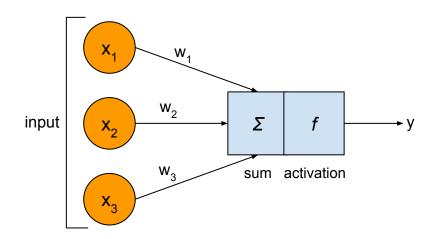
# Computation in neural networks

Valerio Velardo

#### The artificial neuron



$$h = \sum_{i} x_{i}w_{i} = x_{1}w_{1} + x_{2}w_{2} + x_{3}w_{3}$$

$$y = f(h) = f(x_{1}w_{1} + x_{2}w_{2} + x_{3}w_{3})$$

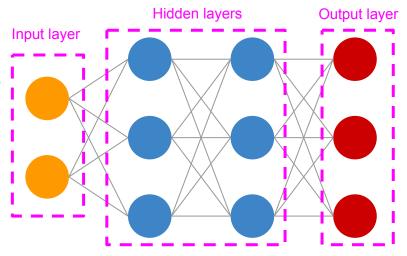
$$y = \frac{1}{1 + e^{-(x_{1}w_{1} + x_{2}w_{2} + x_{3}w_{3})}}$$

#### Why is a neural network needed?

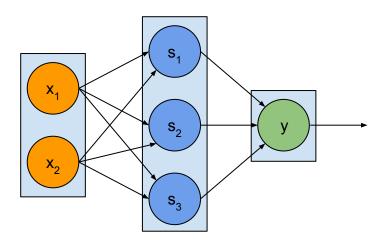
- A single neuron works for linear problems
- Real-world problems are complex
- ANNs can reproduce highly non-linear functions

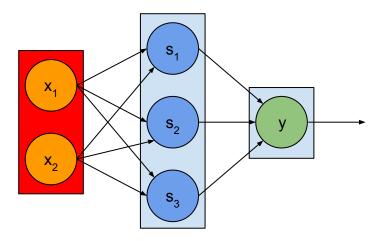
#### The components of an artificial neural network (ANN)

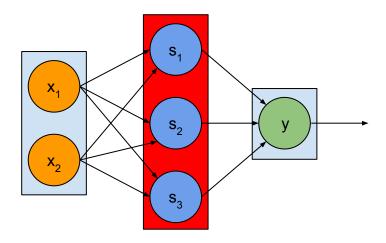
- Neurons
- Input, hidden, output layers
- Weighted connections
- Activation function

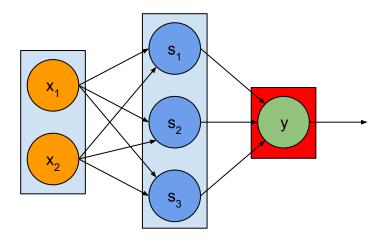


# The multilayer perceptron (MLP)



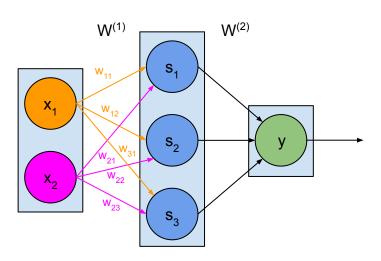




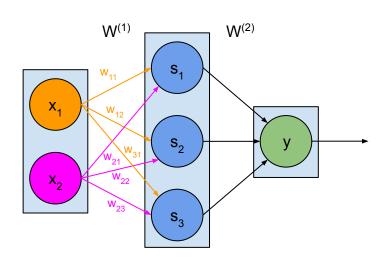


- Weights
- Net inputs (sum of weighted inputs)
- Activations (output of neurons to next layer)

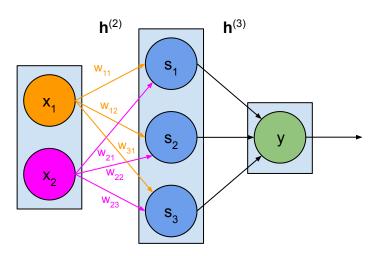
# Weights

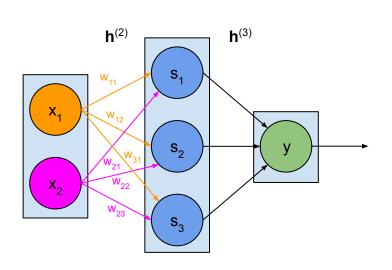


# Weights

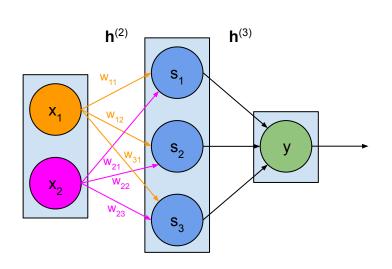


$$W^{(1)} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix}$$

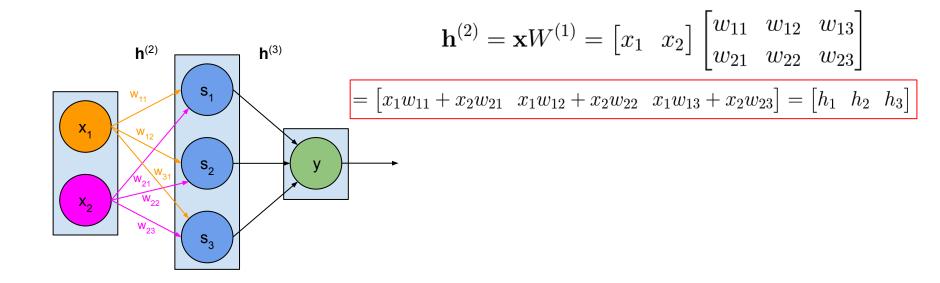




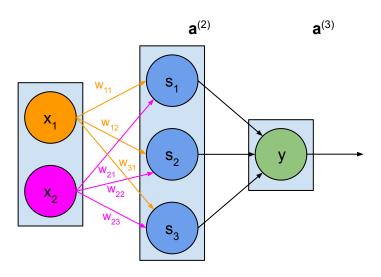
$$\mathbf{h}^{(2)} = \mathbf{x} W^{(1)}$$



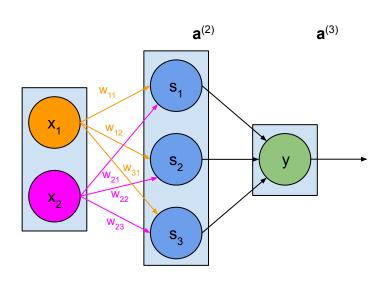
$$\mathbf{h}^{(2)} = \mathbf{x}W^{(1)} = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix}$$



#### Activation

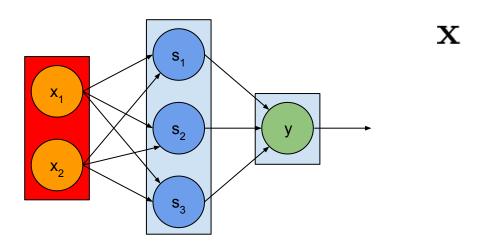


#### Activation

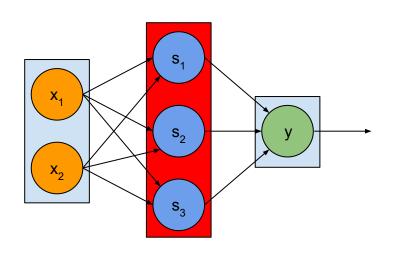


$$\mathbf{a}^{(2)} = f(\mathbf{h}^{(2)})$$

# Computation in MLP (1st layer)



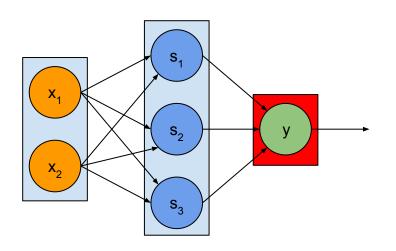
## Computation in MLP (2nd layer)



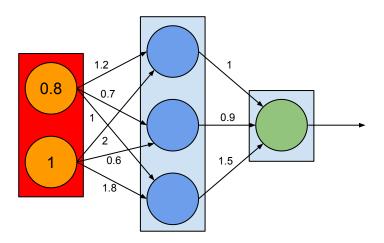
$$\mathbf{h}^{(2)} = \mathbf{x} W^{(1)}$$

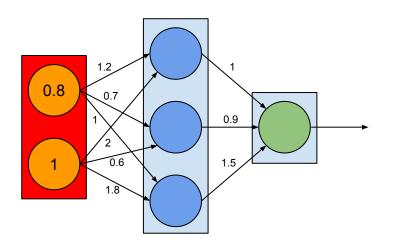
$$\mathbf{h}^{(2)} = \mathbf{x} W^{(1)}$$
  
 $\mathbf{a}^{(2)} = f(\mathbf{h}^{(2)})$ 

## Computation in MLP (3d layer)

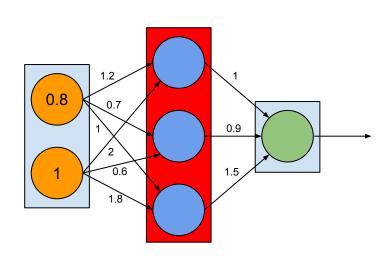


$$\mathbf{h}^{(3)} = \mathbf{a}^{(2)} W^{(2)}$$
$$y = f(\mathbf{h}^{(3)})$$

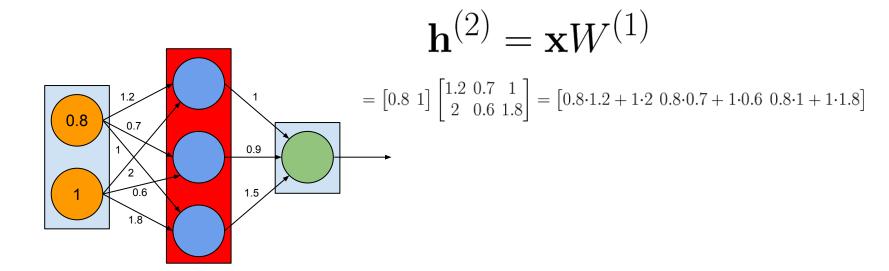


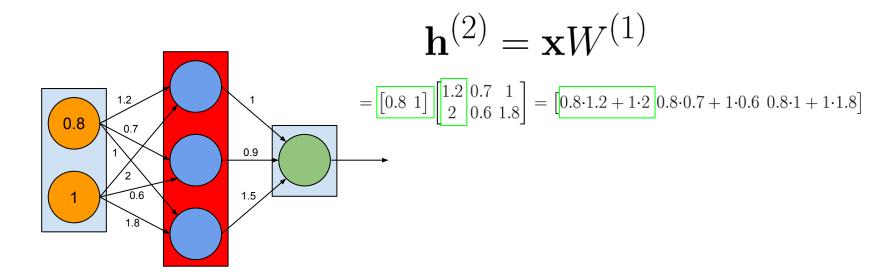


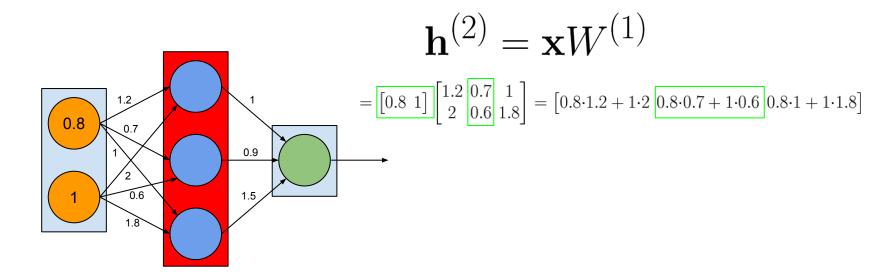
$$\mathbf{x} = \begin{bmatrix} 0.8 & 1 \end{bmatrix}$$

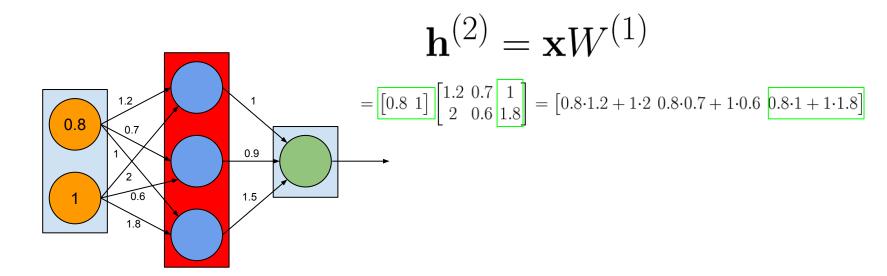


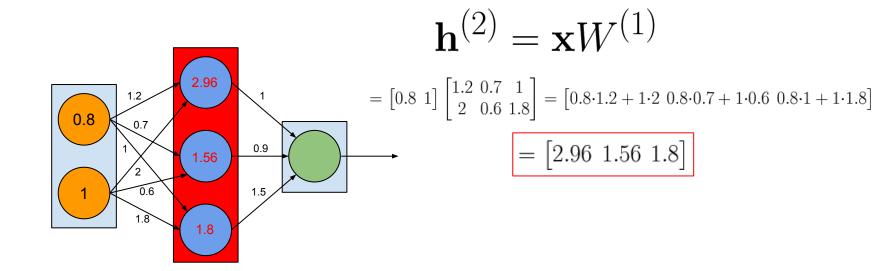
$$\mathbf{h}^{(2)} = \mathbf{x} W^{(1)}$$

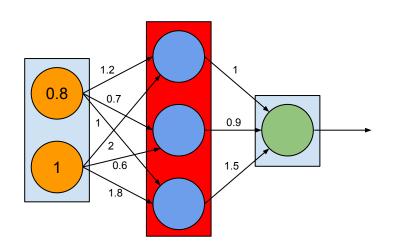






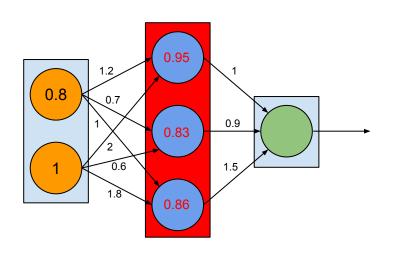






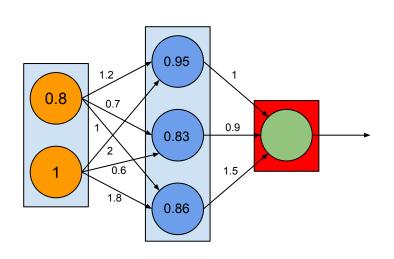
$$\mathbf{h}^{(2)} = \begin{bmatrix} 2.96 & 1.56 & 1.8 \end{bmatrix}$$

$$\mathbf{a}^{(2)} = \frac{1}{1 + e^{-\mathbf{h}^{(2)}}}$$

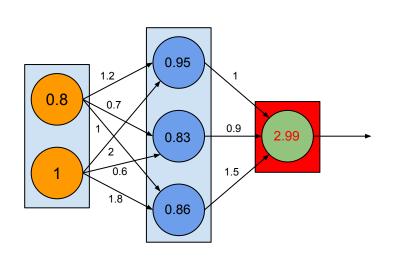


$$\mathbf{h}^{(2)} = \begin{bmatrix} 2.96 & 1.56 & 1.8 \end{bmatrix}$$

$$\mathbf{a}^{(2)} = \frac{1}{1 + e^{-\mathbf{h}^{(2)}}} = \left[ 0.95 \ 0.83 \ 0.86 \right]$$

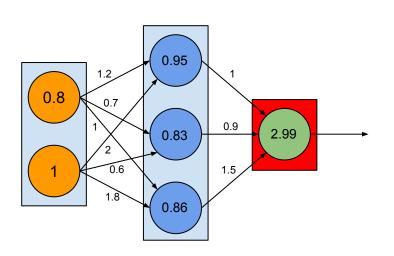


$$\mathbf{h}^{(3)} = \mathbf{a}^{(2)} W^{(2)}$$

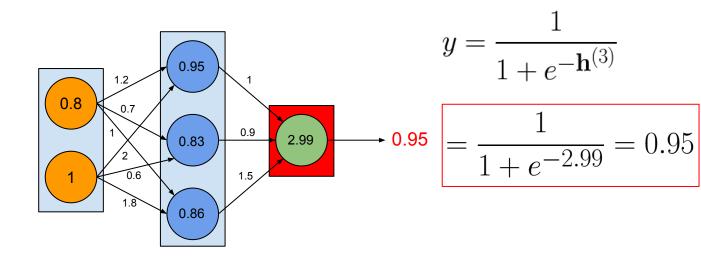


$$\mathbf{h}^{(3)} = \mathbf{a}^{(2)} W^{(2)}$$

$$= \begin{bmatrix} 0.95 & 0.83 & 0.86 \end{bmatrix} \begin{bmatrix} 1 \\ 0.9 \\ 1.5 \end{bmatrix} = 2.99$$



$$y = \frac{1}{1 + e^{-\mathbf{h}^{(3)}}}$$



# Takeaway points

- ANNs work for complex problems
- Computation is distributed
- Signal moves from left to right
- Weights, net inputs and activations

# What's up next?

