'had',
'having',
'do',
'does',
'did',
'doing',
'a',
'an',
'the',
'and',
'but',
'if',
'or',
'because',
'as',
'until',
'while',
'of',
'at',
'by',
'for',
'with',
'about',
'against',
'between',
'into',
```

```
'through',
'during',
'before',
'after',
'above',
'below',
'to',
'from',
'up',
'down',
'in',
'out',
'on',
'off',
'over',
'under',
'again',
'further',
'then',
'once',
'here',
'there',
'when',
'where',
'why',
'how',
'all',
'any',
'both',
'each',
'few',
'more',
'most',
'other',
'some',
'such',
'nor',
'not',
'only',
'own',
'same',
'so',
'than',
'too',
'very',
's',
't',
'can',
'will',
'just',
'should',
"should've",
'now',
'd',
'11',
```

```
'm',
 'o',
 're',
 've',
 'y',
 'isn',
 "isn't",
 'ma',
 'mightn',
 "mightn't",
 'mustn',
 "mustn't",
 'needn',
 "needn't",
 'shan',
 "shan't",
 'shouldn',
 "shouldn't",
 'wasn',
 "wasn't",
 'weren',
 "weren't",
 'won',
 "won't",
 'wouldn',
 "wouldn't"]
from nltk.stem.porter import PorterStemmer
ps=PorterStemmer()
```

Tokenization-(process of converting the normal text strings in to a list of tokens(also known as lemmas)).

```
corpus=[]
for i in range(0,len(dataset)):
    review=re.sub('[^a-zA-Z0-9]',' ',dataset['message'][i])
    review=review.lower()
    review=review.split() #tokenise
    review=[ps.stem(word) for word in review if not word in stopword_list]
    review=' '.join(review)
    corpus.append(review)

corpus[:3]

['search right word thank breather promis wont take help grant fulfil promis wonder bless time',
    'free entri 2 wkli comp win fa cup final tkt 21st may 2005 text fa 87121
    receiv entri question std txt rate c appli 08452810075over18',
    'nah don think goe usf live around though']
```

У

```
## independent features and dependent
y=pd.get dummies(dataset['label'],drop first=True)
```

	spam	
0	0	
1	1	
2	0	
3	0	
4	0	
5562	1	
5563	0	
5564	0	
5565	0	
5566	0	
5567 ro	ws × 1	colum

5567 rows × 1 columns

```
# Train Test Split
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(corpus, y, test_size = 0.20, )
X_train[:3]
    ['lover need',
      'go 4 lunch wif famili aft dat go str 2 orchard lor',
      'pl dont forget studi']
dataset['label'].value_counts()
    ham
             4821
             746
    spam
    Name: label, dtype: int64
```

Now we need to convert each of those messages into a vector the SciKit Learn's algorithm models can work with and machine learning model which we will gonig to use can understand

creating the Bag of Words (BOW)

```
from sklearn.feature extraction.text import CountVectorizer
cv=CountVectorizer(max features=2500,ngram range=(1,2))
X train=cv.fit transform(X train).toarray()
X train
     array([[0, 0, 0, ..., 0, 0, 0],
            [0, 0, 0, \ldots, 0, 0, 0],
            [0, 0, 0, ..., 0, 0, 0],
            [0, 0, 0, \dots, 0, 0, 0],
            [0, 0, 0, \ldots, 0, 0, 0],
            [0, 0, 0, \ldots, 0, 0, 0]])
X test=cv.transform(X test).toarray()
X test
     array([[0, 0, 0, ..., 0, 0, 0],
            [0, 0, 0, \ldots, 0, 0, 0]]
X train.shape
     (4453, 2500)
y train.shape #target column
     (4453, 1)
cv.vocabulary #a dictionary with the mapping of the word index
     {'lover': 1290,
      'need': 1468,
      'go': 899,
      'lunch': 1303,
      'wif': 2406,
      'famili': 763,
      'aft': 189,
      'dat': 588,
      'orchard': 1581,
      'lor': 1275,
      'pl': 1648,
      'dont': 662,
      'forget': 816,
      'studi': 2047,
      'pl dont': 1650,
```

```
'centr': 436,
'someth': 1973,
'like': 1238,
'road': 1814,
'someth like': 1974,
'free': 825,
'1st': 58,
'week': 2373,
'no1': 1508,
'nokia': 1512,
'tone': 2178,
'ur': 2256,
'mob': 1393,
'everi': 732,
'txt': 2220,
'8007': 139,
'get': 877,
'txting': 2230,
'tell': 2104,
'mate': 1334,
'www': 2454,
'getz': 888,
'co': 478,
'uk': 2236,
'pobox': 1669,
'36504': 94,
'w45wq': 2328,
'norm150p': 1524,
'16': 56,
'free 1st': 827,
'1st week': 60,
'week no1': 2377,
'no1 nokia': 1509,
'nokia tone': 1518,
'tone ur': 2183,
'ur mob': 2271,
'mob everi': 1394,
'everi week': 735,
'week txt': 2379,
'txt nokia': 2223,
'nokia 8007': 1515,
'get txting': 884,
'+v+ing +all' • 2221
```

With messages represented as vectors, we can finally train our spam/ham classifier. Now we can actually use almost any sort of classification algorithms. For a variety of reasons, the Naive Bayes classifier algorithm is a good choice.

Random Forest Classifier

print(classification_report(y_test,y_pred))

	precision	recall	f1-score	support
0	0.99	1.00 0.91	0.99	958 156
_	0.33	0.51		
accuracy			0.99	1114
macro avg	0.99	0.95	0.97	1114
weighted avg	0.99	0.99	0.99	1114

10 min break

Spam Classification Application

Naives Bayes Classifier

```
from sklearn.naive_bayes import GaussianNB
clf = GaussianNB()
clf.fit(X_train,y_train)

y pred=clf.predict(X test)
```

	precision	recall	f1-score	support
0	0.99	0.83	0.90	958
1	0.47	0.96	0.63	156
accuracy			0.84	1114
macro avg	0.73	0.89	0.77	1114
weighted avg	0.92	0.84	0.86	1114