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CSE(DS)

Back Propagation in Deep Learning

In simple terms, backpropagation is a supervised learning algorithm that allows a neural network to learn from its mistakes by adjusting its weights and biases. It enables the network to iteratively improve its performance on a given task, such as classification or regression.

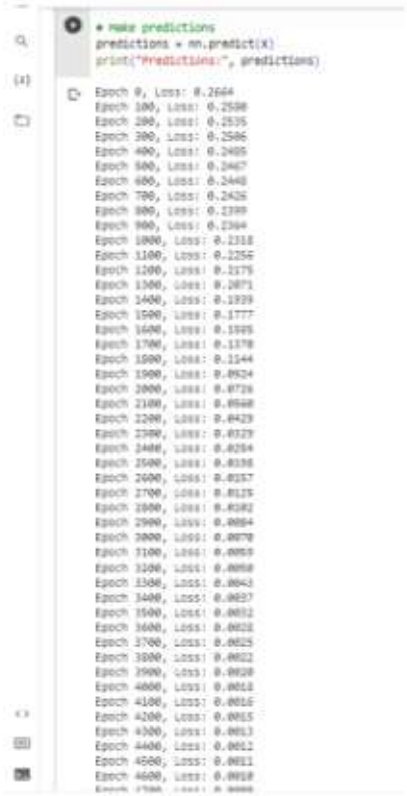
Code:-

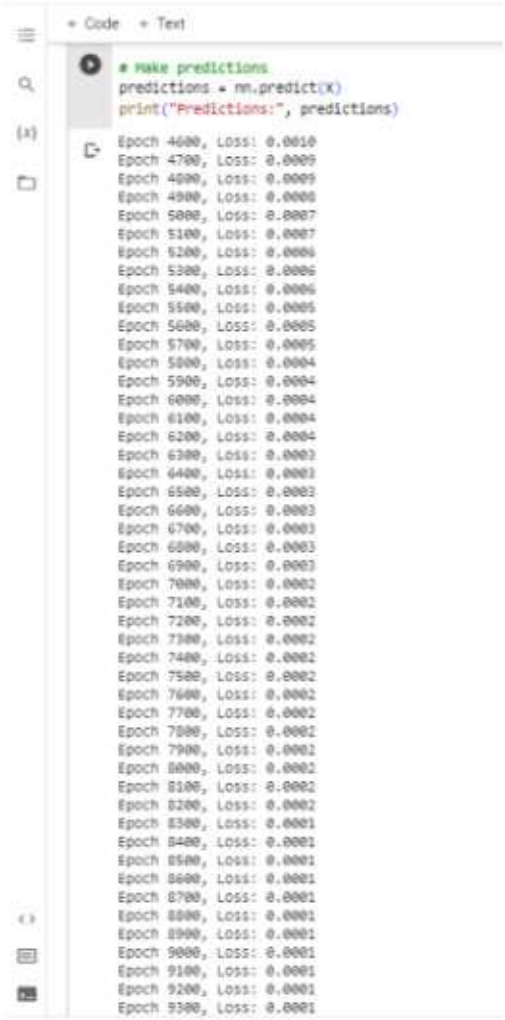
```
import numpy as np
class NeuralNetwork:
    def __init__(self, input_size, hidden_size, output_size):
        self.input_size = input_size
        self.hidden_size = hidden_size
        self.output_size = output_size

        # 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 = 0.1
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:-


# Make predictions
predictions = nn.predict(X)
print("Predictions:", predictions)
Epoch 0, Loss: 0.2664
Epoch 100, Loss: 0.2598
Epoch 200, Loss: 0.2535
Epoch 300, Loss: 0.2506
Epoch 400, Loss: 0.2405
Epoch 500, Loss: 0.2467
Epoch 600, Loss: 0.2448
Epoch 700, Loss: 0.2426
Epoch 800, Loss: 0.2399
Epoch 900, Loss: 0.2364
Epoch 1000, Loss: 0.2318
Epoch 1100, Loss: 0.2256
Epoch 1200, Loss: 0.2175
Epoch 1300, Loss: 0.2071
Epoch 1400, Loss: 0.1939
Epoch 1500, Loss: 0.1777
Epoch 1600, Loss: 0.1585
Epoch 1700, Loss: 0.1378
Epoch 1800, Loss: 0.1144
Epoch 1900, Loss: 0.0924
Epoch 2000, Loss: 0.0726
Epoch 2100, Loss: 0.0560
Epoch 2200, Loss: 0.0429
Epoch 2300, Loss: 0.0329
Epoch 2400, Loss: 0.0254
Epoch 2500, Loss: 0.0198
Epoch 2600, Loss: 0.0157
Epoch 2700, Loss: 0.0125
Epoch 2800, Loss: 0.0102
Epoch 2900, Loss: 0.0084
Epoch 3000, Loss: 0.0070
Epoch 3100, Loss: 0.0059
Epoch 3200, Loss: 0.0050
Epoch 3300, Loss: 0.0043
Epoch 3400, Loss: 0.0037
Epoch 3500, Loss: 0.0032
Epoch 3600, Loss: 0.0028
Epoch 3700, Loss: 0.0025
Epoch 3800, Loss: 0.0022
Epoch 3900, Loss: 0.0020
Epoch 4000, Loss: 0.0018
Epoch 4100, Loss: 0.0016
Epoch 4200, Loss: 0.0015
Epoch 4300, Loss: 0.0013
Epoch 4400, Loss: 0.0012
Epoch 4500, Loss: 0.0011
Epoch 4600, Loss: 0.0010


+ Code
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# Make predictions
predictions = nn.predict(X)
print("Predictions:", predictions)
Epoch 4600, Loss: 0.0010
Epoch 4700, Loss: 0.0009
Epoch 4800, Loss: 0.0009
Epoch 4900, Loss: 0.0008
Epoch 5000, Loss: 0.0007
Epoch 5100, Loss: 0.0007
Epoch 5200, Loss: 0.0006
Epoch 5300, Loss: 0.0006
Epoch 5400, Loss: 0.0006
Epoch 5500, Loss: 0.0005
Epoch 5600, Loss: 0.0005
Epoch 5700, Loss: 0.0005
Epoch 5800, Loss: 0.0004
Epoch 5900, Loss: 0.0004
Epoch 6000, Loss: 0.0004
Epoch 6100, Loss: 0.0004
Epoch 6200, Loss: 0.0004
Epoch 6300, Loss: 0.0003
Epoch 6400, Loss: 0.0003
Epoch 6500, Loss: 0.0003
Epoch 6600, Loss: 0.0003
Epoch 6700, Loss: 0.0003
Epoch 6800, Loss: 0.0003
Epoch 6900, Loss: 0.0003
Epoch 7000, Loss: 0.0002
Epoch 7100, Loss: 0.0002
Epoch 7200, Loss: 0.0002
Epoch 7300, Loss: 0.0002
Epoch 7400, Loss: 0.0002
Epoch 7500, Loss: 0.0002
Epoch 7600, Loss: 0.0002
Epoch 7700, Loss: 0.0002
Epoch 7800, Loss: 0.0002
Epoch 7900, Loss: 0.0002
Epoch 8000, Loss: 0.0002
Epoch 8100, Loss: 0.0002
Epoch 8200, Loss: 0.0002
Epoch 8300, Loss: 0.0001
Epoch 8400, Loss: 0.0001
Epoch 8500, Loss: 0.0001
Epoch 8600, Loss: 0.0001
Epoch 8700, Loss: 0.0001
Epoch 8800, Loss: 0.0001
Epoch 8900, Loss: 0.0001
Epoch 9000, Loss: 0.0001
Epoch 9100, Loss: 0.0001
Epoch 9200, Loss: 0.0001
Epoch 9300, Loss: 0.0001