NLP (Natural Language Processing) with Python

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1 NLP (Natural Language Processing) with Python

```
In [2]: !conda install nltk
        import nltk
        nltk.download()
```

```
Fetching package metadata ...
Solving package specifications: .

# All requested packages already installed.
# packages in environment at /anaconda:
#
nltk                      3.2.5            py27h2e86947_0
showing info https://raw.githubusercontent.com/nltk/nltk_data/gh-pages/index.xml
```

```
Out[2]: True
```

1.1 Get the Data

I will be using a dataset from the UCI datasets!

The file I will be using contains a collection of more than 5 thousand SMS phone messages.

I used rstrip() plus a list comprehension to get a list of all the lines of text messages:

```
In [4]: messages = [line.rstrip() for line in open('SMSSpamCollection')]
        print(len(messages))
```

```
5574
```

A collection of texts is also sometimes called "corpus".

```
In [4]: for message_no, message in enumerate(messages[:10]):
            print(message_no, message)
            print('\n')
```

```
0 ham	Go until jurong point, crazy.. Available only in bugis n great world la e buffet.

1 ham	Ok lar... Joking wif u oni...

2 spam	 Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87

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 around here though

5 spam	 FreeMsg Hey there darling it's been 3 week's now and no word back! I'd like some

6 ham	Even my brother is not like to speak with me. They treat me like aids patent.

7 ham	As per your request 'Melle Melle (Oru Minnaminunginte Nurungu Vettam)' has been se

8 spam	 WINNER!! As a valued network customer you have been selected to receivea č900 pri

9 spam	 Had your mobile 11 months or more? U R entitled to Update to the latest colour mo
```

Due to the spacing we can tell that this is a TSV ("tab separated values") file, where the first column is a label saying whether the given message is a normal message (commonly known as "ham") or "spam". The second column is the message itself. (Note our numbers aren't part of the file, they are just from the **enumerate** call).

Using these labeled ham and spam examples, I'll **train a machine learning model to learn to discriminate between ham/spam automatically**. Then, with a trained model, we'll be able to **classify arbitrary unlabeled messages** as ham or spam.

Instead of parsing TSV manually using Python, I took advantage of pandas!

```
In [5]: import pandas as pd
```

I will use **read_csv** and make note of the **sep** argument, we can also specify the desired column names by passing in a list of *names*.

```
In [7]: messages = pd.read_csv('SMSSpamCollection', sep='\t',
                               names=["label", "message"])
        messages.head()
```

```
Out[7]:   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...
```

1.2 Exploratory Data Analysis

I checked out some of the stats with some plots and the built-in methods in pandas!

```
In [8]: messages.describe()
```

```
Out[8]:        label                 message
        count   5572                    5572
        unique     2                    5169
        top      ham  Sorry, I'll call later
        freq    4825                      30
```

I used **groupby** to use describe by label, this way we can begin to think about the features that separate ham and spam!

```
In [9]: messages.groupby('label').describe()
```

```
Out[9]:                                                         message
        label
        ham   count                                                4825
              unique                                               4516
              top                                Sorry, I'll call later
              freq                                                   30
        spam  count                                                 747
              unique                                                653
              top     Please call our customer service representativ...
              freq                                                    4
```

As we continue our analysis we want to start thinking about the features we are going to be using. This goes along with the general idea of feature engineering. 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.

I made a new column to detect how long the text messages are:

```
In [8]: messages['length'] = messages['message'].apply(len)
        messages.head()
```

```
Out[8]:   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
```

1.2.1 Data Visualization

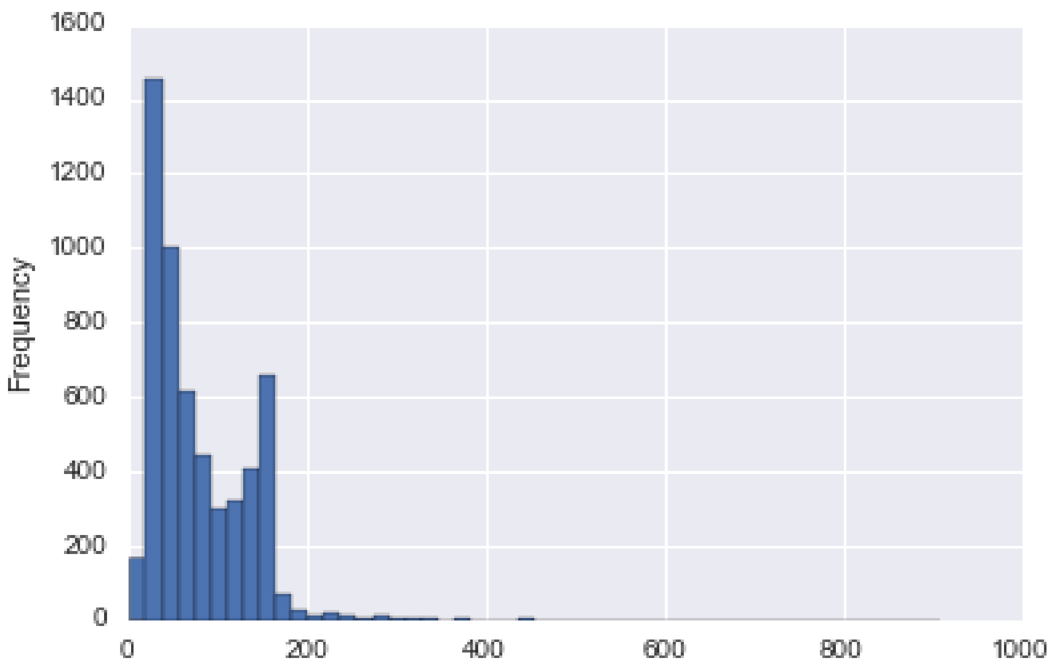
Let's visualize this!

```
In [9]: import matplotlib.pyplot as plt
        import seaborn as sns

        %matplotlib inline
```

```
In [12]: messages['length'].plot(bins=50, kind='hist')
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x11a03c0b8>
```




```
In [13]: messages.length.describe()
```

```
Out[13]: count    5572.000000
         mean       80.489950
         std        59.942907
         min         2.000000
         25%        36.000000
         50%        62.000000
         75%       122.000000
         max       910.000000
         Name: length, dtype: float64
```

Wow! 910 characters, I used masking to find this message:

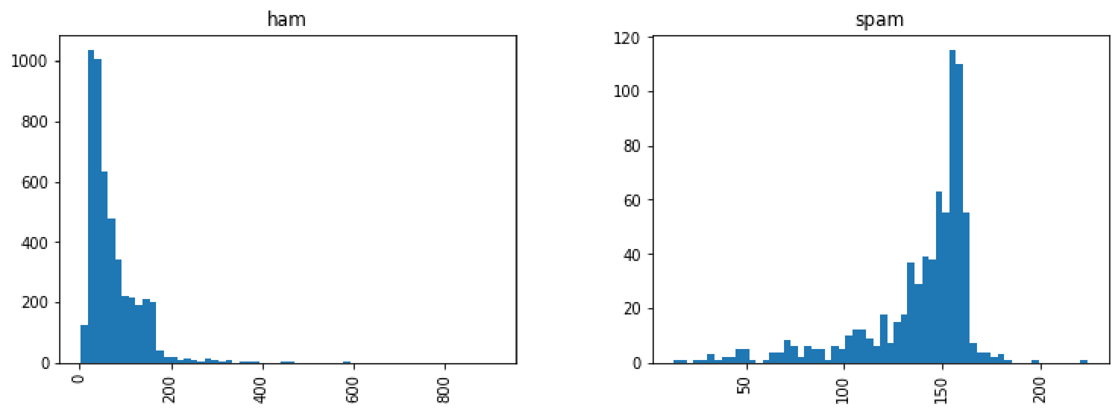
```
In [10]: messages[messages['length'] == 910]['message'].iloc[0]
```

```
Out[10]: "For me the love should start with attraction.i should feel that I need her every time
```

To see if message length is a distinguishing feature between ham and spam:

```
In [12]: messages.hist(column='length', by='label', bins=60,figsize=(12,4))
```

```
Out[12]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x1a21d34050>,
               <matplotlib.axes._subplots.AxesSubplot object at 0x1a21fe5690>], dtype=object)
```



Very interesting! Through just basic EDA I discovered a trend that spam messages tend to have more characters. (Sorry Romeo!)

1.3 Text Pre-processing

Our main issue with the data is that it is all in text format (strings). The classification algorithms that we've learned about so far will need some sort of numerical feature vector in order to perform the classification task. There are actually many methods to convert a corpus to a vector format. The simplest is the the bag-of-words approach, where each unique word in a text will be represented by one number.

This section will show how to convert the raw messages (sequence of characters) into vectors (sequences of numbers).

As a first step, I wrote a function that will split a message into its individual words and return a list. Also, I removed very common words, ('the', 'a', etc..). To do this I took advantage of the NLTK library. It's pretty much the standard library in Python for processing text and has a lot of useful features.

I created a function that will process the string in the message column, then we can just use **apply()** in pandas do process all the text in the DataFrame.

First removing punctuation. I took advantage of Python's built-in **string** library to get a quick list of all the possible punctuation:

```
In [15]: import string
```

```
mess = 'Sample message! Notice: it has punctuation.'
string.punctuation

nopunc = [char for char in mess if char not in string.punctuation]

nopunc = ''.join(nopunc)
```

To remove stopwords. We can import a list of english stopwords from NLTK.

```
In [18]: from nltk.corpus import stopwords
         stopwords.words('english')[0:10] # Show some stop words

Out[18]: [u'i',
          u'me',
          u'my',
          u'myself',
          u'we',
          u'our',
          u'ours',
          u'ourselves',
          u'you',
          u'your']

In [19]: nopunc.split()

Out[19]: ['Sample', 'message', 'Notice', 'it', 'has', 'punctuation']

In [21]: #removed all stopwords
         clean_mess = [word for word in nopunc.split() if word.lower() not in stopwords.words(

In [23]: clean_mess

Out[23]: ['Sample', 'message', 'Notice', 'punctuation']
```

Now let's put both of these together in a function to apply it to our DataFrame later on:

```
In [22]: def text_process(mess):
             """
             Takes in a string of text, then performs the following:
             1. Remove all punctuation
             2. Remove all stopwords
             3. Returns a list of the cleaned text
             """
             # Check characters to see if they are in punctuation
             nopunc = [char for char in mess if char not in string.punctuation]

             # Join the characters again to form the string.
             nopunc = ''.join(nopunc)

             # Now just remove any stopwords
             return [word for word in nopunc.split() if word.lower() not in stopwords.words('en
```

Here is the original DataFrame again:

```
In [25]: messages.head()
```

```
Out[25]:   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
```

Now let's "tokenize" these messages. Tokenization is just the term used to describe the process of converting the normal text strings in to a list of tokens (words that we actually want).

```
In [23]: messages['message'].head(5).apply(text_process)
```

```
Out[23]: 0    [Go, jurong, point, crazy, Available, bugis, n...
         1                       [Ok, lar, Joking, wif, u, oni]
         2    [Free, entry, 2, wkly, comp, win, FA, Cup, fin...
         3        [U, dun, say, early, hor, U, c, already, say]
         4    [Nah, dont, think, goes, usf, lives, around, t...
         Name: message, dtype: object
```

```
In [27]: # Show original dataframe
         messages.head()
```

```
Out[27]:   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
```

1.3.1 Continuing Normalization

There are a lot of ways to continue normalizing this text. Such as Stemming or distinguishing by part of speech.

NLTK has lots of built-in tools and great documentation on a lot of these methods. Sometimes they don't work well for text-messages due to the way a lot of people tend to use abbreviations or shorthand, For example:

```
'Nah dawg, IDK! Wut time u headin to da club?'
```

versus

```
'No dog, I don't know! What time are you heading to the club?'
```

Some text normalization methods will have trouble with this type of shorthand.....

For now I will focus on using what I currently have to convert our list of words to an actual vector that SciKit-Learn can use.

1.4 Vectorization

Currently, we have the messages as lists of tokens (also known as lemmas) and now we need to convert each of those messages into a vector the SciKit Learn's algorithm models can work with.

I'll convert each message, represented as a list of tokens (lemmas) above, into a vector that machine learning models can understand.

We'll do that in three steps using the bag-of-words model:

1. Count how many times does a word occur in each message (Known as term frequency)
2. Weigh the counts, so that frequent tokens get lower weight (inverse document frequency)
3. Normalize the vectors to unit length, to abstract from the original text length (L2 norm)

Each vector will have as many dimensions as there are unique words in the SMS corpus. We will first use SciKit Learn's **CountVectorizer**. This model will convert a collection of text documents to a matrix of token counts.

We can imagine this as a 2-Dimensional matrix. Where the 1-dimension is the entire vocabulary (1 row per word) and the other dimension are the actual documents, in this case a column per text message.

For example:
Message 1
Message 2
...
Message N
Word 1 Count
0
1
...
0
Word 2 Count
0
0
...
0
...
1
2
...
0
Word N Count
0
1
...
1

Since there are so many messages, we can expect a lot of zero counts for the presence of that word in that document. Because of this, SciKit Learn will output a Sparse Matrix.

```
In [33]: from sklearn.feature_extraction.text import CountVectorizer
```

There are a lot of arguments and parameters that can be passed to the CountVectorizer. In this case we will just specify the **analyzer** to be our own previously defined function:

```
In [26]: # Might take awhile...
         bow_transformer = CountVectorizer(analyzer=text_process).fit(messages['message'])

         #total number of vocab words
         print(len(bow_transformer.vocabulary_))
```

```
/anaconda/lib/python2.7/site-packages/ipykernel_launcher.py:15: UnicodeWarning: Unicode equal c
  from ipykernel import kernelapp as app


11425
```

Let's take one text message and get its bag-of-words counts as a vector, putting to use our new `bow_transformer`:

```
In [27]: message4 = messages['message'][3]
         print(message4)
```

```
U dun say so early hor... U c already then say...
```

Now let's see its vector representation:

```
In [28]: bow4 = bow_transformer.transform([message4])
         print(bow4)
         print(bow4.shape)
```

```
  (0, 4068)	2
  (0, 4629)	1
  (0, 5261)	1
  (0, 6204)	1
  (0, 6222)	1
  (0, 7186)	1
  (0, 9554)	2
(1, 11425)
```

This means that there are seven unique words in message number 4 (after removing common stop words). Two of them appear twice, the rest only once. Which ones appear twice?

```
In [31]: print(bow_transformer.get_feature_names()[4073])
         print(bow_transformer.get_feature_names()[9570])
```

```
UIN
schedule
```

Now we can use **.transform** on our Bag-of-Words (bow) transformed object and transform the entire DataFrame of messages. Let's go ahead and check out how the bag-of-words counts for the entire SMS corpus is a large, sparse matrix:

```
In [34]: messages_bow = bow_transformer.transform(messages['message'])
```

```
/anaconda/lib/python2.7/site-packages/ipykernel_launcher.py:15: UnicodeWarning: Unicode equal c
  from ipykernel import kernelapp as app
```

```
In [40]: print('Shape of Sparse Matrix: ', messages_bow.shape)
         print('Amount of Non-Zero occurences: ', messages_bow.nnz)
```

```
Shape of Sparse Matrix:  (5572, 11444)
Amount of Non-Zero occurences:  50795
```

```
In [46]: sparsity = (100.0 * messages_bow.nnz / (messages_bow.shape[0] * messages_bow.shape[1])
         print('sparsity: {}'.format(round(sparsity)))
```

```
sparsity: 0
```

After the counting, the term weighting and normalization can be done with TF-IDF, using scikit-learn's `TfidfTransformer`.

1.4.1 So what is TF-IDF?

TF-IDF stands for *term frequency-inverse document frequency*, and the tf-idf weight is a weight often used in information retrieval and text mining. This weight is a statistical measure used to evaluate how important a word is to a document in a collection or corpus. The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus. Variations of the tf-idf weighting scheme are often used by search engines as a central tool in scoring and ranking a document's relevance given a user query.

One of the simplest ranking functions is computed by summing the tf-idf for each query term; many more sophisticated ranking functions are variants of this simple model.

Typically, the tf-idf weight is composed by two terms: the first computes the normalized Term Frequency (TF), aka. the number of times a word appears in a document, divided by the total number of words in that document; the second term is the Inverse Document Frequency (IDF), computed as the logarithm of the number of the documents in the corpus divided by the number of documents where the specific term appears.

TF: Term Frequency, which measures how frequently a term occurs in a document. Since every document is different in length, it is possible that a term would appear much more times in long documents than shorter ones. Thus, the term frequency is often divided by the document length (aka. the total number of terms in the document) as a way of normalization:

TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document).

IDF: Inverse Document Frequency, which measures how important a term is. While computing TF, all terms are considered equally important. However it is known that certain terms, such as “is”, “of”, and “that”, may appear a lot of times but have little importance. Thus we need to weigh down the frequent terms while scale up the rare ones, by computing the following:

IDF(t) = log_e(Total number of documents / Number of documents with term t in it).

Example:

Consider a document containing 100 words wherein the word cat appears 3 times.

The term frequency (i.e., tf) for cat is then (3 / 100) = 0.03. Now, assume we have 10 million documents and the word cat appears in one thousand of these. Then, the inverse document frequency (i.e., idf) is calculated as log(10,000,000 / 1,000) = 4. Thus, the Tf-idf weight is the product of these quantities: 0.03 * 4 = 0.12. ____

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

         tfidf_transformer = TfidfTransformer().fit(messages_bow)
         tfidf4 = tfidf_transformer.transform(bow4)
         print(tfidf4)
```

```
  (0, 9570)        0.538562626293
  (0, 7197)        0.438936565338
  (0, 6232)        0.318721689295
  (0, 6214)        0.299537997237
  (0, 5270)        0.297299574059
  (0, 4638)        0.266198019061
  (0, 4073)        0.408325899334
```

I checked what is the IDF (inverse document frequency) of the word "u" and of word "university"?

```
In [50]: print(tfidf_transformer.idf_[bow_transformer.vocabulary_['u']])
         print(tfidf_transformer.idf_[bow_transformer.vocabulary_['university']])
```

```
3.28005242674
8.5270764989
```

To transform the entire bag-of-words corpus into TF-IDF corpus at once:

```
In [51]: messages_tfidf = tfidf_transformer.transform(messages_bow)
         print(messages_tfidf.shape)
```

```
(5572, 11444)
```

There are many ways the data can be preprocessed and vectorized. These steps involve feature engineering and building a “pipeline”.

1.5 Training a model

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.

I will be using scikit-learn here, choosing the Naive Bayes classifier to start with:

```
In [52]: from sklearn.naive_bayes import MultinomialNB
         spam_detect_model = MultinomialNB().fit(messages_tfidf, messages['label'])
```

Let's try classifying our single random message and checking how we do:

```
In [54]: print('predicted:', spam_detect_model.predict(tfidf4)[0])
         print('expected:', messages.label[3])
```

```
predicted: ham
expected: ham
```

1.6 Part 6: Model Evaluation

Now we want to determine how well our model will do overall on the entire dataset. All the predictions:

```
In [55]: all_predictions = spam_detect_model.predict(messages_tfidf)
         print(all_predictions)
```

```
['ham' 'ham' 'spam' ..., 'ham' 'ham' 'ham']
```

We can use SciKit Learn's built-in classification report, which returns precision, recall, f1-score, and a column for support (meaning how many cases supported that classification).

```
In [56]: from sklearn.metrics import classification_report
         print (classification_report(messages['label'], all_predictions))
```

```
             precision    recall  f1-score   support

        ham       0.98      1.00      0.99      4825
       spam       1.00      0.85      0.92       747

avg / total       0.98      0.98      0.98      5572
```

There are quite a few possible metrics for evaluating model performance. Which one is the most important depends on the task and the business effects of decisions based off of the model. For example, the cost of mis-predicting "spam" as "ham" is probably much lower than mis-predicting "ham" as "spam".

In the above "evaluation",we evaluated accuracy on the same data we used for training. **You should never actually evaluate on the same dataset you train on!**

Such evaluation tells us nothing about the true predictive power of our model. If we simply remembered each example during training, the accuracy on training data would trivially be 100%, even though we wouldn't be able to classify any new messages.

A proper way is to split the data into a training/test set, where the model only ever sees the **training data** during its model fitting and parameter tuning. The **test data** is never used in any way. This is then our final evaluation on test data is representative of true predictive performance.

1.7 Train Test Split

In [57]:
```
from sklearn.model_selection import train_test_split

msg_train, msg_test, label_train, label_test = \
train_test_split(messages['message'], messages['label'], test_size=0.2)

print(len(msg_train), len(msg_test), len(msg_train) + len(msg_test))
```

```
4457 1115 5572
```

The test size is 20% of the entire dataset (1115 messages out of total 5572), and the training is the rest (4457 out of 5572). Note the default split would have been 30/70.

1.8 Creating a Data Pipeline

Let's run our model again and then predict off the test set. I used SciKit Learn's pipeline capabilities to store a pipeline of workflow. This will allow me to set up all the transformations that we will do to the data for future use.

In [58]:
```
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('bow', CountVectorizer(analyzer=text_process)),  # strings to token integer coun
    ('tfidf', TfidfTransformer()),  # integer counts to weighted TF-IDF scores
    ('classifier', MultinomialNB()),  # train on TF-IDF vectors w/ Naive Bayes classi
])
```

Now we can directly pass message text data and the pipeline will do our pre-processing for us! We can treat it as a model/estimator API:

In [59]:
```
pipeline.fit(msg_train,label_train)
```

Out[59]:
```
Pipeline(steps=[('bow', CountVectorizer(analyzer=<function text_process at 0x11e795bf8
        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), preprocessor=None,...f=False
```

In [60]:
```
predictions = pipeline.predict(msg_test)
```

```
In [61]: print(classification_report(predictions,label_test))

             precision    recall  f1-score   support

        ham       1.00      0.96      0.98      1001
       spam       0.75      1.00      0.85       114

avg / total       0.97      0.97      0.97      1115
```

Now I have a classification report for my model on a true testing set!