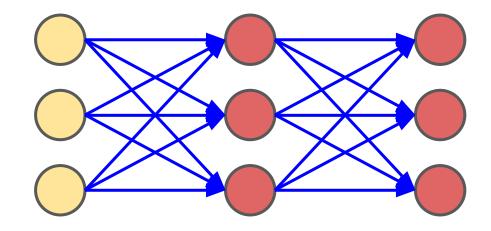
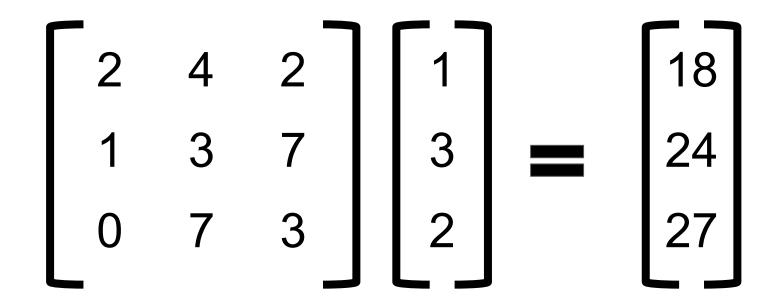
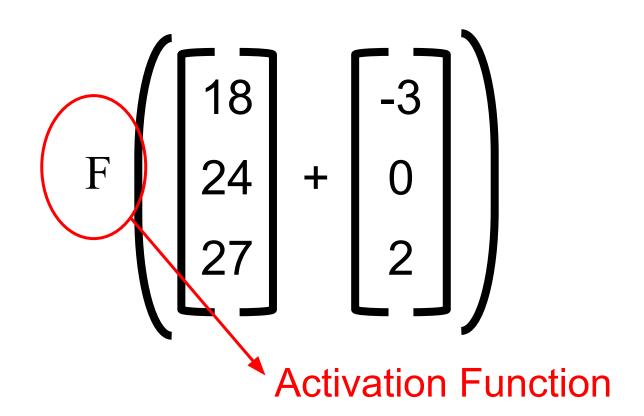
Neural Networks

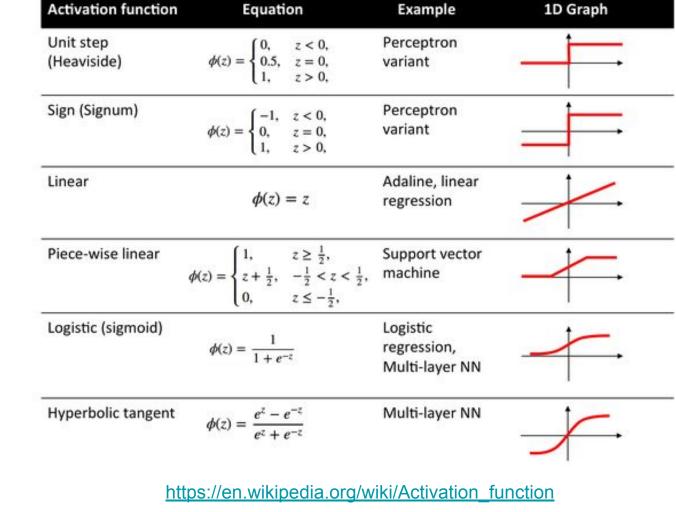
- 1. Single Layer
- 2. Single Neuron
- 3. Multiple Layers
- 4. Input and Output





$$F \left(\begin{bmatrix} 18 \\ 24 \\ 27 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix} \right)$$

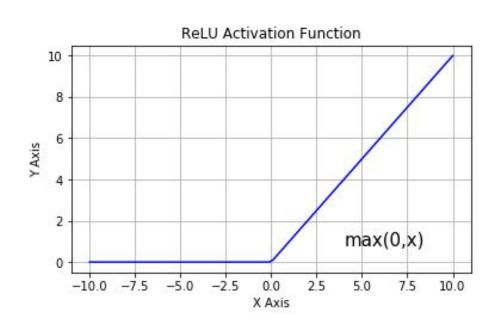


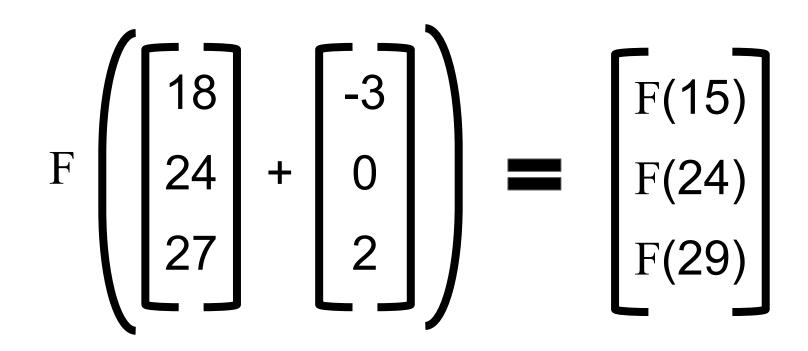


ReLU Activation function

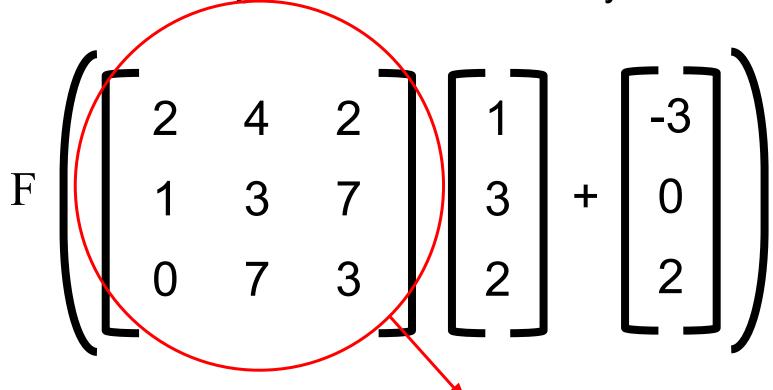
It stands for Rectified Linear Unit

$$ReLU(x) = max(x,0)$$

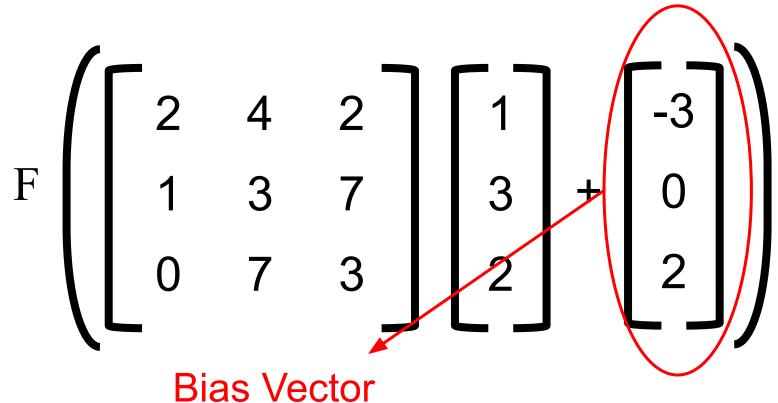


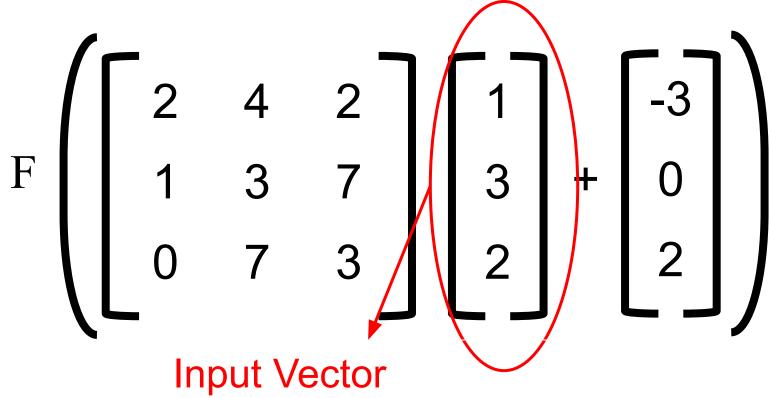


$$F\left(\begin{bmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix}\right)$$



CME 193 - Introduction to Scientific ight Matrix

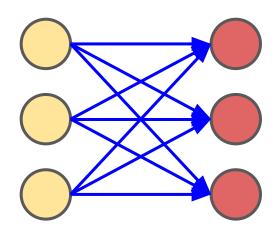




$$F\left(\begin{bmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix}\right)$$

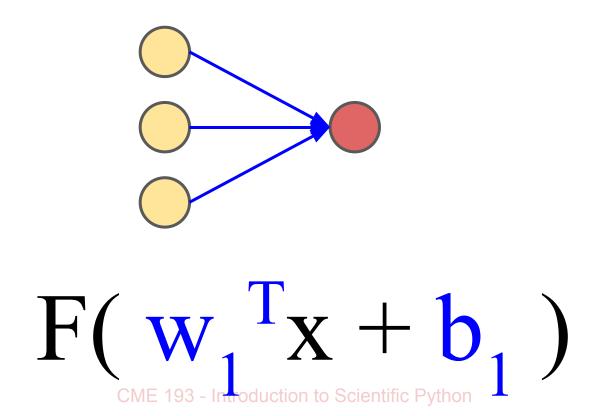
Trainable Parameters

$$F(Wx+b)$$



$$F(Wx+b)$$

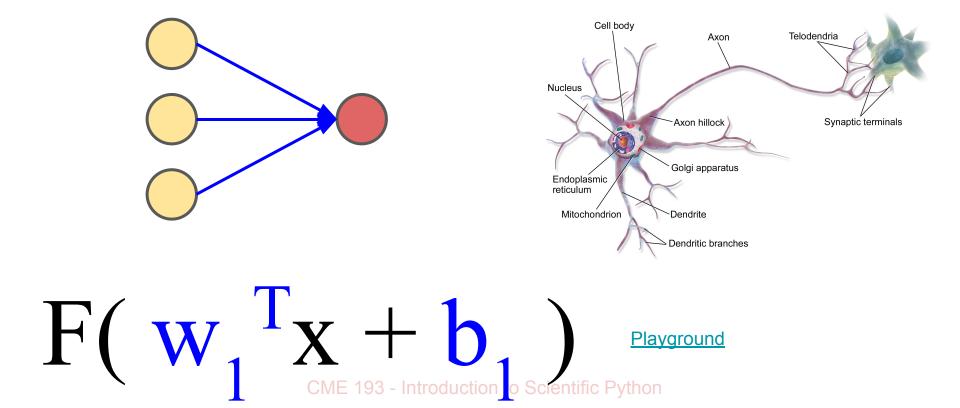
What does a single Neuron do?



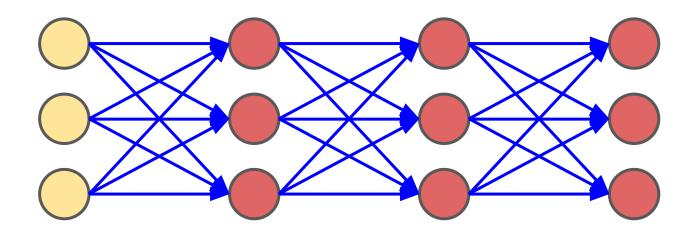
Weights for each neuron

$$\mathbf{W} = \begin{bmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^T \\ \mathbf{w}_2^T \\ \mathbf{w}_3^T \end{bmatrix}$$

What does a single Neuron do?



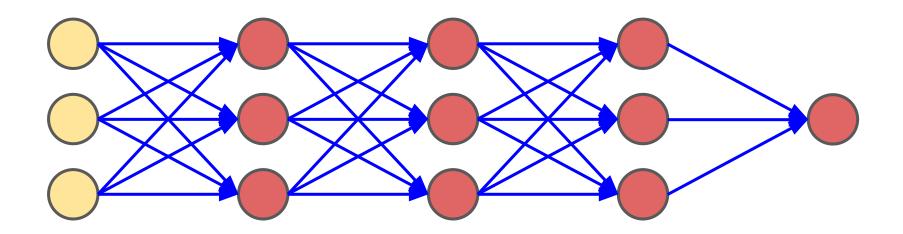
Stacking multiple layers



It's called a *deep* neural network when you use multiple layers

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What are the inputs and outputs?



Gradient Descent

- 1. The Idea is to go downhill according to the linear approximation of your function
- 2. But not too much as your approximation will not be true
- 3. This means updating each weight in proportional to the gradient

$$w' = w - \alpha g$$

Gradient Descent

- 1. The Idea is to go downhill according to the linear approximation of your function
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Learning Rate

How to compute gradients - Backpropagation

Numerically approximating gradients is too slow and computationally expensive

The neural network is a well defined mathematical function, we should be able to differentiate it and calculate the derivatives

This is also too tedious so we instead use an algorithm called backpropagation

Computational Graph

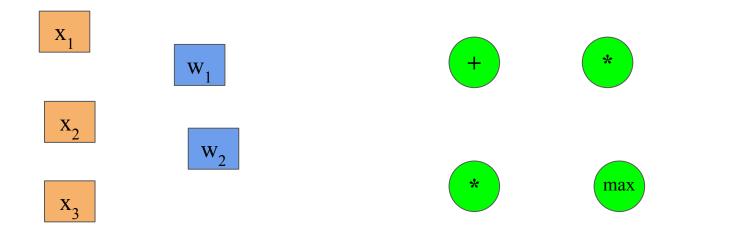
$$F(x_1, x_2, x_3) = \max(w_1x_1 + w_2x_2, x_3)$$

Consider this simple function, imagine that this is the cost function and we want to find the gradients with respect to the two weights

We will first build the computational graph that this function represents

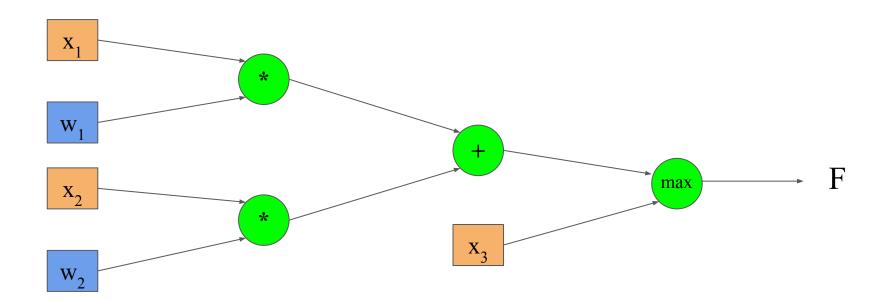
Computational Graph

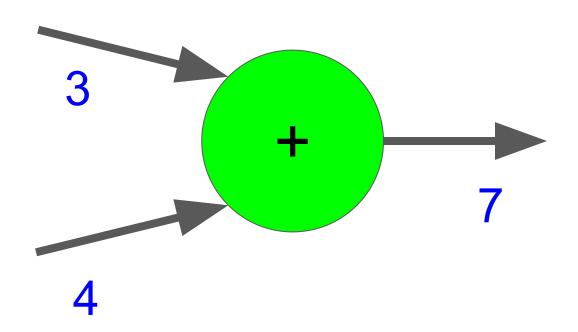
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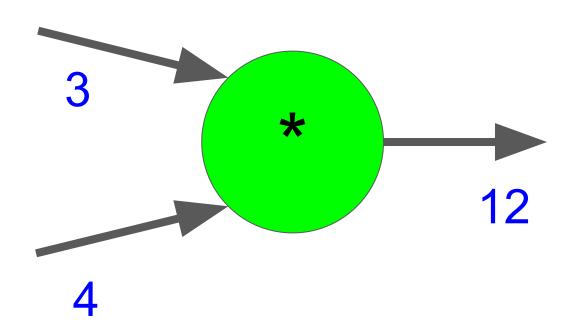


Computational Graph

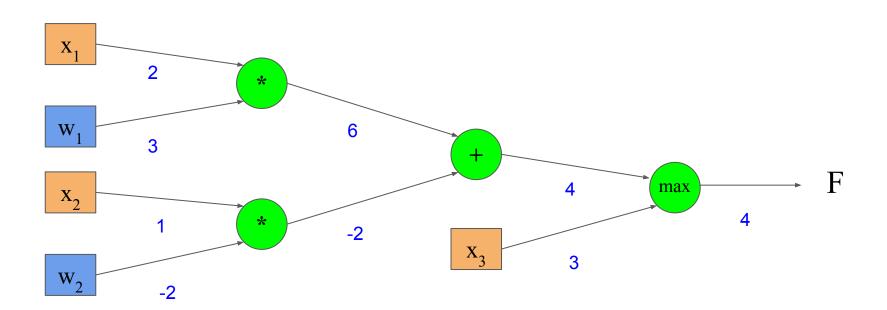
$$F(x_1, x_2, x_3) = \max(w_1x_1 + w_2x_2, x_3)$$





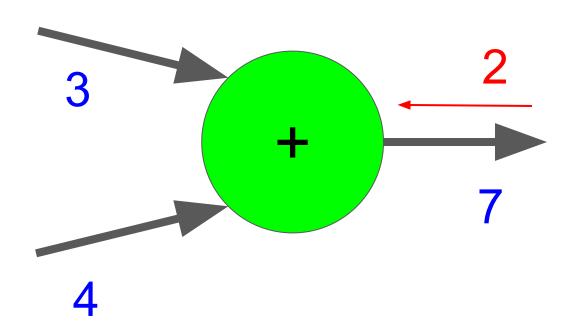


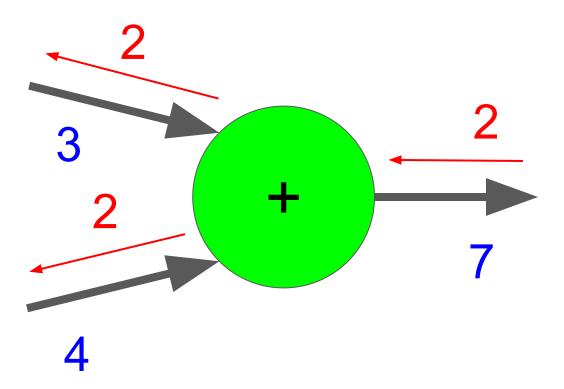
$$F(x_1, x_2, x_3) = \max(w_1x_1 + w_2x_2, x_3)$$

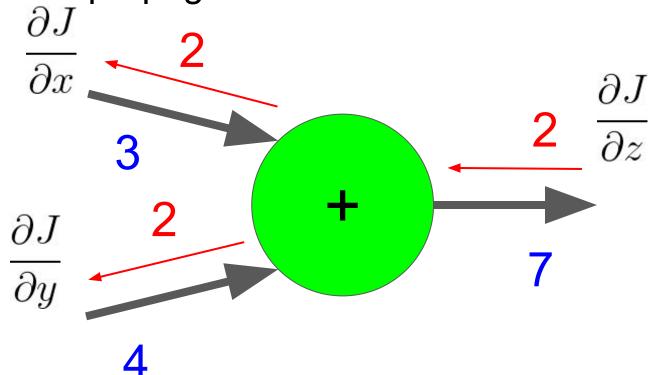


- 1. Each Circle represents a computational operation
- 2. Each arrow is an intermediate quantity that is computed
- 3. Each box contains some value
- 4. Orange boxes are inputs
- 5. Blue boxes are parameters
- 6. Compute the inputs to an operation first then apply the operation to compute its output

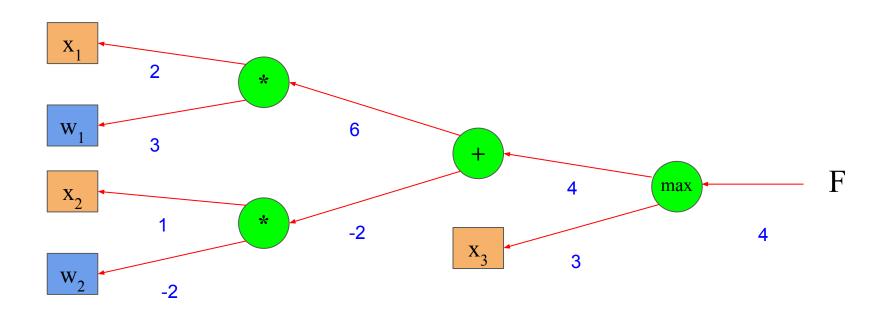
- 1. The numbers flow backwards along the arrows
- 2. At each arrow the quantity represents the gradient of some final function with respect to the quantity at that arrow



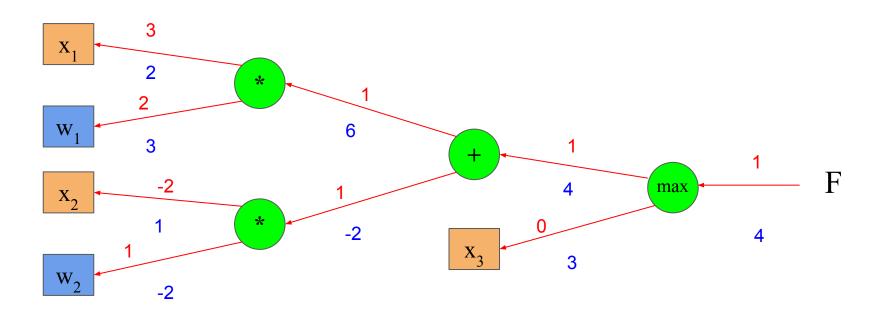




$$F(x_1, x_2, x_3) = \max(w_1x_1 + w_2x_2, x_3)$$



$$F(x_1, x_2, x_3) = \max(w_1x_1 + w_2x_2, x_3)$$



Two Layer Example

$$a_1 = \max(W_1x + b_1, 0)$$

$$\hat{y} = \operatorname{Softmax}(W_2a_1 + b_2)$$

$$J = CE(y, \hat{y})$$

$$x + \bigoplus_{\mathbf{W_1}} \bigoplus_{\mathbf{b_1}} \bigoplus_{\mathbf{W_2}} \bigoplus_{\mathbf{b_2}} \underbrace{\operatorname{Cross Entropy}}_{\mathbf{Loss}} \longrightarrow_{\mathbf{J}}$$

Two Layer Example

$$a_1 = \max(W_1x + b_1, 0)$$

$$\hat{y} = \operatorname{Softmax}(W_2a_1 + b_2)$$

$$J = CE(y, \hat{y})$$

$$||z_1 > 0|d_{a_2}|||z_1 > 0|d_{a_2}||W_2^T(\hat{y} - y)|$$

$$||z_1 > 0|d_{a_2}x^T|$$

$$||z_1 > 0|d_{a_2}x^T|$$

$$||z_1 > 0|d_{a_2}x^T|$$

$$||z_1 > 0|d_{a_2}|$$

$$||x| = (\hat{y} - y)a_1^T|$$

$$|x| = (\hat{y} - y)a_1^T|$$

$$|x| = (\hat{y} - y)$$

$$|x| = (\hat{y} -$$