Q.1. a) Implement AND gate using Neural network with backpropagation.

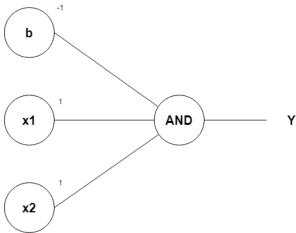
AND gate truth table:

X_1	X ₂	Y
0	0	0
0	1	0
1	0	0
1	1	1

1. Inputs and outputs:

$$X = [[0, 0], [0, 1], [1, 0], [1, 1]]$$
(shape= (4,2))

$$Y = [[0], [0], [0], [1]]$$
(shape= (4,1))



NN representation of AND gate

2. Initialize the weight and bias parameters randomly such that:

$$W = [w_1, w_2] \text{ (shape = (2,1))}$$

 $B = [b] \text{ (shape = (1,1))}$

3. Activation function: Sigmoid function

4. Forward propagation

$$a1 = X \#(4, 2)$$

 $z2 = dot(a1, W) + B \#(4, 1)$
 $a2 = sigmoid(z2) \#(4, 1)$

5. Backward propagation

• Modify sigmoid function for derivative:

```
def sigmoid_der(h):
    return h*(1-h)

Update weights and bias
  error = (Y - a2) #(4, 1)
  delta_output = error * sigmoid_der(a2) # (4, 1)
  update = dot(a1.T, delta_output) #(2, 1)
```

W = W + update #(2,1)

 $B = B + sum(delta _output) #(1,1)$

- 6. Repeat step3 till step 5 for 500 epochs.
- 7. Test it for example inputs

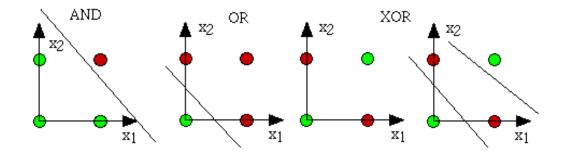
$$X_{t1} = [0,0]$$

$$X_{t2} = [0,1]$$

$$X_{t3} = [1,0]$$

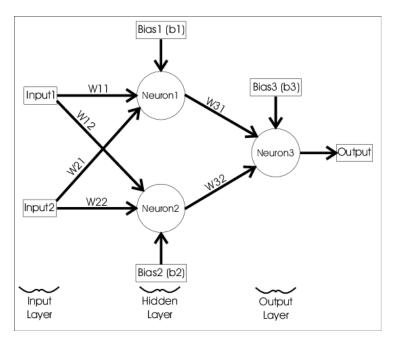
$$X_{t4} = [1,1]$$

- b) Implement OR, NAND and NOR gate in a similar way.
- Q.2. a) Implement XOR gate using Neural network with backpropagation.



XOR gate truth table:

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0



NN representation of XOR gate

1. Inputs and outputs:

$$X = [[0, 0], [0, 1], [1, 0], [1, 1]]$$

$$Y = [[0], [0], [0], [1]]$$

2. Prepare input layer, hidden layer and output layer weights and bias parameters

$$W_h = [[w_{11}, w_{12}], [w_{21}, w_{22}]] \text{ shape} = (2,2)$$

 $B_h = [b_1, b_2] \text{ shape} = (1,2)$
 $W_o = [w_{31}, w_{32}] \text{ shape} = (2,1)$
 $B_o = [b_3] \text{ shape} = (1,1)$

3. Activation function: Sigmoid function

```
def sigmoid(h):
    return 1/(1+exp(-h))
```

4. Forward propagation

$$\begin{aligned} &a1 = X \; \#(4,2) \\ &z2 = dot(a1, W_h) + B_h \; \; \#(4,2) \\ &a2 = sigmoid(z2) \; \#(4,2) \\ &z3 = dot(a2, W_o) + B_o \; \#(4,1) \\ &a3 = sigmoid(z3) \; \#(4,1) \end{aligned}$$

- 5. Backward propagation
 - Modify sigmoid function for derivative:

• Error of output layer error = (Y - a3) #(4,1)

```
delta_output = error * sigmoid_der(a3) #(4,1)
output_update = dot(a2.T, delta_output) #(2,1)
```

• Error of hidden layer

```
error_h = np.dot(output_update, Wo.T) #(4,2)
delta_hidden = error_h * sigmoid_der(a2) #(4,2)
hidden_update = dot(a1.T, delta_hidden) #(2,2)
```

• Update weights and bias of output layer

$$W_o = W_o + \text{output_update #learning ratio } \#(2,1)$$

 $B_o = B_o + \text{node-wise-sum(delta_output) } \#\text{learning ratio } \#(1,1)$

• Update weights and bias of hidden layer

$$W_h = W_h + \text{hidden_update #learning ratio #(2,2)}$$

 $B_h = B_h + \text{node-wise-sum(delta_hidden) #learning ratio #(1,2)}$

- 6. Repeat step3 till step 5 for 500 epochs.
- 7. Test it for example inputs

$$X_{t1} = [0,0]$$

$$X_{t2} = [0,1]$$

$$X_{t3} = [1,0]$$

$$X_{t4} = [1,1]$$

b) Implement XNOR gate using similar neural network model.

X_1	X_2	Y
0	0	1
0	1	0
1	0	0
1	1	1

Outputs expected: Testing with four cases, error vs. epoch plot