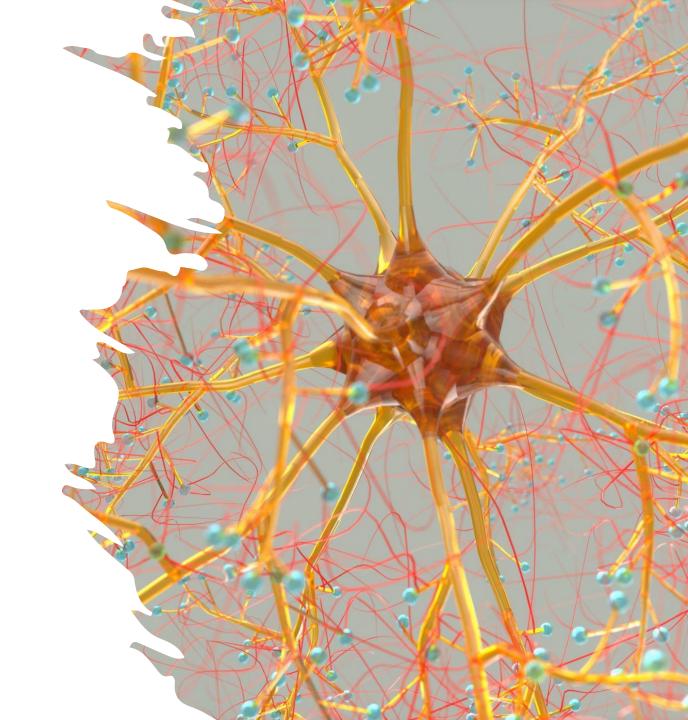
CS826

#### Neural Networks

Week 1 - Summary

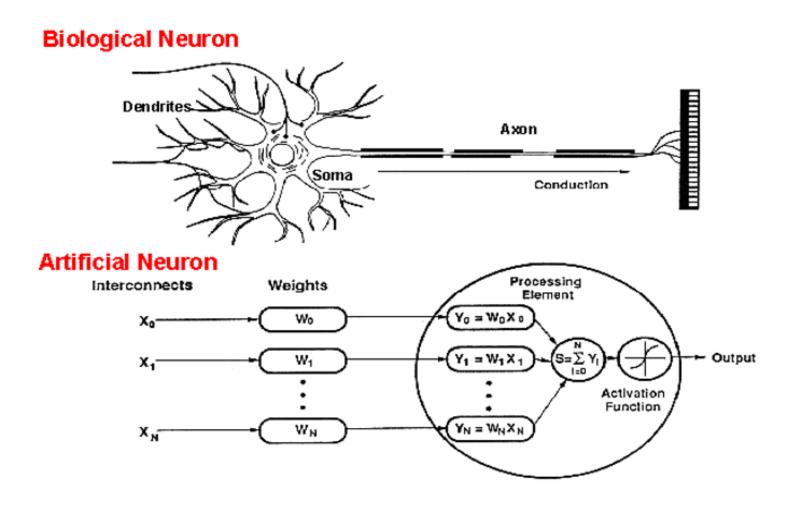


#### Week 1: Review and Getting Started with Neural Networks

This week you will be introduced to:

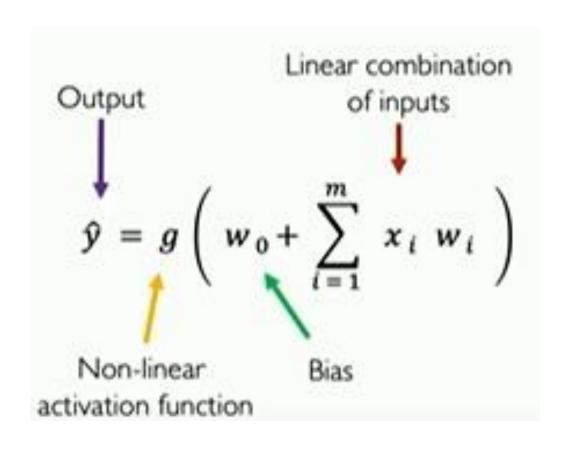
- 1. What is deep learning?
- 2. Motivation, challenges, and applications <a></a>
- 3. Architecture and maths
- 4. Simple examples
- 5. Google Colab for practical sessions

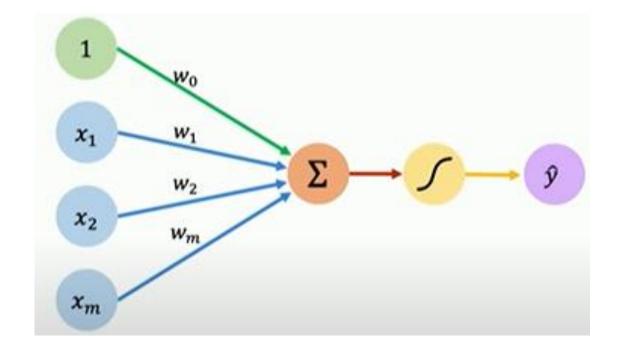
#### How do ANNs work?



An artificial neuron is an imitation of a human neuron

## **Forward Propagation - Perceptron**



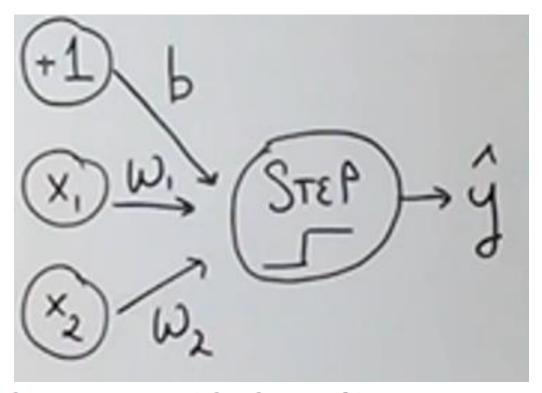


## Perceptron

Let the input feature vector be:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad y \in \{1, 0\}$$

where y is the binary response.



The perceptron model computes a weighted sum of inputs:

$$z = w_1 x_1 + w_2 x_2 + b$$

The perceptron then applies a step function to determine the predicted label  $\hat{y}$ :

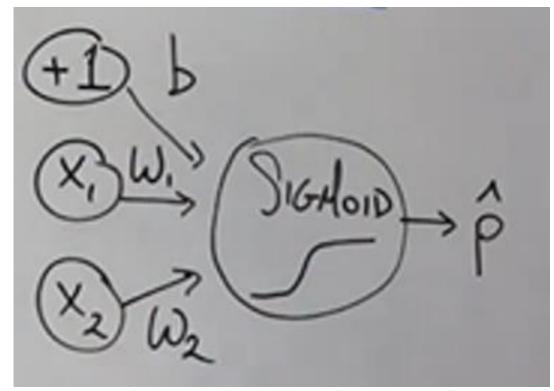
$$\hat{y} = \begin{cases} 1 & \text{if } z \ge 0 \\ 0 & \text{if } z < 0 \end{cases}$$

## Logistic Regression

Let the input feature vector be:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad y \in \{1, 0\}$$

where y is the binary response.



In logistic regression, we compute the same linear combination of inputs:

$$z = w_1 x_1 + w_2 x_2 + b$$

but instead of a step function, we apply the sigmoid function  $\sigma(z)$  to get the predicted probability  $\hat{p}$ :

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

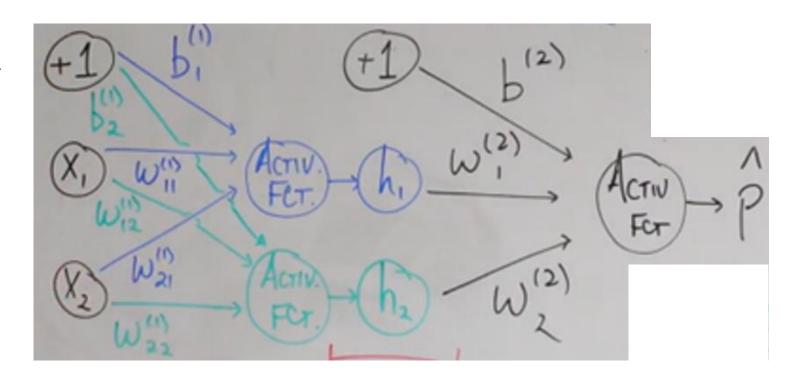
## **Neural Network**

$$z_1^{(1)} = W_{11} X_1 + W_{21} X_2 + b_1^{(1)}$$
  $z_2^{(1)} = W_{12} X_1 + W_{22} X_2 + b_2^{(1)}$ 

$$h_1 = \sigma(z_1^{(1)})$$
 and  $h_2 = \sigma(z_2^{(1)})$ 

$$z^{(2)} = w_1^{(2)} h_1 + w_2^{(2)} h_2 + b^{(2)}$$

$$\hat{p} = \sigma(z^{(2)})$$



Matrix Form:

$$\mathbf{z}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}$$

$$\mathbf{W}^{(1)} = \begin{bmatrix} w_{11}^{(1)} & w_{12}^{(1)} \\ w_{21}^{(1)} & w_{22}^{(1)} \end{bmatrix}, \quad \mathbf{b}^{(1)} = \begin{bmatrix} b_1^{(1)} \\ b_2^{(1)} \end{bmatrix}$$

$$\mathbf{h} = \sigma(\mathbf{z}^{(1)})$$

$$z^{(2)} = \mathbf{w}^{(2)}\mathbf{h} + b^{(2)}$$

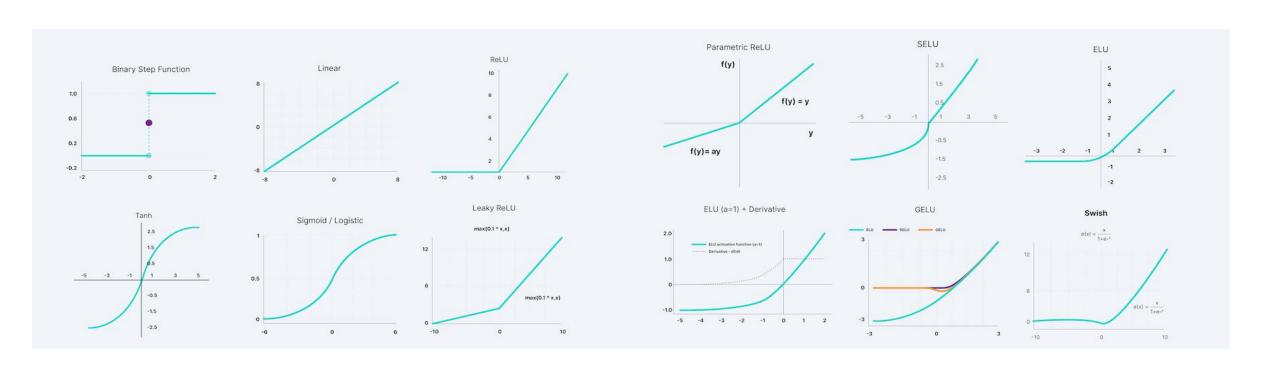
$$\hat{p} = \sigma(z^{(2)})$$

## Vital and Lingering Questions

Some questions regarding neural network architecture and training include:

- How to get weights and biases (w and b)?
- How many hidden layers should be used?
- What activation function to choose?

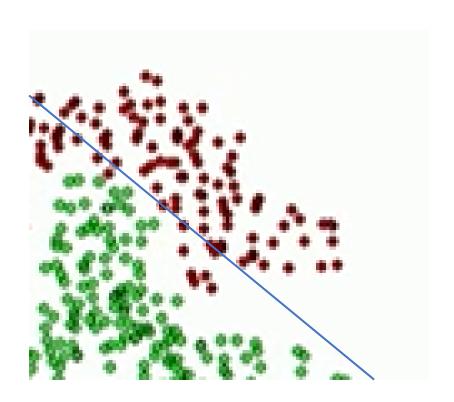
## **Activation Functions**



Source: v7labs.com

## Importance of Activation Functions

Distinguish Red vs Green points



Introduce non-linearities to the network

What is bias, how is used and why it is important?

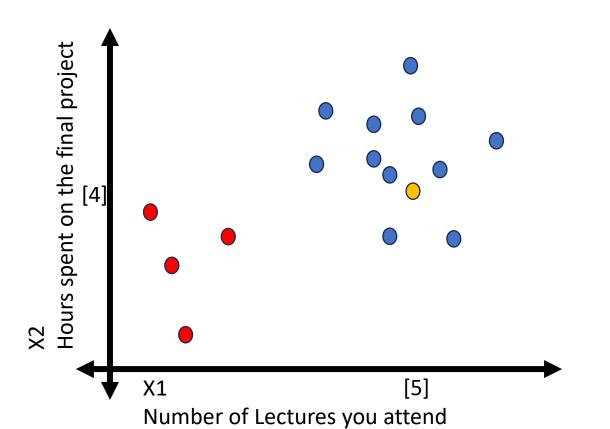
### Toy Problem – Motivating Example

Two Feature Model:

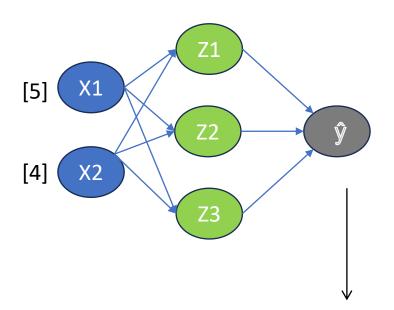
X1 = Number of lectures you attend

X2 = Hours spent on the final group Project

WILL I PASS THIS CLASS?



- PASS
- FAIL
- X = [5,4]



Not trained properly! ← Why NN is so wrong? ←

Predicted:  $\hat{y} = 0.2$ 

Actual: y = 1

$$\frac{1}{n} \sum_{i=1}^{n} \mathcal{L}(\underline{f(x^{(i)}; \boldsymbol{W})}, \underline{y^{(i)}})$$
Predicted Actual

## Loss function

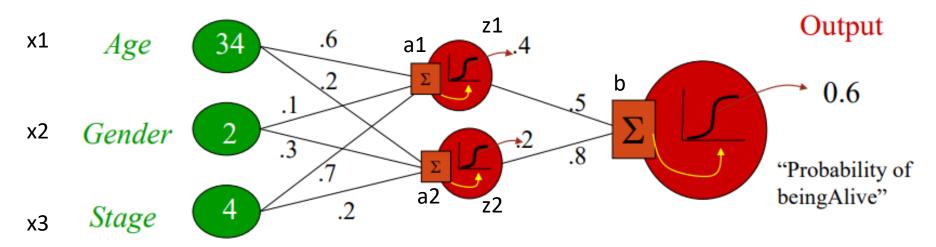
## Loss Optimization

Gradient Descent

- 1. Initialize weights randomly:  $W \sim \mathcal{N}(0, \sigma^2)$
- 2. Loop until convergence:
  - (a) Compute gradient,  $\frac{\partial J(W)}{\partial W}$
  - (b) Update weights,  $W \leftarrow W \eta \frac{\partial J(W)}{\partial W}$
- 3. Return weights

# Example in Python from scratch: NEURAL NETWORK MODEL

#### Inputs



Independent variables

Weights

Hidden Layer

Weights

Dependent variable

Prediction