Machine Learning
Experiment 6

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AIM

To implement Backpropagation.

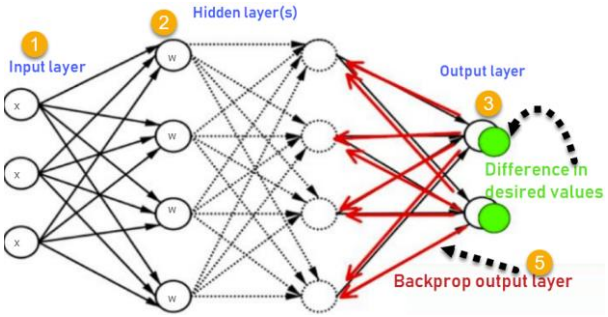
THEORY

A neural network is a group of connected I/O units where each connection has a weight associated with its computer programs. It helps you to build predictive models from large databases. This model builds upon the human nervous system. It helps you to conduct image understanding, human learning, computer speech, etc.

Backpropagation is the essence of neural network training. It is the method of fine-tuning the weights of a neural network based on the error rate obtained in the previous epoch (i.e., iteration). Proper tuning of the weights allows you to reduce error rates and make the model reliable by increasing its generalization.

Backpropagation in neural network is a short form for “backward propagation of errors.” It is a standard method of training artificial neural networks. This method helps calculate the gradient of a loss function with respect to all the weights in the network.

The working -



1. Inputs X, arrive through the preconnected path
2. Input is modeled using real weights W. The weights are usually randomly selected.
3. Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
4. Calculate the error in the outputs

   ErrorB = Actual Output – Desired Output
5. Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased.

Keep repeating the process until the desired output is achieved.

Advantages of Backpropagation

- It is fast, simple, and easy to program.
- It has no parameters to tune apart from the numbers of input.
- It is a flexible method as it does not require prior knowledge about the network.

CODE

```
import numpy as np

class NeuralNetwork:
  def _init_(self, input_dim, hidden_dim, output_dim):
     self.input_dim = input_dim
     self.hidden_dim = hidden_dim
     self.output_dim = output_dim

     # Initialize weights and biases
     self.weights1 = np.random.randn(self.input_dim, self.hidden_dim)
     self.bias1 = np.random.randn(self.hidden_dim)
     self.weights2 = np.random.randn(self.hidden_dim, self.output_dim)
     self.bias2 = np.random.randn(self.output_dim)

  def sigmoid(self, z):
     return 1/(1+np.exp(-z))

  def sigmoid_derivative(self, z):
     return z * (1 - z)

  def train(self, X, y, epochs):
     for i in range(epochs):
       # Forward propagation
       z1 = np.dot(X, self.weights1) + self.bias1
       hidden_layer = self.sigmoid(z1)
       z2 = np.dot(hidden_layer, self.weights2) + self.bias2
       output_layer = self.sigmoid(z2)

       # Backpropagation
       output_error = y - output_layer
       output_delta = output_error * self.sigmoid_derivative(output_layer)
       hidden_error = np.dot(output_delta, self.weights2.T)
       hidden_delta = hidden_error * self.sigmoid_derivative(hidden_layer)

       # Update the weights and biases
```

```
        self.weights2 += np.dot(hidden_layer.T, output_delta)
        self.bias2 += np.sum(output_delta, axis=0)
        self.weights1 += np.dot(X.T, hidden_delta)
        self.bias1 += np.sum(hidden_delta, axis=0)

        # Print the loss every 100 epochs
        if i % 100 == 0:
            loss = np.mean(np.square(y - output_layer))
            print(f"Epoch {i}: Loss = {loss}")

    def predict(self, X):
        # Make a prediction for a new input
        z1 = np.dot(X, self.weights1) + self.bias1
        hidden_layer = self.sigmoid(z1)
        z2 = np.dot(hidden_layer, self.weights2) + self.bias2
        output_layer = self.sigmoid(z2)

        return output_layer

# Create a dataset
X = np.array([[0,0,1], [0,1,1], [1,0,1], [1,1,1]])
y = np.array([[0], [1], [1], [0]])

# Create a neural network with 3 input nodes, 4 hidden nodes, and 1 output node
nn = NeuralNetwork()
nn._init_(3, 4, 1)

# Train the neural network for 1000 epochs
nn.train(X, y, 1000)

# Make a prediction for a new input
new_input = np.array([[1, 0, 0]])
print(nn.predict(new_input))
```

OUTPUT

```
Epoch 0: Loss = 0.3874651821847994
Epoch 100: Loss = 0.22308014757336586
Epoch 200: Loss = 0.06550820285020104
Epoch 300: Loss = 0.01803979072695123
Epoch 400: Loss = 0.008996793353942182
Epoch 500: Loss = 0.00574453349169824
Epoch 600: Loss = 0.004145272677354018
Epoch 700: Loss = 0.003212858570125505
Epoch 800: Loss = 0.002608610663163388
Epoch 900: Loss = 0.0021879221875389784
[[0.23915884]]
```

CONCLUSION

Hence, we have successfully implemented Backpropagation.