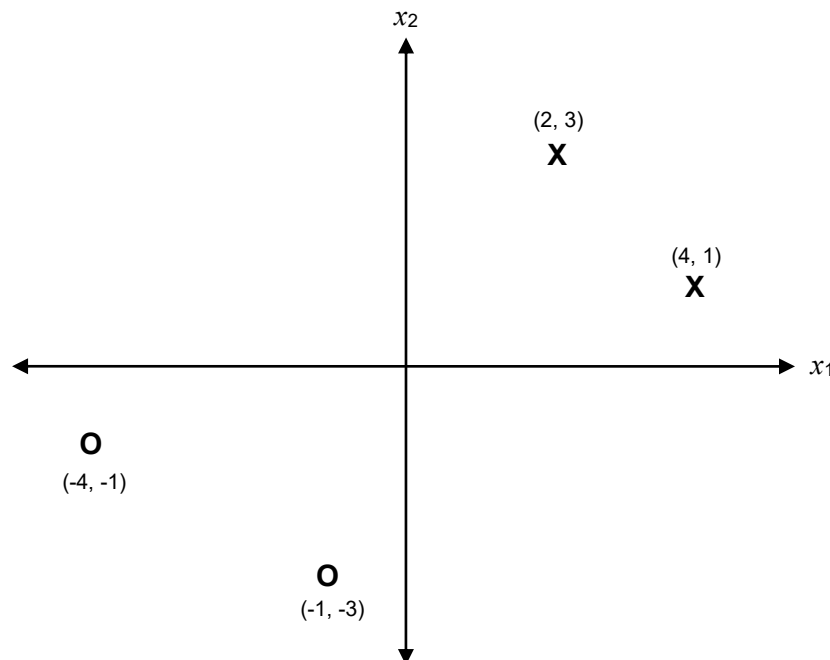


CSEN1083 – Data Mining
Problem Set #4

Problem 1

For the data given below, use the maximum likelihood estimate of Gaussian generative model to find the classifier parameters.



Solution:

- Let the target value for class C_1 (**X**) be $t = 1$ and for class C_2 (**O**) be $t = 0$.
- The prior probability of class C_1 is

$$p(C_1) = \pi = \frac{1}{4} \sum_{n=1}^4 t_n = \frac{1}{4} (1 + 1 + 0 + 0) = 0.5$$

- The prior probability of class C_2 is thus

$$p(C_2) = 1 - \pi = 0.5$$

- The mean of the input vectors in class C_1 is

$$\mu_1 = \frac{1}{N_1} \sum_{n=1}^4 t_n \mathbf{x}_n = \frac{1}{2} \left(1 \times \begin{bmatrix} 2 \\ 3 \end{bmatrix} + 1 \times \begin{bmatrix} 4 \\ 1 \end{bmatrix} + 0 \times \begin{bmatrix} -1 \\ -3 \end{bmatrix} + 0 \times \begin{bmatrix} -4 \\ -1 \end{bmatrix} \right) = \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

- The mean of the input vectors in class C_2 is

$$\mu_2 = \frac{1}{N_2} \sum_{n=1}^4 (1 - t_n) \mathbf{x}_n = \frac{1}{2} \left(0 \times \begin{bmatrix} 2 \\ 3 \end{bmatrix} + 0 \times \begin{bmatrix} 4 \\ 1 \end{bmatrix} + 1 \times \begin{bmatrix} -1 \\ -3 \end{bmatrix} + 1 \times \begin{bmatrix} -4 \\ -1 \end{bmatrix} \right) = \begin{bmatrix} -2.5 \\ -2 \end{bmatrix}$$

- The covariance matrix Σ is given by

CSEN1083 – Data Mining
Problem Set #4

$$\Sigma = \frac{N_1}{N} \mathbf{S}_1 + \frac{N_2}{N} \mathbf{S}_2 = 0.5\mathbf{S}_1 + 0.5\mathbf{S}_2$$

$$\begin{aligned} \mathbf{S}_1 &= \sum_{\mathbf{x}_n \in C_1} (\mathbf{x}_n - \boldsymbol{\mu}_1)(\mathbf{x}_n - \boldsymbol{\mu}_1)^T \\ &= \left(\begin{bmatrix} 2 \\ 3 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right) \left(\begin{bmatrix} 2 \\ 3 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right)^T + \left(\begin{bmatrix} 4 \\ 1 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right) \left(\begin{bmatrix} 4 \\ 1 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \end{bmatrix} \right)^T \\ &= \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} + \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} = \begin{bmatrix} 2 & -2 \\ -2 & 2 \end{bmatrix} \end{aligned}$$

$$\begin{aligned} \mathbf{S}_2 &= \sum_{\mathbf{x}_n \in C_2} (\mathbf{x}_n - \boldsymbol{\mu}_2)(\mathbf{x}_n - \boldsymbol{\mu}_2)^T \\ &= \left(\begin{bmatrix} -1 \\ -3 \end{bmatrix} - \begin{bmatrix} -2.5 \\ -2 \end{bmatrix} \right) \left(\begin{bmatrix} -1 \\ -3 \end{bmatrix} - \begin{bmatrix} -2.5 \\ -2 \end{bmatrix} \right)^T + \left(\begin{bmatrix} -4 \\ -1 \end{bmatrix} - \begin{bmatrix} -2.5 \\ -2 \end{bmatrix} \right) \left(\begin{bmatrix} -4 \\ -1 \end{bmatrix} - \begin{bmatrix} -2.5 \\ -2 \end{bmatrix} \right)^T \\ &= \begin{bmatrix} 2.25 & -1.5 \\ -1.5 & 1 \end{bmatrix} + \begin{bmatrix} 2.25 & -1.5 \\ -1.5 & 1 \end{bmatrix} = \begin{bmatrix} 4.5 & -3 \\ -3 & 2 \end{bmatrix} \end{aligned}$$

$$\Sigma = 0.5\mathbf{S}_1 + 0.5\mathbf{S}_2 = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} + \begin{bmatrix} 2.25 & -1.5 \\ -1.5 & 1 \end{bmatrix} = \begin{bmatrix} 3.25 & -2.5 \\ -2.5 & 2 \end{bmatrix}$$

CSEN1083 – Data Mining
Problem Set #4

Problem 2

Consider the data about conditions for playing tennis given below:

Day	Outlook	Temperature	Humidity	Play Tennis?
1	Sunny	Hot	High	No
2	Cloudy	Hot	High	Yes
3	Rain	Mild	High	No
4	Rain	Cool	Normal	No
5	Cloudy	Cool	Normal	Yes
6	Sunny	Mild	High	Yes
7	Sunny	Cool	Normal	Yes
8	Rain	Mild	Normal	No
9	Sunny	Mild	Normal	Yes
10	Cloudy	Mild	High	Yes

Using Naïve Bayes classifier, predict if one should play tennis on a Sunny, Hot with Normal humidity day. Note that since the data is discrete, you can use the frequentist statistics to compute the needed probabilities.

Solution:

Since the goal is to classify a sunny, hot with normal humidity day as good day to play tennis or not, we first define two classes C_1 and C_2 , corresponding to Play = Yes and Play = No, respectively. To classify the given day with attributes \mathbf{x} , we need to compute $p(C_1 | \mathbf{x})$:

$$p(\text{Play} = \text{Yes} \mid \text{Outlook} = \text{Sunny}, \text{Temperature} = \text{Hot}, \text{Humidity} = \text{Normal})$$

and $p(C_2 | \mathbf{x})$:

$$p(\text{Play} = \text{No} \mid \text{Outlook} = \text{Sunny}, \text{Temperature} = \text{Hot}, \text{Humidity} = \text{Normal})$$

and find which conditional probability is larger. If the first one is larger, then our prediction is Play = Yes. If the second one is larger, then our prediction is Play = No. Note that \mathbf{x} here is 3 dimensional corresponding to Outlook, Temperature and Humidity.

$$\text{Since } p(C_1 | \mathbf{x}) = \frac{p(\mathbf{x} | C_1)p(C_1)}{p(\mathbf{x})}$$

CSEN1083 – Data Mining
Problem Set #4

We need to compute $p(\mathbf{x} | C_1) = p(\text{Outlook} = \text{Sunny}, \text{Temperature} = \text{Hot}, \text{Humidity} = \text{Normal} | \text{Play} = \text{Yes})$. Using the Naïve Bayes assumption which assumes that the dimensions of the input data (the attributes of the day) are

independent, we can re-write $p(\mathbf{x} | C_1)$ as $p(\mathbf{x} | C_1) = \prod_{i=1}^D p(x_i | C_1)$

$$p(\text{Outlook} = \text{Sunny} | \text{Play} = \text{Yes}) p(\text{Temperature} = \text{Hot} | \text{Play} = \text{Yes}) p(\text{Humidity} = \text{Normal} | \text{Play} = \text{Yes})$$

Similarly, $p(\mathbf{x} | C_2)$ can be re-written as $p(\mathbf{x} | C_2) = \prod_{i=1}^D p(x_i | C_2)$

$$p(\text{Outlook} = \text{Sunny} | \text{Play} = \text{No}) p(\text{Temperature} = \text{Hot} | \text{Play} = \text{No}) p(\text{Humidity} = \text{Normal} | \text{Play} = \text{No})$$

From the available data in the table and using frequentist statistics:

$$p(\text{Outlook} = \text{Sunny} | \text{Play} = \text{Yes}) = 3/6$$

$$p(\text{Temperature} = \text{Hot} | \text{Play} = \text{Yes}) = 1/6$$

$$p(\text{Humidity} = \text{Normal} | \text{Play} = \text{Yes}) = 3/6$$

$$p(\text{Play} = \text{Yes}) = 6/10$$

$$p(\text{Outlook} = \text{Sunny} | \text{Play} = \text{No}) = 1/4$$

$$p(\text{Temperature} = \text{Hot} | \text{Play} = \text{No}) = 1/4$$

$$p(\text{Humidity} = \text{Normal} | \text{Play} = \text{No}) = 2/4$$

$$p(\text{Play} = \text{No}) = 4/10$$

Therefore,

$$p(\mathbf{x} | C_1) = p(\text{Outlook} = \text{Sunny}, \text{Temperature} = \text{Hot}, \text{Humidity} = \text{Normal} | \text{Play} = \text{Yes}) = (3/6) \times (1/6) \times (3/6)$$

And

$$p(\mathbf{x} | C_2) = p(\text{Outlook} = \text{Sunny}, \text{Temperature} = \text{Hot}, \text{Humidity} = \text{Normal} | \text{Play} = \text{No}) = (1/4) \times (1/4) \times (2/4)$$

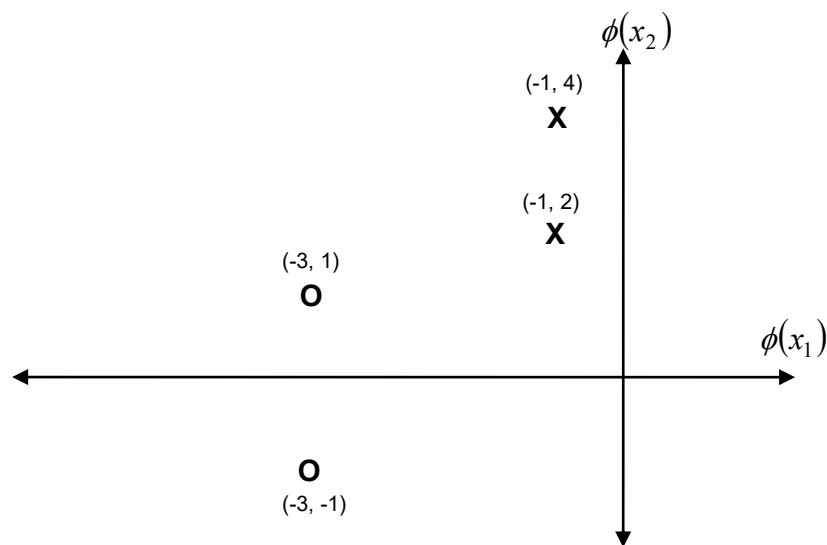
$$\frac{p(C_1 | \mathbf{x})}{p(C_2 | \mathbf{x})} = \frac{p(\mathbf{x} | \text{Play} = \text{Yes}) p(\text{Play} = \text{Yes})}{p(\mathbf{x} | \text{Play} = \text{No}) p(\text{Play} = \text{No})} = \frac{0.025}{0.0125} = 2$$

Since $\frac{p(C_1 | \mathbf{x})}{p(C_2 | \mathbf{x})} > 1$ then $\mathbf{x} \in C_1$ Therefore, one should play tennis in a sunny, hot with normal humidity day.

CSEN1083 – Data Mining
Problem Set #4

Problem 3

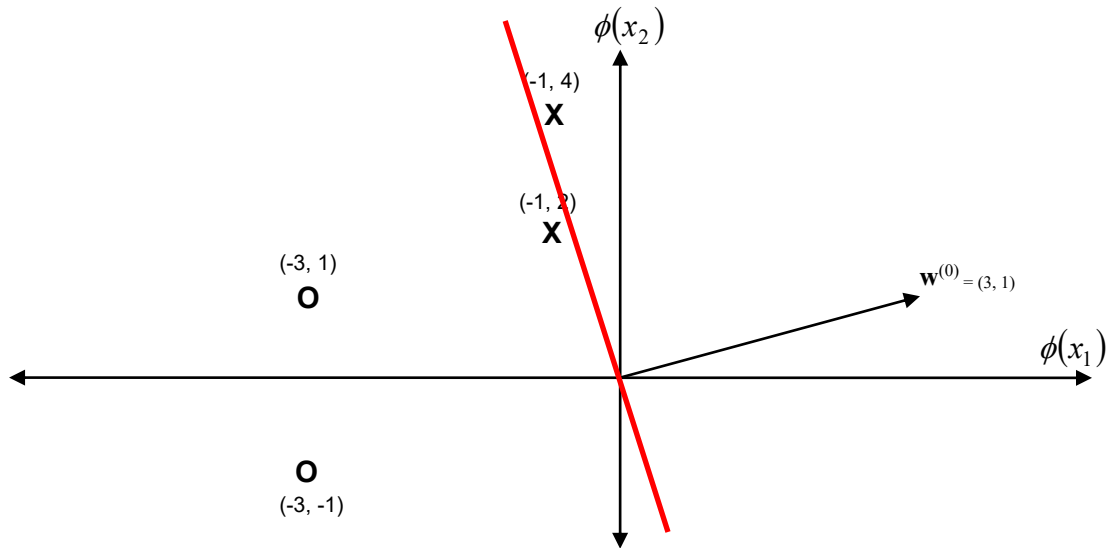
For the data given below, apply the logistic regression algorithm to find the weight vector \mathbf{w} of the decision boundary. Show the output of each iteration till all the points are classified correctly. Assume that the weight vector is initialized $\mathbf{w}^{(0)} = [3 \ 1]$. Use learning rate parameter $\eta = 0.5$.



Solution:

The initial weight vector is shown below and the corresponding decision boundary $w_1x_1 + w_2x_2 = 0$ shown in red (which is perpendicular to the weight vector). For $\mathbf{w}^{(0)}$, the decision boundary is $3x_1 + x_2 = 0$. Let the target value t for points in the **X** class be 1 and for the **O** class be 0.

CSEN1083 – Data Mining
Problem Set #4



For iteration 1, based on the shown decision boundary, the y value for the points (Refer to slide 20 in Lecture 4)

$$(-1, 4) \rightarrow y = 1 / (1 + \exp(-w_1 x_1 - w_2 x_2)) = 1 / (1 + \exp(-3 * (-1) - 1 * 4)) = 0.73$$

$$(-1, 2) \rightarrow y = 1 / (1 + \exp(-3 * (-1) - 1 * 2)) = 0.27$$

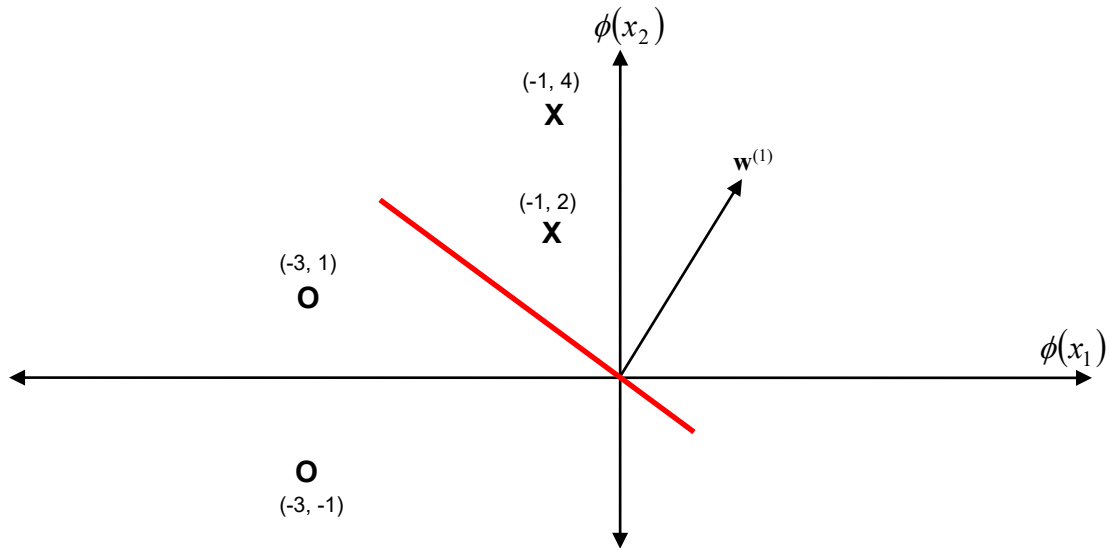
$$(-3, 1) \rightarrow y = 1 / (1 + \exp(-3 * (-3) - 1 * 1)) = 0$$

$$(-3, -1) \rightarrow y = 1 / (1 + \exp(-3 * (-3) - 1 * (-1))) = 0$$

The logistic regression update rule is given by $\mathbf{w}^{(\tau+1)} = \mathbf{w}^{(\tau)} - \eta \sum_{n=1}^N (y_n - t_n) \phi(\mathbf{x}_n)$

$$\mathbf{w}^{(1)} = \begin{bmatrix} 3 \\ 1 \end{bmatrix} - 0.5 \left((0.73 - 1) \begin{bmatrix} -1 \\ 4 \end{bmatrix} + (0.27 - 1) \begin{bmatrix} -1 \\ 2 \end{bmatrix} + (0 - 0) \begin{bmatrix} -3 \\ 1 \end{bmatrix} + (0 - 0) \begin{bmatrix} -3 \\ -1 \end{bmatrix} \right) = \begin{bmatrix} 2.5 \\ 2.27 \end{bmatrix}$$

CSEN1083 – Data Mining
Problem Set #4



Since all points are classified correctly, the algorithm stops.