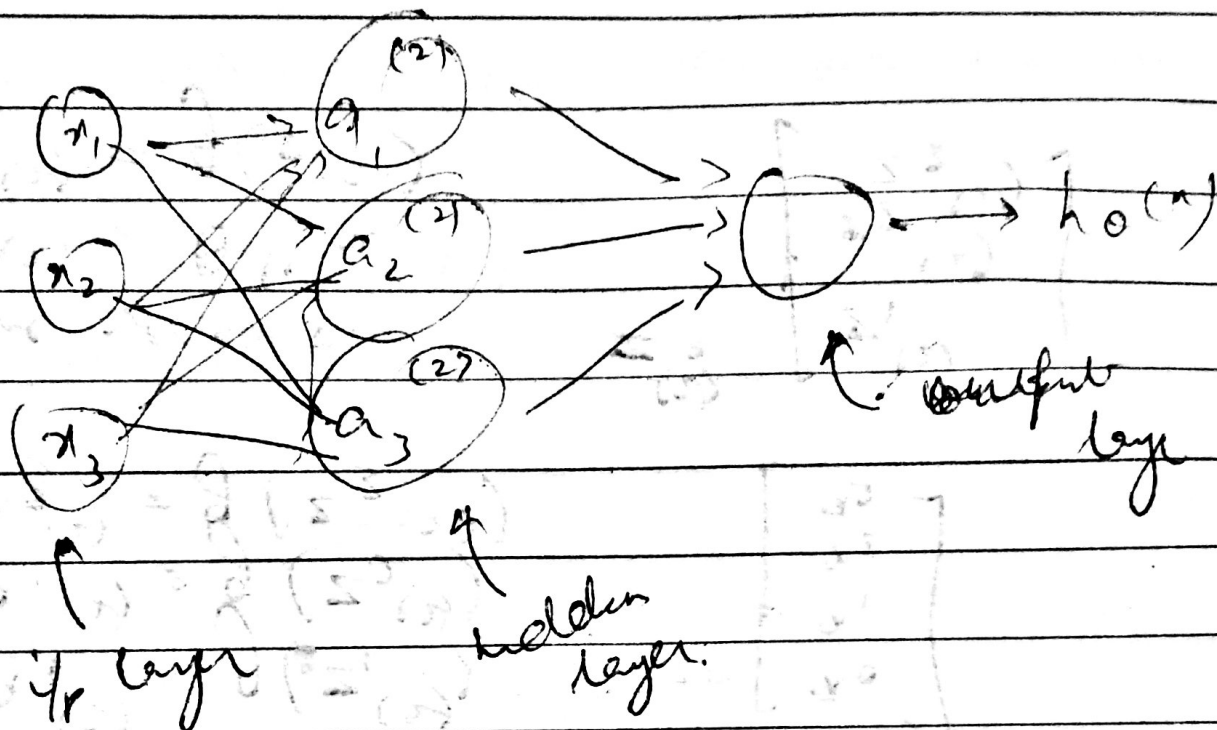


Week 4

Alberik.

Neural Network

these = parameters or weights



$a_i^{(j)}$ = activation of unit 'i' in layer 'j'

θ_j = matrix of weights controlling function mapping from layer j to layer j+1

$$a_1^{(2)} = g(\theta_{10}^{(1)} x_0 + \theta_{11}^{(1)} x_1 + \theta_{12}^{(1)} x_2 + \theta_{13}^{(1)} x_3)$$

$$a_2^{(2)} = g(\theta_{20}^{(1)} x_0 + \theta_{21}^{(1)} x_1 + \theta_{22}^{(1)} x_2 + \theta_{23}^{(1)} x_3)$$

$$a_3^{(2)} = g(\theta_{30}^{(1)} x_0 + \theta_{31}^{(1)} x_1 + \theta_{32}^{(1)} x_2 + \theta_{33}^{(1)} x_3)$$

$$h_o(n) = g(\theta_{h0}^{(2)} a_0^{(2)} + \theta_{h1}^{(2)} a_1^{(2)} + \theta_{h2}^{(2)} a_2^{(2)} + \theta_{h3}^{(2)} a_3^{(2)})$$

if network has s_j units in layer j ,
 s_{j+1} units in layer $j+1$, then
 $\theta^{(j)}$ will be of dimension
 $(s_{j+1} \times s_j)$

$$a_1^{(2)} = g(\theta_{10}^{(1)} x_0^{(1)} + \theta_{11}^{(1)} x_1^{(1)} + \theta_{12}^{(1)} x_2^{(1)} + \theta_{13}^{(1)} x_3^{(1)})$$

$$a_2^{(2)} = g(\theta_{20}^{(1)} x_0^{(1)} + \theta_{21}^{(1)} x_1^{(1)} + \theta_{22}^{(1)} x_2^{(1)} + \theta_{23}^{(1)} x_3^{(1)})$$

$$a_3^{(2)} = g(\theta_{30}^{(1)} x_0^{(1)} + \theta_{31}^{(1)} x_1^{(1)} + \theta_{32}^{(1)} x_2^{(1)} + \theta_{33}^{(1)} x_3^{(1)})$$

$$\therefore a_1^{(2)} = g(z_1^{(2)}) \quad \text{if } x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$a_2^{(2)} = g(z_2^{(2)})$$

$$a_3^{(2)} = g(z_3^{(2)})$$

Now, we vectorize

$$Z^{(2)} = \theta^{(1)} x$$

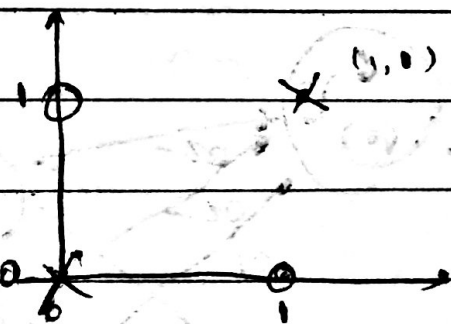
$$a^{(2)} = g(Z^{(2)})$$

$$Z^{(2)} = \begin{bmatrix} z_1^{(2)} \\ z_2^{(2)} \\ z_3^{(2)} \end{bmatrix}$$

That was forward propagation
because we got from i/p to o/p.

Neural Network learns its own features.

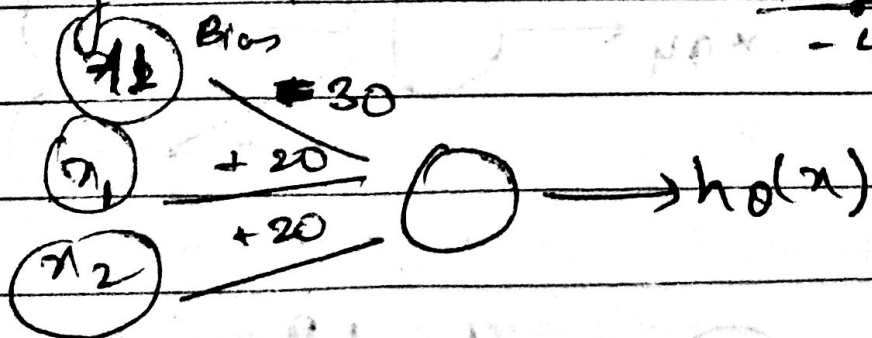
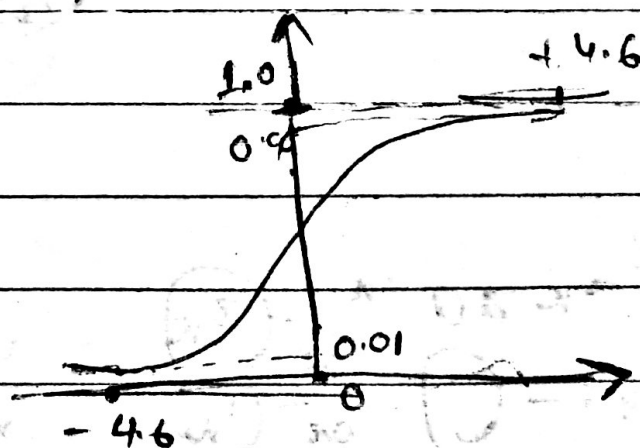
x_1, x_2 are binary
 $y = x_1 \text{ XOR } x_2$



Simple example: AND

$x_1, x_2 \in \{0, 1\}$

$y = x_1 \text{ AND } x_2$



$$h_0(x) = g(-30 + 20x_1 + 20x_2)$$

x_1	x_2	$h_0(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$