Exp 2

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CSE(DS)_22

Back propogation in Deep Learning

Backpropagation is a crucial component of deep learning and forms the basis for training neural networks. It is an optimization algorithm used to adjust the parameters (weights and biases) of a neural network so that it can learn to make accurate predictions on a given task. The process involves two main steps: the forward pass and the backward pass.

Code:

```
import numpy as np
class NeuralNetwork:
     def __init__(self, input_size, hidden_size, output_size):
          self.input_size = input_size
          self.hidden_size = hidden_size
          self.output_size = output_size
          # Initialize weights and biases for the hidden layer and output layer
          self.W1 = np.random.randn(hidden_size, input_size)
          self.b1 = np.zeros((hidden_size, 1))
          self.W2 = np.random.randn(output_size, hidden_size)
          self.b2 = np.zeros((output_size, 1))
     def sigmoid(self, x):
          return 1/(1 + np.exp(-x))
```

```
def sigmoid_derivative(self, x):
     return x * (1 - x)
def forward(self, X):
     # Forward pass
     self.z1 = np.dot(self.W1, X) + self.b1
     self.a1 = self.sigmoid(self.z1)
     self.z2 = np.dot(self.W2, self.a1) + self.b2
     self.a2 = self.sigmoid(self.z2)
     return self.a2
def backward(self, X, y, learning_rate):
     m = X.shape[1]
     # Compute the gradients
     dZ2 = self.a2 - y
     dW2 = (1 / m) * np.dot(dZ2, self.a1.T)
     db2 = (1/m) * np.sum(dZ2, axis=1, keepdims=True)
     dZ1 = np.dot(self.W2.T, dZ2) * self.sigmoid_derivative(self.a1)
     dW1 = (1 / m) * np.dot(dZ1, X.T)
     db1 = (1/m) * np.sum(dZ1, axis=1, keepdims=True)
     # Update weights and biases using gradients and learning rate
     self.W2 -= learning rate * dW2
     self.b2 -= learning_rate * db2
```

```
self.W1 -= learning_rate * dW1
          self.b1 -= learning_rate * db1
     def train(self, X, y, epochs, learning_rate):
          for epoch in range(epochs):
               # Forward pass
               predictions = self.forward(X)
               # Compute the mean squared error loss
               loss = np.mean((predictions - y) ** 2)
               # Backward pass to update weights and biases
               self.backward(X, y, learning_rate)
               if epoch % 100 == 0:
                    print(f"Epoch {epoch}, Loss: {loss:.4f}")
     def predict(self, X):
          return self.forward(X)
# Example usage:
input_size = 2
hidden_size = 4
output_size = 1
learning_rate = 0.5
epochs = 10000
```

```
# Generate some sample data
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]]).T
y = np.array([[0, 1, 1, 0]])
# Create the neural network
nn = NeuralNetwork(input_size, hidden_size, output_size)
# Train the neural network
nn.train(X, y, epochs, learning_rate)
# Make predictions
predictions = nn.predict(X)
print("Predictions:", predictions)
```

Output:

