

# CHAPTER 1

## Rosenblatt's Perceptron

### Problem 1.1

- (1) If  $\mathbf{w}^T(n)\mathbf{x}(n) > 0$ , then  $y(n) = +1$ .  
 If also  $\mathbf{x}(n)$  belongs to  $C_1$ , then  $d(n) = +1$ .  
 Under these conditions, the error signal is  

$$e(n) = d(n) - y(n) = 0$$
 and from Eq. (1.22) of the text:  

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \eta e(n)\mathbf{x}(n) = \mathbf{w}(n)$$
 This result is the same as line 1 of Eq. (1.5) of the text.
  
- (2) If  $\mathbf{w}^T(n)\mathbf{x}(n) < 0$ , then  $y(n) = -1$ .  
 If also  $\mathbf{x}(n)$  belongs to  $C_2$ , then  $d(n) = -1$ .  
 Under these conditions, the error signal  $e(n)$  remains zero, and so from Eq. (1.22) we have  

$$\mathbf{w}(n+1) = \mathbf{w}(n)$$
 This result is the same as line 2 of Eq. (1.5).
  
- (3) If  $\mathbf{w}^T(n)\mathbf{x}(n) > 0$  and  $\mathbf{x}(n)$  belongs to  $C_2$  we have  

$$y(n) = +1$$

$$d(n) = -1$$
 The error signal  $e(n)$  is -2, and so Eq. (1.22) yields  

$$\mathbf{w}(n+1) = \mathbf{w}(n) - 2\eta\mathbf{x}(n)$$
 which has the same form as the first line of Eq. (1.6), except for the scaling factor 2.
  
- (4) Finally if  $\mathbf{w}^T(n)\mathbf{x}(n) < 0$  and  $\mathbf{x}(n)$  belongs to  $C_1$ , then  

$$y(n) = -1$$

$$d(n) = +1$$
 In this case, the use of Eq. (1.22) yields  

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\eta\mathbf{x}(n)$$
 which has the same mathematical form as line 2 of Eq. (1.6), except for the scaling factor 2.

### Problem 1.2

The output signal is defined by

$$y = \tanh\left(\frac{v}{2}\right)$$

$$= \tanh\left(\frac{b}{2} + \frac{1}{2}\sum_i w_i x_i\right)$$

Equivalently, we may write

$$b + \sum_i w_i x_i = y' \quad (1)$$

where

$$y' = 2 \tanh^{-1}(y)$$

Equation (1) is the equation of a hyperplane.

### Problem 1.3

(a) AND operation: Truth Table 1

Inputs		Output
$x_1$	$x_2$	$y$
1	1	1
0	1	0
1	0	0
0	0	0

This operation may be realized using the perceptron of Fig. 1

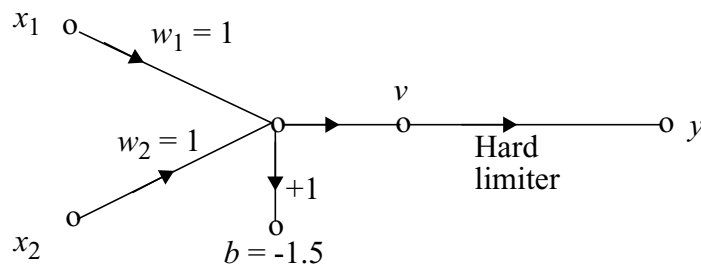


Figure 1: Problem 1.3

The hard limiter input is

$$\begin{aligned} v &= w_1 x_1 + w_2 x_2 + b \\ &= x_1 + x_2 - 1.5 \end{aligned}$$

If  $x_1 = x_2 = 1$ , then  $v = 0.5$ , and  $y = 1$

If  $x_1 = 0$ , and  $x_2 = 1$ , then  $v = -0.5$ , and  $y = 0$

If  $x_1 = 1$ , and  $x_2 = 0$ , then  $v = -0.5$ , and  $y = 0$

If  $x_1 = x_2 = 0$ , then  $v = -1.5$ , and  $y = 0$

These conditions agree with truth table 1.

OR operation: Truth Table 2

Inputs		Output
$x_1$	$x_2$	$y$
1	1	1
0	1	1
1	0	1
0	0	0

The OR operation may be realized using the perceptron of Fig. 2:

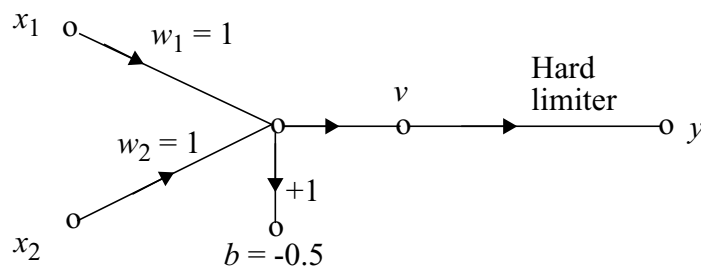


Figure 2: Problem 1.3

In this case, the hard limiter input is

$$v = x_1 + x_2 - 0.5$$

If  $x_1 = x_2 = 1$ , then  $v = 1.5$ , and  $y = 1$

If  $x_1 = 0$ , and  $x_2 = 1$ , then  $v = 0.5$ , and  $y = 1$

If  $x_1 = 1$ , and  $x_2 = 0$ , then  $v = 0.5$ , and  $y = 1$

If  $x_1 = x_2 = 0$ , then  $v = -0.5$ , and  $y = -1$

These conditions agree with truth table 2.

COMPLEMENT operation: Truth Table 3

Input $x$ ,	Output, $y$
1	0
0	1

The COMPLEMENT operation may be realized as in Figure 3::

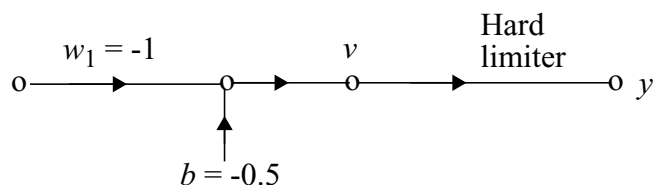


Figure 3: Problem 1.3

The hard limiter input is

$$v = wx + b = -x + 0.5$$

If  $x = 1$ , then  $v = -0.5$ , and  $y = 0$

If  $x = 0$ , then  $v = 0.5$ , and  $y = 1$

These conditions agree with truth table 3.

(b) EXCLUSIVE OR operation: Truth table 4

Inputs		Output
$x_1$	$x_2$	$y$
1	1	0
0	1	1
1	0	1
0	0	0

This operation is nonlinearly separable, which cannot be solved by the perceptron.

### Problem 1.4

The Gaussian classifier consists of a single unit with a single weight and zero bias, determined in accordance with Eqs. (1.37) and (1.38) of the textbook, respectively, as follows:

$$\begin{aligned}
 w &= \frac{1}{\sigma^2}(\mu_1 - \mu_2) \\
 &= -20
 \end{aligned}$$

$$\begin{aligned}
 b &= \frac{1}{2\sigma^2}(\mu_2^2 - \mu_1^2) \\
 &= 0
 \end{aligned}$$

### Problem 1.5

Using the condition

$$\mathbf{C} = \sigma^2 \mathbf{I}$$

in Eqs. (1.37) and (1.38) of the textbook, we get the following formulas for the weight vector and bias of the Bayes classifier:

$$\mathbf{w} = \frac{1}{\sigma^2}(\mu_1 - \mu_2)$$

$$\mathbf{b} = \frac{1}{2\sigma^2}(\|\mu_1\|^2 - \|\mu_2\|^2)$$