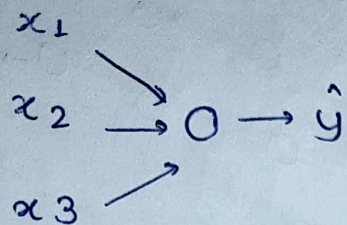
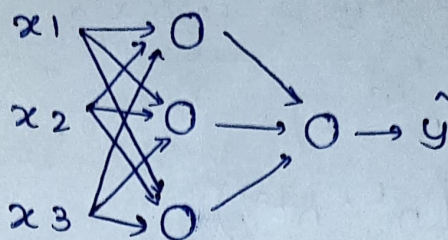


DEEP NEURAL NETWORK (L layered)



Logistic \rightarrow 1 Layer
Regression NN
[SHALLOW]



1 hidden layer
(NN) \rightarrow 2 Layer
[DEEP]

* 4 layer NN = 3 hidden layers

No. of nodes: Layer 1 = 5

Layer 2 = 5

Layer 3 = 3

Layer 4 = 1

Layers = L (4)
No. of nodes in layer l = $n^{[l]}$

$$\therefore n^{[1]} = 5 ; n^{[2]} = 5 ; n^{[3]} = 3 ; n^{[4]} = 1 \text{ \& } n^{[0]} = 3$$

$$\underline{n^{[1]} = n^{[4]} = 1}$$

$q^{[l]}$ = activations of layer l . $\Rightarrow q^{[l]} = g^{[l]}(z^{[l]})$
$w^{[l]}$ = weights for $z^{[l]}$
$b^{[l]}$ = biases.

FORWARD PROPAGATION

$$z^{[1]} = w^{[1]}x + b^{[1]}$$

$$q^{[1]} = g^{[1]}(z^{[1]})$$

$$z^{[2]} = w^{[2]}q^{[1]} + b^{[2]}$$

$$q^{[2]} = g^{[2]}(z^{[2]})$$

\vdots

$$z^{[4]} = w^{[4]}q^{[3]} + b^{[4]}$$

$$q^{[4]} = \hat{y} = g^{[4]}(z^{[4]})$$

vectorized

$$Z^{[1]} = W^{[1]}X + b^{[1]}$$

$$A^{[1]} = g^{[1]}(Z^{[1]})$$

$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]} \text{ here}$$

$$A^{[2]} = g^{[2]}(Z^{[2]})$$

\vdots

$$\hat{y} = A^{[4]} = g^{[4]}(Z^{[4]})$$

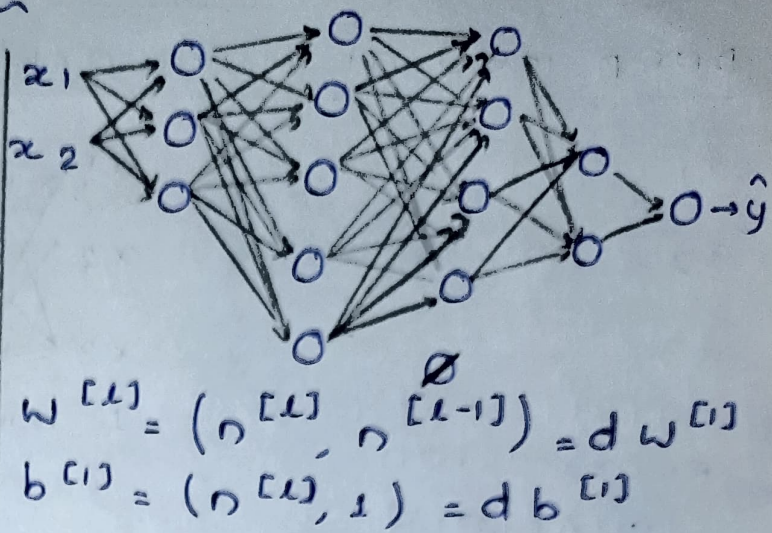
for $l=1$ to L

$L=4$

MATRIX DIMENSIONS

$$\begin{aligned}
 L &= 5 \\
 n^{[1]} &= 3 \\
 n^{[2]} &= 5 \\
 n^{[3]} &= 4 \\
 n^{[4]} &= 2 \\
 n^{[5]} &= 1
 \end{aligned}$$

$$\begin{aligned}
 z^{[1]} &= w^{[1]}x + b^{[1]} \\
 (3,1) &= (3,2)(2,1) + (3,1) \\
 z^{[l]} &= (n^{[l]}, 1) \\
 w^{[l]} &= (n^{[l]}, n^{[l-1]}) \\
 x &= (n^{[0]}, 1) \\
 b &= (n^{[1]}, 1)
 \end{aligned}$$



* vectorized

$$\begin{aligned}
 z^{[l]} &= w^{[l]}x + b^{[l]} \\
 (n^{[l]}, m) & \quad (n^{[l-1]}, m) \quad (n^{[l]}, 1) \xrightarrow{\text{broadcast}} (n^{[l]}, m)
 \end{aligned}$$

$$\begin{aligned}
 z^{[l]}, A^{[l]} : (n^{[l]}, m) &= d z^{[l]}, d A^{[l]} \\
 \text{when } l=0 \quad A^{[0]} &= x = (n^{[0]}, m)
 \end{aligned}$$

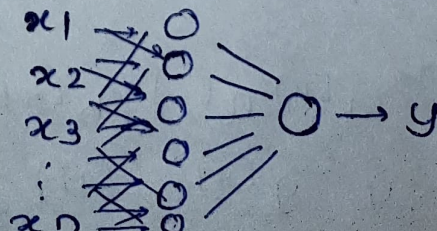
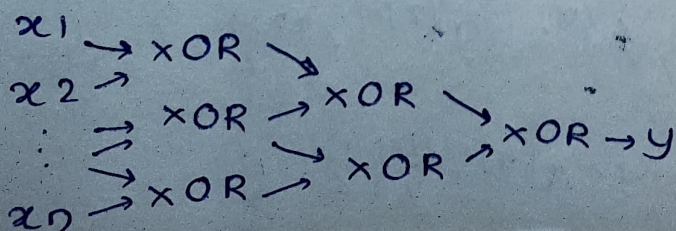
• Deep Network Importance

As we progress through layers of networks, the features detected go from simple to complex.

eg: $y = x_1 \text{ XOR } x_2 \text{ XOR } \dots \text{ XOR } x_n$ (LOGICAL)

Deep network [log₂] layers

one hidden layer $[2^{n-1}]$ nodes



FORWARD & BACKWARD PROPAGATION

Layer l : $w^{[l]}, b^{[l]}$

→ Forward : input $a^{[l-1]}$, output $a^{[l]}$

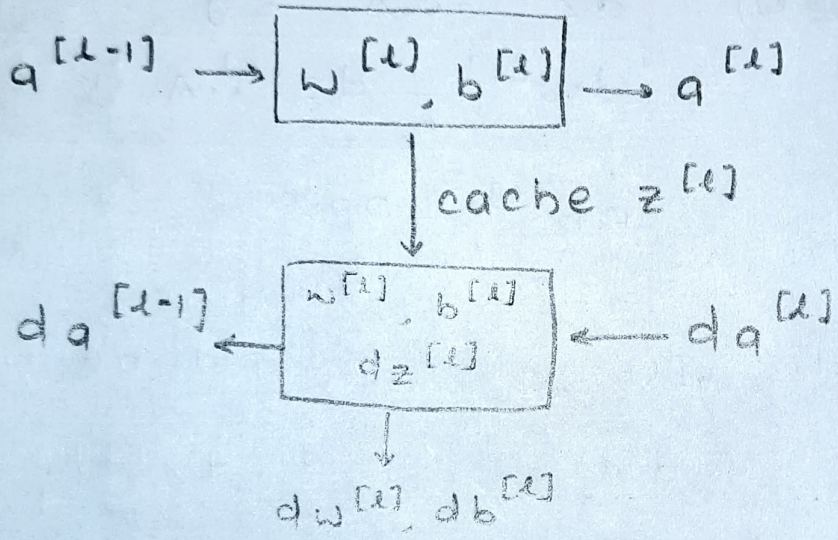
$$z^{[l]} = w^{[l]} a^{[l-1]} + b^{[l]}, \text{ cache } z^{[l]}$$

$$a^{[l]} = g^{[l]}(z^{[l]})$$

→ Backward : input $da^{[l]}$, output $da^{[l-1]}$

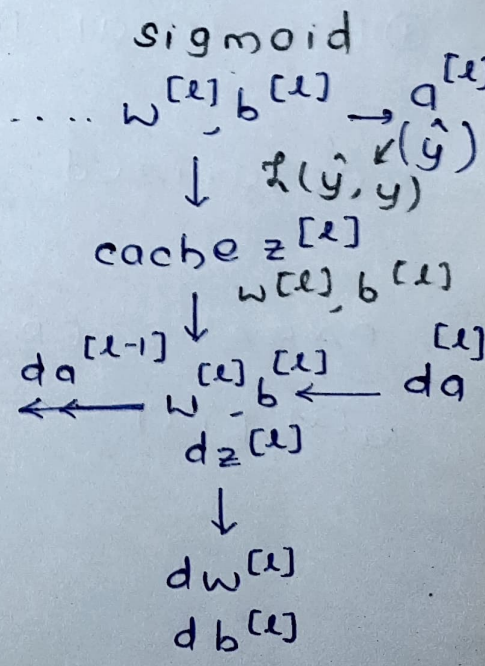
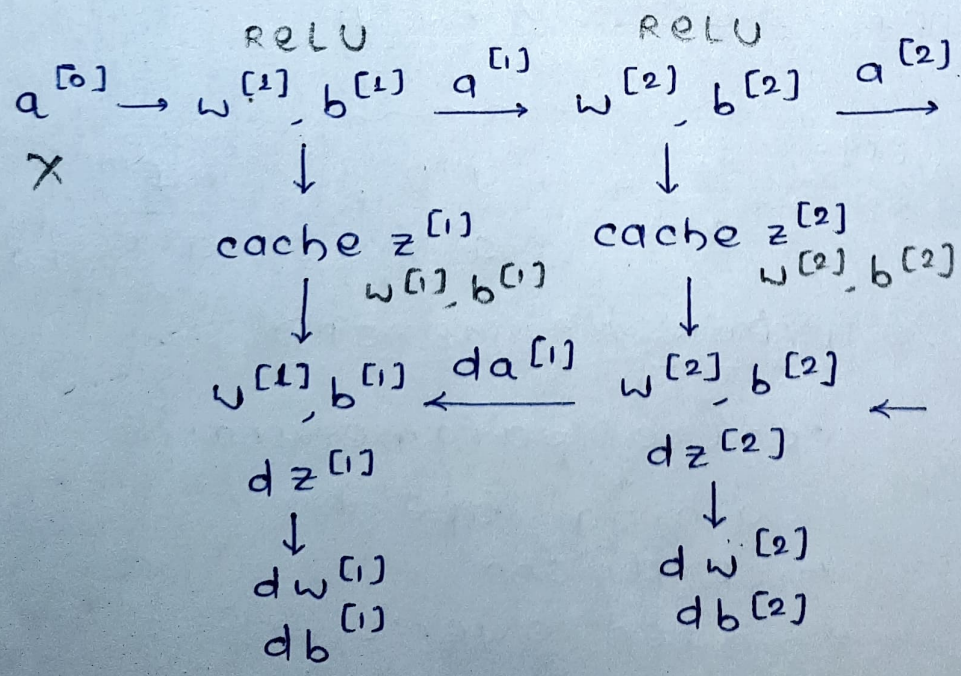
~~cache~~ cache $z^{[l]}$ $dw^{[l]}$
 $db^{[l]}$

layer l



cache

↓
passes info from forward to back propagation step.



$$\Rightarrow w^{[l]} := w^{[l]} - \alpha dw^{[l]}$$

$$\Rightarrow b^{[l]} := b^{[l]} - \alpha db^{[l]}$$

• FORWARD PROPAGATION FOR LAYER l

Input: $a^{[l-1]}$

output: $a^{[l]}$, cache ($z^{[l]}$)

VECTORIZED

$$z^{[l]} = W^{[l]} \cdot A^{[l-1]} + b^{[l]}$$

$$A^{[l]} = g^{[l]}(z^{[l]})$$

• BACKWARD PROPAGATION FOR LAYER l

Input: $da^{[l]}$

output: $da^{[l-1]}$, $dW^{[l]}$, $db^{[l]}$

VECTORIZED

$$dz^{[l]} = da^{[l]} * g^{[l]'}(z^{[l]})$$

$$dW^{[l]} = dz^{[l]} \cdot a^{[l-1]T}$$

$$db^{[l]} = dz^{[l]}$$

$$da^{[l-1]} = W^{[l]T} \cdot dz^{[l]}$$

$$dz^{[l]} = W^{[l+1]T} dz^{[l+1]} * g^{[l]'}(z^{[l]})$$

$$dz^{[l]} = dA^{[l]} * g^{[l]'}(z^{[l]})$$

$$dW^{[l]} = \frac{1}{m} dz^{[l]} \cdot A^{[l-1]T}$$

$$db^{[l]} = \frac{1}{m} \text{np.sum}$$

($dz^{[l]}$, axis=1, keepdims=True)

$$dA^{[l-1]} = W^{[l]T} \cdot dz^{[l]}$$

⊛ For final layer: $da^{[L]} = \frac{-y}{a} + \frac{(1-y)}{(1-a)}$

vectorized: $dA^{[L]} = \frac{-y^{(1)}}{a^{(1)}} + \frac{(1-y^{(1)})}{(1-a^{(1)})} + \dots + \frac{-y^{(m)}}{a^{(m)}} + \frac{(1-y^{(m)})}{(1-a^{(m)})}$

• PARAMETERS & HYPERPARAMETERS

$W^{[l]}$, $b^{[l]}$

↓
control parameters

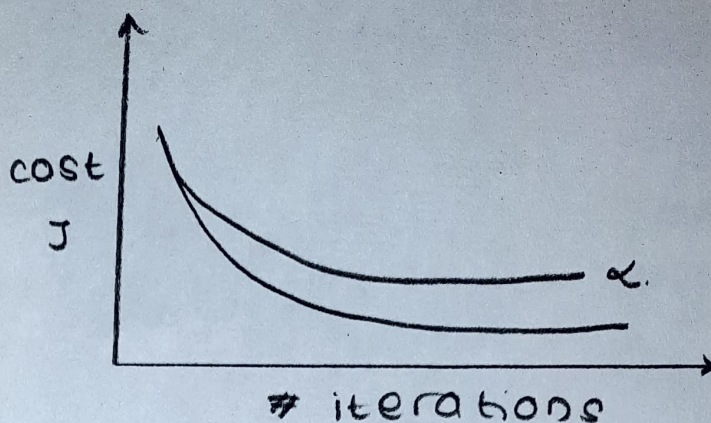
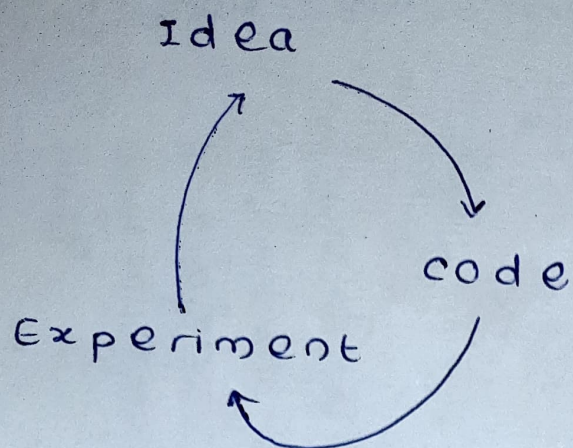
↓
Learning rate (α)

iterations

hidden layer L

hidden units $n^{[1]}$, $n^{[2]}$, ...

choice of activation function



IMP

$$dz^{[L]} = A^{[L]} - y$$

$$dw^{[L]} = \frac{1}{m} dz^{[L]} A^{[L-1]T}$$

$$db^{[L]} = \frac{1}{m} np.sum(dz^{[L]}, axis=1, keepdims=True)$$

$$dz^{[L-1]} = w^{[L]T} dz^{[L]} \otimes g'^{[L-1]}(z^{[L-1]})$$

element wise multiplication

$$\therefore dz^{[1]} = A^{[1]} - y$$

$$dw^{[1]} = \frac{1}{m} dz^{[1]} \underbrace{A^{[0]T}}_{X^T}$$

$$A^{[0]T} = X^T$$

$$db^{[1]} = \frac{1}{m} np.sum(dz^{[1]}, axis=1, keepdims=True)$$