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Experiment No. 2
Implement Multilayer Perceptron algorithm to simulate XOR gate
Date of Performance:
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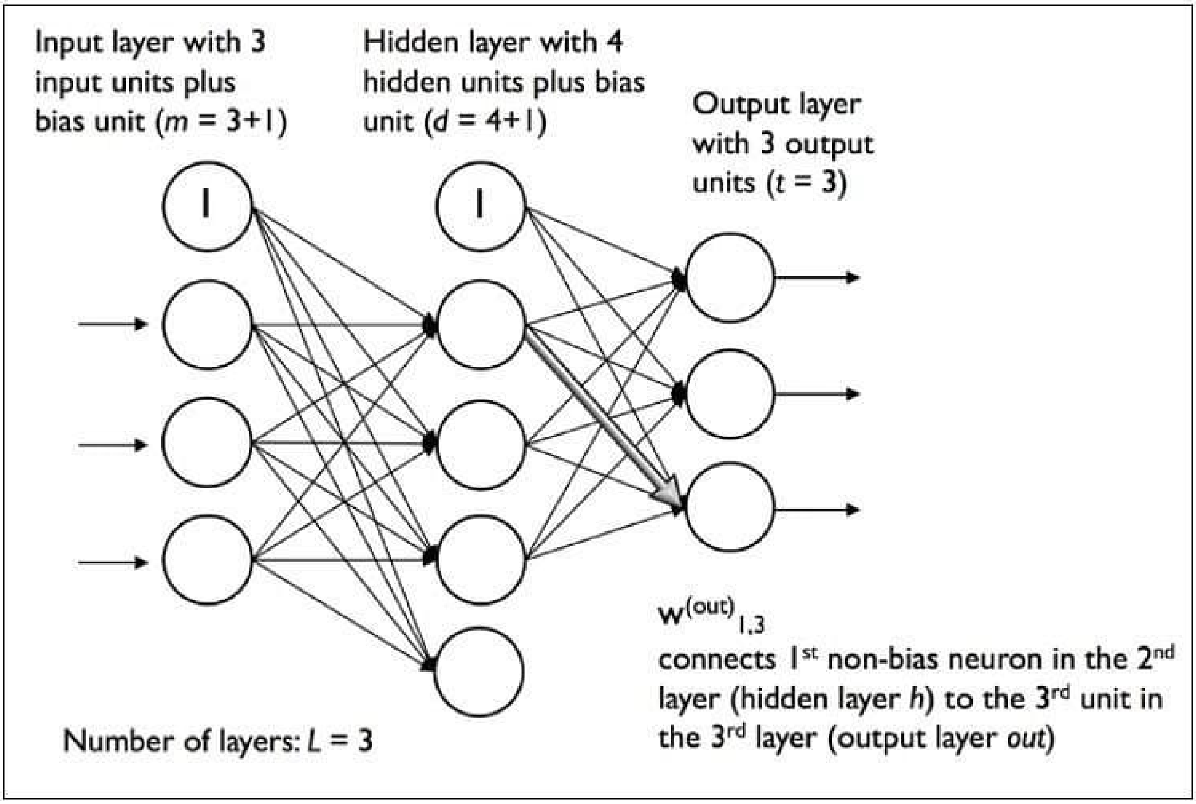
Aim: Implement Multilayer Perceptron algorithm to simulate XOR gate.

Objective: Ability to perform experiments on different architectures of multilayer perceptron.

Theory:

multilayer artificial neuron network is an integral part of deep learning. And this lesson will help you with an overview of multilayer ANN along with overfitting and underfitting.



A fully connected multi-layer neural network is called a Multilayer Perceptron (MLP).

At has 3 layers including one hidden layer. If it has more than 1 hidden layer, it is called a deep ANN. An MLP is a typical example of a feedforward artificial neural network. In this figure, the ith activation unit in the lth layer is denoted as ai(l).

The number of layers and the number of neurons are referred to as hyperparameters of a neural network, and these need tuning. Cross-validation techniques must be used to find ideal values for these.

The weight adjustment training is done via backpropagation. Deeper neural networks are better at processing data. However, deeper layers can lead to vanishing gradient problems. Special algorithms are required to solve this issue.

A multilayer perceptron (MLP) is a feed forward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input nodes connected as a directed graph between the input and output layers. MLP uses backpropagation for training the network. MLP is a deep learning method.

Code:

```
# importing Python library

import numpy as np


# define Unit Step Function

def unitStep(v):

    if v >= 0:

        return 1

    else:

        return 0


# design Perceptron Model
```

```
def perceptronModel(x, w, b):
    v = np.dot(w, x) + b
    y = unitStep(v)
    return y


# NOT Logic Function
# wNOT = -1, bNOT = 0.5
def NOT_logicFunction(x):
    wNOT = -1
    bNOT = 0.5
    return perceptronModel(x, wNOT, bNOT)


# AND Logic Function
# here w1 = wAND1 = 1,
# w2 = wAND2 = 1, bAND = -1.5
def AND_logicFunction(x):
    w = np.array([1, 1])
    bAND = -1.5
    return perceptronModel(x, w, bAND)


# OR Logic Function
```

```
# w1 = 1, w2 = 1, bOR = -0.5
def OR_logicFunction(x):
    w = np.array([1, 1])
    bOR = -0.5
    return perceptronModel(x, w, bOR)


# XOR Logic Function
# with AND, OR and NOT
# function calls in sequence
def XOR_logicFunction(x):
    y1 = AND_logicFunction(x)
    y2 = OR_logicFunction(x)
    y3 = NOT_logicFunction(y1)
    final_x = np.array([y2, y3])
    finalOutput = AND_logicFunction(final_x)
    return finalOutput


# testing the Perceptron Model
test1 = np.array([0, 1])
test2 = np.array([1, 1])
test3 = np.array([0, 0])
```

```
test4 = np.array([1, 0])


print("XOR({}, {}) = {}".format(0, 1, XOR_logicFunction(test1)))

print("XOR({}, {}) = {}".format(1, 1, XOR_logicFunction(test2)))

print("XOR({}, {}) = {}".format(0, 0, XOR_logicFunction(test3)))

print("XOR({}, {}) = {}".format(1, 0, XOR_logicFunction(test4)))
```

Output:

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

Conclusion:

The network consists of an input layer with two neurons, one or more hidden layers with non-linear activation functions, and an output layer. This enables the MLP to capture XOR gate's intricate relationships.Backpropagation is crucial for training. It adjusts weights and biases using gradients of the loss function, minimizing output differences. This guides the network to convergence.