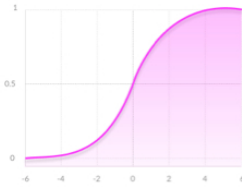


Author: Dr Mike Lakoju

## Sigmoid Function

$$y = \frac{1}{1 + e^{-x}}$$



- \* If X is high, the value is approximately 1
- \* if X is small, the value is approximately 0

## Import Libraries

```
In [2]: import numpy as np
```

## Define the Sigmoid Function

```
In [3]: def sigmoid(sum_func):  
        return 1 / (1 + np.exp(-sum_func))
```

```
In [4]: sigmoid(0)
```

```
Out[4]: 0.5
```

```
In [5]: np.exp(2)
```

```
Out[5]: 7.38905609893065
```

```
In [6]: np.exp(1)
```

```
Out[6]: 2.718281828459045
```

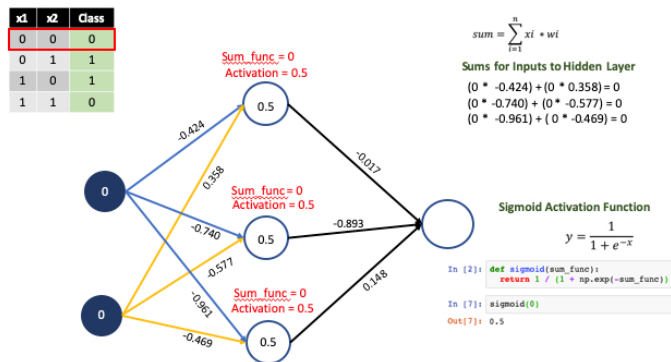
```
In [7]: sigmoid(40)
```

```
Out[7]: 1.0
```

```
In [8]: sigmoid(-20.5)
```

```
Out[8]: 1.2501528648238605e-09
```

## Input Layer to Hidden Layer



## Define "Inputs, outputs and weights" as Numpy arrays

### Inputs

```
In [9]: inputs = np.array([[0,0],  
                           [0,1],  
                           [1,0],  
                           [1,1]])
```

```
In [10]: inputs
```

```
Out[10]: array([[0, 0],  
                [0, 1],  
                [1, 0],  
                [1, 1]])
```

```
In [11]: inputs.shape
```

```
Out[11]: (4, 2)
```

### Outputs

```
In [12]: outputs = np.array([[0],
```

```
[1],  
[1],  
[0]])
```

```
In [13]: outputs.shape
```

```
Out[13]: (4, 1)
```

## Weights

These weights are for the connection between the inputs and the hidden layer

```
In [14]: # First row holds the weights for x1, 2nd row contains the weights for x2
```

```
weights_0 = np.array([[ -0.424, -0.740, -0.961],  
                      [ 0.358, -0.577, -0.469]])  
weights_0.shape
```

```
Out[14]: (2, 3)
```

These weights are for the connection between the hidden layer and the output

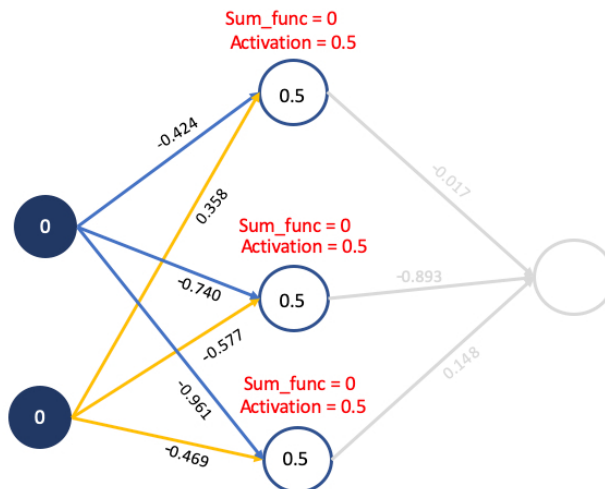
```
In [15]: weights_1 = np.array([[ -0.017],  
                              [-0.893],  
                              [ 0.148]])  
weights_1.shape
```

```
Out[15]: (3, 1)
```

## Epochs & Learning Rate

```
In [16]: epochs = 100  
learning_rate = 0.3
```

```
In [17]: #for epoch in epochs:
```



Dealing with the first side

```
In [18]: input_layer = inputs  
input_layer
```

```
Out[18]: array([[0, 0],  
               [0, 1],  
               [1, 0],  
               [1, 1]])
```

```
In [19]: # "sum_synapse_0" This holds the sum function total of weights for the hidden layer  
# For the Output: Each row holds the sum_func for each input data [0,0,0 -> data 0,0],[0.358, -0.577, -0.469 -> 0,1]  
# The dot product does the matrix multiplication and also the sum
```

```
sum_synapse_0 = np.dot(input_layer, weights_0)  
sum_synapse_0
```

```
Out[19]: array([[ 0. ,  0. ,  0. ],  
               [ 0.358, -0.577, -0.469],  
               [-0.424, -0.74 , -0.961],  
               [-0.066, -1.317, -1.43 ]])
```

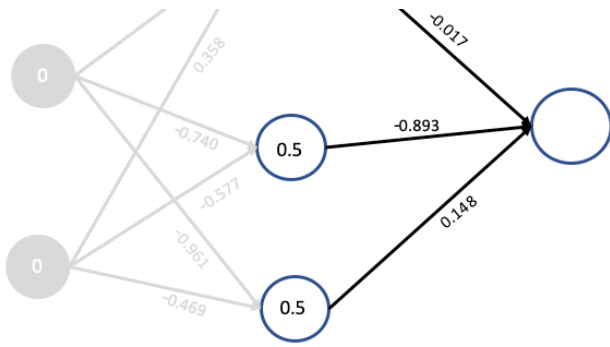
```
In [20]: # Computing the Sigmoid function for the Hidden layer
```

```
hidden_layer = sigmoid(sum_synapse_0)  
hidden_layer
```

```
Out[20]: array([[0.5 , 0.5 , 0.5 ],  
               [0.5885562, 0.35962319, 0.38485296],  
               [0.39555998, 0.32300414, 0.27667802],  
               [0.48350599, 0.21131785, 0.19309868]])
```

Dealing with the 2nd side





In [21]: weights\_1

Out[21]: array([[ -0.017],  
[ -0.893],  
[ 0.148]])

In [22]: # "sum\_synapse\_1" This holds the sum function total of weights for the output layer  
# For the Output: Each row holds the sum\_func for each input data

```
sum_synapse_1 = np.dot(hidden_layer, weights_1)
sum_synapse_1
```

Out[22]: array([[ -0.381 ],  
[ -0.27419072],  
[ -0.25421887],  
[ -0.16834784]])

In [23]: output\_layer = sigmoid(sum\_synapse\_1)  
output\_layer

Out[23]: array([[0.40588573],  
[0.43187857],  
[0.43678536],  
[0.45801216]])

## XOR Operator – Error (Loss Function)

Error = correct (class) - prediction

x1	x2	Class	Prediction	Error
0	0	0	0.405	-0.405
0	1	1	0.431	0.569
1	0	1	0.436	0.564
1	1	0	0.458	-0.458

Average Error = abs(error) = 0.499

In [24]: outputs

Out[24]: array([[0],  
[1],  
[1],  
[0]])

In [25]: output\_layer

Out[25]: array([[0.40588573],  
[0.43187857],  
[0.43678536],  
[0.45801216]])

In [26]: error\_output\_layer = outputs - output\_layer  
error\_output\_layer

Out[26]: array([[ -0.40588573],  
[ 0.56812143],  
[ 0.56321464],  
[ -0.45801216]])

In [27]: average\_error = np.mean(abs(error\_output\_layer))  
average\_error

Out[27]: 0.49880848923713045

Sigmoid Derivative

$$y = \frac{1}{1 + e^{-x}}$$



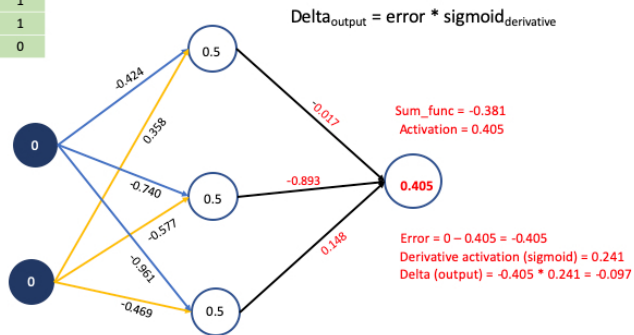
$$d = y * (1 - y)$$

```
In [28]: def sigmoid_derivative(sigmoid):
         return sigmoid * (1 - sigmoid)
```

## Delta output Calculation

x1	x2	Class
0	0	0
0	1	1
1	0	1
1	1	0

### Output Layer - Delta



```
In [29]: # output_layer holds the results of our application of the sigmoid, computed above
         output_layer
```

```
Out[29]: array([[0.40588573],
               [0.43187857],
               [0.43678536],
               [0.45801216]])
```

```
In [30]: # derivative_output is our Derivative of the activation function (sigmoid) which we have on the slide
         # each row is for each instance of our input dataset
         derivative_output = sigmoid_derivative(output_layer)
         derivative_output
```

```
Out[30]: array([[0.2411425 ],
               [0.24535947],
               [0.24600391],
               [0.24823702]])
```

```
In [31]: error_output_layer
```

```
Out[31]: array([[ -0.40588573],
               [ 0.56812143],
               [ 0.56321464],
               [-0.45801216]])
```

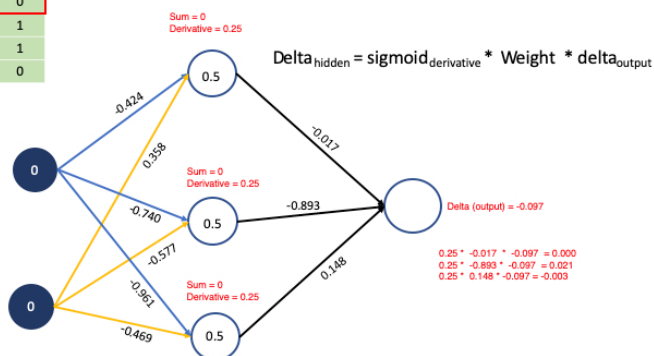
```
In [32]: # Delta output
         # each row is for each instance of our input dataset
         delta_output = error_output_layer * derivative_output
         delta_output
```

```
Out[32]: array([[ -0.0978763 ],
               [ 0.13939397],
               [ 0.138553 ],
               [-0.11369557]])
```

## Delta calculations for the Hidden Layer

x1	x2	Class
0	0	0
0	1	1
1	0	1
1	1	0

### Hidden Layer - Delta



```
In [33]: delta_output
```

```
Out[33]: array([[ -0.0978763 ],
               [ 0.13939397],
               [ 0.138553 ],
               [-0.11369557]])
```

```
[-0.11369557]])
```

```
In [34]: weights_1
```

```
Out[34]: array([[ -0.017],
               [-0.893],
               [ 0.148]])
```

NOTE THAT:

- \* Lets deal with this part first (Weight \* delta\_output)
- \* Notice that we will get an error below because of the shape of the weights\_1 (Transpose)

```
In [35]: delta_output_x_weight = delta_output.dot(weights_1)
```

```
ValueError                                Traceback (most recent call last)
<ipython-input-35-50b740e5a31c> in <module>
----> 1 delta_output_x_weight = delta_output.dot(weights_1)

ValueError: shapes (4,1) and (3,1) not aligned: 1 (dim 1) != 3 (dim 0)
```

```
In [36]: weights_1.shape
```

```
Out[36]: (3, 1)
```

```
In [37]: weights_1T = weights_1.T
         weights_1T
```

```
Out[37]: array([[ -0.017, -0.893,  0.148]])
```

```
In [38]: weights_1T.shape
```

```
Out[38]: (1, 3)
```

Each one of the weights will have to be multiplied by each delta\_output for each data instance

```
array([[ -0.017],
       [-0.893],
       [ 0.148]])
```

```
In [39]: delta_output_x_weight = delta_output.dot(weights_1T)
         delta_output_x_weight
```

```
Out[39]: array([[ 0.0016639,  0.08740354, -0.01448569],
               [-0.0023697, -0.12447882,  0.02063031],
               [-0.0023554, -0.12372783,  0.02050584],
               [ 0.00193282,  0.10153015, -0.01682694]])
```

NOTE THAT:

- \* Now we need to deal with the last part of the equation
- \* sigmoid\_derivative \* delta\_output\_x\_weight

```
In [40]: hidden_layer
```

```
Out[40]: array([[0.5, 0.5, 0.5],
               [0.5885562, 0.35962319, 0.38485296],
               [0.39555998, 0.32300414, 0.27667802],
               [0.48350599, 0.21131785, 0.19309868]])
```

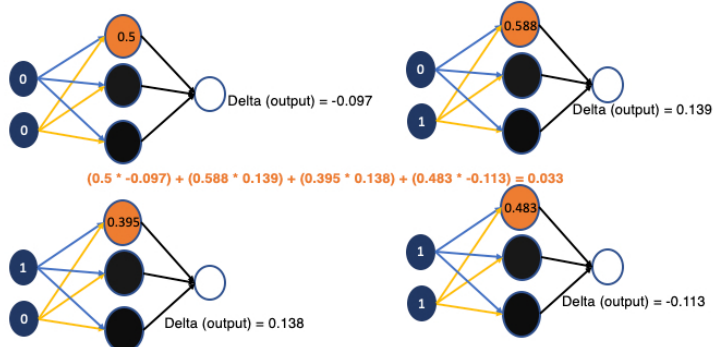
```
In [41]: # Each row in the output of delta_hidden_layer is for the data input values
```

```
delta_hidden_layer = delta_output_x_weight * sigmoid_derivative(hidden_layer)
delta_hidden_layer
```

```
Out[41]: array([[ 0.00041597,  0.02185088, -0.00362142],
               [-0.00057384, -0.02866677,  0.00488404],
               [-0.00056316, -0.02705587,  0.00410378],
               [ 0.00048268,  0.01692128, -0.00262183]])
```

## Weight Update – Output Layer To Hidden Layer

$$\text{Weight}_{n+1} = \text{weight}_n + (\text{input} * \text{delta} * \text{learning\_rate})$$



We will deal with the (input \* delta) first

- The first column in "hidden\_layer" holds the activation value for the first neuron

```
In [42]: hidden_layer
```

```
Out[42]: array([[0.5, 0.5, 0.5],
               [0.5885562, 0.35962319, 0.38485296],
               [0.39555998, 0.32300414, 0.27667802],
               [0.48350599, 0.21131785, 0.19309868]])
```

```
[0.39555998, 0.32300414, 0.27667802],
[0.48350599, 0.21131785, 0.19309868]]]
```

```
In [43]: delta_output
```

```
Out[43]: array([[ -0.0978763 ],
 [  0.13939397 ],
 [  0.138553   ],
 [ -0.11369557 ]])
```

- We need to multiply the "inputs" by "delta" however, for the matrix multiplication we need to transpose the values in the hidden\_layer, so we have all of them on one row for each neuron

```
In [44]: hidden_layerT = hidden_layer.T
hidden_layerT
```

```
Out[44]: array([[0.5      ,  0.5885562 ,  0.39555998,  0.48350599],
 [0.5      ,  0.35962319,  0.32300414,  0.21131785],
 [0.5      ,  0.38485296,  0.27667802,  0.19309868]])
```

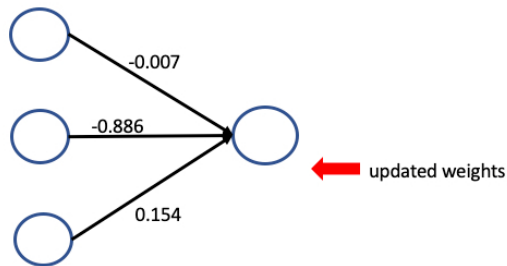
```
In [45]: input_x_delta1 = hidden_layerT.dot(delta_output)
input_x_delta1
```

```
Out[45]: array([[0.03293657],
 [0.02191844],
 [0.02108814]])
```

Let us now update the "weights\_1"

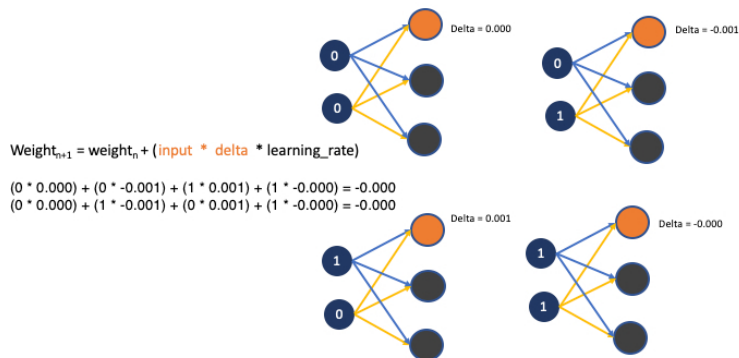
```
In [48]: weights_1 = weights_1 + (input_x_delta1 * learning_rate)
weights_1
```

```
Out[48]: array([[ -0.00711903],
 [-0.88642447],
 [  0.15432644]])
```



## Dealing with the Hidden Layer to Input Layer

### Weight Update – Hidden Layer to Input Layer



```
In [54]: # First column is X1, and 2nd column is X2 (our input values )
```

```
input_layer
```

```
Out[54]: array([[0, 0],
 [0, 1],
 [1, 0],
 [1, 1]])
```

```
In [50]: delta_hidden_layer
```

```
Out[50]: array([[ 0.00041597,  0.02185088, -0.00362142],
 [-0.00057384, -0.02866677,  0.00488404],
 [-0.00056316, -0.02705587,  0.00410378],
 [ 0.00048268,  0.01692128, -0.00262183]])
```

```
In [51]: # we need to transpose the values just as we did before
```

```
input_layerT = input_layer.T
input_layerT
```

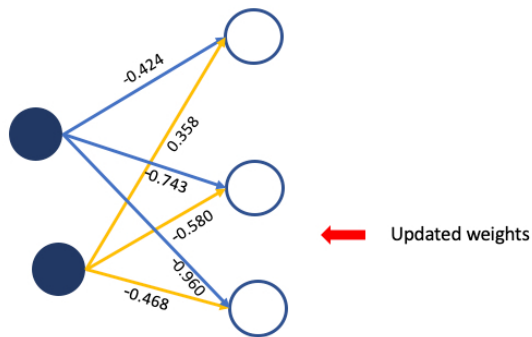
```
Out[51]: array([[0, 0, 1, 1],
 [0, 1, 0, 1]])
```

```
In [52]: input_x_delta0 = input_layerT.dot(delta_hidden_layer)
input_x_delta0
```

```
Out[52]: array([[ -8.04778516e-05, -1.01345901e-02,  1.48194623e-03],
               [-9.11603819e-05, -1.17454886e-02,  2.26221011e-03]])
```

```
In [53]: weights_0 = weights_0 + (input_x_delta0 * learning_rate)
weights_0
```

```
Out[53]: array([[ -0.42402414, -0.74304038, -0.96055542],
               [ 0.35797265, -0.58052365, -0.46832134]])
```



So all the lines of code above, has allowed us to complete our first epoch. we will need to put all the code together so we can run multiple epochs

## Complete Artificial Neural Network

```
In [55]: #Importing Numpy
import numpy as np

# This is the sigmoid Function
def sigmoid(sum):
    return 1 / (1 + np.exp(-sum))

#This is the sigmoid derivative as used before
def sigmoid_derivative(sigmoid):
    return sigmoid * (1 - sigmoid)

# Our input values
inputs = np.array([[0,0],
                   [0,1],
                   [1,0],
                   [1,1]])

#Our output values
outputs = np.array([[0],
                    [1],
                    [1],
                    [0]])
```

```
In [89]: # weights_0 = np.array([[ -0.424, -0.740, -0.961],
#                               [0.358, -0.577, -0.469]])

# weights_1 = np.array([[ -0.017,
#                          [-0.893],
#                          [0.148]])
```

### Initializing our weights with random values

- **Note:** Multiplying the random number by 2 and subtracting by 1, allows us to have a mix of both positive and negative random numbers for the weights

```
In [90]: weights_0 = 2 * np.random.random((2, 3)) - 1
weights_1 = 2 * np.random.random((3, 1)) - 1
```

```
In [91]: epochs = 400000
learning_rate = 0.6
error = []

for epoch in range(epochs):
    input_layer = inputs
    sum_synapse0 = np.dot(input_layer, weights_0)
    hidden_layer = sigmoid(sum_synapse0)

    sum_synapse1 = np.dot(hidden_layer, weights_1)
    output_layer = sigmoid(sum_synapse1)

    error_output_layer = outputs - output_layer
    average = np.mean(abs(error_output_layer))
    #print after every specified range of the value
    if epoch % 100000 == 0:
        print('Epoch: ' + str(epoch + 1) + ' Error: ' + str(average))
        error.append(average)

    derivative_output = sigmoid_derivative(output_layer)
    delta_output = error_output_layer * derivative_output

    weights1T = weights1.T
    delta_output_weight = delta_output.dot(weights1T)
    delta_hidden_layer = delta_output_weight * sigmoid_derivative(hidden_layer)

    hidden_layerT = hidden_layer.T
    input_x_delta1 = hidden_layerT.dot(delta_output)
    weights_1 = weights_1 + (input_x_delta1 * learning_rate)

    input_layerT = input_layer.T
    input_x_delta0 = input_layerT.dot(delta_hidden_layer)
    weights_0 = weights_0 + (input_x_delta0 * learning_rate)
```

```
Epoch: 1 Error: 0.4999269690201742
Epoch: 100001 Error: 0.015563199459768319
Epoch: 200001 Error: 0.010326071808337757
Epoch: 300001 Error: 0.008192022809586367
```

At this point after runing for 1million epochs you can see the value is very low.

```
In [67]: #1 million epochs with a learning rate of 0.3
1 - 0.009670967930930745
```

```
Out[67]: 0.9903290320690693
```

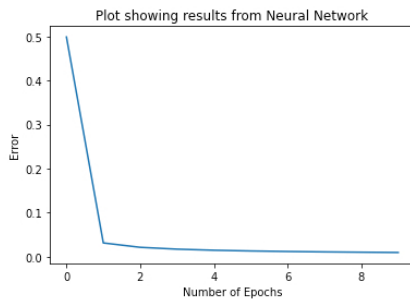
```
In [92]: #after 400,000 epochs, with a learning rate of 0.6
1 - 0.008192022809586367
```

```
Out[92]: 0.9918079771904136
```

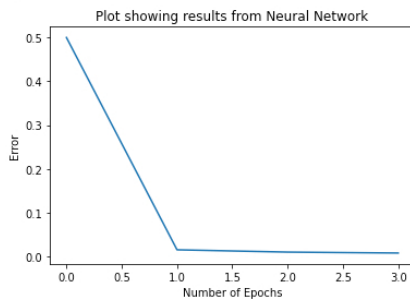
## Let's visualize this result

```
In [68]: import matplotlib.pyplot as plt
```

```
In [70]: plt.xlabel('Number of Epochs')
plt.ylabel('Error')
plt.title('Plot showing results from Neural Network')
plt.plot(error)
plt.show()
```



```
In [93]: plt.xlabel('Number of Epochs')
plt.ylabel('Error')
plt.title('Plot showing results from Neural Network')
plt.plot(error)
plt.show()
```



## Compearing the outputs and the predictions

```
In [74]: outputs
```

```
Out[74]: array([[0],
               [1],
               [1],
               [0]])
```

```
In [75]: output_layer
```

```
Out[75]: array([[0.0105802 ],
               [0.9826343 ],
               [0.98124727],
               [0.02222762]])
```

\* We see that our neural network was able to get values close to the actual values from the results.

\* This shows that our neural network can handle the complexity of the XOR operator dataset.

- Let us see the updated weights. These are the weights we will require if we want to make future predictions

```
In [77]: weights_0
```

```
Out[77]: array([[ -0.04578885, -5.45125419, -1.01868082],
               [ 1.04772434, -5.25578328, -0.5958262 ]])
```

```
In [78]: weights_1
```

```
Out[78]: array([[ -14.93268248],
               [-37.16040415],
               [ 43.01681387]])
```

```
In [94]: # This function accepts an instance of a dataset
```

```
def test_model(dataset):
```



```
def calculate_output(instance):  
    #input to hidden layer  
    hidden_layer = sigmoid(np.dot(instance, weights_0))  
    #hidden to output layer  
    output_layer = sigmoid(np.dot(hidden_layer, weights_1))  
    return output_layer[0]
```

In [95]: round(calculate\_output(np.array([0, 0])))

Out[95]: 0

In [96]: round(calculate\_output(np.array([0, 1])))

Out[96]: 1

In [97]: round(calculate\_output(np.array([1, 0])))

Out[97]: 1

In [98]: round(calculate\_output(np.array([1, 1])))

Out[98]: 0

In [ ]: