

4.1 What are the values of weights  $w_0$ ,  $w_1$ , and  $w_2$  for the perceptron whose decision surface is illustrated in Figure 4.3? Assume the surface crosses the  $x_1$  axis at -1, and the  $x_2$  axis at 2.

Ans. The function of the decision surface is:  $2+2x_1-x_2 = 0$ , so  $w_0 = -2$ ,  $w_1 = 2$ ,  $w_2 = -1$ .

4.2. Design a two-input perceptron that implements the boolean function  $A \wedge \neg B$ . Design a two-layer network of perceptrons that implements  $A \text{ XOR } B$ .

Ans. We assume 1 for true, -1 for false.

(1)  $A \wedge \neg B$ :  $w_0 = -0.8$ ,  $w_1 = 0.5$ ,  $w_2 = -0.5$ .

$x_1(A)$	$x_2(B)$	$w_0+w_1x_1+w_2x_2$	output
-1	-1	-0.8	-1
-1	1	-1.8	-1
1	-1	0.2	1
1	1	-0.8	-1

(2)  $A \text{ XOR } B = (A \wedge \neg B) \vee (\neg A \wedge B)$

The weights are:

Hidden unit 1:  $w_0 = -0.8$ ,  $w_1 = 0.5$ ,  $w_2 = -0.5$

Hidden unit 2:  $w_0 = -0.8$ ,  $w_1 = -0.5$ ,  $w_2 = 0.5$

Output unit:  $w_0 = 0.3$ ,  $w_1 = 0.5$ ,  $w_2 = 0.5$

$x_1(A)$	$x_2(B)$	Hidden unit 1 value	Hidden unit 2 value	Output value
-1	-1	-1	-1	-1
-1	1	-1	1	1
1	-1	1	-1	1
1	1	-1	-1	-1

4.3. Consider two perceptrons defined by the threshold expression  $w_0 + w_1x_1 + w_2x_2 > 0$ . Perceptron A has weight values:  $w_0 = 1$ ,  $w_1 = 2$ ,  $w_2 = 1$ , and perceptron B has the weight values:  $w_0 = 0$ ,  $w_1 = 2$ ,  $w_2 = 1$ . True or false? Perceptron A is *more-general-than* perceptron B. (*more-general-than* is defined in Chapter 2.)

Ans. True.

For each input instance  $x=(x_1, x_2)$ , if  $x$  is satisfied by B, which means  $2x_1+x_2>0$ , then we have  $2x_1+x_2+1>0$ . Hence,  $x$  is also satisfied by the A.

4.5. Derive a gradient descent training rule for a single unit with output  $o$ , where

$$o = w_0 + w_1x_1 + w_1x_1^2 + \dots + w_nx_n + w_nx_n^2$$

Ans.

$$\text{The gradient descent is: } \nabla E(\vec{w}) = \left[ \frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \dots, \frac{\partial E}{\partial w_n} \right]$$

$$\begin{aligned}
\frac{\partial E}{\partial w_i} &= \frac{\partial}{\partial w_i} \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2 \\
&= \sum_{d \in D} (t_d - o_d) \frac{\partial}{\partial w_i} (t_d - o_d) \\
&= \sum_{d \in D} (t_d - o_d) (-x_{id} - x_{id}^2)
\end{aligned}$$

The training rule for gradient descent is:  $w_i = w_i + \Delta w_i$ , where

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} = \eta \sum_{d \in D} (t_d - o_d) (x_{id} + x_{id}^2)$$