# **ASSIGNMENT 8**

CS 432 Web Science

## Contents

Problem 1	2
Problem 2	2
Problem 3	3
Problem 4	3

#### Problem 1

1. Create two datasets; the first called Testing, the second called Training. Upload your datasets on GitHub

#### Solution

Spam mail testing 11 and 12 are from my inbox, the rest of spam testing and training are downloaded from <a href="http://www.linuxfocus.org/common/src/article279/spam\_samples.html">http://www.linuxfocus.org/common/src/article279/spam\_samples.html</a> as Gmail deletes spam mail over time. The training and testing non-spam emails are all from my own inbox and have been scrubbed of personal information. The document sets are on GitHub and are in the hierarchy of the rightmost image.

Originally n1-10 and s1-10 were training and n11-20 and s11-20 were testing, and while all the spam was correctly classified, all but 2 of the genuine emails were classified as spam. I swapped n1-4 and n11-14 and the results shifted to 8/10 correctly marked spam messages, and 6/10 correctly marked genuine messages. After a bit more swapping, I got the results to 9/10 correct spam classification, and 10/10 correct not spam classification.

#### Problem 2

2. Using the PCI book modified docclass.py code and test.py
Use your Training dataset to train the Naive Bayes classifier
Use your Testing dataset to test the Naive Bayes classifier and report
the classification results.

#### Solution

The train function calls the docclass function of the same name for each line in every file in the specified path, with the designation of 'spam' or 'not spam'

The test function calls the classify function for each file in the specified path and prints it to the console.

```
def test(filepath):
    file_list = os.listdir(filepath)
    for each in file_list:
        test_string = ""
        for line in open(filepath+each, 'r'):
            if line != '\n':
                 test_string += line
            print train_set.classify(test_string)
```

assignment\_8 ▼ **l**testing ▼ 🖿 not\_spam 🖆 n1.txt f n4.txt n6.txt 🖆 n8.txt 🗂 n10.txt # n14.txt 🖆 n15.txt 🖆 n17.txt 🖆 n18.txt 🗂 n19.txt spam spam 🖆 s10.txt 🛔 s11.txt **₫** s14.txt ₫ s15.txt ₫ s16.txt 🖆 s17.txt 🖆 s18.txt 🖆 s20.txt training ▼ Image not\_spam an2.txt an3.txt 🖆 n5.txt 🗂 n7.txt f n9.txt # n11.txt 🖆 n12.txt 🖆 n13.txt # n16.txt # n20.txt spam spam 🖆 s1.txt 🖆 s2.txt 🛔 s3.txt 🛔 s4.txt 🖆 s5.txt 🖆 s6.txt \rm 🗗 s7.txt

The main body and final output of the program:

```
print "training with spam"
train(training_path_spam, 'spam')

print "training with not spam"
train(training_path_not_spam, 'not_spam')

print "testing for spam----"
test(testing_path_spam)

print "testing for not spam----"
test(testing_path_not_spam)
```

#### **Problem 3**

3. Draw a confusion matrix for your classification results  ${\bf Solution}$ 

		actual designation	
		spam	not spam
predicted designation	spam	9	0
	not spam	1	10

#### Problem 4

4. Report the precision and accuracy scores of your classification results  $\mathbf{Solution}$ 

Of the 9 emails predicted to be spam, 9 were correct, out of the actual 10 spam messages. The precision is therefore 9/9, and the recall is 9/10.

According to the Wikipedia page listed in the assignment document, accuracy is:

 $\frac{tp+tn}{tp+tn+fp+fn}$  where tp = true positive (predicted spam, actual spam), tn = true negative (predicted not spam, actual not spam), fp = false positive (predicted spam, actual not spam), and fn = false negative (predicted not spam, actual spam).

By this measurement my classification results have an accuracy rating of 95%.

Sunday, April 14, 2019

### References

[1] http://www.linuxfocus.org/common/src/article279/spam\_samples.html