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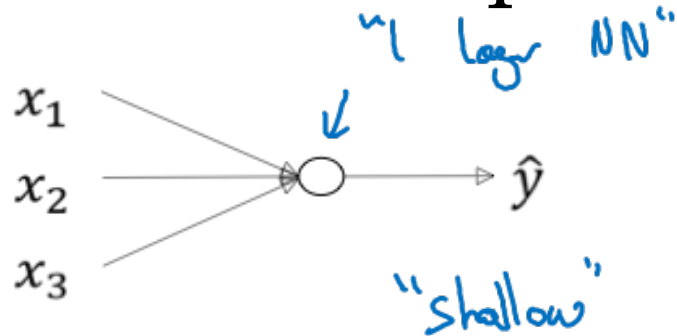
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# Deep Neural Networks

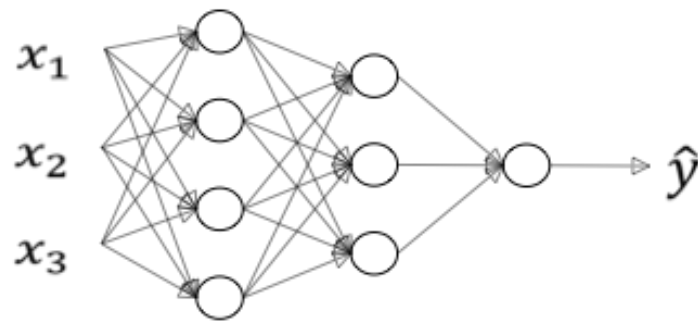
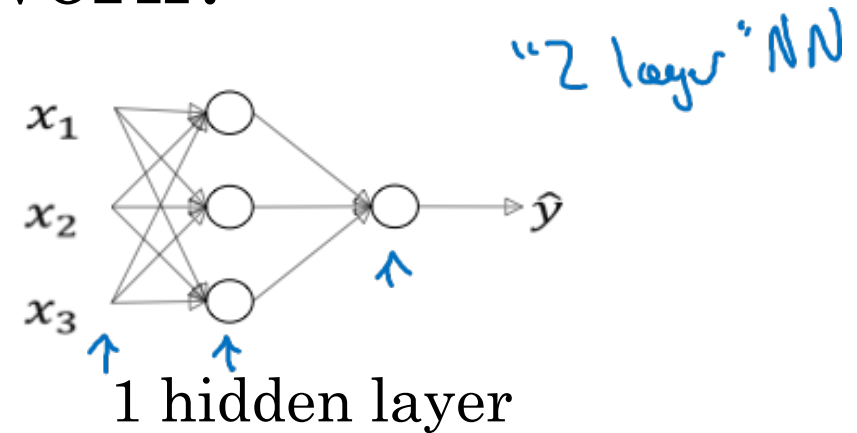
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Deep L-layer  
Neural network

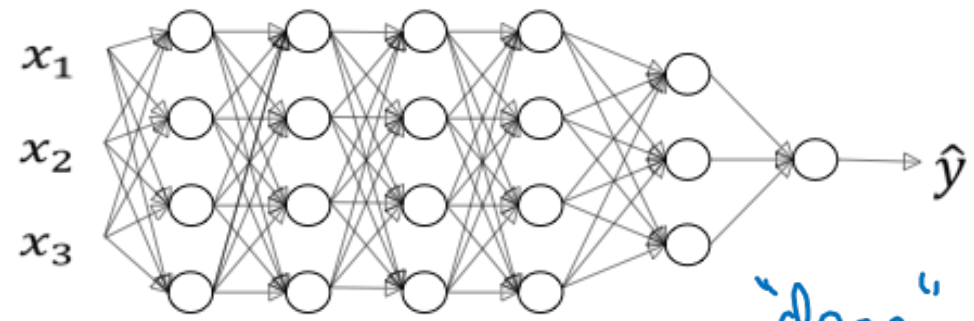
# What is a deep neural network?



logistic regression



2 hidden layers

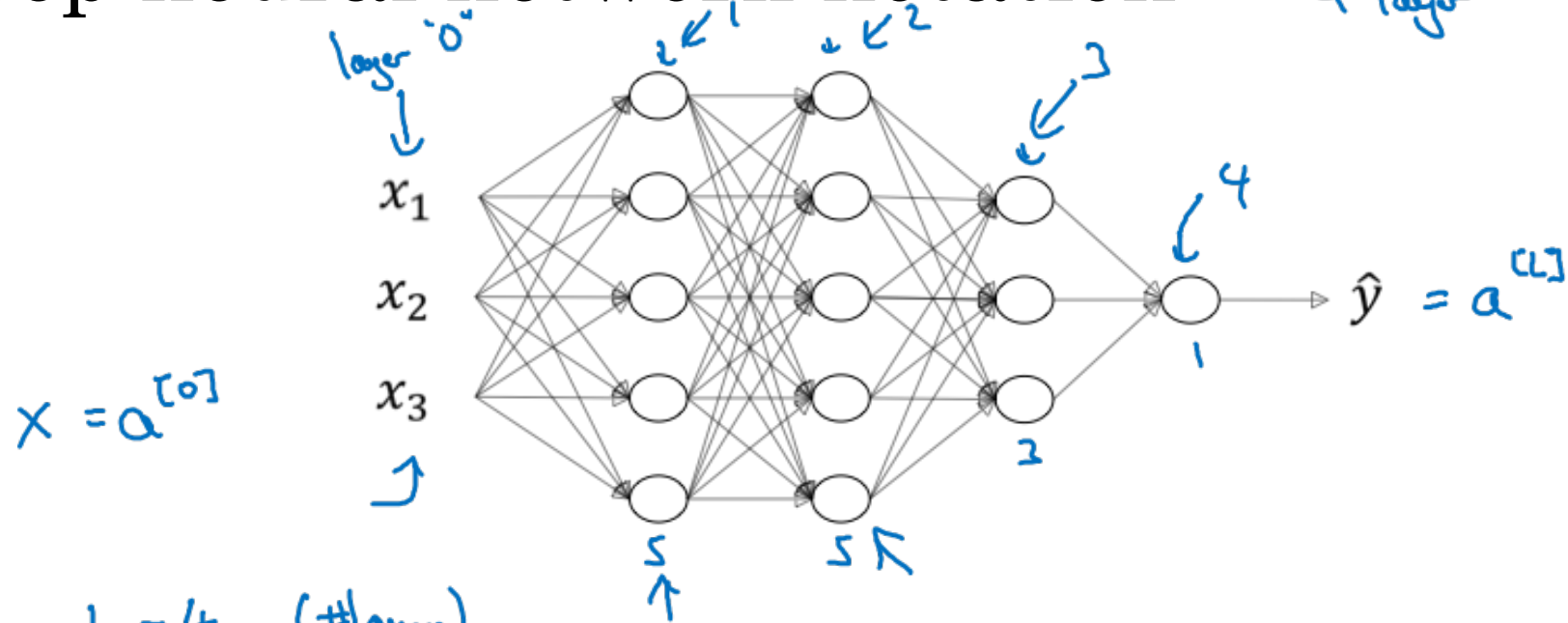


5 hidden layers

"deep"

# Deep neural network notation

4 layer NN



$L = 4$  (#layers)

$n^{[l]} = \# \text{units in layer } l$

$a^{[l]} = \text{activations in layer } l$

$a^{[l]} = g(z^{[l]})$ ,  $w_{\delta a}^{[l]} = \text{weights for } \underline{z^{[l]}}$

$n^{[1]} = 5, n^{[2]} = 5, n^{[3]} = 3, n^{[4]} = n^{[L]} = 1$   
 $n^{[0]} = n_x = 3$



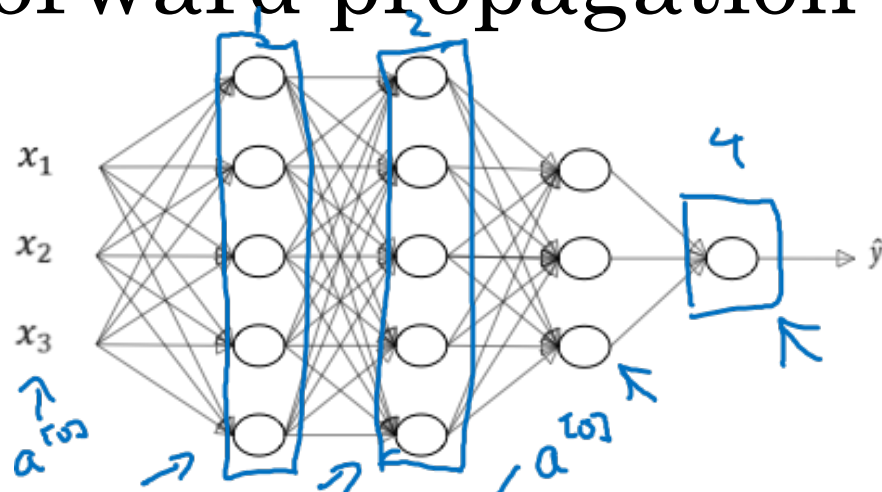
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# Deep Neural Networks

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## Forward Propagation in a Deep Network

# Forward propagation in a deep network



$$\begin{aligned} z^{[l]} &= W^{[l]} A^{[l-1]} + b^{[l]} \\ A^{[l]} &= g^{[l]}(z^{[l]}) \end{aligned}$$

Handwritten note:  $A^{[0]} = X$

$$X : z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$$

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

$$z^{[2]} = W^{[2]} a^{[1]} + b^{[2]}$$

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

$$z^{[4]} = W^{[4]} a^{[3]} + b^{[4]}, a^{[4]} = g^{[4]}(z^{[4]}) = \hat{y}$$

$$\begin{bmatrix} z^{[1]}_1 & z^{[1]}_2 & \dots & z^{[1]}_n \\ z^{[2]}_1 & z^{[2]}_2 & \dots & z^{[2]}_n \\ \vdots & \vdots & \ddots & \vdots \\ z^{[4]}_1 & z^{[4]}_2 & \dots & z^{[4]}_n \end{bmatrix}$$

Vertical:

$$\begin{aligned} z^{[l]} &= W^{[l]} A^{[l-1]} + b^{[l]} \\ A^{[l]} &= g^{[l]}(z^{[l]}) \end{aligned}$$

for  $l=1 \dots 4$

Handwritten note:  $X = A^{[0]}$

Handwritten note:  $\hat{y} = g(z^{[4]}) = A^{[4]}$



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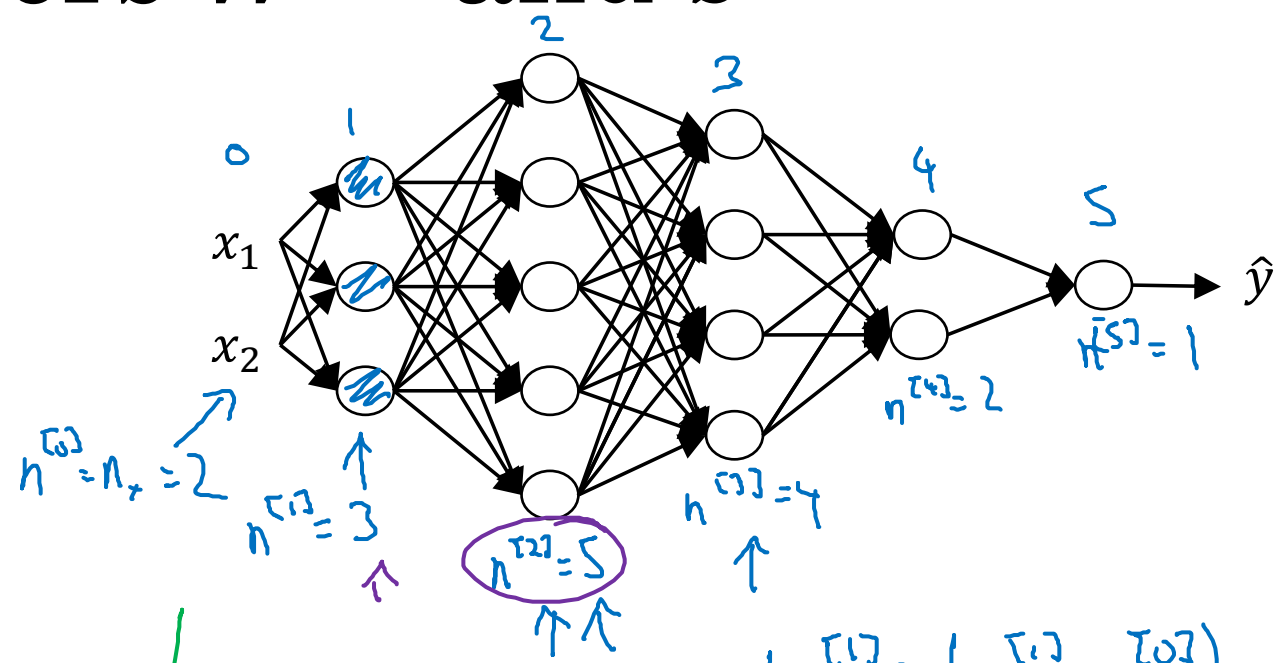
# Deep Neural Networks

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Getting your matrix  
dimensions right

# Parameters $W^{[l]}$ and $b^{[l]}$

$\downarrow$   
 $z^{[L]} = g^{[L]}(a^{[L]})$   
 $\uparrow$   
 $\downarrow$   
 $a^{[L]}$



$L=5$

$\rightarrow W^{[L]}: (n^{[L]}, n^{[L-1]})$   
 $\rightarrow b^{[L]}: (n^{[L]}, 1)$   
 $\rightarrow \Delta W^{[L]}: (n^{[L]}, n^{[L-1]})$   
 $\rightarrow \Delta b^{[L]}: (n^{[L]}, 1)$

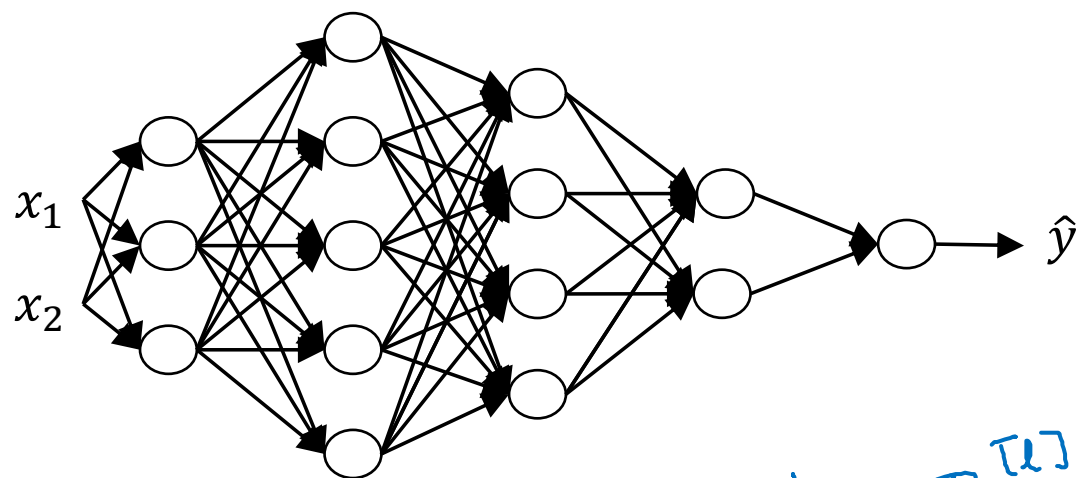
$\downarrow$   
 $z^{[1]} = \boxed{W^{[1]} \cdot x} + \boxed{b^{[1]}}$   
 $(3,1) \leftarrow (3,2) \quad (2,1)$   
 $(n^{[1]}, 1) \quad (n^{[1]}, n^{[0]}) \quad (n^{[0]}, 1)$   
 $(3,1)$   
 $(n^{[1]}, 1)$

$\begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix} = \begin{bmatrix} \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \end{bmatrix} \begin{bmatrix} \cdot \\ \cdot \end{bmatrix}$

$W^{[1]}: (n^{[1]}, n^{[0]})$   
 $W^{[2]}: (5, 3) \quad (n^{[2]}, n^{[1]})$   
 $z^{[2]} = \boxed{W^{[2]} \cdot a^{[1]}} + \boxed{b^{[2]}}$   
 $\uparrow \quad \uparrow \quad \uparrow$   
 $\rightarrow (5,1) \quad (5,3) \quad (3,1)$   
 $(5,1)$   
 $(n^{[2]}, 1)$   
 $W^{[3]}: (4, 5)$   
 $W^{[4]}: (2, 4)$ ,  $W^{[5]}: (1, 2)$



# Vectorized implementation



$$z^{[1]} = W^{[1]} \cdot x + b^{[1]}$$

$(n^{[1]}, 1)$      $(n^{[1]}, n^{[0]})$      $(n^{[0]}, 1)$      $(n^{[1]}, 1)$

$$[z^{[1](1)} \ z^{[1](2)} \ \dots \ z^{[1](m)}]$$

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

$(n^{[1]}, m)$      $(n^{[1]}, n^{[0]})$      $(n^{[0]}, m)$      $(n^{[1]}, 1)$   
 $\uparrow$      $\uparrow$      $(n^{[0]}, m)$      $(n^{[1]}, m)$

$$z^{[L]}, a^{[L]} : (n^{[L]}, 1)$$

$$Z^{[L]}, A^{[L]} : (n^{[L]}, m)$$

$$l=0 \quad A^{[0]} = X = (n^{[0]}, m)$$

$$dZ^{[L]}, dA^{[L]} : (n^{[L]}, m)$$



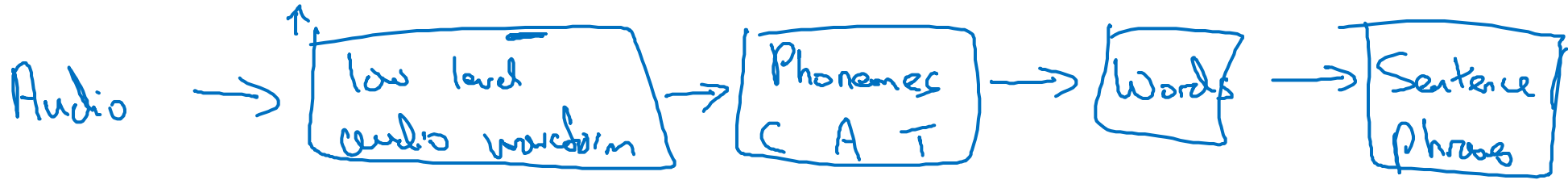
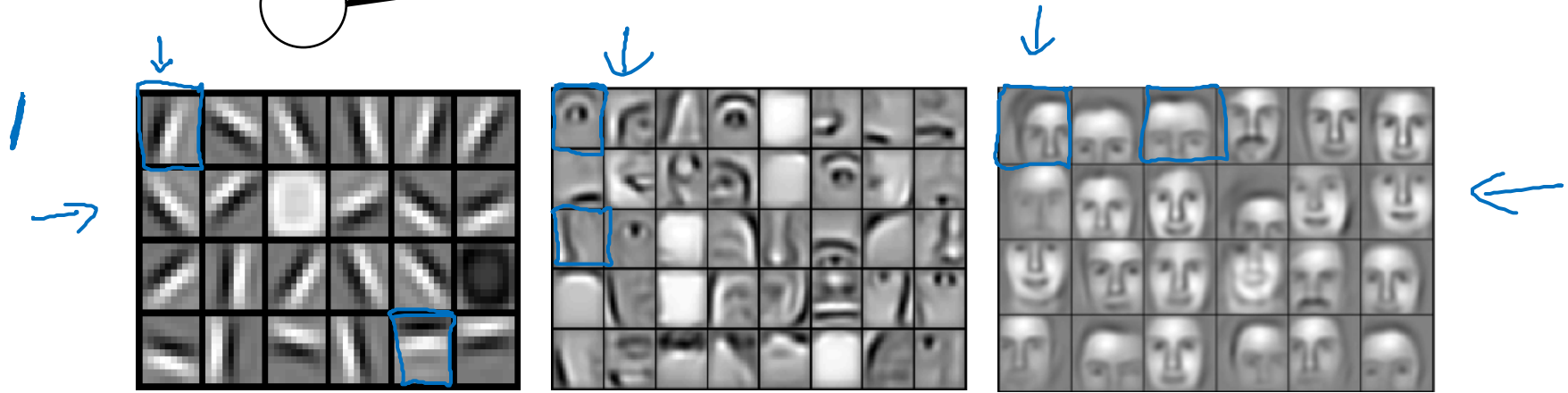
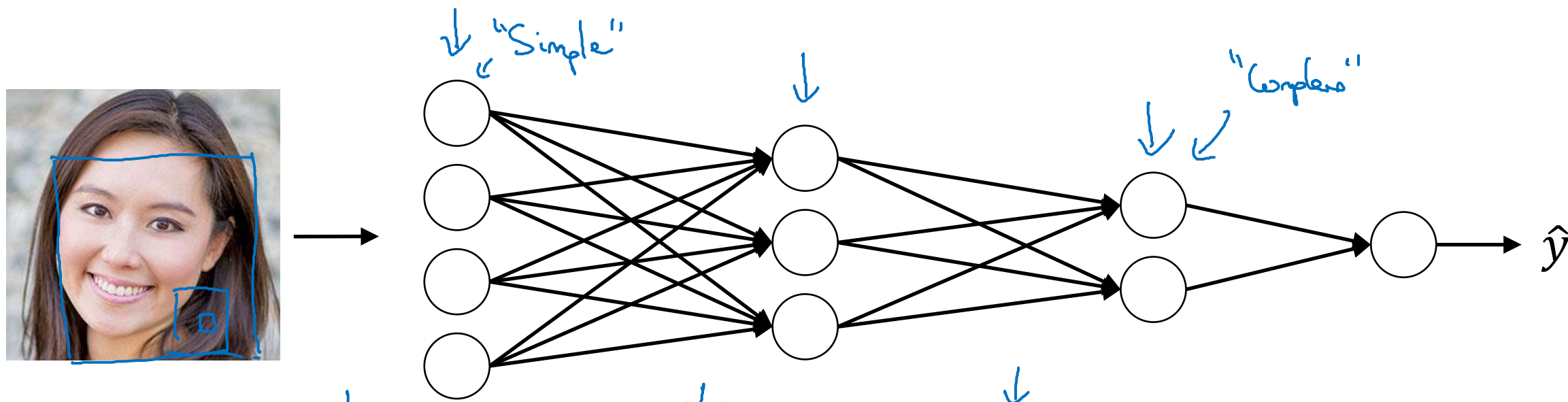
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# Deep Neural Networks

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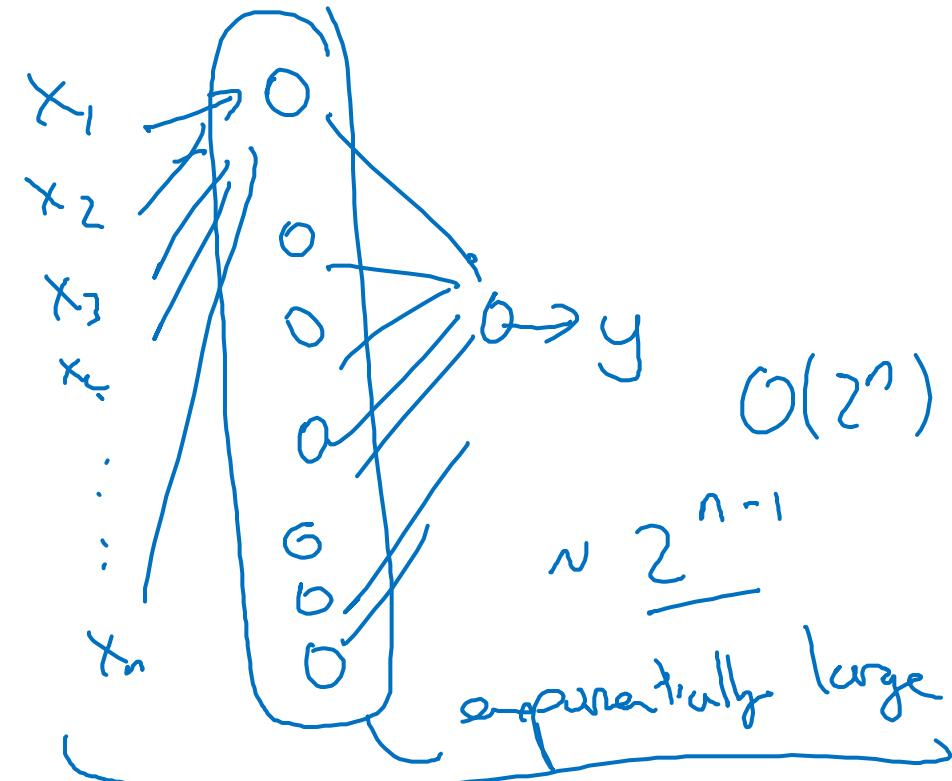
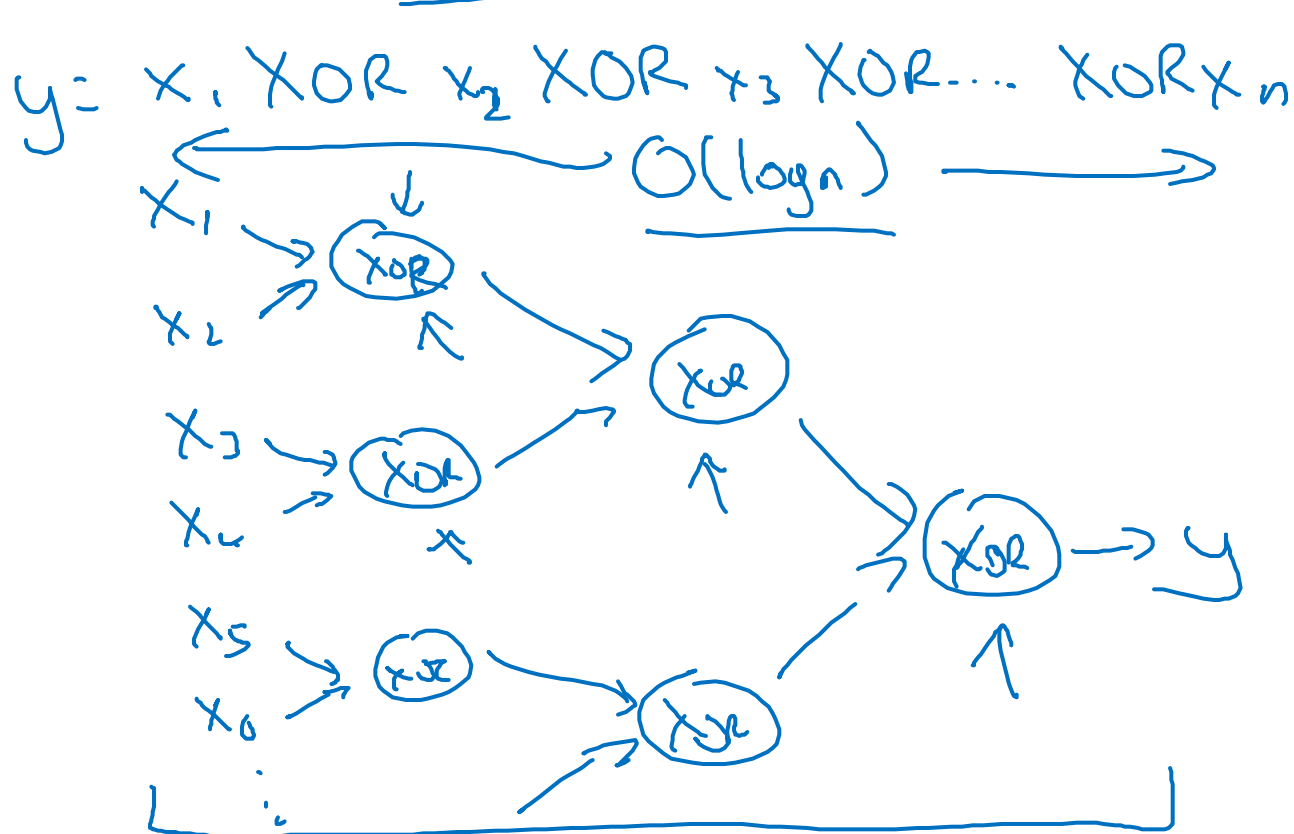
Why deep  
representations?

# Intuition about deep representation



# Circuit theory and deep learning

Informally: There are functions you can compute with a “small” L-layer deep neural network that shallower networks require exponentially more hidden units to compute.





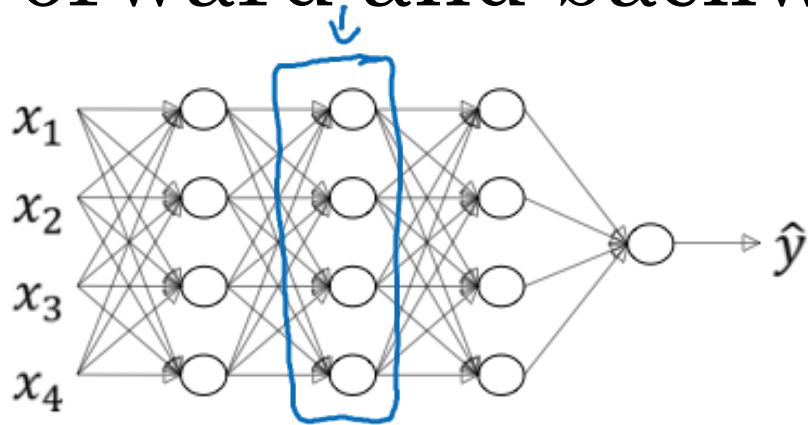
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# Deep Neural Networks

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Building blocks of  
deep neural networks

# Forward and backward functions



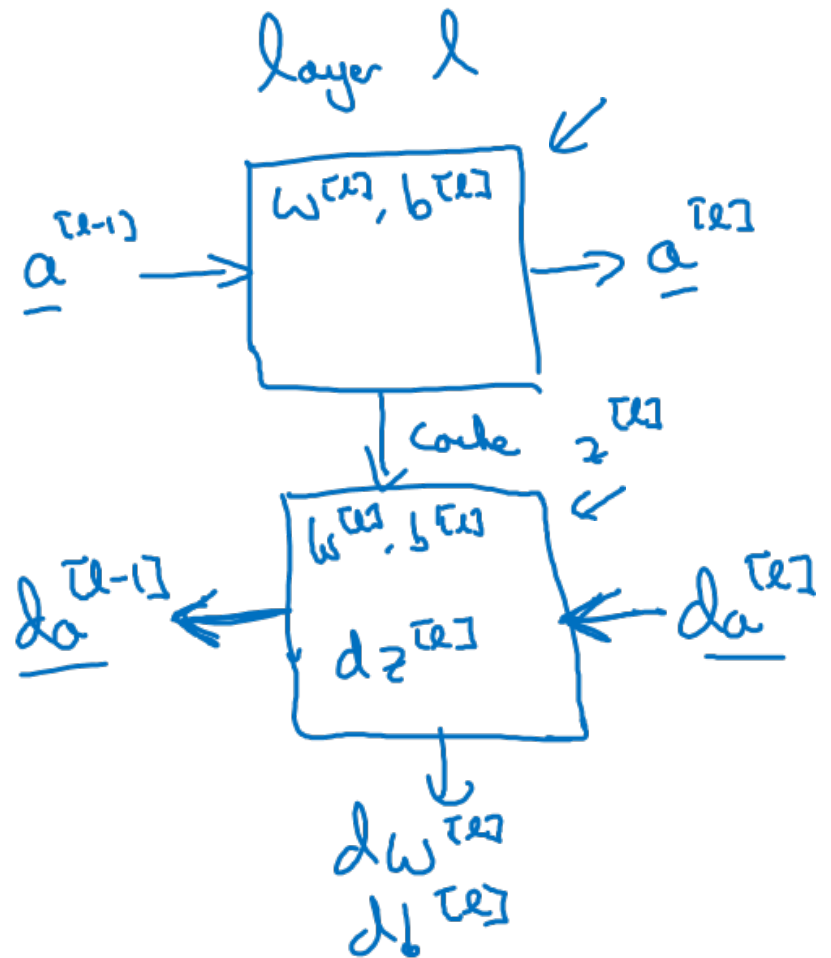
layer  $l$ :  $W^{[l]}, b^{[l]}$

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

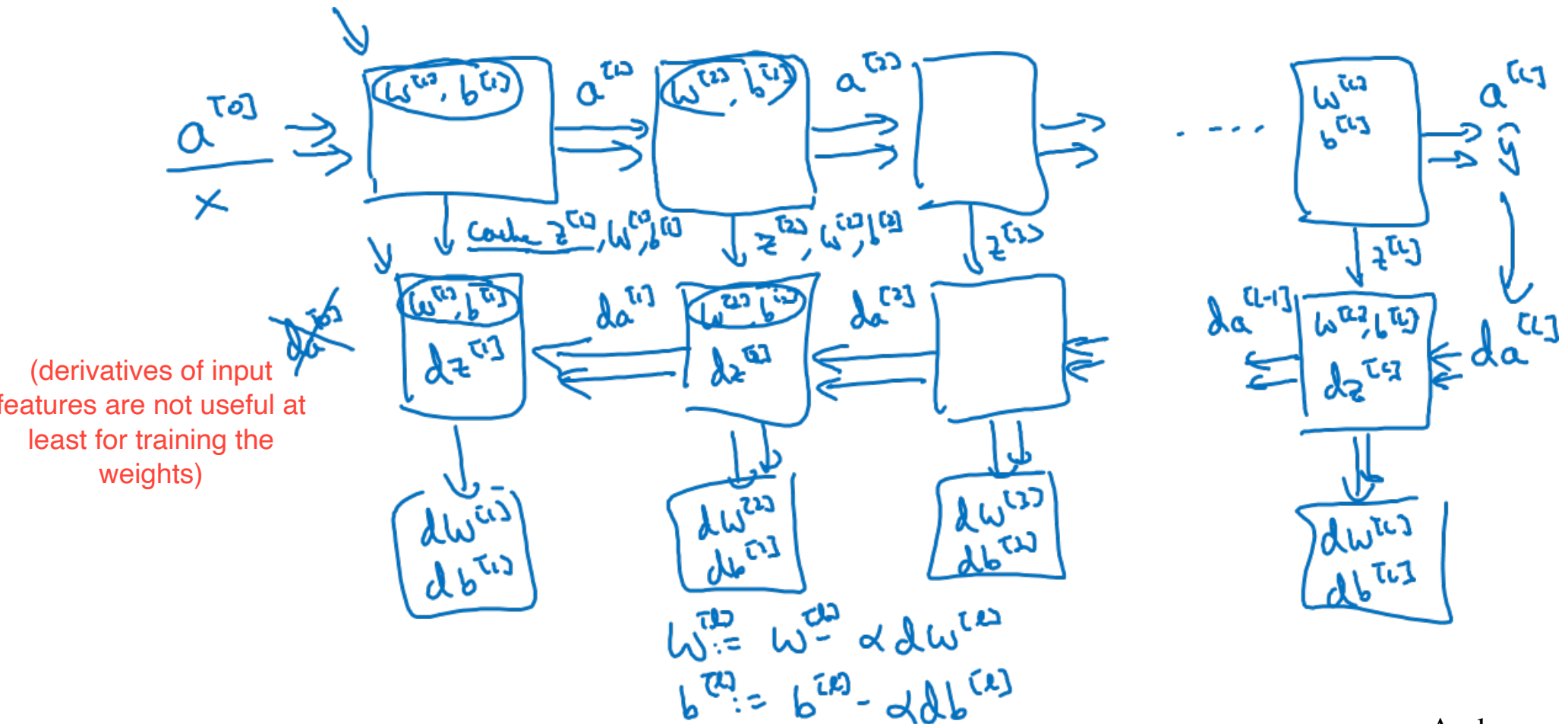
$$z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]} \quad \text{cache } z^{[l]}$$

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

→ Backward: Input  $da^{[l]}$ , output  $da^{[l-1]}$   
 cache  $(z^{[l]})$   
 $\frac{dL}{dW^{[l]}}$   
 $\frac{dL}{db^{[l]}}$



# Forward and backward functions



(derivatives of input features are not useful at least for training the weights)



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# Deep Neural Networks

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Forward and backward  
propagation



# Backward propagation for layer $l$

→ Input  $da^{[l]}$

→ Output  $da^{[l-1]}, dW^{[l]}, db^{[l]}$

$g$  is the activation function

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

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

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

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

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

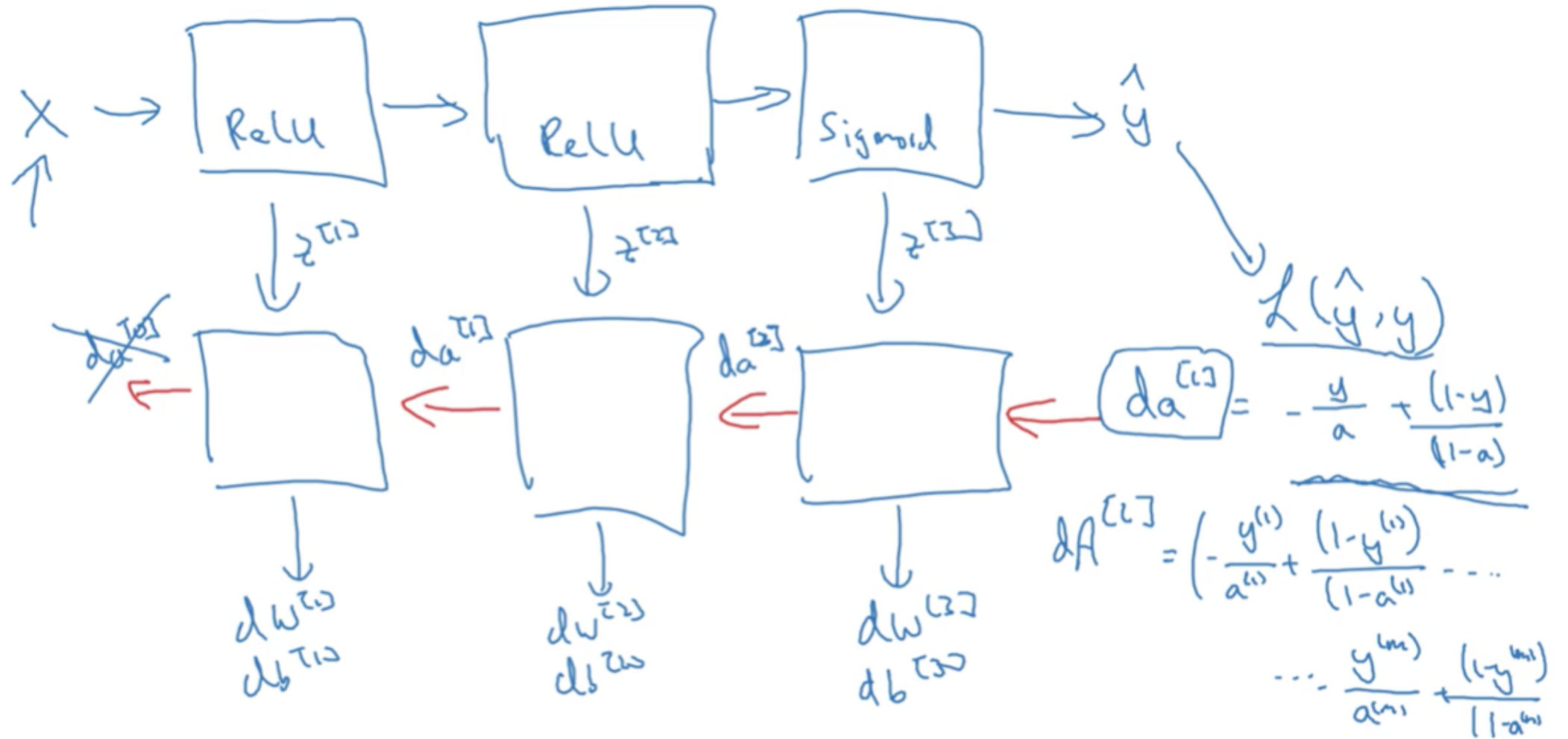
$$dz^{[l]} = dA^{[l]} * g'(z^{[l]})$$

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

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

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

# Summary





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# Deep Neural Networks

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## Parameters vs Hyperparameters

# What are hyperparameters?

Parameters:  $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, W^{[3]}, b^{[3]} \dots$

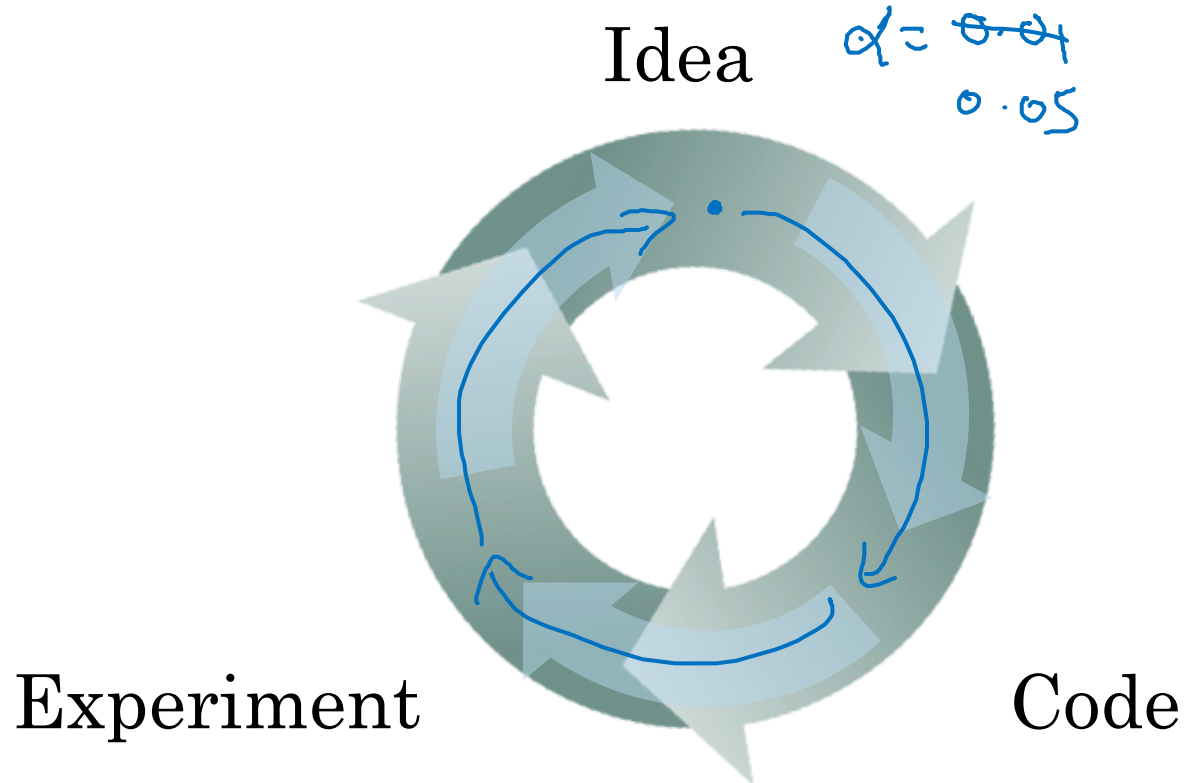


Hyperparameters:

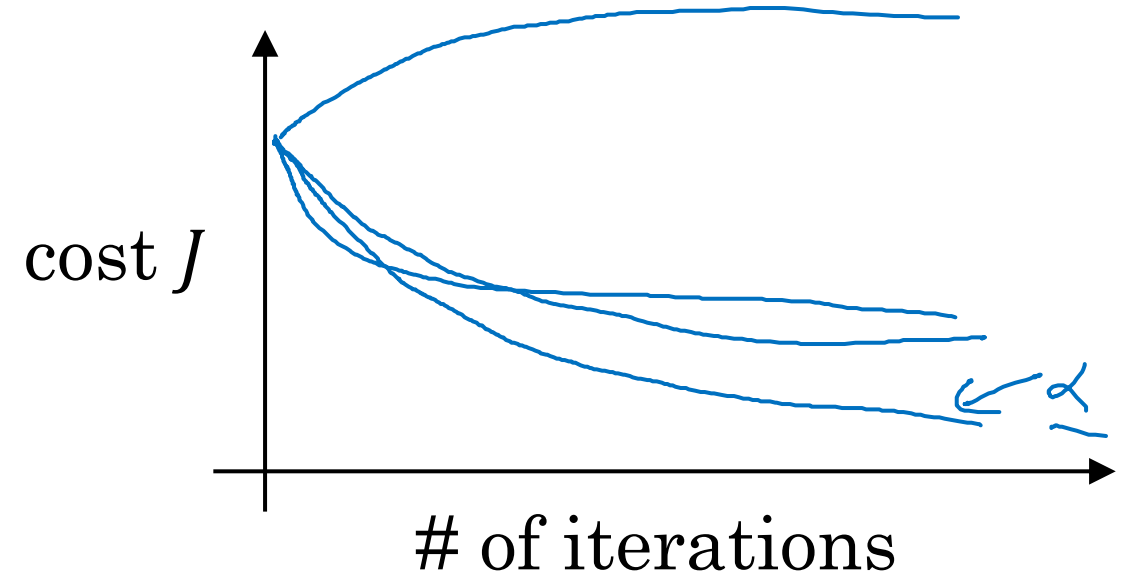
- learning rate  $\alpha$
- $\frac{1}{\epsilon}$
- #iterations
- #hidden layers  $L$
- # hidden units  $n^{[1]}, n^{[2]}, \dots$
- choice of activation function

Later: Momentum, mini-batch size, regularizations, ...

# Applied deep learning is a very empirical process



Vision, Speech, NLP, Ad, Search, Recommendation.





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# Deep Neural Networks

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What does this  
have to do with  
the brain?

# Forward and backward propagation

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

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

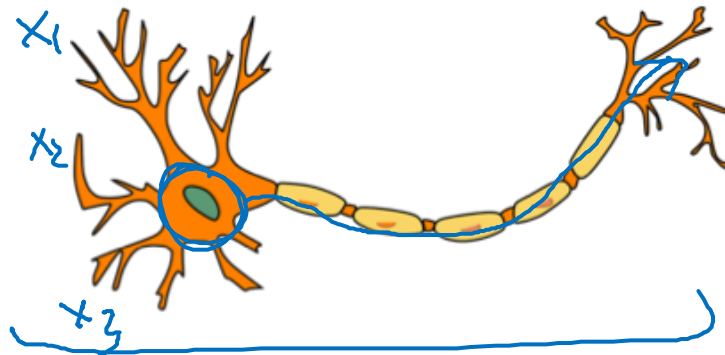
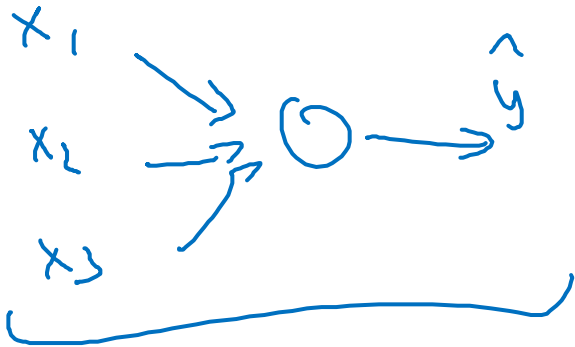
$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$

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

$$\vdots$$

$$A^{[L]} = g^{[L]}(Z^{[L]}) = \hat{Y}$$

"It's like the brain"



$$dZ^{[L]} = A^{[L]} - Y$$

$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L]T}$$

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

$$dZ^{[L-1]} = dW^{[L]T} dZ^{[L]} g'^{[L]}(Z^{[L-1]})$$

$$\vdots$$
$$dZ^{[1]} = dW^{[L]T} dZ^{[2]} g'^{[1]}(Z^{[1]})$$

$$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[1]T}$$

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