

0907542 Patter Recognition (Spring 2012)
Midterm Exam Solution

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Instructions: Time **60** min. Closed books & notes. No calculators or mobile phones. No questions are allowed. **Bold** case is used for vectors and matrices. Show your work clearly. Every problem is for 6 marks.

Q1. Using Bayes classification rule, find to what class the Point $x = 1$ belongs to? Given that:

$$P(\omega_1) = 0.75, \quad P(\omega_2) = 0.25, \quad p(1|\omega_1) = 0.4, \quad p(1|\omega_2) = 0.8$$

$$P(\omega_1) p(1|\omega_1) < (>) P(\omega_2) p(1|\omega_2)$$

$$0.75 \times 0.4 < (>) 0.25 \times 0.8$$

$$0.3 > 0.2$$

Hence x belongs to ω_1

Q2. Recall that the decision hyper-plane in the sum of error squares method is found through the Equation $\hat{\mathbf{w}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$. Write the Matlab code to find the decision hyper-plane for the following four samples:

$$\omega_1: \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \omega_2: \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

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x = [0 0 1; 0 1 1; 1 0 1; 1 1 1];
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y = [1 1 -1 -1]';
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A = x' * x;
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B = x' * y;
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w = inv(A)*B;
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Q3. Consider a two-class (equi-probable), one-dimensional problem with samples distributed according to the Rayleigh pdf in each class, that is,

$$p(x|\omega_i) = \begin{cases} \frac{x}{\sigma_i^2} e^{\left(\frac{-x^2}{2\sigma_i^2}\right)} & x \geq 0 \\ 0 & x < 0 \end{cases}, \quad \sigma_1 = 1, \quad \sigma_2 = 2$$

Compute the threshold value x_0 for minimum risk if the loss matrix is:

$$\mathbf{L} = \begin{pmatrix} 0 & 0.5 \\ 1.0 & 0 \end{pmatrix}$$

The threshold x_0 occurs when

$$\lambda_{11}p(x|\omega_1)P(\omega_1) + \lambda_{21}p(x|\omega_2)P(\omega_2) = \lambda_{12}p(x|\omega_1)P(\omega_1) + \lambda_{22}p(x|\omega_2)P(\omega_2)$$

$$p(x|\omega_1) = p(x|\omega_2) \frac{P(\omega_2) \lambda_{21} - \lambda_{22}}{P(\omega_1) \lambda_{12} - \lambda_{11}}$$

$$\frac{x}{\sigma_1^2} e^{\left(\frac{-x^2}{2\sigma_1^2}\right)} = \frac{x}{\sigma_2^2} e^{\left(\frac{-x^2}{2\sigma_2^2}\right)} \times 1 \times \frac{1.0 - 0}{0.5 - 0}$$

$$\frac{x}{1} e^{\left(\frac{-x^2}{2}\right)} = \frac{x}{4} e^{\left(\frac{-x^2}{2 \times 4}\right)} \times 2$$

$$e^{\left(\frac{-x^2}{2}\right)} = \frac{1}{2} e^{\left(\frac{-x^2}{8}\right)}$$

Take the ln of both sides

$$\left(\frac{-x^2}{2}\right) = \ln \frac{1}{2} + \left(\frac{-x^2}{8}\right)$$

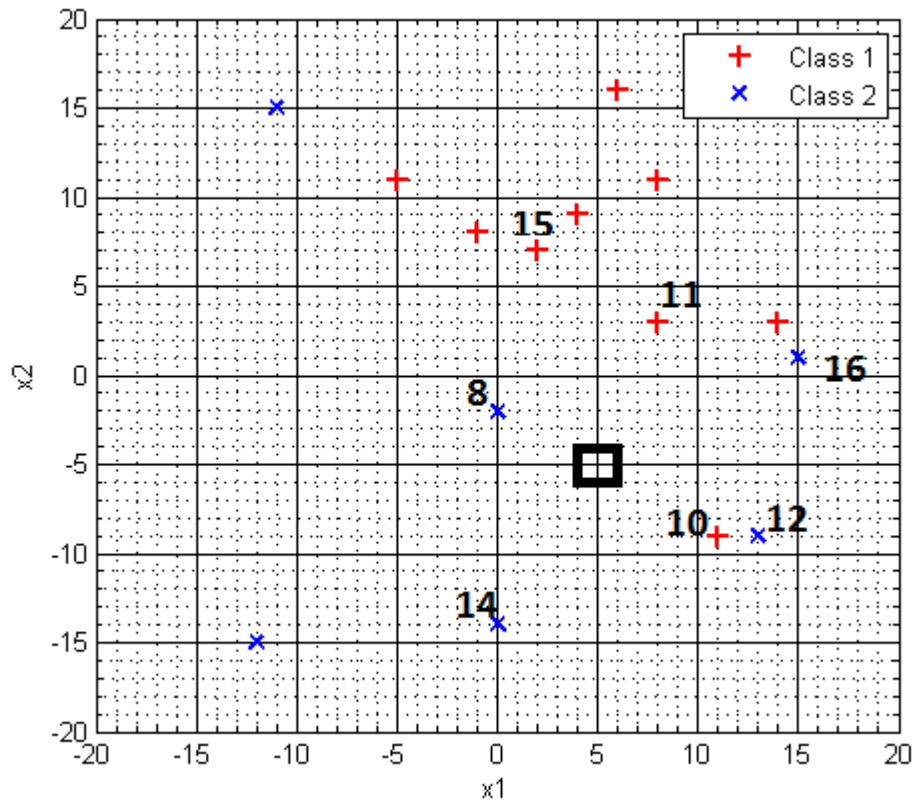
$$\frac{x^2}{2} - \frac{x^2}{8} = \ln 2$$

$$\frac{3x^2}{4} = 2 \ln 2$$

$$x^2 = \frac{8}{3} \ln 2$$

$$x_0 = \sqrt{\frac{8}{3} \ln 2}$$

Q4. It is required to classify the point $x = [5 \ -5]^T$ using the k -nearest neighbor method. The known points are shown in the figure below and belong to Class 1 and Class 2. All feature values are integers. Classify this point for $k=1, 3,$ and 5 and using the City Block distance metric.



The figure is marked with the distances of the nearest neighbors.

- a) For $k = 1$ and distance metric is city block distance, the class is Class 2
Nearest neighbor is 8(x)
- b) For $k = 3$ and distance metric is city block distance, the class is Class 1
Nearest 3 neighbors are 8(x), 10(+), 11(+)
- c) For $k = 5$ and distance metric is city block distance, the class is Class 2
Nearest 5 neighbors are 8(x), 10(+), 11(+), 12(x), 14(x)

Q5. In the sum of error squares method, the cost function used is

$$J(\mathbf{w}) = \sum_{i=1}^N (y_i - \mathbf{w}^T \mathbf{x}_i)^2$$

Show that the decision hyper-plane is $\hat{\mathbf{w}} = ((\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T) \mathbf{y}$, where $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1^T \\ \mathbf{x}_2^T \\ \dots \\ \mathbf{x}_N^T \end{bmatrix}$, $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{bmatrix}$

The minimum error occurs when:

$$\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}} = \frac{\partial}{\partial \mathbf{w}} \sum_{i=1}^N (y_i - \mathbf{w}^T \mathbf{x}_i)^2 = 0$$

$$\sum_{i=1}^N 2\mathbf{x}_i (y_i - \mathbf{w}^T \mathbf{x}_i) = 0$$

$$\sum_{i=1}^N \mathbf{x}_i y_i - \mathbf{x}_i (\mathbf{w}^T \mathbf{x}_i) = 0$$

$$\sum_{i=1}^N \mathbf{x}_i (\mathbf{w}^T \mathbf{x}_i) = \sum_{i=1}^N \mathbf{x}_i y_i$$

$$\sum_{i=1}^N \mathbf{x}_i (\mathbf{x}_i^T \mathbf{w}) = \sum_{i=1}^N \mathbf{x}_i y_i$$

$$\sum_{i=1}^N \mathbf{x}_i^T \mathbf{x}_i \mathbf{w} = \sum_{i=1}^N \mathbf{x}_i y_i$$

$$\left(\sum_{i=1}^N \mathbf{x}_i^T \mathbf{x}_i \right) \mathbf{w} = \sum_{i=1}^N \mathbf{x}_i y_i$$

$$(\mathbf{X}^T \mathbf{X}) \mathbf{w} = \mathbf{X}^T \mathbf{y}$$

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

<Good Luck>