

4 Perceptron Learning Rule

$${}_1\mathbf{w} = \begin{bmatrix} -3 \\ -1 \end{bmatrix} \text{ and } {}_2\mathbf{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}.$$

Note that the lengths of the weight vectors is not important, only their directions. They must be orthogonal to the decision boundaries. Now we can calculate the bias by picking a point on a boundary and satisfying Eq. (4.15):

$$b_1 = -{}_1\mathbf{w}^T \mathbf{p} = -\begin{bmatrix} -3 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 1,$$

$$b_2 = -{}_2\mathbf{w}^T \mathbf{p} = -\begin{bmatrix} 1 & -2 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0.$$

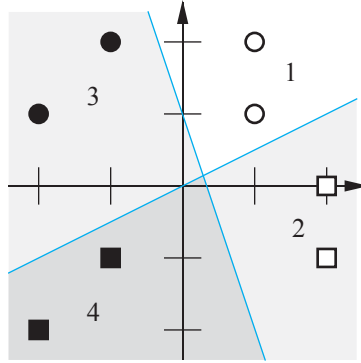


Figure P4.5 Decision Regions for Problem P4.3

In matrix form we have

$$\mathbf{W} = \begin{bmatrix} {}_1\mathbf{w}^T \\ {}_2\mathbf{w}^T \end{bmatrix} = \begin{bmatrix} -3 & -1 \\ 1 & -2 \end{bmatrix} \text{ and } \mathbf{b} = \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

which completes our design.

P4.4 Solve the following classification problem with the perceptron rule. Apply each input vector in order, for as many repetitions as it takes to ensure that the problem is solved. Draw a graph of the problem only after you have found a solution.

$$\left\{ \mathbf{p}_1 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}, t_1 = 0 \right\} \left\{ \mathbf{p}_2 = \begin{bmatrix} 1 \\ -2 \end{bmatrix}, t_2 = 1 \right\} \left\{ \mathbf{p}_3 = \begin{bmatrix} -2 \\ 2 \end{bmatrix}, t_3 = 0 \right\} \left\{ \mathbf{p}_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, t_4 = 1 \right\}$$

Use the initial weights and bias:

$$\mathbf{W}(0) = \begin{bmatrix} 0 & 0 \end{bmatrix} \quad b(0) = 0.$$

We start by calculating the perceptron's output a for the first input vector \mathbf{p}_1 , using the initial weights and bias.

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(0)\mathbf{p}_1 + b(0)) \\ &= \text{hardlim}\left(\begin{bmatrix} 0 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 0\right) = \text{hardlim}(0) = 1 \end{aligned}$$

The output a does not equal the target value t_1 , so we use the perceptron rule to find new weights and biases based on the error.

$$\begin{aligned} e &= t_1 - a = 0 - 1 = -1 \\ \mathbf{W}(1) &= \mathbf{W}(0) + e\mathbf{p}_1^T = \begin{bmatrix} 0 & 0 \end{bmatrix} + (-1) \begin{bmatrix} 2 & 2 \end{bmatrix} = \begin{bmatrix} -2 & -2 \end{bmatrix} \\ b(1) &= b(0) + e = 0 + (-1) = -1 \end{aligned}$$

We now apply the second input vector \mathbf{p}_2 , using the updated weights and bias.

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(1)\mathbf{p}_2 + b(1)) \\ &= \text{hardlim}\left(\begin{bmatrix} -2 & -2 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} - 1\right) = \text{hardlim}(1) = 1 \end{aligned}$$

This time the output a is equal to the target t_2 . Application of the perceptron rule will not result in any changes.

$$\begin{aligned} \mathbf{W}(2) &= \mathbf{W}(1) \\ b(2) &= b(1) \end{aligned}$$

We now apply the third input vector.

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$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(2)\mathbf{p}_3 + b(2)) \\ &= \text{hardlim}\left(\begin{bmatrix} -2 & -2 \end{bmatrix} \begin{bmatrix} -2 \\ 2 \end{bmatrix} - 1\right) = \text{hardlim}(-1) = 0 \end{aligned}$$

The output in response to input vector \mathbf{p}_3 is equal to the target t_3 , so there will be no changes.

$$\begin{aligned} \mathbf{W}(3) &= \mathbf{W}(2) \\ b(3) &= b(2) \end{aligned}$$

We now move on to the last input vector \mathbf{p}_4 .

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(3)\mathbf{p}_4 + b(3)) \\ &= \text{hardlim}\left(\begin{bmatrix} -2 & -2 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} - 1\right) = \text{hardlim}(-1) = 0 \end{aligned}$$

This time the output a does not equal the appropriate target t_4 . The perceptron rule will result in a new set of values for \mathbf{W} and b .

$$\begin{aligned} e &= t_4 - a = 1 - 0 = 1 \\ \mathbf{W}(4) &= \mathbf{W}(3) + e\mathbf{p}_4^T = \begin{bmatrix} -2 & -2 \end{bmatrix} + (1) \begin{bmatrix} -1 & 1 \end{bmatrix} = \begin{bmatrix} -3 & -1 \end{bmatrix} \\ b(4) &= b(3) + e = -1 + 1 = 0 \end{aligned}$$

We now must check the first vector \mathbf{p}_1 again. This time the output a is equal to the associated target t_1 .

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(4)\mathbf{p}_1 + b(4)) \\ &= \text{hardlim}\left(\begin{bmatrix} -3 & -1 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 0\right) = \text{hardlim}(-8) = 0 \end{aligned}$$

Therefore there are no changes.

$$\begin{aligned} \mathbf{W}(5) &= \mathbf{W}(4) \\ b(5) &= b(4) \end{aligned}$$

Solved Problems

The second presentation of \mathbf{p}_2 results in an error and therefore a new set of weight and bias values.

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(5)\mathbf{p}_2 + b(5)) \\ &= \text{hardlim}\left(\begin{bmatrix} -3 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} + 0\right) = \text{hardlim}(-1) = 0 \end{aligned}$$

Here are those new values:

$$\begin{aligned} e &= t_2 - a = 1 - 0 = 1 \\ \mathbf{W}(6) &= \mathbf{W}(5) + e\mathbf{p}_2^T = \begin{bmatrix} -3 & -1 \end{bmatrix} + (1) \begin{bmatrix} 1 & -2 \end{bmatrix} = \begin{bmatrix} -2 & -3 \end{bmatrix} \\ b(6) &= b(5) + e = 0 + 1 = 1. \end{aligned}$$

Cycling through each input vector once more results in no errors.

$$\begin{aligned} a &= \text{hardlim}(\mathbf{W}(6)\mathbf{p}_3 + b(6)) = \text{hardlim}\left(\begin{bmatrix} -2 & -3 \end{bmatrix} \begin{bmatrix} -2 \\ 2 \end{bmatrix} + 1\right) = 0 = t_3 \\ a &= \text{hardlim}(\mathbf{W}(6)\mathbf{p}_4 + b(6)) = \text{hardlim}\left(\begin{bmatrix} -2 & -3 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} + 1\right) = 1 = t_4 \\ a &= \text{hardlim}(\mathbf{W}(6)\mathbf{p}_1 + b(6)) = \text{hardlim}\left(\begin{bmatrix} -2 & -3 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 1\right) = 0 = t_1 \\ a &= \text{hardlim}(\mathbf{W}(6)\mathbf{p}_2 + b(6)) = \text{hardlim}\left(\begin{bmatrix} -2 & -3 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} + 1\right) = 1 = t_2 \end{aligned}$$

Therefore the algorithm has converged. The final solution is:

$$\mathbf{W} = \begin{bmatrix} -2 & -3 \end{bmatrix} \quad b = 1.$$

Now we can graph the training data and the decision boundary of the solution. The decision boundary is given by

$$n = \mathbf{W}\mathbf{p} + b = w_{1,1}p_1 + w_{1,2}p_2 + b = -2p_1 - 3p_2 + 1 = 0.$$

To find the p_2 intercept of the decision boundary, set $p_1 = 0$:

$$p_2 = -\frac{b}{w_{1,2}} = -\frac{1}{-3} = \frac{1}{3} \quad \text{if } p_1 = 0.$$

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To find the p_1 intercept, set $p_2 = 0$:

$$p_1 = -\frac{b}{w_{1,1}} = -\frac{1}{-2} = \frac{1}{2} \quad \text{if } p_2 = 0$$

The resulting decision boundary is illustrated in Figure P4.6.

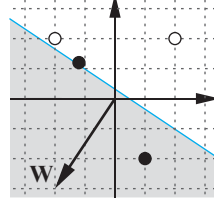


Figure P4.6 Decision Boundary for Problem P4.4

Note that the decision boundary falls across one of the training vectors. This is acceptable, given the problem definition, since the hard limit function returns 1 when given an input of 0, and the target for the vector in question is indeed 1.

P4.5 Consider again the four-class decision problem that we introduced in Problem P4.3. Train a perceptron network to solve this problem using the perceptron learning rule.

If we use the same target vectors that we introduced in Problem P4.3, the training set will be:

$$\left\{ \mathbf{p}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{t}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right\} \left\{ \mathbf{p}_2 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \mathbf{t}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right\} \left\{ \mathbf{p}_3 = \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \mathbf{t}_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

$$\left\{ \mathbf{p}_4 = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \mathbf{t}_4 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \left\{ \mathbf{p}_5 = \begin{bmatrix} -1 \\ 2 \end{bmatrix}, \mathbf{t}_5 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\} \left\{ \mathbf{p}_6 = \begin{bmatrix} -2 \\ 1 \end{bmatrix}, \mathbf{t}_6 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}$$

$$\left\{ \mathbf{p}_7 = \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \mathbf{t}_7 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \left\{ \mathbf{p}_8 = \begin{bmatrix} -2 \\ -2 \end{bmatrix}, \mathbf{t}_8 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}.$$

Let's begin the algorithm with the following initial weights and biases:

$$\mathbf{W}(0) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \mathbf{b}(0) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

The first iteration is