SAP ID:

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

COURSE CODE: DJ19DSC501

COURSE NAME: Machine Learning - II **CLASS: AY 2022-23**

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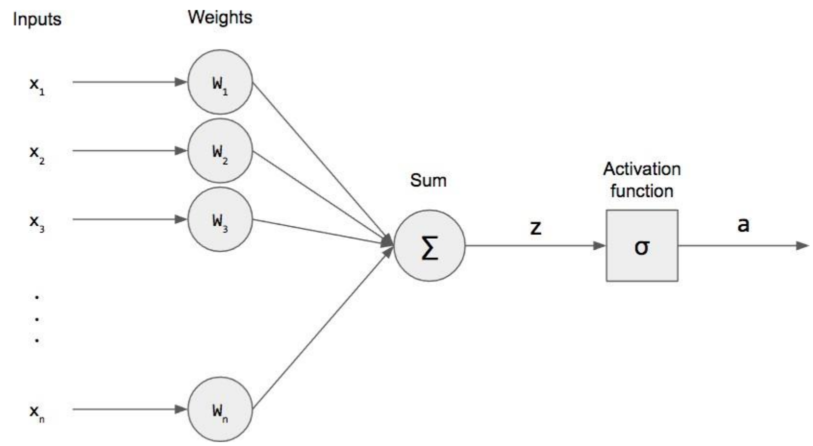
LAB EXPERIMENT NO.1

AIM :

Implement Boolean gates using perceptron – Neural representation of Logic Gates.

THEORY:

Perceptron is a Supervised Learning Algorithm for binary classifiers.



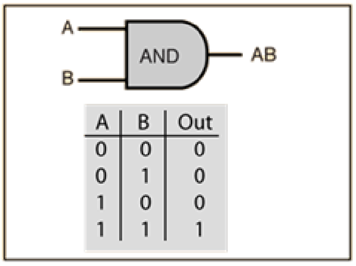
For a particular choice of the weight vector w and bias parameter b, the model predicts output ŷ for the corresponding input vector x.

$$
\begin{aligned}
\hat{y} &= \Theta\left(w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + b\right) \\
&= \Theta(\mathbf{w} \cdot \mathbf{x} + b) \\
\text{where } \Theta(v) &= \begin{cases} 1 & \text{if } v \geqslant 0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

The input values, i.e., x1, x2, and bias is multiplied with their respective weight matrix that is W1, W2, and W0. The corresponding value is then fed to the summation neuron where the summed value is calculated. This is fed to a neuron which has a non-linear function(sigmoid in our case) for scaling the output to a desirable range. The scaled output of sigmoid is 0 if the output is less than 0.5 and 1 if the output is greater than 0.5. The main aim is to find the value of weights or the weight vector which will enable the system to act as a particular gate.

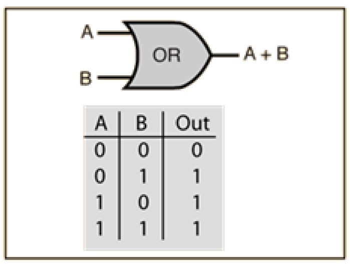
Boolean gates – Logic gates are the basic building blocks of any digital system. It is an electronic circuit having one or more than one input and only one output. The relationship between the input and the output is based on a certain logic.

1) AND



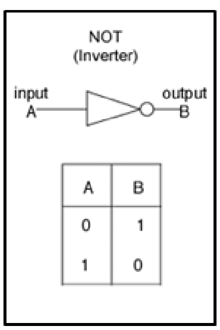
A	B	Out
0	0	0
0	1	0
1	0	0
1	1	1

2) OR



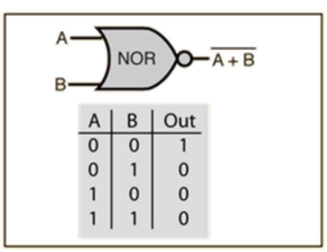
A	B	Out
0	0	0
0	1	1
1	0	1
1	1	1

3) NOT



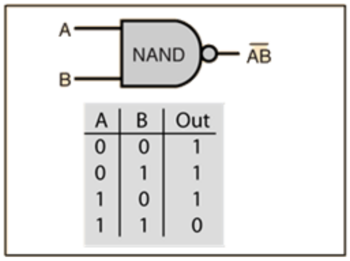
A	B
0	1
1	0

4) NOR



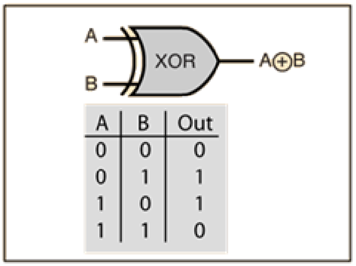
A	B	Out
0	0	1
0	1	0
1	0	0
1	1	0

5) NAND



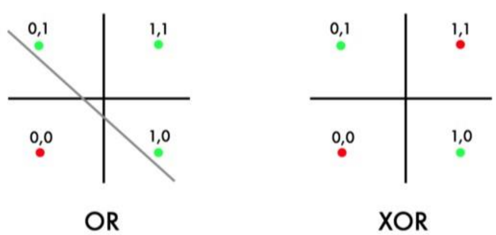
A	B	Out
0	0	1
0	1	1
1	0	1
1	1	0

6) XOR



A	B	Out
0	0	0
0	1	1
1	0	1
1	1	0

For the XOR gate, the output can't be linearly separated. Uni layered perceptrons can only work with linearly separable data. But in the following diagram drawn in accordance with the truth table of the XOR logical operator, we can see that the data is NOT linearly separable.



To solve this problem, we add an extra layer to our vanilla perceptron, i.e., we create a Multi Layered Perceptron (or MLP). We call this extra layer as the Hidden layer. To build a perceptron, we first need to understand that the XOR gate can be written as a combination of AND gates, NOT gates and OR gates in the following way: $XOR(x_1, x_2) = AND(NOT(AND(x_1, x_2)), OR(x_1, x_2))$

Hidden layers are those layers with nodes other than the input and output nodes. An MLP is generally restricted to having a single hidden layer. The hidden layer allows for non-linearity. A node in the hidden layer isn't too different to an output node: nodes in the previous layers connect to it with their own weights and biases, and an output is computed, generally with an activation function.

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1. **Implement the 6 Boolean gates above using perceptrons. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y**
2. **Display final weights and bias of each perceptron.**

```python
import numpy as np
```

```python
def step_function(v):
  if v>=0:
    return 1
  else:
    return 0
```

```python
def perceptron(x,w,b):
  yin = np.dot(x,w) + b
  yhat = step_function(yin)
  return yhat
```

```python
def AND_function(x):
  w = np.array([1,1])
  b = -2
  return perceptron(x,w,b)
```

```
test = ([0,0], [0,1], [1,0], [1,1])

print("AND({}, {}) = {}".format(0, 0, AND_function(test[0])))
print("AND({}, {}) = {}".format(0, 1, AND_function(test[1])))
print("AND({}, {}) = {}".format(1, 0, AND_function(test[2])))
print("AND({}, {}) = {}".format(1, 1, AND_function(test[3])))
```

```
AND(0, 0) = 0
AND(0, 1) = 0
AND(1, 0) = 0
AND(1, 1) = 1
```

```
def OR_function(x):
  w = np.array([1,1])
  b = -1
  return perceptron(x,w,b)
```

```
test = ([0,0], [0,1], [1,0], [1,1])

print("OR({}, {}) = {}".format(0, 0, OR_function(test[0])))
print("OR({}, {}) = {}".format(0, 1, OR_function(test[1])))
print("OR({}, {}) = {}".format(1, 0, OR_function(test[2])))
print("OR({}, {}) = {}".format(1, 1, OR_function(test[3])))
```

```
OR(0, 0) = 0
OR(0, 1) = 1
OR(1, 0) = 1
OR(1, 1) = 1
```

```python
def NOT_function(x):
    w = -1
    b = 0
    return perceptron(x, w, b)
```

```python
test = [0,1]

print("NOT({}) = ({})".format(0,NOT_function(test[0])))
print("NOT({}) = ({})".format(1,NOT_function(test[1])))
```

```
NOT(0) = (1)
NOT(1) = (0)
```

```python
def NOR_function(x):
    output_OR = OR_function(x)
    output_NOT = NOT_function(output_OR)
    return output_NOT
```

```python
test = ([0,0], [0,1], [1,0], [1,1])

print("NOR({}, {}) = {}".format(0, 0, NOR_function(test[0])))
print("NOR({}, {}) = {}".format(0, 1, NOR_function(test[1])))
print("NOR({}, {}) = {}".format(1, 0, NOR_function(test[2])))
print("NOR({}, {}) = {}".format(1, 1, NOR_function(test[3])))
```

```
NOR(0, 0) = 1
NOR(0, 1) = 0
NOR(1, 0) = 0
NOR(1, 1) = 0
```

```python
def NAND_function(x):
    output_AND = AND_function(x)
    output_NOT = NOT_function(output_AND)
    return output_NOT
```

```python
test = ([0,0], [0,1], [1,0], [1,1])

print("NAND({}, {}) = {}".format(0, 0, NAND_function(test[0])))
print("NAND({}, {}) = {}".format(0, 1, NAND_function(test[1])))
print("NAND({}, {}) = {}".format(1, 0, NAND_function(test[2])))
print("NAND({}, {}) = {}".format(1, 1, NAND_function(test[3])))
```

```
NAND(0, 0) = 1
NAND(0, 1) = 1
NAND(1, 0) = 1
NAND(1, 1) = 0
```

```
def XOR_function(x):
  return AND_function([NAND_function(x),OR_function(x)])
```

```
test = ([0,0], [0,1], [1,0], [1,1])

print("XOR({}, {}) = {}".format(0, 0, XOR_function(test[0])))
print("XOR({}, {}) = {}".format(0, 1, XOR_function(test[1])))
print("XOR({}, {}) = {}".format(1, 0, XOR_function(test[2])))
print("XOR({}, {}) = {}".format(1, 1, XOR_function(test[3])))
```

```
XOR(0, 0) = 0
XOR(0, 1) = 1
XOR(1, 0) = 1
XOR(1, 1) = 0
```

3. What are the limitations of the perceptron network?

- The output of a perceptron can only be a binary number (0 or 1) due to the hard limit transfer function.
- Perceptron can only be used to classify the linearly separable sets of input vectors. If input vectors are non-linear, it is not easy to classify them properly.

CONCLUSION:

In this experiment, we successfully implemented basic Boolean logic gates using perceptrons. The perceptrons were able to simulate the behavior of these logic gates by learning appropriate weights and biases. These results demonstrate the capability of perceptrons to perform binary classification tasks and represent fundamental logic operations. However, it's important to note that perceptrons have limitations, such as their inability to handle non-linearly separable problems or more complex logic gates, which may require more advanced neural network architectures.