

Dhanesh Yadav

Roll No:67

CSE(DS)

Exp3 Deep Learning

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:-

- [Introduction](#)
- [Getting started](#)
- [Getting started](#)

Q

 $\{x\}$

< >

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

	+ Code	+ Text
●	Epoch 13900,	Loss: 0.0000
	Epoch 14000,	Loss: 0.0000
□	Epoch 14100,	Loss: 0.0000
	Epoch 14200,	Loss: 0.0000
{x}	Epoch 14300,	Loss: 0.0000
	Epoch 14400,	Loss: 0.0000
□	Epoch 14500,	Loss: 0.0000
	Epoch 14600,	Loss: 0.0000
	Epoch 14700,	Loss: 0.0000
	Epoch 14800,	Loss: 0.0000
	Epoch 14900,	Loss: 0.0000
	Epoch 15000,	Loss: 0.0000
	Epoch 15100,	Loss: 0.0000
	Epoch 15200,	Loss: 0.0000
	Epoch 15300,	Loss: 0.0000
	Epoch 15400,	Loss: 0.0000
	Epoch 15500,	Loss: 0.0000
	Epoch 15600,	Loss: 0.0000
	Epoch 15700,	Loss: 0.0000
	Epoch 15800,	Loss: 0.0000
	Epoch 15900,	Loss: 0.0000
	Epoch 16000,	Loss: 0.0000
	Epoch 16100,	Loss: 0.0000
	Epoch 16200,	Loss: 0.0000
	Epoch 16300,	Loss: 0.0000
	Epoch 16400,	Loss: 0.0000
	Epoch 16500,	Loss: 0.0000
	Epoch 16600,	Loss: 0.0000
	Epoch 16700,	Loss: 0.0000
	Epoch 16800,	Loss: 0.0000
	Epoch 16900,	Loss: 0.0000
	Epoch 17000,	Loss: 0.0000
	Epoch 17100,	Loss: 0.0000
	Epoch 17200,	Loss: 0.0000
	Epoch 17300,	Loss: 0.0000
	Epoch 17400,	Loss: 0.0000
	Epoch 17500,	Loss: 0.0000
	Epoch 17600,	Loss: 0.0000
	Epoch 17700,	Loss: 0.0000
	Epoch 17800,	Loss: 0.0000
	Epoch 17900,	Loss: 0.0000
	Epoch 18000,	Loss: 0.0000
	Epoch 18100,	Loss: 0.0000
	Epoch 18200,	Loss: 0.0000
	Epoch 18300,	Loss: 0.0000
	Epoch 18400,	Loss: 0.0000
	Epoch 18500,	Loss: 0.0000
<>	Epoch 18600,	Loss: 0.0000

```
Epoch 18600, Loss: 0.0000
Epoch 18700, Loss: 0.0000
Epoch 18800, Loss: 0.0000
Epoch 18900, Loss: 0.0000
Epoch 19000, Loss: 0.0000
Epoch 19100, Loss: 0.0000
Epoch 19200, Loss: 0.0000
Epoch 19300, Loss: 0.0000
Epoch 19400, Loss: 0.0000
Epoch 19500, Loss: 0.0000
Epoch 19600, Loss: 0.0000
Epoch 19700, Loss: 0.0000
Epoch 19800, Loss: 0.0000
Epoch 19900, Loss: 0.0000
Predictions: [[0.00424371 0.99688135 0.99530621 0.00330101]]
```