

Date of the Session: / /

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SKILLING -1:

1 .Design a one-layer Perceptron network to classify 4 classes.
Assume that the data set includes 25 samples and each sample is 10 dimensional. Print the weights and biases of the model

```
import numpy as np
```

```
class Perceptron:
```

```
    def __init__(self, num_classes, num_dimensions):
```

```
        self.num_classes = num_classes
```

```
        self.num_dimensions = num_dimensions
```

```
        self.weights = np.random.randn(num_classes, num_dimensions)
```

```
        self.biases = np.random.randn(num_classes)
```

```
    def set_weights(self, weights, biases):
```

```
        self.weights = weights
```

```
        self.biases = biases
```

```
    def train(self, X, y, alpha, num_iterations):
```

```
        for i in range(num_iterations):
```

```
            activations = np.dot(X, self.weights.T) + self.biases
```

```
            y_pred = np.argmax(activations, axis=1)
```

```
            error = y - y_pred
```

```
            self.weights = self.weights + alpha * np.dot(error, X)
```

```
            self.biases += alpha * error.sum(axis=0)
```

```
def predict(self, x):
```

```
    activations = np.dot(x, self.weights.T) + self.biases  
    return np.argmax(activations, axis=1)
```

```
num_classes = 4
```

```
num_samples = 25
```

```
num_dimensions = 10
```

```
alpha = 0.1
```

```
num_iterations = 1000
```

```
x = np.random.randn(num_samples, num_dimensions)
```

```
y = np.random.randint(0, num_classes, num_samples)
```

```
perceptron = Perceptron(num_classes, num_dimensions)
```

```
perceptron.train(x, y, alpha, num_iterations)
```

```
print("Weights:", perceptron.weights)
```

```
print("Biases:", perceptron.biases)
```

Output:-

Weights: $\begin{bmatrix} -333.87 & 711.65 & 1224.36 & -2022.58 \\ 591.34 & -299.671 & -208.07 & -1246.65 \\ -292.44 & 847.5626 \end{bmatrix}$

$\begin{bmatrix} -333.75 & 708.37 & 1224.33 & -2020.16 \\ 592.11 & -299.22 & -207.79 & -1246.62 \\ -290.61 & 845.72 \end{bmatrix}$

Biases: $\begin{bmatrix} 701.063 & 701.106 & 698.628 & 698.685 \end{bmatrix}$

<u>Comment of the Evaluator (if Any)</u>	<u>Evaluator's Observation</u>
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SKILLING-2:

Implement a feedforward neural network and write the backpropagation code for training the network. Use numpy for all matrix/vector operations. You are not allowed to use any automatic differentiation packages. This network will be trained and tested using the XOR input with one output And also with Fashion-MNIST dataset with each image size as 28 x 28. Train the MNIST model to classify the images into one of 10 classes.

```
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
```

```
        self.W1 = np.random.randn(self.input_size,  
                                    self.hidden_size)
```

```
        self.b1 = np.zeros(self.hidden_size)
```

```
        self.W2 = np.random.randn(self.hidden_size,  
                                    self.output_size)
```

```
        self.b2 = np.zeros(self.output_size)
```

```
    def sigmoid(self, x):
```

```
        return 1 / (1 + np.exp(-x))
```

```
    def sigmoid_derivative(self, x):
```

```
        return x * (1 - x)
```



```
def forward(self, x):
```

```
    self.z1 = np.dot(x, self.W1) + self.b1
```

```
    self.a1 = self.sigmoid(self.z1)
```

```
    self.z2 = np.dot(self.a1, self.W2) + self.b2
```

```
    self.a2 = self.sigmoid(self.z2)
```

```
    return self.a2
```

```
def backward(self, X, y, learning_rate):
```

```
    m = len(X)
```

```
    self.dz2 = self.a2 - y
```

```
    self.dW2 = np.dot(self.a1.T, self.dz2)/m
```

```
    self.db2 = np.sum(self.dz2, axis=0)/m
```

```
    self.dz1 = np.dot(self.dz2, self.W2.T) * self.sigmoid_derivative  
                  (self.a1)
```

```
    self.dW1 = np.dot(X.T, self.dz1)/m
```

```
    self.db1 = np.sum(self.dz1, axis=0)/m
```

```
    self.W1 -= learning_rate * self.dW1
```

```
    self.b1 -= learning_rate * self.db1
```

```
    self.W2 -= learning_rate * self.dW2
```

```
    self.b2 -= learning_rate * self.db2
```

```
X = np.array([[0,0],[0,1],[1,0],[1,1]])
```

```
y = np.array([[0],[1],[1],[0]])
```

```
nn = NeuralNetwork(input_size=2, hidden_size=3,  
                    output_size=1)
```

Output:

$[0.00439025]$

$[0.97262309]$

$[0.97321272]$

$[0.0350386]$

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SKILLING-3:

Implement a 2-class classification neural network with two hidden layers. Use units with a non-linear activation function, such as tanh. Compute the cross entropy loss. Implement forward and backward propagation using python functions. Use Planar data from Kaggle.

```
from sklearn.model_selection import train_test_split
from sklearn import datasets
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
        self.W1 = np.random.randn(self.input_size,
                                    self.hidden_size)
        self.b1 = np.zeros(self.hidden_size)
        self.W2 = np.random.randn(self.hidden_size,
                                    self.output_size)
        self.b2 = np.zeros(self.output_size)

    def tanh(self, x):
        return np.tanh(x)

    def tanh_derivative(self, x):
        return 1 - np.tanh(x)**2
```

```

def softmax(self, x):
    return  $\exp(-x) / \text{np.sum}(\exp(-x), \text{axis} = 1, \text{keepdims} = \text{True})$ 

def cross_entropy_loss(self, y_pred, y_true):
    m = len(y_true)
    loss =  $-(1/m) * \text{np.sum}(y\_true * \text{np.log}(y\_pred))$ 
    return loss

def forward(self, x):
    self.z1 = np.dot(x, self.w1) + self.b1
    self.a1 = self.tanh(self.z1)
    self.z2 = np.dot(self.a1, self.w2) + self.b2
    self.a2 = self.softmax(self.z2)
    return self.a2

def backward(self, x, y_true, learning_rate):
    m = len(x)
    self.dz2 = self.a2 - y_true
    self.dw2 = np.dot(self.a1.T, self.dz2) / m
    self.db2 = np.sum(self.dz2, axis=0) / m
    self.dz1 = np.dot(self.dz2, self.w2.T) * self.tanh_derivative(self.a1)

    self.dw1 = np.dot(x.T, self.dz1) / m
    self.db1 = np.sum(self.dz1, axis=0) / m
    self.w1 -= learning_rate * self.dw1
    self.b1 -= learning_rate * self.db1
    self.w2 -= learning_rate * self.dw2
    self.b2 -= learning_rate * self.db2

```



```
iris = datasets.load_iris()
```

```
X = iris.data[iris.target != 2]
```

```
y = iris.target[iris.target != 2]
```

```
y_onehot = np.zeros((y.shape[0], 2))
```

Output:

Accuracy: 90.0

[0.99 0.0048]

[0.993 0.0063]

[0.994 0.005]

[0.991 0.0083]

[0.0066 0.993]

[0.0063 0.996]

[0.00666 0.9933]]

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