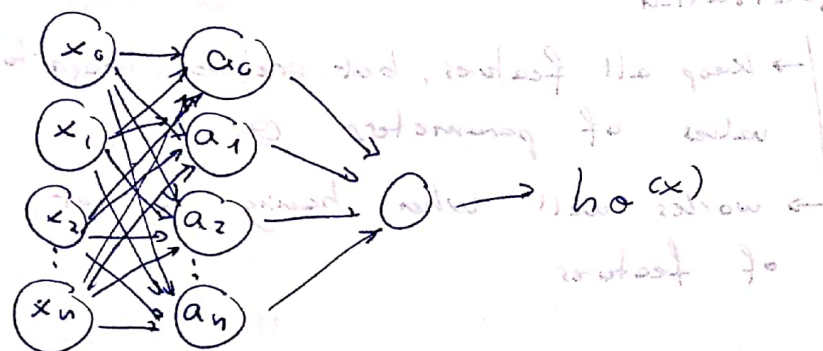
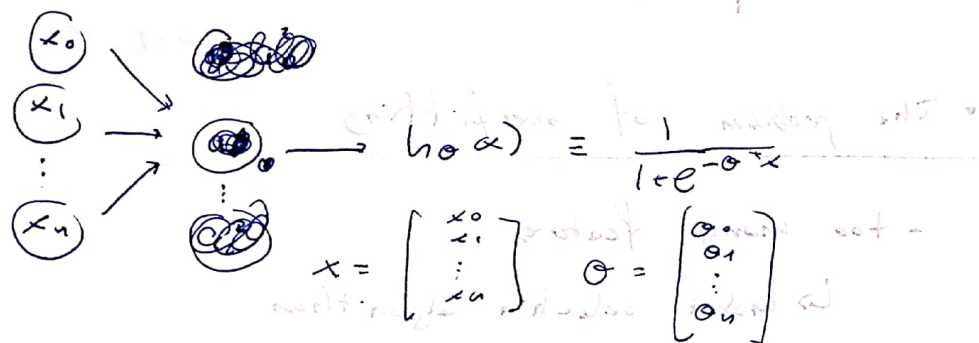


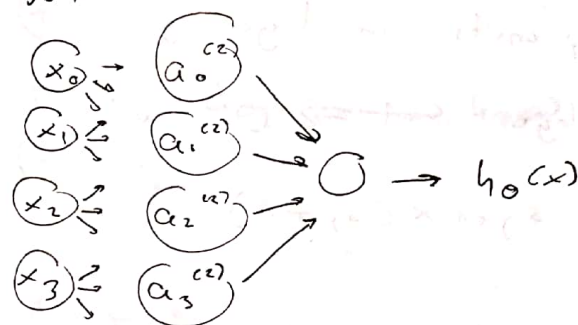
# NEURAL NETWORKS

## Logistic unit



page 20

NN



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

$\theta^{(j)}$  = matrix of weights controlling function mapping from layer  $j$  to layer  $j+1$

$$a_i^{(j)} = g(\theta_{i0}^{(j)} x_0 + \theta_{i1}^{(j)} x_1 + \theta_{i2}^{(j)} x_2 + \theta_{i3}^{(j)} x_3)$$

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

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

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

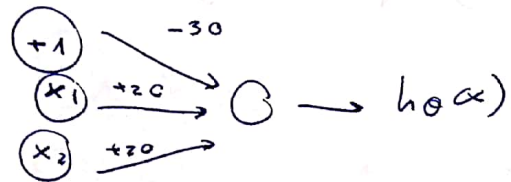
$$h_0(x) = a_1^{(3)} = g(\theta_{10}^{(3)} a_0^{(2)} + \theta_{11}^{(3)} a_1^{(2)} + \theta_{12}^{(3)} a_2^{(2)} + \theta_{13}^{(3)} a_3^{(2)})$$

If network has  $s_j$  units in layer  $j$ ,  
 $s_{j+1}$  units in layer  $j+1 \Rightarrow \Theta^j$  will  
 be of dimension  $s_{j+1} \times (s_j + 1)$

Simple example: AND

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

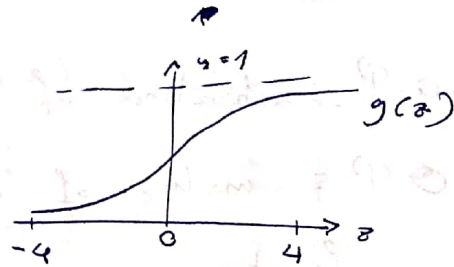
$$y = x_1 \text{ AND } x_2$$



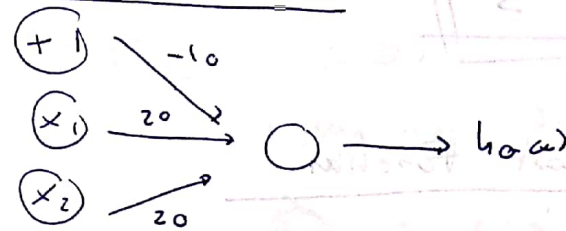
$$h(a) = g(\underbrace{-30}_{\Theta_{10}} + \underbrace{20}_{\Theta_{11}}x_1 + \underbrace{20}_{\Theta_{12}}x_2)$$

$x_1$	$x_2$	$h(a)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

$$h(a) \approx x_1 \text{ AND } x_2$$

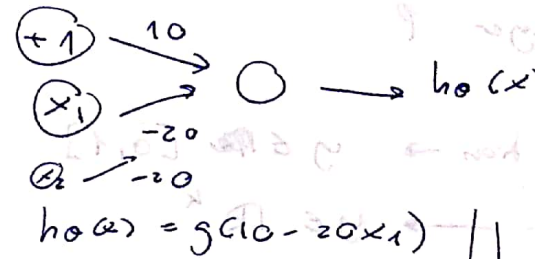


OR function



$x_1$	$x_2$	$h(a)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	$g(10) \approx 1$
1	1	$g(20) \approx 1$

Negation



$x_1$	$h(a)$
0	$g(10) \approx 1$
1	$g(-10) \approx 0$

$$h(a) = g(10 - 20x_1)$$

NOT  $x_1$  AND NOT  $x_2$

$$= 1 \Leftrightarrow x_1, x_2 = 0$$

"I need more info about this"

Week 5

## Neural network Cost Function

$L \equiv$  no. of layers in neural network

$s_l \equiv$  no. of units (without counting bias unit) in layer  $l$

- Binary classification  $\rightarrow y \in [0, 1]$

- Multiclass class  $\rightarrow y \in \mathbb{R}^k$

Logistic regression

$$J(\theta) = -\frac{1}{m} \left[ \sum_{i=1}^m y^{(i)} \log h_{\theta}(x^{(i)}) \right]$$

$h_{\theta}(x) \in \mathbb{R}^k ; (h_{\theta}(x))_i =$

Neural network

$$J(\theta) = -\frac{1}{m} \left[ \sum_{i=1}^m \sum_{k=1}^K y_k^i \log (h_{\theta}(x^{(i)}))_k \right]$$

• steps

1.  $J(\theta)$

• Minimize  $J(\theta)$

$$\Rightarrow \frac{\partial}{\partial \theta_j} J(\theta)$$

$$+ \left[ (1 - y^{(i)}) \log (1 - h_{\theta}(x^{(i)})) \right] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$

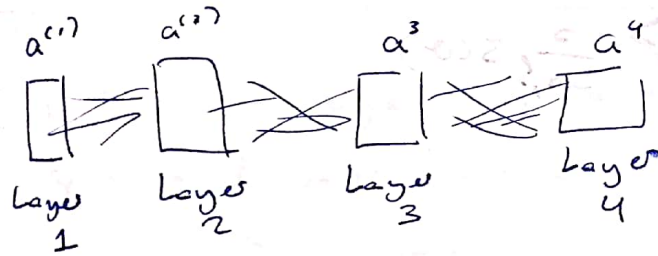
$i$ th output

$$+ \left[ (1 - y_k^{(i)}) \log (1 - h_{\theta}(x^{(i)}))_k \right] + \frac{\lambda}{2m} \sum_{l=1}^{L-1} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} \theta_{j,l}^2$$



## • Gradient computation

$(x, y) \equiv$  training example



$$\begin{cases} a^1 = x \\ z^2 = \Theta^1 a^1 \\ a^2 = g(z^2) \end{cases} \text{ add } a_0^2$$

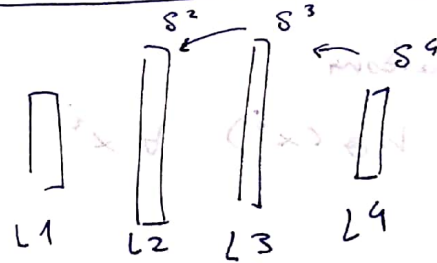
$$\begin{cases} z^3 = \Theta^2 a^2 \\ a^3 = g(z^3) \end{cases} \text{ add } a_0^3$$

$$\begin{cases} z^4 = \Theta^3 a^3 \\ a^4 = h(x) = g(z^4) \end{cases}$$

$$\begin{cases} z^l = a^{l-1} a^{l-1} \\ a^l = g(z^l) \end{cases}$$

## • Backpropagation

$$s_j^l = a_j^l - y_j$$



$$s_j^4 = a_j^4 - y_j$$

$$s_j^3 = (\Theta^3)^T s^4 \cdot g'(z^3)$$

$$s_j^2 = (\Theta^2)^T s^3 \cdot g'(z^2)$$

$$g'(z^l) \approx a^l(1 - a^l)$$

## • Pseudo algorithm

- Training set  $\rightarrow \{(x^1, y^1), \dots, (x^m, y^m)\}$

-  $\Delta_{ij}^l = 0 \quad \forall i, j, l$

- For  $i = 1, m$

$$a^l = x^i$$

Forward prop for  $a^l, l = 2, 3, \dots, L$

$$\text{Compute } s^L = a^L - y^i$$

$$\text{Compute } s^{L-1}, s^{L-2}, \dots, s^2$$

$$\Delta_{ij}^l := \Delta_{ij}^l + a_j^l s_{i+1}^{l+1} \rightarrow s_{i+1}^{l+1} a_j^{l+1 T}$$

$$D_{ij}^l := \frac{1}{m} \Delta_{ij}^l + \lambda \Theta_{ij}^l \text{ if } j \neq 0 \quad \left\| \frac{\partial}{\partial \Theta_{ij}^l} J(\Theta) = D_{ij}^l \right.$$

$$D_{ij}^l := \frac{1}{m} \Delta_{ij}^l \text{ if } j = 0$$

## Training a Neural Network

- 1 - Initialize weights random
- 2 - Forward prop to get  $h_{\theta}(x^i)$  &  $x^i$
- 3 - Cost function  $J(\theta)$
- 4 - Backprop to get  $\frac{\partial}{\partial \theta_{jk}} J(\theta)$
- 5 - Gradient checking to compare this with a numerical estimation of  $\nabla J(\theta)$
- 6 - Disable 5
- 7 - Gradient descent or other algorithm with backprop to minimize  $J(\theta)$