intel Software

Introduction to Neural Nets

Materials from

- Intel Deep Learning https://www.intel.com/content/www/us/en/developer/learn/course-deep-learning.html

Legal Notices and Disclaimers

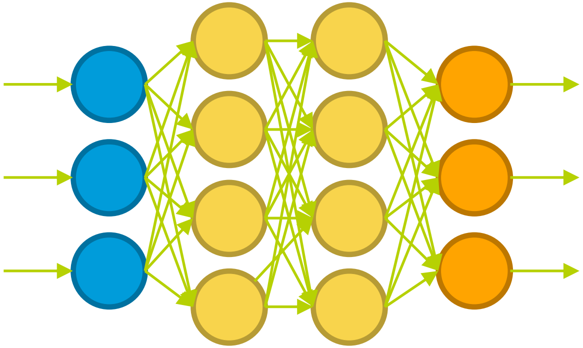
This presentation is for informational purposes only. INTEL MAKES NO WARRANTIES, EXPRESS OR IMPLIED, IN THIS SUMMARY.

Intel technologies' features and benefits depend on system configuration and may require enabled hardware, software or service activation. Performance varies depending on system configuration. Check with your system manufacturer or retailer or learn more at intel.com.

This sample source code is released under the Intel Sample Source Code License Agreement.

Motivation for Neural Nets

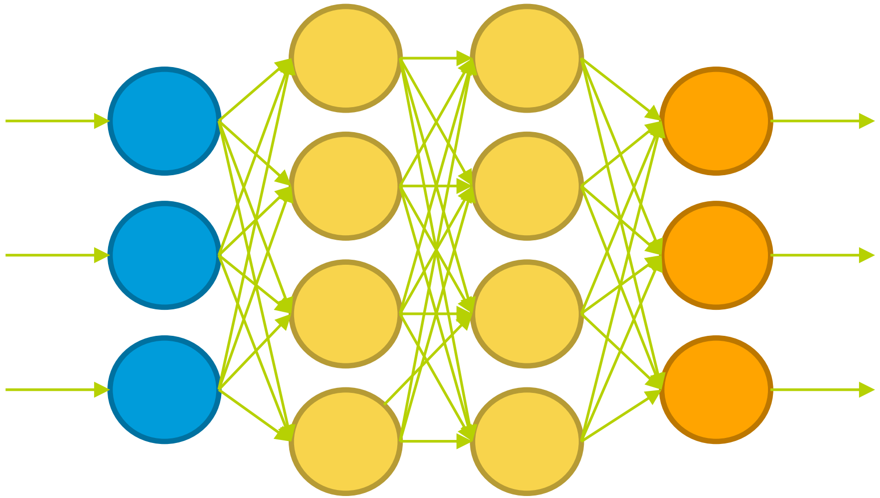
- Use biology as inspiration for mathematical model
- Get signals from previous neurons
- Generate signals (or not) according to inputs
- Pass signals on to next neurons
- By layering many neurons, can create complex model



Neural Net Structure

Input

(Feature Vector)

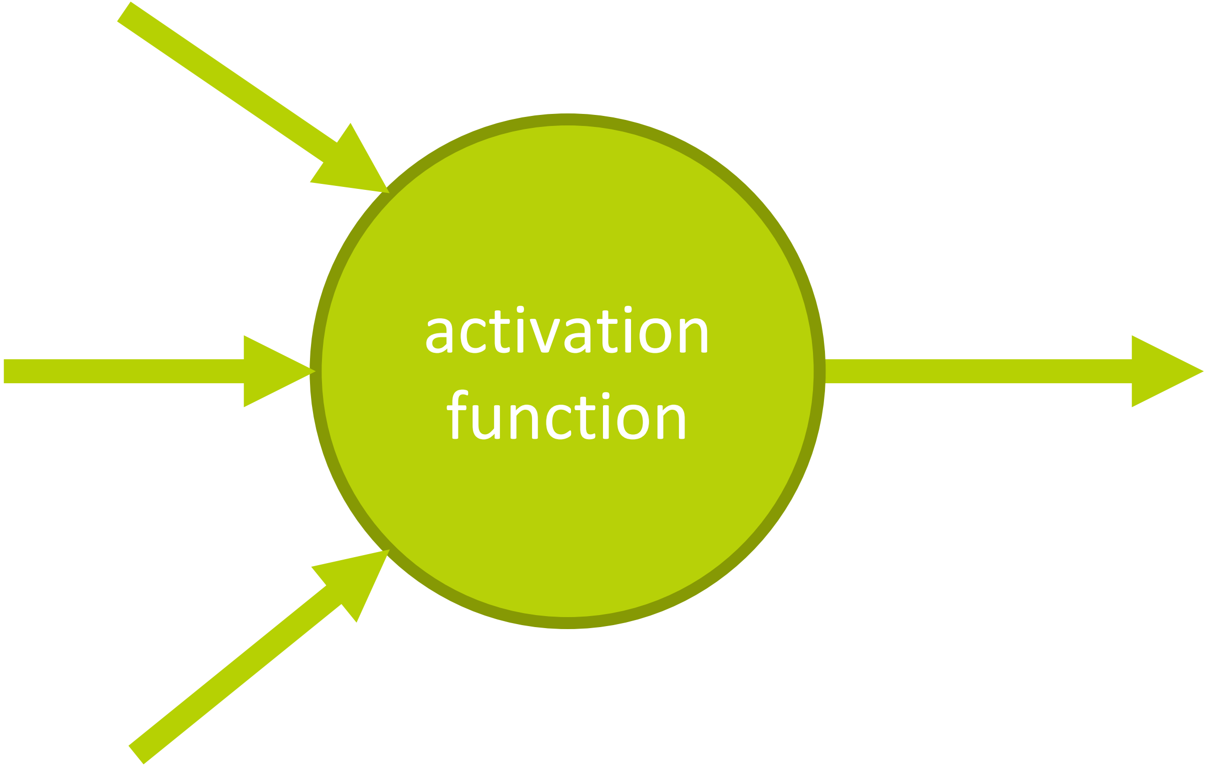


Output

(Label)

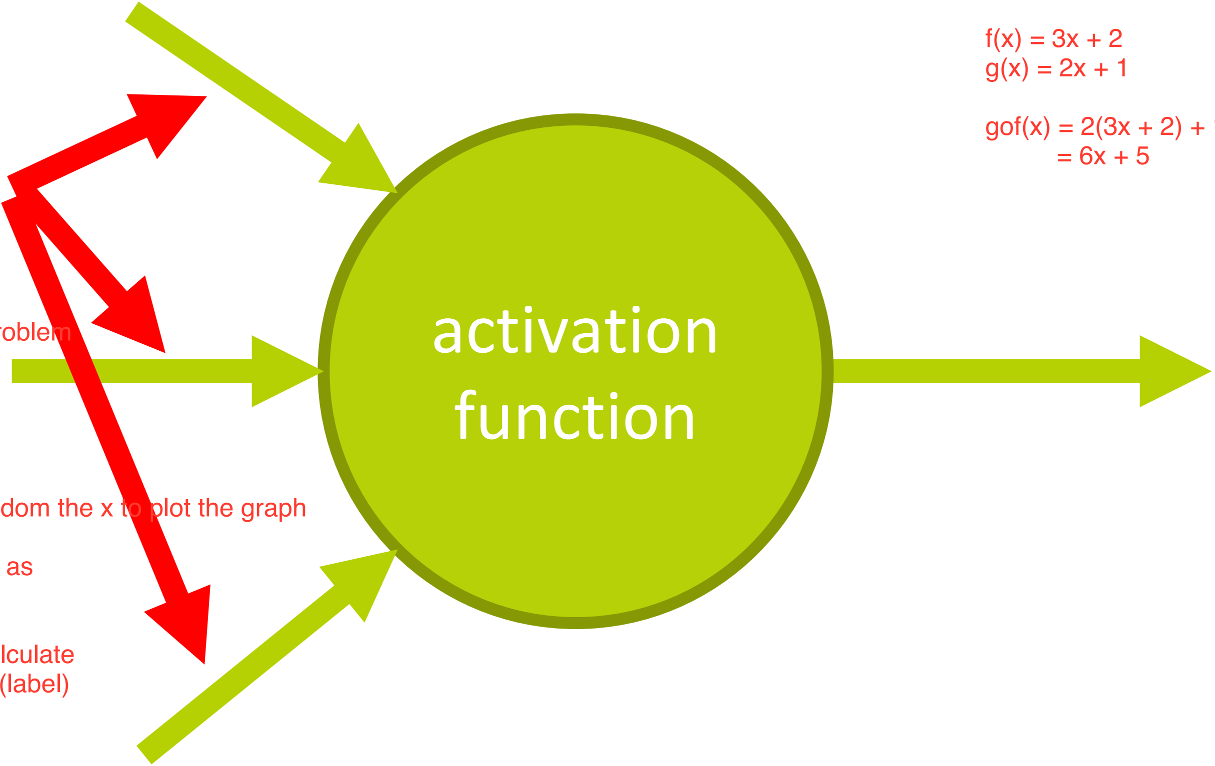
- Can think of it as a complicated computation engine
- We will ”train it” using our training data
- Then (hopefully) it will give good answers on new data

Basic Neuron Visualization



Basic Neuron Visualization

Data from previous layer



Linear function can't solve much problem
so in deep learning we prefer
more complex function

from y = ax + b

generally we know a, b and we random the x to plot the graph

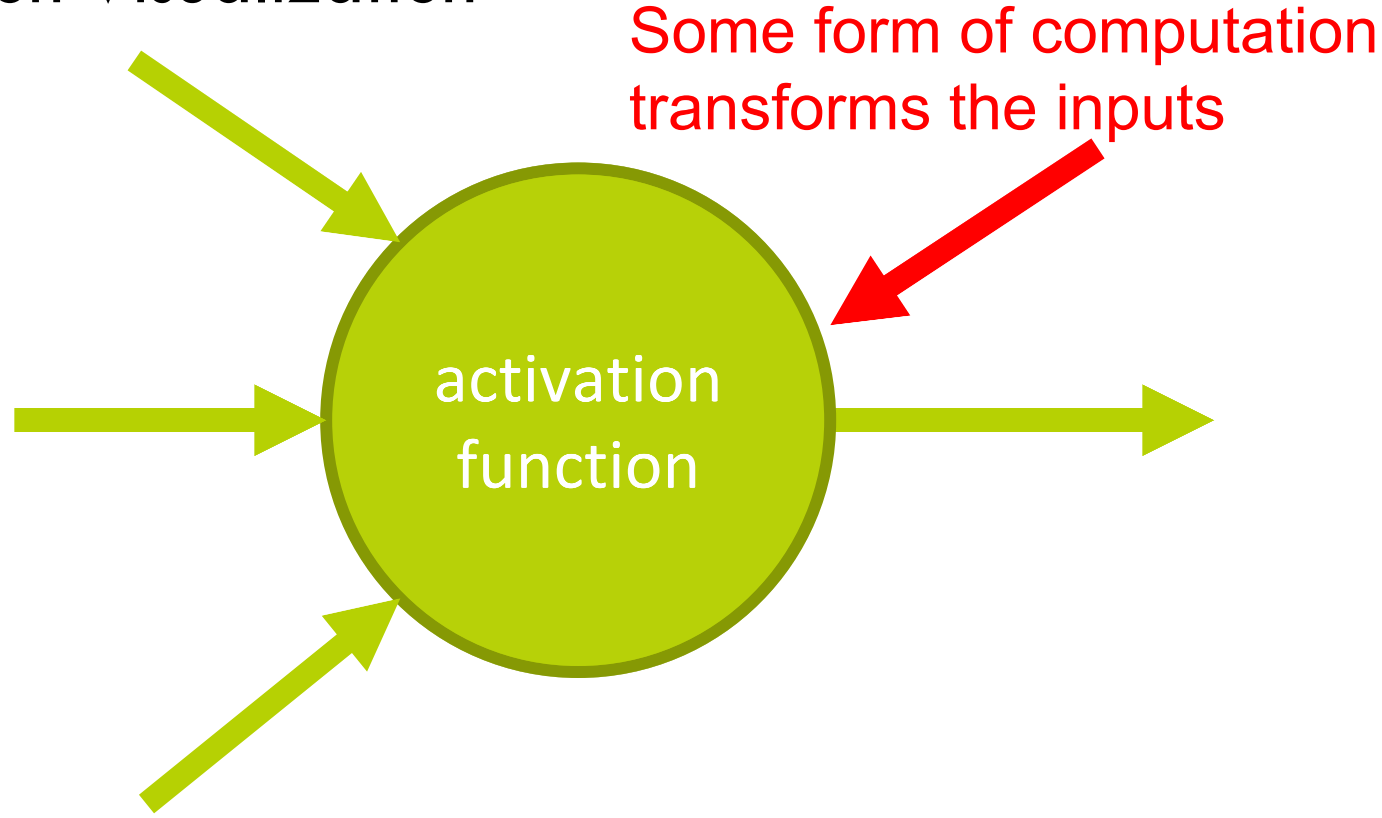
but in this term we will get the data as
x (input data) and y (label)

and we will train the a and be to calculate
the y hat correctly, closest to the y (label)

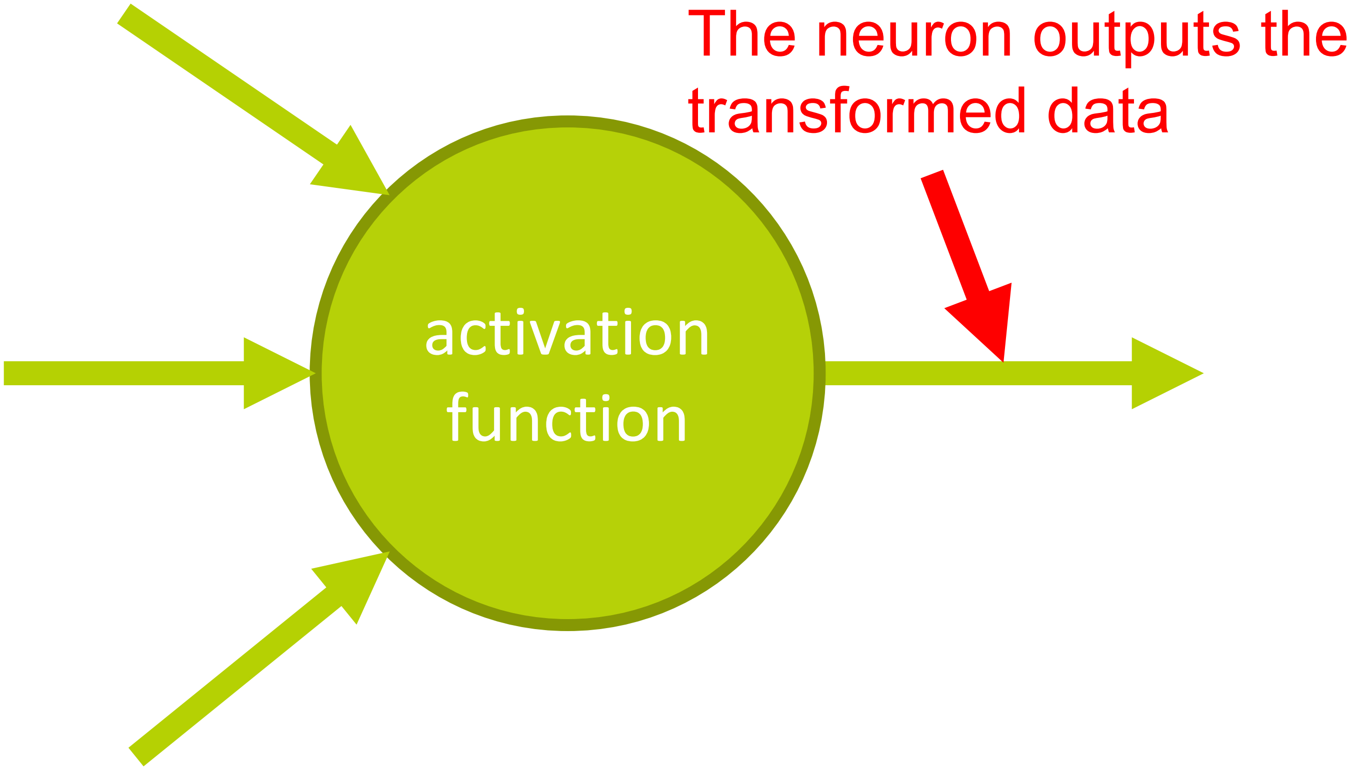
$f(x) = 3x + 2$
$g(x) = 2x + 1$

$gof(x) = 2(3x + 2) + 1$
$= 6x + 5$

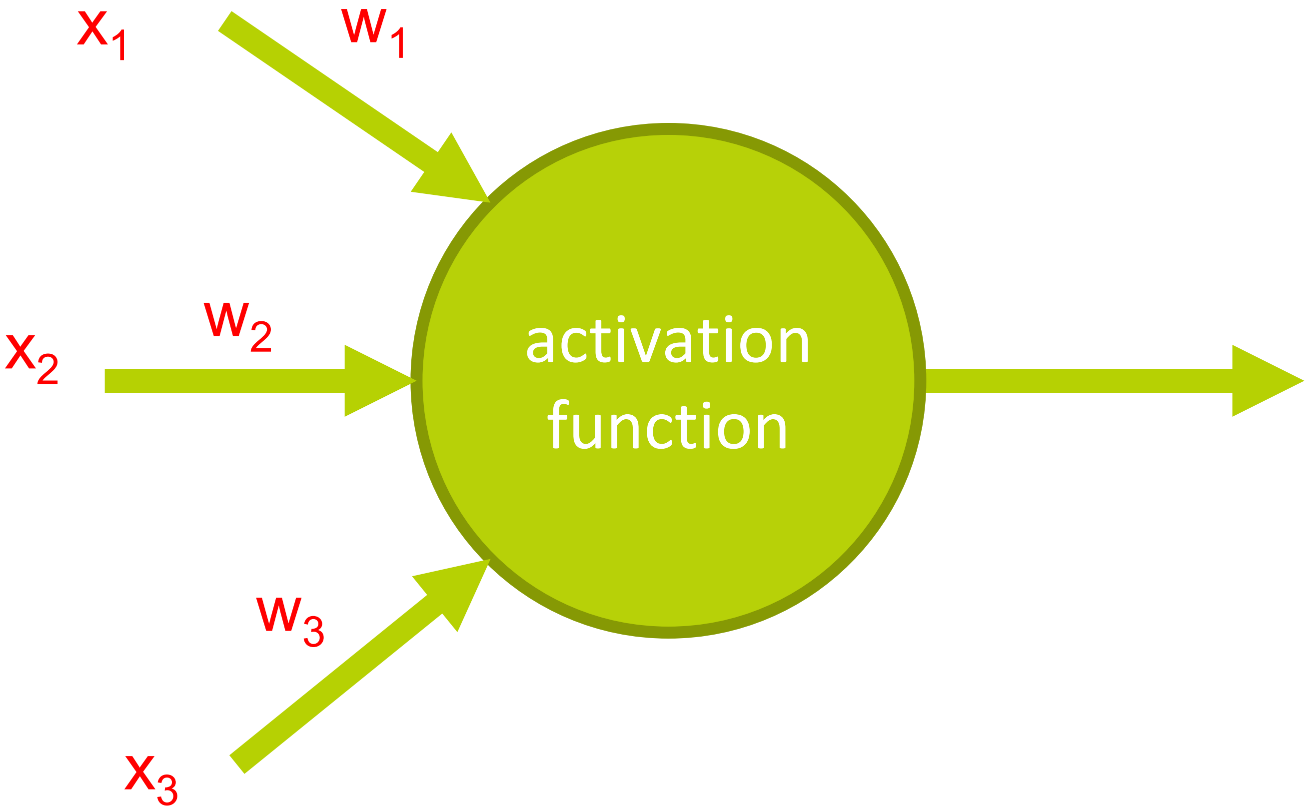
Basic Neuron Visualization



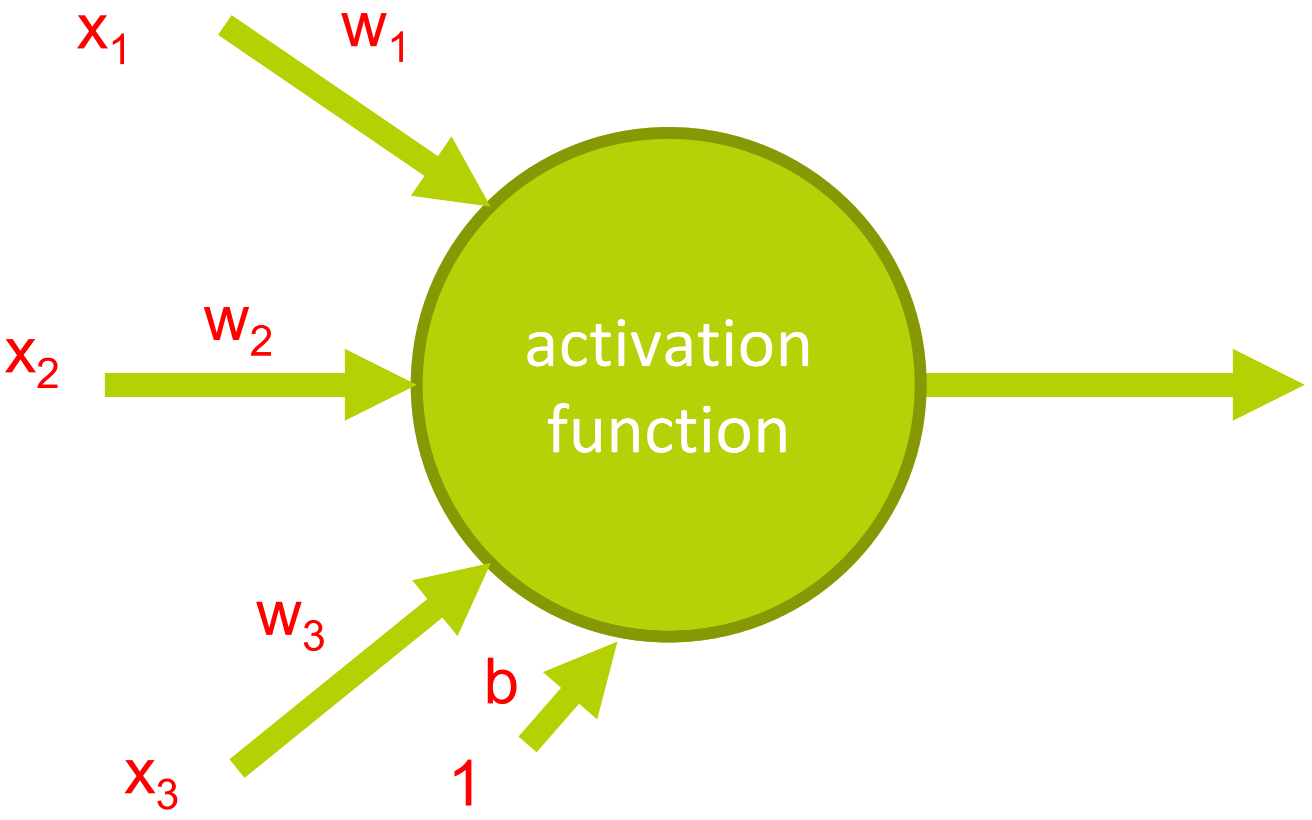
Basic Neuron Visualization



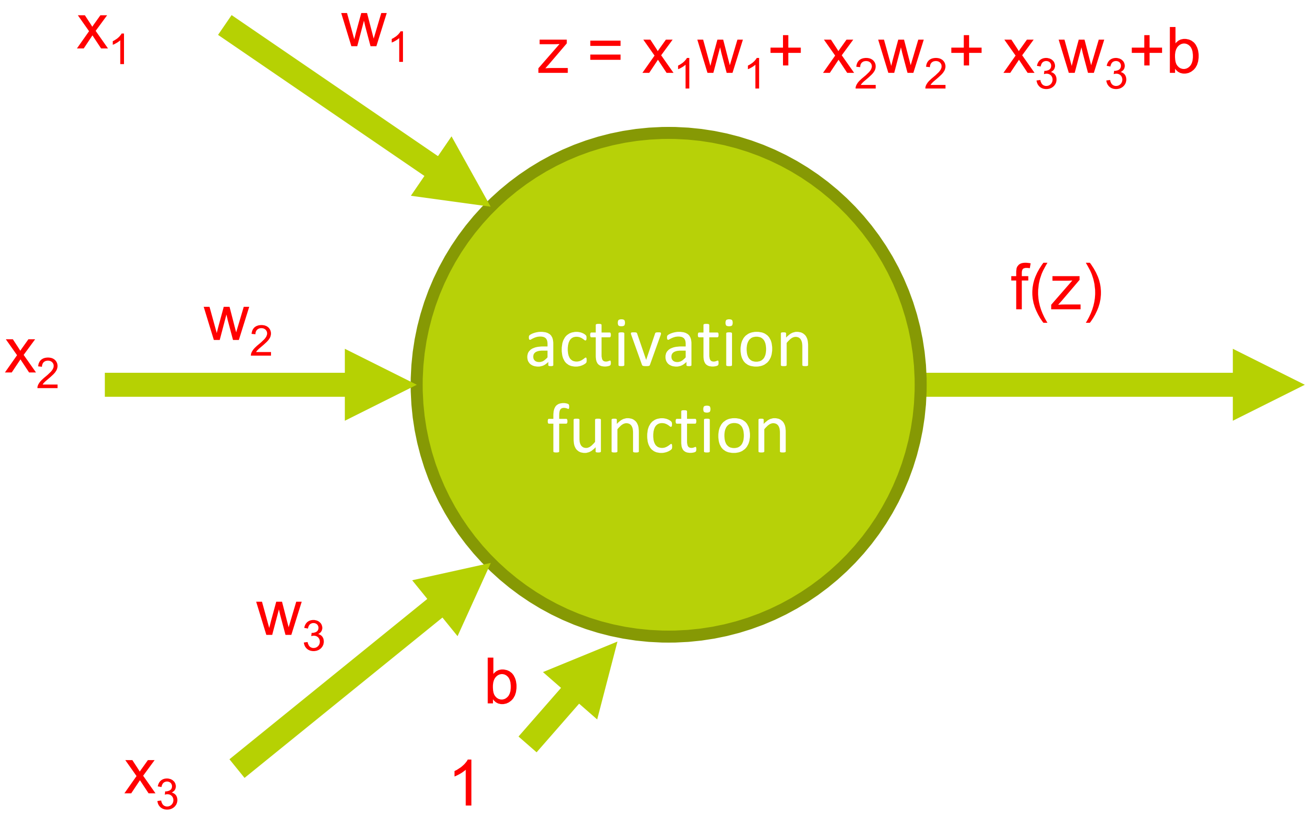
Basic Neuron Visualization



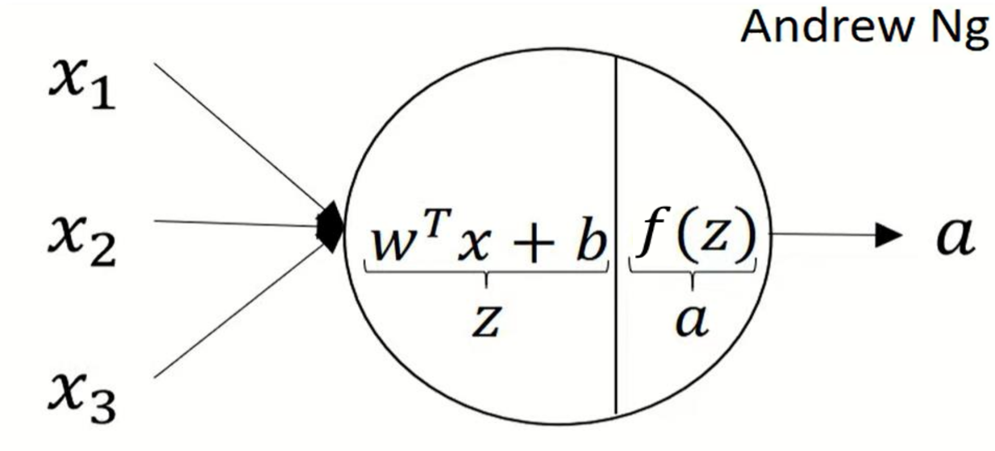
Basic Neuron Visualization



Basic Neuron Visualization



In Vector Notation



$$z = b + x_1 w_1 + x_2 w_2 + \cdots + x_m w_m$$

z = "net input"

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

b = "bias term"

f = activation function

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

a = output to next layer

$$a = f(z)$$

Relation to Logistic Regression

Logistic Regression is for “Binary Classification”

The output is kinda probability (0 - 1)

Sigmoid function (1 of the activaition function)

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

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

Possible feature = m + 1

1 is the bias

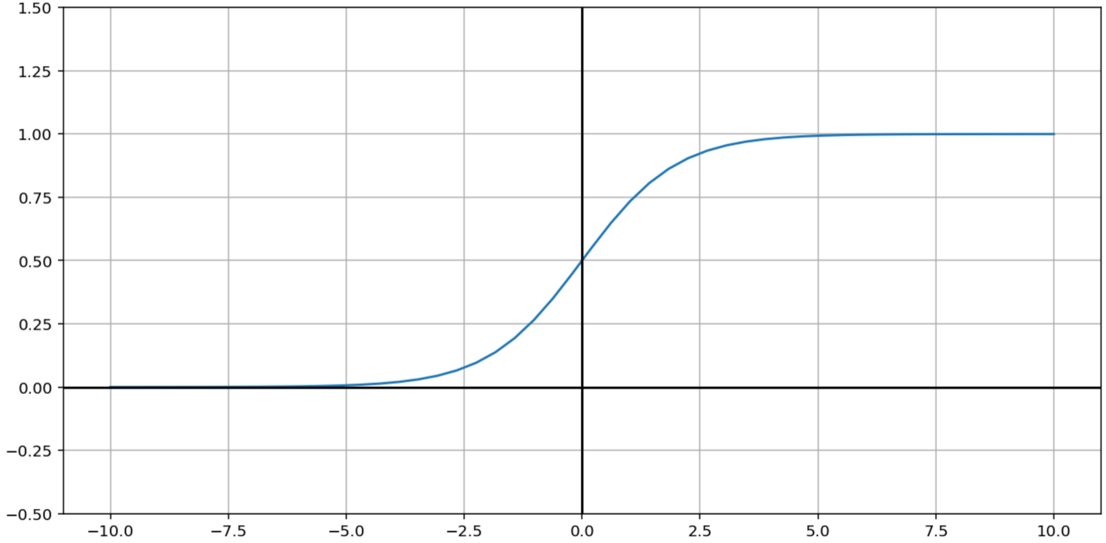
Then a neuron is simply a ”unit” of logistic regression!

weights ⇔ coefficients   inputs ⇔ variables

bias term ⇔ constant term

Relation to Logistic Regression

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



Nice Property of Sigmoid Function

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

Quotient rule

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

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

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

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

$$\sigma'(z) = \sigma(z)(1-\sigma(z))$$

This will be helpful!

ReLU activation function

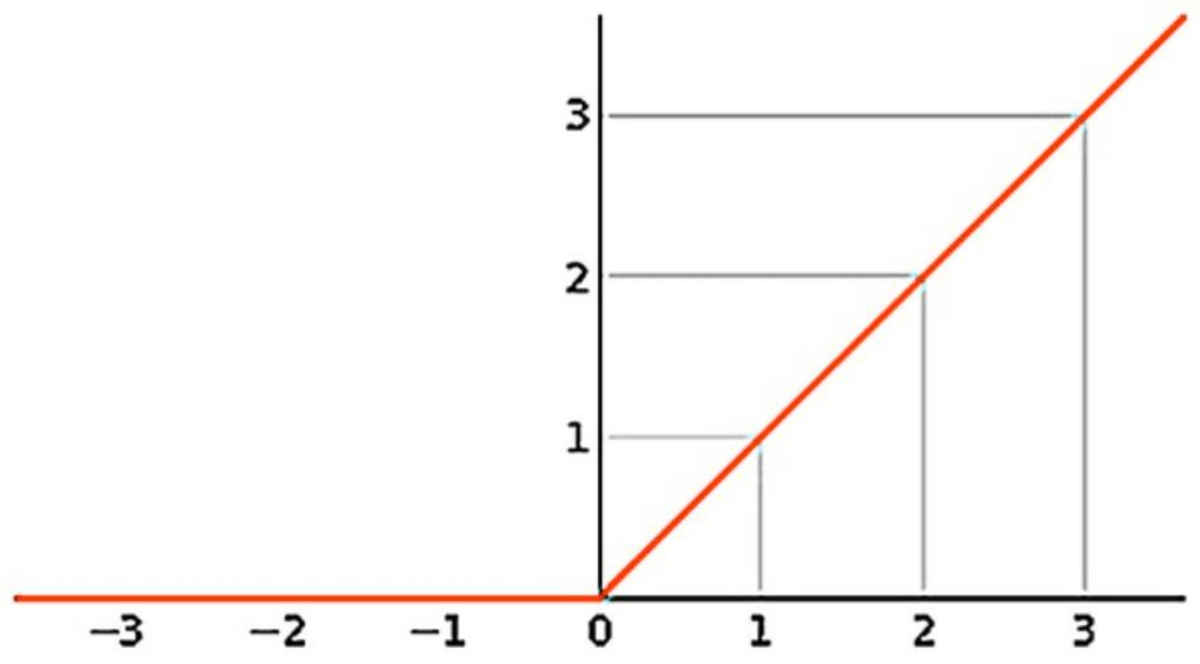
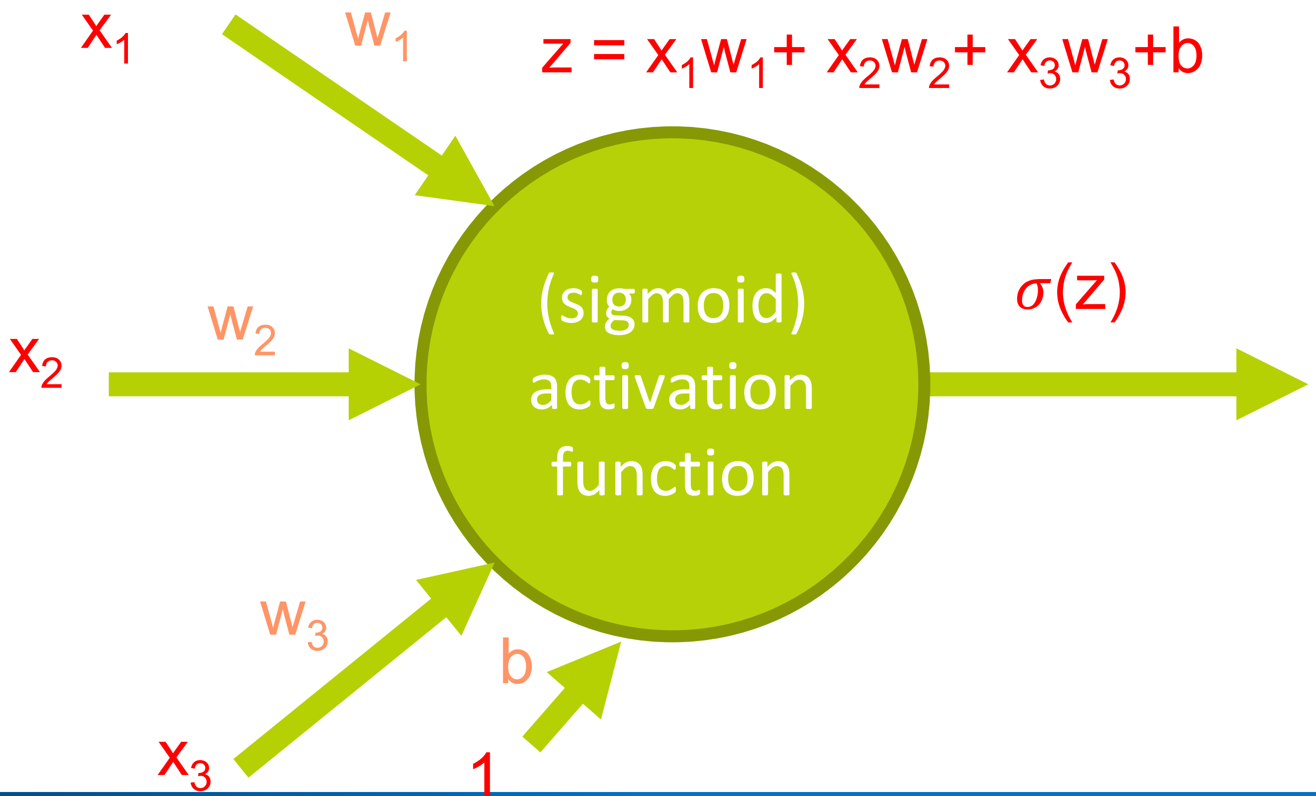


Image from [Automatic Reclaimed Wafer Classification Using Deep Learning Neural Networks](#) by Po-Chou Shih, Chun-Chin Hsu and Fang-Chih Tien (2020)

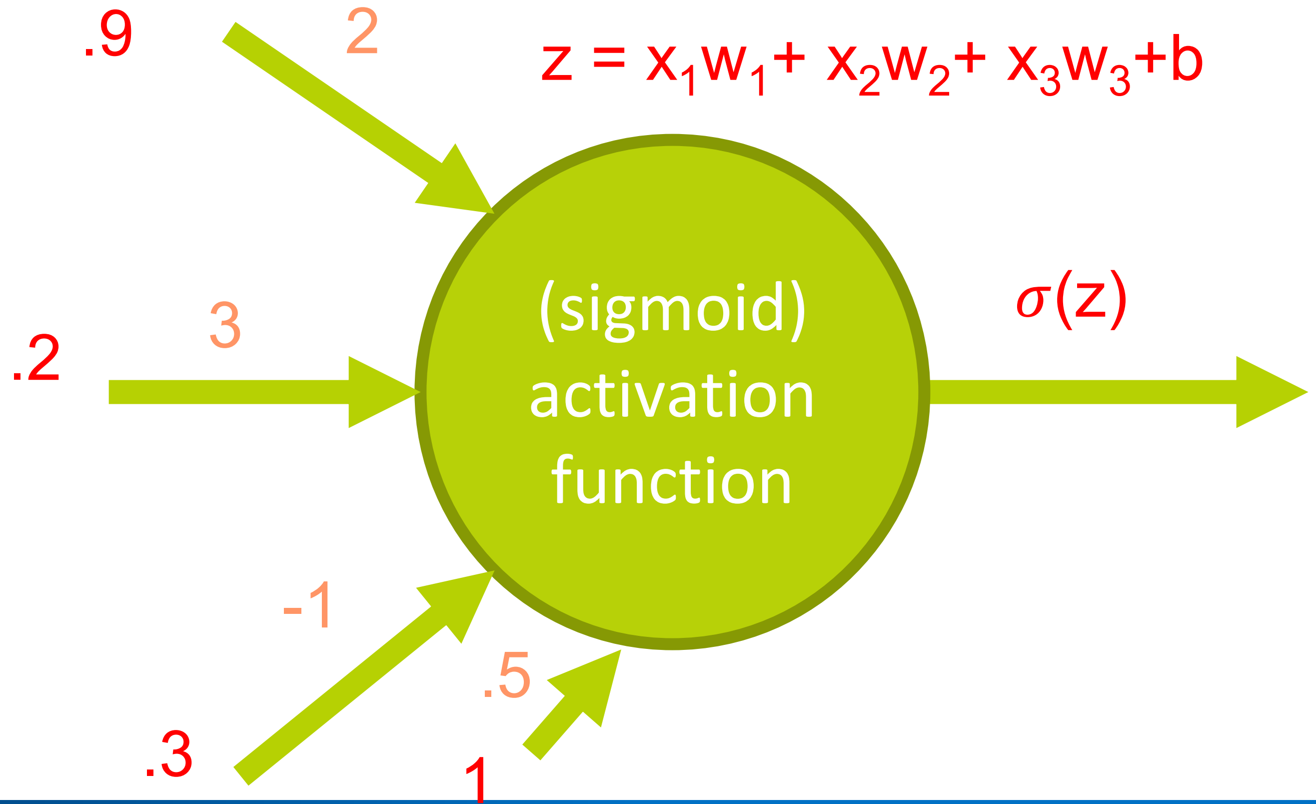
Example Neuron Computation

$$z = x_1w_1 + x_2w_2 + x_3w_3 + b$$



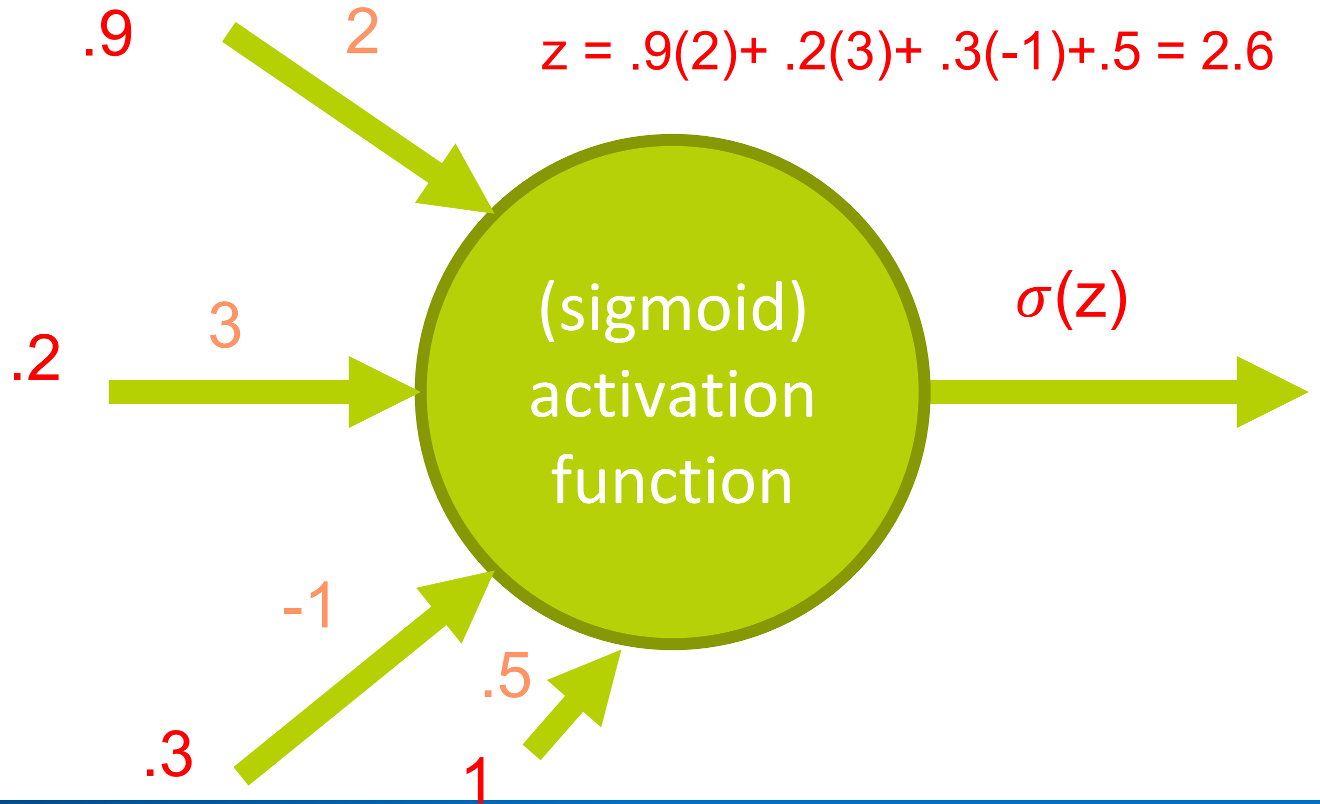
Example Neuron Computation

$z = x_1w_1 + x_2w_2 + x_3w_3 + b$

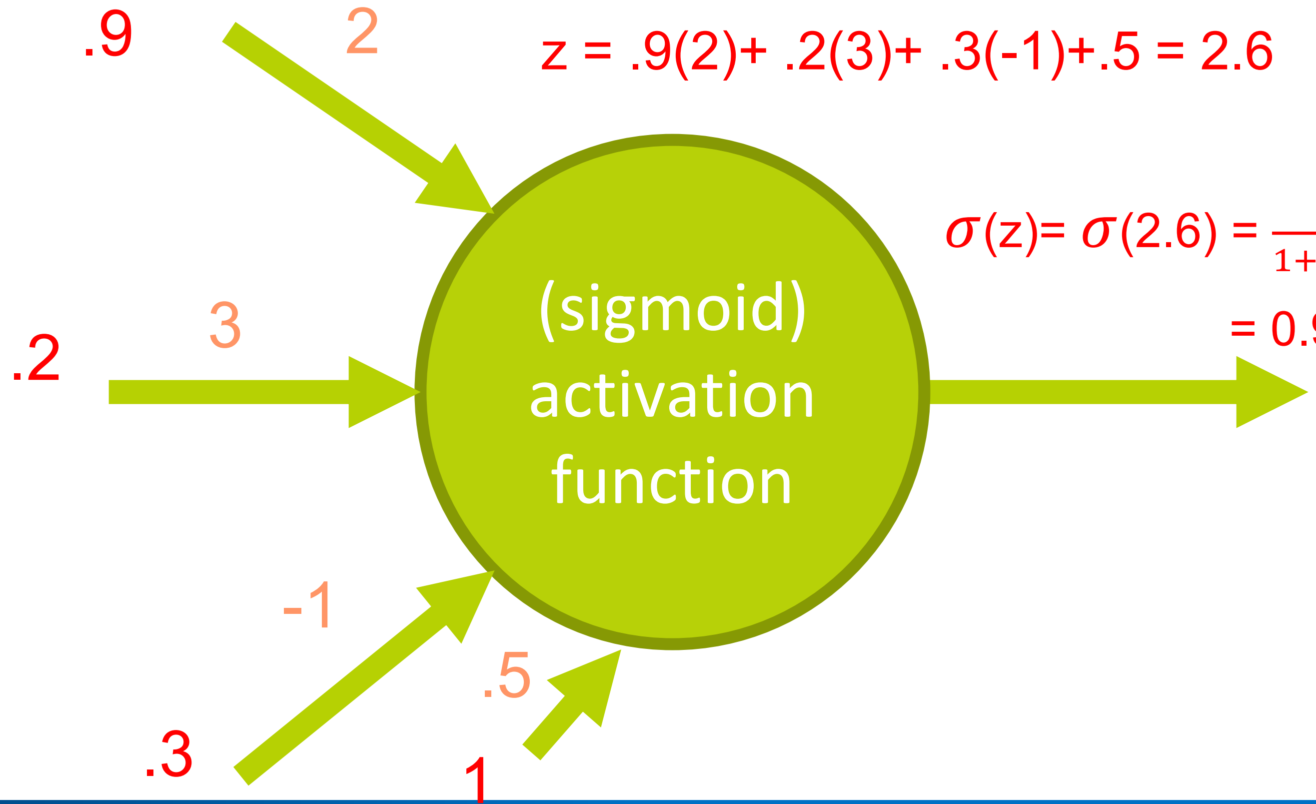


Example Neuron Computation

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



Example Neuron Computation

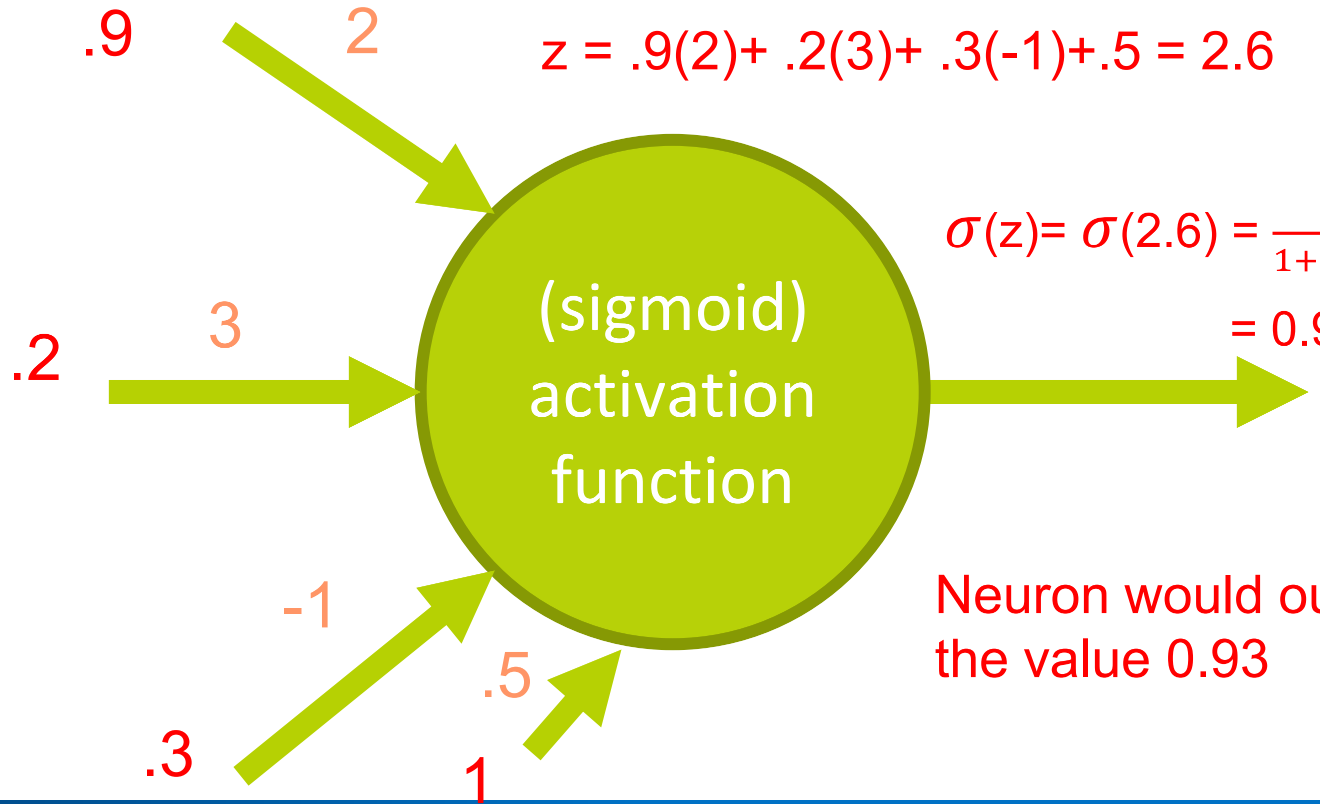


$z = .9(2) + .2(3) + .3(-1) + .5 = 2.6$

$\sigma(z) = \sigma(2.6) = \frac{1}{1+e^{-2.6}}$

$= 0.93$

Example Neuron Computation



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

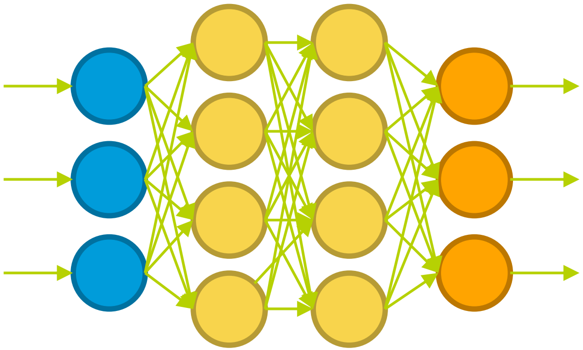
$\sigma(z) = \sigma(2.6) = \frac{1}{1+e^{-2.6}}$

$= 0.93$

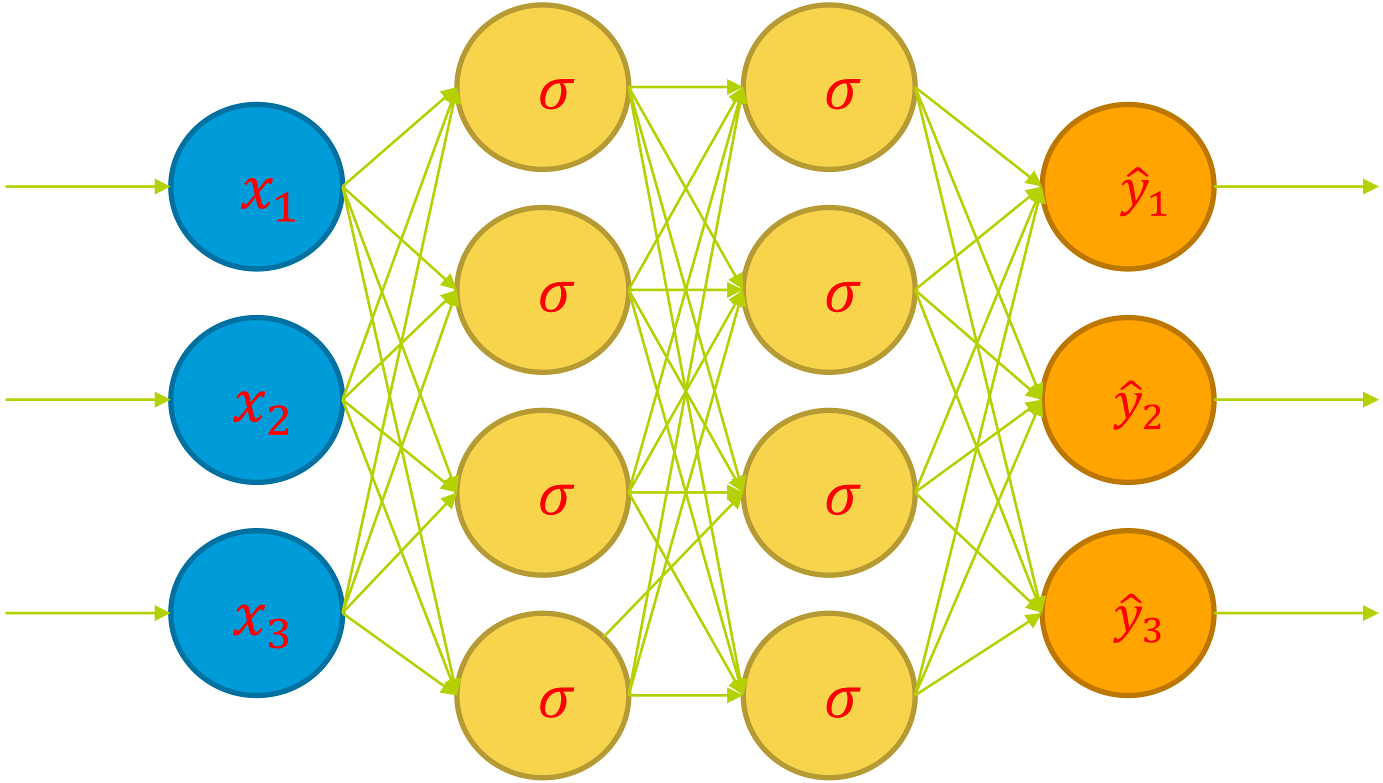
Neuron would output the value 0.93

Why Neural Nets?

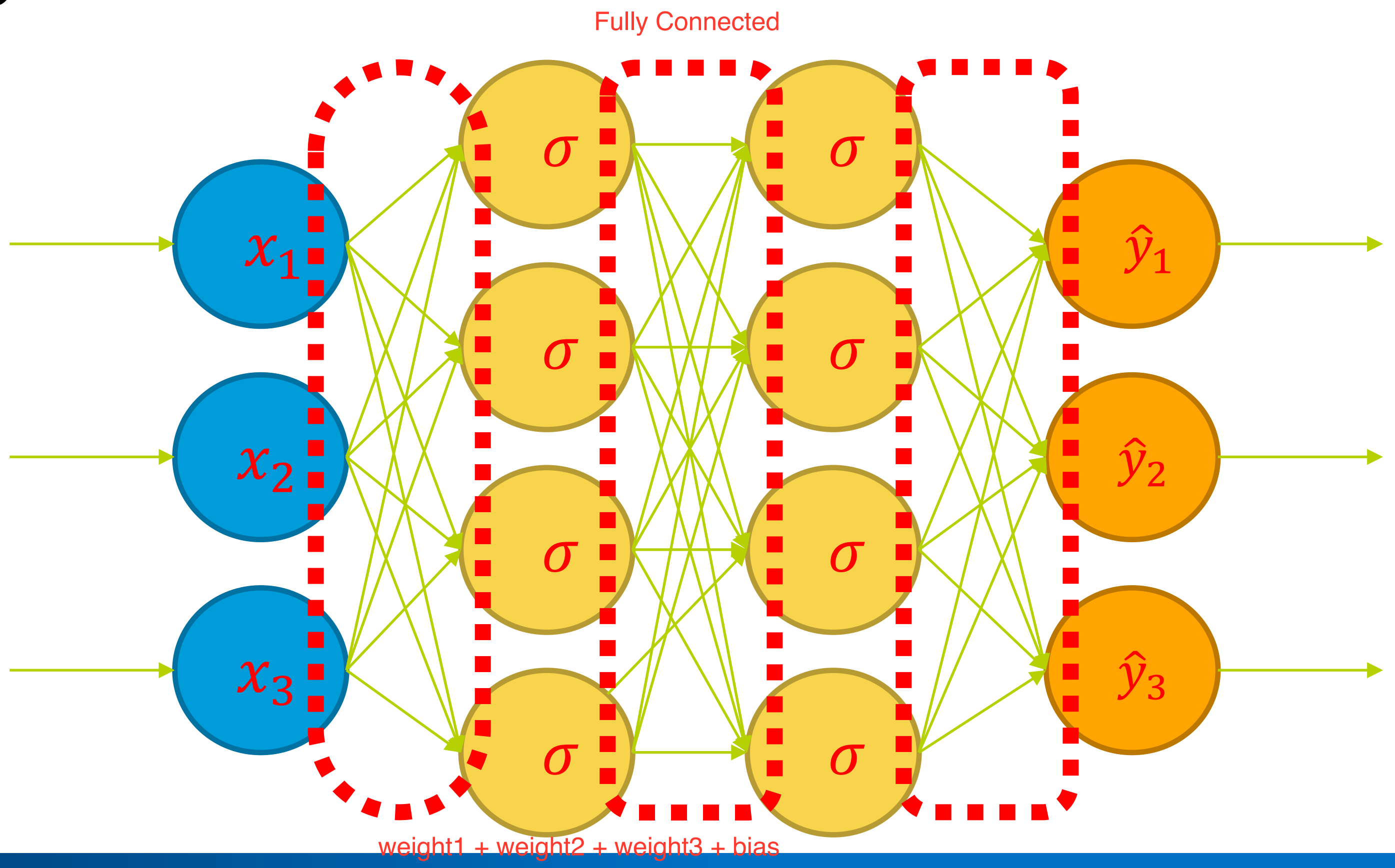
- Why not just use a single neuron? Why do we need a larger network?
- A single neuron (like logistic regression) only permits a linear decision boundary.
- Most real-world problems are considerably more complicated!



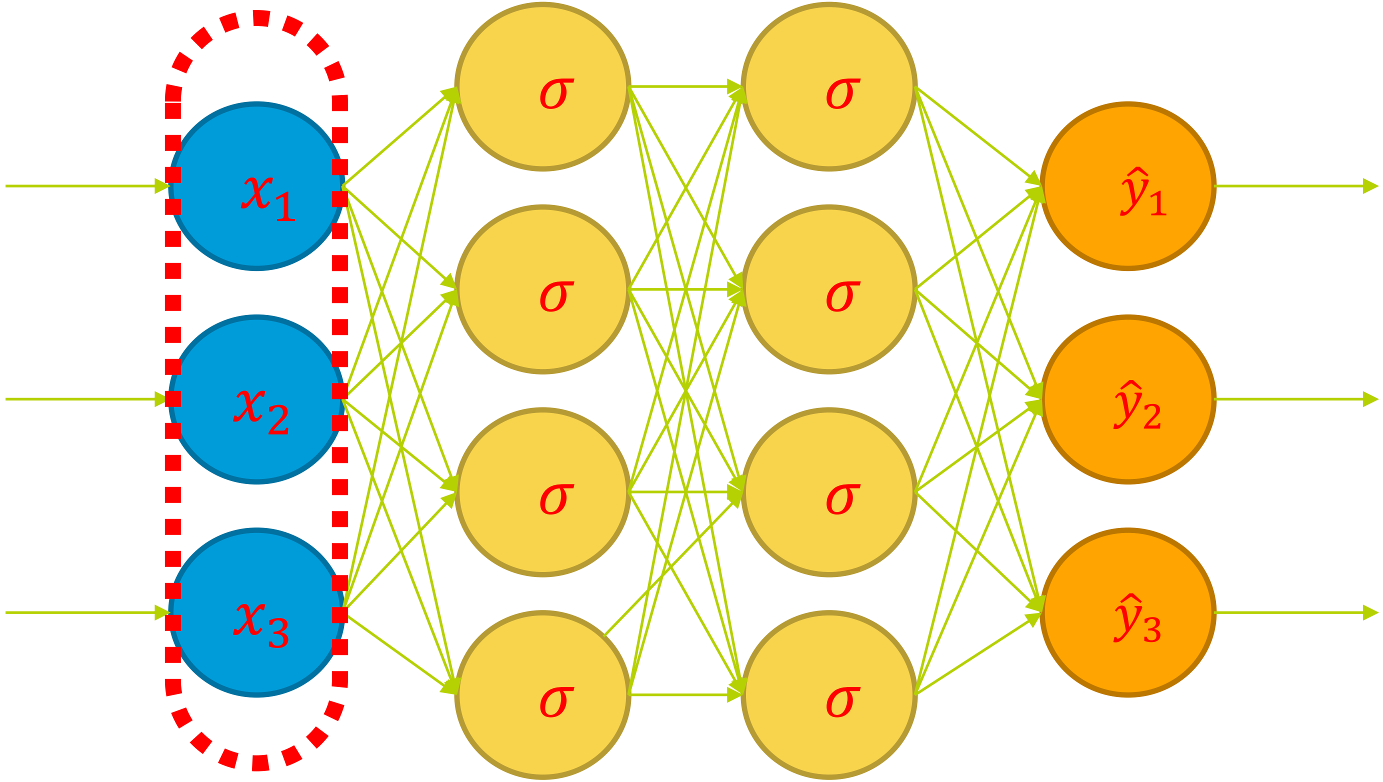
Feedforward Neural Network



Weights

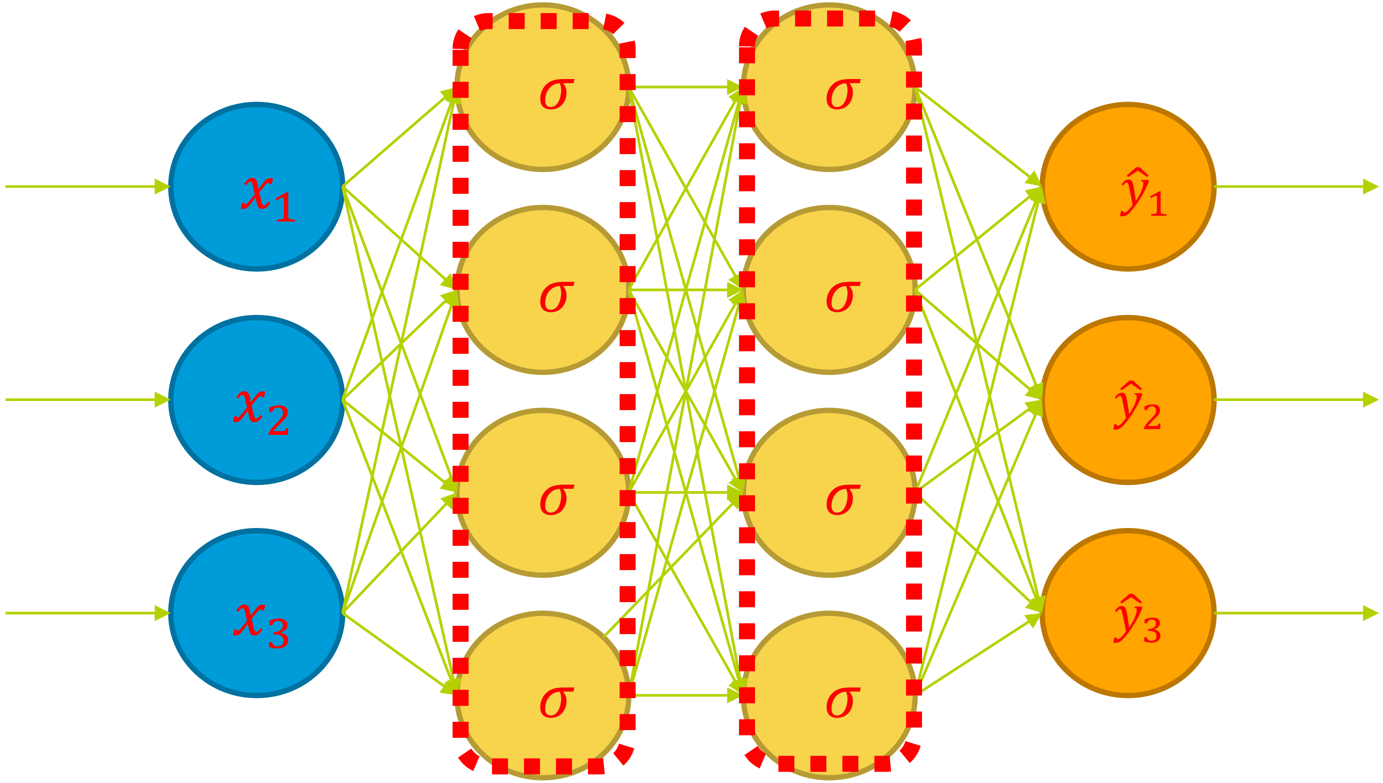

Fully Connected
x_1
x_2
x_3
σ
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_3$
weight1 + weight2 + weight3 + bias

Input Layer

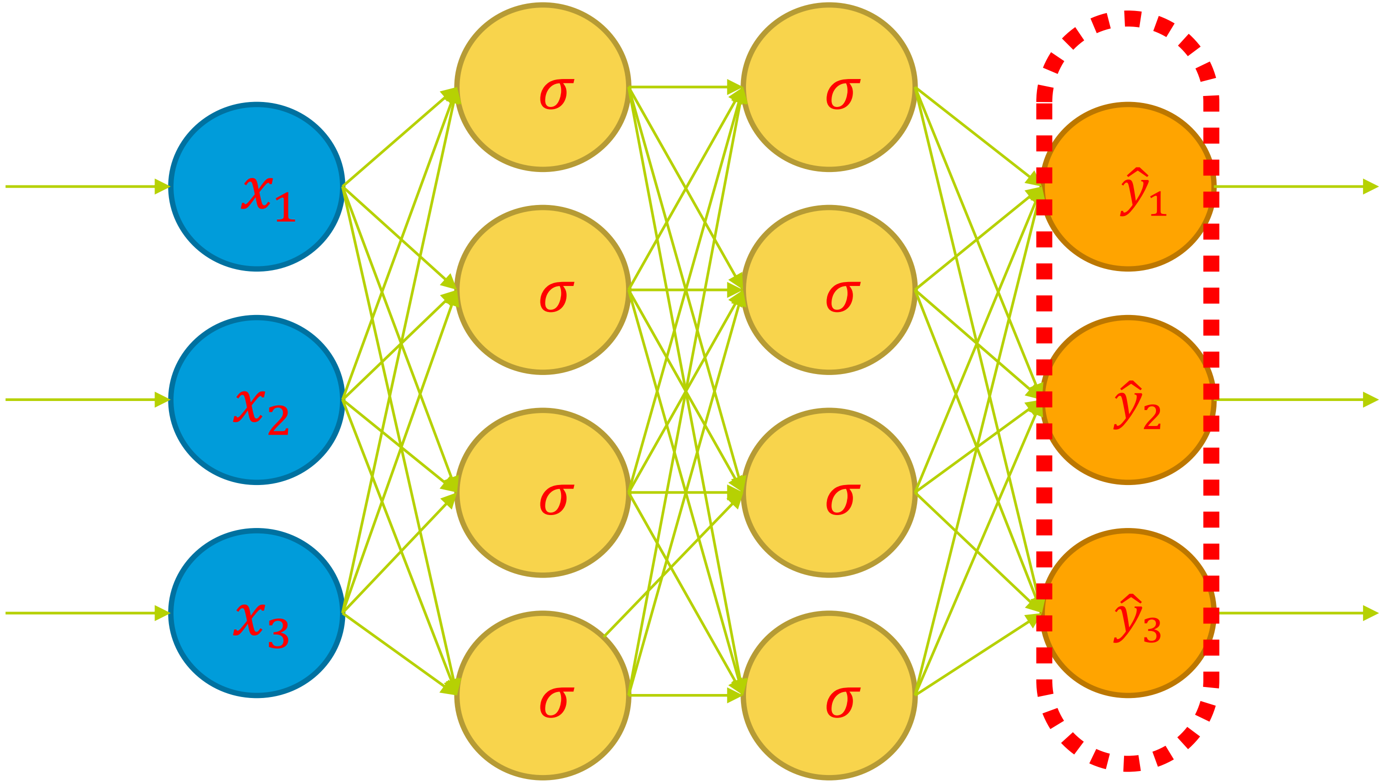


x_1
x_2
x_3
σ
σ
σ
σ
σ
σ
σ
σ
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_3$

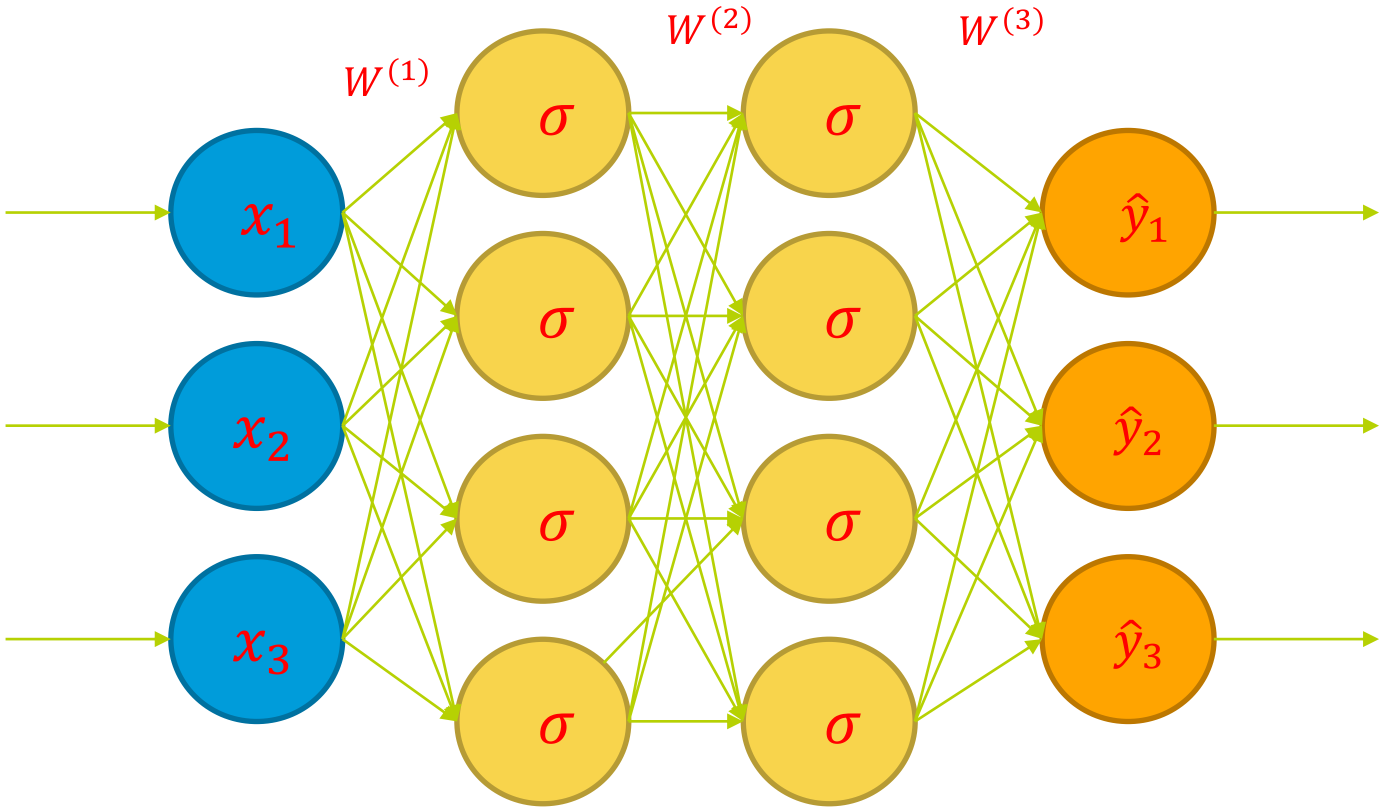
Hidden Layers



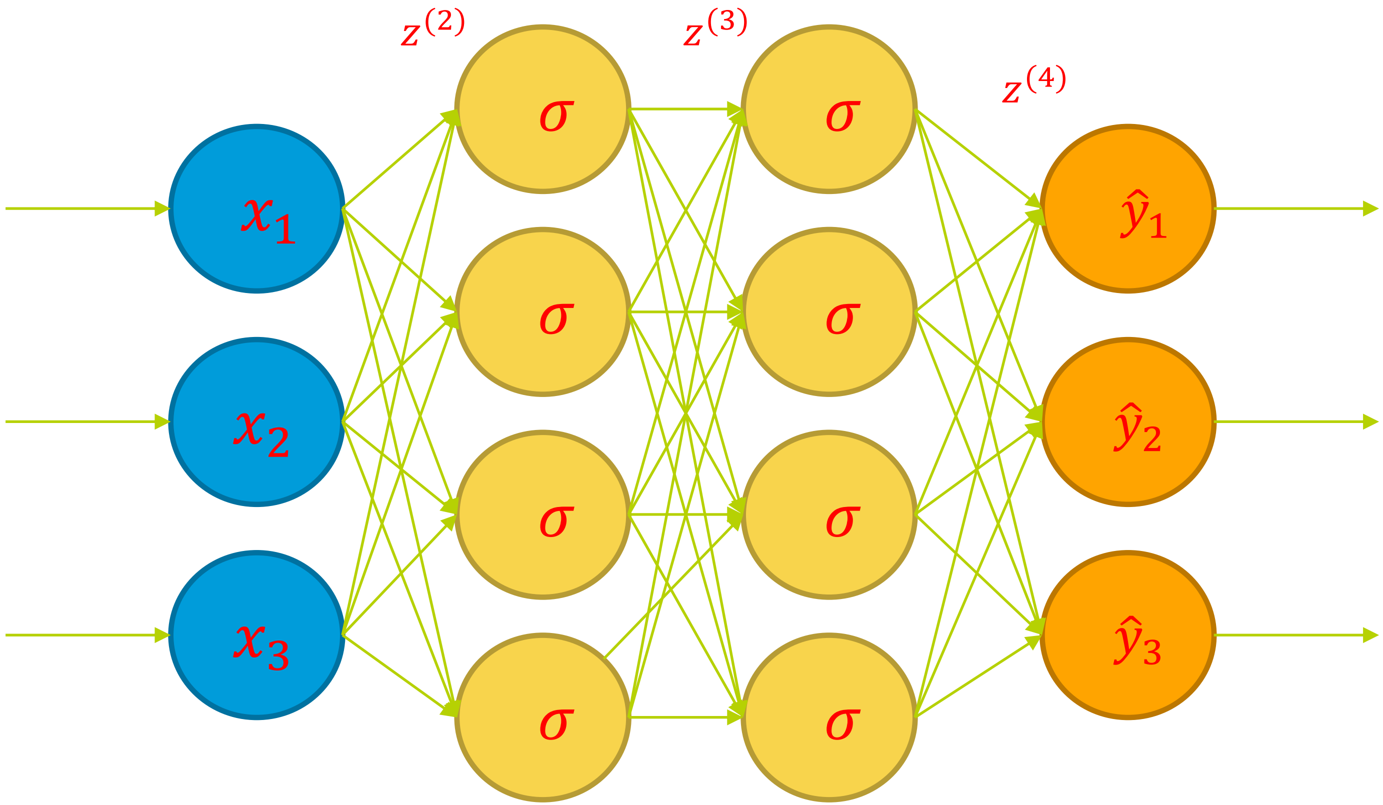
Output Layer



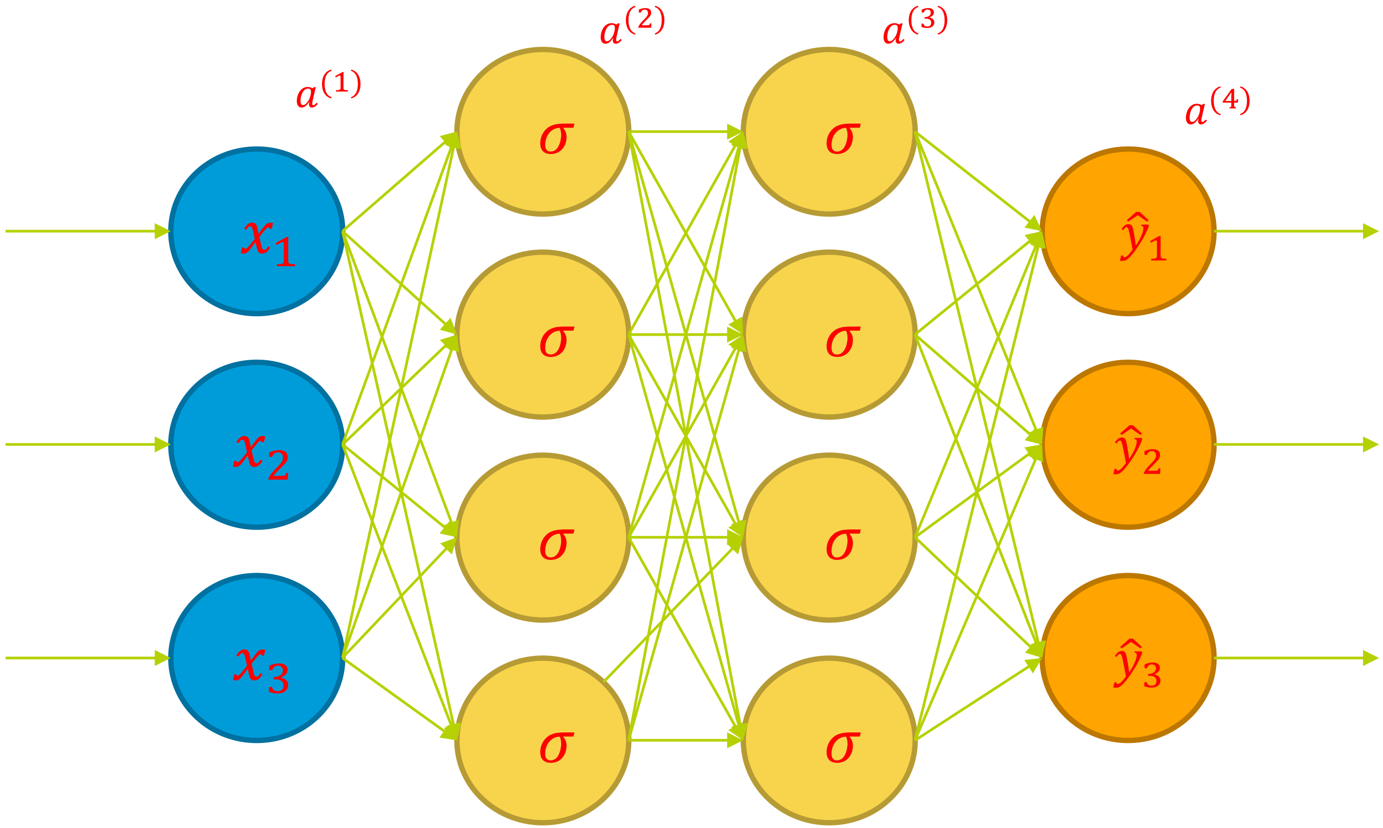
Weights (represented by matrices)



Net Input (sum of weighted inputs, before activation function)



Activations (output of neurons to next layer)

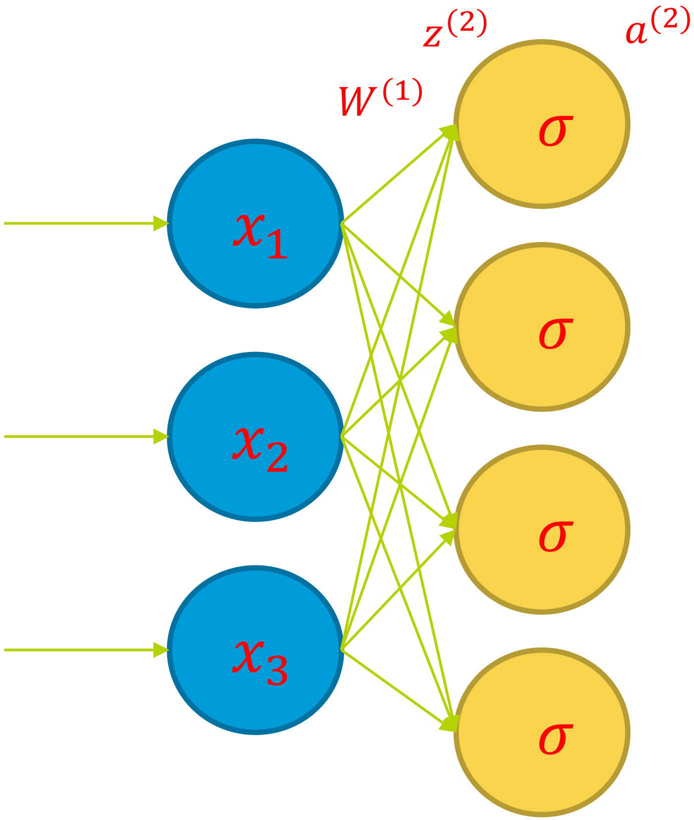


Matrix representation of computation

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

$z^{(2)} = xW^{(1)}$ $z^{(2)}$ is a 4-vector

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

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

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

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

Multiple data points

In practice, we do these computation for many data points at the same time, by “stacking” the rows into a matrix.

But the equations look the same!

Input: matrix x (an nx3 matrix) (each row a single instance)

Output: vector $\hat{y}$ (an nx3 matrix) (each row a single prediction)

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

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

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

Now we know how feedforward NNs do Computations.

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

intel®

Software