Homework-5

Code for home grown fully connected multi-layer backpropagation network:

```
import numpy as np
from random import *
def sigmoid(x):
    return 1.0/(1.0 + np.exp(-x))
def sigmoid_prime(x):
    return sigmoid(x)*(1.0-sigmoid(x))

def compute_cost(A, Y):
    cost = np.multiply(np.log(A), Y) + np.multiply((1 - Y), np.log(1 - A))
    cost = -1 * cost
    cost = np.squeeze(cost)
    return cost

def CrossEntropy(yhat, y):
#     if y == 1:
#       return -np.log(yHat)+dummy
#     else:
#       return np.log(1 - yHat)
    res = -y/yhat + (1-y)/(1-yhat)
    if abs(res) < 0.1:
      return 0
    else:
      return -1*res
class NeuralNetwork:

    def __init__(self, layers, activation='sigmoid'):
        if activation == 'sigmoid':
            self.activation = sigmoid
            self.activation_prime = sigmoid_prime
            self.cost = compute_cost
            self.ce = CrossEntropy
        self.weights = []
#         layers = [2,2,1]
#         range of weight values (-1,1)
        # input and hidden layers - random((2+1, 2+1)) : 3 x 3
        for i in range(1, len(layers) - 1):
            r = 2*np.random.random((layers[i-1] + 1, layers[i] + 1)) -1
            self.weights.append(r)
        # output layer - random((2+1, 1)) : 3 x 1
        r = 2*np.random.random( (layers[i] + 1, layers[i+1])) - 1
        self.weights.append(r)

    def fit(self, X, y, learning_rate=0.2, epochs=100000):
          # Add column of ones to X
```

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          # This is to add the bias unit to the input layer
          ones = np.atleast_2d(np.ones(X.shape[0]))
          X = np.concatenate((ones.T, X), axis=1)
          arr = []

          for k in range(epochs):
            if k % 10000 == 0: print('epochs:', k)

            i = np.random.randint(X.shape[0])
            a = [X[i]]
            arr=[X[i]]

            for l in range(len(self.weights)):
                dot_value = np.dot(a[l], self.weights[l])
                arr.append(dot_value)
                activation = self.activation(dot_value)
                a.append(activation)
              # output layer
#           error = y[i] - a[-1]
#           error = self.cost(a[-1], y[i])
            error  = self.ce(a[-1], y[i])
            deltas = [error * self.activation_prime(arr[-1])]

              # we need to begin at the second to last layer
              # (a layer before the output layer)
            for l in range(len(a) - 2, 0, -1):
                deltas.append(deltas[-
1].dot(self.weights[l].T)*self.activation_prime(arr[l]))

              # reverse
              # [level3(output)->level2(hidden)]  => [level2(hidden)-
>level3(output)]
            deltas.reverse()

              # backpropagation
              # 1. Multiply its output delta and input activation
              #    to get the gradient of the weight.
              # 2. Subtract a ratio (percentage) of the gradient from the
weight.
            for i in range(len(self.weights)):
                layer = np.atleast_2d(a[i])
                delta = np.atleast_2d(deltas[i])
                self.weights[i] += learning_rate * layer.T.dot(delta)

#           print(np.max(arr))

    def predict(self, x):
        a = np.concatenate((np.ones(1).T, np.array(x)))
```

```
        for l in range(0, len(self.weights)):
            a = self.activation(np.dot(a, self.weights[l]))
        return a

nn = NeuralNetwork([2,3,3,1])
inp_class1=[[1,0],[-1,0]]
inp_class2=[[0,1],[0,-1]]
out_class1=[0,0]
out_class2=[1,1]
for i in range(0,48):
    x=uniform(1,10)
    y=uniform(-1,0)
    a=uniform(-1,0)
    b=uniform(1,10)
    foo=[x,y]
    foo1=[a,b]
    inp_class1.append(foo)
    out_class1.append(0)
    inp_class2.append(foo1)
    out_class2.append(1)
inp=inp_class1+inp_class2
out=out_class1+out_class2
X = np.array(inp)
y = np.array(out)
nn.fit(X, y)
for e in X:
  print(e,nn.predict(e))
print("The weights are:")
print(nn.weights)
```

1.100% classification was achieved with as much as just 1 hidden layer. Subsequent hidden layers also performed the same. So using a single hidden layer was enough to obtain 100% classification. Three hidden units per layer were used for all layers.

2.The weights that were learned after the final epoch to achieve 100% classification using 1 hidden layer was:

```
The weights are:
[array([[ 3.4567762 , -3.76820817,  3.25401411,  4.73080111],
       [ 0.45141204,  0.34519883, -0.39284026, -4.9277709 ],
       [ 6.40775739,  5.61454257, -4.21068074, -0.13569049]]), array([[-8.98417619],
       [ 8.08000711],
       [-5.40810615],
       [ 9.76937696]])]
```

Keeping learning rate=0.2 and epochs=100000, the sigmoidal slope parameter(beta) was varied.

Beta	Accuracy
0.1	98%
0.3	98%
0.5	98%
1	100%

Keeping Beta = 1 and epochs =100000, learning rate(alpha) was varied.

Alpha	Accuracy
0.01	98%
0.1	98%
0.15	98%
0.2	100%

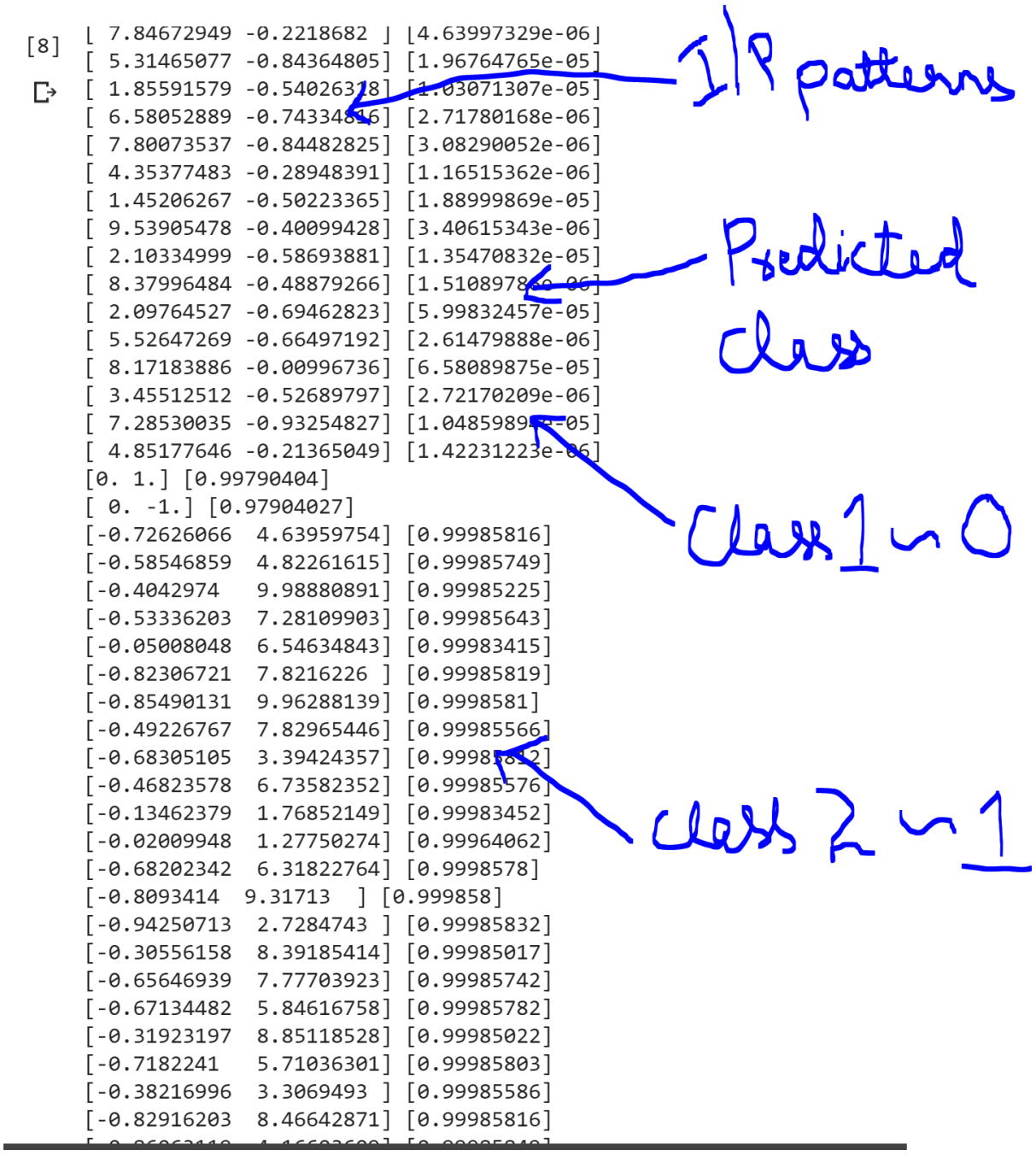
Keeping Beta=1 and learning rate(alpha)=0.2, epochs were varied.

Epochs	Accuracy
10000	98%
30000	98%
50000	98%
100000	100%

Therefore the optimal solution to obtain 100% classification was

Beta	Alpha	Epochs
1	0.2	100000

Output for the above code(only a part of it is shown):



Input Patterns are on the left side with their predicted class labels. Here we attribute values approximately equal to 0 as belonging to Class 1 and values approximately equal to 1 as belonging to Class 2.

Code for the same implementation using Keras/Tensorflow:

```
import numpy as np
from random import *
from keras.models import Sequential
from keras.layers.core import Dense
inp_class1=[[1,0],[-1,0]]
inp_class2=[[0,1],[0,-1]]
out_class1=[0,0]
out_class2=[1,1]
for i in range(0,48):
  x=uniform(1,10)
  y=uniform(-1,0)
  a=uniform(-1,0)
  b=uniform(1,10)
  foo=[x,y]
  foo1=[a,b]
  inp_class1.append(foo)
  out_class1.append(0)
  inp_class2.append(foo1)
  out_class2.append(1)
inp=inp_class1+inp_class2
out=out_class1+out_class2
X = np.array(inp)
y = np.array(out)
training_data = np.array(X, "float32")
target_data = np.array(y, "float32")

model = Sequential()
model.add(Dense(3, input_dim=2, activation='sigmoid'))
model.add(Dense(3, input_dim=2, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['binary_accuracy'])

model.fit(training_data, target_data, nb_epoch=500, verbose=2)

print(model.predict(training_data).round())
```

In comparison to the homegrown neural network, the keras implementation achieved 100% classification at epochs=500, learning rate=0.2.