


# Neural Networks

A thin vertical line is positioned to the right of the text. At the bottom of the slide, there is a solid horizontal bar in a dark orange color.

# Content

- Neurons and Activation Functions
- Cost Functions
- Gradient Descent
- Backpropagation

# Deep Learning

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Once we build a general high level understanding we will code out all these topics manually with Python, without the use of a deep learning library.

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Then we can move on to using TensorFlow!

# NN

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UNDERSTANDING A HIGH LEVEL OVERVIEW  
OF THESE KEY ELEMENTS WILL MAKE IT  
MUCH EASIER TO UNDERSTAND WHAT IS  
HAPPENING WHEN WE BEGIN TO USE  
TENSORFLOW!



TENSORFLOW HAS DIRECT CONNECTIONS  
TO THESE CONCEPTS IN ITS SYNTAX!

# Let's get started!

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# Introduction to the Perceptron

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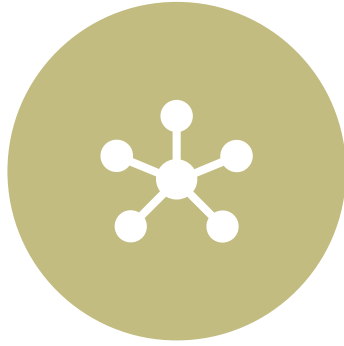
# Deep Learning



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- Before we start work into neural networks, we need to understand the individual components first, such as a single “neuron”.

# Deep Learning

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ARTIFICIAL NEURAL NETWORKS (ANN)  
ACTUALLY HAVE A BASIS IN BIOLOGY!



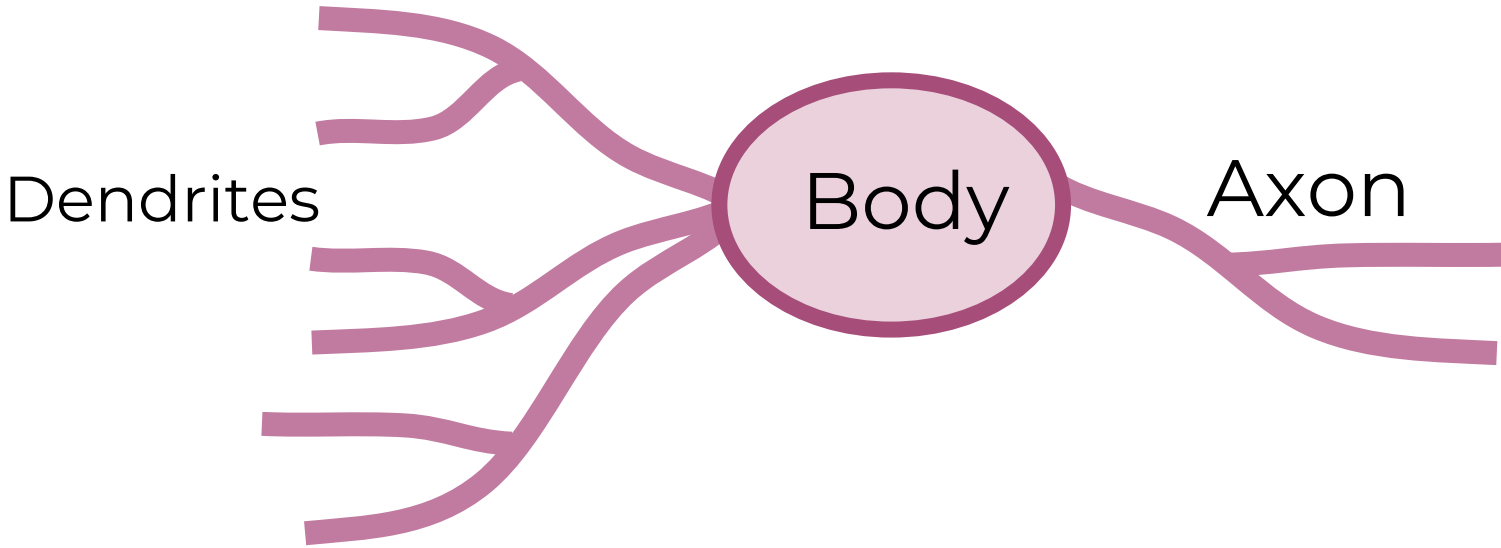
LET'S SEE HOW WE CAN ATTEMPT TO  
MIMIC BIOLOGICAL NEURONS WITH AN  
ARTIFICIAL NEURON, KNOWN AS A  
PERCEPTRON!



# Deep Learning

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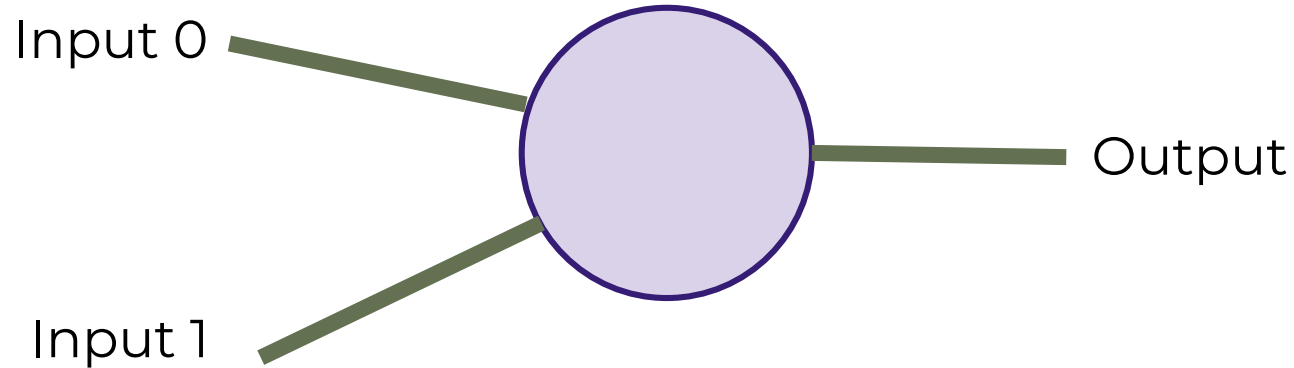
- The biological neuron:



# Deep Learning

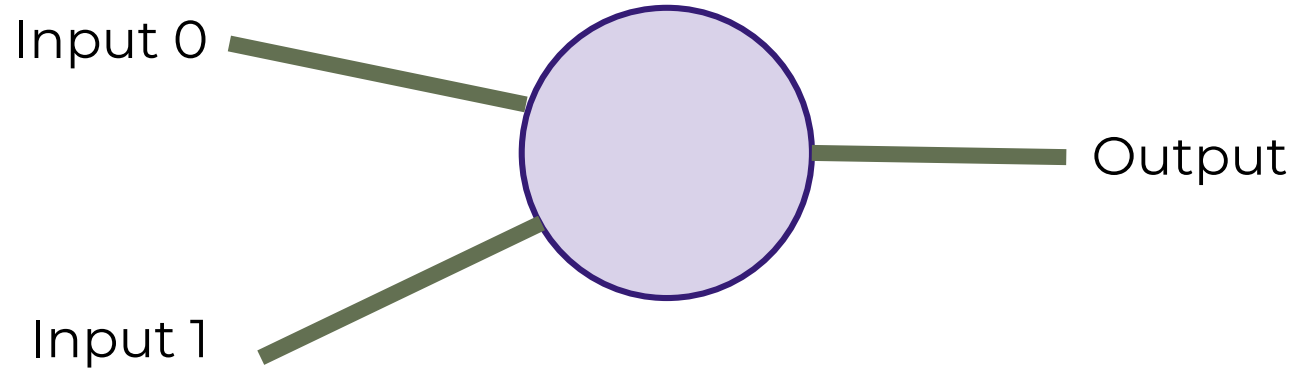
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- The artificial neuron also has inputs and outputs!



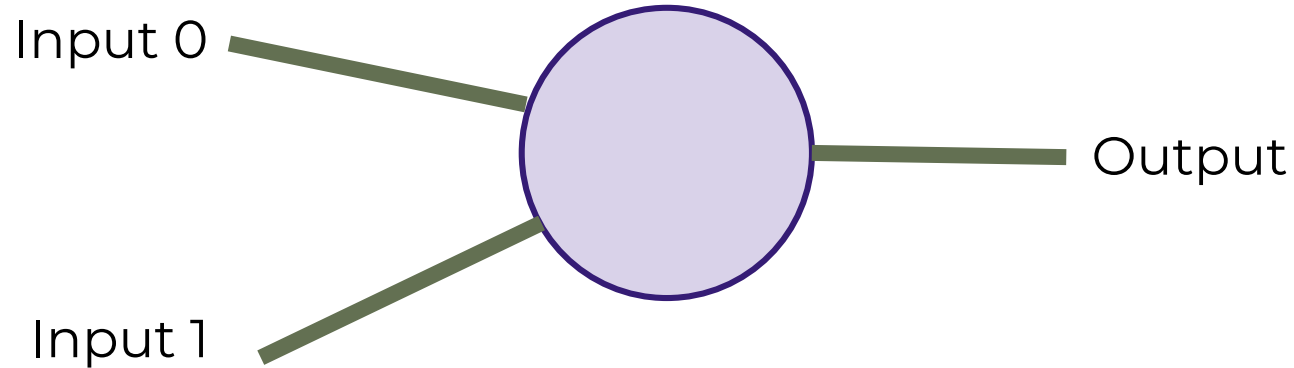
# Deep Learning

- This simple model is known as a perceptron.



# Deep Learning

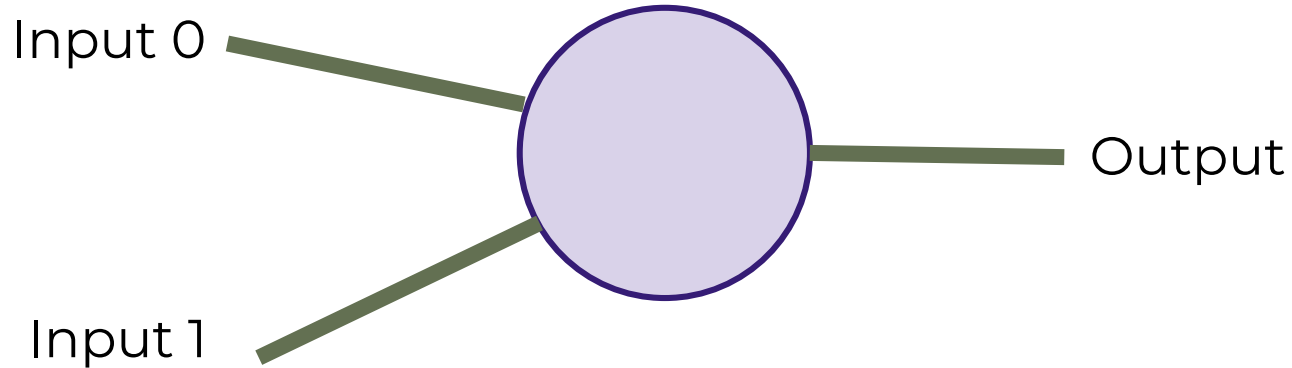
- Simple example of how it can work.



# Deep Learning

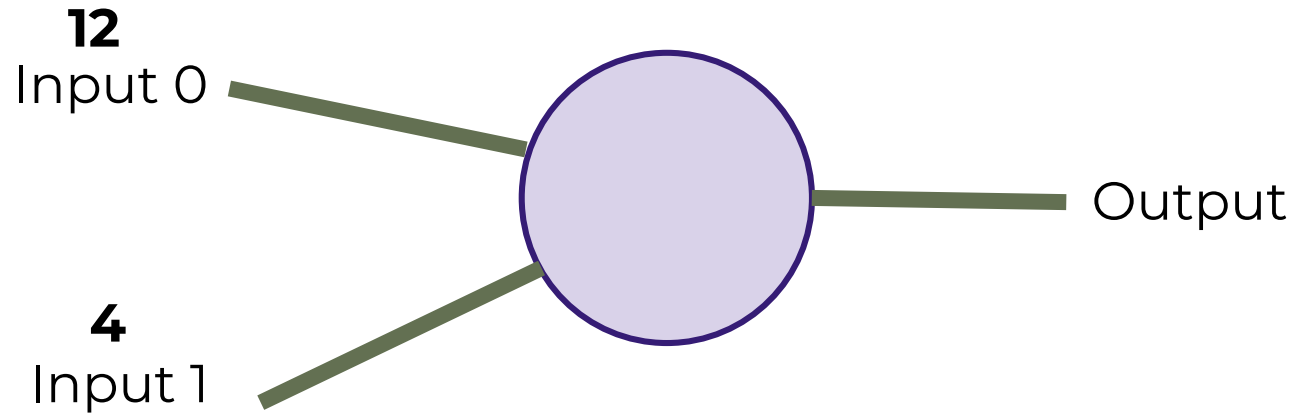
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- We have two inputs and an output



# Deep Learning

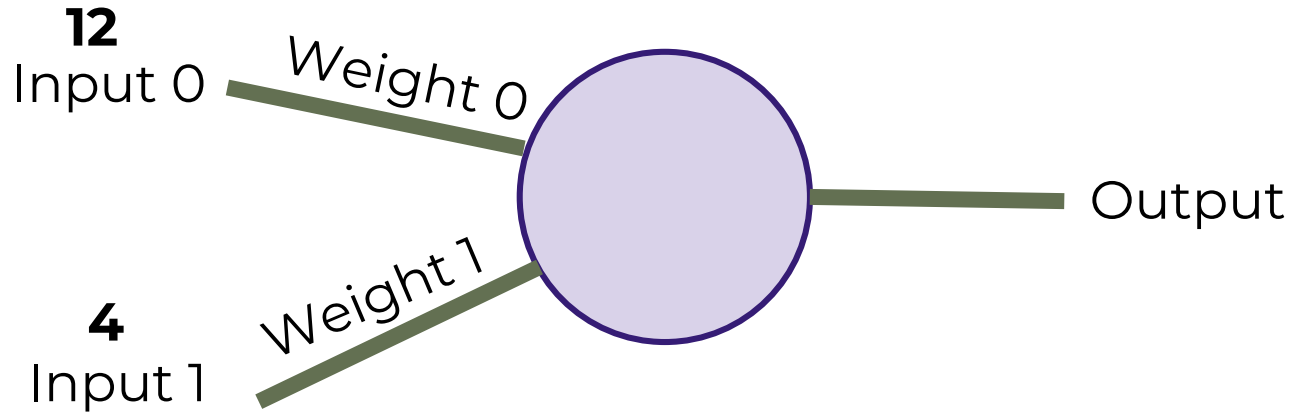
- Inputs will be values of features



# Deep Learning

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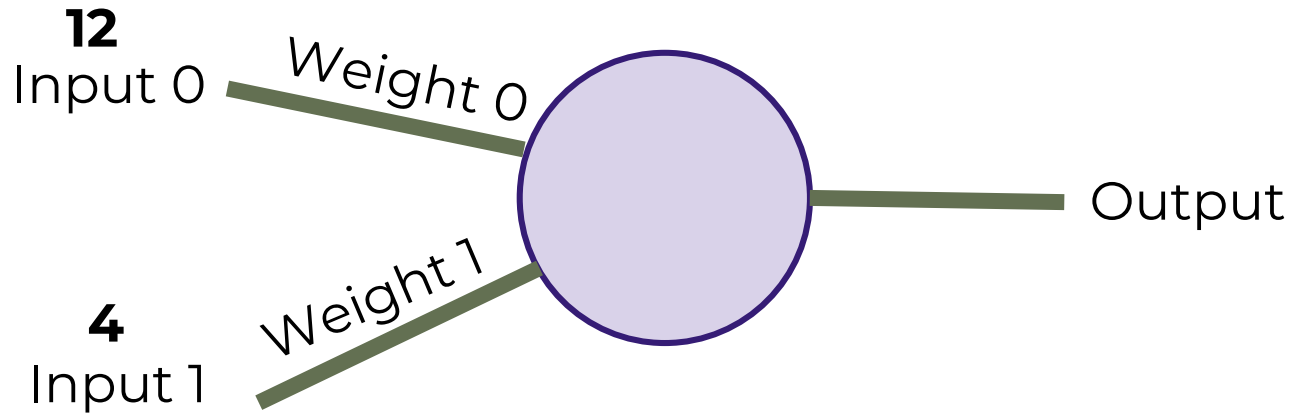
- Inputs are multiplied by a weight



# Deep Learning

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- Weights initially start off as random

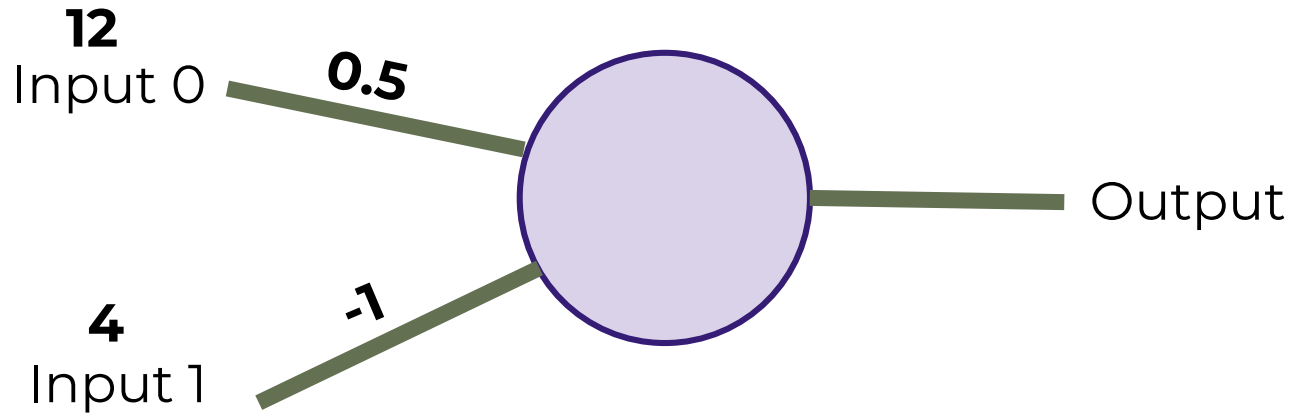




# Deep Learning

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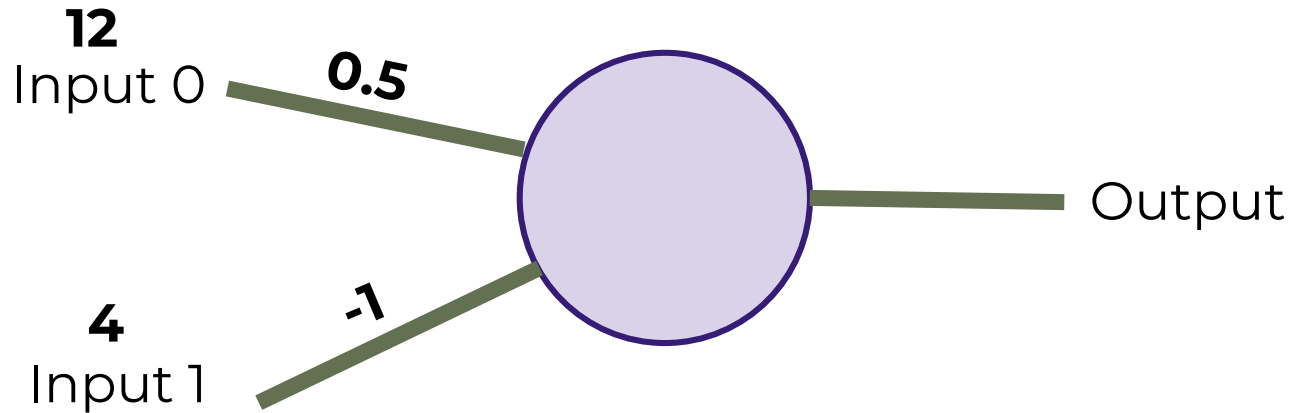
- Weights initially start off as random



# Deep Learning

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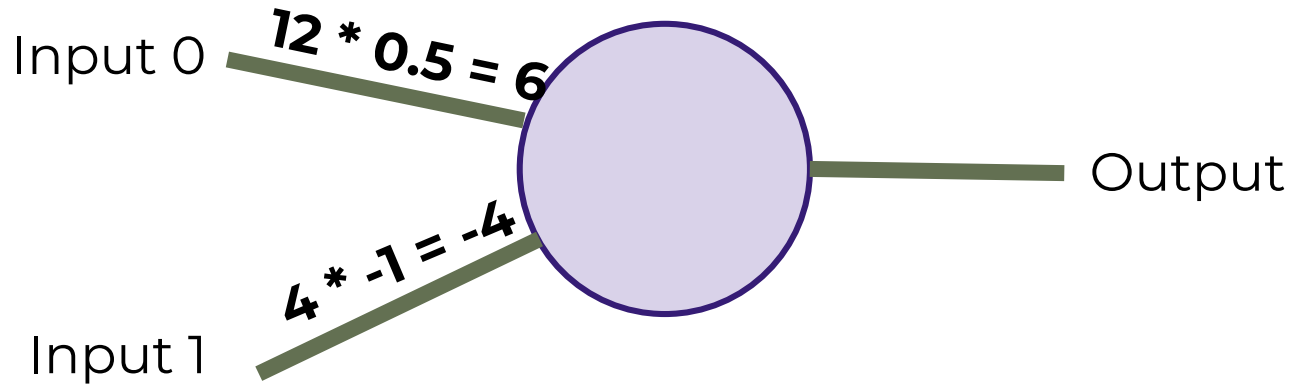
- Inputs are now multiplied by weights



# Deep Learning

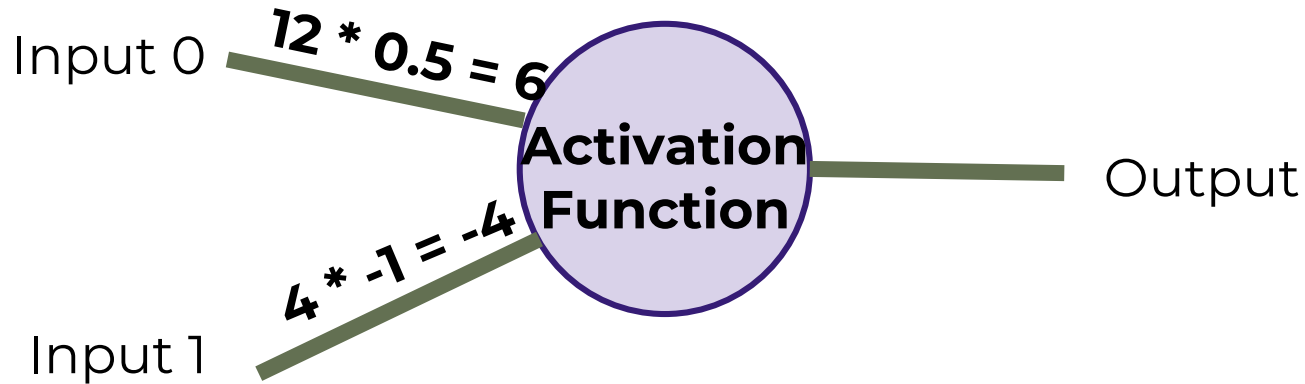
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- Inputs are now multiplied by weights



# Deep Learning

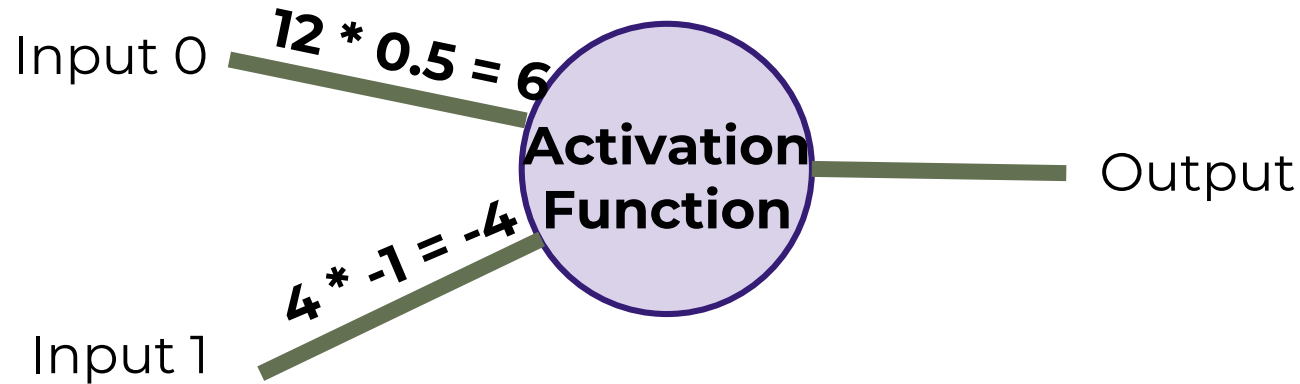
- Then these results are passed to an activation function.



# Deep Learning

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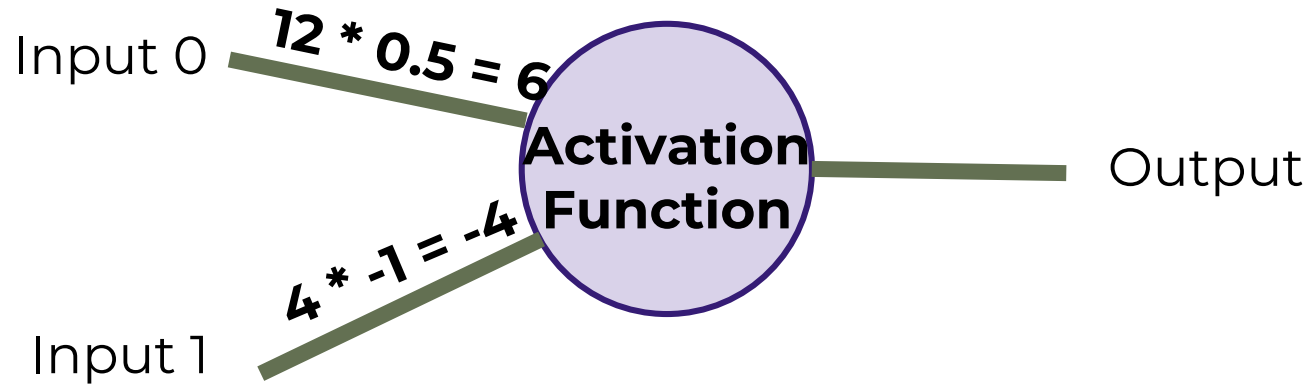
- Different activation functions to choose from



# Deep Learning

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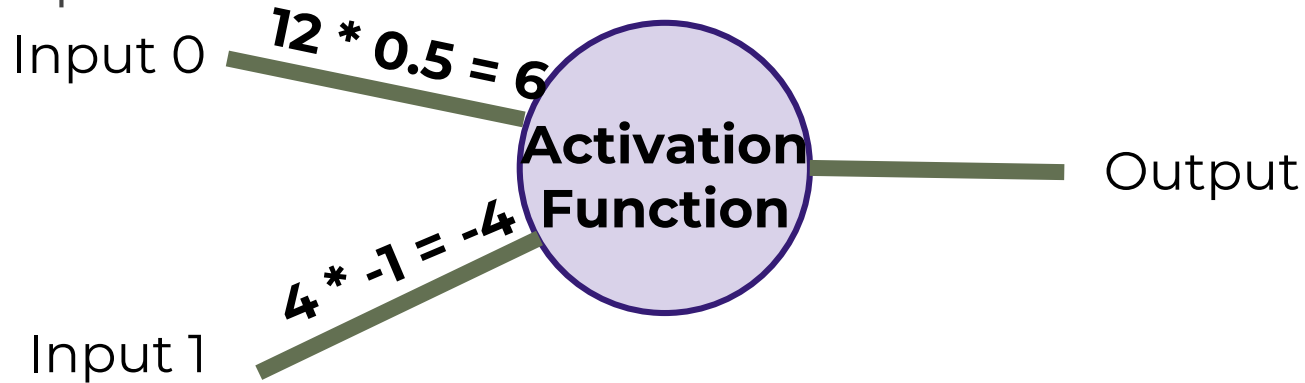
- our activation function will be very simple...



# Deep Learning

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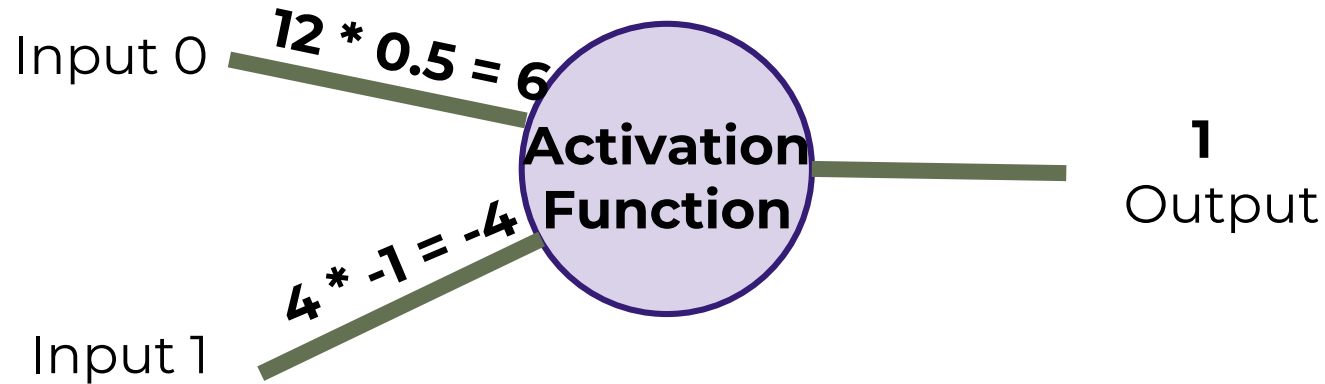
- If sum of inputs is positive return 1, if sum is negative output 0.



# Deep Learning

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- In our case  $6 - 4 = 2$  so the activation function returns 1.

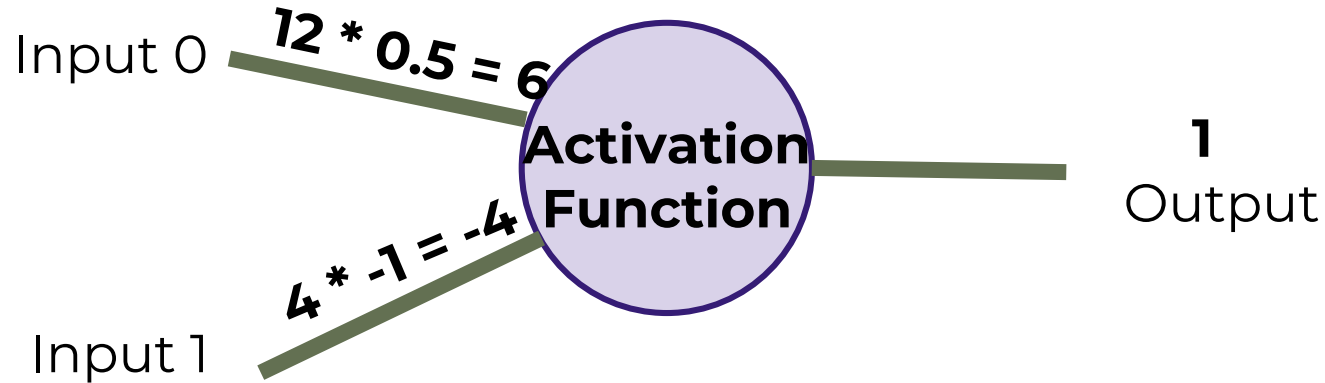




# Deep Learning

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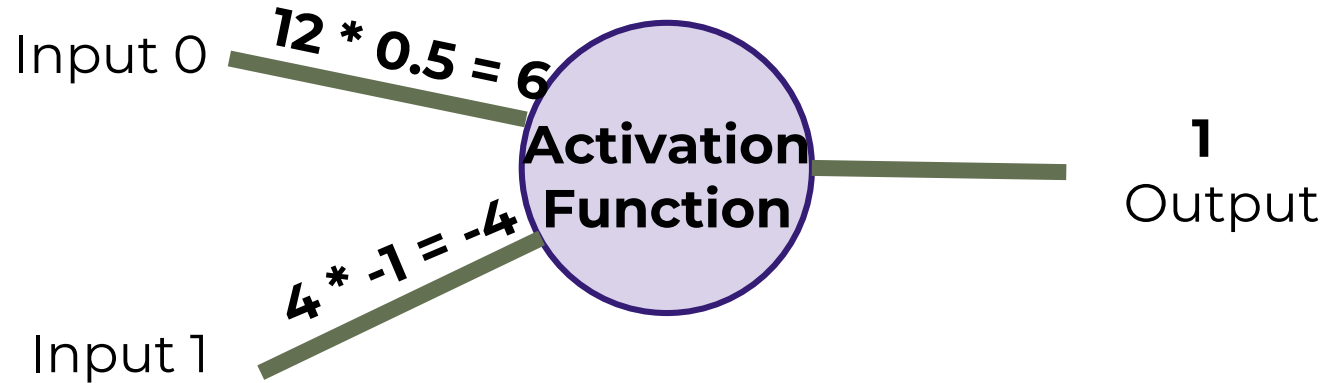
- There is a possible issue. What if the original inputs started off as zero?



# Deep Learning

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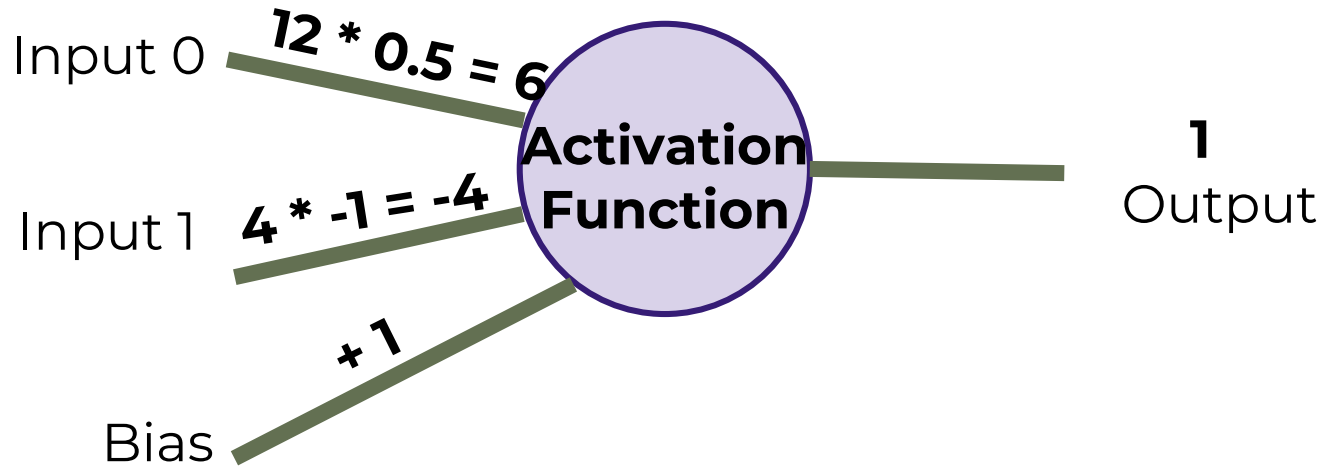
- Then any weight multiplied by the input would still result in zero!



# Deep Learning

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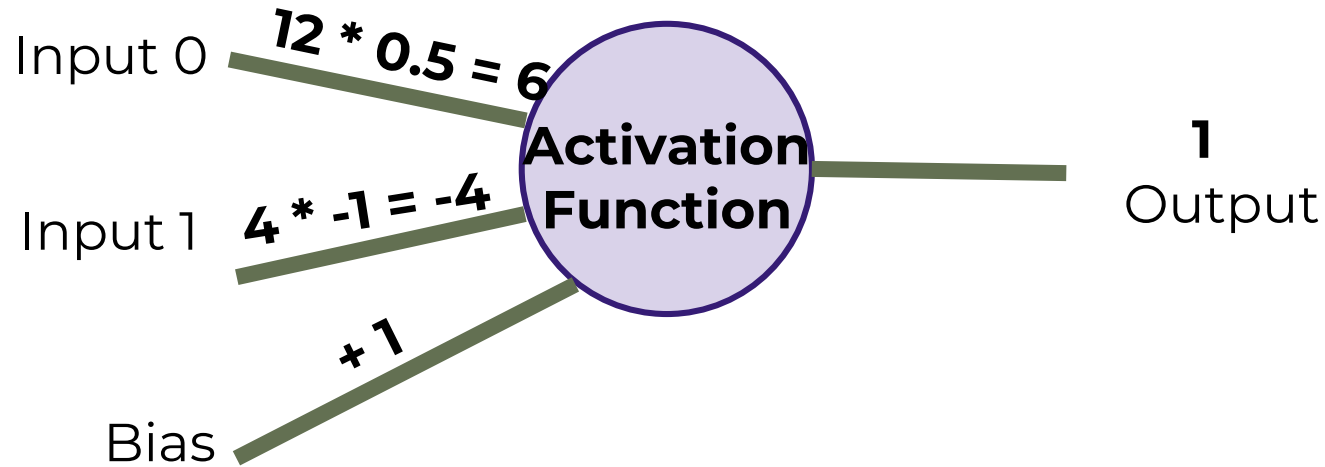
- We fix this by adding in a bias term, in this case we choose 1.



# Deep Learning

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- So what does this look like mathematically?



# Deep Learning

$$\sum_{i=0}^n w_i x_i + b$$

- 
- Let's quickly think about how we can represent this perceptron model mathematically:

# Deep Learning

$$\sum_{i=0}^n w_i x_i + b$$

- 
- Once we have many perceptrons in a network we'll see how we can easily extend this to a matrix form!

# Deep Learning



## Review



Biological Neuron



Perceptron Model



Mathematical Representation

# Introduction to Neural Networks





# Deep Learning

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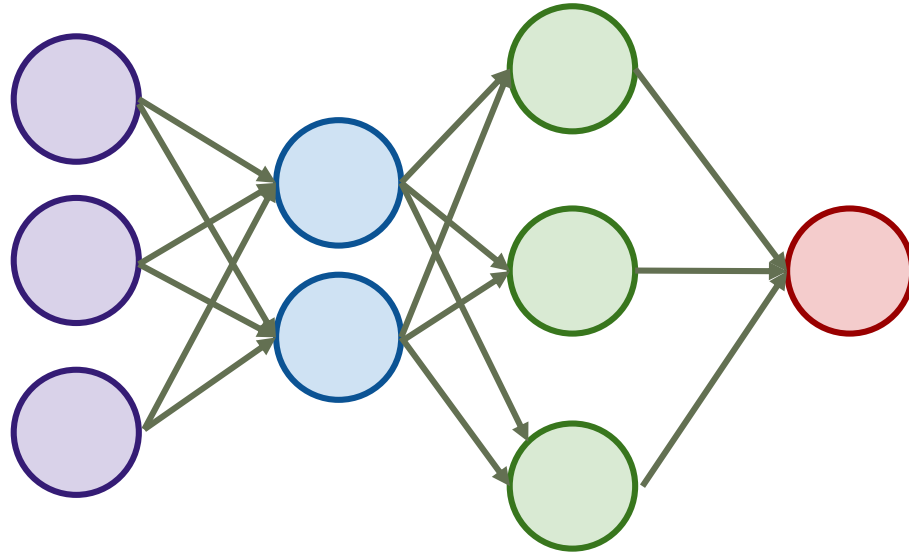
a single perceptron behaves,  
now let's expand this concept  
to the idea of a neural  
network!



how to connect many  
perceptron's together and  
then how to represent this  
mathematically!

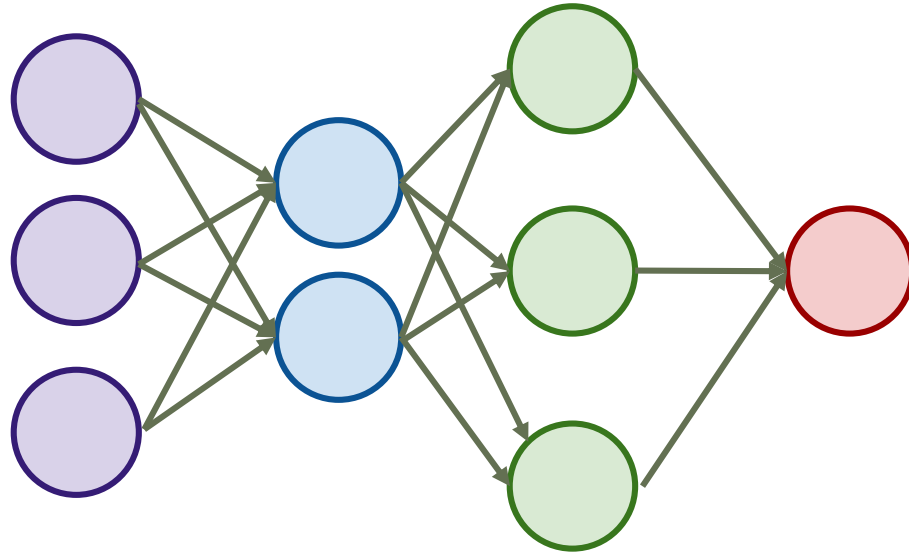
# Deep Learning

- Multiple Perceptrons Network



# Deep Learning

- Input Layer. 2 hidden layers. Output Layer



# Deep Learning

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## Input Layers

Real values from the data



## Hidden Layers

Layers in between input and output

3 or more layers is “deep network”



## Output Layer

Final estimate of the output

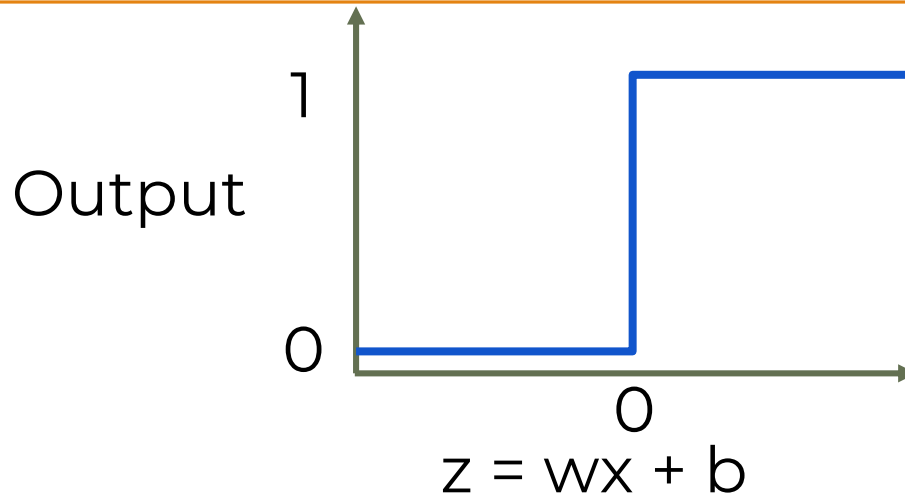
# Deep Learning

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- As we go forwards through more layers, the level of abstraction increases.
  - Let's now discuss the activation function in a little more detail!



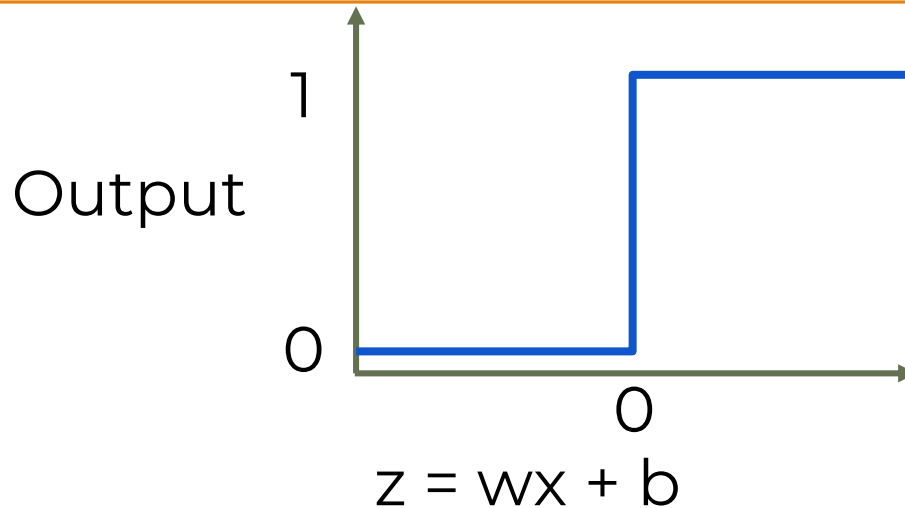
# Deep Learning

- initially your activation function was just a simple function that output 0 or 1.



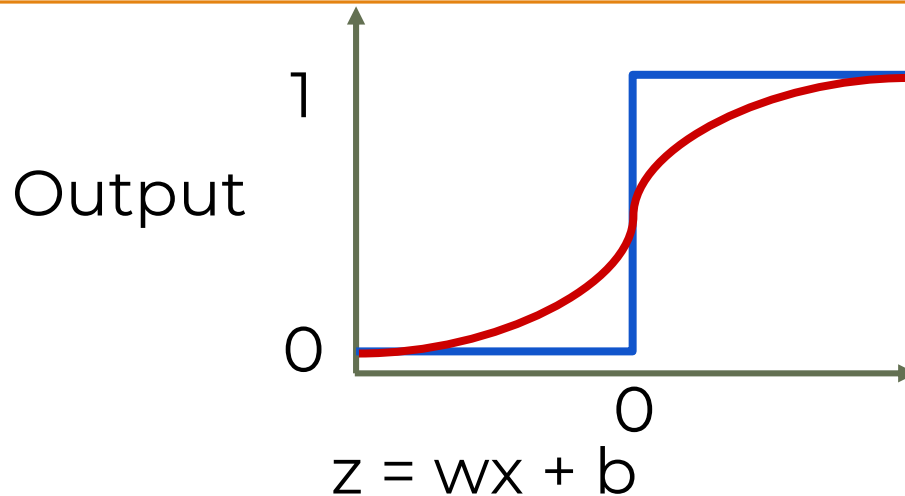
# Deep Learning

- This is a pretty dramatic function, since small changes aren't reflected.



# Deep Learning

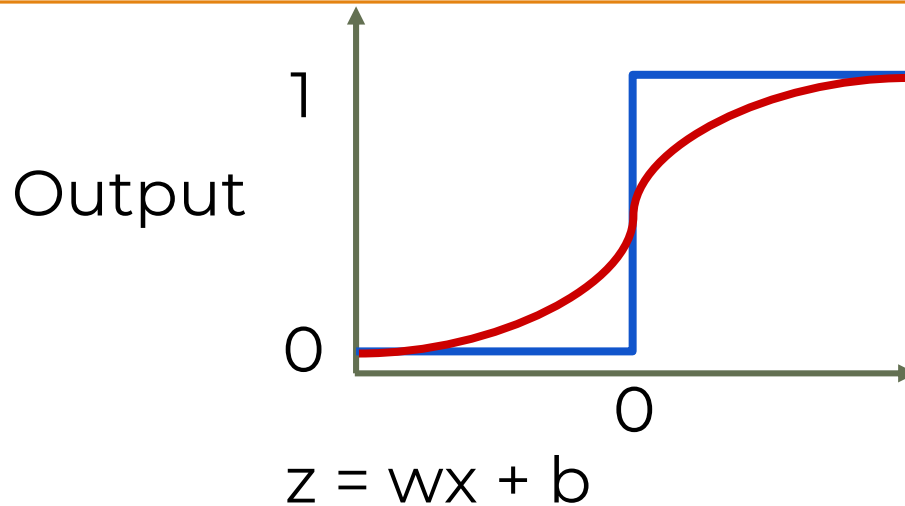
- It would be nice if we could have a more dynamic function, for example the red line!





# Deep Learning

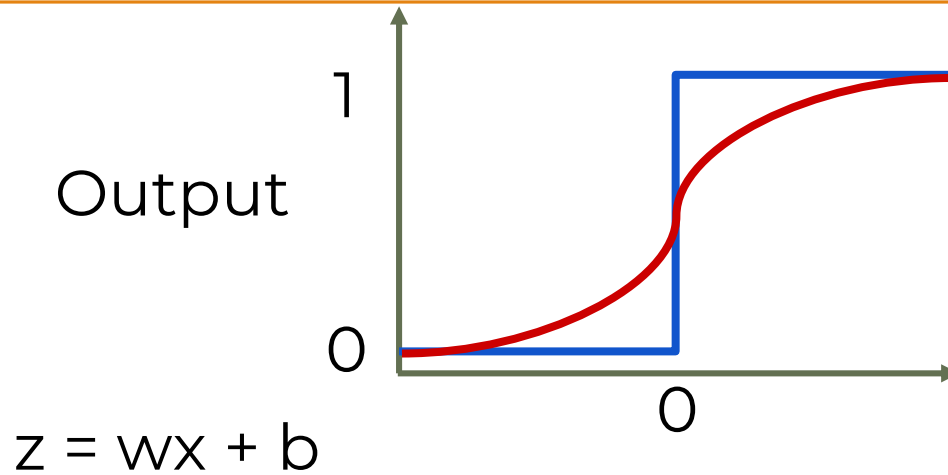
- This is the sigmoid function!



$$f(x) = \frac{1}{1 + e^{-(x)}}$$

# Deep Learning

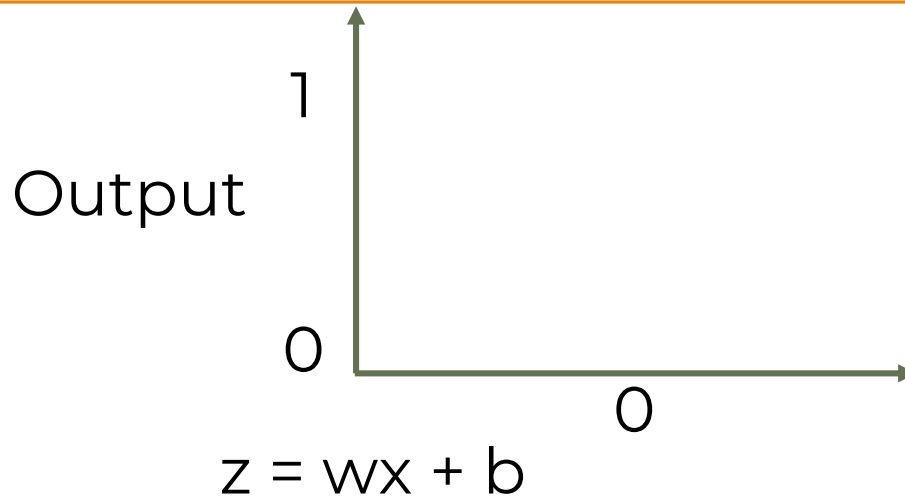
- Changing the activation function used can be beneficial depending on the task!



$$f(x) = \frac{1}{1 + e^{-(x)}}$$

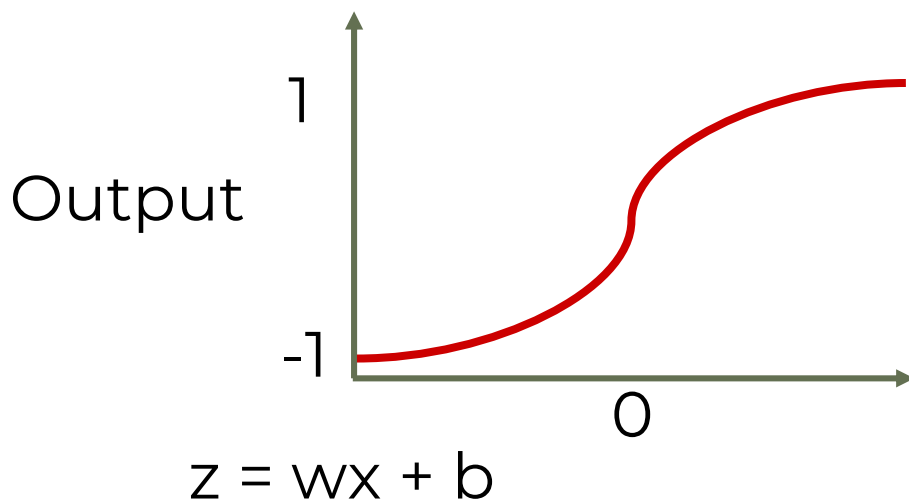
# Deep Learning

- Let's discuss a few more activation functions that we'll encounter!



# Deep Learning

- Hyperbolic Tangent:  $\tanh(z)$



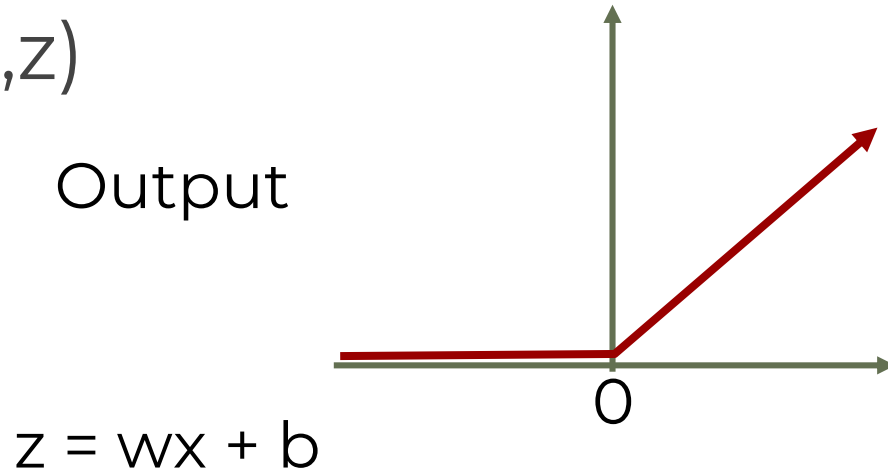
$$\cosh x = \frac{e^x + e^{-x}}{2}$$

$$\sinh x = \frac{e^x - e^{-x}}{2}$$

$$\tanh x = \frac{\sinh x}{\cosh x}$$

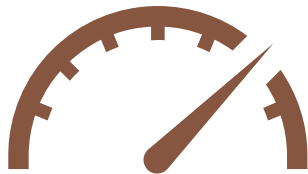
# Deep Learning

- Rectified Linear Unit (ReLU): This is actually a relatively simple function:  $\max(0, z)$



# Deep Learning

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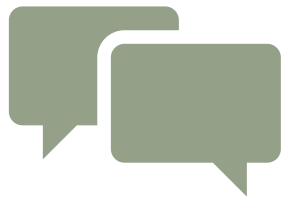
ReLu and tanh tend to have the best performance, so we will focus on these two.



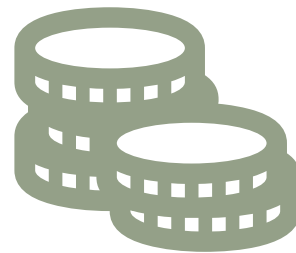
Deep Learning libraries have these built in for us, so we don't need to worry about having to implement them manually!

# Deep Learning

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As we continue on, we'll also talk about some more state of the art activation functions.



Up next, we'll discuss cost functions, which will allow us to measure how well these neurons are performing!

# Cost Functions



# Deep Learning

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Now explore  
how we can  
evaluate  
performance of  
a neuron!

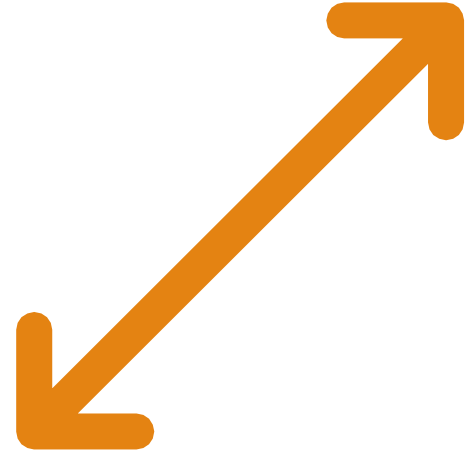


We can use a  
cost function to  
measure how  
far off we are  
from the  
expected value.

# Deep Learning

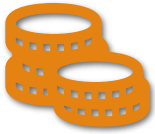
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- We'll use the following variables:
  - $y$  to represent the true value
  - $a$  to represent neuron's prediction
- In terms of weights and bias:
  - $w * x + b = z$
  - Pass  $z$  into activation function  $\sigma(z) = a$



# Deep Learning

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## Quadratic Cost

$$C = \sum (y-a)^2 / n$$



**We can see that larger errors are more prominent due to the squaring.**



**Unfortunately this calculation can cause a slowdown in our learning speed.**

# Deep Learning

Cross Entropy

$$C = (-1/n) \sum (y \cdot \ln(a) + (1-y) \cdot \ln(1-a))$$



This cost function allows for faster learning.



The larger the difference, the faster the neuron can learn.

# Deep Learning

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We now have 2 key aspects of learning with neural networks, the neurons with their activation function and the cost function.



We're still missing a key step, actually "learning"!

# Deep Learning

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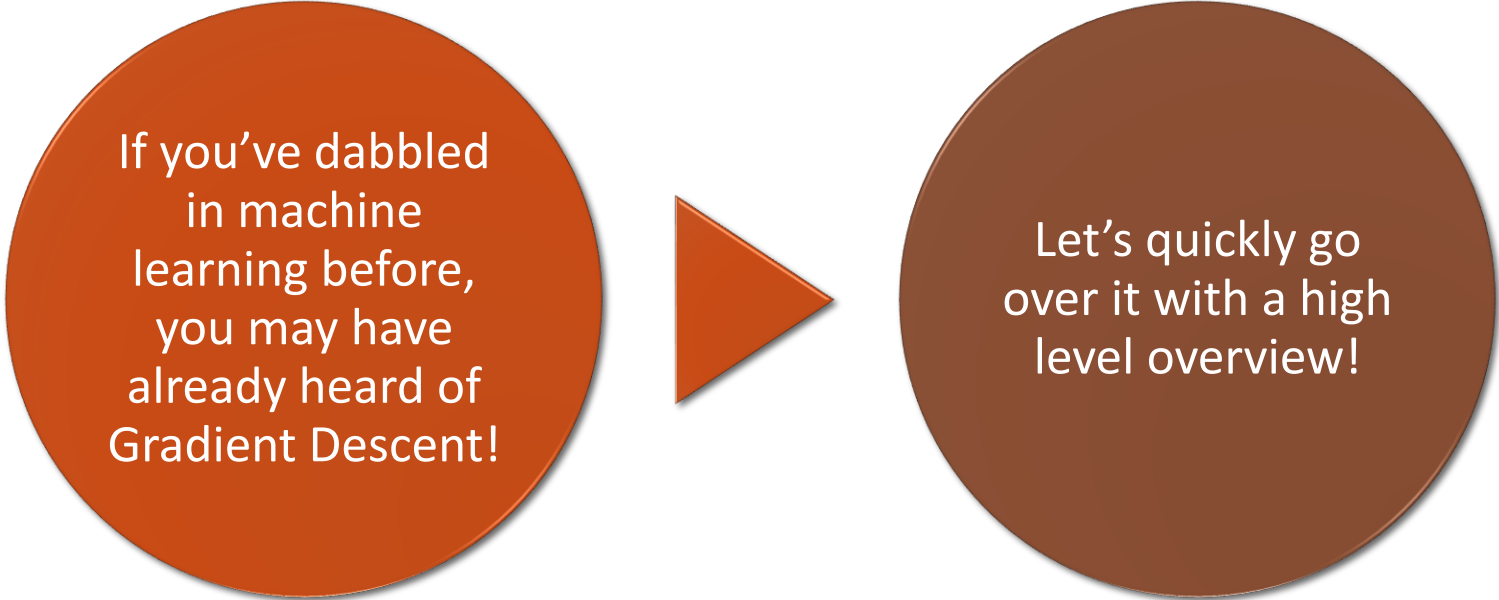
- We need to figure out how we can use our neurons and the measurement of error (our cost function) and then attempt to correct our prediction, in other words, “learn”!



# Gradient Descent and Backpropagation

# Deep Learning

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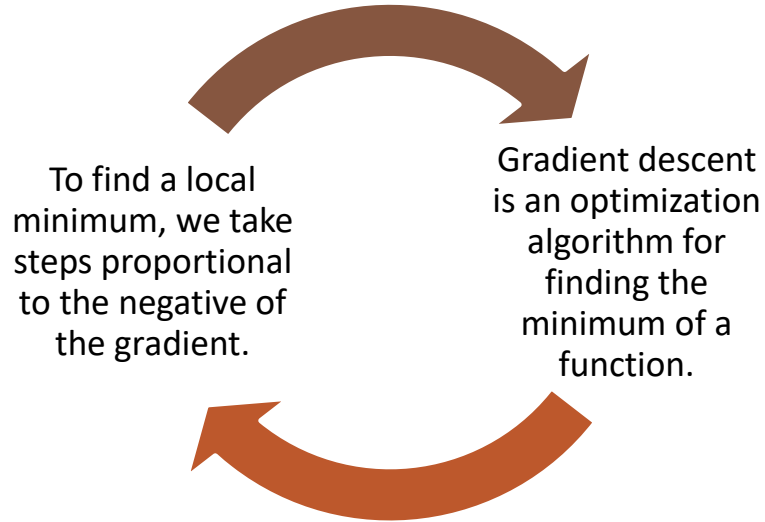
If you've dabbled  
in machine  
learning before,  
you may have  
already heard of  
Gradient Descent!

Let's quickly go  
over it with a high  
level overview!



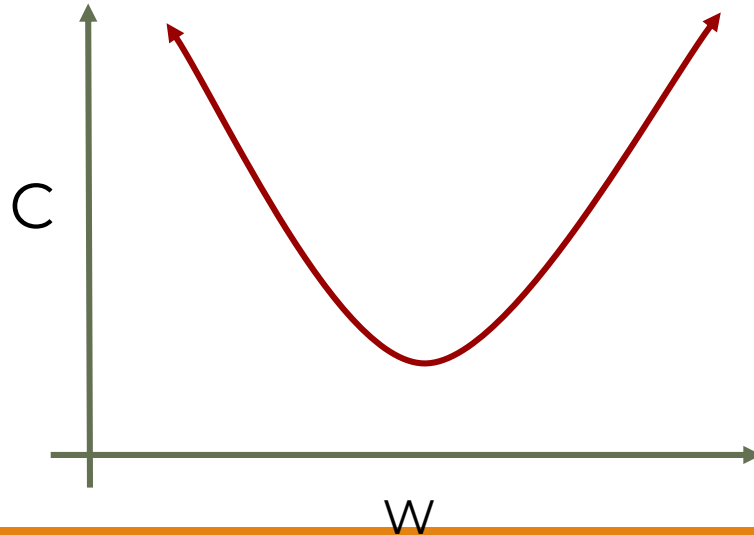
# Deep Learning

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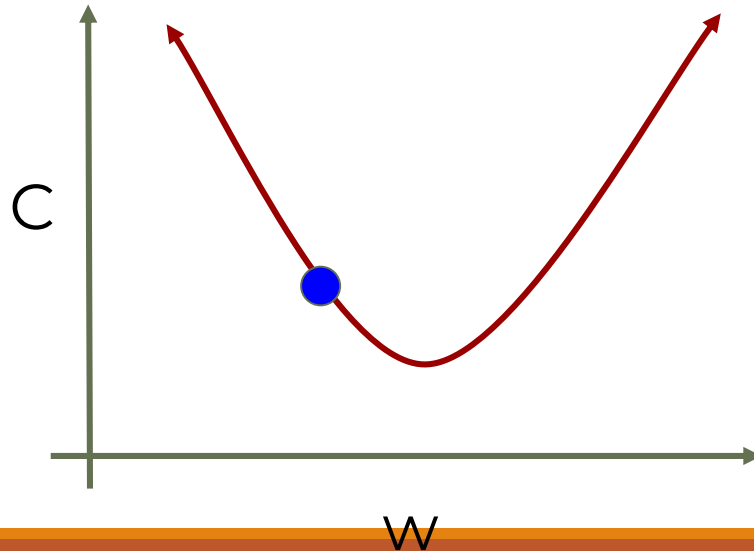
# Deep Learning

- Gradient Descent (in 1 dimension)



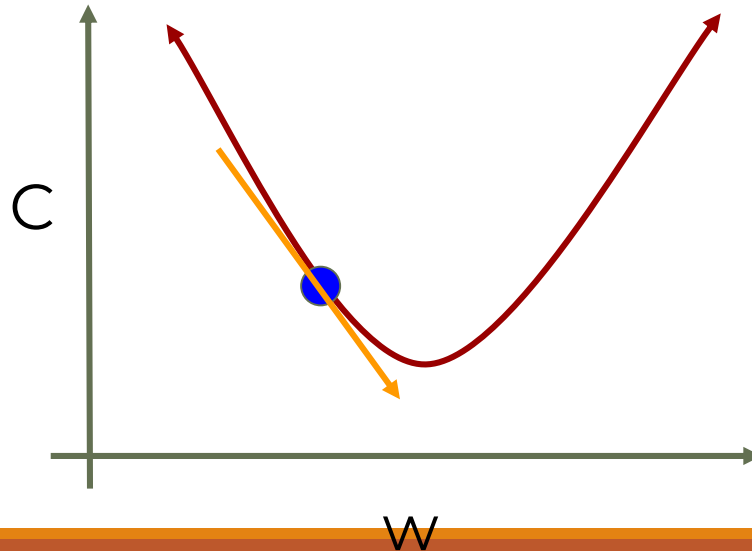
# Deep Learning

- Gradient Descent (in 1 dimension)



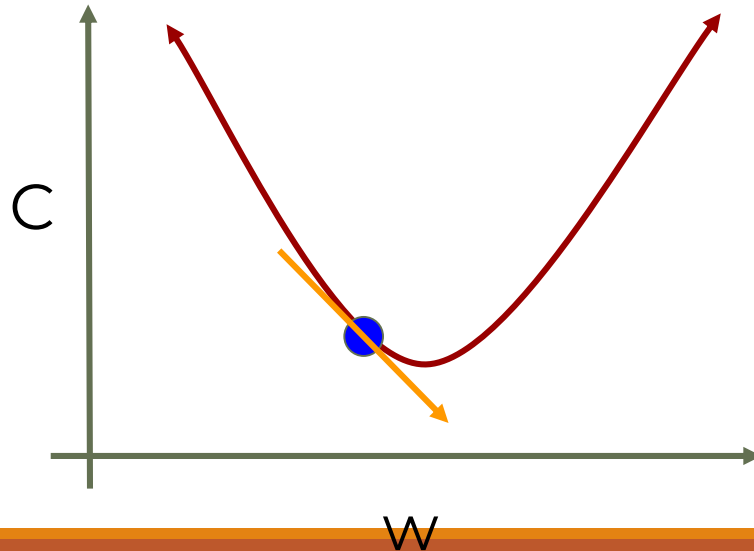
# Deep Learning

- Gradient Descent (in 1 dimension)



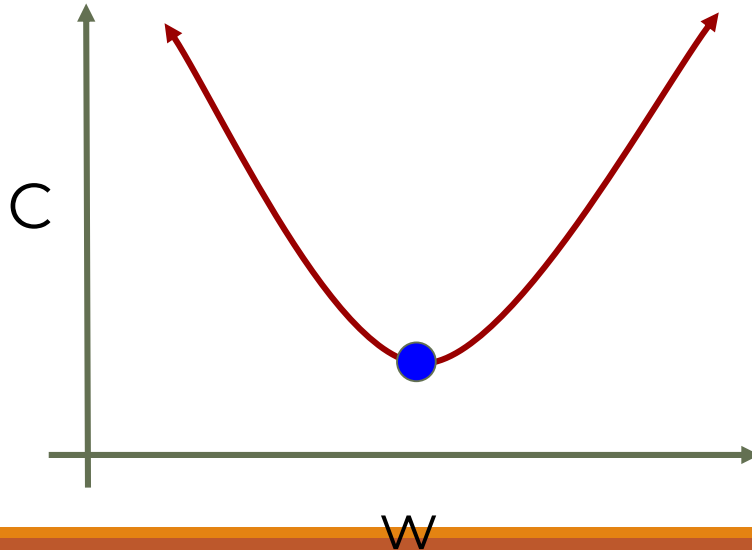
# Deep Learning

- Gradient Descent (in 1 dimension)



# Deep Learning

- Visually we can see what parameter value to choose to minimize our Cost!



# Deep Learning

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- Finding this minimum is simple for 1 dimension, but our cases will have many more parameters, meaning we'll need to use the built-in linear algebra that our Deep Learning library will provide!



# Deep Learning

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- Using gradient descent we can figure out the best parameters for minimizing our cost, for example, finding the best values for the weights of the neuron inputs.





# Deep Learning

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- We now just have one issue to solve, how can we quickly adjust the optimal parameters or weights across our entire network?
- This is where backpropagation comes in!



# Deep Learning

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Backpropagation is used to calculate the error contribution of each neuron after a batch of data is processed.



It relies heavily on the chain rule to go back through the network and calculate these errors.

# Deep Learning

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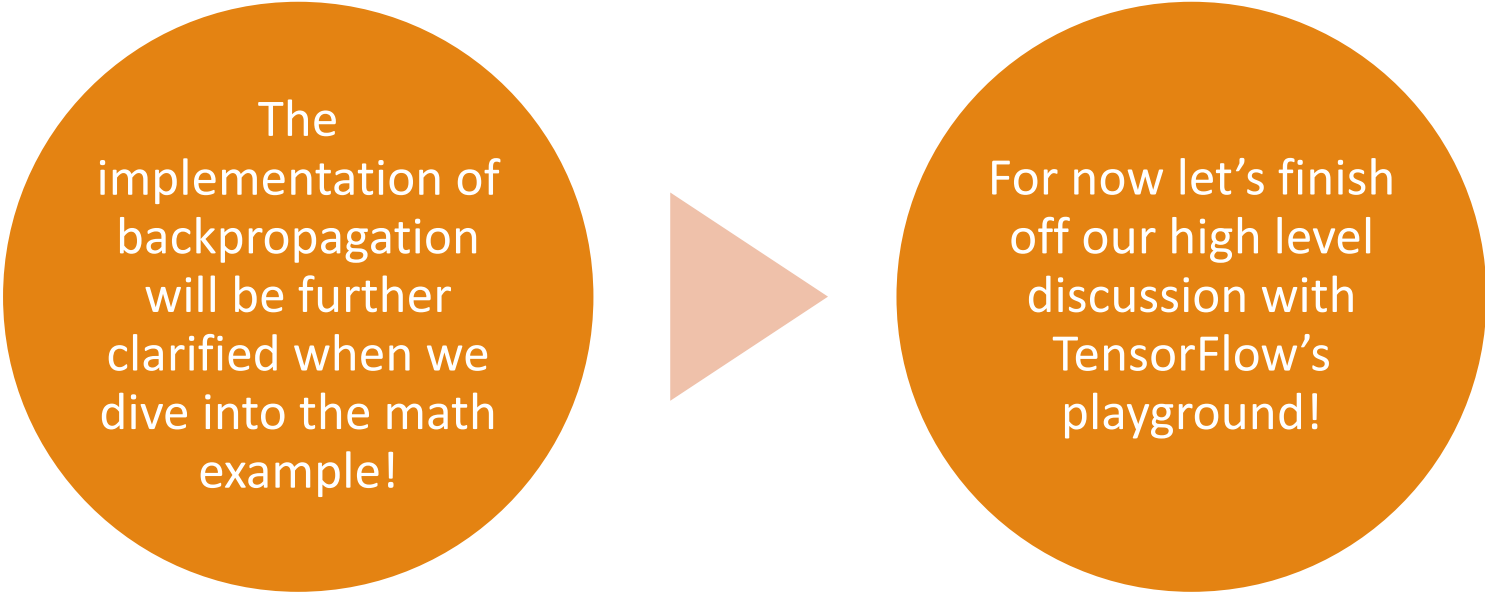
Backpropagation works by calculating the error at the output and then distributes back through the network layers.



It requires a known desired output for each input value (supervised learning).

# Deep Learning

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The  
implementation of  
backpropagation  
will be further  
clarified when we  
dive into the math  
example!

For now let's finish  
off our high level  
discussion with  
TensorFlow's  
playground!