MACHINE LEARNING LAB-5

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1. MULTI LAYER PERCEPTRON:

Importing the required libraries.

```
[1]: import numpy as np
[2]: def sigmoid (x):
    return 1/(1 + np.exp(-x))

[3]: def sigmoid_derivative(x):
    return x * (1 - x)
```

```
def mlp(inputs,expected_output,epochs=10000,lr=0.5,inputLayerNeurons=2,hiddenLayerNeurons=2,outputLayerNeurons=1):
    hidden weights = np.random.uniform(size=(inputLayerNeurons, hiddenLayerNeurons))
   hidden_bias =np.random.uniform(size=(1,hiddenLayerNeurons))
    output weights = np.random.uniform(size=(hiddenLayerNeurons,outputLayerNeurons))
    output_bias = np.random.uniform(size=(1,outputLayerNeurons))
    print("Initial hidden weights: ",end='')
    print(*hidden_weights)
   print("Initial hidden biases: ",end='')
    print(*hidden bias)
    print("Initial output weights: ",end='')
   print(*output_weights)
    print("Initial output biases: ",end='')
    print(*output_bias)
    for _ in range(epochs):
        hidden_layer_activation = np.dot(inputs, hidden_weights)
       hidden_layer_activation += hidden_bias
        hidden_layer_output = sigmoid(hidden_layer_activation)
        output_layer_activation = np.dot(hidden_layer_output,output_weights)
        output layer activation += output bias
        predicted_output = sigmoid(output_layer_activation)
        error = expected_output - predicted_output
        d_predicted_output = error * sigmoid_derivative(predicted_output)
        error_hidden_layer = d_predicted_output.dot(output_weights.T)
        d_hidden_layer = error_hidden_layer * sigmoid_derivative(hidden_layer_output)
        output_weights += hidden_layer_output.T.dot(d_predicted_output) * lr
        output_bias += np.sum(d_predicted_output,axis=0,keepdims=True) * lr
        hidden_weights += inputs.T.dot(d_hidden_layer) * lr
        hidden bias += np.sum(d hidden layer,axis=0,keepdims=True) * lr
    return hidden_weights, hidden_bias, output_weights, output_bias, predicted_output
```

Random array is created and MLP is applied to it.

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

hidden_weights,hidden_bias,output_weights,output_bias,predicted_output = mlp(inputs,expected_output)

Initial hidden weights: [0.09069827 0.64224379] [0.46950825 0.27398655]
Initial hidden biases: [0.06397014 0.94643633]
Initial output weights: [0.81775456] [0.53614158]
Initial output biases: [0.21095038]
```

```
7]: print("Final hidden weights: ",end='')
    print(hidden_weights)
    print("Final hidden bias: ",end='')
    print(hidden_bias)
    print("Final output weights: ",end='')
    print(output_weights)
    print("Final output bias: ",end='')
    print(output_bias)
    Final hidden weights: [[4.58927602 6.44884421]
     [4.59113773 6.45643385]]
    Final hidden bias: [[-7.04340524 -2.8635691 ]]
    Final output weights: [[-10.25943731]
     [ 9.57294339]]
    Final output bias: [[-4.43135451]]
8]: print("\nOutput from neural network after 10,000 epochs: ",end='')
    print(predicted_output)
    Output from neural network after 10,000 epochs: [[0.01938924]
     [0.9832398]
     [0.98323143]
     [0.01737316]]
```

The accuracy is been calculated.

2. MULTI LAYER PERCEPTRON USING XOR:

Importing the required libraries.

If the input patterns for XOR gate are plotted according to their outputs, it is seen that these points are not linearly separable. Hence the neural network has to be modeled to separate these input patterns using decision planes. This is achieved by using the concept of hidden layers. To Implement XOR gate, we will be using a Sigmoid Neuron as nodes in the neural network.

```
import numpy as np
import pandas as pd
data = pd.read_csv("diabetes2.csv")
data = data.sample(frac=1).reset_index(drop=True)
data.head()
   Pregnancies Glucose
                        BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome
0
                    159
                                                              27.4
                                    64
                                                                                       0.294
                                                                                               40
                                                                                                          0
1
                     95
                                    54
                                                  14
                                                          88
                                                              26.1
                                                                                       0.748
                                                                                               22
                                                                                                          0
2
                    105
                                   100
                                                  36
                                                              43.3
                                                                                       0.239
                                                                                               45
                                                           0
                                                                                                          1
                     94
3
                                    70
                                                  27
                                                              43.5
                                                                                       0.347
                                                                                               21
                                                                                                          0
                                                         115
4
             0
                                                           0 35.8
                                                                                       0.238
                     86
                                    68
                                                  32
                                                                                               25
                                                                                                          0
```

The data is converted into array.

```
X = np.array(data)[:,1:-1]

print(X)

[[1.59e+02 6.40e+01 0.00e+00 ... 2.74e+01 2.94e-01 4.00e+01]
  [9.50e+01 5.40e+01 1.40e+01 ... 2.61e+01 7.48e-01 2.20e+01]
  [1.05e+02 1.00e+02 3.60e+01 ... 4.33e+01 2.39e-01 4.50e+01]
  ...

[1.06e+02 7.00e+01 2.80e+01 ... 3.42e+01 1.42e-01 2.20e+01]
  [1.17e+02 6.20e+01 1.20e+01 ... 2.97e+01 3.80e-01 3.00e+01]
  [1.05e+02 7.20e+01 2.90e+01 ... 3.69e+01 1.59e-01 2.80e+01]]
```

The accuracy is been calculated:

```
print("Testing Accuracy: {}".format(Accuracy(X_test, Y_test, weights, display = True)))
Input:
 [96.
        64.
              27. 87. 33.2
                                0.289 21.
Predicted:
[1, 0]
Actual:
 [1.0, 0.0]
Input:
                 0. 0. 38.5 0.304 41. ]
 [129.
         0.
Predicted:
[1, 0]
Actual:
 [1.0, 0.0]
Input:
 [127.
          80.
                 37.
                       210.
                              36.3 0.804 23. ]
Predicted:
[1, 0]
Actual:
 [1.0, 0.0]
Input:
 [130.
        64.
                0. 0.
                               23.1
                                     0.314 22. ]
Predicted:
 [1, 0]
Actual:
 [1.0, 0.0]
```

Calculating the final weights

```
print("Final weights:\n",weights)
Final weights:
 [matrix([[ 0.96065986, 3.2871523 , -2.35888122, 0.03552078, 1.82221295
         -0.97423125, -0.02374021, -0.91763199],
        [ 0.84348617, 0.56375397, 0.37839956, 0.74503813, 0.85311255, -0.82999787, -0.50727101, 0.87742271],
        [ 0.08245552, -0.39162808, -0.66480653, 0.94276714, -0.97409234,
         0.51380313, 0.6632706, -0.83862125],
        \hbox{$[-0.46873168,\ -0.80135391,\ 0.6174883\ ,\ -0.48937134,\ -0.73985205,}
         0.48861742, 0.08603182, -0.67767906],
        [ 0.07821509, 1.18252925, 1.08735476, -0.70994612, 0.41087396,
         -0.13666399, 0.06100686, 0.96486982]]), matrix([[ 0.52076355, -
         1.70253029],
        [-1.36121246, 2.52312713, -0.23143287, -0.6928267, 2.6383596,
         -1.56783576]])]
from sklearn.preprocessing import OneHotEncoder
one_hot_encoder = OneHotEncoder(sparse=False,categories='auto')
Y = np.array(data)[:,-1]
Y = one_hot_encoder.fit_transform(np.array(Y).reshape(-1, 1))
```

```
from sklearn.model selection import train test split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25)
def NeuralNetwork(X_train, Y_train, X_val=None, Y_val=None, epochs=10, nodes=[], lr=0.07):
    hidden_layers = len(nodes) - 1
    weights = InitializeWeights(nodes)
    for epoch in range(1, epochs+1):
        weights = Train(X_train, Y_train, lr, weights)
        if(epoch % 50 == 0):
            print("Epoch {}".format(epoch))
            print("Training Accuracy:{}".format(Accuracy(X_train, Y_train, weights)))
            if X_val is not None:
                print("Validation Accuracy:{}".format(Accuracy(X_val, Y_val, weights)))
    return weights
def InitializeWeights(nodes):
    layers = len(nodes)
    weights = []
    for i in range(1, layers):
        w = [[np.random.uniform(-1, 1) for k in range(nodes[i-1] + 1)]
              for j in range(nodes[i])]
        weights.append(np.matrix(w))
    return weights
def ForwardPropagation(x, weights, layers):
    activations, layer_input = [x], x
    for j in range(layers):
        activation = Sigmoid(np.dot(layer_input, weights[j].T))
        activations.append(activation)
        layer_input = np.append(1, activation)
    return activations
def BackPropagation(y, activations, weights, layers):
    outputFinal = activations[-1]
    error = np.matrix(y - outputFinal)
    for j in range(layers, 0, -1):
```

currActivation = activations[j]

prevActivation = activations[0]

w = np.delete(weights[j-1], [0], axis=1)

error = np.dot(delta, w)

prevActivation = np.append(1, activations[j-1])

delta = np.multiply(error, SigmoidDerivative(currActivation))
weights[j-1] += lr * np.multiply(delta.T, prevActivation)

if(j > 1):

else:

return weights

```
def Train(X, Y, lr, weights):
   layers = len(weights)
   for i in range(len(X)):
       x, y = X[i], Y[i]
       x = np.matrix(np.append(1, x))
       activations = ForwardPropagation(x, weights, layers)
       weights = BackPropagation(y, activations, weights, layers)
   return weights
def Sigmoid(x):
    return 1.0 / (1.0 + np.exp(-x))
def SigmoidDerivative(x):
   return np.multiply(x, 1.0-x)
def Predict(item, weights):
   layers = len(weights)
   item = np.append(1, item)
   activations = ForwardPropagation(item, weights, layers)
   outputFinal = activations[-1].A1
   m, index = outputFinal[0], 0
   for i in range(1, len(outputFinal)):
       if(outputFinal[i] > m):
            m, index = outputFinal[i], i
   y = [0 for i in range(len(outputFinal))]
   y[index] = 1
    return y
```

```
def Accuracy(X, Y, weights, display=False):
    correct = 0

for i in range(len(X)):
        x, y = X[i], list(Y[i])
        guess = Predict(x, weights)
        if display == True:
            print("\n\nInput:\n",x,"\nPredicted:\n",guess,"\nActual:\n",y)
        if(y == guess):
            correct += 1
        elif display == True:
            print("mispredicted")

return correct / len(X)
```

```
layers = [len(X[0]),5,len(Y[0])]
 print(layers)
 lr, epochs = 0.1,1000
 weights = NeuralNetwork(X_train, Y_train, epochs=epochs, nodes=layers, lr=lr)
 /srv/conda/envs/notebook/lib/python3.7/site-packages/ipykernel_launcher.py:2:
 [7, 5, 2]
 Epoch 50
 Training Accuracy: 0.6475694444444444
 Epoch 100
 Training Accuracy: 0.6475694444444444
 Epoch 150
 Training Accuracy: 0.6475694444444444
 Epoch 200
 Training Accuracy: 0.6475694444444444
 Epoch 250
 Training Accuracy: 0.6475694444444444
 Epoch 300
 Training Accuracy: 0.6475694444444444
 Epoch 350
 Training Accuracy: 0.6475694444444444
 Epoch 400
 Training Accuracy: 0.6475694444444444
 Epoch 450
 Training Accuracy: 0.6475694444444444
 Epoch 500
print("Final weights:\n",weights)
Final weights:
[matrix([[ 0.96065986, 3.2871523 , -2.35888122, 0.03552078, 1.82221295
        -0.97423125, -0.02374021, -0.91763199],
        [ 0.84348617, 0.56375397, 0.37839956, 0.74503813, 0.85311255,
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        [ 0.08245552, -0.39162808, -0.66480653,  0.94276714, -0.97409234,
          0.51380313, 0.6632706, -0.83862125],
        [-0.46873168, -0.80135391, 0.6174883 , -0.48937134, -0.73985205,
         0.48861742, 0.08603182, -0.67767906],
        [ 0.07821509, 1.18252925, 1.08735476, -0.70994612, 0.41087396,
```

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[-1.36121246, 2.52312713, -0.23143287, -0.6928267 , 2.6383596 ,

1.70253029],

-1.56783576]])]

```
Input:
            27. 87. 33.2 0.289 21. ]
[96.
      64.
Predicted:
[1, 0]
Actual:
[1.0, 0.0]
Input:
[129. 0. 0. 0. 38.5 0.304 41. ]
Predicted:
[1, 0]
Actual:
[1.0, 0.0]
Input:
[127.
               37. 210. 36.3 0.804 23. ]
        80.
Predicted:
[1, 0]
Actual:
[1.0, 0.0]
Input:
[130. 64. 0. 0. 23.1 0.314 22. ]
Predicted:
[1, 0]
Actual:
[1.0, 0.0]
import sklearn
Y_result = []
for x in X_test:
   guess = Predict(x,weights)
   Y_result.append(guess)
print("R2 score : %f" % sklearn.metrics.r2_score(Y_test,Y_result))
R2 score : -0.511811
```

print("Testing Accuracy: {}".format(Accuracy(X_test, Y_test, weights, display = True)))