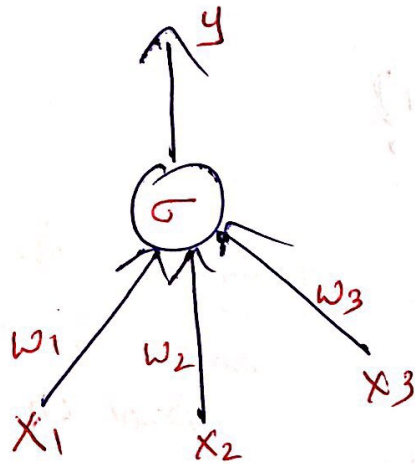


# Lecture - 2

## Part 1

### Biological Neuron



Layer 1  $\rightarrow$  Detect Edge & Corners

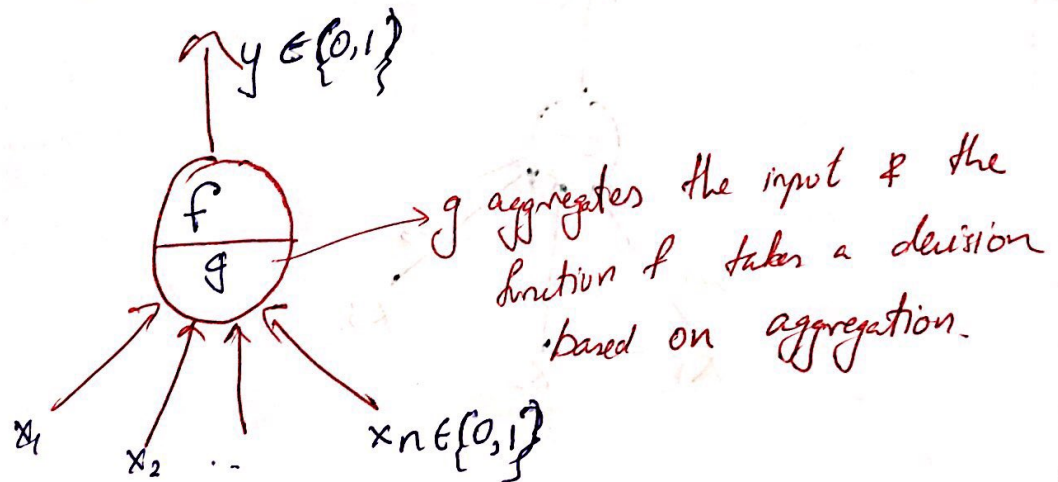
Layer 2  $\rightarrow$  Low Feature Groups

Layer 3  $\rightarrow$  detect high level features

Lecture - 2  
Episode - 2 {2.2}

## McCulloch Pitts Neuron

Highly simplified computation model

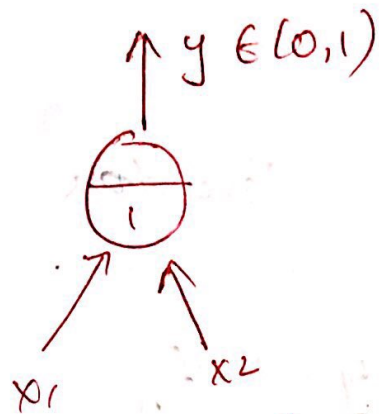


$$g(x_1, x_2, \dots, x_n) = g(x) = \sum_{i=1}^n x_i$$

$$y = \begin{cases} f(g(x)) = 1, & \text{if } g(x) \geq \theta \\ = 0, & \text{if } g(x) < \theta \end{cases}$$

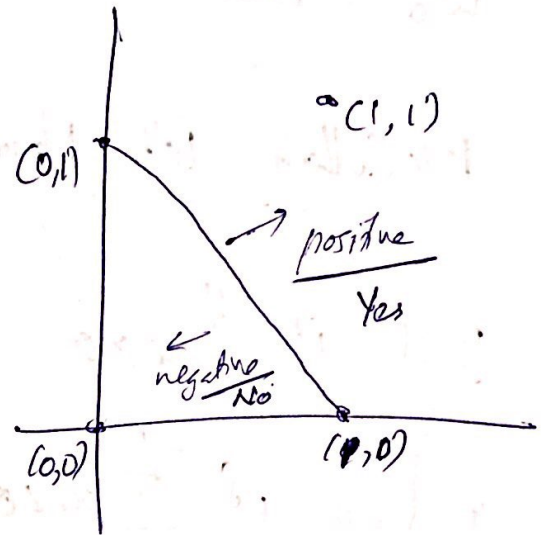
Thresholding  
Parameter

Thresholding Logic.



$$x_1 + x_2 = \sum_{i=1}^2 x_i \geq 1$$

$$x_1 + x_2 \geq 1 \quad (\text{line})$$

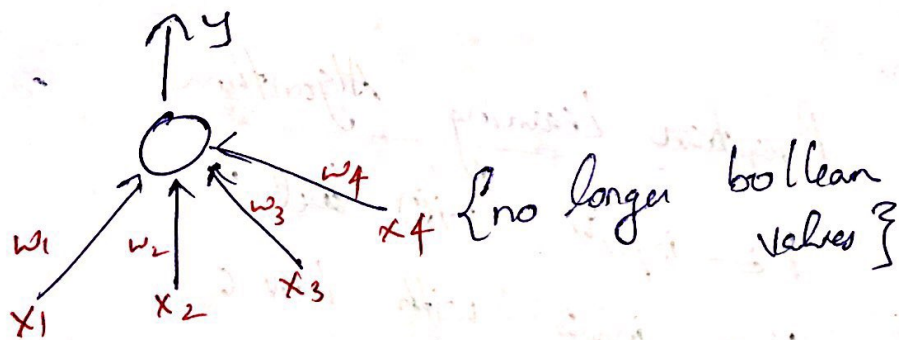


Lecture 2 {2.3}  
Episode-3

## Perceptrons

→ Non-Boolean (say, real) inputs?

1958, Frank Rosenblatt



$$y = 1 \quad \text{if} \quad \sum_{i=1}^n w_i x_i \geq \sigma$$

$$= 0 \quad \text{if} \quad \sum_{i=1}^n w_i x_i < \sigma$$

$w_0$  - bias.

McCulloch Pitts Neuron

$$y = \begin{cases} 1 & \text{if } \sum_{i=0}^n x_i \geq \theta \\ 0 & \text{if } \sum_{i=0}^n x_i < \theta \end{cases}$$

Perceptron

$$y = 1 \text{ if } \sum_{i=0}^n w_i x_i \geq \theta$$

$$= 0 \text{ if } \sum_{i=0}^n w_i x_i < \theta$$

Lecture 2  
Chapter 4

Error & Error Surfaces  
To minimise error.

Lecture 2  
Chapter 5

Perceptron Learning Algorithm

$P \leftarrow$  inputs with label 1

$N \leftarrow$  inputs with label 0

$W = [w_0, w_1, w_2, \dots, w_n]$  randomly;



while !convergence do

Pick random  $x \in P \cup N$ ;

if  $x \in P$  and  $\sum_{i=0}^n w_i x_i < 0$  (error)

$w = w + x$

end

if  $x \in N$  and  $\sum_{i=0}^n w_i x_i \geq 0$  then (true)

end

$w = w - x$

end

Convergence  
(no more errors)

Two vech

$$w = [w_0, w_1, \dots, w_n]$$

$$x = [x_0, \dots, x_n]$$

$$w \cdot x = w^T x = \sum_{i=0}^n w_i x_i$$

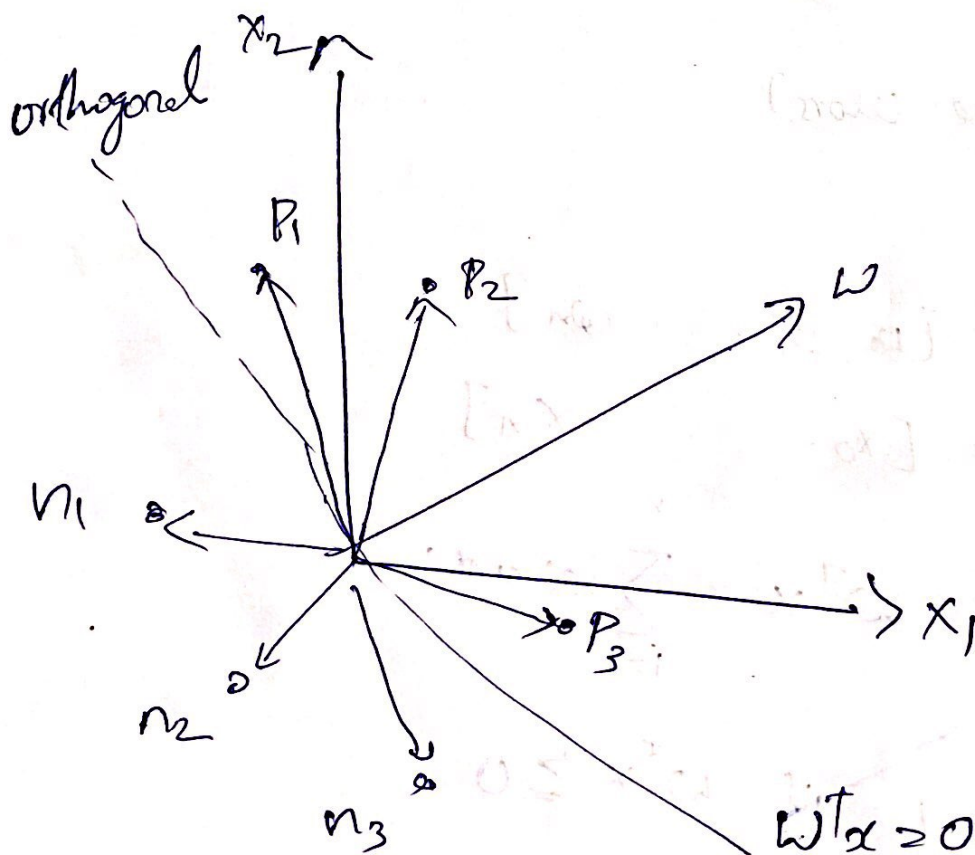
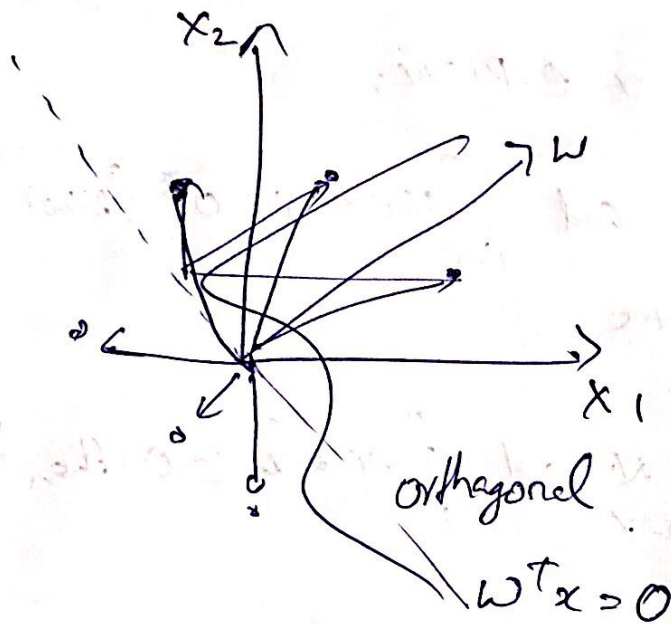
$$y = 1 \text{ if } w^T x \geq 0$$

$$0 \text{ if } w^T x < 0$$

$[w^T x = 0]$  line divides into.

(a) Angle b/w  $w$  &  $x$  should be  $90^\circ$

$$\cos(\alpha) = \frac{w^T x}{|w| |x|} = 0$$



~~(a) Angle of P~~

(Positive points)

(a) Angle of  $P_1, P_2, P_3 \leq 90$

(d) Angle of  $n_1, n_2, n_3 > 90$   
 (negative points)

$x \in P$  and  $w \cdot x < 0$  then

$$w = w + x$$

How this works !!

$$w_{\text{new}} = w + x.$$

$$\cos(\alpha_{\text{new}}) \propto w_{\text{new}}^T x$$

$$\propto (w + x)^T x$$

$$\propto w^T x + x^T x$$

$$\propto \cos \alpha + x^T x$$

$$\cos(\alpha_{\text{new}}) > \cos \alpha$$

$x \in N$  and  $w \cdot x \geq 0$ . then

$$w = w - x$$

$$\cos(\alpha_{\text{new}}) \propto w_{\text{new}}^T x$$

$$\propto (w - x)^T x$$

$$\propto w^T x - x^T x$$

$$\cos(\alpha_{\text{new}}) < \cos \alpha.$$

## Lecture-6

### Proof of Convergence of Perceptron Learning Algorithm

$P$  &  $N$  are finite & linearly separable, the perceptron learning algorithm updates the weights vector  $w \in$ , a finite number of times,

---

•  $x \in N$  then  $-x \in P$

$$(\because w^T x < 0 \Rightarrow w^T (-x) \geq 0)$$

•  $P' = P \cup N^-$ , for every element  
 $p \in P'$ ,  $w^T p \geq 0$

---

$P \leftarrow$  inputs label 1:

$N \leftarrow$  inputs label 0:

$N^- \leftarrow$  negations of  $N$

$P' \leftarrow P \cup N^-$

initialize  $w$  randomly



while ! convergence do

random  $p \in P'$ :

$$p \leftarrow \frac{p}{\|p\|}$$

if  $w \cdot p < 0$  then

$$w = w + p:$$

end

end

$w^*$   $\rightarrow$  solution vector

lecture-7 2.7

Linearly Separable Boolean Functions

$$(2^2)^n$$
$$(2^2)^3$$

2.8 Representation Power of Network of Perceptrons

