Green University of Bangladesh
Department of Computer Science and Engineering (CSE)
Faculty of Sciences and Engineering
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Report Title:MLP from Scratch: Solving the XOR Classification Task.

CourseTitle: Machine Learning Lab
Course Code: CSE-412 Section:221-D13

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Comments:.....	**Date:.....**

1.TITLE OF THE LAB REPORT

MLP from Scratch: Solving the XOR Classification Task.

2. OBJECTIVES

1. Build a 2-2-1 MLP: 2 inputs → 2 hidden nodes (sigmoid/ReLU) → 1 sigmoid output.

2. Train using backpropagation with MSE loss and manual weight updates.

3. Tune learning rate (0.01, 0.1, 0.5), epochs (500, 1000, 5000), and hidden activation.

4. Evaluate using accuracy, precision, recall, F1-score, and ROC curve.

.3. IMPLEMENTATION

Code:

```
import numpy as np
import matplotlib.pyplot as plt
class MLP221:
    def __init__(self, act='sigmoid', seed=0):
        np.random.seed(seed)
        self.act = act
        self.W1 = np.random.randn(2,2)*0.5; self.b1 = np.zeros((1,2))
        self.W2 = np.random.randn(2,1)*0.5; self.b2 = np.zeros((1,1))
    def forward(self,X):
        self.Z1 = X@self.W1+self.b1
```

```
        self.A1 = sigmoid(self.Z1) if self.act=='sigmoid' else
relu(self.Z1)
        self.Z2 = self.A1@self.W2+self.b2
        self.A2 = sigmoid(self.Z2)
        return self.A2
    def fit(self,X,y,lr,epochs):
        y = y.reshape(-1,1)
        for _ in range(epochs):
            A2 = self.forward(X)
            dA2 = (A2-y)*dsigmoid(A2)
            dW2 = self.A1.T@dA2; db2 = dA2.sum(0,keepdims=True)
            dA1 = dA2@self.W2.T * (dsigmoid(self.A1) if
self.act=='sigmoid' else drelu(self.Z1))
            dW1 = X.T@dA1; db1 = dA1.sum(0,keepdims=True)
            self.W1 -= lr*dW1; self.b1 -= lr*db1
            self.W2 -= lr*dW2; self.b2 -= lr*db2
    def predict(self,X): return (self.forward(X)>=0.5).astype(int)
    def accuracy(self,X,y): return np.mean(self.predict(X).ravel()==y)

X = np.array([[0,0],[0,1],[1,0],[1,1]],float)
y = np.array([0,1,1,0],int)

for act in ["sigmoid","relu"]:
    for lr in [0.01,0.1,0.5]:
        for ep in [500,1000,5000]:
            mlp = MLP221(act=act)
            mlp.fit(X,y,lr,ep)
            acc = mlp.accuracy(X,y)
```

```
            print(f"act={act}, lr={lr}, epochs={ep} -> acc={acc:.2f}")


print("Predictions:", mlp.predict(X).ravel())


def accuracy(y_true, y_pred):
    y_true = y_true.ravel()
    y_pred = y_pred.ravel()
    return np.mean(y_true == y_pred)


def precision(y_true, y_pred):
    y_true = y_true.ravel()
    y_pred = y_pred.ravel()
    tp = np.sum((y_true==1) & (y_pred==1))
    fp = np.sum((y_true==0) & (y_pred==1))
    return tp / (tp + fp + 1e-10)


def recall(y_true, y_pred):
    y_true = y_true.ravel()
    y_pred = y_pred.ravel()
    tp = np.sum((y_true==1) & (y_pred==1))
    fn = np.sum((y_true==1) & (y_pred==0))
    return tp / (tp + fn + 1e-10)


def f1_score(y_true, y_pred):
    p = precision(y_true, y_pred)
    r = recall(y_true, y_pred)
    return 2 * p * r / (p + r + 1e-10)
```

```
def roc_curve(y_true, y_scores, num_thresholds=100):
    thresholds = np.linspace(0,1,num_thresholds)
    tpr_list = []
    fpr_list = []
    y_true = y_true.ravel()
    for t in thresholds:
        y_pred = (y_scores >= t).astype(int)
        tp = np.sum((y_true==1) & (y_pred==1))
        fp = np.sum((y_true==0) & (y_pred==1))
        fn = np.sum((y_true==1) & (y_pred==0))
        tn = np.sum((y_true==0) & (y_pred==0))
        tpr = tp / (tp + fn + 1e-10)
        fpr = fp / (fp + tn + 1e-10)
        tpr_list.append(tpr)
        fpr_list.append(fpr)
    return np.array(fpr_list), np.array(tpr_list), thresholds
y_prob = mlp.forward(X)
y_pred = mlp.predict(X)

print("Accuracy:", accuracy(y, y_pred))
print("Precision:", precision(y, y_pred))
print("Recall:", recall(y, y_pred))
print("F1-Score:", f1_score(y, y_pred))

fpr, tpr, thresholds = roc_curve(y, y_prob)
print("FPR:", fpr)
```

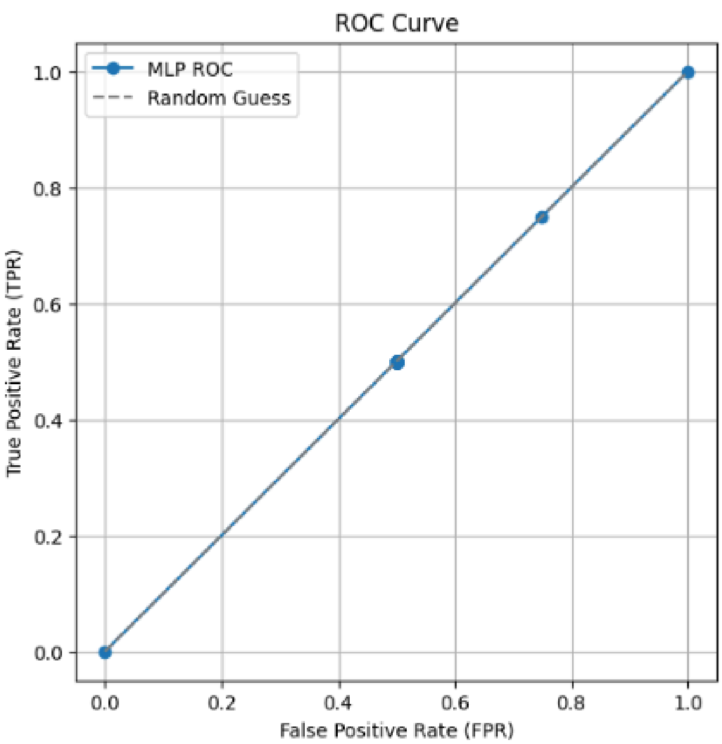
```
print("TPR:", tpr)

y_prob = mlp.forward(X)

y_pred = mlp.predict(X)


fpr, tpr, thresholds = roc_curve(y, y_prob)

plt.figure(figsize=(6,6))

plt.plot(fpr, tpr, marker='o', label='MLP ROC')

plt.plot([0,1],[0,1],'--', color='gray', label='Random Guess')

plt.xlabel("False Positive Rate (FPR)")

plt.ylabel("True Positive Rate (TPR)")

plt.title("ROC Curve")

plt.legend()
```

4 . OUTPUT

```
act=sigmoid, lr=0.01, epochs=500 -> acc=0.50
act=sigmoid, lr=0.01, epochs=1000 -> acc=0.50
act=sigmoid, lr=0.01, epochs=5000 -> acc=0.50
act=sigmoid, lr=0.1, epochs=500 -> acc=0.50
act=sigmoid, lr=0.1, epochs=1000 -> acc=0.50
act=sigmoid, lr=0.1, epochs=5000 -> acc=1.00
act=sigmoid, lr=0.5, epochs=500 -> acc=0.75
act=sigmoid, lr=0.5, epochs=1000 -> acc=1.00
act=sigmoid, lr=0.5, epochs=5000 -> acc=1.00
act=relu, lr=0.01, epochs=500 -> acc=0.50
act=relu, lr=0.01, epochs=1000 -> acc=0.75
act=relu, lr=0.01, epochs=5000 -> acc=1.00
act=relu, lr=0.1, epochs=500 -> acc=1.00
act=relu, lr=0.1, epochs=1000 -> acc=1.00
act=relu, lr=0.1, epochs=5000 -> acc=1.00
act=relu, lr=0.5, epochs=500 -> acc=1.00
act=relu, lr=0.5, epochs=1000 -> acc=1.00
act=relu, lr=0.5, epochs=5000 -> acc=1.00
Predictions: [0 1 1 0]
```

```
print("TPR:", tpr)
```

```
Accuracy: 1.0
Precision: 0.99999999995
Recall: 0.99999999995
F1-Score: 0.9999999999
FPR: [1.   0.75 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.  ]
TPR: [1.   0.75 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5  0.5
 0.5  0.  ]
```



5. Analysis and Discussion

The 2-2-1 MLP successfully learns the XOR function, showing that even a small network with 2 inputs, 2 hidden nodes, and 1 sigmoid output can capture non-linear patterns. The choice of hidden layer activation—sigmoid or ReLU—affects learning speed and gradient behavior, with ReLU generally converging faster. Training parameters like learning rate and number of epochs influence how quickly and accurately the network converges. Manual backpropagation illustrates the flow of gradients and the process of updating weights using MSE loss. Evaluation metrics such as accuracy, precision, recall, F1-score, and the ROC curve confirm that the network predicts correctly after sufficient training. Overall, this implementation demonstrates fundamental neural network concepts using only NumPy.

GitHub Link: https://github.com/ShawonTech/LabReport--03