Testing_Bayes_Classifier

November 30, 2019

0.1 Notebook Imports

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

0.2 Constants

In [2]:
```
TOKEN_SPAM_PROB_FILE = 'SpamData/03_Testing/prob-spam.txt'
TOKEN_HAM_PROB_FILE = 'SpamData/03_Testing/prob-nonspam.txt'
TOKEN_ALL_PROB_FILE = 'SpamData/03_Testing/prob-all-tokens.txt'

TEST_FEATURE_MATRIX = 'SpamData/03_Testing/test-features.txt'
TEST_TARGET_FILE = 'SpamData/03_Testing/test-target.txt'

VOCAB_SIZE = 2500
```

0.3 Load the Data

In [3]:
```
X_test = np.loadtxt(TEST_FEATURE_MATRIX, delimiter=' ')
y_test = np.loadtxt(TEST_TARGET_FILE, delimiter=' ')

prob_token_spam = np.loadtxt(TOKEN_SPAM_PROB_FILE, delimiter=' ')
prob_token_ham = np.loadtxt(TOKEN_HAM_PROB_FILE, delimiter=' ')
prob_all_tokens = np.loadtxt(TOKEN_ALL_PROB_FILE, delimiter=' ')
```

In [4]:
```
X_test[:5]
```

Out[4]:
```
array([[4., 0., 1., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.]])
```

0.4 Calculating the Joint Probability

0.4.1 Set the Prior

$$P(Spam \mid X) = \frac{P(X \mid Spam)\, P(Spam)}{P(X)}$$

```
In [5]: PROB_SPAM = 0.3116
```

0.4.2 Joint probability in log format

```
In [6]: joint_log_spam = X_test.dot(np.log(prob_token_spam)) + np.log(PROB_SPAM)

In [7]: joint_log_spam[:5]

Out[7]: array([-609.11347945, -171.76923907, -138.77860341, -429.67261243,
               -267.39676488])
```

$$P(Ham \mid X) = \frac{P(X \mid Ham)\,(1 - P(Spam))}{P(X)}$$

```
In [8]: joint_log_ham = X_test.dot(np.log(prob_token_ham )) + np.log(1-PROB_SPAM)

In [9]: joint_log_ham[:5]

Out[9]: array([-653.84077417, -194.13257637, -137.83302812, -493.14861362,
               -285.66603157])

In [10]: joint_log_ham.size

Out[10]: 1722
```

1 Making Predictions

1.0.1 Checking for the higher joint probability

$$P(Spam \mid X) > P(Ham \mid X)$$

OR

$$P(Spam \mid X) < P(Ham \mid X)$$

```
In [11]: prediciton = joint_log_spam > joint_log_ham

In [12]: prediciton[-5:]*1

Out[12]: array([0, 0, 0, 0, 0])

In [13]: y_test[-5:]

Out[13]: array([0., 0., 0., 0., 0.])
```

1.0.2 Simplify

$$P(X \mid Spam)\, P(Spam) \frac{P(X \mid Spam)\, P(Spam)}{P(X)}$$

1.1 Metrics and Evaluation

1.1.1 Accuracy

```
In [14]: correct_docs = (y_test == prediciton).sum()
         print('Docs classified correctly', correct_docs)
         numdocs_wrong = X_test.shape[0] - correct_docs
         print('Docs classified incorrectly',numdocs_wrong)
```

```
Docs classified correctly 1677
Docs classified incorrectly 45
```

```
In [15]: accuracy = correct_docs/len(X_test)
         print('Accuracy :', accuracy)
```

```
Accuracy : 0.9738675958188153
```

```
In [16]: fraction_wrong = numdocs_wrong/len(X_test)
         print('Fraction classified incorrectly is {:.2%}'.format(fraction_wrong))
         print('Accuracy of the model is {:.2%}'.format(1-fraction_wrong))
```

```
Fraction classified incorrectly is 2.61%
Accuracy of the model is 97.39%
```

1.2 Visualising the Results

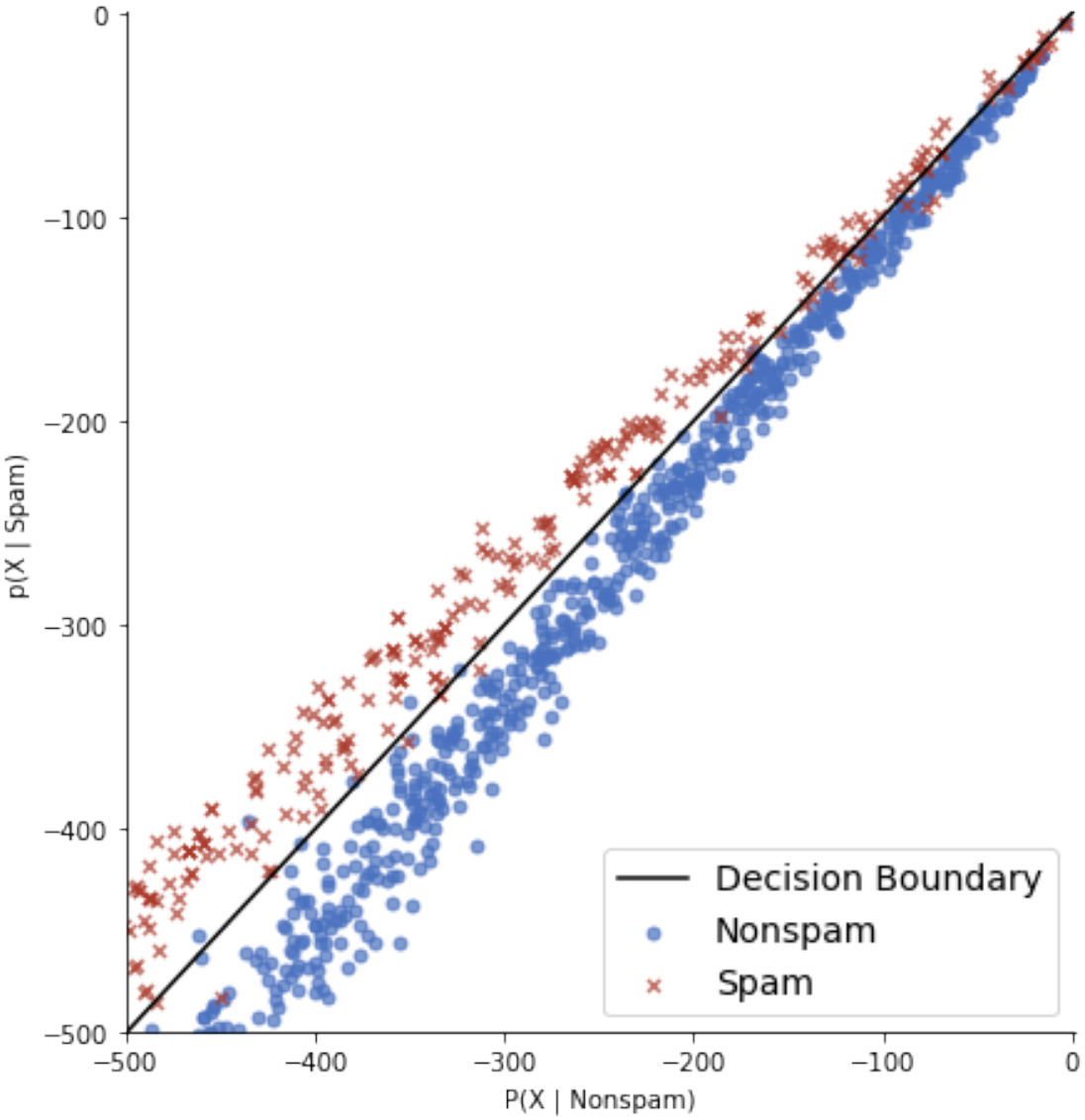
```
In [17]: yaxis_label = 'p(X | Spam)'
         xaxis_label = 'P(X | Nonspam)'

         linedata = np.linspace(start=-14000, stop=1, num=1000)
```

1.3 The Decision Boundary

```
In [18]: my_colours = ['#4A71C0', '#AB3A2C']
         labels = 'Actual Category'
         summary_df = pd.DataFrame({yaxis_label: joint_log_spam, xaxis_label: joint_log_ham, la
         sns.lmplot(x=xaxis_label, y=yaxis_label, data=summary_df, size=6.5, fit_reg=False, leg
                    scatter_kws={'alpha': 0.7, 's': 25}, hue=labels, markers=['o', 'x'], palette

         plt.xlim([-500, 1])
         plt.ylim([-500, 1])
```

```
        plt.plot(linedata, linedata, color='black')

        plt.legend(('Decision Boundary', 'Nonspam', 'Spam'), loc='lower right', fontsize=14)

        plt.show()
```

```
/home/anish/anaconda3/lib/python3.7/site-packages/seaborn/regression.py:546: UserWarning: The
  warnings.warn(msg, UserWarning)
```



1.4 False Positives and False Negatives

```
In [19]: np.unique(prediciton, return_counts=True)
```

```
Out[19]: (array([False,  True]), array([1150,  572]))

In [20]: true_pos = (y_test == 1) & (prediciton == 1)

In [21]: true_pos.sum()

Out[21]: 557

In [22]: false_pos = (y_test == 0) & (prediciton == 1)
         false_pos.sum()

Out[22]: 15

In [23]: false_neg = (y_test == 1) & (prediciton == 0)
         false_neg.sum()

Out[23]: 30
```

1.5 Recall Score

```
In [24]: recall_score = true_pos.sum() / (true_pos.sum() + false_neg.sum())
         print('Recall score is {:.2%}'.format(recall_score))

Recall score is 94.89%
```

1.6 Precision Score

```
In [25]: precision_score = true_pos.sum() / (true_pos.sum() + false_pos.sum())
         print('Precision score is {:.3}'.format(precision_score))

Precision score is 0.974
```

1.7 F-Score

```
In [26]: f_score = 2 * (precision_score * recall_score) / (precision_score + recall_score)
         print('F Score is {:.2}'.format(f_score))

F Score is 0.96
```