Machine Learning Classifier to create a Spam Detection Filter:

Dataset source: University California Irvine

https://archive.ics.uci.edu/ml/index.php (https://archive.ics.uci.edu/ml/index.php)

Import NLTK & Basic python packages:

Load Dataset:

Out[22]:

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

Exploratory Data Analysis:

In [24]: df.describe()

Out[24]:

	Label	Message
count	5572	5572
unique	2	5169
top	ham	Sorry, I'll call later
freq	4825	30

```
In [25]: df.groupby('Label').describe()
```

Out[25]:

Message

	count	unique	top	freq
Label				
ham	4825	4516	Sorry, I'll call later	30
spam	747	653	Please call our customer service representativ	4

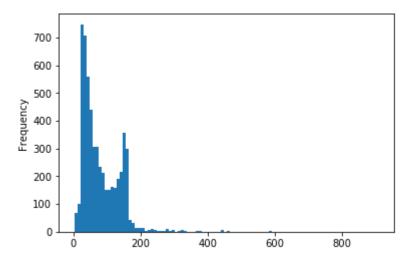
```
In [26]: # Creating new column for message length:
         df['Length'] = df['Message'].apply(len)
         df.head()
```

Out[26]:

	Label	Message	Length
0	ham	Go until jurong point, crazy Available only	111
1	ham	Ok lar Joking wif u oni	29
2	spam	Free entry in 2 a wkly comp to win FA Cup fina	155
3	ham	U dun say so early hor U c already then say	49
4	ham	Nah I don't think he goes to usf, he lives aro	61

```
In [27]: # Visualizing message length:
         df['Length'].plot.hist(bins=100)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x20f5d884088>

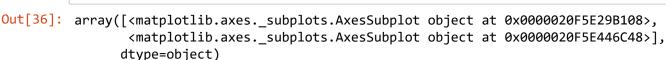


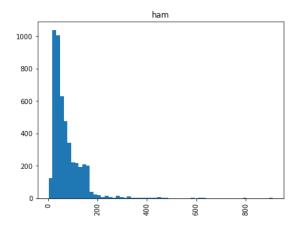
```
In [28]: df['Message'].describe()
Out[28]: count
                                       5572
         unique
                                       5169
          top
                    Sorry, I'll call later
          freq
         Name: Message, dtype: object
In [29]: | df['Label'].describe()
Out[29]: count
                    5572
         unique
                       2
          top
                     ham
```

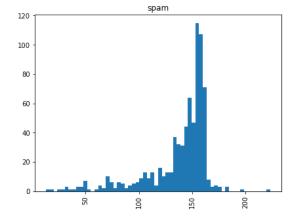
freq

4825 Name: Label, dtype: object

```
In [30]: df['Length'].describe()
Out[30]: count
                   5572.000000
                     80.489950
         mean
                     59.942907
         std
         min
                      2.000000
         25%
                     36.000000
         50%
                     62.000000
         75%
                    122.000000
         max
                    910.000000
         Name: Length, dtype: float64
In [31]:
         # Checking highest and lowest message:
          print(df[df['Length']==910])
          print(df[df['Length']==2])
               Label
                                                                  Message
                                                                           Length
         1085
                 ham
                      For me the love should start with attraction.i...
                                                                               910
               Label Message
                              Length
         1925
                          0k
                                    2
                 ham
         3051
                          0k
                                    2
                 ham
         4498
                          0k
                                    2
                 ham
                                    2
         5357
                 ham
                          0k
In [36]:
         # Comparing Ham vs Spam:
          df.hist(column='Length', by='Label', bins=60, figsize=(15,5))
```







Removing Punctuations:

```
In [37]: import string
    string.punctuation
Out[37]: '!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

```
In [42]: # Checking punctuation removal
sample_message = 'This is a !@string with $lots of ,punctutations..'
nopunc = [p for p in sample_message if p not in string.punctuation]
''.join(nopunc)

Out[42]: 'This is a string with lots of punctutations'
```

Import Stopwords from NLTK Corpus:

```
In [44]: from nltk.corpus import stopwords
stopwords.words('english')
```

```
Out[44]: ['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',
'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',
'no',
'nor',
'not',
'only',
'own',
'same',
'so',
'than',
'too',
'very',
's',
't',
'can',
'will',
'just',
'don',
"don't",
'should',
"should've",
'now',
'd',
'11',
'm',
'o',
're',
've',
'y',
'ain',
'aren',
"aren't",
'couldn',
"couldn't",
'didn',
"didn't",
'doesn',
"doesn't",
'hadn',
"hadn't",
'hasn',
"hasn't",
'haven',
"haven't",
'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"]
```

Remove Stopwords & Punctuations from the Dataset:

```
In [46]: df.head()
```

Out[46]:

	Label	Message	Length
0	ham	Go until jurong point, crazy Available only	111
1	ham	Ok lar Joking wif u oni	29
2	spam	Free entry in 2 a wkly comp to win FA Cup fina	155
3	ham	U dun say so early hor U c already then say	49
4	ham	Nah I don't think he goes to usf, he lives aro	61

Stemming won't be helpful in this scenario due to presence of multiple shorthands. Hence now, we will move on to representing the text data in numerical manner for our Machine Learning model to interpret and predict

Vectorization: Word count from text:

```
In [48]: from sklearn.feature_extraction.text import CountVectorizer
```

Transformation: Sparse Matrix Creation:

Perform TF-IDF Transformation:

```
In [54]: from sklearn.feature_extraction.text import TfidfTransformer
    tfidf_transformer = TfidfTransformer()

In [55]: tfidf_transformer.fit(messages_bag_of_words)
    messages_tfidf = tfidf_transformer.transform(messages_bag_of_words)
```

Split Dataset into Train & Test Split:

```
In [56]: from sklearn.model_selection import train_test_split
    msg_train, msg_test, label_train, label_test = train_test_split(df['Message'],
    df['Label'], test_size=0.3)
```

Build Naive Bayes Classifier Model:

```
In [57]: from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import MultinomialNB
```

```
In [58]: classifier = MultinomialNB()
         pipeline = Pipeline(
In [59]:
              ('bagofwords', CountVectorizer(analyzer=stopword removal)),
              ('tfidf', TfidfTransformer()),
              ('classifier',MultinomialNB())
         1)
         pipeline.fit(msg_train, label_train)
Out[59]: Pipeline(memory=None,
              steps=[('bagofwords', CountVectorizer(analyzer=<function stopword remova
         1 at 0x0000020F6223C4C8>,
                 binary=False, decode_error='strict', dtype=<class 'numpy.int64'>,
                 encoding='utf-8', input='content', lowercase=True, max_df=1.0,
                 max features=None, min df=1, ngram range=(1, 1), ...f=False, use idf=
         True)), ('classifier', MultinomialNB(alpha=1.0, class prior=None, fit prior=T
         rue))])
         predictions = pipeline.predict(msg test)
In [60]:
```

Model Evaluation Metrics:

```
In [61]:
         from sklearn.metrics import classification report, confusion matrix
         print(confusion matrix(label test,predictions))
In [62]:
         [[1449
                    0]
             76 147]]
         print(classification_report(label_test,predictions))
In [63]:
                        precision
                                      recall f1-score
                                                         support
                             0.95
                                       1.00
                                                  0.97
                                                            1449
                   ham
                  spam
                             1.00
                                       0.66
                                                  0.79
                                                             223
             micro avg
                             0.95
                                       0.95
                                                  0.95
                                                            1672
                             0.98
                                                  0.88
             macro avg
                                       0.83
                                                            1672
                             0.96
                                       0.95
                                                  0.95
                                                            1672
         weighted avg
```