NLP Project

Section 1: Getting Familiar with the Dataset

Read in semi-structured text data from a dataset obtained from UCI Machine Learning Repository

In [2]:

```
# Read in the raw text
rawData = open("SMSSpamCollection.tsv").read()

# Print the raw data
rawData[0:500]
```

Out[2]:

```
"ham\tI've been searching for the right words to thank you for this breather. I promise
i wont take your help for granted and will fulfil my promise. You have been wonderful an
d a blessing at all times.\nspam\tFree entry in 2 a wkly comp to win FA Cup final tkts 2
1st May 2005. Text FA to 87121 to receive entry question(std txt rate)T&C's apply 084528
10075over18's\nham\tNah I don't think he goes to usf, he lives around here though\nham\t
Even my brother is not like to speak with me. They treat me like aid"
```

In [3]:

```
import pandas as pd
data = pd.read_csv('SMSSpamCollection.tsv', sep='\t', header=None)
data.columns = ['label', 'body_text']

data.head()
```

Out[3]:

	label	body_text
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!!

In [4]:

```
# What is the shape of the dataset?

print("Input data has {} rows and {} columns".format(len(data), len(data.columns)))

# How many spam/ham are there?

print("Out of {} rows, {} are spam, {} are ham".format(len(data),
                                                       len(data[data['label']=='spam'])
                                                       len(data[data['label']=='ham']))
# How much missing data is there?

print("Number of null in label: {}".format(data['label'].isnull().sum()))
print("Number of null in text: {}".format(data['body_text'].isnull().sum()))
```

```
Input data has 5568 rows and 2 columns
Out of 5568 rows, 746 are spam, 4822 are ham
```

```
Number of null in label: 0
Number of null in text: 0
```

Section 2: Feature Engineering: adding Features to the data

later on we will clean the text and remove punctuation from it. However, these pieces of information may be helpful for our spam filter somehow. Therefore, it would be efficient to analyze these feature before cleaning the data

In [5]:

```
import string
def count_punct(text):
    count = sum([1 for char in text if char in string.punctuation])
    return round(count/(len(text) - text.count(" ")), 3)*100

data['body_len'] = data['body_text'].apply(lambda x: len(x) - x.count(" "))
data['punct%'] = data['body_text'].apply(lambda x: count_punct(x))

data.head()
```

Out[5]:

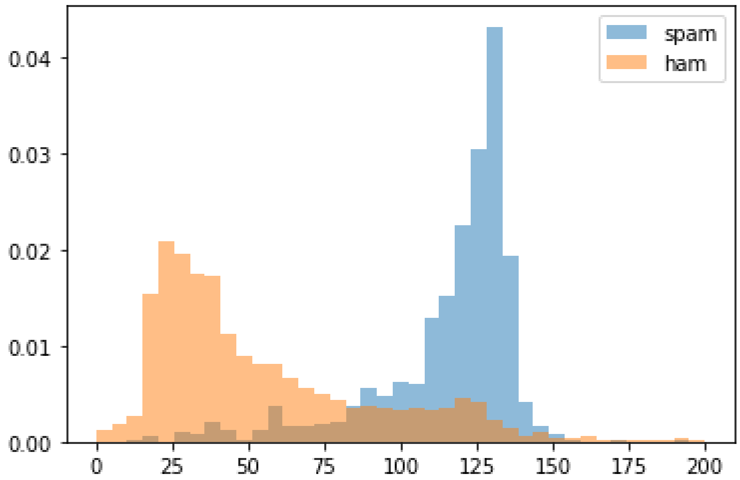
	label	body_text	body_len	punct%
0	ham	I've been searching for the right words to tha...	160	2.5
1	spam	Free entry in 2 a wkly comp to win FA Cup fina...	128	4.7
2	ham	Nah I don't think he goes to usf, he lives aro...	49	4.1
3	ham	Even my brother is not like to speak with me. ...	62	3.2
4	ham	I HAVE A DATE ON SUNDAY WITH WILL!!	28	7.1

In [6]:

```
from matplotlib import pyplot
import numpy as np
%matplotlib inline
```

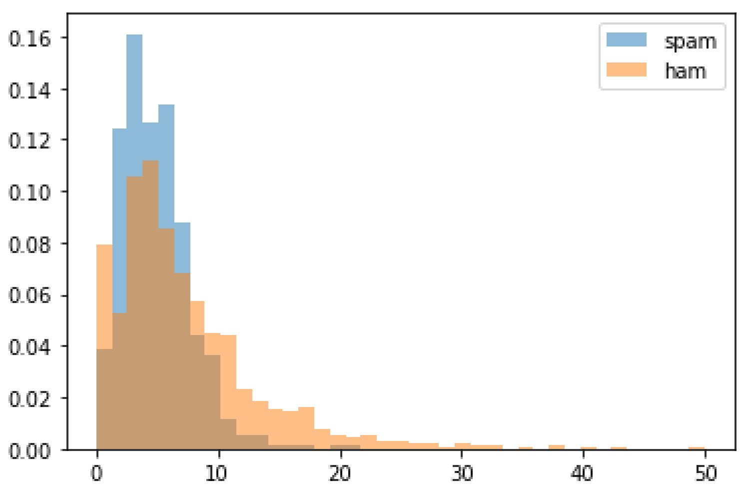
In [7]:

```
bins = np.linspace(0, 200, 40)

pyplot.hist(data[data['label']=='spam']['body_len'], bins, alpha=0.5,density=True,stack
pyplot.hist(data[data['label']=='ham']['body_len'], bins, alpha=0.5,density=True,stacke
pyplot.legend(loc='upper right')
pyplot.show()
```



In [8]:

```
bins = np.linspace(0, 50, 40)

pyplot.hist(data[data['label']=='spam']['punct%'], bins, alpha=0.5, density=True,stacke
pyplot.hist(data[data['label']=='ham']['punct%'], bins, alpha=0.5, density=True,stacked
pyplot.legend(loc='upper right')
pyplot.show()
```



Section 3: Text Analysis and Cleaning

In [9]:

```
import nltk
import re
stopwords = nltk.corpus.stopwords.words('english')

def clean_text(text):
    text = "".join([word for word in text if word not in string.punctuation])
    tokens = re.split('\W+', text)
    text = [word for word in tokens if word not in stopwords]
    return text

data['body_text_clean'] = data['body_text'].apply(lambda x: clean_text(x.lower()))

data.head()
```

Out[9]:

label	body_text	body_len	punct%	body_text_clean

	label	body_text	body_len	punct%	body_text_clean
0	ham	I've been searching for the right words to tha...	160	2.5	[ive, searching, right, words, thank, breather...
1	spam	Free entry in 2 a wkly comp to win FA Cup fina...	128	4.7	[free, entry, 2, wkly, comp, win, fa, cup, fin...
2	ham	Nah I don't think he goes to usf, he lives aro...	49	4.1	[nah, dont, think, goes, usf, lives, around, t...
3	ham	Even my brother is not like to speak with me. ...	62	3.2	[even, brother, like, speak, treat, like, aids...
4	ham	I HAVE A DATE ON SUNDAY WITH WILL!!	28	7.1	[date, sunday]

In [10]:

```
ps = nltk.PorterStemmer()
wn = nltk.WordNetLemmatizer()

def lemmatizing(tokenized_text):
    text = [wn.lemmatize(word) for word in tokenized_text]
    return text

def stemming(tokenized_text):
    text = [ps.stem(word) for word in tokenized_text]
    return text

trial_data = pd.DataFrame()
trial_data['body_text_lemmatized'] = data['body_text_clean'].apply(lambda x: lemmatizin
trial_data['body_text_stemmed'] = data['body_text_clean'].apply(lambda x: stemming(x))

trial_data.head()
```

Out[10]:

	body_text_lemmatized	body_text_stemmed
0	[ive, searching, right, word, thank, breather,...	[ive, search, right, word, thank, breather, pr...
1	[free, entry, 2, wkly, comp, win, fa, cup, fin...	[free, entri, 2, wkli, comp, win, fa, cup, fin...
2	[nah, dont, think, go, usf, life, around, though]	[nah, dont, think, goe, usf, live, around, tho...
3	[even, brother, like, speak, treat, like, aid,...	[even, brother, like, speak, treat, like, aid,...
4	[date, sunday]	[date, sunday]

from now on, we will move on with the limitizer instead of the stemmer since it makes smarter and more meaningful transformation to the vocabulary

Section 4: Data Preprocessing

Method 1: Apply CountVectorizer

In [11]:

```
def analyze_text(text):
    return lemmatizing(clean_text(text))
from sklearn.feature_extraction.text import CountVectorizer

count_vect = CountVectorizer(analyzer=analyze_text)
```

```python
X_counts = count_vect.fit_transform(data['body_text'])
print(X_counts.shape)
X_counts
```

```
(5568, 11039)
```

Out[11]:

```
<5568x11039 sparse matrix of type '<class 'numpy.int64'>'
	with 56278 stored elements in Compressed Sparse Row format>
```

Vectorizers output sparse matrices

***Sparse Matrix**: A matrix in which most entries are 0. In the interest of efficient storage, a sparse matrix will be stored by only storing the locations of the non-zero elements. We will use a dataframe instead to better represent the sparse matrix*

In [12]:

```python
X_counts_feat = pd.DataFrame(X_counts.toarray())
X_counts_feat.columns = count_vect.get_feature_names()
X_counts_feat=pd.concat([data['body_len'], data['punct%'], X_counts_feat],axis =1)
X_counts_feat.head()
```

Out[12]:

	body_len	punct%		0	008704050406	0089my	0121	01223585236	01223585334	0125698789
0	160	2.5	0	0	0	0	0	0	0	0
1	128	4.7	0	0	0	0	0	0	0	0
2	49	4.1	0	0	0	0	0	0	0	0
3	62	3.2	0	0	0	0	0	0	0	0
4	28	7.1	0	0	0	0	0	0	0	0

5 rows × 11041 columns

Method 2: Apply TF-IDF

Creates a document-term matrix where the columns represent single unique terms (unigrams) but the cell represents a weighting meant to represent how important a word is to a document.

In [13]:

```python
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf_vect = TfidfVectorizer(analyzer=analyze_text)
X_tfidf = tfidf_vect.fit_transform(data['body_text'])
print(X_tfidf.shape)
X_tfidf
```

```
(5568, 11039)
```

Out[13]:

```
<5568x11039 sparse matrix of type '<class 'numpy.float64'>'
	with 56278 stored elements in Compressed Sparse Row format>
```

In [14]:

```python
X_tfidf_feat = pd.DataFrame(X_tfidf.toarray())
X_tfidf_feat.columns = tfidf_vect.get_feature_names()
X_tfidf_feat=pd.concat([data['body_len'], data['punct%'], X_tfidf_feat],axis =1)
X_tfidf_feat.head()
```

Out[14]:

	body_len	punct%		0	008704050406	0089my	0121	01223585236	01223585334	012569878
0	160	2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
1	128	4.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
2	49	4.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
3	62	3.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
4	28	7.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(

5 rows × 11041 columns

_Section Summary: we have the data represented in two ways: X_counts_feat and X_tfidf*feat*

Section 5: Building Machine Learning Classifiers

Tool 1: A basic Random Forest model

In [15]:

```
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

In [16]:

```
def train_RF(n_est, depth):
    rf = RandomForestClassifier(n_estimators=n_est, max_depth=depth, n_jobs=-1)
    rf_model = rf.fit(X_train, y_train)
    y_pred = rf_model.predict(X_test)
    precision, recall, fscore, support = score(y_test, y_pred, pos_label='spam', averag
    print('Est: {} / Depth: {} ---- Precision: {} / Recall: {} / Accuracy: {}'.format(
        n_est, depth, round(precision, 3), round(recall, 3),
        round((y_pred==y_test).sum() / len(y_pred), 3)))
```

In [17]:

```
print('using TF-IDF Method')
X_features = X_tfidf_feat
X_train, X_test, y_train, y_test = train_test_split(X_features, data['label'], test_siz

for n_est in [10, 150, 300]:
    for depth in [30, 60, 90, None]:
        train_RF(n_est, depth)
```

```
using TF-IDF Method
Est: 10 / Depth: 30 ---- Precision: 1.0 / Recall: 0.599 / Accuracy: 0.943
Est: 10 / Depth: 60 ---- Precision: 1.0 / Recall: 0.847 / Accuracy: 0.978
Est: 10 / Depth: 90 ---- Precision: 0.985 / Recall: 0.854 / Accuracy: 0.978
Est: 10 / Depth: None ---- Precision: 1.0 / Recall: 0.803 / Accuracy: 0.972
Est: 150 / Depth: 30 ---- Precision: 1.0 / Recall: 0.675 / Accuracy: 0.954
Est: 150 / Depth: 60 ---- Precision: 1.0 / Recall: 0.815 / Accuracy: 0.974
Est: 150 / Depth: 90 ---- Precision: 1.0 / Recall: 0.854 / Accuracy: 0.979
Est: 150 / Depth: None ---- Precision: 1.0 / Recall: 0.841 / Accuracy: 0.978
Est: 300 / Depth: 30 ---- Precision: 1.0 / Recall: 0.669 / Accuracy: 0.953
Est: 300 / Depth: 60 ---- Precision: 1.0 / Recall: 0.809 / Accuracy: 0.973
```

```
Est: 300 / Depth: 90 ---- Precision: 1.0 / Recall: 0.847 / Accuracy: 0.978
Est: 300 / Depth: None ---- Precision: 1.0 / Recall: 0.866 / Accuracy: 0.981
```

In [18]:

```python
print('using CountVectorizer Method')
X_features = X_counts_feat
X_train, X_test, y_train, y_test = train_test_split(X_features, data['label'], test_siz

for n_est in [10, 150, 300]:
    for depth in [30, 60, 90, None]:
        train_RF(n_est, depth)
```

```
using CountVectorizer Method
Est: 10 / Depth: 30 ---- Precision: 1.0 / Recall: 0.658 / Accuracy: 0.952
Est: 10 / Depth: 60 ---- Precision: 1.0 / Recall: 0.748 / Accuracy: 0.965
Est: 10 / Depth: 90 ---- Precision: 0.992 / Recall: 0.794 / Accuracy: 0.97
Est: 10 / Depth: None ---- Precision: 1.0 / Recall: 0.723 / Accuracy: 0.961
Est: 150 / Depth: 30 ---- Precision: 1.0 / Recall: 0.639 / Accuracy: 0.95
Est: 150 / Depth: 60 ---- Precision: 1.0 / Recall: 0.761 / Accuracy: 0.967
Est: 150 / Depth: 90 ---- Precision: 1.0 / Recall: 0.787 / Accuracy: 0.97
Est: 150 / Depth: None ---- Precision: 1.0 / Recall: 0.787 / Accuracy: 0.97
Est: 300 / Depth: 30 ---- Precision: 1.0 / Recall: 0.652 / Accuracy: 0.952
Est: 300 / Depth: 60 ---- Precision: 1.0 / Recall: 0.761 / Accuracy: 0.967
Est: 300 / Depth: 90 ---- Precision: 1.0 / Recall: 0.768 / Accuracy: 0.968
Est: 300 / Depth: None ---- Precision: 1.0 / Recall: 0.787 / Accuracy: 0.97
```

Tool 2: A basic Gradient Boosting Classifier

In [19]:

```python
from sklearn.ensemble import GradientBoostingClassifier
```

In [20]:

```python
def train_GB(est, max_depth, lr):
    gb = GradientBoostingClassifier(n_estimators=est, max_depth=max_depth, learning_rat
    gb_model = gb.fit(X_train, y_train)
    y_pred = gb_model.predict(X_test)
    precision, recall, fscore, train_support = score(y_test, y_pred, pos_label='spam',
    print('Est: {} / Depth: {} / LR: {} ---- Precision: {} / Recall: {} / Accuracy: {}'
        est, max_depth, lr, round(precision, 3), round(recall, 3),
        round((y_pred==y_test).sum()/len(y_pred), 3)))
```

In [21]:

```python
print('using TF-IDF Method')
X_features = X_tfidf_feat
X_train, X_test, y_train, y_test = train_test_split(X_features, data['label'], test_siz

for n_est in [100, 150]:
    for max_depth in [7, 11, 15]:
        train_GB(n_est, max_depth, lr=0.1)
```

```
using TF-IDF Method
Est: 100 / Depth: 7 / LR: 0.1 ---- Precision: 0.973 / Recall: 0.838 / Accuracy: 0.971
Est: 100 / Depth: 11 / LR: 0.1 ---- Precision: 0.973 / Recall: 0.832 / Accuracy: 0.97
Est: 100 / Depth: 15 / LR: 0.1 ---- Precision: 0.974 / Recall: 0.85 / Accuracy: 0.973
Est: 150 / Depth: 7 / LR: 0.1 ---- Precision: 0.973 / Recall: 0.838 / Accuracy: 0.971
Est: 150 / Depth: 11 / LR: 0.1 ---- Precision: 0.973 / Recall: 0.838 / Accuracy: 0.971
Est: 150 / Depth: 15 / LR: 0.1 ---- Precision: 0.973 / Recall: 0.838 / Accuracy: 0.971
```

In [22]:

```python
print('using CountVectorizer Method')
X_features = X_counts_feat
```

```
X_train, X_test, y_train, y_test = train_test_split(X_features, data['label'], test_siz

for n_est in [100, 150]:
    for max_depth in [7, 11, 15]:
        train_GB(n_est, max_depth, lr=0.1)
```

```
using CountVectorizer Method
Est: 100 / Depth: 7 / LR: 0.1 ---- Precision: 0.972 / Recall: 0.839 / Accuracy: 0.979
Est: 100 / Depth: 11 / LR: 0.1 ---- Precision: 0.963 / Recall: 0.847 / Accuracy: 0.979
Est: 100 / Depth: 15 / LR: 0.1 ---- Precision: 0.964 / Recall: 0.855 / Accuracy: 0.98
Est: 150 / Depth: 7 / LR: 0.1 ---- Precision: 0.972 / Recall: 0.831 / Accuracy: 0.978
Est: 150 / Depth: 11 / LR: 0.1 ---- Precision: 0.981 / Recall: 0.855 / Accuracy: 0.982
Est: 150 / Depth: 15 / LR: 0.1 ---- Precision: 0.981 / Recall: 0.847 / Accuracy: 0.981
```

Conclusion Section: Final Implementation

_for the Random Forest Classifier: the best fit was having 150 n_estimators with a max_depth of None and enabling paralelism by having n*jobs equal to -1*
_for the Gradient Boosting Classifier: the best fit was also having 150 n_estimators and a max*depth of 11*

In this section, the whole process is repeated from start to end while hiding the training part of the dataset from the very beginning and using only these classifiers with the specific findings from the previous sections measuring time to fit and evaluate a text as well.

In [23]:

```
X_train, X_test, y_train, y_test = train_test_split(data[['body_text', 'body_len', 'pun
```

Vectorize Text

In [24]:

```
tfidf_vect = TfidfVectorizer(analyzer=clean_text)
tfidf_vect_fit = tfidf_vect.fit(X_train['body_text'])

tfidf_train = tfidf_vect_fit.transform(X_train['body_text'])
tfidf_test = tfidf_vect_fit.transform(X_test['body_text'])

X_train_vect = pd.concat([X_train[['body_len', 'punct%']].reset_index(drop=True),
           pd.DataFrame(tfidf_train.toarray())], axis=1)
X_test_vect = pd.concat([X_test[['body_len', 'punct%']].reset_index(drop=True),
           pd.DataFrame(tfidf_test.toarray())], axis=1)

X_train_vect.head()
```

Out[24]:

	body_len	punct%	0	1	2	3	4	5	6	7	...	10164	10165	10166	10167	10168	1(
0	47	6.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
1	22	4.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
2	30	6.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
3	27	3.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	
4	24	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	

5 rows × 10176 columns

Final evaluation of models

In [25]:

```
import time
rf = RandomForestClassifier(n_estimators=150, max_depth=None, n_jobs=-1)

start = time.time()
rf_model = rf.fit(X_train_vect, y_train)
end = time.time()
fit_time = (end - start)

start = time.time()
y_pred = rf_model.predict(X_test_vect)
end = time.time()
pred_time = (end - start)

precision, recall, fscore, train_support = score(y_test, y_pred, pos_label='spam', aver
print('Fit time: {} / Predict time: {} ---- Precision: {} / Recall: {} / Accuracy: {}'.
    round(fit_time, 3), round(pred_time, 3), round(precision, 3), round(recall, 3), rou
```

```
Fit time: 6.166 / Predict time: 0.243 ---- Precision: 0.992 / Recall: 0.913 / Accuracy:
0.988
```

In [26]:

```
gb = GradientBoostingClassifier(n_estimators=150, max_depth=11)

start = time.time()
gb_model = gb.fit(X_train_vect, y_train)
end = time.time()
fit_time = (end - start)

start = time.time()
y_pred = gb_model.predict(X_test_vect)
end = time.time()
pred_time = (end - start)

precision, recall, fscore, train_support = score(y_test, y_pred, pos_label='spam', aver
print('Fit time: {} / Predict time: {} ---- Precision: {} / Recall: {} / Accuracy: {}'.
    round(fit_time, 3), round(pred_time, 3), round(precision, 3), round(recall, 3), rou
```

```
Fit time: 332.589 / Predict time: 0.257 ---- Precision: 0.984 / Recall: 0.877 / Accurac
y: 0.983
```

In [ ]: