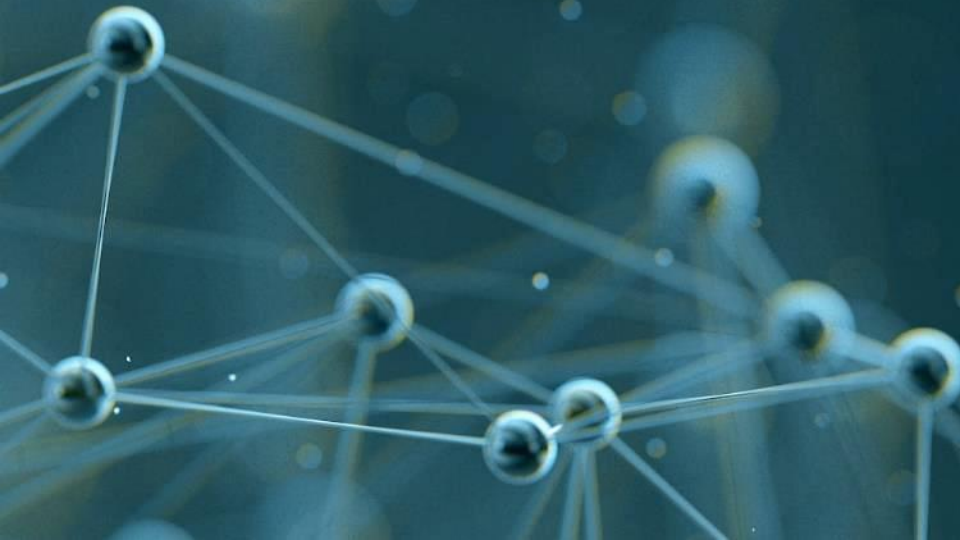
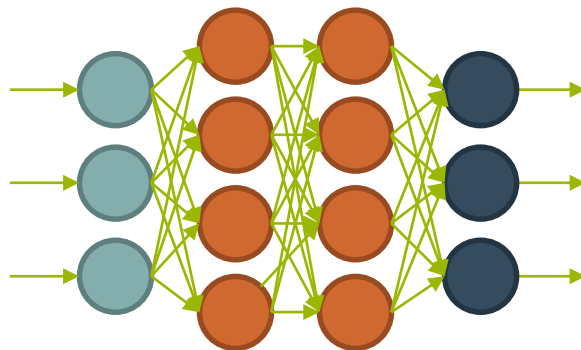


INTRODUCTION TO NEURAL NETS

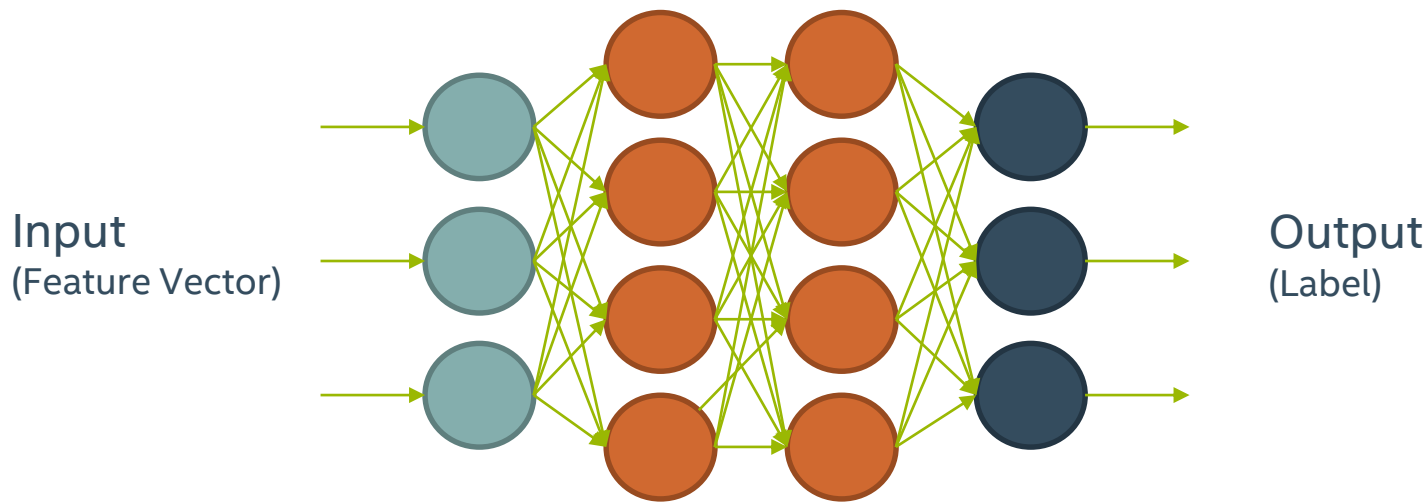


MOTIVATION FOR NEURAL NETS

- Use biology as inspiration for mathematical model
- Get signals from previous neurons
- Generate signals (or not) according to inputs
- Pass signals on to next neurons
- By layering many neurons, can create complex model

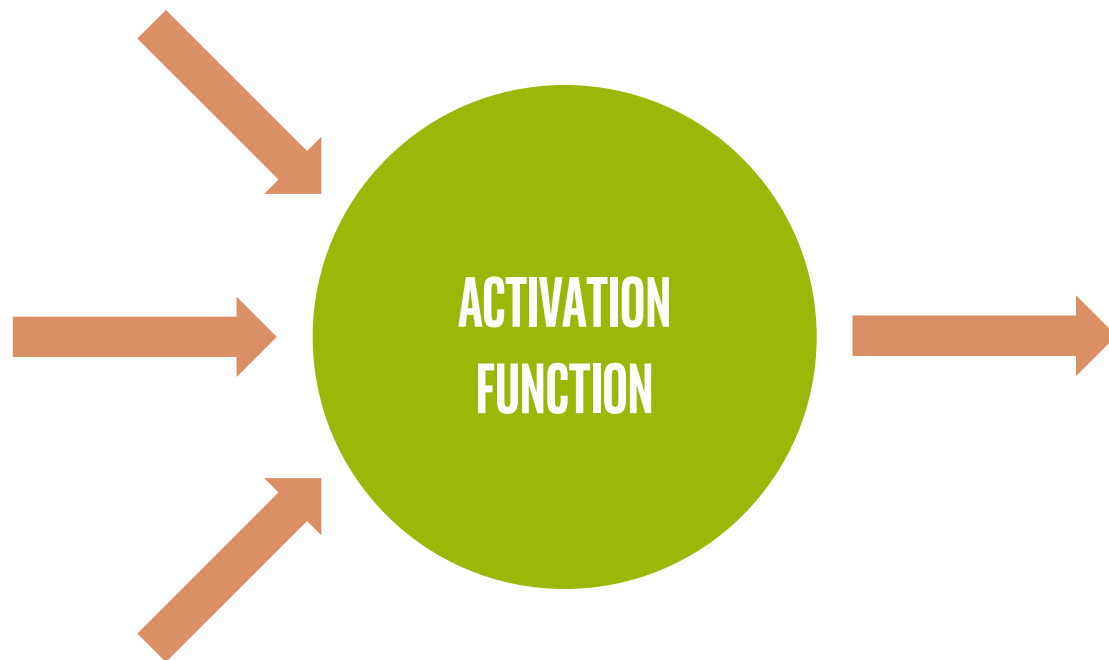


NEURAL NET STRUCTURE

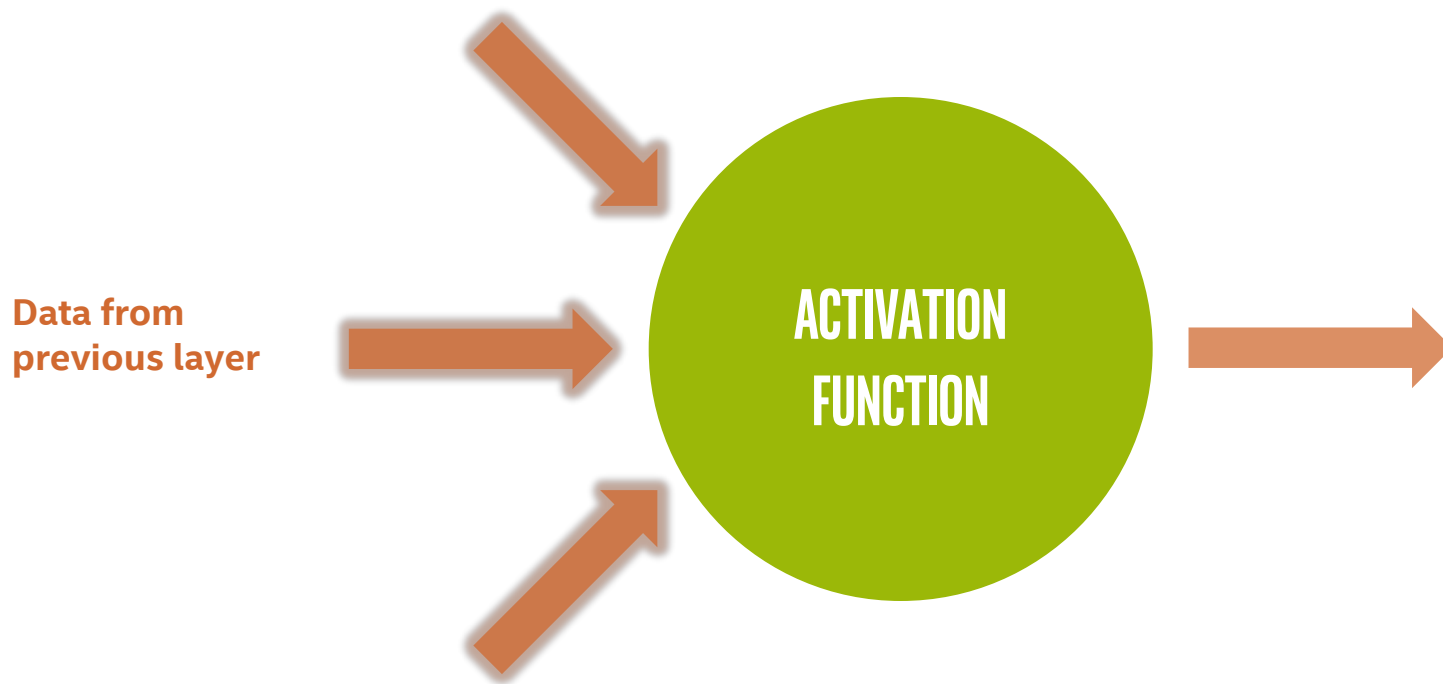


- Can think of it as a complicated computation engine
- We will "train it" using our training data
- Then (hopefully) it will give good answers on new data

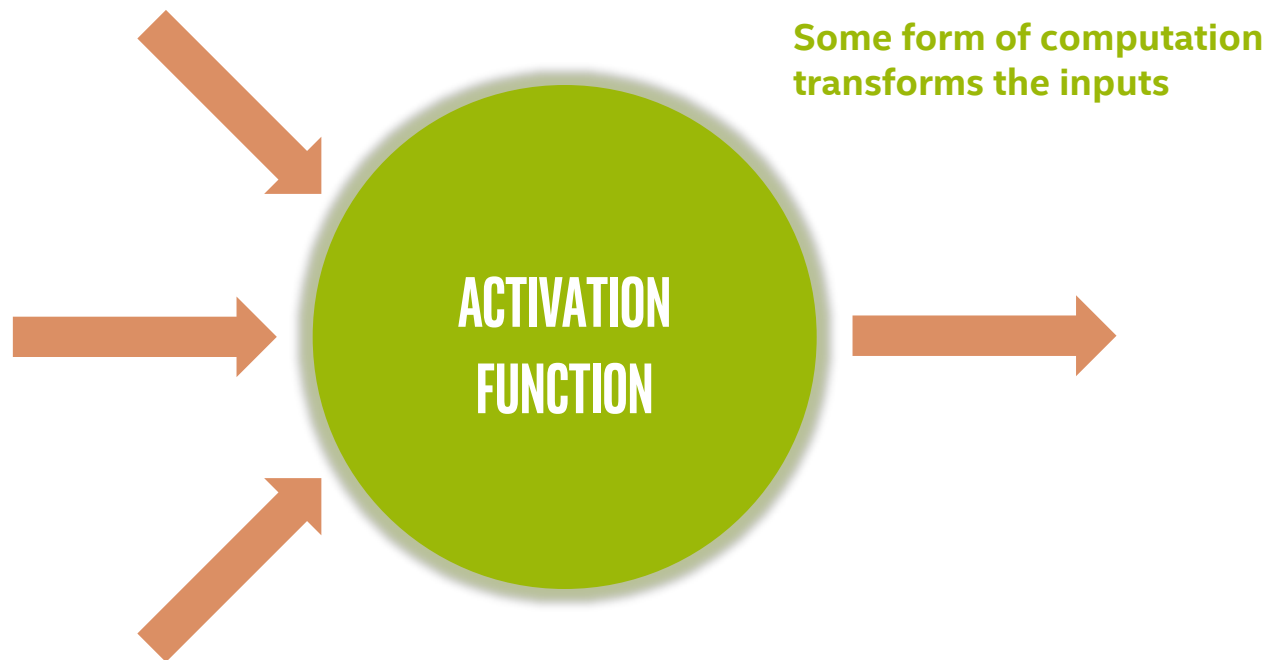
BASIC NEURON VISUALIZATION



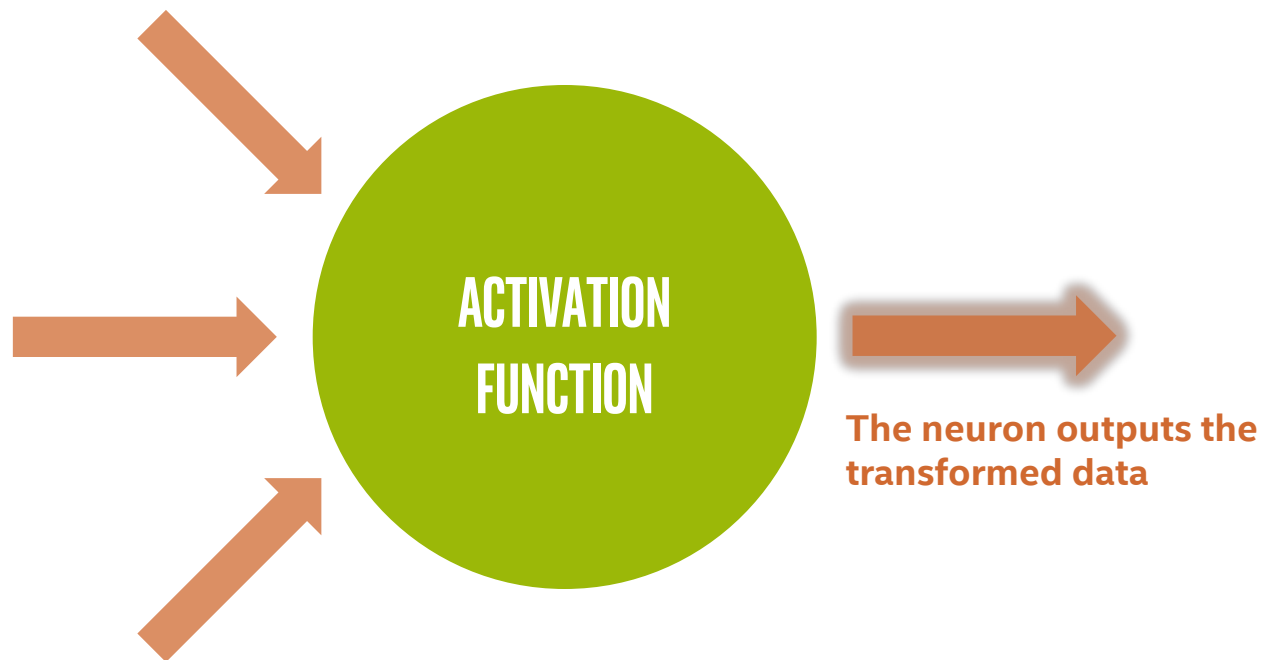
BASIC NEURON VISUALIZATION



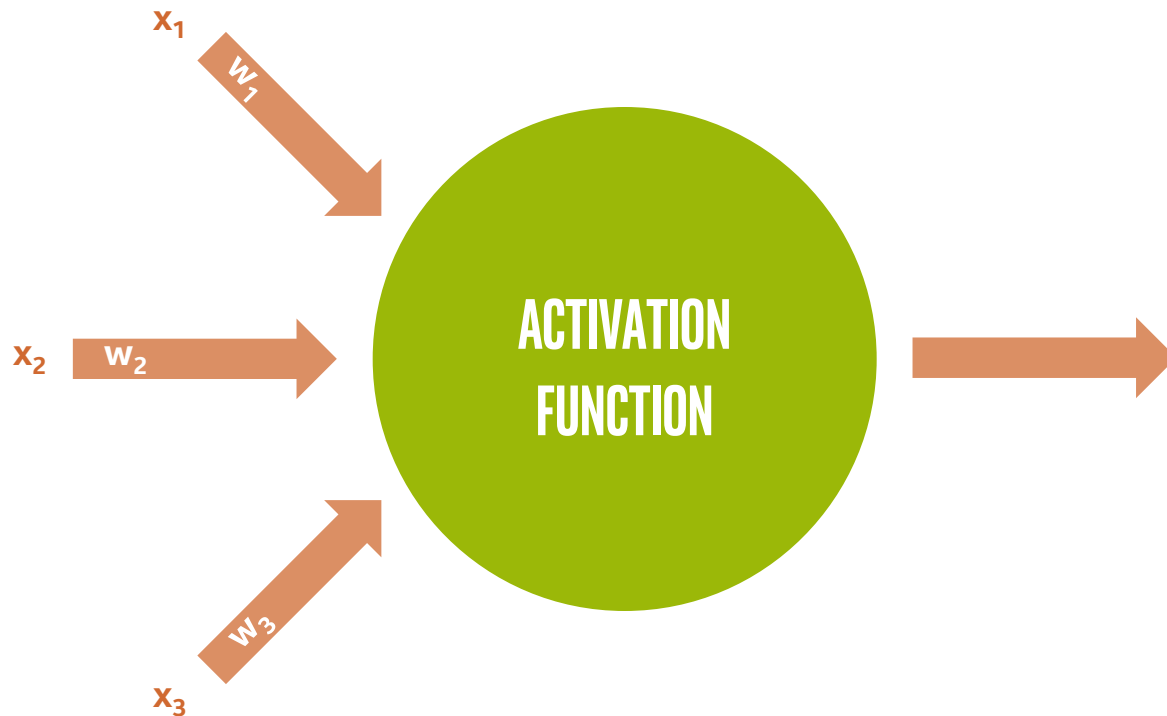
BASIC NEURON VISUALIZATION



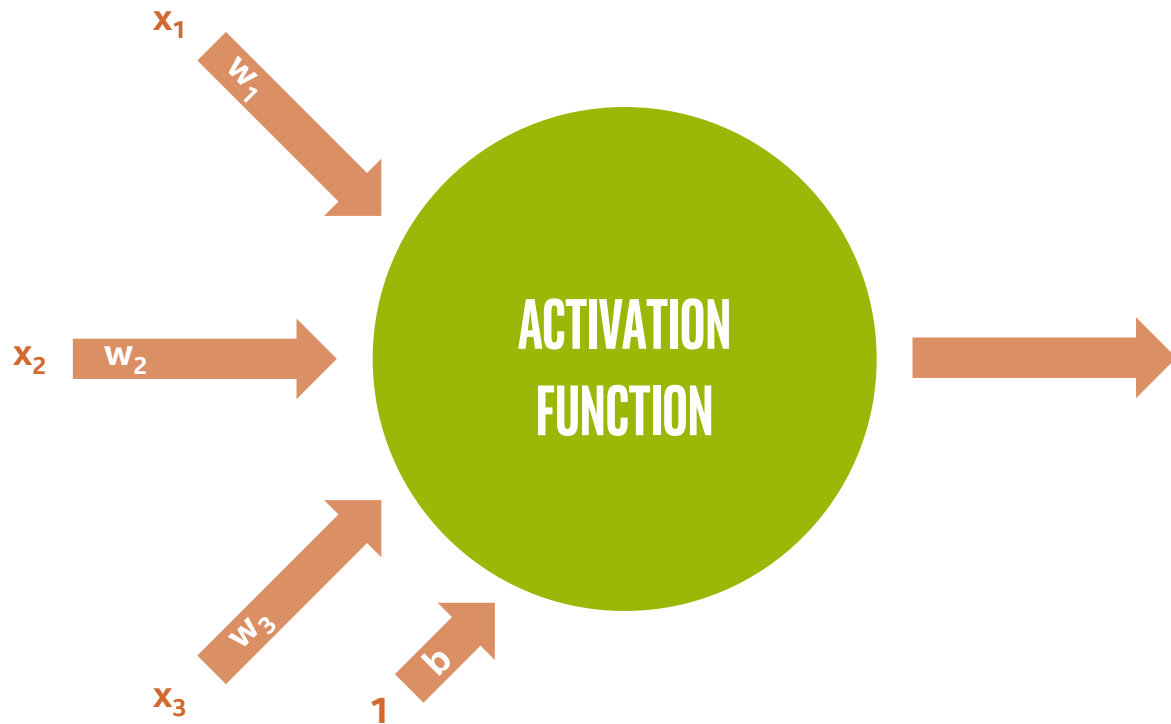
BASIC NEURON VISUALIZATION



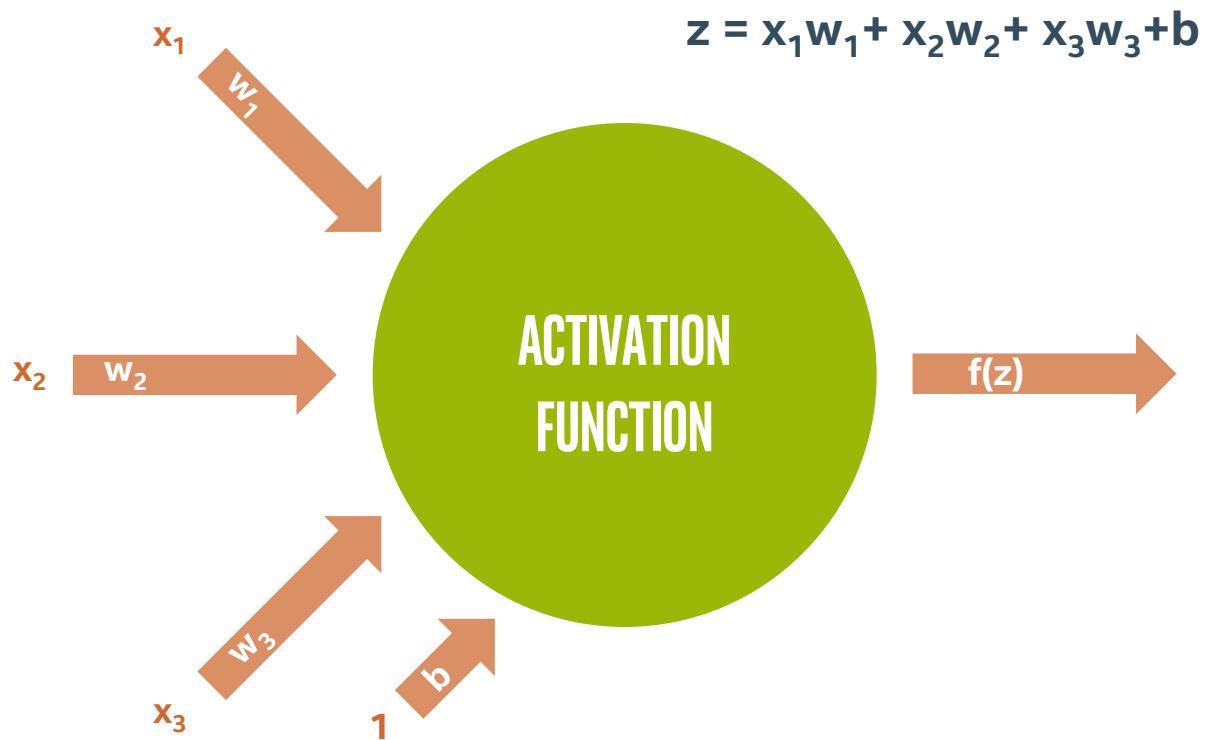
BASIC NEURON VISUALIZATION



BASIC NEURON VISUALIZATION



BASIC NEURON VISUALIZATION



IN VECTOR NOTATION

z = “net input”

b = “bias term”

f = activation function

a = output to next layer

$$z = b + \sum_{i=1}^m x_i w_i$$

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

$$a = f(z)$$

RELATION TO LOGISTIC REGRESSION

When we choose: $f(z) = \frac{1}{1+e^{-z}}$

$$z = b + \sum_{i=1}^m x_i w_i = x_1 w_1 + x_2 w_2 + \dots + x_m w_m + b$$

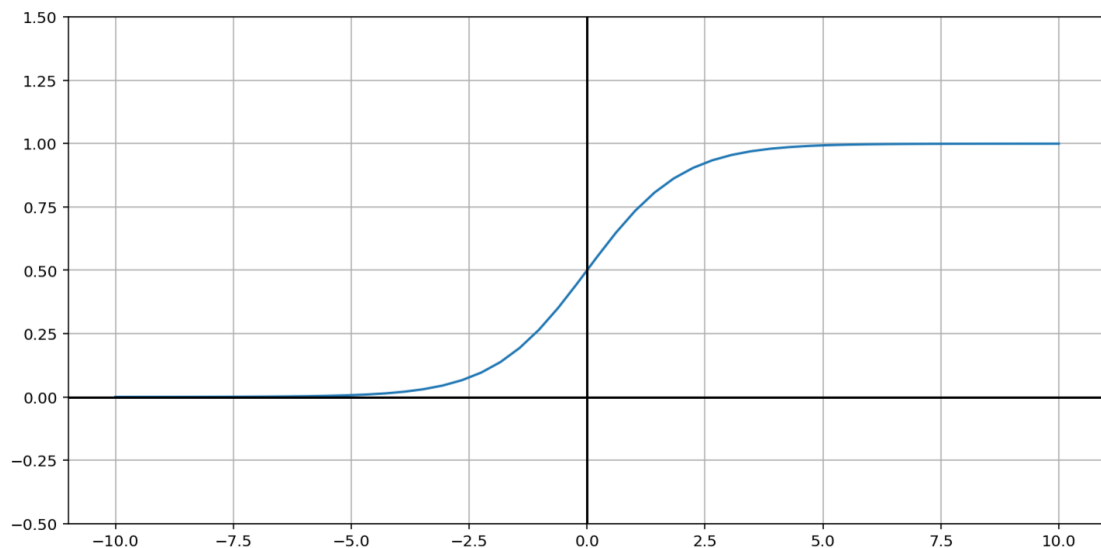
Then a neuron is simply a "unit" of logistic regression!

weights \Leftrightarrow coefficients inputs \Leftrightarrow variables

bias term \Leftrightarrow constant term

RELATION TO LOGISTIC REGRESSION

This is called the “sigmoid” function: $\sigma(z) = \frac{1}{1 + e^{-z}}$



NICE PROPERTY OF SIGMOID FUNCTION

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma'(z) = \frac{0 - (-e^{-z})}{(1 + e^{-z})^2} = \frac{e^{-z}}{(1 + e^{-z})^2}$$

$$= \frac{1 + e^{-z} - 1}{(1 + e^{-z})^2} = \frac{1 + e^{-z}}{(1 + e^{-z})^2} - \frac{1}{(1 + e^{-z})^2}$$

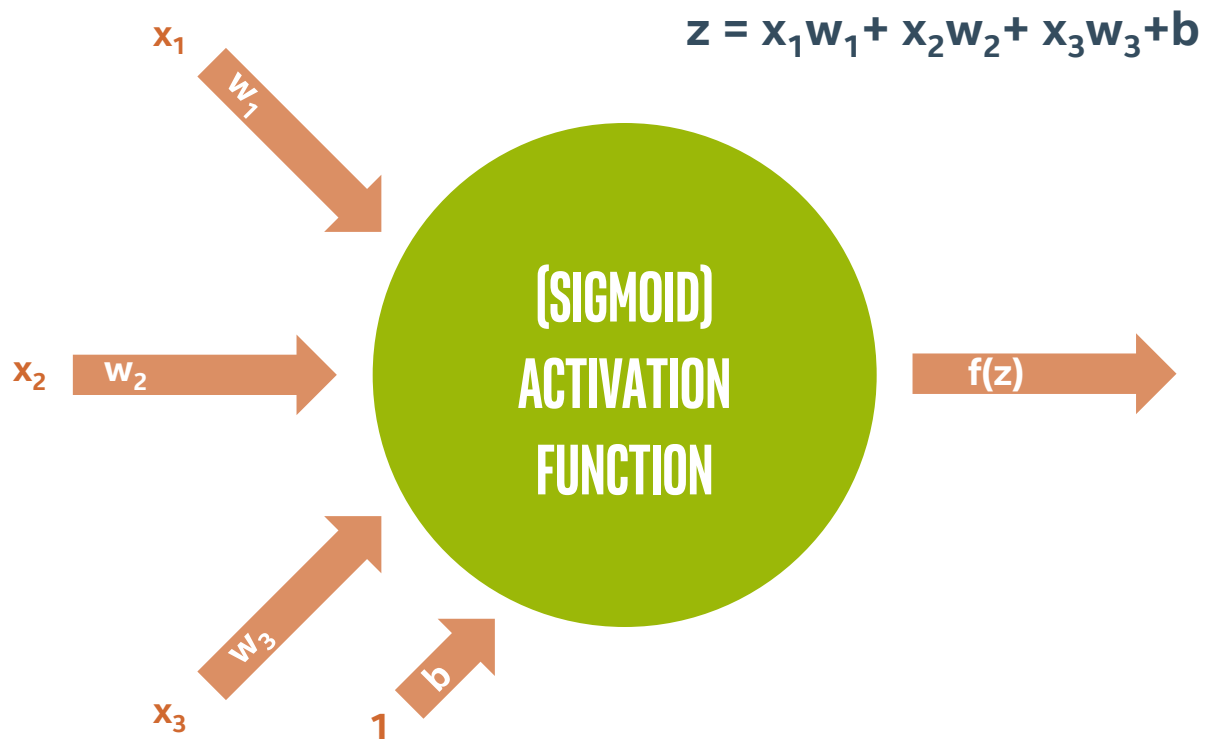
$$= \frac{1}{1 + e^{-z}} - \frac{1}{(1 + e^{-z})^2} = \frac{1}{1 + e^{-z}} \left(1 - \frac{1}{1 + e^{-z}} \right)$$

$$\sigma'(z) = \sigma(z)(1 - \sigma(z)) \quad \text{This will be helpful!}$$

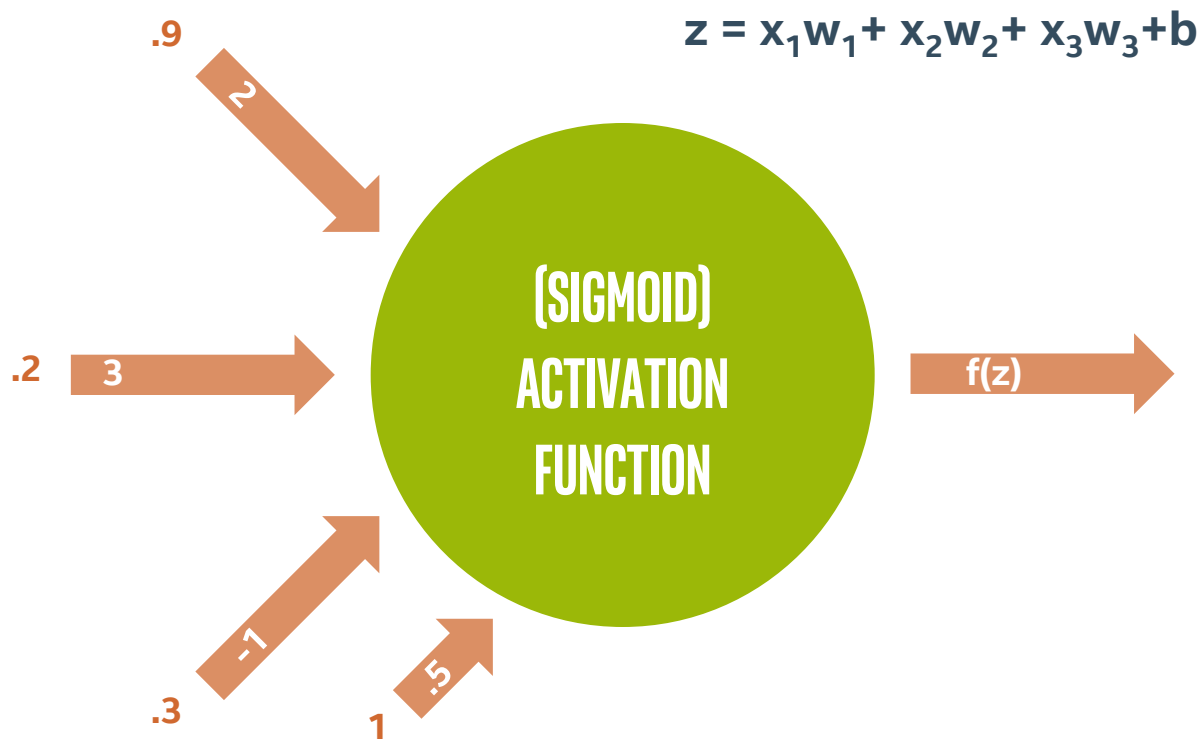
Quotient rule

$$\frac{d}{dx} \cdot \frac{f(x)}{g(x)} = \frac{f'(x)g(x) - f(x)g'(x)}{g(x)^2}$$

EXAMPLE NEURON COMPUTATION

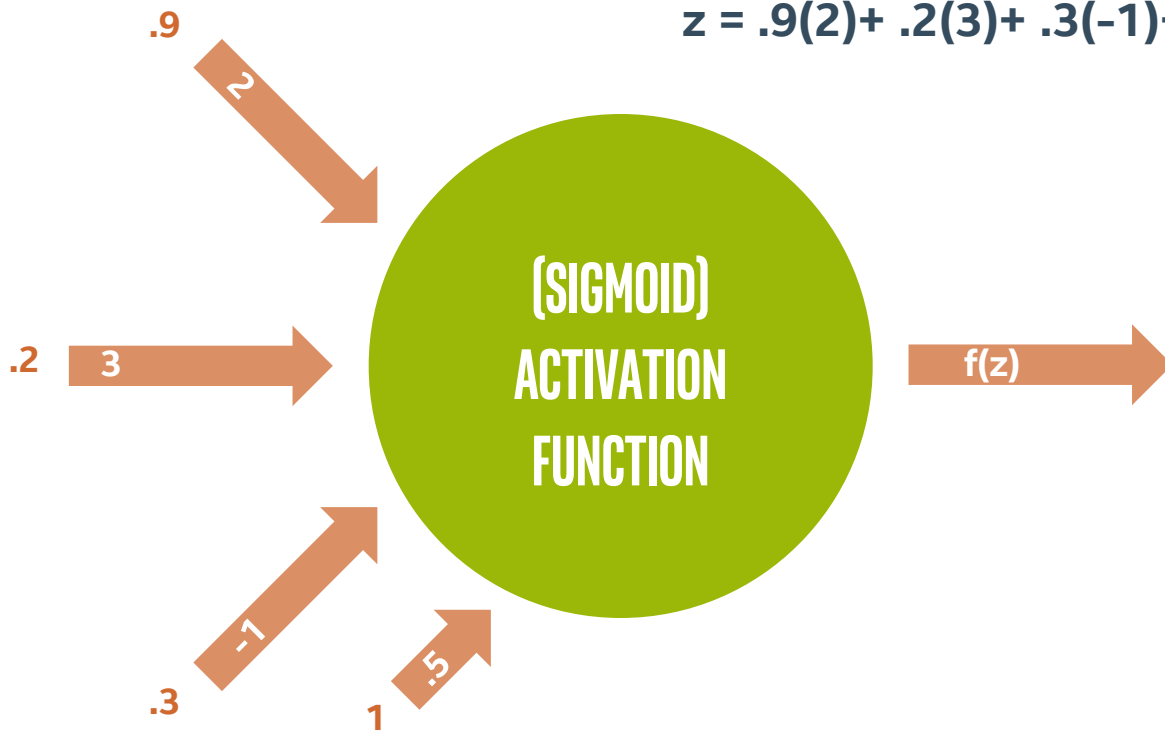


EXAMPLE NEURON COMPUTATION

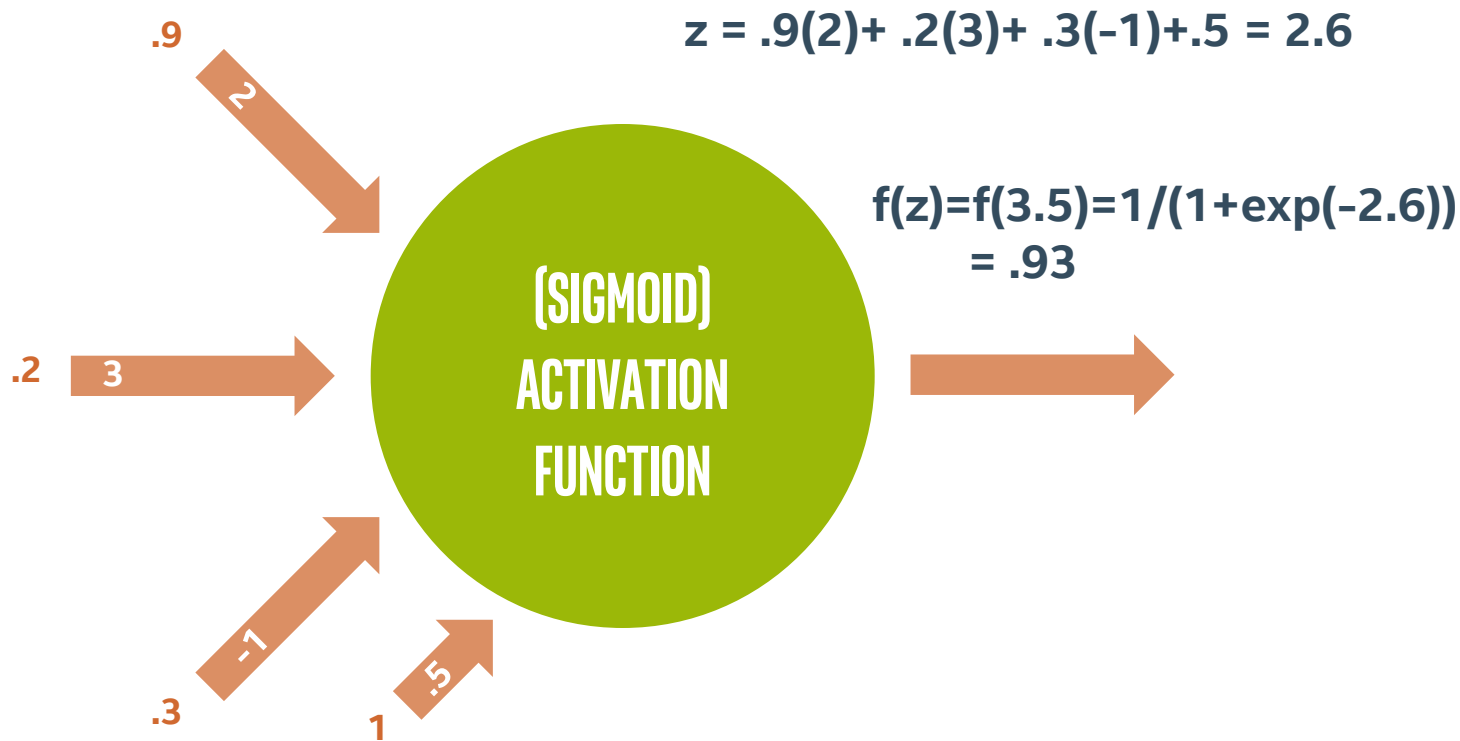


EXAMPLE NEURON COMPUTATION

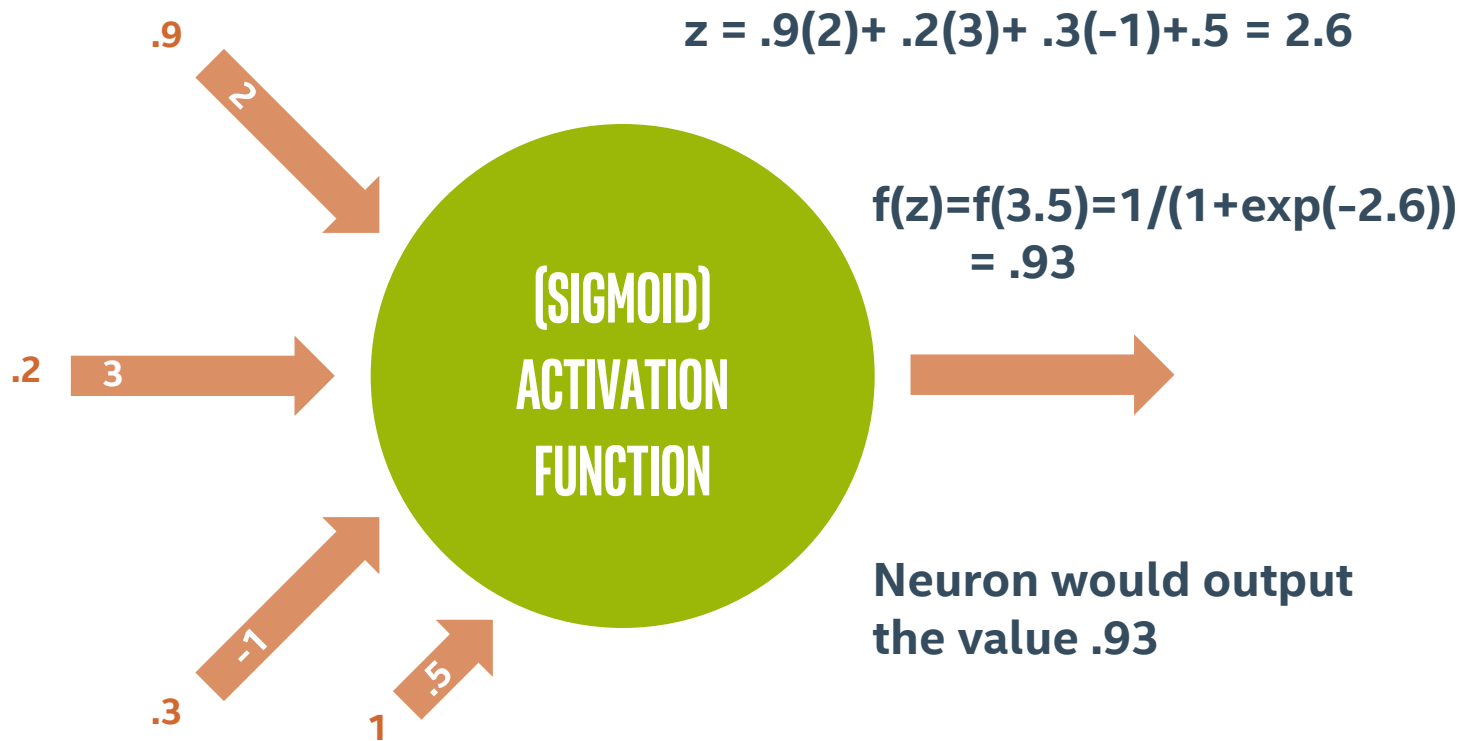
$$z = .9(2) + .2(3) + .3(-1) + .5 = 2.6$$



EXAMPLE NEURON COMPUTATION

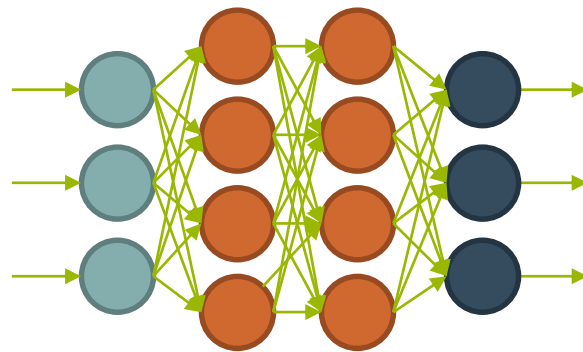


EXAMPLE NEURON COMPUTATION

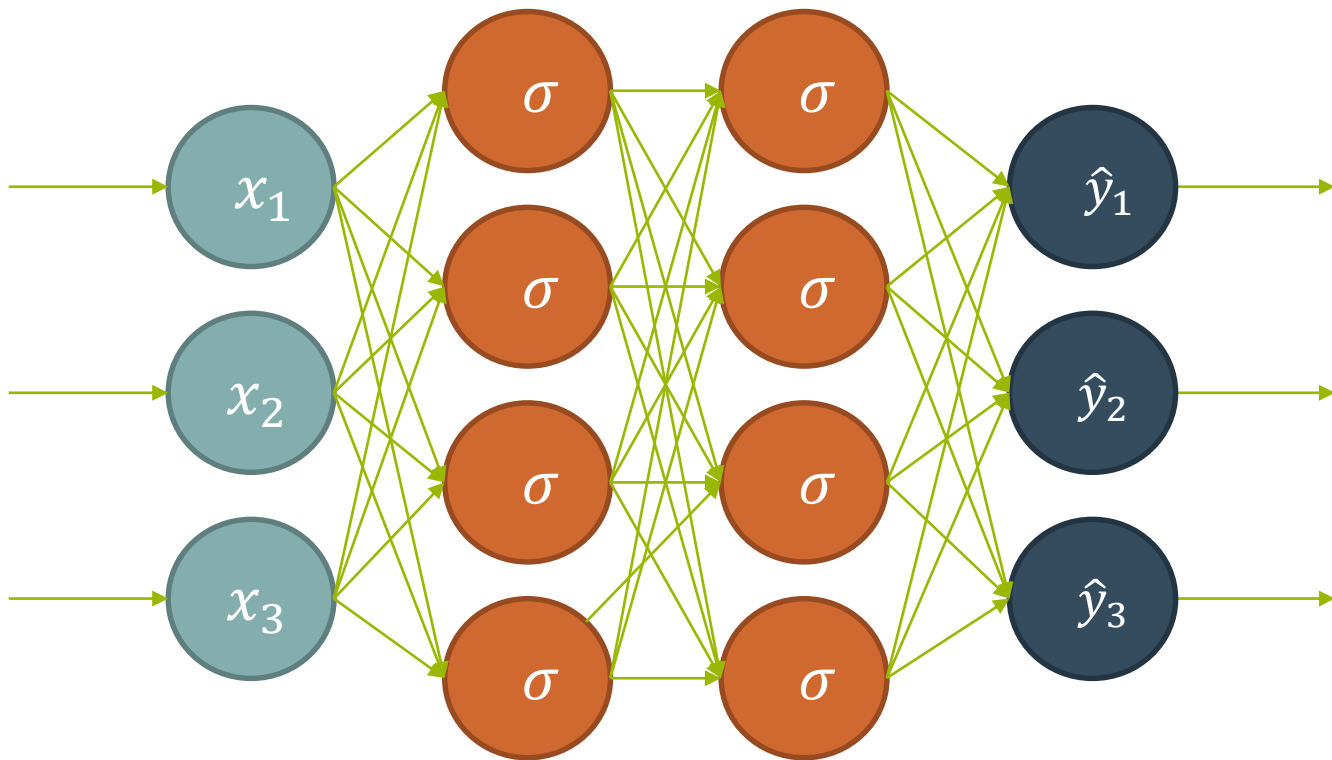


WHY NEURAL NETS?

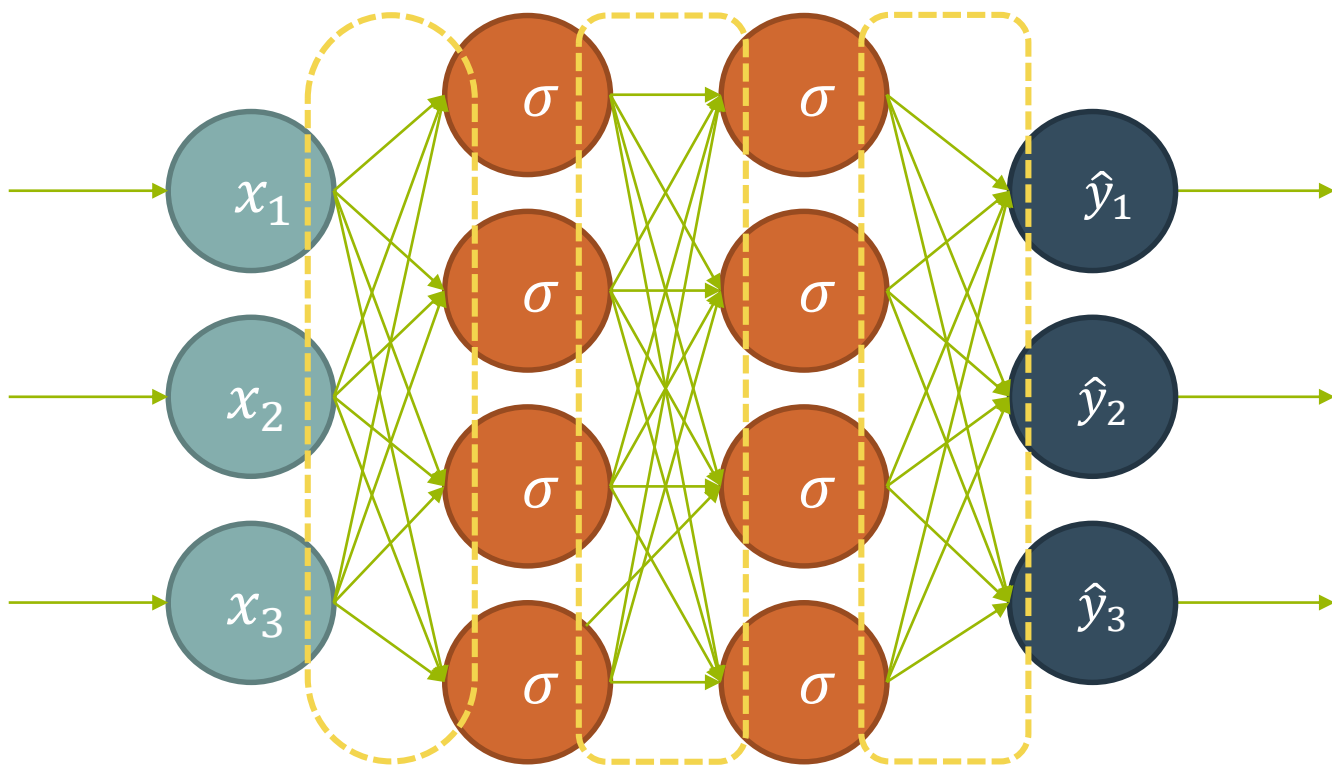
- Why not just use a single neuron?
Why do we need a larger network?
- A single neuron (like logistic regression) only permits a linear decision boundary.
- Most real-world problems are considerably more complicated!



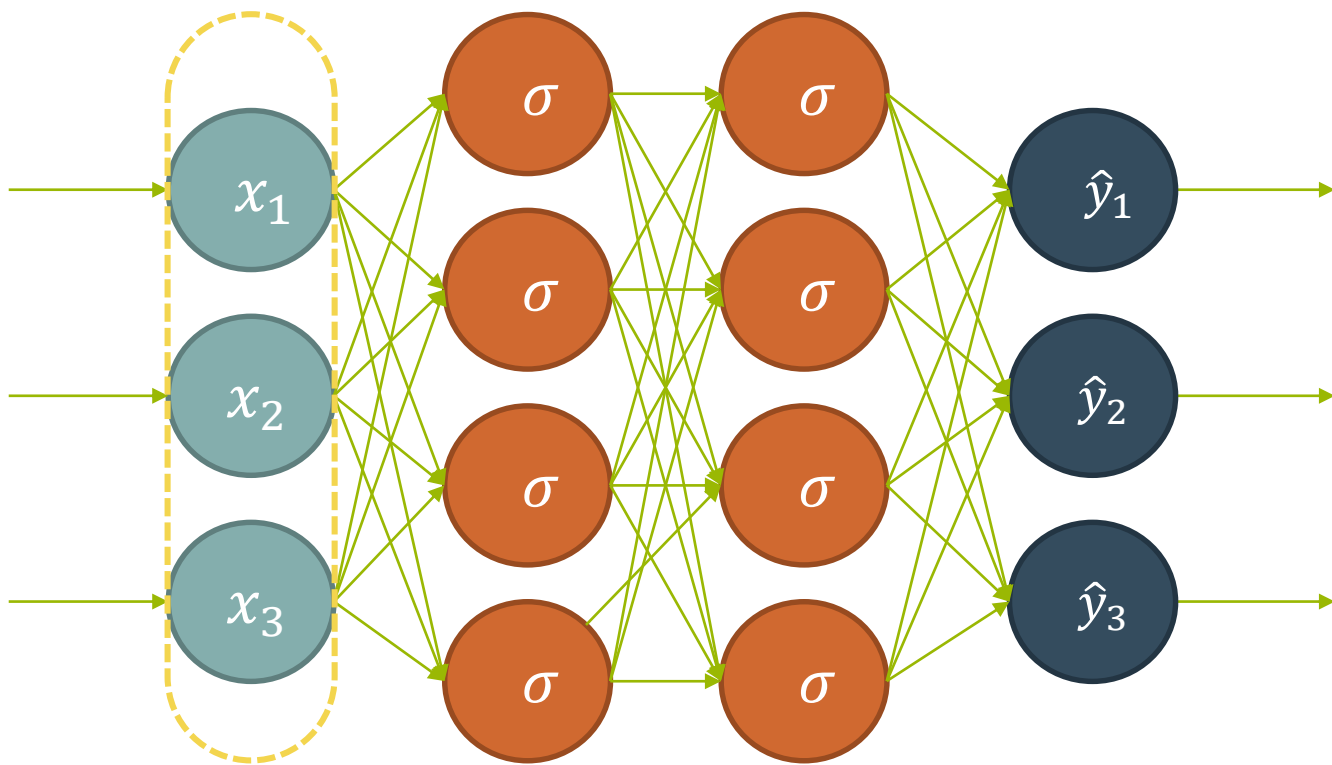
FEEDFORWARD NEURAL NETWORK



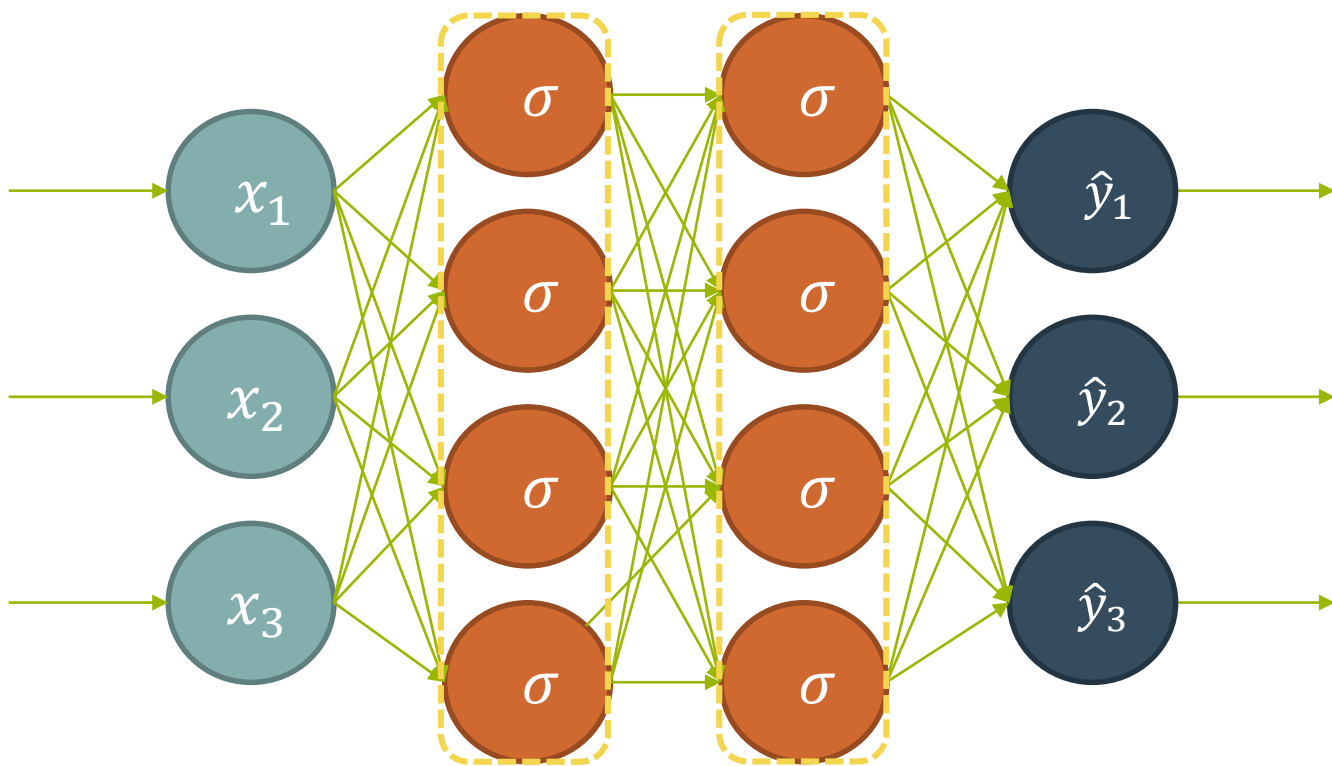
WEIGHTS



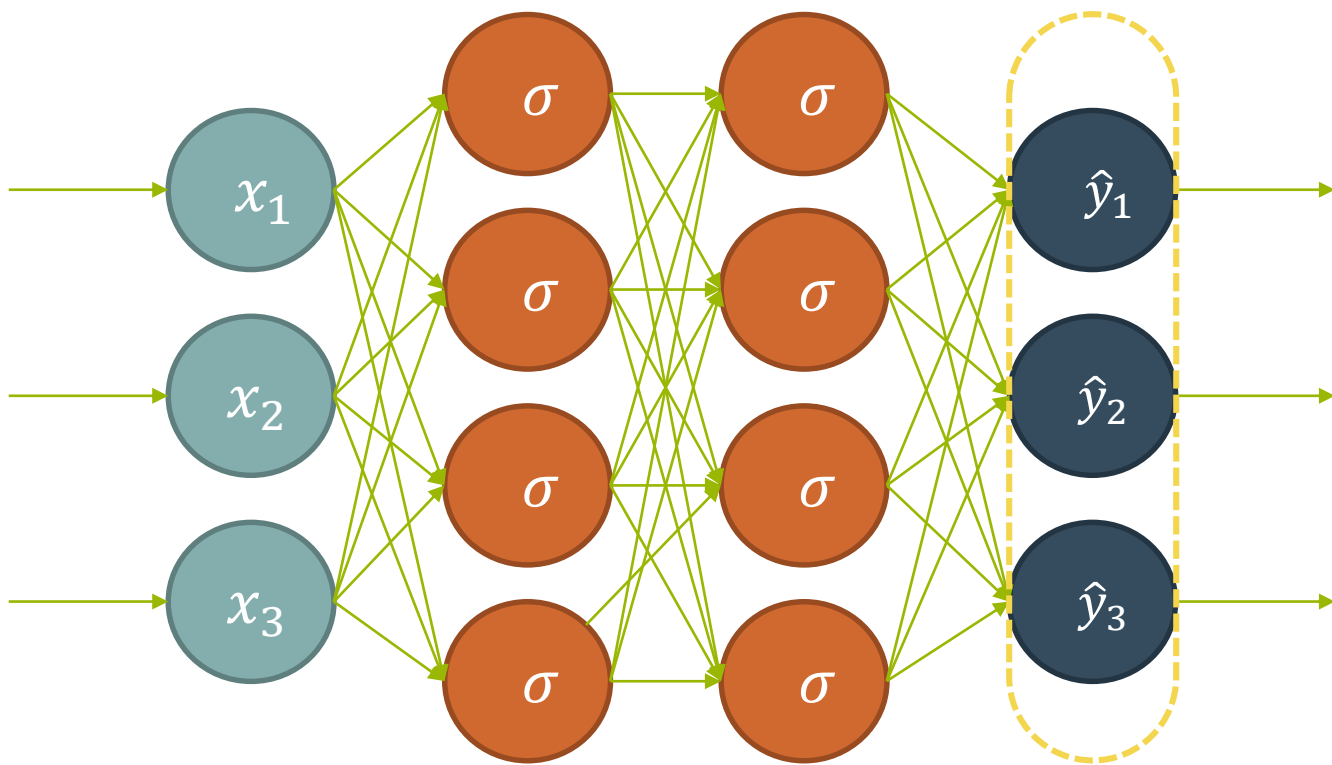
INPUT LAYER



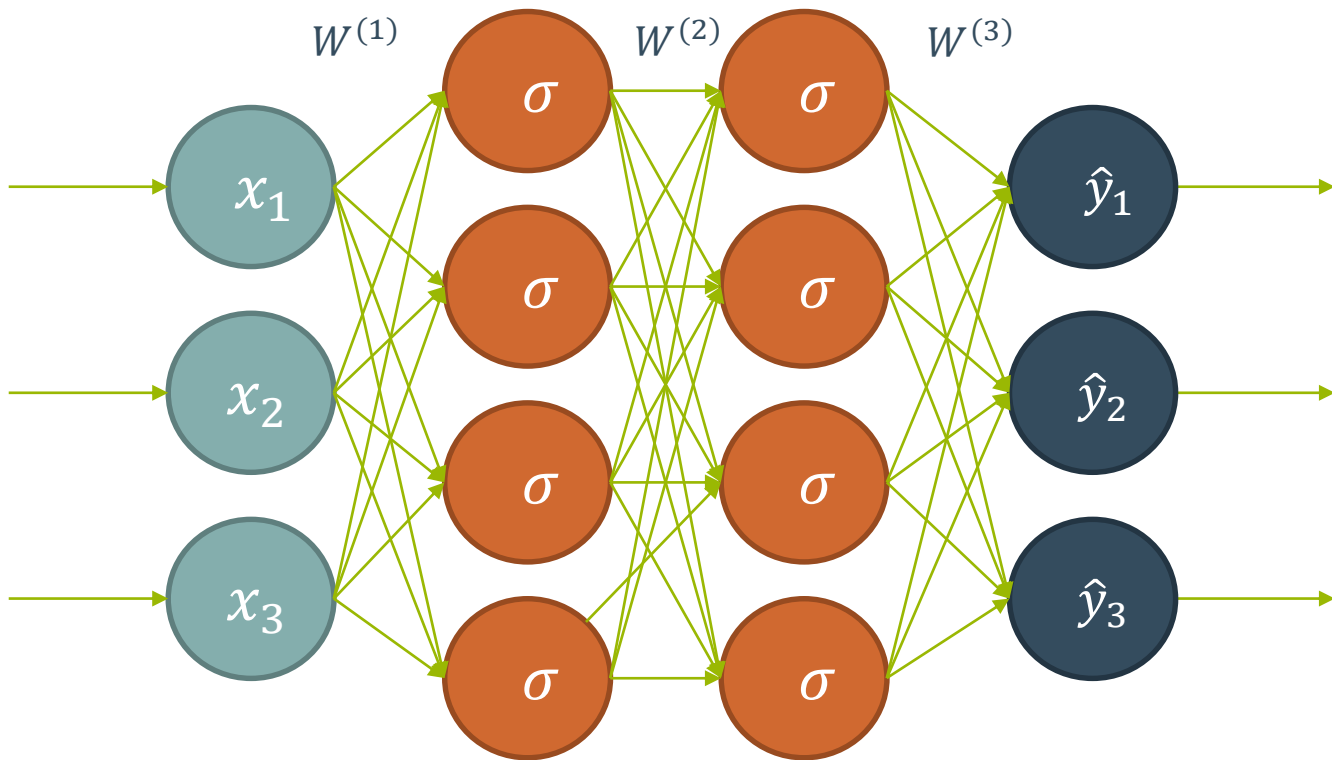
HIDDEN LAYERS



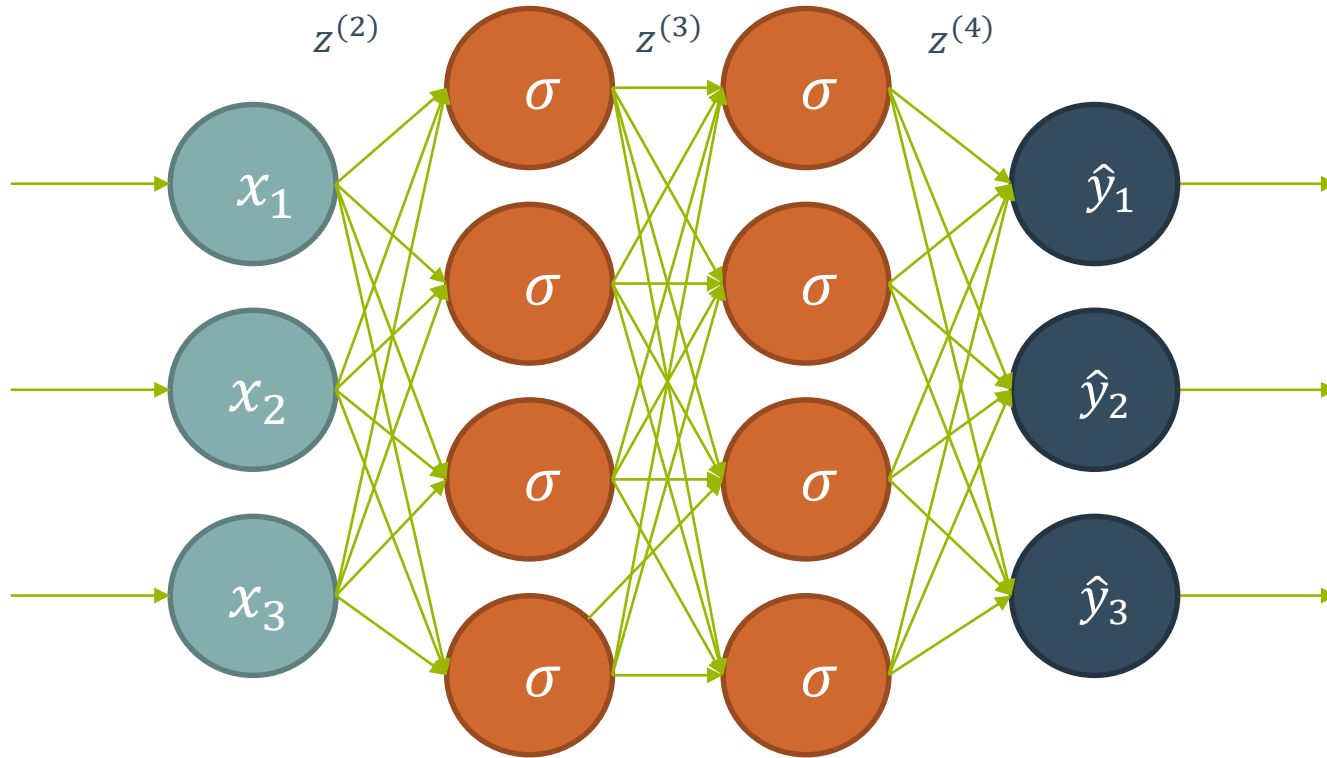
OUTPUT LAYER



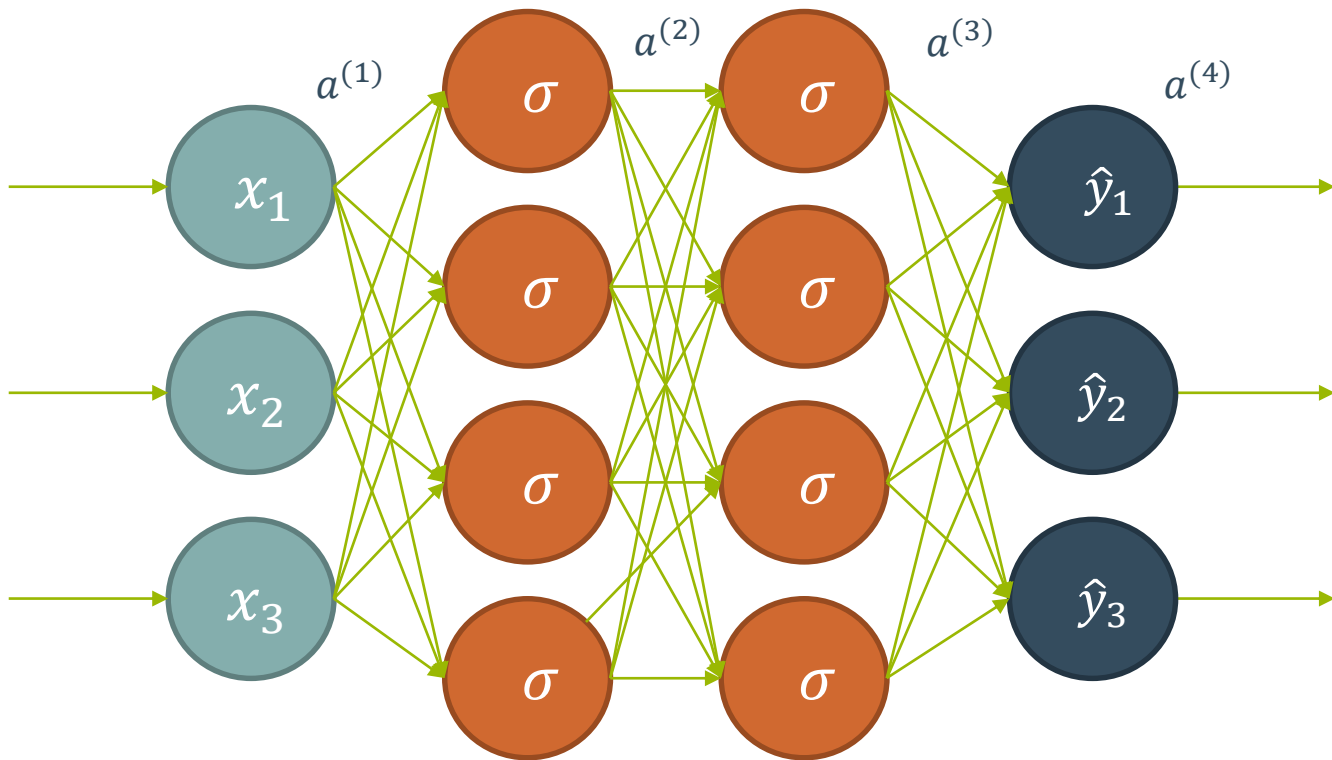
WEIGHTS (REPRESENTED BY MATRICES)



NET INPUT (SUM OF WEIGHTED INPUTS, BEFORE ACTIVATION FUNCTION)



ACTIVATIONS (OUTPUT OF NEURONS TO NEXT LAYER)



MATRIX REPRESENTATION OF COMPUTATION

x

$$(x = a^{(1)})$$

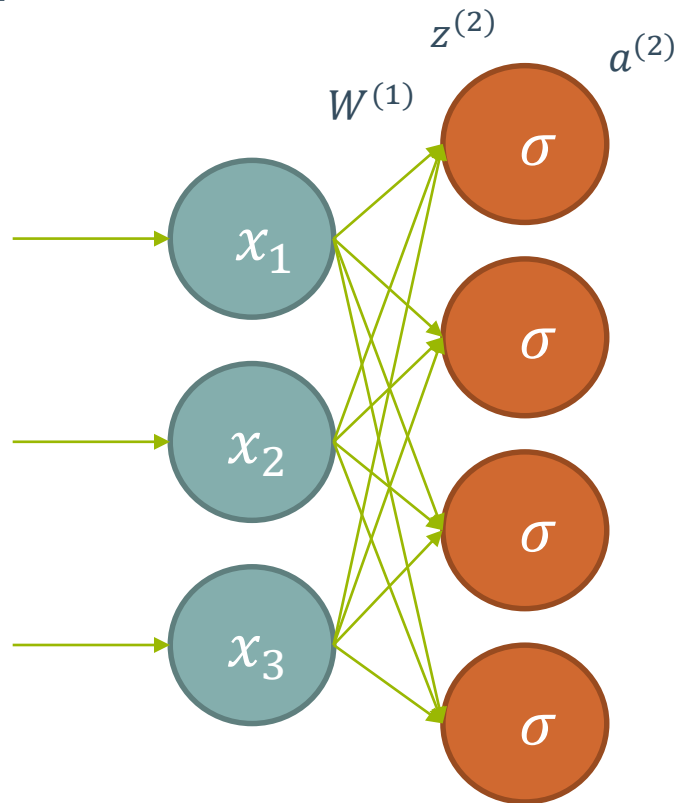
$$z^{(2)} = xW^{(1)}$$

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

$W^{(1)}$ is a
3x4 matrix

$z^{(2)}$ is a
4-vector

$a^{(2)}$ is a
4-vector



CONTINUING THE COMPUTATION

For a single training instance (data point)

Input: vector x (a row vector of length 3)

Output: vector \hat{y} (a row vector of length 3)

$$z^{(2)} = xW^{(1)} \qquad a^{(2)} = \sigma(z^{(2)})$$

$$z^{(3)} = a^{(2)}W^{(2)} \qquad a^{(3)} = \sigma(z^{(3)})$$

$$z^{(4)} = a^{(3)}W^{(3)} \qquad \hat{y} = \textit{softmax}(z^{(4)})$$

Now we know how feedforward NNs do Computations.

Next, we will learn how to adjust the weights to learn from data.

