

Advanced School in Artificial Intelligence

Introduction to Neural Networks

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**Università
degli Studi
di Ferrara**

Outline

- Introduction to Python
- Introduction to Neural Networks
- Convolutional NN
- Recurrent NN
- Autoencoders and self supervised learning

Sources

- These slides are taken from:

- Intel Nervana AI Academy Instructional Content

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- Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016.

https://www.deeplearningbook.org/lecture_slides.html

- Chapter “Neural Networks” of “A Course in Machine Learning” by Hal Daume III.

<http://ciml.info/>

- Some parts from “CS231n: Convolutional Neural Networks for Visual Recognition”, Stanford University

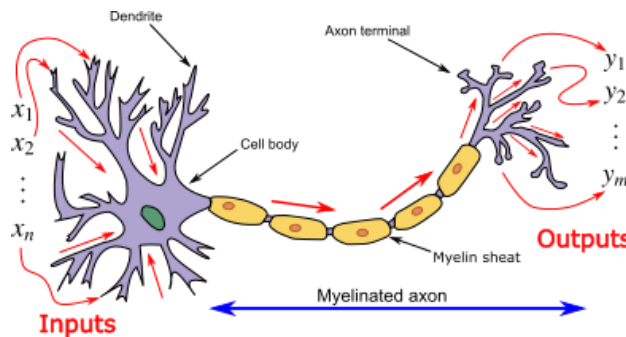
<http://cs231n.stanford.edu/>

Outline

- Introduction to Python
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Neural Networks

- The human brain is composed of about 10^{11} **neurons** (100 billion).
- Each neuron is connected to others and receives electrical signals through the **dendrites**.
- Each neuron sends messages through a long dendrite appendix called an **axon**.
- At the end of each axon a series of ramifications branch out called **synapses**.
- The synapses have the purpose of **stimulating** the other neurons, through electrical signals, in order to activate them.
- **Learning** influences the ability of synapses to activate other neurons or not.



Img from Wikipedia, CC BY-SA 4.0, Prof. Loc Vu-Quoc. https://en.wikipedia.org/wiki/Artificial_neural_network#/media/File:Neuron3.png

Neural Networks

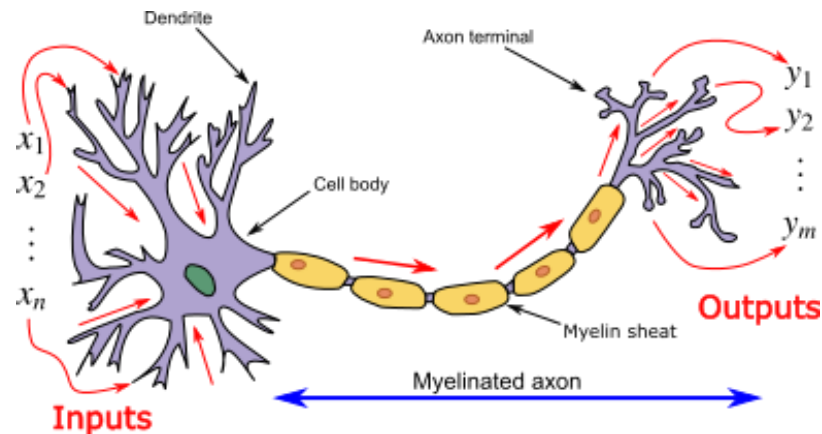
- Two different reasons have historically driven the study of **Artificial Neural Networks** (ANN):
 - Reproduction (and therefore understanding) of the human brain by building reliable models of all or at least part of the brain, reproducing neuro-physiological phenomena, and performing experimental verification (does the proposed model reproduce biological data?)
 - Extraction of the fundamental principles of calculation used by the human brain to produce artificial systems, possibly different from the brain, that reproduce its functions, perhaps in a faster and more efficient way.

A bit of history...

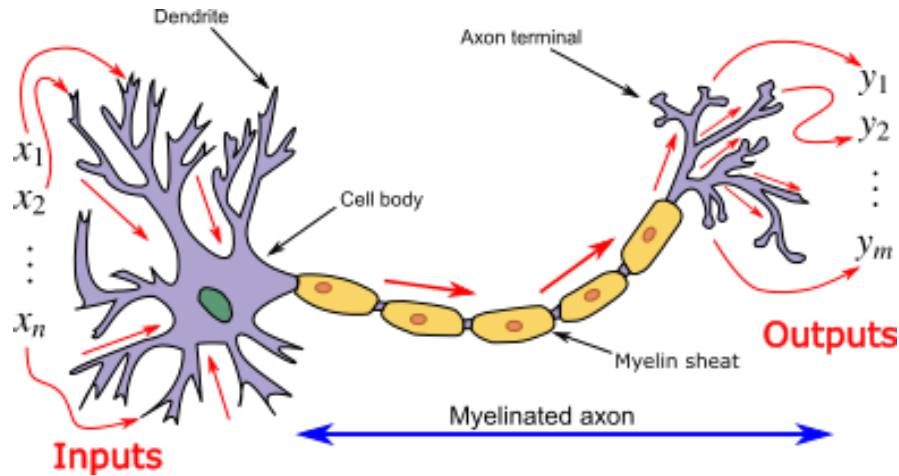
- 1943 McCulloch and Pitts: first mathematical model of an NN, binary input, linear threshold combination, binary output.
- 1958 first neural network scheme, called **Perceptron**, forerunner of the current neural networks. Great enthusiasm.
- 1969 Minsky and Papert show limits of Perceptron. Research in this field has a considerable drop in funding.
- 1986 Rumelhart and al. proposed the **Backpropagation algorithm** for learning the weights of a multilayer network. New life to research.

Neural Networks

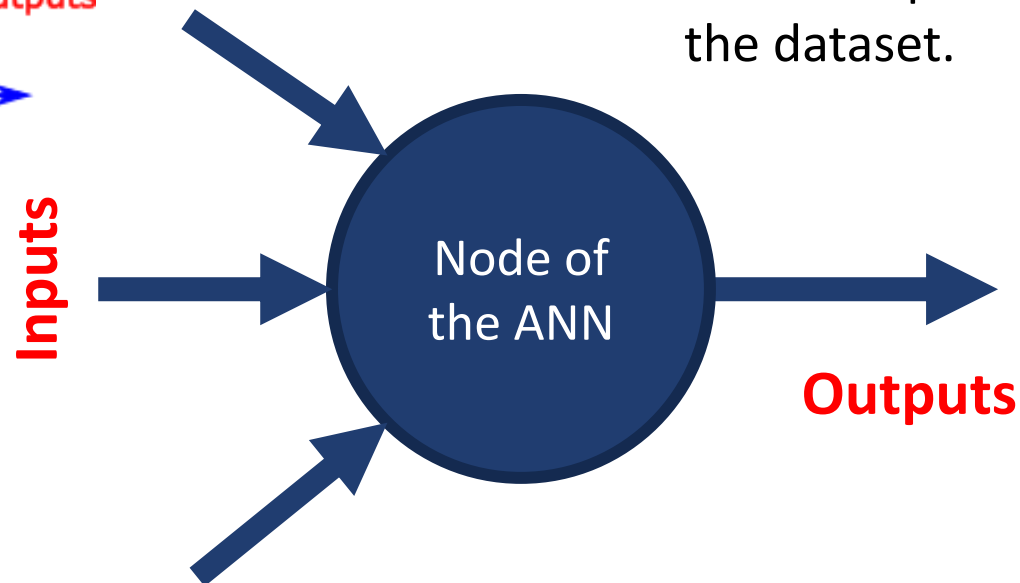
- Use biology as inspiration for mathematical model
- Get signals from previous neurons
- Generate signals (or not) according to inputs
- Pass signals on to next neurons
- By layering many neurons, can create complex models



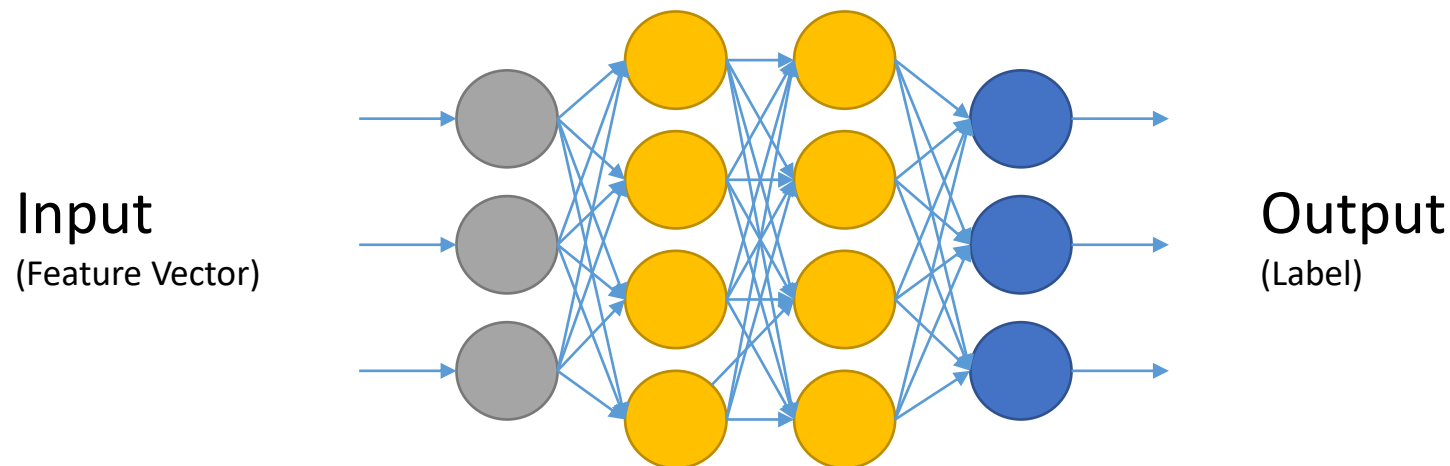
Neural Networks



- We model neurons as a node, with input connections, and output connections.
- By having many neurons, layers, we can capture value hidden in the dataset.



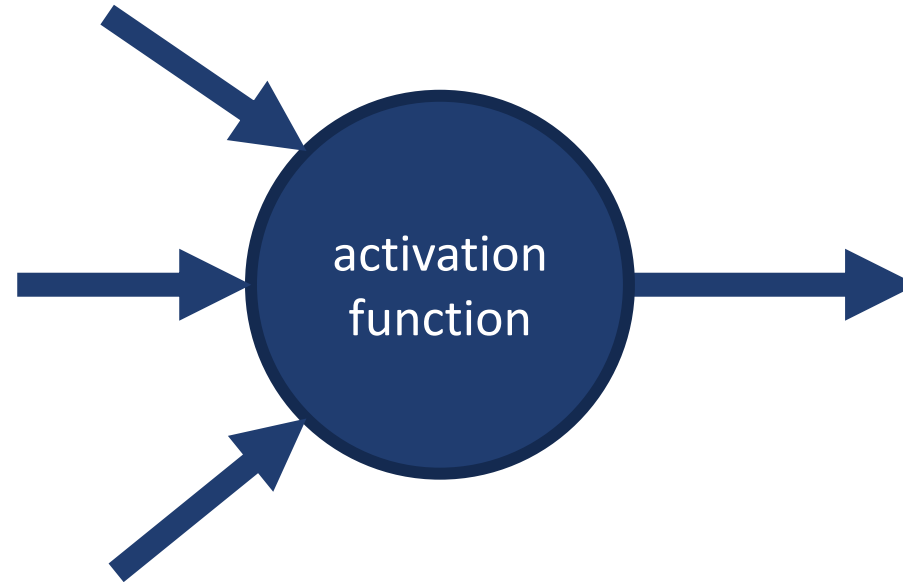
Neural Network Structure



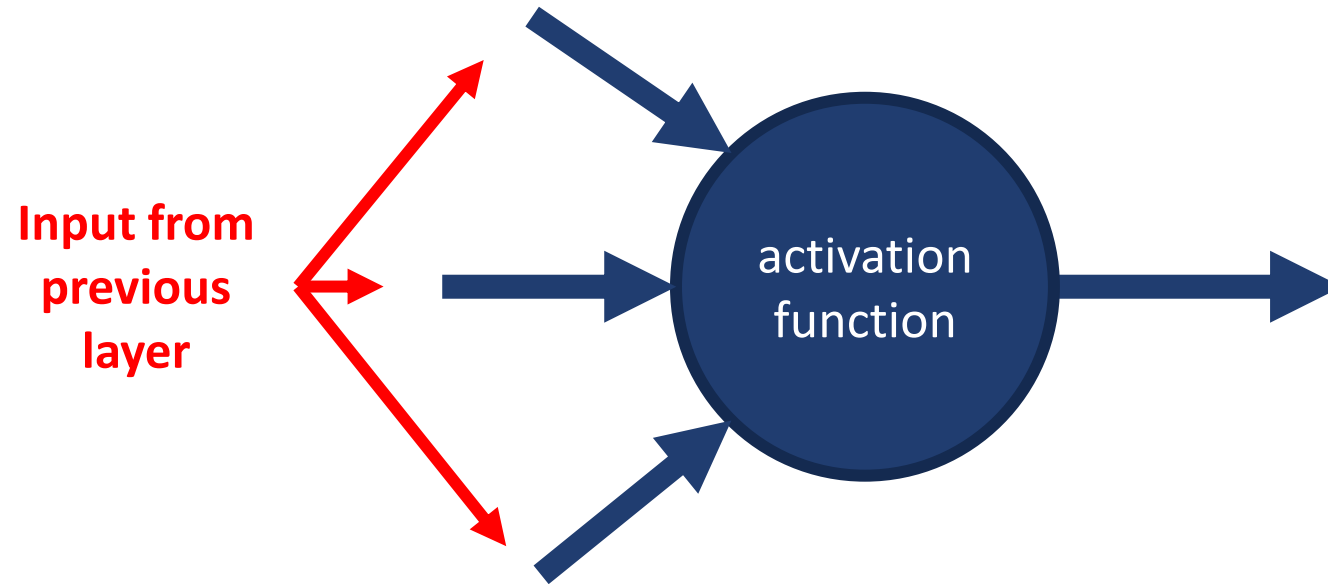
- Can think of it as a complicated computation engine
- We will "train it" using our training data
- Then (hopefully) it will give good answers on new data



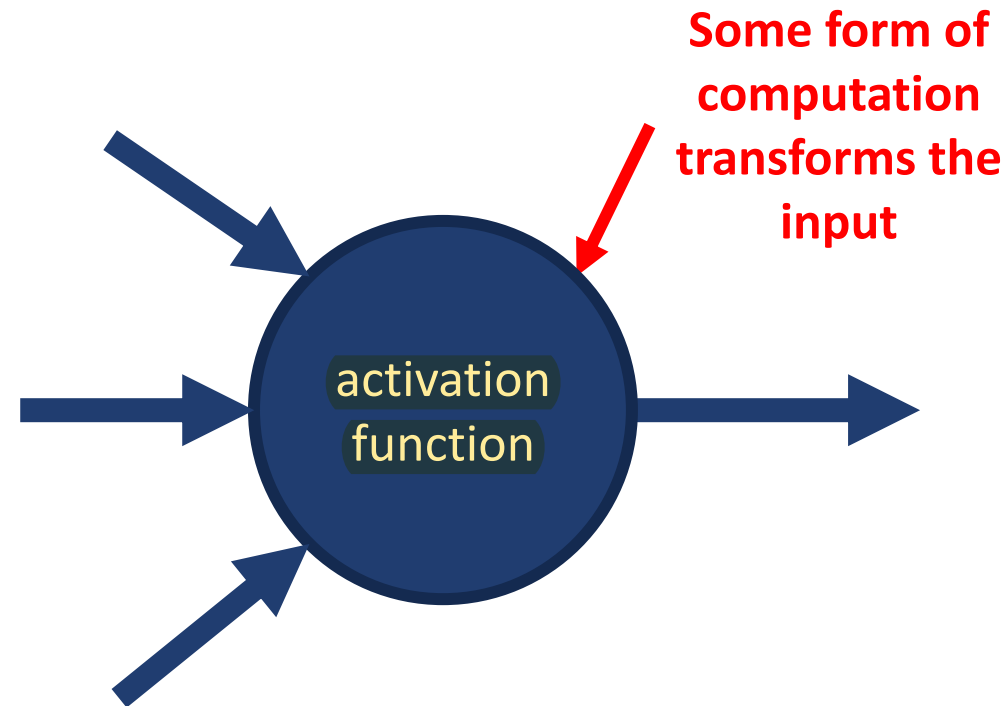
Basic neuron visualization



Basic neuron visualization

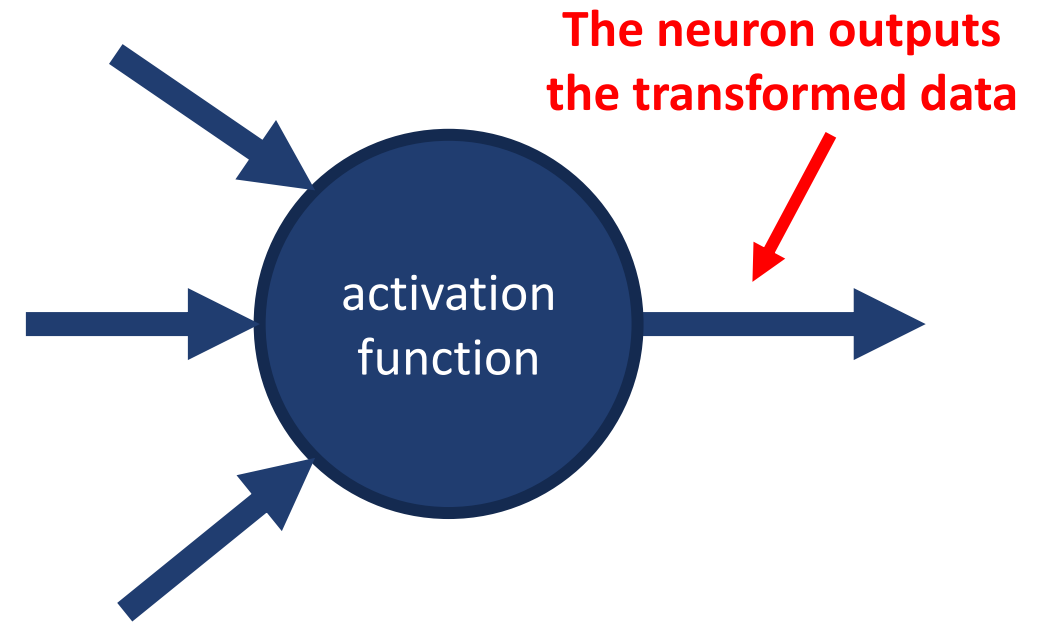


Basic neuron visualization



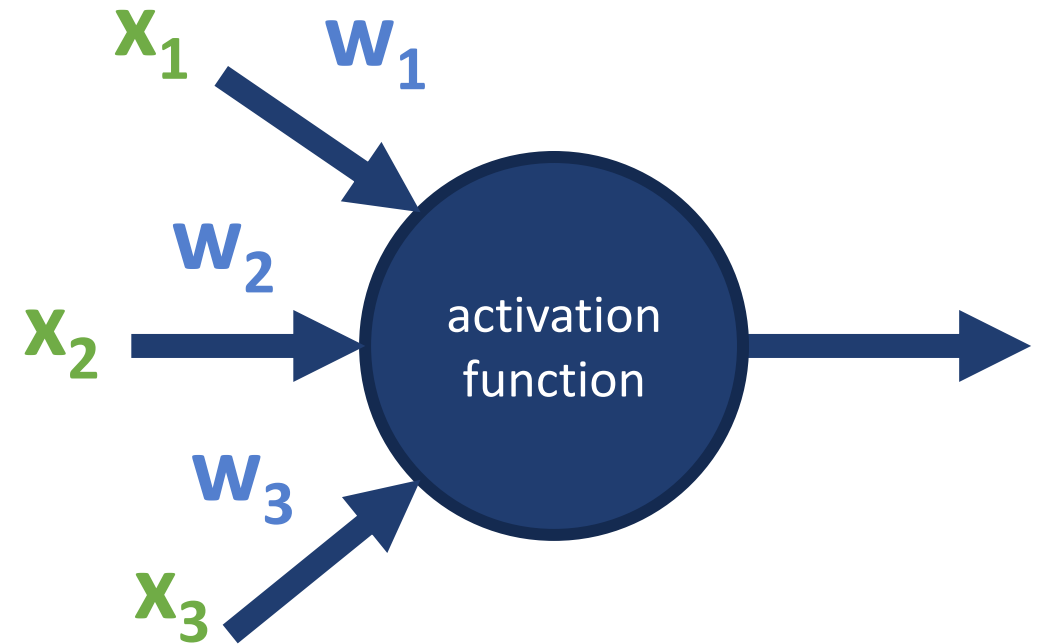
Basic neuron visualization

- Note that there can be more than one connection to the next layer
- The activation function is the same for all of those.



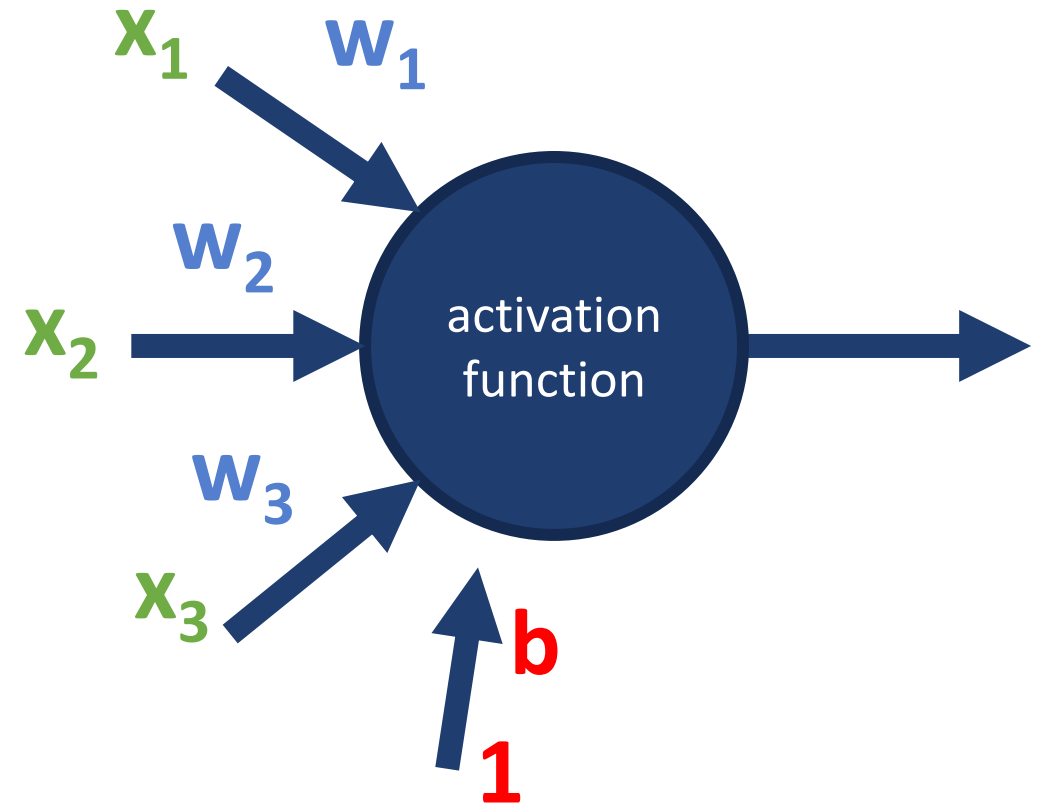
Basic neuron visualization

- x_1, x_2, x_3 are inputs. They are real numbers.
- We have coefficients w_1, w_2 , and w_3 . They are real numbers. They form a row vector $[w_1, w_2, w_3]$

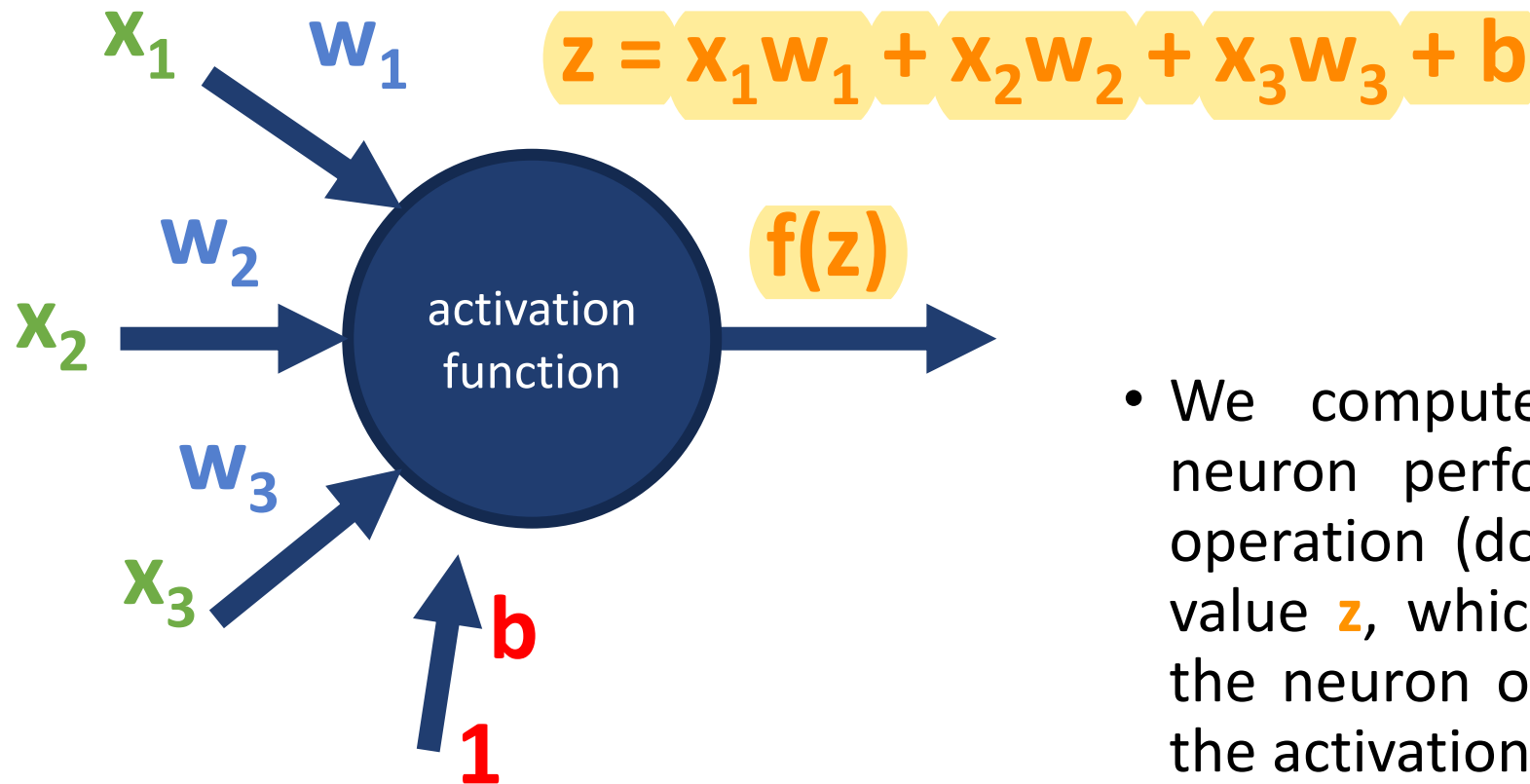


Basic neuron visualization

- We can also add another input, called **bias term**.
- This is the analogue of intercept in Linear regression
- So our row vector of parameters is $[w_1, w_2, w_3, b]$



Basic neuron visualization



- We compute the value of the neuron performing linear algebra operation (dot product), and get a value z , which is used to compute the neuron outputs $f(z)$, where f is the activation function.

In vector notation

b = “bias term”

z = “net input”

f = activation function

a = output to next layer

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

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

$$a = f(z)$$

Most of the operations
are matrix multiplication,
or element-wise
operations on matrices
and vectors

Relation to logistic regression

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

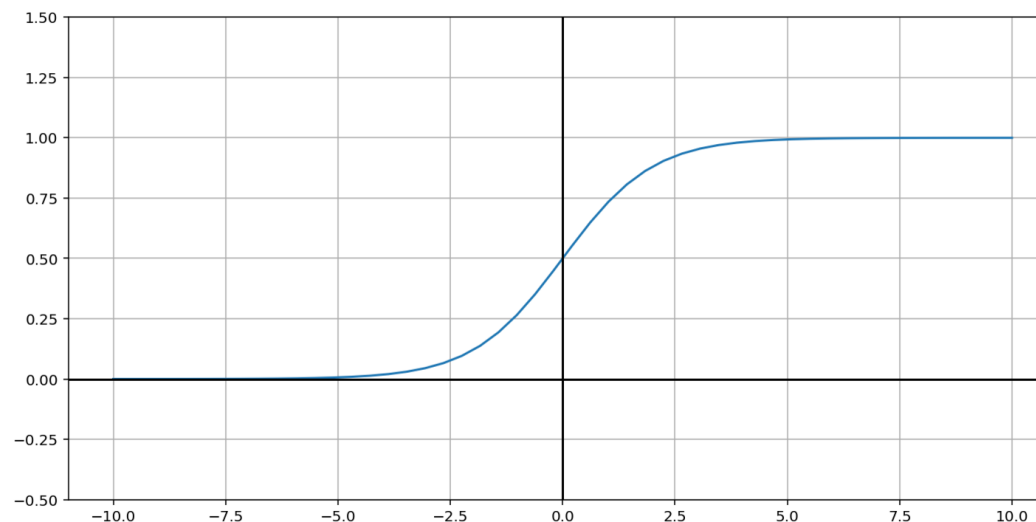
$$z = b + \sum_{i=1}^m x_i w_i = x_1 w_1 + x_2 w_2 + \cdots + x_m w_m + b$$

then a neuron is simply a "unit" of logistic regression where

- **weights** are coefficients
 - **inputs** are variables
 - **bias term** is the constant term
- This neuron is doing logistic regression on the input

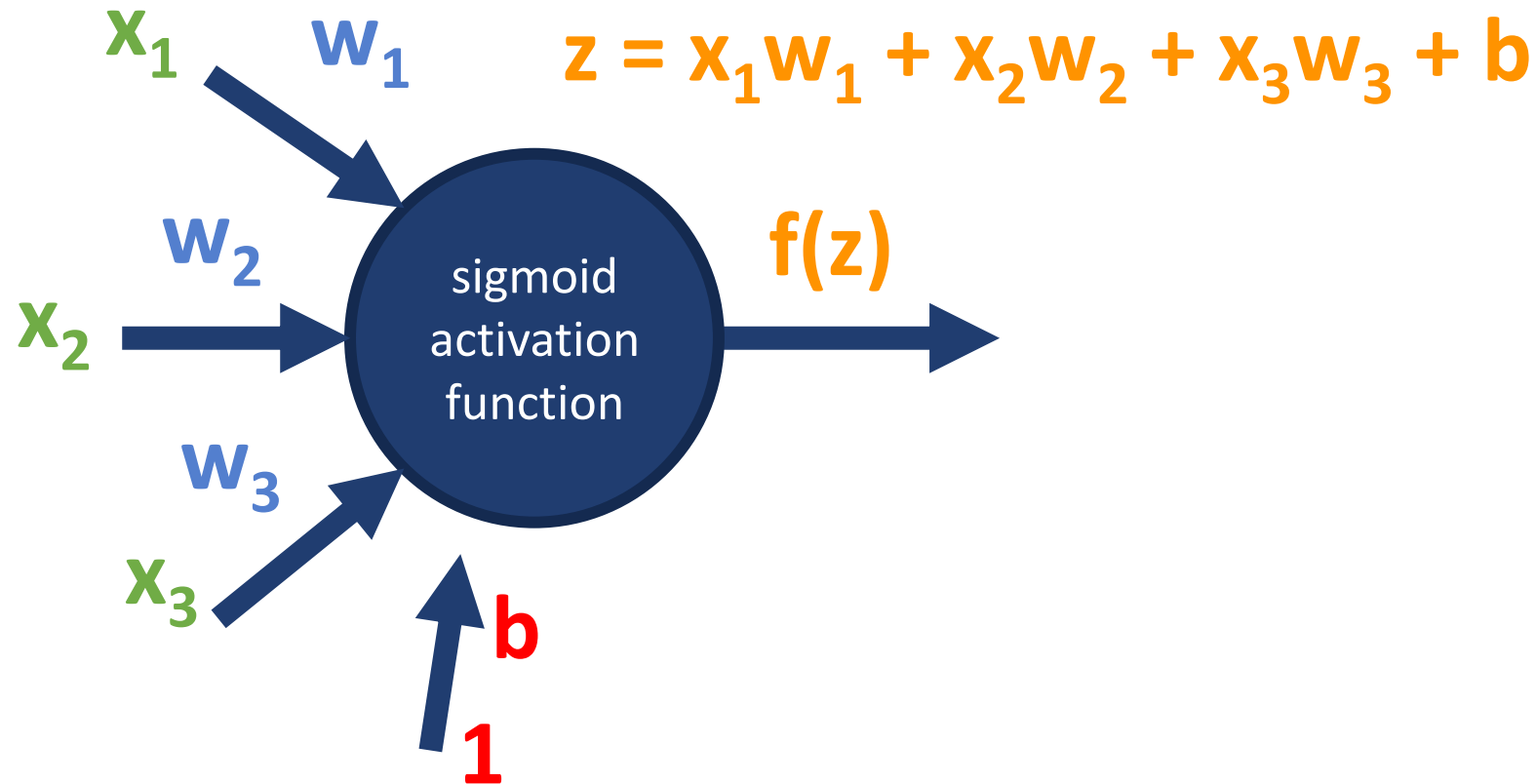
Relation to Logistic Regression

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

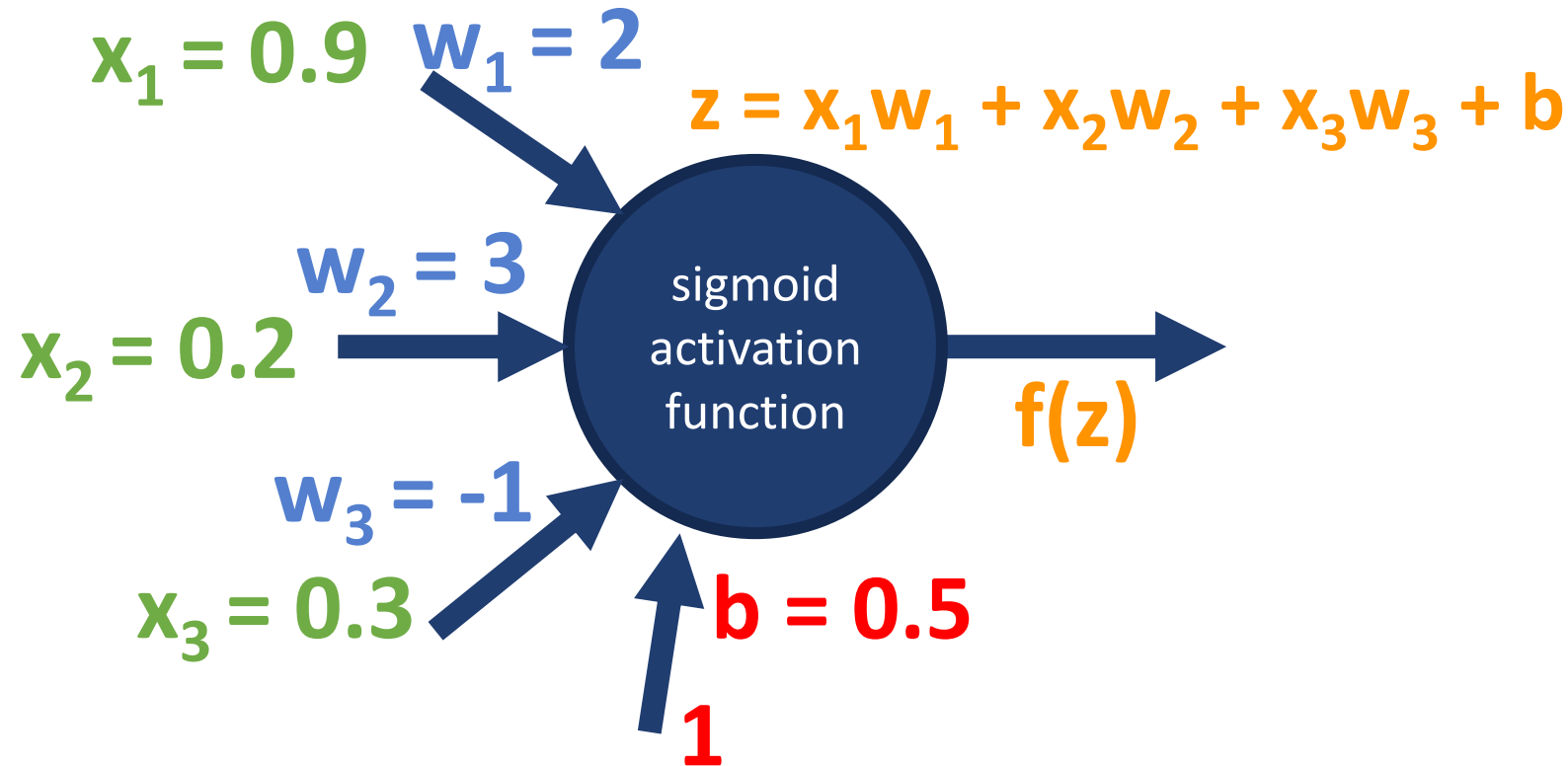


- There are many other activation functions. We will view some of them later on.

Example of Neuron Computation

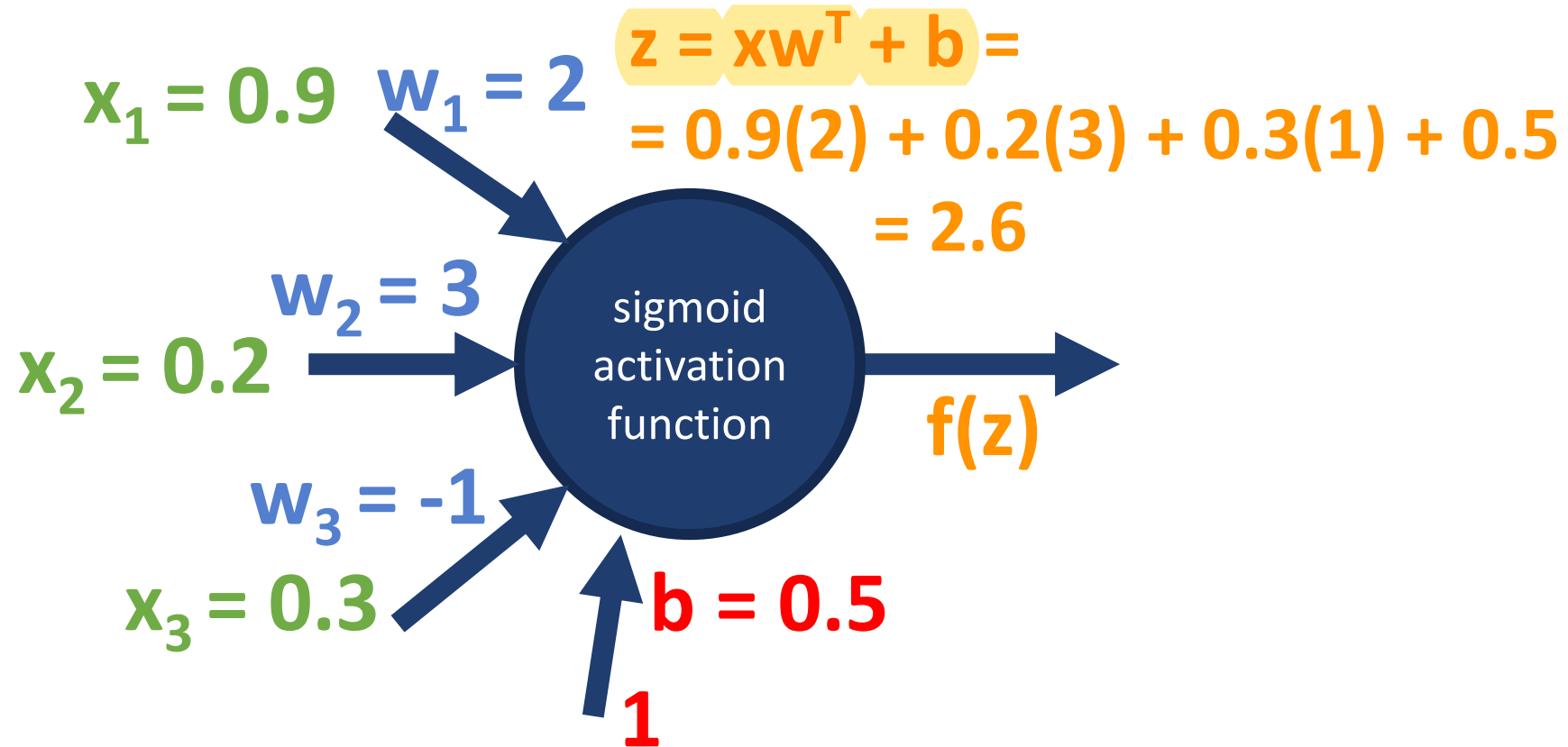


Example of Neuron Computation



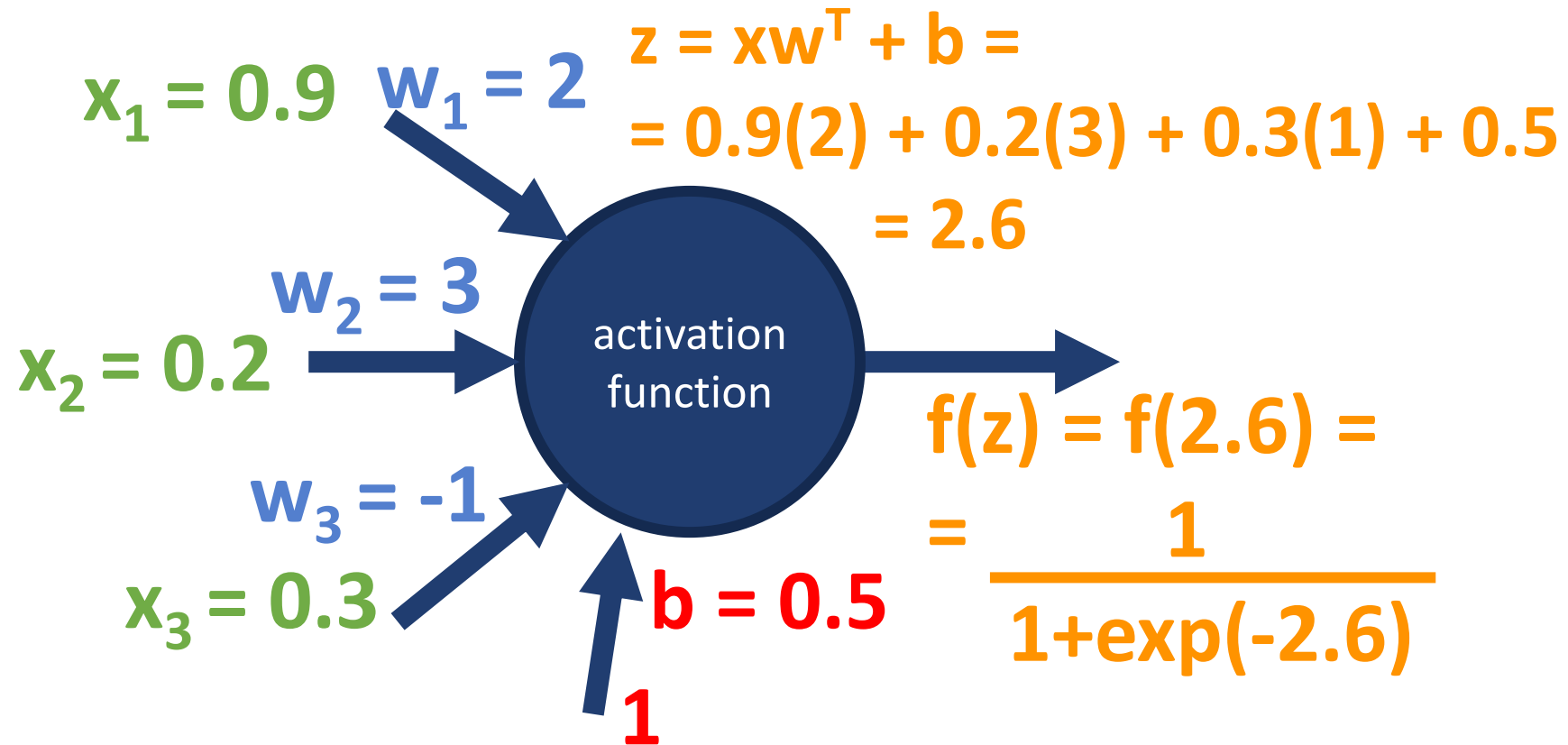
- The weights are $[2, 3, -1]$, the bias term 0.5 , the inputs $[0.9, 0.2, 0.3]$.

Example of Neuron Computation



- The weights are $[2, 3, -1]$, the bias term 0.5 , the inputs $[0.9, 0.2, 0.3]$.

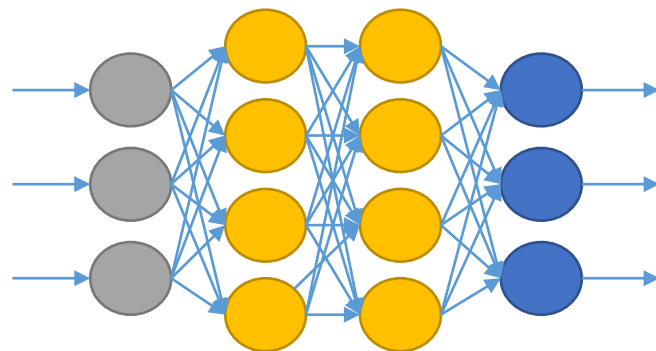
Example of Neuron Computation



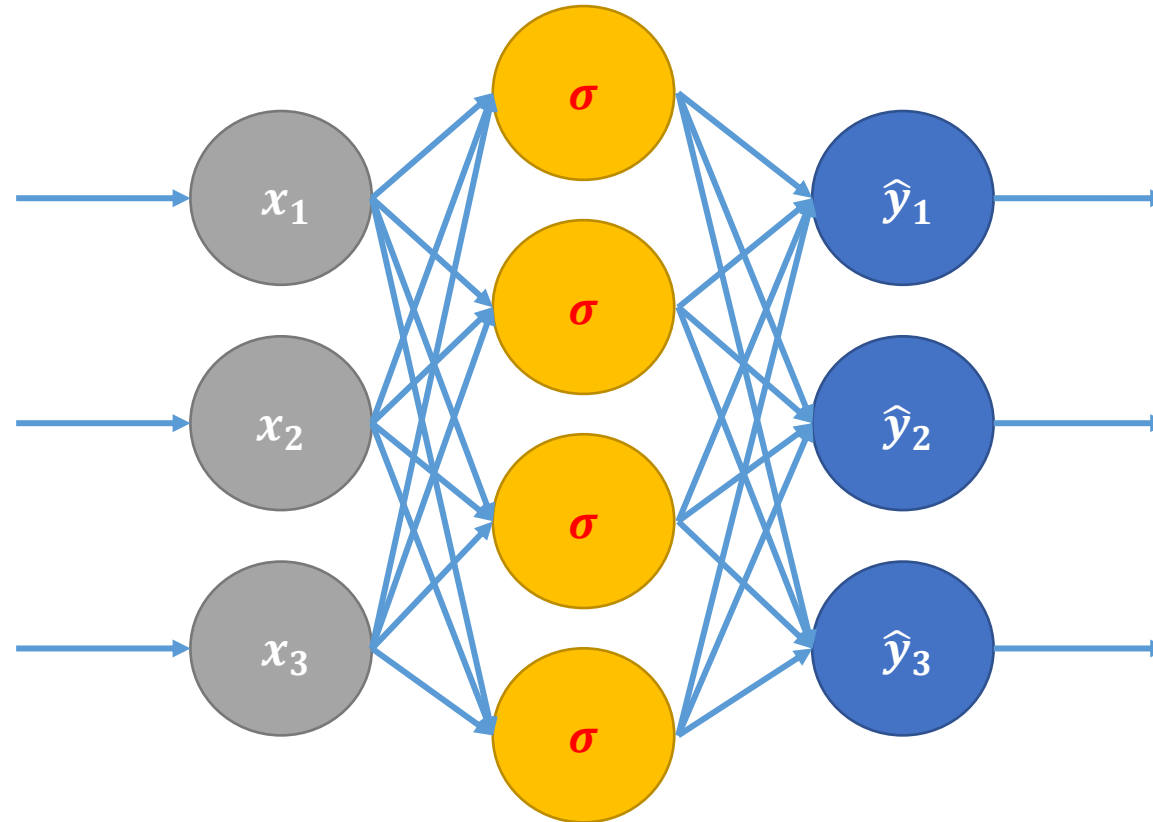
This neuron would output the value **0.93**

Why neural nets?

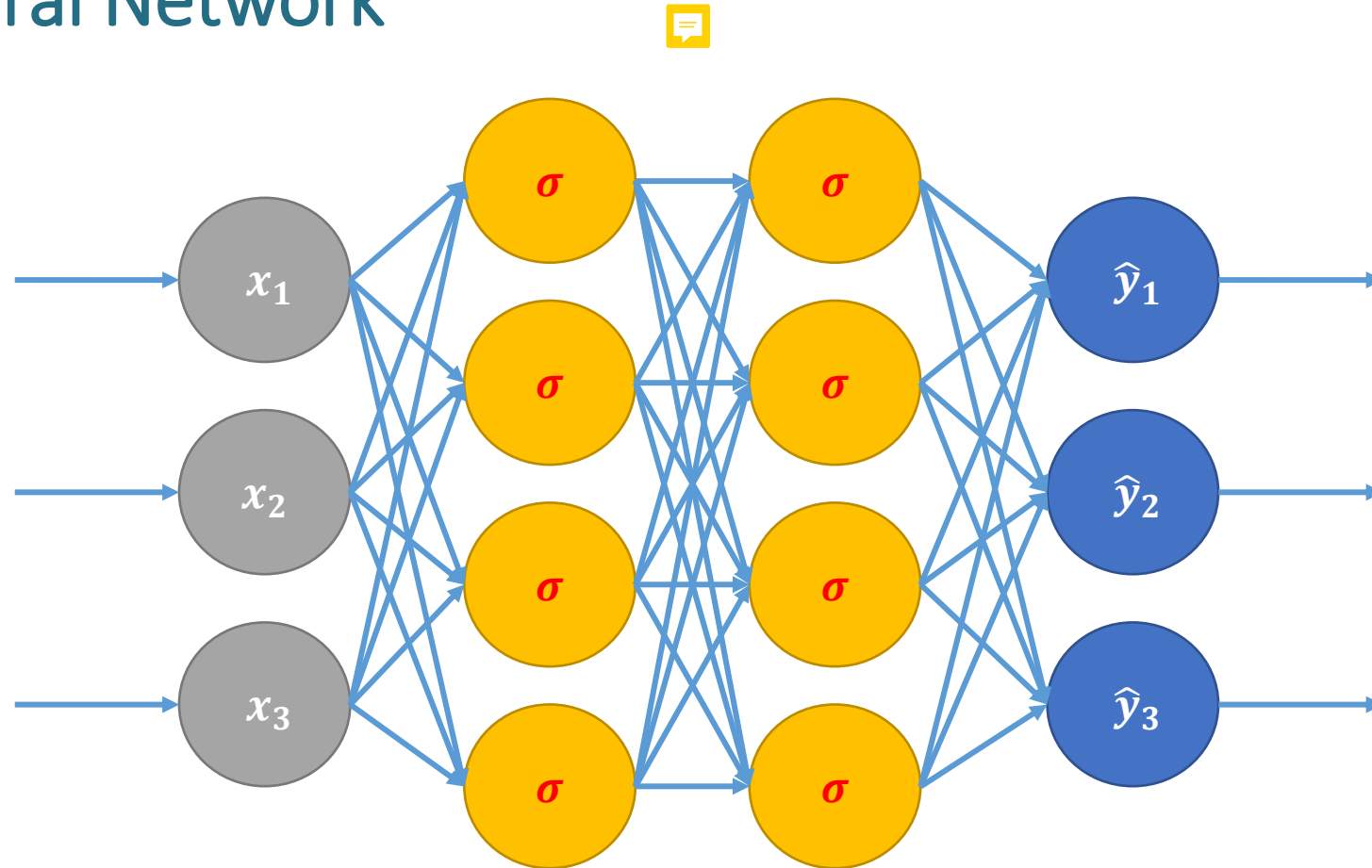
- Deeper structures allow the build-up of more “intermediate” results that are then used to make the final prediction
- The layers in between act like “feature generation” for the final layer, which predicts the output.



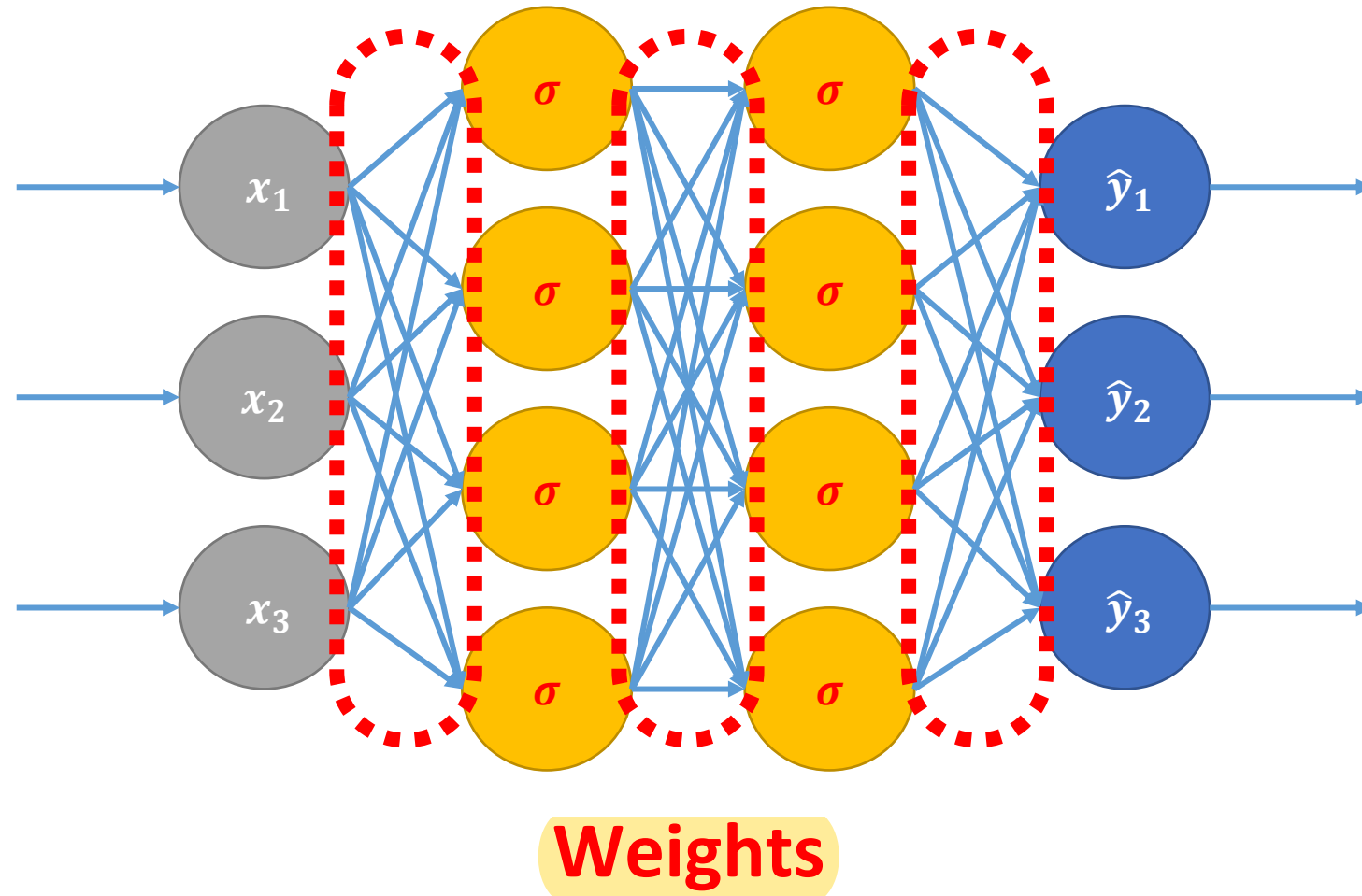
Shallow Neural Network



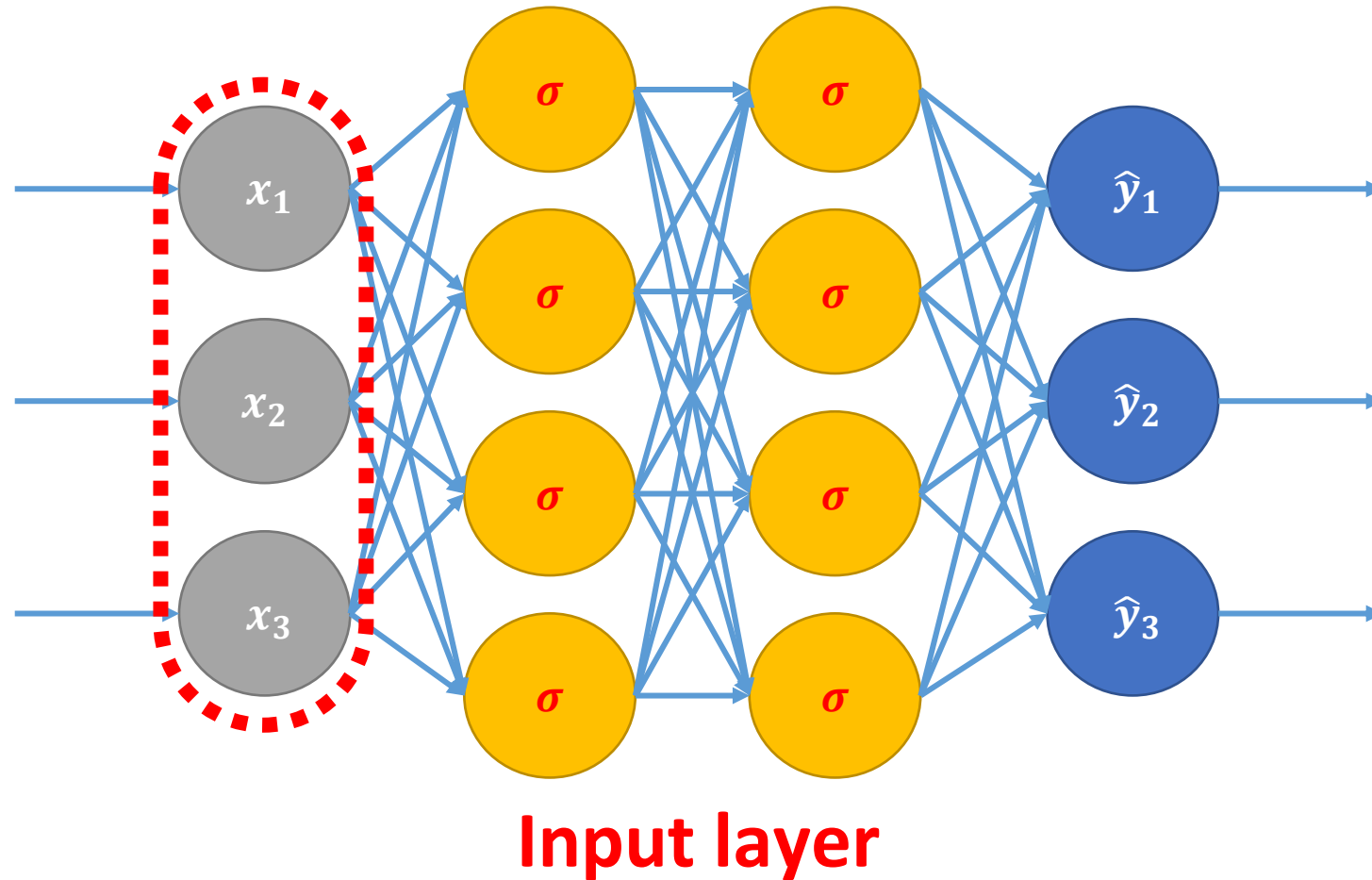
Deep Neural Network



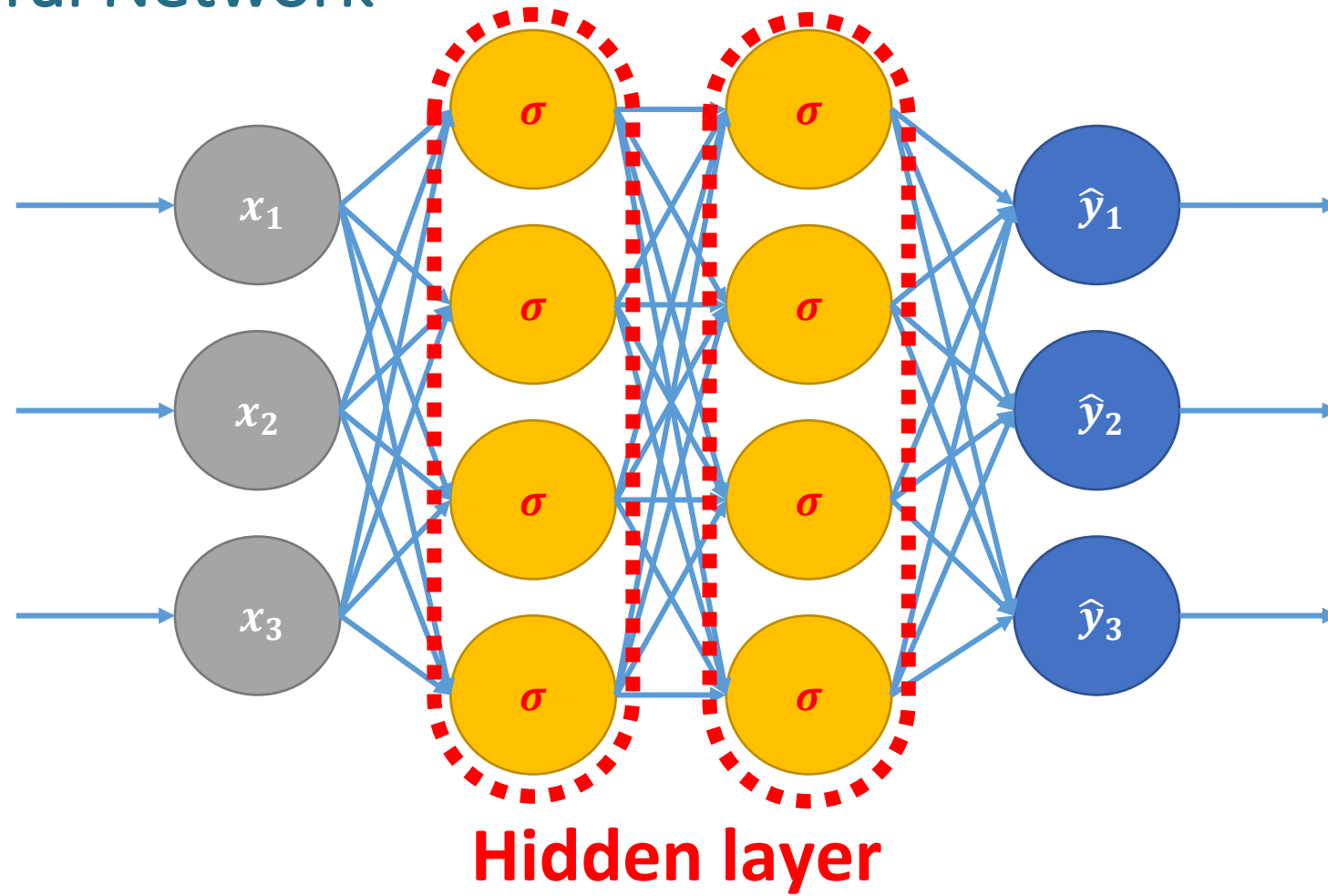
Deep Neural Network



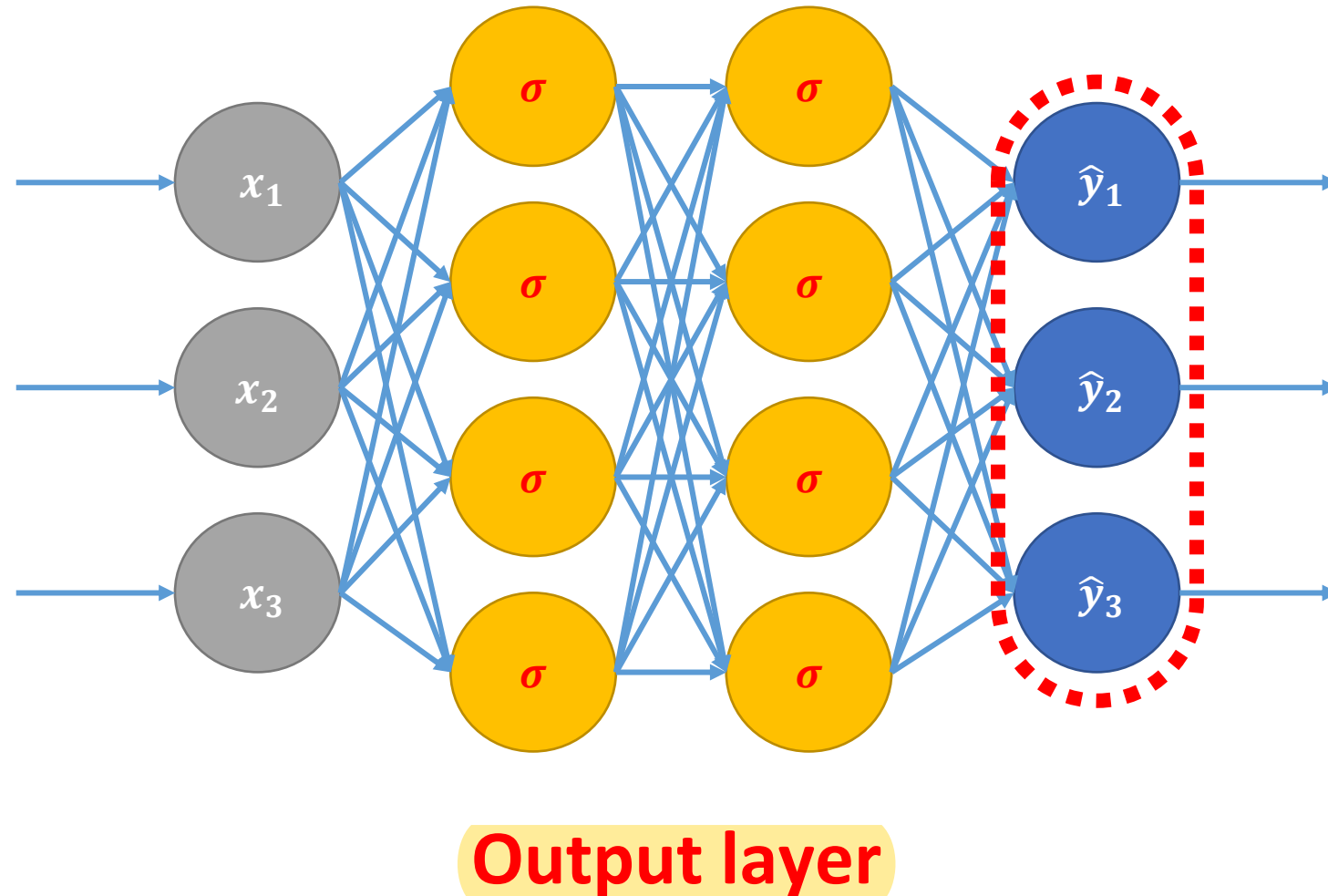
Deep Neural Network



Deep Neural Network

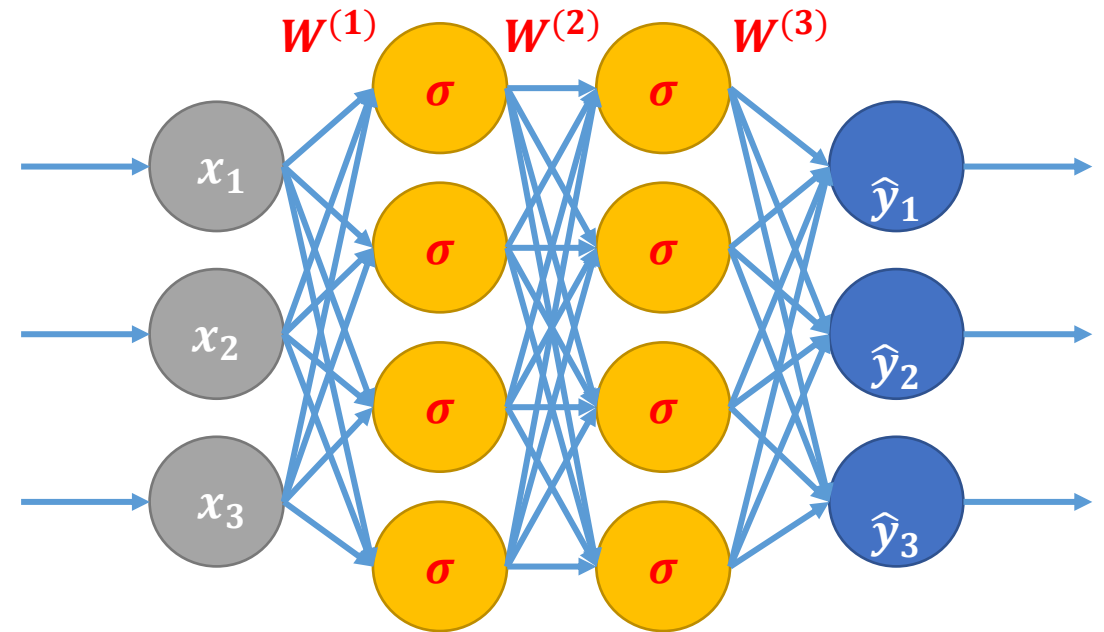


Deep Neural Network



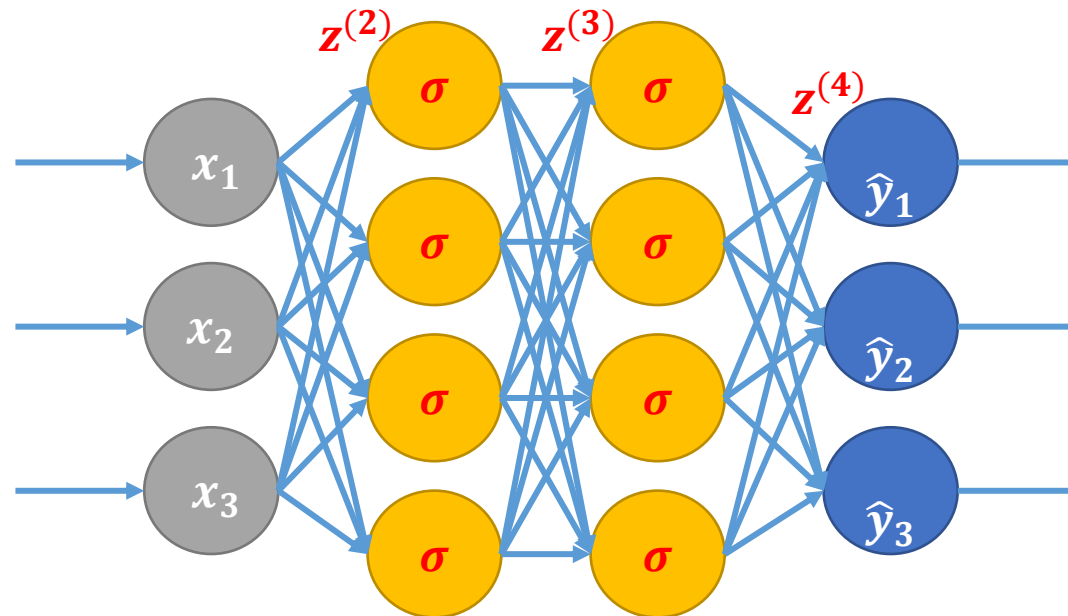
Deep Neural Network

- **Weights** between layers can be represented as a **matrix**, by putting every incoming weight to a given node as a row vector, and stacking those rows.
- So, between the input layer and the first hidden layer, we have a 3x4 matrix.
- Note that bias is not considered here.



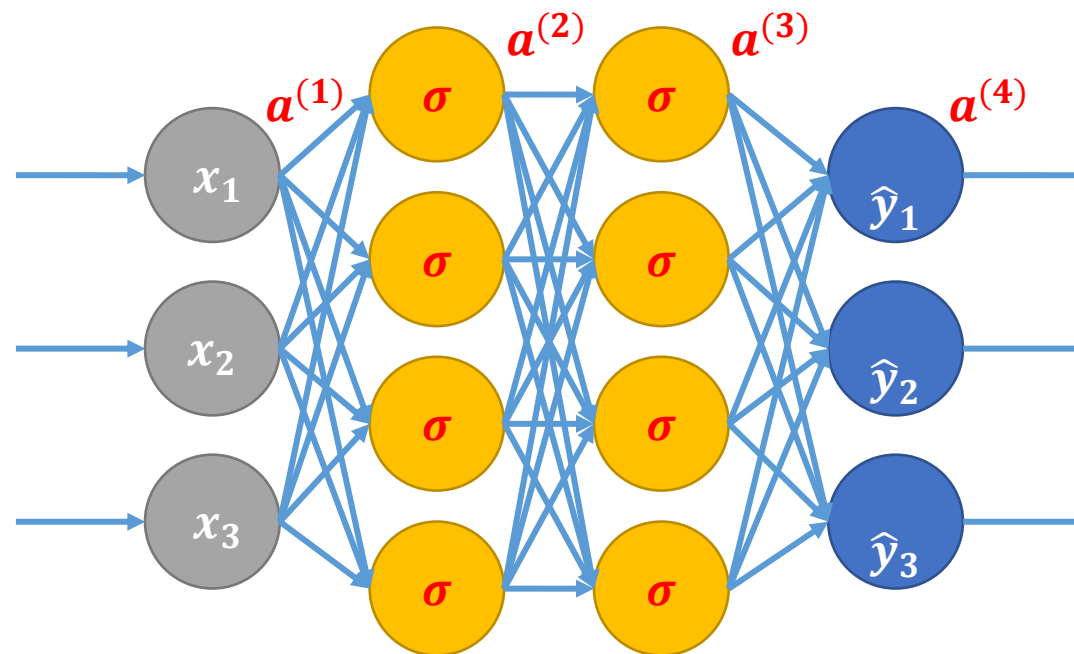
Deep Neural Network

- Once we have the weights, then we can compute the **net inputs**
- It just corresponds to a **matrix multiplication**.

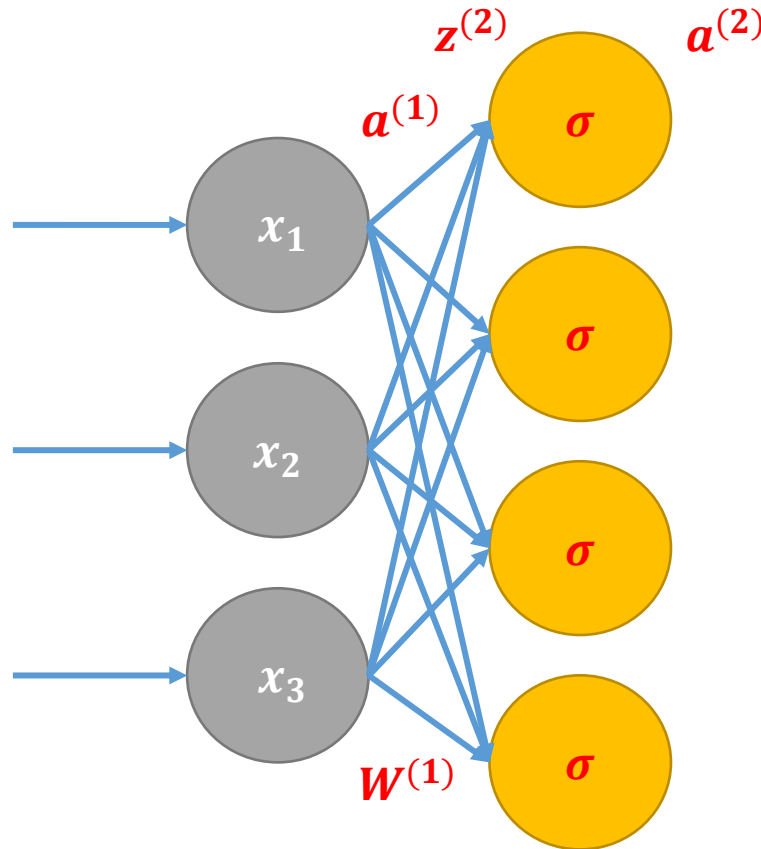


Deep Neural Network

- Once the net input is prepared, it is fed into the **activation function**, and passed as input to the next layer.



Deep Neural Network



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

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

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

$a^{(1)}$ is a 3-row vector
 $W^{(1)}$ is a 3x4 matrix
 $z^{(2)}$ is a 4-row vector
 $a^{(2)}$ is a 4-row 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)

$$\begin{aligned}z^{(2)} &= xW^{(1)} & a^{(2)} &= \sigma(z^{(2)}) \\z^{(3)} &= a^{(2)}W^{(2)} & a^{(3)} &= \sigma(z^{(3)}) \\z^{(4)} &= a^{(3)}W^{(3)} & \hat{y} &= \text{softmax}(z^{(4)})\end{aligned}$$

Softmax is another activation function.

Continuing the computation

- In practice, we do these computation for many data points at the same time, by “stacking” the rows into a matrix.
 - Input: matrix x (a $n \times 3$ matrix) (each row a single instance)
 - Output: vector \hat{y} (a $n \times 3$ matrix) (each row a single prediction)

$$\begin{aligned} z^{(2)} &= xW^{(1)} & a^{(2)} &= \sigma(z^{(2)}) \\ z^{(3)} &= a^{(2)}W^{(2)} & a^{(3)} &= \sigma(z^{(3)}) \\ z^{(4)} &= a^{(3)}W^{(3)} & \hat{y} &= \text{softmax}(z^{(4)}) \end{aligned}$$

- Equations look the same!