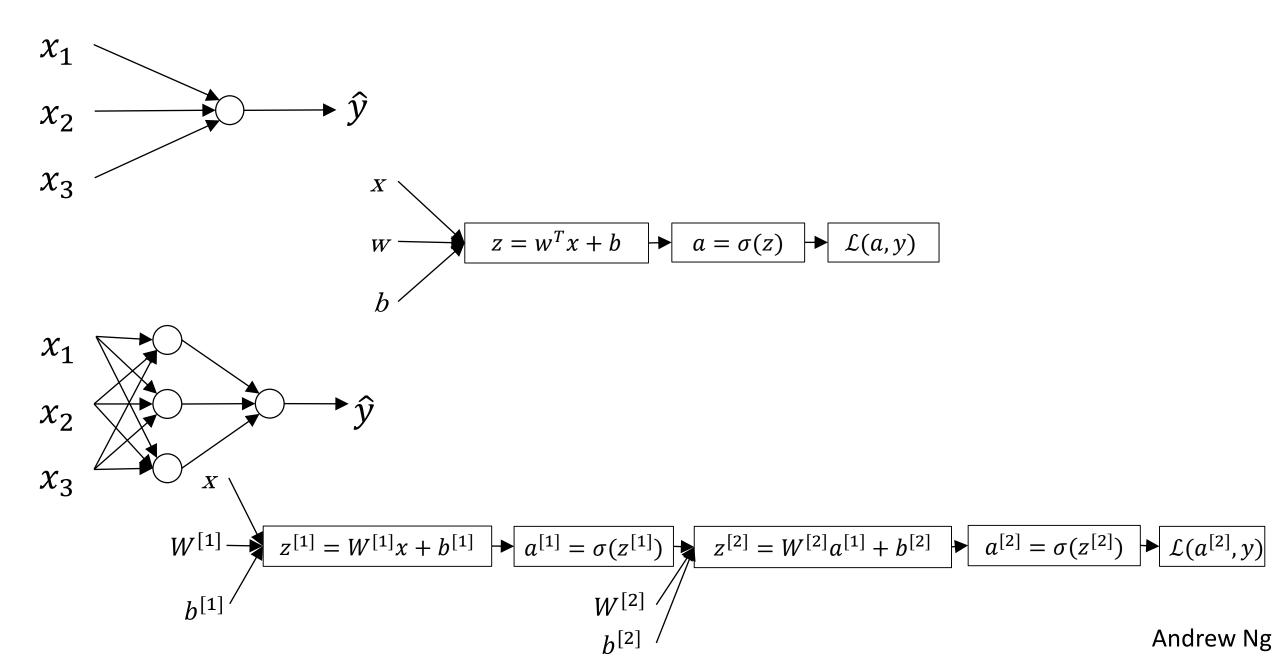


One hidden layer Neural Network

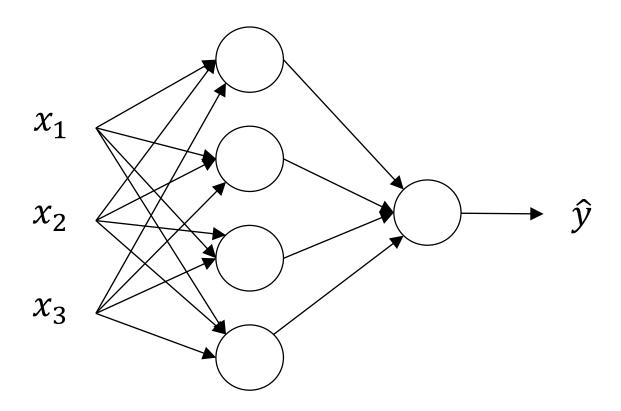
Neural Networks Overview

What is a Neural Network?





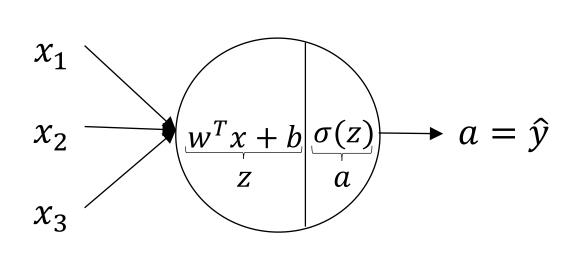
One hidden layer Neural Network

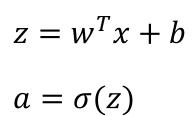


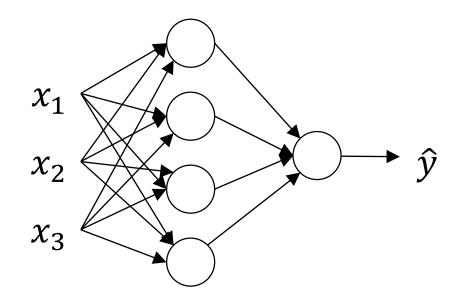


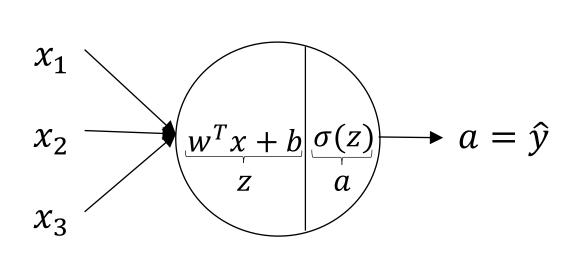
One hidden layer Neural Network

Computing a Neural Network's Output



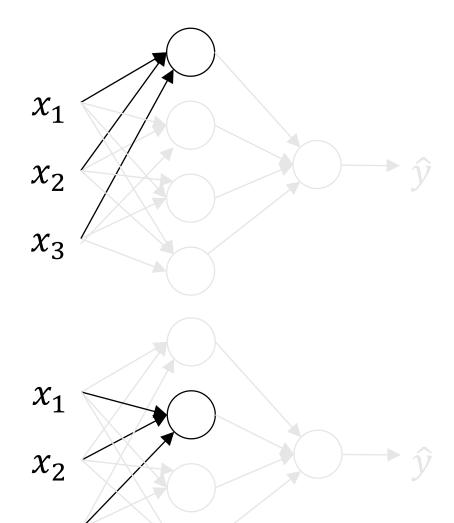


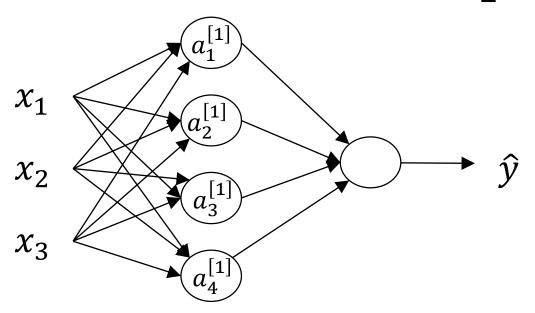




$$z = w^T x + b$$

$$a = \sigma(z)$$





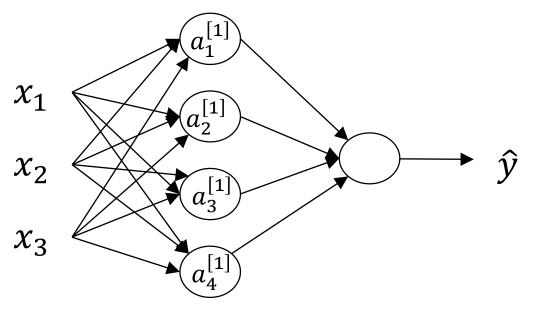
$$z_{1}^{[1]} = w_{1}^{[1]T} x + b_{1}^{[1]}, \ \alpha_{1}^{[1]} = \sigma(z_{1}^{[1]})$$

$$z_{2}^{[1]} = w_{2}^{[1]T} x + b_{2}^{[1]}, \ \alpha_{2}^{[1]} = \sigma(z_{2}^{[1]})$$

$$z_{3}^{[1]} = w_{3}^{[1]T} x + b_{3}^{[1]}, \ \alpha_{3}^{[1]} = \sigma(z_{3}^{[1]})$$

$$z_{4}^{[1]} = w_{4}^{[1]T} x + b_{4}^{[1]}, \ \alpha_{4}^{[1]} = \sigma(z_{4}^{[1]})$$

Neural Network Representation learning



Given input x:

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

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

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

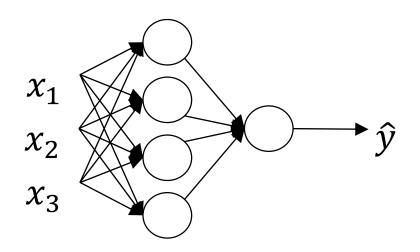
$$a^{[2]} = \sigma(z^{[2]})$$



One hidden layer Neural Network

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)})
```

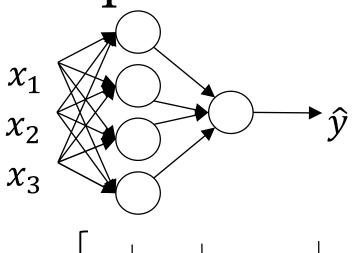


One hidden layer Neural Network

Explanation for vectorized implementation

Justification for vectorized implementation

Recap of vectorizing across multiple examples



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

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

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

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

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

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

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

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

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

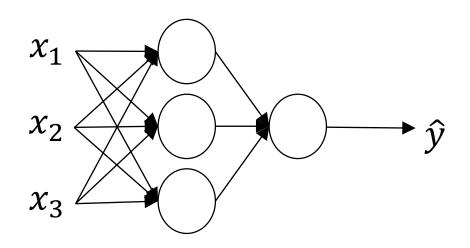
$$A^{[2]} = \sigma(Z^{[2]})$$



One hidden layer Neural Network

Activation functions

Activation functions



Given x:

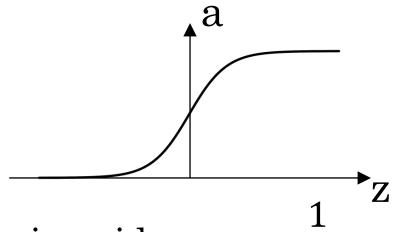
$$z^{[1]} = W^{[1]}x + b^{[1]}$$

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

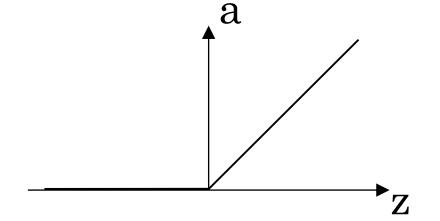
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

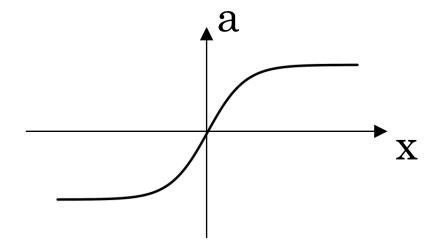
$$a^{[2]} = \sigma(z^{[2]})$$

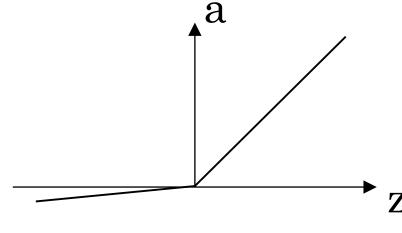
Pros and cons of activation functions



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





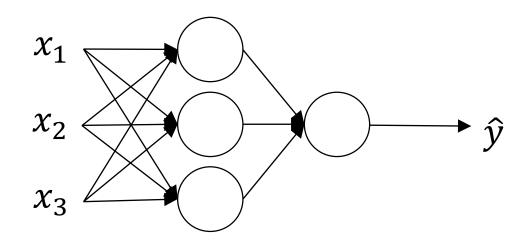




One hidden layer Neural Network

Why do you need non-linear activation functions?

Activation function



Given x:

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

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

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

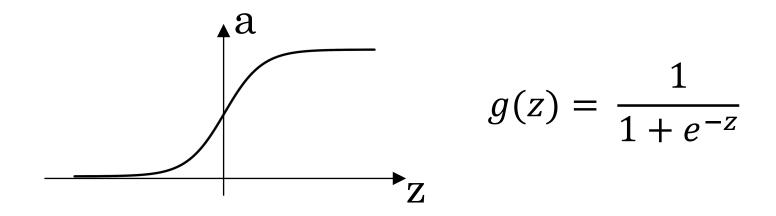
$$a^{[2]} = g^{[2]}(z^{[2]})$$



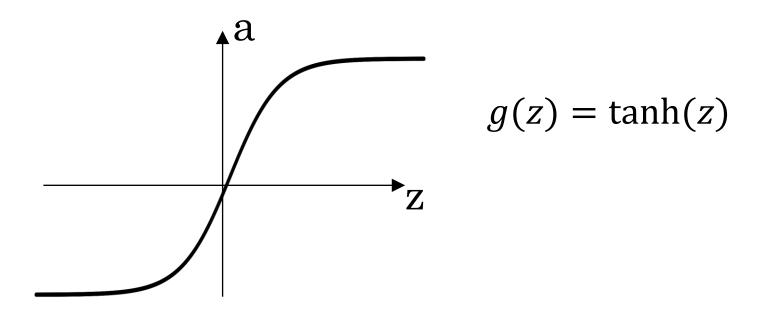
One hidden layer Neural Network

Derivatives of activation functions

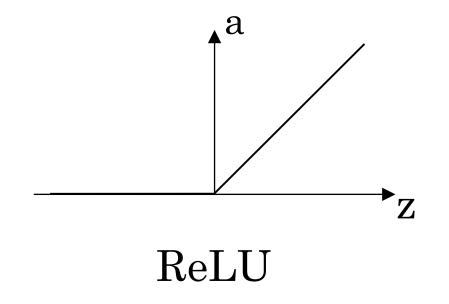
Sigmoid activation function

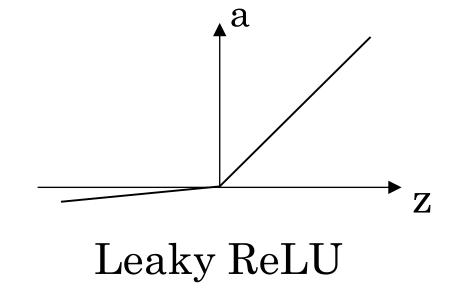


Tanh activation function



ReLU and Leaky ReLU







One hidden layer Neural Network

Gradient descent for neural networks

Gradient descent for neural networks

Formulas for computing derivatives

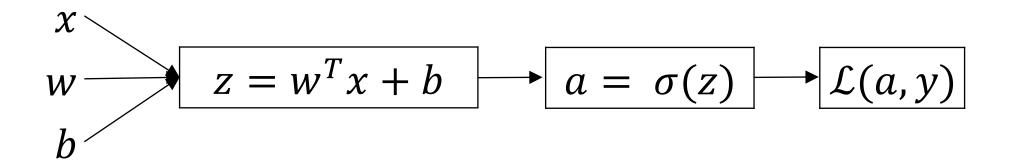


One hidden layer Neural Network

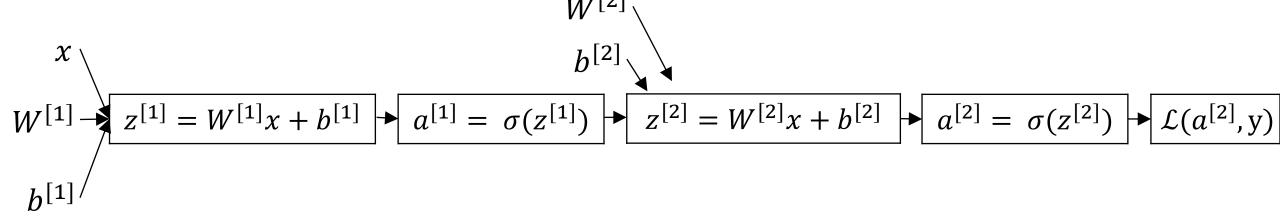
Backpropagation intuition (Optional)

Computing gradients

Logistic regression



Neural network gradients $W^{[2]}$



Summary of gradient descent

$$dz^{[2]} = a^{[2]} - y$$
 $dW^{[2]} = dz^{[2]}a^{[1]^T}$
 $db^{[2]} = dz^{[2]}$
 $dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]'}(z^{[1]})$
 $dW^{[1]} = dz^{[1]}x^T$
 $db^{[1]} = dz^{[1]}$

Summary of gradient descent

$$\begin{aligned} dz^{[2]} &= a^{[2]} - y \\ dW^{[2]} &= dz^{[2]}a^{[1]^T} \\ db^{[2]} &= dz^{[2]} \end{aligned} \qquad \begin{aligned} dW^{[2]} &= \frac{1}{m}dZ^{[2]}A^{[1]^T} \\ db^{[2]} &= dz^{[2]} \\ dz^{[1]} &= W^{[2]T}dz^{[2]} * g^{[1]'}(z^{[1]}) \end{aligned} \qquad \begin{aligned} dZ^{[1]} &= W^{[2]T}dZ^{[2]} * g^{[1]'}(Z^{[1]}) \\ dW^{[1]} &= dz^{[1]}x^T \end{aligned} \qquad \begin{aligned} dW^{[1]} &= \frac{1}{m}dZ^{[1]}X^T \\ db^{[1]} &= dz^{[1]} \end{aligned} \qquad \end{aligned}$$

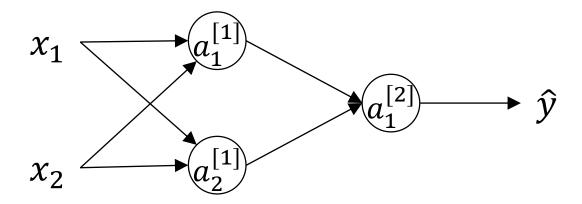
$$\begin{split} dZ^{[2]} &= A^{[2]} - Y \\ dW^{[2]} &= \frac{1}{m} dZ^{[2]} A^{[1]^T} \\ db^{[2]} &= \frac{1}{m} np. sum(dZ^{[2]}, axis = 1, keepdims = True) \\ dZ^{[1]} &= W^{[2]T} dZ^{[2]} * g^{[1]'}(Z^{[1]}) \\ dW^{[1]} &= \frac{1}{m} dZ^{[1]} X^T \\ db^{[1]} &= \frac{1}{m} np. sum(dZ^{[1]}, axis = 1, keepdims = True) \end{split}$$



One hidden layer Neural Network

Random Initialization

What happens if you initialize weights to zero?



Random initialization

