

# EXPERIMENT-1

## SANJAY DHAKAR

### (24UADS1046)

**Objective :-** WAP to visualize the Perceptron Learning Algorithm using numpy and matplotlib/seaborn in Python. Evaluate performance of a single perceptron for NAND and XOR truth tables as input dataset

**Description :-**

- The Perceptron Learning Algorithm is a supervised binary classification algorithm.
- It computes a weighted sum of inputs and applies a step activation function.
- Weights and bias are updated only when a sample is misclassified.
- Performance is evaluated using loss and accuracy per epoch.
- The perceptron converges for NAND (linearly separable) with 100% accuracy.
- The perceptron fails for XOR (not linearly separable), showing its limitation.

**Source Code :-**

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

sns.set(style="whitegrid")

class Perceptron:
    def __init__(self, lr=0.1, epochs=20):
        self.lr = lr
        self.epochs = epochs

    def step(self, z):
        return np.where(z >= 0, 1, 0)

    def predict(self, X):
        z = np.dot(X, self.w) + self.b
        return self.step(z)
```

```

def fit(self, X, y):
    self.w = np.zeros(X.shape[1])
    self.b = 0

    self.weight_history = []
    self.loss_history = []
    self.acc_history = []

    for epoch in range(self.epochs):
        total_error = 0
        print(f"\nEpoch {epoch+1}")

        for i in range(len(X)):
            z = np.dot(X[i], self.w) + self.b
            y_pred = self.step(z)

            error = y[i] - y_pred
            total_error += abs(error)

            self.w += self.lr * error * X[i]
            self.b += self.lr * error

        print(f"Sample {i+1} | w={self.w} | b={self.b}")

    self.loss_history.append(total_error)

    # Accuracy per epoch
    y_epoch_pred = self.predict(X)
    acc = np.mean(y_epoch_pred == y)
    self.acc_history.append(acc)

    print(f"Loss={total_error}, Accuracy={acc*100:.2f}%")

    if total_error == 0:
        print("✅ Converged!")
        break

def plot_decision_boundary(X, y, w, b, title):
    plt.figure(figsize=(5,5))

```

```

sns.scatterplot(x=X[:,0], y=X[:,1], hue=y, s=100)

x_vals = np.array([0, 1])
y_vals = -(w[0]*x_vals + b) / w[1]
plt.plot(x_vals, y_vals, 'k--')

plt.title(title)
plt.xlabel("x1")
plt.ylabel("x2")
plt.show()

def plot_loss(loss, title):
    plt.figure(figsize=(5,3))
    plt.plot(loss, marker='o')
    plt.title(title)
    plt.xlabel("Epoch")
    plt.ylabel("Total Misclassifications")
    plt.show()

def plot_accuracy(acc, title):
    plt.figure(figsize=(5,3))
    plt.plot(acc, marker='o')
    plt.ylim(0, 1.05)
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.title(title)
    plt.show()

X_nand = np.array([
    [0,0],
    [0,1],
    [1,0],
    [1,1]
])

y_nand = np.array([1,1,1,0])

p_nand = Perceptron(lr=0.1, epochs=10)
p_nand.fit(X_nand, y_nand)

```

```

plot_loss(p_nand.loss_history, "NAND - Training Error")
plot_decision_boundary(X_nand, y_nand, p_nand.w, p_nand.b, "NAND - Final
Decision Boundary")

y_pred_nand = p_nand.predict(X_nand)
nand_acc = np.mean(y_pred_nand == y_nand)

print("Final NAND Accuracy:", nand_acc)

plot_accuracy(p_nand.acc_history, "NAND Accuracy vs Epoch")

X_xor = np.array([
    [0,0],
    [0,1],
    [1,0],
    [1,1]
])

y_xor = np.array([0,1,1,0])

p_xor = Perceptron(lr=0.1, epochs=10)
p_xor.fit(X_xor, y_xor)

plot_loss(p_xor.loss_history, "XOR - Training Error")
plot_decision_boundary(X_xor, y_xor, p_xor.w, p_xor.b, "XOR - Final
Decision Boundary")

y_pred_xor = p_xor.predict(X_xor)
xor_acc = np.mean(y_pred_xor == y_xor)

print("Final XOR Accuracy:", xor_acc)

plot_accuracy(p_xor.acc_history, "XOR Accuracy vs Epoch")

```

**Output:- For NAND**

Epoch 1  
Sample 1 | w=[0. 0.] | b=0.0

Sample 2 |  $w=[0.0]$  |  $b=0.0$   
Sample 3 |  $w=[0.0]$  |  $b=0.0$   
Sample 4 |  $w=[-0.1 -0.1]$  |  $b=-0.1$   
Loss=1, Accuracy=25.00%

#### Epoch 2

Sample 1 |  $w=[-0.1 -0.1]$  |  $b=0.0$   
Sample 2 |  $w=[-0.1 0.]$  |  $b=0.1$   
Sample 3 |  $w=[-0.1 0.]$  |  $b=0.1$   
Sample 4 |  $w=[-0.2 -0.1]$  |  $b=0.0$   
Loss=3, Accuracy=50.00%

#### Epoch 3

Sample 1 |  $w=[-0.2 -0.1]$  |  $b=0.0$   
Sample 2 |  $w=[-0.2 0.]$  |  $b=0.1$   
Sample 3 |  $w=[-0.1 0.]$  |  $b=0.2$   
Sample 4 |  $w=[-0.2 -0.1]$  |  $b=0.1$   
Loss=3, Accuracy=75.00%

#### Epoch 4

Sample 1 |  $w=[-0.2 -0.1]$  |  $b=0.1$   
Sample 2 |  $w=[-0.2 -0.1]$  |  $b=0.1$   
Sample 3 |  $w=[-0.1 -0.1]$  |  $b=0.2$   
Sample 4 |  $w=[-0.2 -0.2]$  |  $b=0.1$   
Loss=2, Accuracy=50.00%

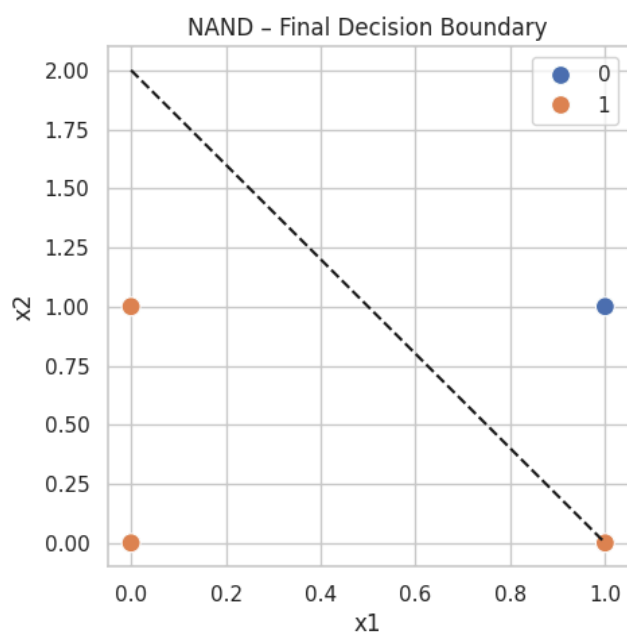
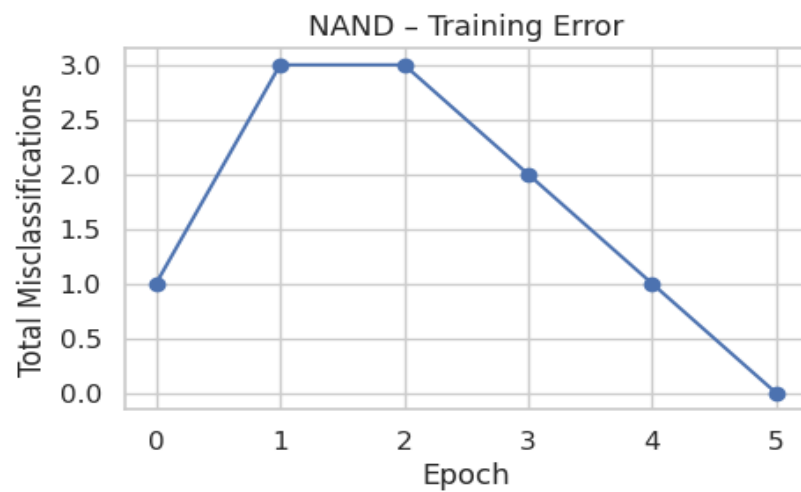
#### Epoch 5

Sample 1 |  $w=[-0.2 -0.2]$  |  $b=0.1$   
Sample 2 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Sample 3 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Sample 4 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Loss=1, Accuracy=100.00%

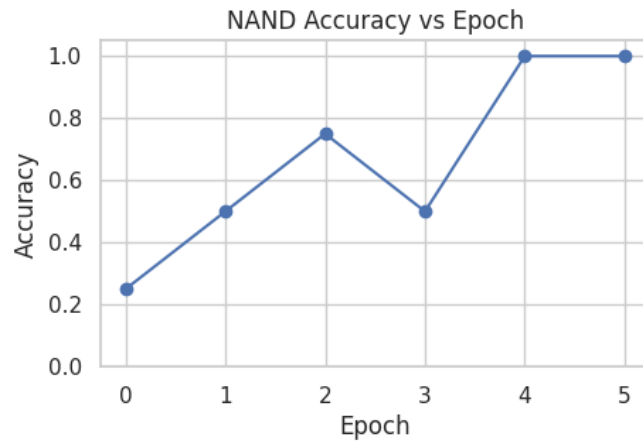
#### Epoch 6

Sample 1 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Sample 2 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Sample 3 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Sample 4 |  $w=[-0.2 -0.1]$  |  $b=0.2$   
Loss=0, Accuracy=100.00%

 **Converged!**



**Final NAND Accuracy: 1.0**



**FOR XOR :**

**Epoch 1**

Sample 1 |  $w=[0.0]$  |  $b=-0.1$   
 Sample 2 |  $w=[0.01]$  |  $b=0.0$   
 Sample 3 |  $w=[0.01]$  |  $b=0.0$   
 Sample 4 |  $w=[-0.10]$  |  $b=-0.1$   
 Loss=3, Accuracy=50.00%

**Epoch 2**

Sample 1 |  $w=[-0.10]$  |  $b=-0.1$   
 Sample 2 |  $w=[-0.101]$  |  $b=0.0$   
 Sample 3 |  $w=[0.01]$  |  $b=0.1$   
 Sample 4 |  $w=[-0.10]$  |  $b=0.0$   
 Loss=3, Accuracy=50.00%

**Epoch 3**

Sample 1 |  $w=[-0.10]$  |  $b=-0.1$   
 Sample 2 |  $w=[-0.101]$  |  $b=0.0$   
 Sample 3 |  $w=[0.01]$  |  $b=0.1$   
 Sample 4 |  $w=[-0.10]$  |  $b=0.0$   
 Loss=4, Accuracy=50.00%

**Epoch 4**

Sample 1 |  $w=[-0.10]$  |  $b=-0.1$   
 Sample 2 |  $w=[-0.101]$  |  $b=0.0$   
 Sample 3 |  $w=[0.01]$  |  $b=0.1$   
 Sample 4 |  $w=[-0.10]$  |  $b=0.0$   
 Loss=4, Accuracy=50.00%

**Epoch 5**

Sample 1 |  $w=[-0.10]$  |  $b=-0.1$   
 Sample 2 |  $w=[-0.101]$  |  $b=0.0$   
 Sample 3 |  $w=[0.01]$  |  $b=0.1$

Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%

#### Epoch 6

Sample 1 |  $w=[-0.1 \ 0.]$  |  $b=-0.1$   
Sample 2 |  $w=[-0.1 \ 0.1]$  |  $b=0.0$   
Sample 3 |  $w=[0. \ 0.1]$  |  $b=0.1$   
Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%

#### Epoch 7

Sample 1 |  $w=[-0.1 \ 0.]$  |  $b=-0.1$   
Sample 2 |  $w=[-0.1 \ 0.1]$  |  $b=0.0$   
Sample 3 |  $w=[0. \ 0.1]$  |  $b=0.1$   
Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%

#### Epoch 8

Sample 1 |  $w=[-0.1 \ 0.]$  |  $b=-0.1$   
Sample 2 |  $w=[-0.1 \ 0.1]$  |  $b=0.0$   
Sample 3 |  $w=[0. \ 0.1]$  |  $b=0.1$   
Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%

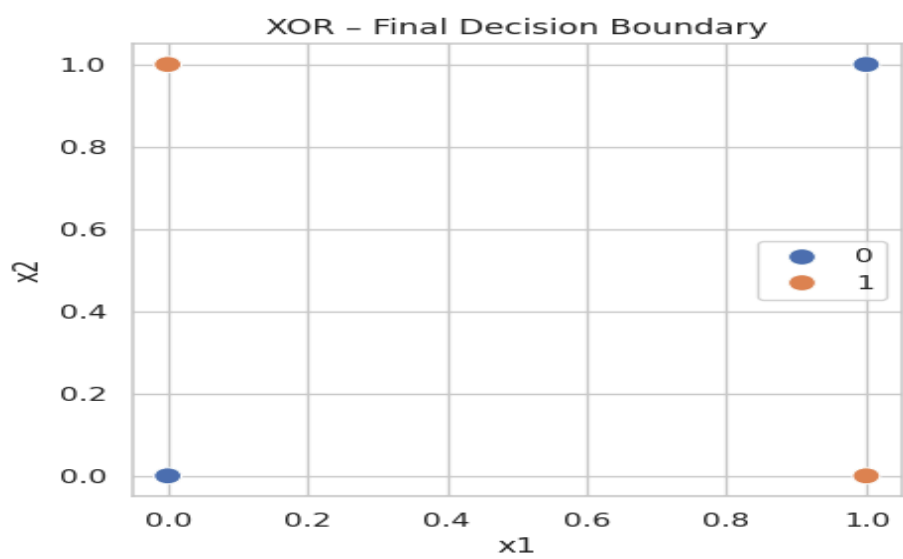
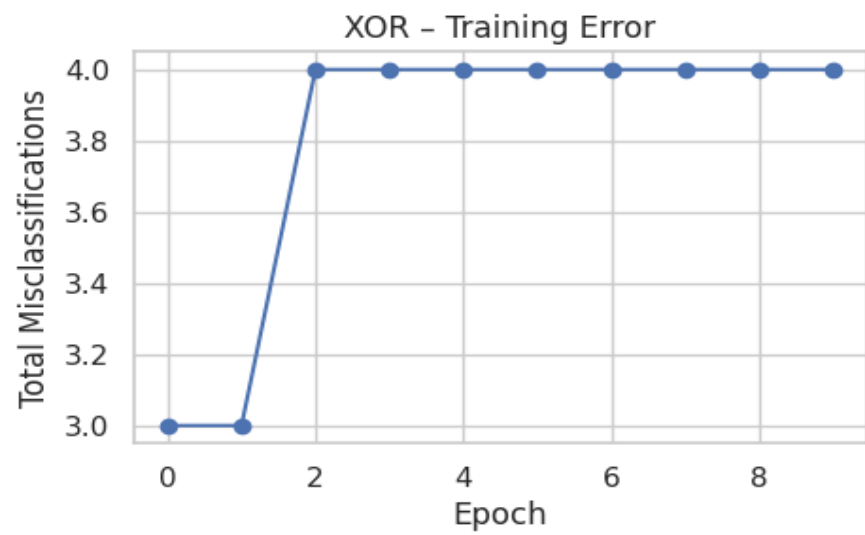
#### Epoch 9

Sample 1 |  $w=[-0.1 \ 0.]$  |  $b=-0.1$   
Sample 2 |  $w=[-0.1 \ 0.1]$  |  $b=0.0$   
Sample 3 |  $w=[0. \ 0.1]$  |  $b=0.1$   
Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%

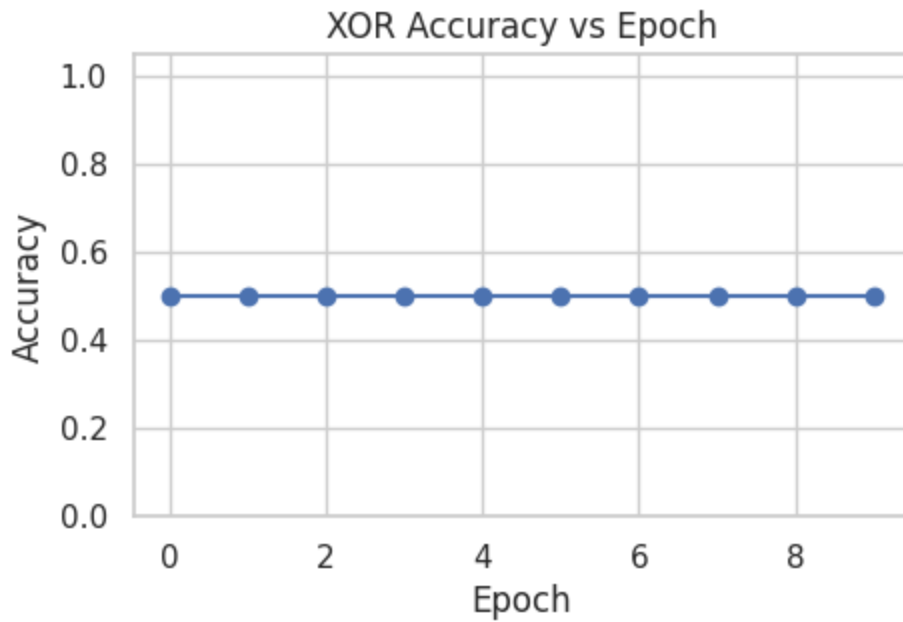
#### Epoch 10

Sample 1 |  $w=[-0.1 \ 0.]$  |  $b=-0.1$   
Sample 2 |  $w=[-0.1 \ 0.1]$  |  $b=0.0$   
Sample 3 |  $w=[0. \ 0.1]$  |  $b=0.1$   
Sample 4 |  $w=[-0.1 \ 0.]$  |  $b=0.0$   
Loss=4, Accuracy=50.00%





**Final XOR Accuracy: 0.5**



#### **MY COMMENTS :-**

From this experiment about training and learning algorithm of single layer perceptron, i understood the concept of weights and biases and how they modified at each step to improve the results . I also understand the concept of convergence .

The Key learning from this experiment i have are :

1. The learning algorithm convergence for the NAND Gate which shows that it is linearly separable.
2. The Learning algorithm fails to convergence for XOR gate logic which shows it is not linearly separable and accuracy remained constant at 50 %