

# Artificial Intelligence and Machine Learning

## Neural Networks

# Lecture Outline

- Logistic Regression Review
- Neural Networks
  - Forward pass
  - Backward pass



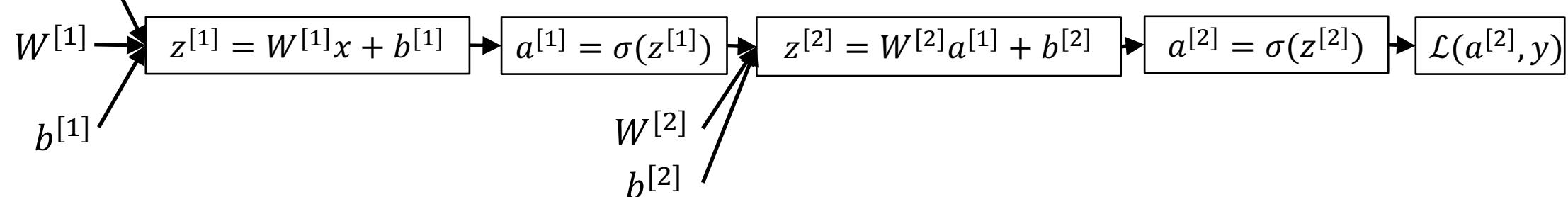
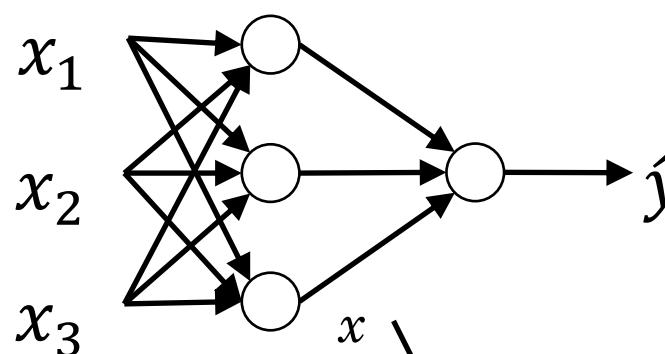
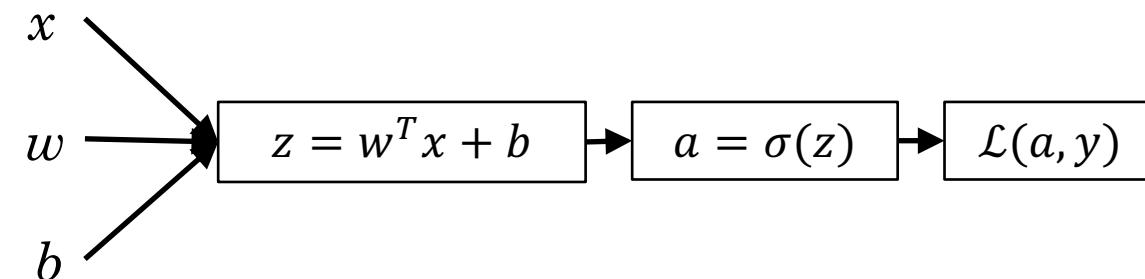
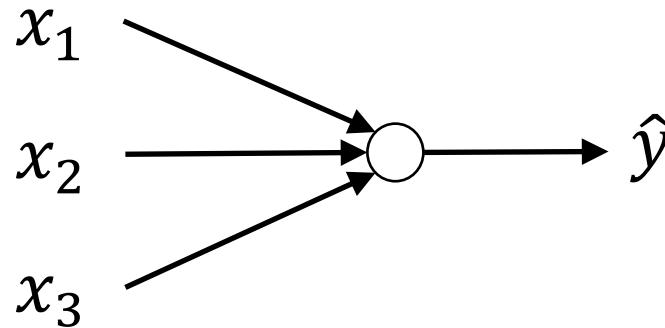
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# One hidden layer Neural Network

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# Neural Networks Overview

# What is a Neural Network?





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# Introduction to Deep Learning

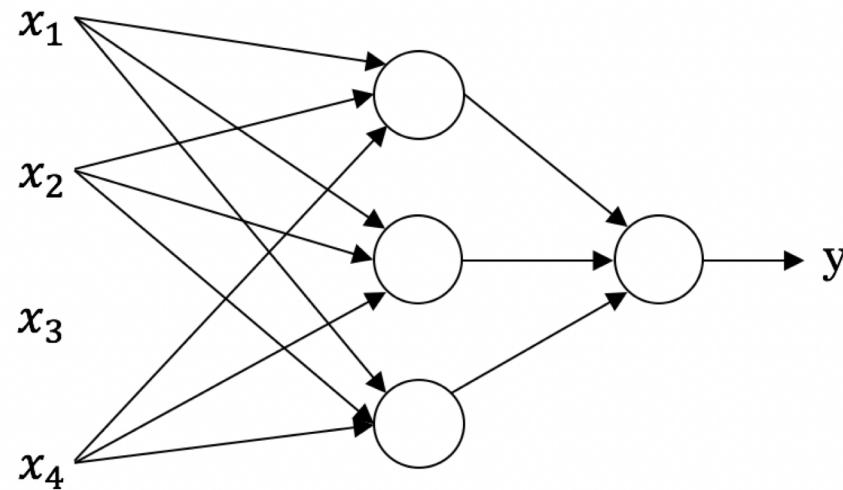
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## Supervised Learning with Neural Networks

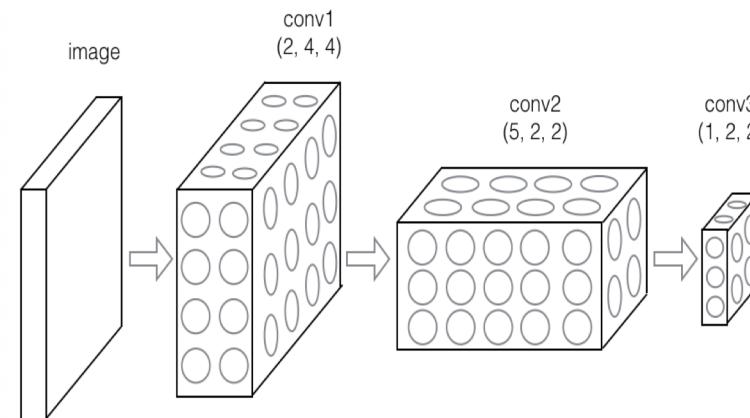
# Supervised Learning

Input(x)	Output (y)	Application
Home features	Price	Real Estate
Ad, user info	Click on ad? (0/1)	Online Advertising
Image	Object (1,...,1000)	Photo tagging
Audio	Text transcript	Speech recognition
English	Chinese	Machine translation
Image, Radar info	Position of other cars	Autonomous driving

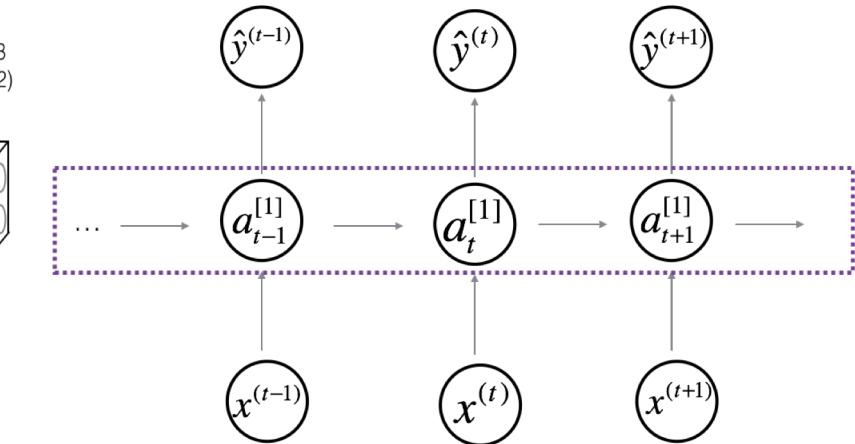
# Neural Network examples



Standard NN



Convolutional NN



Recurrent NN



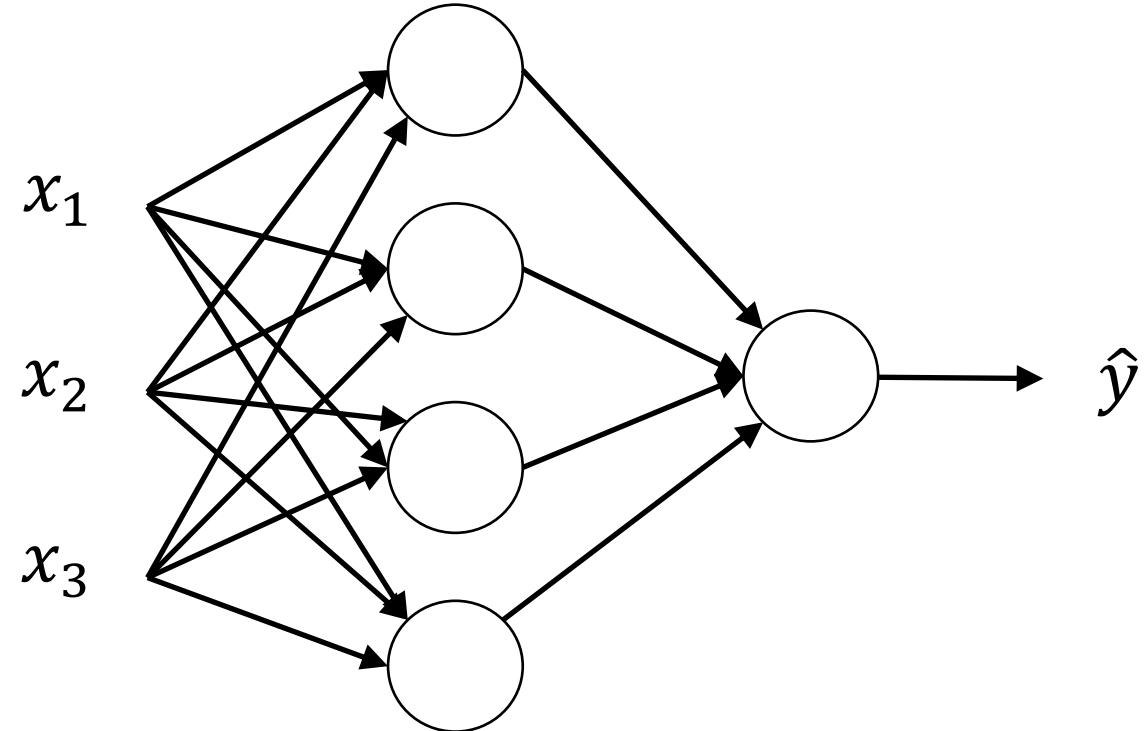
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# One hidden layer Neural Network

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# Neural Network Representation

# Neural Network Representation





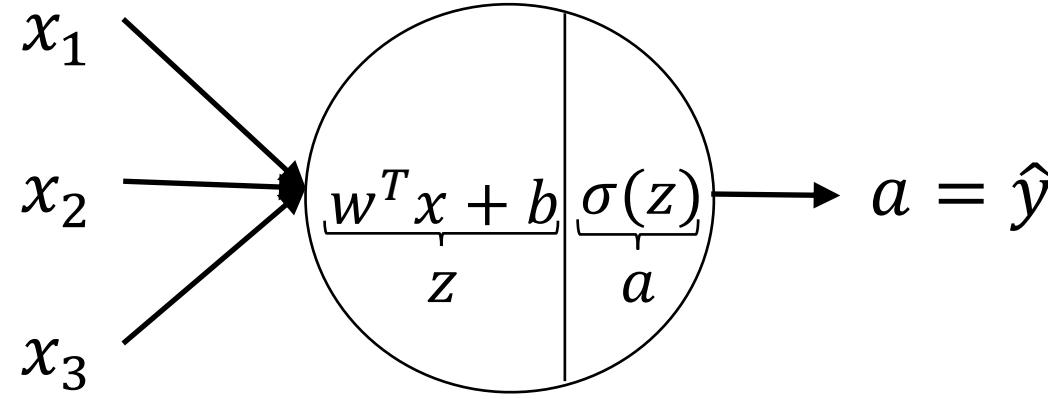
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# One hidden layer Neural Network

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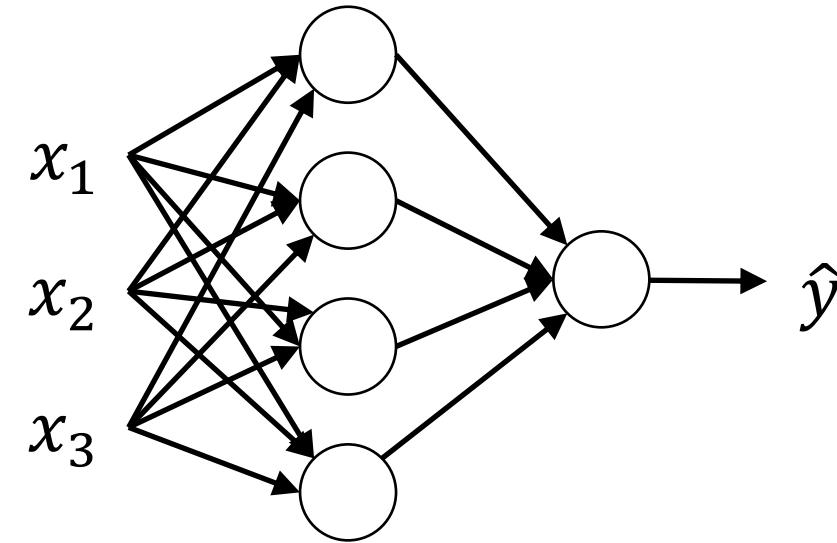
## Computing a Neural Network's Output

# Neural Network Representation

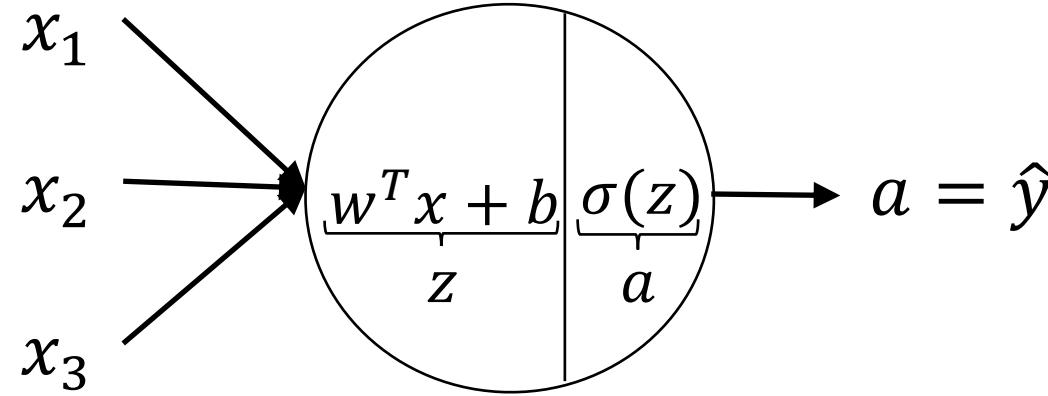


$$z = w^T x + b$$

$$a = \sigma(z)$$

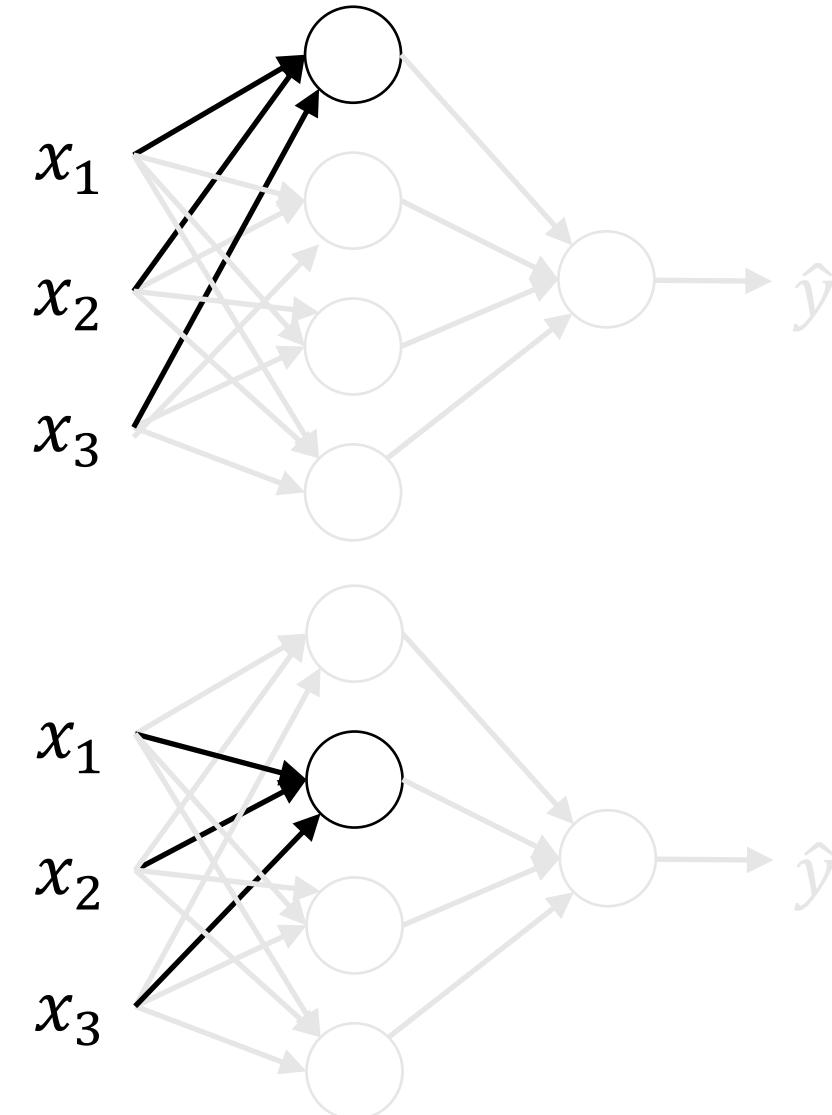


# Neural Network Representation

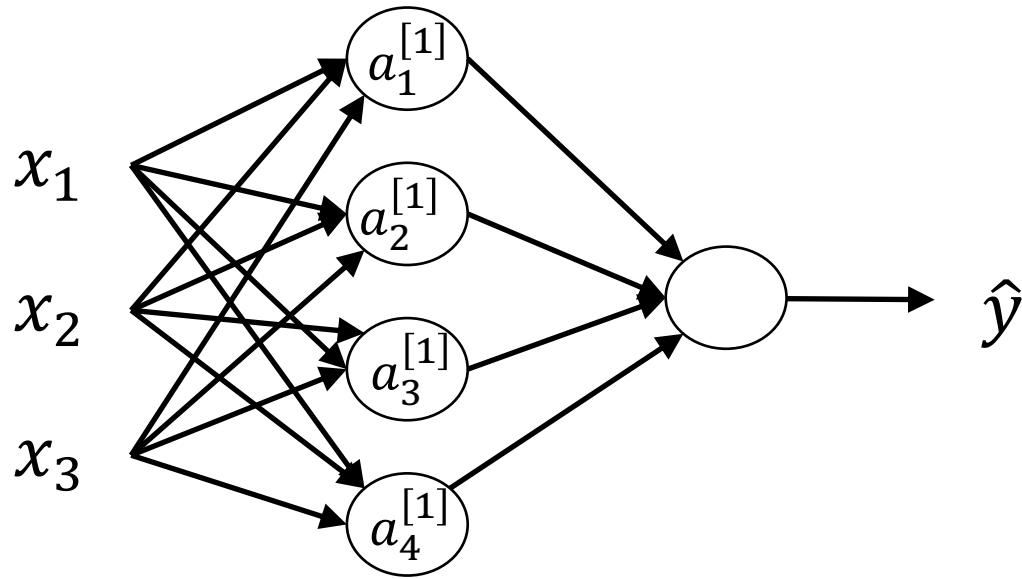


$$z = w^T x + b$$

$$a = \sigma(z)$$



# Neural Network Representation



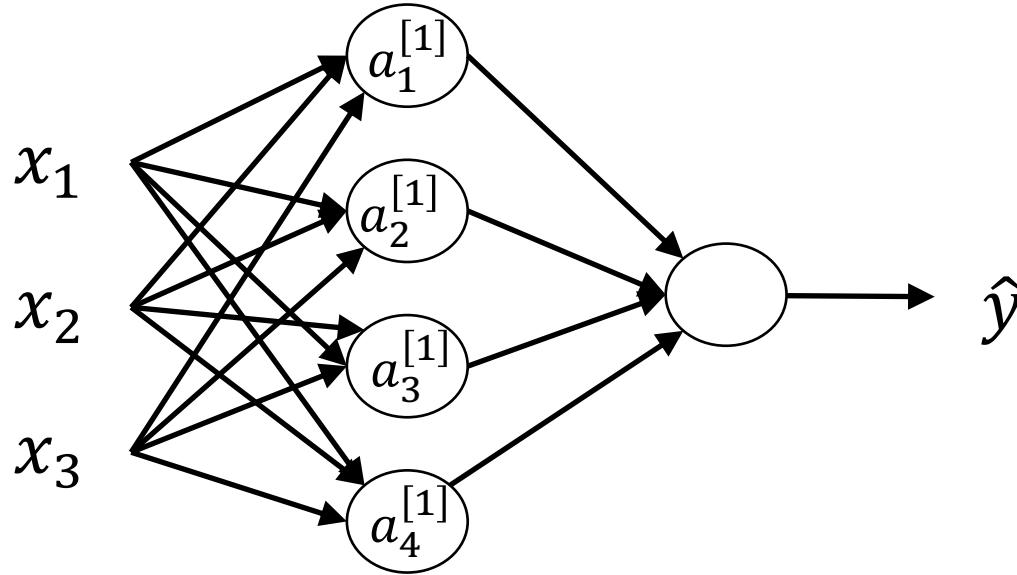
$$z_1^{[1]} = w_1^{[1]T} x + b_1^{[1]}, \quad a_1^{[1]} = \sigma(z_1^{[1]})$$

$$z_2^{[1]} = w_2^{[1]T} x + b_2^{[1]}, \quad a_2^{[1]} = \sigma(z_2^{[1]})$$

$$z_3^{[1]} = w_3^{[1]T} x + b_3^{[1]}, \quad a_3^{[1]} = \sigma(z_3^{[1]})$$

$$z_4^{[1]} = w_4^{[1]T} x + b_4^{[1]}, \quad a_4^{[1]} = \sigma(z_4^{[1]})$$

# Neural Network Representation learning



Given input  $x$ :

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

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

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

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



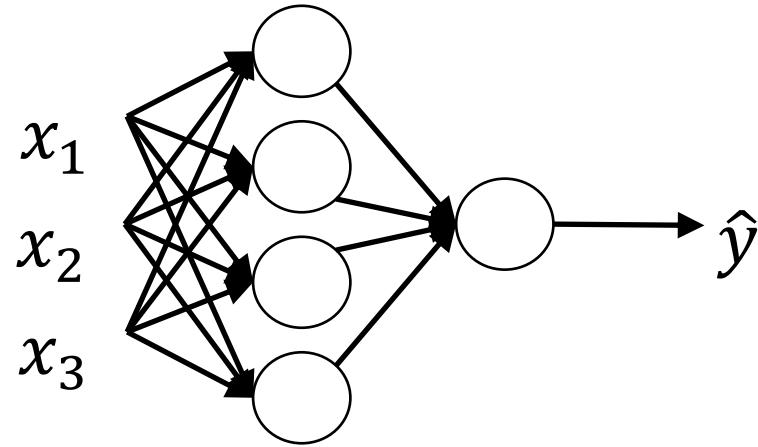
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# One hidden layer Neural Network

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## Vectorizing across multiple examples

# Vectorizing across multiple examples



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

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

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

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

# Vectorizing across multiple examples



for i = 1 to m:

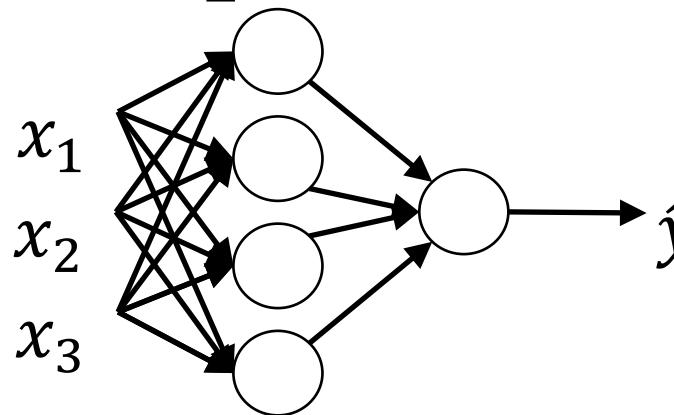
$$z^{[1]}(i) = W^{[1]}x^{(i)} + b^{[1]}$$

$$a^{[1]}(i) = \sigma(z^{[1]}(i))$$

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

$$a^{[2]}(i) = \sigma(z^{[2]}(i))$$

# Recap of vectorizing across multiple examples



$$X = \begin{bmatrix} | & | & | \\ x^{(1)} & x^{(2)} & \dots & x^{(m)} \\ | & | & & | \end{bmatrix}$$

$$A^{[1]} = \begin{bmatrix} | & | & | \\ a^{[1](1)} & a^{[1](2)} & \dots & a^{[1](m)} \\ | & | & & | \end{bmatrix}$$

for i = 1 to m

$$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]}$$

$$a^{[1](i)} = \sigma(z^{[1](i)})$$

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

$$a^{[2](i)} = \sigma(z^{[2](i)})$$

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

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

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

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



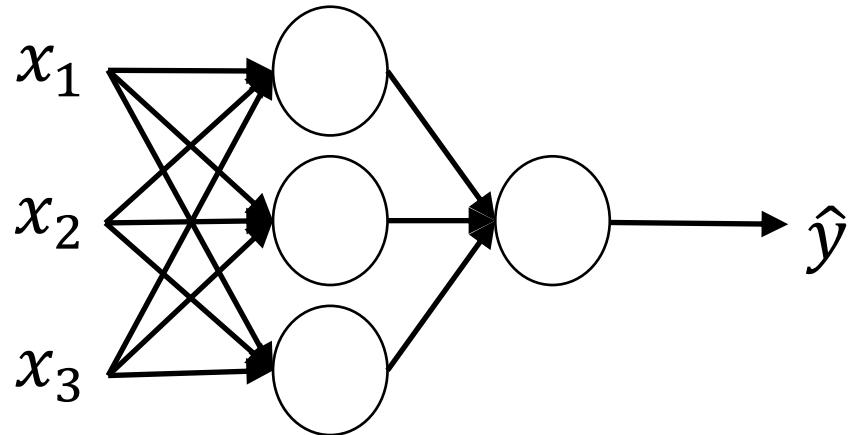
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# One hidden layer Neural Network

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## Activation functions

# Activation functions



Given  $x$ :

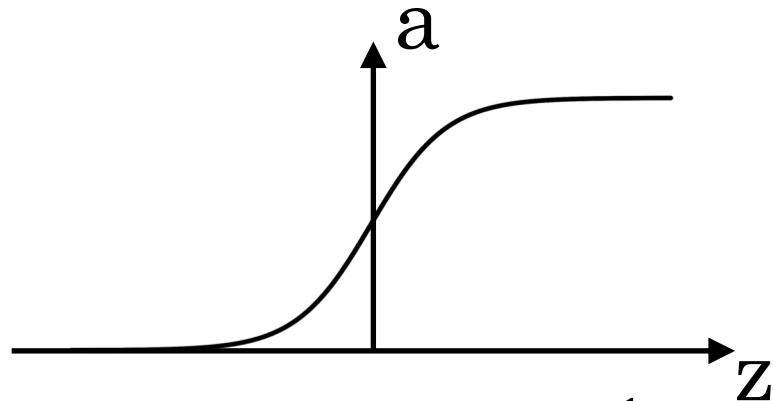
$$z^{[1]} = W^{[1]}x + b^{[1]}$$

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

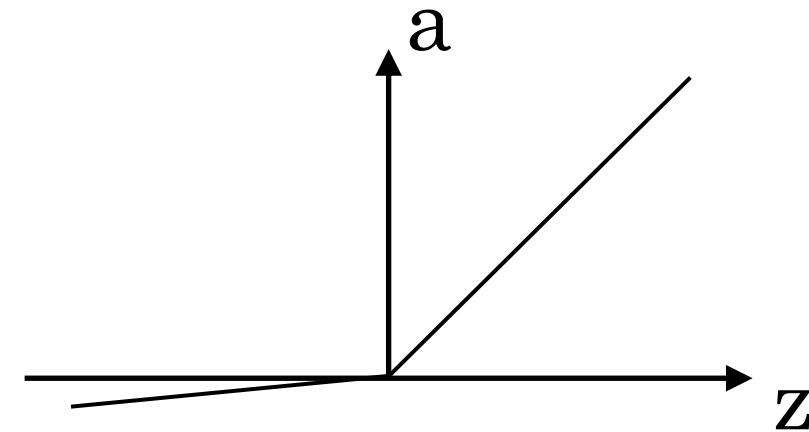
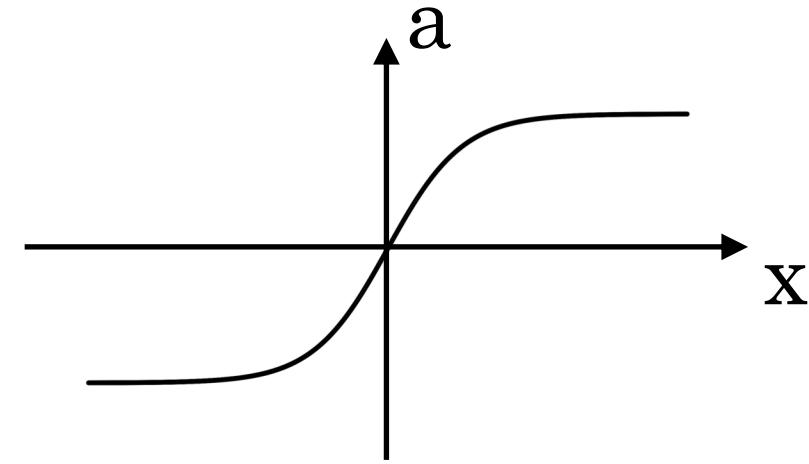
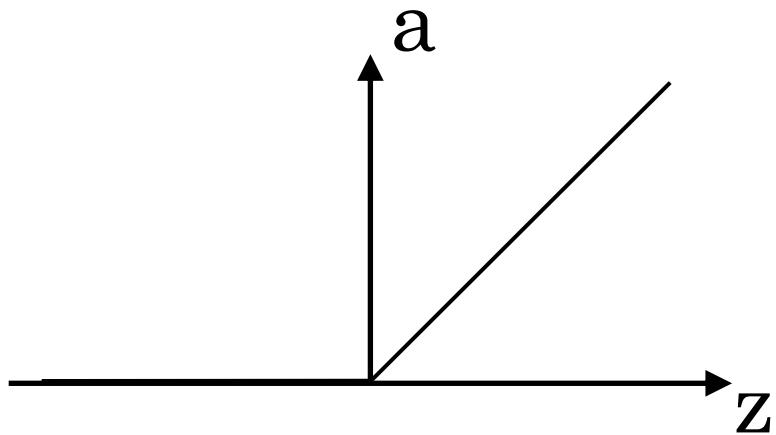
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

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

# Pros and cons of activation functions



$$\text{sigmoid: } a = \frac{1}{1 + e^{-z}}$$





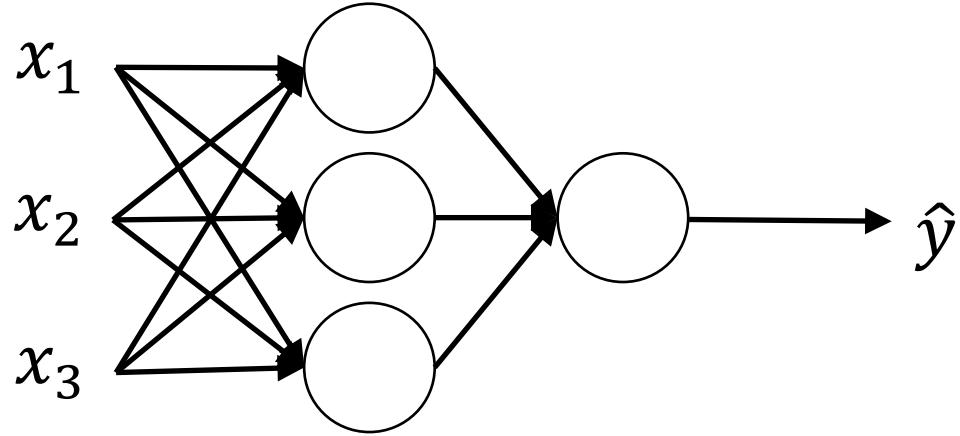
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# One hidden layer Neural Network

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Why do you  
need non-linear  
activation functions?

# Activation function



Given  $\mathbf{x}$ :

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

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

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

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



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# One hidden layer Neural Network

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## Gradient descent for neural networks

# Gradient descent for neural networks

# Formulas for computing derivatives

Forward propagation:

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

$$A^{[1]} = g^{[1]}(z^{[1]}) \leftarrow$$

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

$$A^{[2]} = g^{[2]}(z^{[2]}) = \underline{g}(z^{[2]})$$

Back propagation:

$$d\hat{z}^{[2]} = A^{[2]} - Y \leftarrow$$

$$dW^{[2]} = \frac{1}{m} d\hat{z}^{[2]} A^{[1]T}$$

$$db^{[2]} = \frac{1}{m} \text{np.sum}(d\hat{z}^{[2]}, \text{axis}=1, \text{keepdims=True})$$

$$d\hat{z}^{[1]} = \underbrace{W^{[2]T} d\hat{z}^{[2]}}_{(n^{[2]}, m)} \times \underbrace{g^{[1]'}(z^{[1]})}_{\text{element-wise product}} (n^{[1]}, m)$$

$$dW^{[1]} = \frac{1}{m} d\hat{z}^{[1]} X^T$$

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

$$Y = [y^{(1)} \ y^{(2)} \ \dots \ y^{(m)}]$$

$$(n^{[1]}) \leftarrow$$

$$\downarrow (n^{[2]}, 1) \leftarrow$$



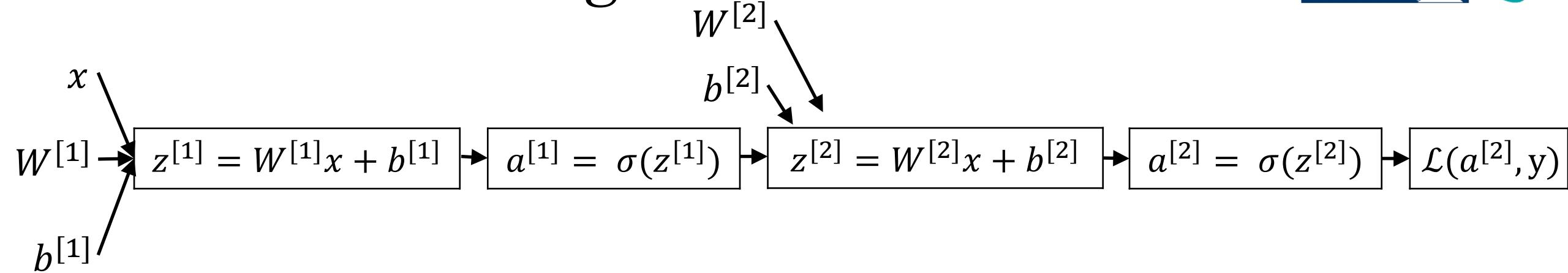
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# One hidden layer Neural Network

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## Backpropagation intuition

# Neural network gradients



# Summary of gradient descent

$$dz^{[2]} = a^{[2]} - y$$

$$dW^{[2]} = dz^{[2]} a^{[1]T}$$

$$db^{[2]} = dz^{[2]}$$

$$dz^{[1]} = W^{[2]T} dz^{[2]} * g^{[1]\prime}(z^{[1]})$$

$$dW^{[1]} = dz^{[1]} \chi^T$$

$$db^{[1]} = dz^{[1]}$$

$$dZ^{[2]} = A^{[2]} - Y$$

$$dW^{[2]} = \frac{1}{m} dZ^{[2]} A^{[1]T}$$

$$db^{[2]} = \frac{1}{m} np.sum(dZ^{[2]}, axis = 1, keepdims = True)$$

$$dZ^{[1]} = W^{[2]T} dz^{[2]} * g^{[1]\prime}(Z^{[1]})$$

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

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



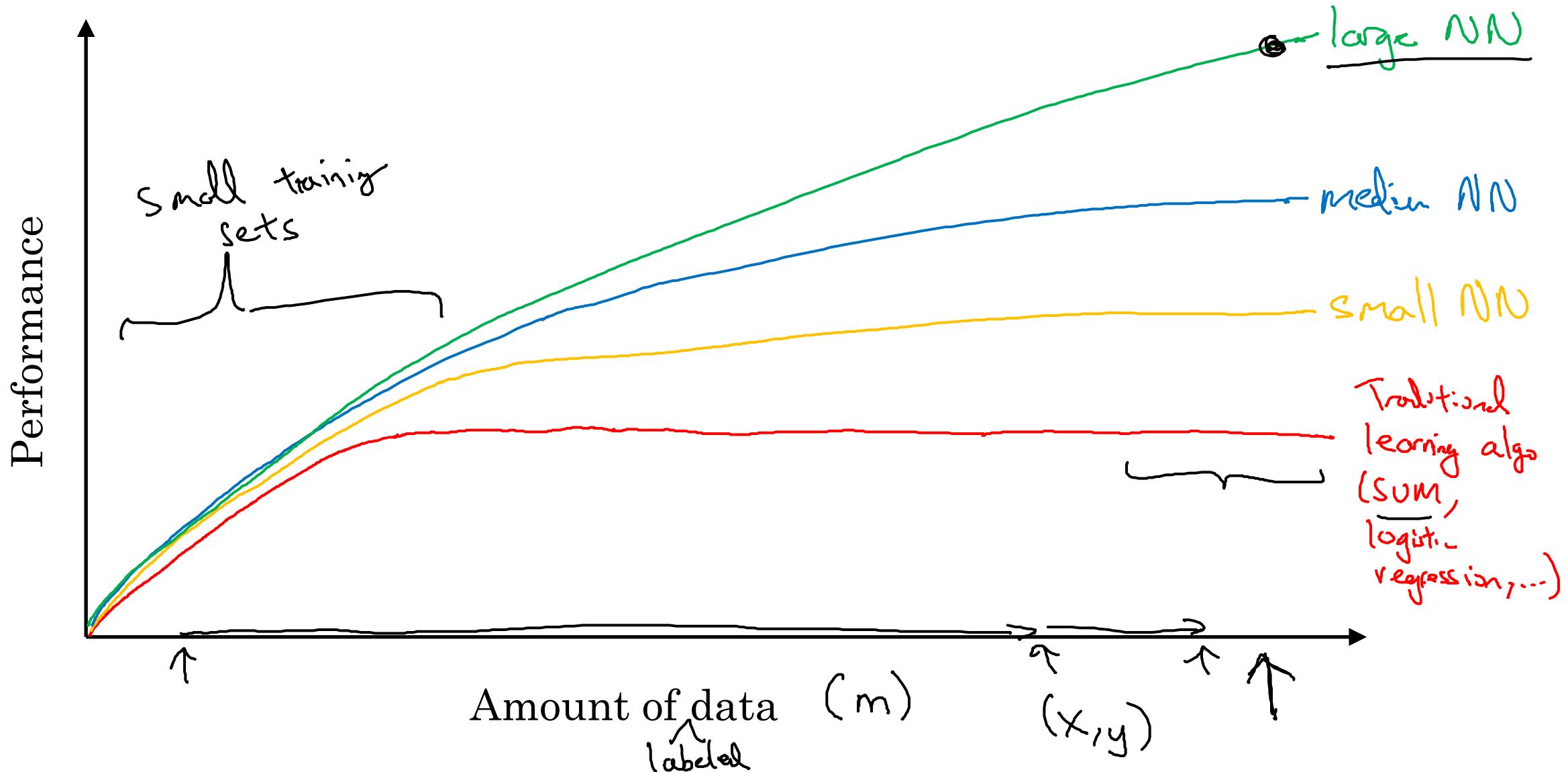
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# Introduction to Neural Networks

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# Why is Deep Learning taking off?

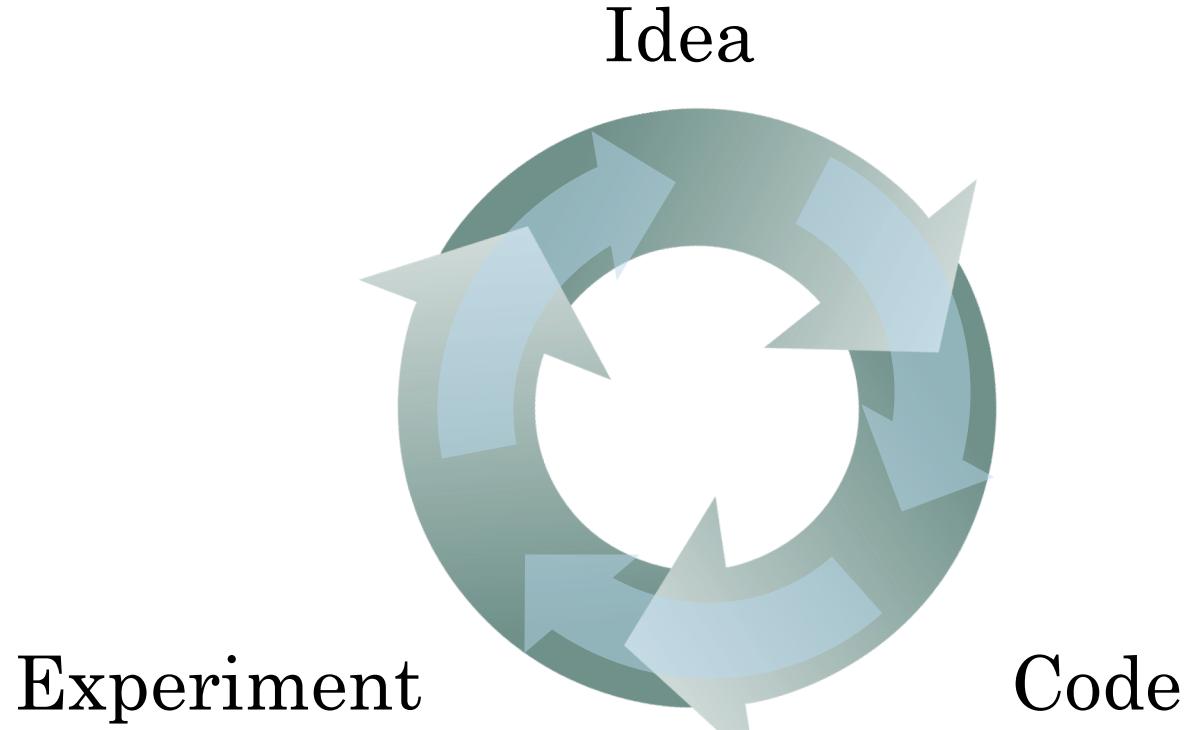
# Scale drives deep learning progress



# Scale drives deep learning progress



- Data
- Computation
- Algorithms





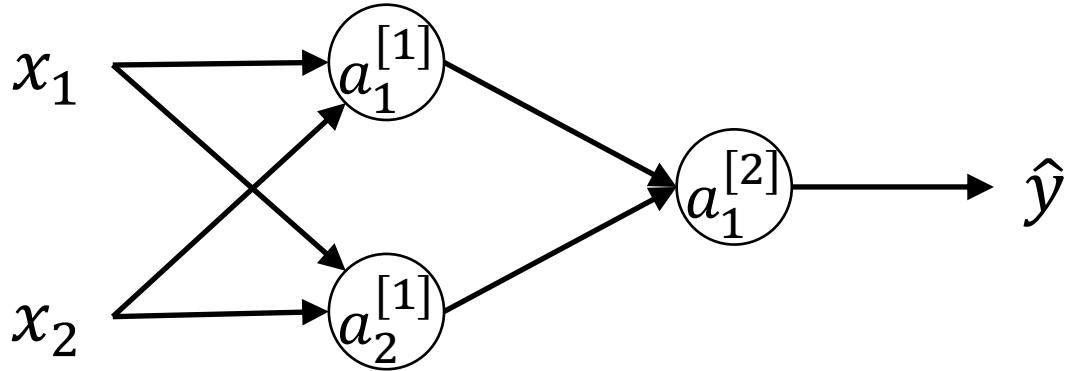
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# One hidden layer Neural Network

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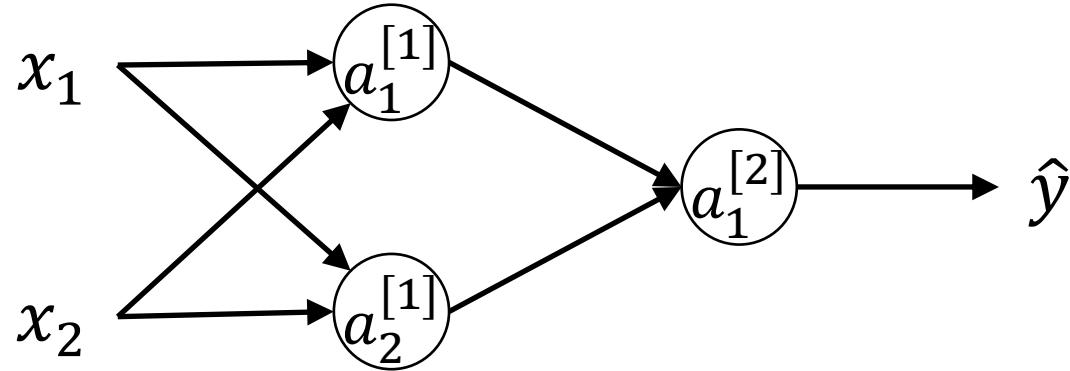
## Random Initialization

# What happens if you initialize weights to zero?



- 1. Symmetry Problem**
- 2. Impact on Activation Functions**

# Random initialization



Very close to zero, but randomly

In numpy:

`np.random.randn(layer_size[l], layer_size[l-1])`, generates a matrix of random numbers drawn from a standard normal distribution (mean = 0, standard deviation = 1). This matrix has a shape determined by the size of the current layer (`layer_size[l]`) and the size of the previous layer (`layer_size[l-1]`).



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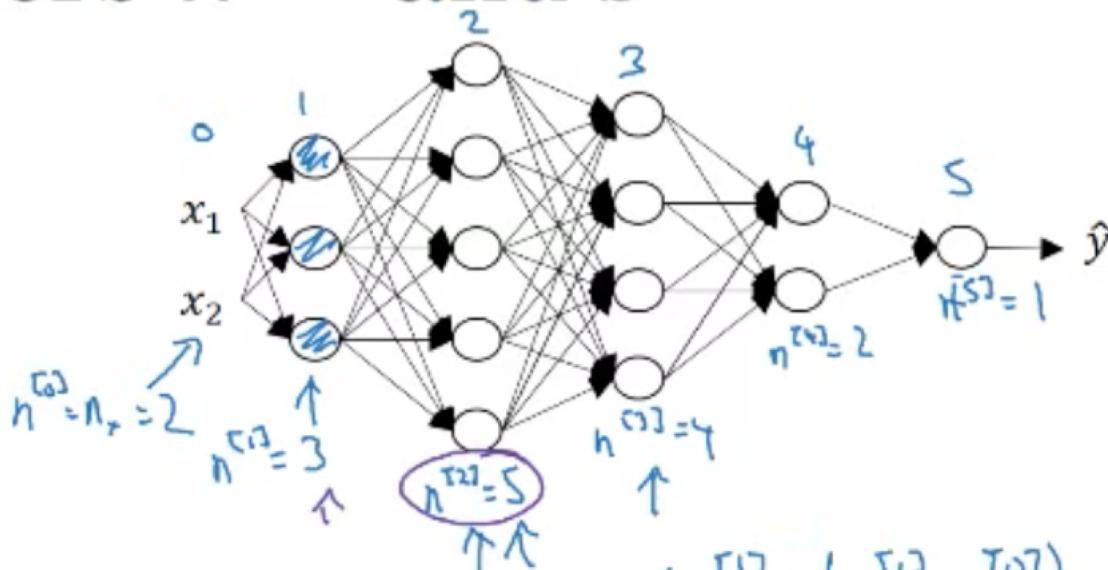
# Deep Neural Networks

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## Getting your matrix dimensions right

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

$L = 5$



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

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

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

$$\partial b^{[L]}: (n^{[L]}, 1)$$

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

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

$$\begin{bmatrix} \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots & \vdots \\ \vdots & \vdots \end{bmatrix} \quad \begin{bmatrix} \vdots \\ \vdots \end{bmatrix}$$

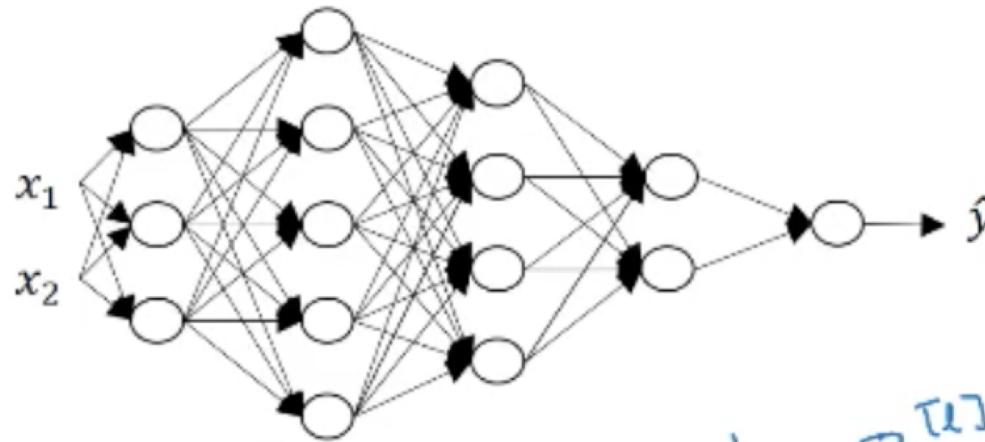
$$W^{[2]}: (5, 3) \quad (n^{[2]}, n^{[1]})$$

$$\begin{aligned} z^{[2]} &= \boxed{W^{[2]}} \cdot a^{[1]} + \boxed{b^{[2]}} \\ \rightarrow (5,1) &\quad (5,3) \quad (2,1) \quad (5,1) \\ &\quad (n^{[2]}, 1) \end{aligned}$$

$$W^{[3]}: (4, 5)$$

$$W^{[4]}: (2, 4) \quad , \quad W^{[5]}: (1, 2)$$

# Vectorized implementation



$$z^{[l]} = \omega^{[l]} \cdot x + b^{[l]}$$

$$\underbrace{(n^{[l]}, 1)}_{\text{Input}} \quad \underbrace{(n^{[l]}, n^{[l+1]})}_{\text{Weights}} \quad \underbrace{(n^{[l]}, 1)}_{\text{Bias}} \quad \underbrace{(n^{[l+1]}, 1)}_{\text{Output}}$$

$$\left[ z^{[0](1)} \ z^{[0](2)} \dots z^{[0](m)} \right]$$

$$\overbrace{z^{[l]}}^{\text{Vector}} = \omega^{[l]} \cdot X + b^{[l]}$$

$$\underbrace{(n^{[l]}, m)}_{\text{Input}} \quad \underbrace{(n^{[l]}, n^{[l+1]})}_{\text{Weights}} \quad \underbrace{(n^{[l]}, m)}_{\text{Bias}} \quad \underbrace{(n^{[l+1]}, m)}_{\text{Output}}$$

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

$$z^{[l]}, A^{[l]} : (n^{[l]}, m)$$

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

$$dz^{[l]}, dA^{[l]} : (n^{[l]}, m)$$



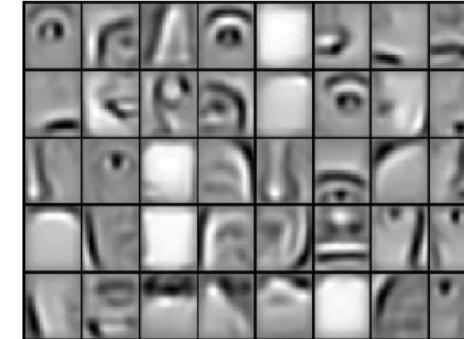
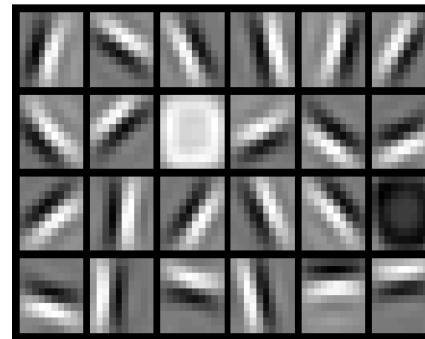
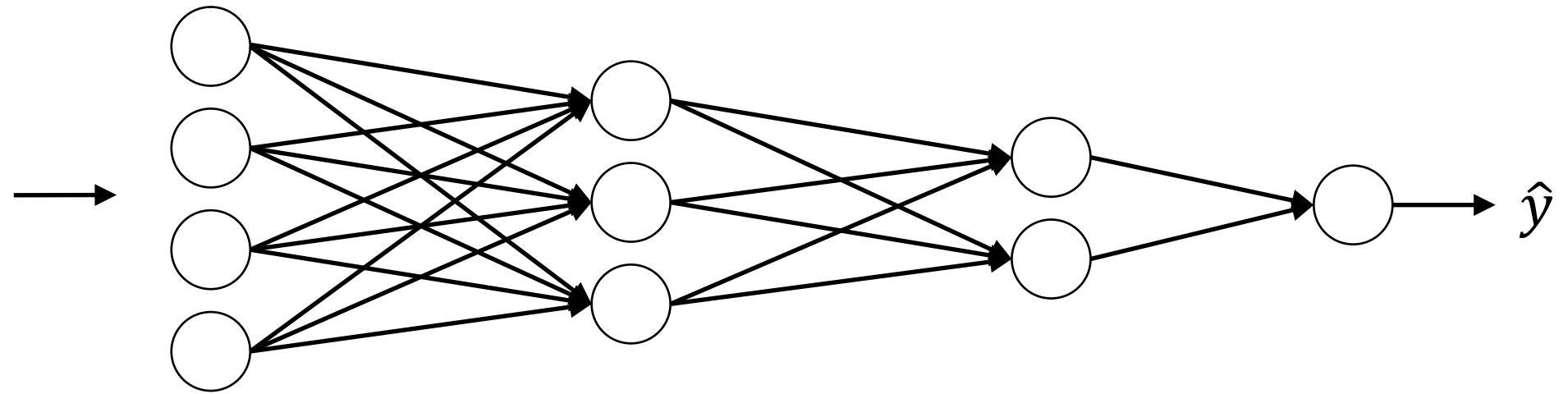
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# Deep Neural Networks

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## Why deep representations?

# Intuition about deep representation

 $\hat{y}$



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# Deep Neural Networks

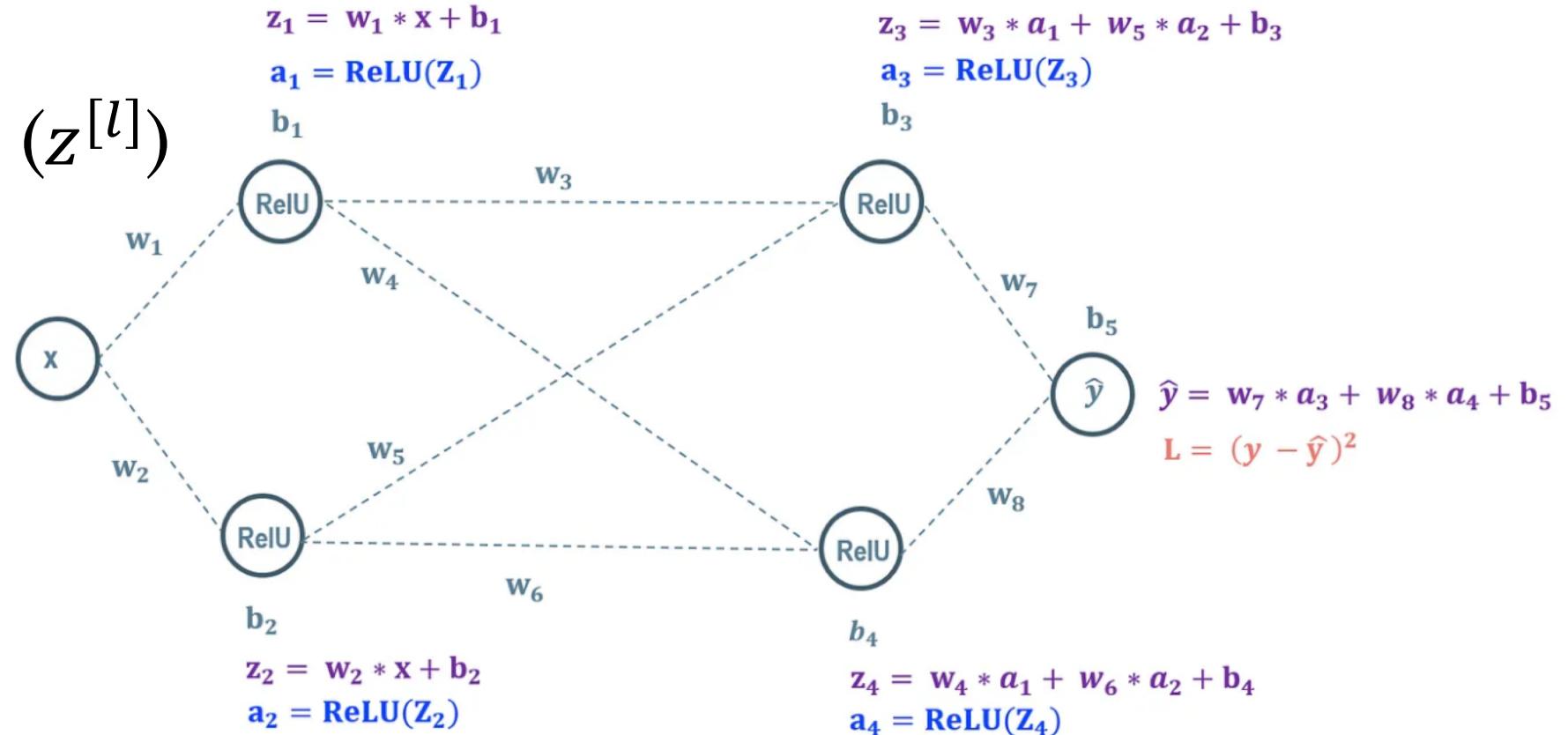
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## Forward and backward propagation

# Forward and Backpropagation propagation for layer $l$

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

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



# Summary

