Rajshahi University of Engineering & Technology

Department of Computer Science & Engineering

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Experiment No. : 03

Name of the experiment : Design and Apply Multi-layer Perceptron Algorithm.

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1 Theory

The Multilayer Perceptron (MLP) is a fundamental building block of deep learning, capable of solving complex classification and regression tasks.
Some of the key concepts of MLP are:

1. **Perceptron:**
   - The basic unit of an MLP is the perceptron, a simple neuron-inspired model.
   - It takes weighted inputs, sums them, and applies a threshold function to generate an output (0 or 1).
2. **Multilayer Architecture:**
   - MLPs go beyond single perceptrons by stacking them in layers.
   - The output of a layer becomes the input for the next layer, creating a chain of information processing.
3. **Activation Functions:**
   - Instead of a simple threshold, MLPs use non-linear activation functions to introduce complexity.
   - Popular choices include sigmoid, ReLU, and tanh, which allow the network to model diverse relationships beyond just linear ones.
4. **Learning and Backpropagation:**
   - MLPs learn by adjusting the weights connecting neurons based on their performance on training data.
   - Backpropagation compares the network's actual output to the desired output and propagates the error backwards through the layers, updating weights to minimize the error in future predictions.
5. **Loss function:**
   - Measures the error between network output and desired output (e.g., mean squared error).
6. **Learning rate:**
   - Controls how much the weights are adjusted based on the error.
7. **Advantages:**
   - **Versatile:** Handles various tasks like classification, regression, and pattern recognition.
   - **Interpretable:** Can analyze learned weights to understand how the network makes decisions.
   - **Efficient:** Relatively fast to train compared to other deep learning models.
8. **Limitations:**

- Can struggle with high-dimensional data and complex problems requiring significant feature engineering.
- Prone to overfitting if not regularized properly.
- Requires careful hyperparameter tuning for optimal performance.

2 Algorithm

Steps:

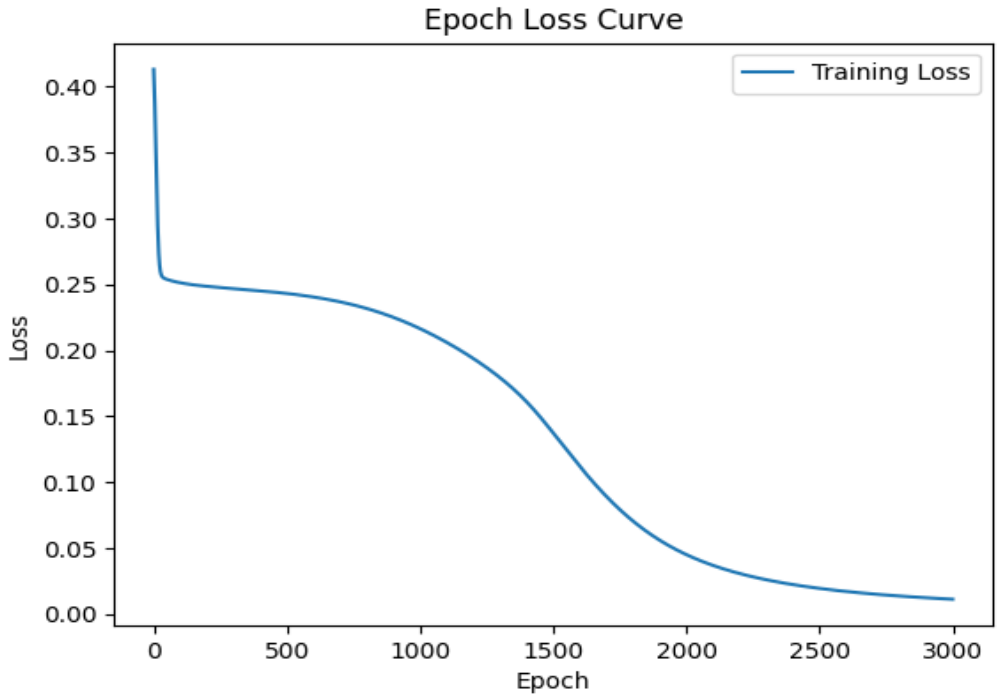
1. Initialize weigths, biases and learning rate
2. Present inputs and desired outputs (dataset)
3. Calculate actual output
4. Calculate error
5. Adapt weights with backpropagation

3 Code

```
import numpy as np
import matplotlib.pyplot as plt

epoch_losses = []

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def forward(X, W1, b1, W2, b2):
    z1 = np.dot(X, W1) + b1
    a1 = sigmoid(z1)

    z2 = np.dot(a1, W2) + b2
    a2 = sigmoid(z2)

    return a1, a2

def train(X, Y, W1, b1, W2, b2, epochs=3000, learning_rate=0.1):
    for epoch in range(epochs):
        A1, A2 = forward(X, W1, b1, W2, b2)

        E = Y - A2

        delta2 = E * (A2 * (1 - A2))

        delta1 = np.dot(delta2, W2.T) * (A1 * (1 - A1))

        W2 += learning_rate * np.dot(A1.T, delta2)
        b2 += learning_rate * np.sum(delta2, axis=0)
```

```
        W1 += learning_rate * np.dot(X.T, delta1)
        b1 += learning_rate * np.sum(delta1, axis=0)

        loss = np.mean(np.power(E, 2))

        if epoch % 300 == 0:
            print(f"Epoch {epoch}: loss = {loss}")
        epoch_losses.append(loss)

X = np.array([[0, 0, 0],[0, 0, 1],[0, 1, 0],[0, 1, 1],
    [1, 0, 0],[1, 0, 1],[1, 1, 0],[1, 1, 1]
])
Y = np.array([
    [0],[1],[1],[0],
    [1],[0],[0],[1]
])

W1 = np.random.randn(X.shape[1], 4)
b1 = np.random.randn(4)
W2 = np.random.randn(4, 1)
b2 = np.random.randn(1)

train(X, Y, W1, b1, W2, b2)

_, predictions = forward(X, W1, b1, W2, b2)
for i in range(len(predictions)):
    predictions[i] = predictions[i].round()

def calculate_accuracy(predictions, labels):
    correct_predictions = np.sum(predictions == labels)
    total_samples = len(labels)
    accuracy = correct_predictions / total_samples
    return accuracy


def plot_loss_curve(loss_values):
    plt.plot(loss_values, label='Training Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Epoch Loss Curve')
    plt.legend()
    plt.show()

accuracy = calculate_accuracy(predictions, Y)
print(f"Accuracy: {accuracy}")
plot_loss_curve(epoch_losses)
```

4 Performance Analysis




```
80      plt.xlabel('Epoch')
81      plt.ylabel('Loss')
```

PROBLEMS OUTPUT DEBUG CONSOLE PORTS TERMINAL POSTMAN CONSOLE GITLENS

```
Epoch 1200: loss = 0.19384553688785008
Epoch 1500: loss = 0.13731236423561563
Epoch 1800: loss = 0.07049171812426297
Epoch 2100: loss = 0.036965423272286885
Epoch 2400: loss = 0.022441648667351592
Epoch 2700: loss = 0.015333082609037924
Accuracy: 1.0
```

5 Discussion

The implemented Multilayer Perceptron achieved 100% in the 3 bit X-OR dataset. From the epoch-loss curve we can see the curve starts around 0.4 initially and decreases rapidly. This suggests the model quickly learned basic patterns in the data. After nearly 2500 epochs the loss is nearly 0 (< 0.05), which means the model converges to the problem properly. Overall, the Multi Layer Perceptron successfully solved the X-OR problem. .