p5

September 18, 2017

```
In [168]: # import package
          import numpy as np
          from collections import OrderedDict
          from collections import defaultdict
          from collections import Counter
          import matplotlib.pyplot as plt
          %matplotlib inline
```

```
In [169]: # Load data
          train_lines = open('./data/train.txt','r').readlines()
          test_lines = open('./data/test','r').readlines()
```

1 (a) Data preprocessing

```
In [170]: # Preprocess data
          # Tranfer line from raw txt line to default dict containing
          # id: id number is_spam: 1 represent spam word_count: word count in docu
          def preprocess(lines):
              output_list = []
              for line in lines:
                  doc_dict = {}
                  splitted = line.split()
                  doc_dict['id'] = splitted[0]
                  doc_dict['is_spam'] = splitted[1]=='spam'
                  doc_dict['word_count'] = OrderedDict(zip(splitted[2:][::2], np.ar
                  output_list.append(doc_dict)
              return output_list
```

```
In [171]: # Get training and test documents
          train_docs = preprocess(train_lines)
          test_docs = preprocess(test_lines)
```

```
In [172]: # Filter to get spam and ham in training sample
          train_spam_docs = list(filter(lambda x: x['is_spam'], train_docs))
          train_ham_docs = list(filter(lambda x: not x['is_spam'], train_docs))
```

2 (b) What is p(spam) in training data

```
In [173]: p_spam_train = len(train_spam_docs)/len(train_docs)
          print('Probability of spam: %.4f' % p_spam_train)
```

```
Probability of spam: 0.5737
```

```
In [174]: print('Probability of ham: %.4f' % (1-p_spam_train))
```

```
Probability of ham: 0.4263
```

3 (c) Determine $p(w_i|spam)$

Get vocabulary counts that in spam and all training documents

```
In [175]: # Function to get a vocabulary dict with key=word value=count of word in
          def get_vocabulary_count(doc_list):
              output_vocabulary_dict = defaultdict(lambda :0)
              for doc_dict in doc_list:
                  for word, word_count in doc_dict['word_count'].items():
                      output_vocabulary_dict[word]+=word_count
              return output_vocabulary_dict
```

```
In [176]: # Get word count in all trainign documents and spam training documents
          train_vocab_count = get_vocabulary_count(train_docs)
          train_spam_vocab_count = get_vocabulary_count(train_spam_docs)
          train_ham_vocab_count = get_vocabulary_count(train_ham_docs)
```

Apply m-estimate and get $p(wi|spam)$ or $p(wi|ham)$

```
In [189]: # Apply m-estimate and get p(wi|spam) or p(wi|ham)
          def get_p_wi_spam(w, train_vocab_count, subset_vocab_count, m_multiplier=
              output_dict = defaultdict()
              n = np.sum(list(subset_vocab_count.values()))
              vocab_sum = np.sum(list(train_vocab_count.values()))
              #vocab_sum = len(train_vocab_count)
              p = 1.0/vocab_sum
              m = m_multiplier*vocab_sum
              for w_i in w:
                  n_c = subset_vocab_count[w_i]
                  output_dict[w_i]=(n_c + m*p)/(n+m)
              return output_dict
```

```
In [190]: words = [key for key in train_vocab_count.keys()]
          p_w_given_spam = get_p_wi_spam(words, train_vocab_count, train_spam_vocab
          p_w_given_ham = get_p_wi_spam(words, train_vocab_count, train_ham_vocab_c
```

```
In [191]: print('The top 5 most likely word in spam are:\n\n%s' %
                '\n'.join([word for word, prob in Counter(p_w_given_spam).most_comm
```

```
The top 5 most likely word in spam are:

enron
a
corp
the
to
```

```
In [192]: print('The top 5 most likely word in ham are:\n\n%s' %
                '\n'.join([word for word, prob in Counter(p_w_given_ham).most_commo
```

```
The top 5 most likely word in ham are:

aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa
enron
the
to
a
```

4 (d) Classifier and accuracy

A classifier that make predicison by comparing the $log(p(w, spam))$ and $log(p(w, ham))$

```
In [193]: # Code of Naive Bayes Classifier
          def classify(test_docs, train_docs, m_multiplier = 1):
              train_spam_docs = list(filter(lambda x: x['is_spam'], train_docs))
              train_ham_docs = list(filter(lambda x: not x['is_spam'], train_docs))

              p_spam_train = len(train_spam_docs)/len(train_docs)
              p_ham_train = 1-p_spam_train

              train_vocab_count = get_vocabulary_count(train_docs)
              train_spam_vocab_count = get_vocabulary_count(train_spam_docs)
              train_ham_vocab_count = get_vocabulary_count(train_ham_docs)

              preds = []
              for doc in test_docs:
                  word_count_dict = doc['word_count']
                  words = list(word_count_dict.keys())

                  p_w_given_spam = get_p_wi_spam(words, train_vocab_count, train_sp
                  p_w_given_ham = get_p_wi_spam(words, train_vocab_count, train_ham
```

```
            log_likelihood_spam = np.log(p_spam_train)
            log_likelihood_ham = np.log(p_ham_train)
            for word, word_count in word_count_dict.items():
                log_likelihood_spam += np.log(p_w_given_spam[word])*word_coun
                log_likelihood_ham += np.log(p_w_given_ham[word])*word_count

            preds.append(log_likelihood_spam>log_likelihood_ham)
        return preds
```

```
In [194]: # predictions
          preds = classify(test_docs, train_docs,1)
```

```
In [195]: # Evaluation of predictions results
          def evaluate_predictions(preds, test_docs):
              true_labels = np.array([doc['is_spam'] for doc in test_docs])
              return (preds==true_labels).sum()/len(test_docs)
```

```
In [196]: print('Accuracy: %.3f'% evaluate_predictions(preds, test_docs))
```

```
Accuracy: 0.914
```

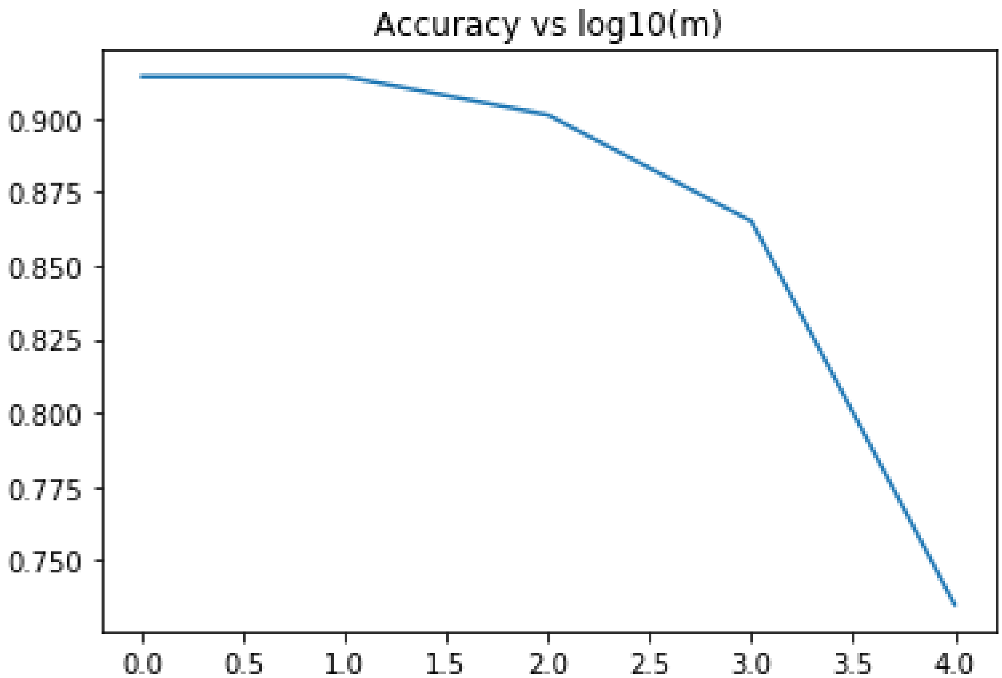
```
In [197]: accuracy = []
          m_multiplier_list = [1,10,100,1000,10000]
          for m_multiplier in m_multiplier_list:
              preds = classify(test_docs, train_docs, m_multiplier)
              accuracy.append(evaluate_predictions(preds,test_docs))
```

5 (e) Vary m parameter

Plot are shown below

```
In [198]: plt.plot(np.log10(m_multiplier_list), accuracy)
          plt.title('Accuracy vs log10(m)')
```

```
Out[198]: <matplotlib.text.Text at 0x10edb7dd8>
```



5.1 What does m assume?

m represents the size of the imaginary training data in which word distribution follow practitioner defined priors $p(w_i|spam)$. The larger the m is, the more weight you put in the prior. More 'counts' are assigned to unobserved word relative to observed word.

A small m assume that training samples are very good representations of global samples.

A large m assume that training samples are less representative and we believe the prior distribution more.

In our case the a large m harms test accuracy.

6 (f) What to do if I am a spammer?

If the spam detector is a naive bayes classifer. We should avoid using spam-common words. And we should make our spam email long and make the percentage of common and ham-common words higher. In a word, we should write a spam that contains spam message, while seems like ham in bag of words.