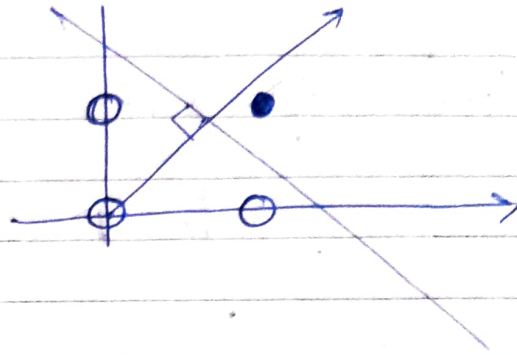


$$\text{Ex} \rightarrow \begin{array}{ccc} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \end{array}$$

① design the decision boundary.

② choose a weight vector that is orthogonal to the decision boundary.



Example: -

$$\begin{array}{l} p_1 \rightarrow \begin{array}{|c|c|} \hline 1 & 2 \\ \hline \end{array} \quad 1 \\ p_2 \rightarrow \begin{array}{|c|c|} \hline -1 & 2 \\ \hline \end{array} \quad 0 \\ p_3 \rightarrow \begin{array}{|c|c|} \hline 0 & -1 \\ \hline \end{array} \quad 0 \end{array}$$

$$W = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix}$$

start with  $x_1$

$$a = \text{hardlim}(W_1^T x_1) = \text{hardlim}\left([1.0 \ -0.8] \begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) \\ = \text{hardlim}(-0.6) = 0$$

it's output is not correct.

update the weight vector.

$$W^{\text{new}} = W^{\text{old}} + x$$

$$W_1^{\text{new}} = W_1^{\text{old}} + x_1 = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 2.0 \\ 1.2 \end{bmatrix}$$

move on to the next input vector.

$$a = \text{hardlim}(w_1^T x_2) = \text{hardlim}\left(\begin{bmatrix} 2 & 1.2 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix}\right)$$

$$= \text{hardlim}(0.4) = 1$$

target associated with  $x_2$  is 0 & the output  $a$  is 1. A class 0 vector was misclassified as a 1.

update the weight

if  $t = 0$  and  $a = 1$  then

$$w_1^{\text{new}} = w_1^{\text{old}} - x_2$$

$$= \begin{bmatrix} 2 \\ 1.2 \end{bmatrix} - \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ 0.8 \end{bmatrix}$$

Now move to next vector

$$a = \text{hardlim}\left(\begin{bmatrix} 3.0 & 0.8 \end{bmatrix} \begin{bmatrix} 0 \\ -1 \end{bmatrix}\right) = \text{hardlim}(0.8) = 1$$

It is also misclassified  $x_3$

update weight

$$w_1^{\text{new}} = w_1^{\text{old}} - \beta x_3 = \begin{bmatrix} 3.0 \\ 0.8 \end{bmatrix} - \begin{bmatrix} 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 3.0 \\ 1.8 \end{bmatrix}$$

continue with iterations you will find that both i/p values will be correctly classified.

perception error  $e = \text{target} - \text{actual} = t - a$

we can update bias

$$b^{\text{new}} = b^{\text{old}} + e$$

The algo has converged to a solution.

Ex  $\rightarrow$   $w_1 = \begin{bmatrix} 0.5 \\ -1 \\ 0.5 \end{bmatrix}$ ,  $b = 0.5$

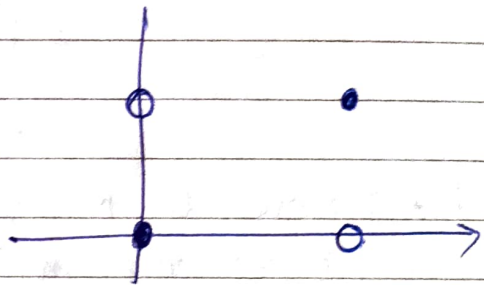
$$x_1 = \begin{bmatrix} +1 \\ -1 \\ -1 \end{bmatrix}, t_1 = [0], x_2 = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}, t_2 = [1]$$

**Limitation** - The perceptron learning rule is guaranteed to converge to a solution in a finite number of steps, so long as a solution exists.

The perceptron can be used to classify input vectors that can be separated by a linear boundary. We call such vectors linearly separable.

Unfortunately, many problems are not linearly separable. **⊗ XOR gate problem.**

|   |   |   |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |



$$\text{Ex} \rightarrow \left\{ P_1 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}, t_1 = 0 \right\}$$

$$\left\{ P_2 = \begin{bmatrix} 1 \\ -2 \end{bmatrix}, t_2 = 1 \right\}$$

$$\left\{ P_3 = \begin{bmatrix} -2 \\ 2 \end{bmatrix}, t_3 = 0 \right\}$$

$$\left\{ P_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, t_4 = 1 \right\}$$

① Initial weight & bias.

$$W(0) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$b(0) = 0$$

② Calculating perceptron output after first input vector  $P_1$ .

③  $W = \begin{bmatrix} -2 \\ -3 \end{bmatrix}, b = 1$

④ Draw Decision Boundary.