

HW1 Q3 Written Responses

- 1) The discriminant function for: “Multivariate Gaussian classifier assuming class-dependent covariance” is given by the following:

$$g_i(x) = -\frac{1}{2} \log |S_i| - \frac{1}{2} (x - m_i)^T S_i^{-1} (x - m_i) + \log \hat{P}(C_i)$$

How I coded this equation in my program:

```
m = self.mean[c].reshape(8,1)
dot = np.float(np.dot(np.dot((x - m).T, inv(self.S[c])), (x - m)))
val = -0.5 * math.log(det(self.S[c])) - 0.5 * dot + math.log(self.p[c])
```

The discriminant function for: “Multivariate Gaussian classifier assuming class-independent covariance” is given by the following:

$$g_i(x) = -\frac{1}{2} (x - m_i)^T S^{-1} (x - m_i) + \log \hat{P}(C_i)$$

How I coded this equation in my program:

```
m = self.mean[c].reshape(8,1)
dot = np.float(np.dot(np.dot((x - m).T, inv(self.S)), (x - m)))
val = - 0.5 * dot + math.log(self.p[c])
```

The discriminant function takes in the sample mean, \mathbf{m}_i , covariance matrix, \mathbf{S}_i , priors, $\mathbf{p}(\mathbf{C}_i)$, and sample test, \mathbf{x} , to calculate a score value. This value is used to determine which class the sample test, \mathbf{x} , belongs to. The main difference between the two discriminant functions: the second equation is a reduced version of the first equation. The reason for this reduction: the second equation utilizes a common covariance matrix whereas the first equation has separate \mathbf{S}_i for each class, C_1 and C_2 .

- 2) Confusion Matrix on the test set for each assumption:

```
In [1]: runfile('/Users/kiavang/CSCI5521/hw1_programming/hw1.py', wdir='/Users/kiavang/CSCI5521/hw1_programming')
Confusion Matrix for Gaussian Discriminant with class-dependent covariance
[[20  7]
 [10 63]]
Confusion Matrix for Gaussian Discriminant with class-independent covariance
[[25  5]
 [ 5 65]]
```

The Confusion Matrix is visual representation (of TP, FP, FN, and TN) that shows the prediction performance of the algorithm.

Confusion Matrix		Actual Class	
		P	N
Predicted Class	P	TP	FP
	N	FN	TN

Class-dependent Covariance Case:

$$\text{Sensitivity (True Positive Rate)} = \frac{TP}{TP+FN} = \frac{20}{20+10} = \frac{2}{3} \approx 0.667$$

- 66.7%, proportion of positives that were correctly identified

$$\text{Specificity (True Negative Rate)} = \frac{TN}{TN+FP} = \frac{63}{63+7} = \frac{63}{70} \approx 0.90$$

- 90%, proportion of negatives that were correctly identified

Class-independent Covariance Case:

$$\text{Sensitivity (True Positive Rate)} = \frac{TP}{TP+FN} = \frac{25}{25+5} = \frac{5}{6} \approx 0.833$$

- → 83.3%, proportion of positives that were correctly identified

$$\text{Specificity (True Negative Rate)} = \frac{TN}{TN+FP} = \frac{65}{65+5} = \frac{65}{70} \approx 0.928$$

- → 92.8%, proportion of negatives that were correctly identified