Engineent 6 Implement gradient Descent 9/9/2025 & Backpropagation Aim: To implement a deep neural network demonstrating the use of forward Propagation, backpropagation and gradient Objectives: inearly separable dataset. > Perform backpropagation to compute gradients Doundary of the network. l'sludocode: - Import by Torch > Define XOR dataset » Initialize hidden læger » Buitialize output læger > Use sigmoid , Define the forward function > mitialize Model: model = XORNet () loss-function = MSE loss (for each epoch set number of epoclas 7 Forward pass -computa loss > Train the model > tackpropagation: loss. s End. supdate weights > Reset gradients Drimented Exceptiops Action in a deep neural network.

Pseudocode: Plotting Decision Boundary - Impost libraries screate a grid of points covering input space > Plet decision boundary using courtours > blue =0, red=1 > Cond. Ob rervation Cipoch O, Loss: 0.2595 epoch 1000, loss: 0.2497 epoch 9000. Loss: 0.0194 epock 19000 / loss: 0.0024 tensor ([[0.0494], [0.9517], [0.9860], loss is computed using $L = \frac{1}{N} \sum_{i=1}^{N} (y_i^2 - y_i)^{L}$ yradients using $\frac{\partial L}{\partial w} = (\hat{y} - y) \cdot \hat{y} \cdot (1 - \hat{y}) \cdot \alpha_{prev}$ this weight. W=W-ndL

Training Loss curve properties are formal organ, bleepaperin y jose 0.0016 ment sparable hatest. 0.0014mum backpropagation to Paralie the training lass and 58000:0 0 2500 5000 7500 10000 2000 exports : charactery suport Rytorch pipe xor dataset Decision Boundary of Neural Network

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biampin and were the forward fundion wholly world: 075 model = XORNESTADEMB 2.0 UN junction: MSE (613 (0.25 200 8:00ch -0.15 permet consoque de redalea un -0.50 -0.15 0.0 025 0.5 0.75 01 NILS N. 50 W. Jupilale weights Result: Successfully implemented backpropagation to train a deep neural network.

```
import torch
import torch.nn as nn
import torch.optim as optim
# Dataset (XOR problem)
X = torch.tensor([[0,0],[0,1],[1,0],[1,1]], dtype=torch.float32)
y = torch.tensor([[0],[1],[1],[0]], dtype=torch.float32)
# Define a simple neural network
class XORNet(nn.Module):
    def __init__(self):
        super(XORNet, self).__init__()
        self.hidden = nn.Linear(2, 4)
                                        # input layer -> hidden
        self.output = nn.Linear(4, 1) # hidden -> output
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        x = self.sigmoid(self.hidden(x))
        x = self.sigmoid(self.output(x))
        return x
# Initialize model, loss, and optimizer
model = XORNet()
criterion = nn.MSELoss()
optimizer = optim.SGD(model.parameters(), lr=0.1)
# Training Loop
epochs = 20000
for epoch in range(epochs):
    # Forward pass
    outputs = model(X)
    loss = criterion(outputs, y)
    # Backward pass + update
    optimizer.zero_grad() # reset gradients
    loss.backward()
                            # compute gradients
    optimizer.step()
                            # update weights
    if epoch % 1000 == 0:
        print(f"Epoch {epoch}, Loss: {loss.item():.4f}")
# Final predictions
print("Final predictions:")
```

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```
Epoch 0, Loss: 0.2595
Epoch 1000, Loss: 0.2497
Epoch 2000, Loss: 0.2492
Epoch 3000, Loss: 0.2483
Epoch 4000, Loss: 0.2458
Epoch 5000, Loss: 0.2361
Epoch 6000, Loss: 0.1899
Epoch 7000, Loss: 0.0877
Epoch 8000, Loss: 0.0361
Epoch 9000, Loss: 0.0194
Epoch 10000, Loss: 0.0125
Epoch 11000, Loss: 0.0089
Epoch 12000, Loss: 0.0069
Epoch 13000, Loss: 0.0055
Epoch 14000, Loss: 0.0046
Epoch 15000, Loss: 0.0039
Epoch 16000, Loss: 0.0034
Epoch 17000, Loss: 0.0030
Epoch 18000, Loss: 0.0027
Epoch 19000, Loss: 0.0024
Final predictions:
tensor([[0.0494],
        [0.9517],
        FA 95691
```

print(model(X).detach())

```
Epoch 19000, Loss: 0.0024
       Final predictions:
       tensor([[0.0494],
               [0.9517],
               [0.9560],
               [0.0455]])
In [6]:
         import matplotlib.pyplot as plt
         losses = []
         for epoch in range(epochs):
             outputs = model(X)
             loss = criterion(outputs, y)
             optimizer.zero_grad()
             loss.backward()
             optimizer.step()
             losses.append(loss.item())
         # Plot loss curve
         plt.plot(losses)
         plt.xlabel("Epochs")
         plt.ylabel("Loss")
         plt.title("Training Loss Curve")
         plt.show()
```





