NN-3Layers

June 26, 2018

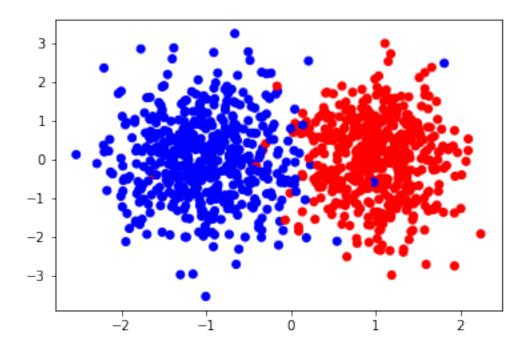
1 Programming Assignment - 1

Subdivision 3,4,5,7 Goals: 1) Implement a 3 layer NN (1 hidden layer) 2) Train the model with linear data 3) Visualize the decision boundary learned by this model 4) Train this model on non-linear data 5) Visualize the decision boundary learned by this model 6) Visualize the effect of learning rate on NN 7) Tabularize the effect of number of nodes in the hidden layer 8) L2 Regularization

```
In [ ]: # Import Python libraries
        import numpy as np
        import matplotlib.pyplot as plt
        import copy as cpy
        import pandas as pd
        import time as tm
  #1) Implement a 3 layer NN (1 hidden layer)
In [72]: class NeuralNetwork 3layer:
             This module implements a Neural Netowrk with hidden layers.
             def __init__(self, input_dim, hidden_dim, output_dim):
                 self.W1 = (np.random.randn(input_dim+1, hidden_dim))/np.sqrt(input_dim)
                 self.W2 = (np.random.randn(hidden_dim+1, output_dim))/np.sqrt(hidden_dim)
                 \#self.exp\_v = np.vectorize(lambda x : math1.e ** x)
             def compute_cost(self,X,y):
                 num_examples = np.shape(X)[0]
                 a1 = np.append(np.ones([len(X),1]),X,1)
                 z1 = np.dot(a1, self.W1)
                 \#exp_z1 = math1.e**(z1)
                 exp_z1 = np.exp((-1)*z1)
                 x2 = (1.)/(1 + \exp z1)
                 a2 = np.append(np.ones([len(x2),1]),x2,1)
                 z2 = np.dot(a2, self.W2)
                 \#exp_z2 = math1.e**(z2)
                 exp z2 = np.exp(z2)
                 softmax_scores = exp_z2 / np.sum(exp_z2, axis=1, keepdims=True)
```

```
\#exp_z2 = np.exp((-1)*z2)
          \#softmax\_scores = 1./(exp\_z2 + 1)
          one_hot_y = np.zeros((num_examples,np.max(y)+1))
          logloss = np.zeros((num_examples,))
          for i in range(np.shape(X)[0]):
                    one_hot_y[i,y[i]] = 1
                    logloss[i] = -np.sum(np.log(softmax_scores[i,:]) * one_hot_y[i,:])
          data_loss = np.sum(logloss)
          return 1./num_examples * data_loss
def predict(self,X):
         a1 = np.append(np.ones([len(X),1]),X,1)
         z1 = np.dot(a1,self.W1)
          \#exp_z1 = self.exp_v((-1)*z1)
         \exp_z1 = np.exp((-1)*z1)
         x2 = (1.)/(1 + exp_z1)
         a2 = np.append(np.ones([len(x2),1]),x2,1)
         z2 = np.dot(a2,self.W2)
          \#exp_z2 = self.exp_v((-1)*z2)
          exp_z2 = np.exp(z2)
          softmax_scores = exp_z2 / np.sum(exp_z2, axis=1, keepdims=True)
          \#exp_z2 = np.exp((-1)*z2)
          \#softmax\_scores = 1./(exp\_z2 + 1)
          predictions = np.argmax(softmax_scores, axis = 1)
         return predictions
def plot_learningRate(self, X, y, num_epochs, alpha, lambda1):
          #Error in each epoch:
          Error = np.zeros(num_epochs,)
         for epoch in range(0, num_epochs):
                    self.one_epoch(X, y, alpha, lambda1)
                   p = self.predict(X)
                   Error[epoch] = 0.5*(np.sum((y-p)**2) + lambda1*(np.sum(self.W2**2)) + lambda1*(np.sum(self.
                    #print(Error)
          return Error
def one_epoch(self, X, y, alpha, lambda1):
          # Forward propagation
          a1 = np.append(np.ones([len(X),1]),X,1)
          z1 = np.dot(a1, self.W1)
          \#exp_z1 = self.exp_v((-1)*z1)
          exp_z1 = np.exp((-1)*z1)
         x2 = (1.)/(1 + exp_z1)
         a2 = np.append(np.ones([len(x2),1]),x2,1)
          z2 = np.dot(a2,self.W2)
          \#exp_z2 = self.exp_v((-1)*z2)
```

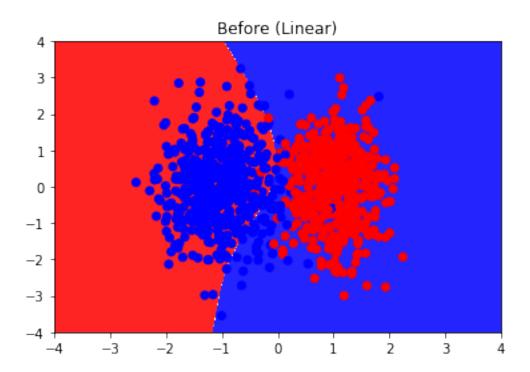
```
exp_z2 = np.exp(z2)
                 softmax_scores = exp_z2 / np.sum(exp_z2, axis=1, keepdims=True)
                 \#exp_z2 = np.exp((-1)*z2)
                 \#softmax\ scores = 1./\ (exp\ z2 + 1)
                 # Backpropagation
                 #compute gradients
                 Count_updates = 0
                 beta3 = np.zeros_like(softmax_scores)
                 one_hot_y = np.zeros_like(softmax_scores)
                 for i in range(X.shape[0]):
                     one_hot_y[i,y[i]] = 1
                 beta3 = softmax_scores - one_hot_y
                 gdash2 = np.multiply(x2,(1-x2))
                 beta2 = np.multiply(np.dot(beta3, np.transpose(self.W2[1:,:])) , gdash2)
                 #Update weights
                 updW2 = alpha * (np.dot(np.transpose(a2),beta3) + lambda1*self.W2)
                 updW1 = alpha * (np.dot(np.transpose(a1),beta2) + lambda1*self.W1)
                 self.W2 = self.W2 - updW2
                 self.W1 = self.W1 - updW1
                 Count_updates = Count_updates + (np.sum(updW1!=0) + np.sum(updW2!=0))
                 #print(epoch, self.W1, beta2)
                 return Count_updates
             def fit(self,X,y,num_epochs,alpha=0.01,lambda1=0):
                 #print(self.W1, self.W2)
                 for epoch in range(0, num_epochs):
                     count_upd = self.one_epoch(X, y, alpha, lambda1)
                 return count_upd
In [62]: X = np.genfromtxt('/Users/pavithraraghavan/Downloads/DATA/NonlinearX.csv', delimiter=
         y = np.genfromtxt('/Users/pavithraraghavan/Downloads/DATA/NonlinearY.csv', delimiter=
         from sklearn.model_selection import train_test_split
         Xtrain, Xtest, ytrain, ytest = train_test_split(X,y)
In [107]: def plot_decision_boundary(model, X, y, title, filename):
              x1_{array}, x2_{array} = np.meshgrid(np.arange(-4, 4, 0.01), np.arange(-4, 4, 0.01))
              grid_coordinates = np.c_[x1_array.ravel(), x2_array.ravel()]
              Z = model.predict(grid_coordinates)
              Z = Z.reshape(x1_array.shape)
              plt.contourf(x1_array, x2_array, Z, cmap=plt.cm.bwr)
              plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.bwr)
              plt.title(title)
              plt.savefig(filename)
              plt.show()
  Load Data (Linear)
```



```
In [112]: #Initialize model
    input_dim = np.shape(X)[1]
    output_dim = np.max(y) + 1
    hidden_dim = 10
    NN = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
```

In [113]: #Plot decision boundary

plot_decision_boundary(NN, X, y, 'Before (Linear)','/Users/pavithraraghavan/Documents



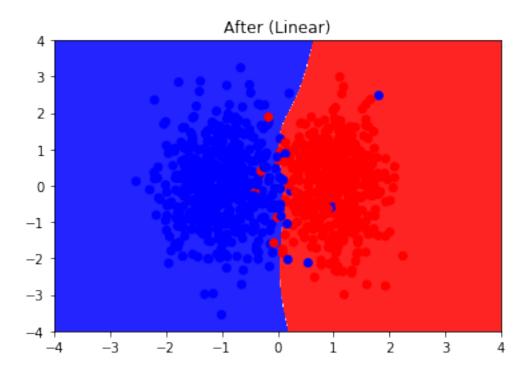
2 2)Training the Model with Linear data

In [114]: NN.fit(X,y,750,alpha=0.01, lambda1=0)

Out[114]: 52

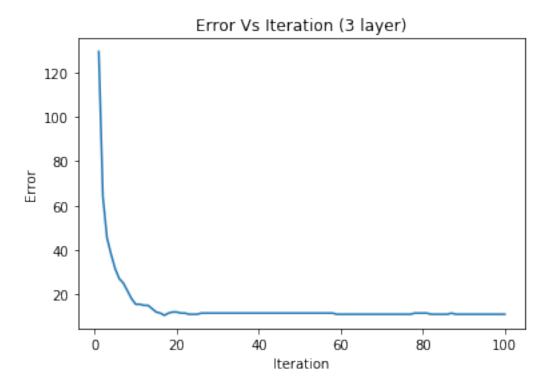
#3)Visualize & evaluate the decision boundary learned by this model

In [115]: #Plot decision boundary after training plot_decision_boundary(NN, X, y,'After (Linear)','/Users/pavithraraghavan/Documents.

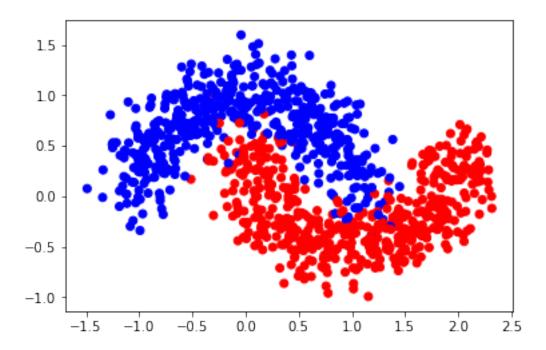


```
In [116]: #Compute accuracy and confusion matrix
          acc = 0
          y_pred = NN.predict(X)
          con_mat = np.zeros((output_dim, output_dim))
          for i in range(len(y_pred)):
              con_mat[y_pred[i], y[i]] += 1
              if y[i] == y_pred[i]:
                  acc += 1.0
          acc = acc/len(y_pred)
          print ('ACCURACY: ', acc)
          print ('CONFUSION MATRIX: \n', con_mat)
('ACCURACY: ', 0.983)
('CONFUSION MATRIX: \n', array([[492., 8.],
       [ 9., 491.]]))
In [142]: #Plot error w.r.t number of iterations, for different learning rates:
          x = np.linspace(1, 100, 100)
          input_dim = np.shape(X)[1]
          output_dim = np.max(y) + 1
          hidden_dim = 10
          NN1 = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
          Error = NN1.plot_learningRate(X,y,100, 0.001, lambda1=0)
          plt.plot(x, Error)
```

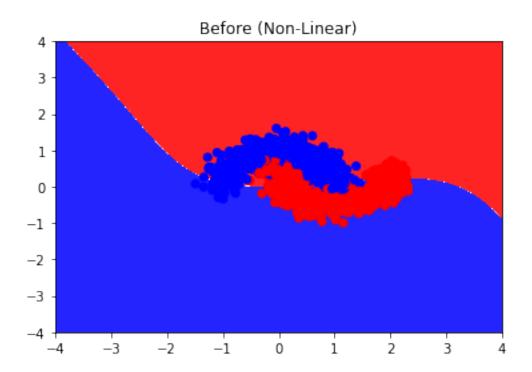
```
#print(Error)
#plt.legend(loc='best')
plt.xlabel('Iteration')
plt.ylabel('Error')
plt.title('Error Vs Iteration (3 layer)')
plt.savefig('/Users/pavithraraghavan/Documents/BU/2nd_sem/AI/P1/Plots/LR_Hidden.png')
plt.show()
```



Load Data (Non-Linear)



```
In [125]: #Initialize model
    input_dim = np.shape(X)[1]
    output_dim = np.max(y) + 1
    hidden_dim = 10
    NN = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
```



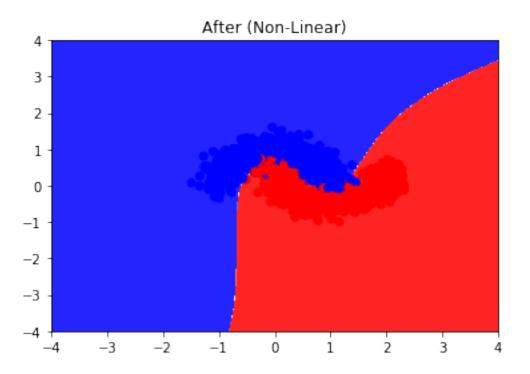
3 4)Training the Model with Non-Linear data

In [127]: NN.fit(X,y,1000,alpha=0.01, lambda1=0)

Out[127]: 52

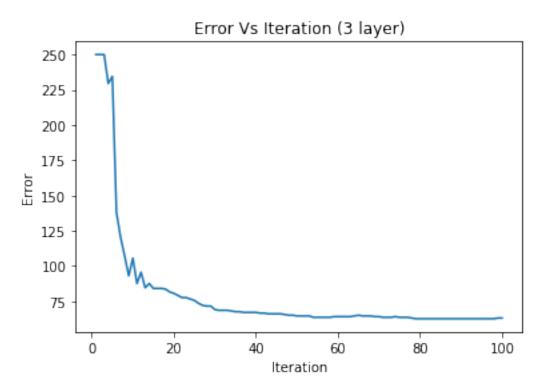
#5) Visualize and Evaluate decision boundary learned by this Model

In [128]: #Plot decision boundary after training plot_decision_boundary(NN, X, y,'After (Non-Linear)', '/Users/pavithraraghavan/Documents', '/Users/pavithrarag



```
In [17]: #Compute accuracy and confusion matrix
         acc = 0
         y_pred = NN.predict(X)
         con_mat = np.zeros((output_dim, output_dim))
         for i in range(len(y_pred)):
             con_mat[y_pred[i], y[i]] += 1
             if y[i] == y_pred[i]:
                 acc += 1.0
         print(acc)
         #print(np.sum(y_pred==y))
         acc = acc/len(y_pred)
         print ('ACCURACY: ', acc)
         print ('CONFUSION MATRIX: ')
         print(con_mat)
969.0
('ACCURACY: ', 0.969)
CONFUSION MATRIX:
[[483. 14.]
 [ 17. 486.]]
In [144]: #Plot error w.r.t number of iterations, for different learning rates:
          x = np.linspace(1, 100, 100)
          input_dim = np.shape(X)[1]
```

```
output_dim = np.max(y) + 1
hidden_dim = 10
NN1 = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
Error = NN1.plot_learningRate(X,y,100, 0.001, lambda1=0)
plt.plot(x, Error)
#print(Error)
#print(Error)
#plt.legend(loc='best')
plt.xlabel('Iteration')
plt.ylabel('Error')
plt.title('Error Vs Iteration (3 layer)')
plt.savefig('/Users/pavithraraghavan/Documents/BU/2nd_sem/AI/P1/Plots/LR_Hidden.png')
plt.show()
```

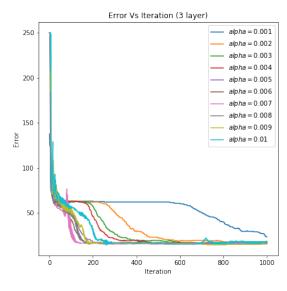


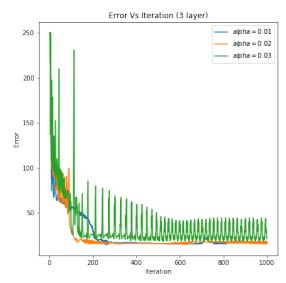
4 6) Effect of learning rate on NN

NN has 10 hidden layers

```
In [148]: #Plot error w.r.t number of iterations, for different learning rates:
    x = np.linspace(1, 1000, 1000)
    input_dim = np.shape(X)[1]
    output_dim = np.max(y) + 1
    hidden_dim = 10
    NN = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
```

```
f,ax = plt.subplots(1,2,figsize=(15,15))
for i in range(1, 11): #10 plots
    NN1 = cpy.deepcopy(NN)
    Error = NN1.plot_learningRate(X,y,1000, 0.001*i, lambda1=0)
    plt.subplot(221)
    plt.plot(x, Error, label='$alpha = {j}$'.format(j=0.001*i))
    #print(Error)
for i in range(1, 4): #10 plots
    NN1 = cpy.deepcopy(NN)
    Error = NN1.plot_learningRate(X,y,1000, 0.01*i, lambda1=0)
    plt.subplot(222)
    plt.plot(x, Error, label='$alpha = {j}$'.format(j=0.01*i))
plt.subplot(221)
plt.legend(loc='best')
plt.xlabel('Iteration')
plt.ylabel('Error')
plt.title('Error Vs Iteration (3 layer)')
plt.subplot(222)
plt.legend(loc='best')
plt.xlabel('Iteration')
plt.ylabel('Error')
plt.title('Error Vs Iteration (3 layer)')
plt.savefig('/Users/pavithraraghavan/Documents/BU/2nd_sem/AI/P1/Plots/LR_Hidden_new.
plt.show()
```





5 7) Effect of number of Hidden Layer nodes

Evaluation through Accuracy, Cost function, time elapsed and number of updates

```
In [149]: #for different number of nodes in the hidden layer:
          x = np.linspace(1, 1000, 1000)
          X = np.genfromtxt('/Users/pavithraraghavan/Downloads/DATA/NonlinearX.csv', delimiter
          y = np.genfromtxt('/Users/pavithraraghavan/Downloads/DATA/NonlinearY.csv', delimiter
          input_dim = np.shape(X)[1]
          output_dim = np.max(y) + 1
          display_mat = np.zeros([20,5]) #num of nodes, accuracy, cost, time, num of updates
          #print(display_mat)
          for i in range(0, 20): #20 plots
              hidden_dim = i+1
              NN = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
              start_time = tm.time()
              count_upd = NN.fit(X,y,1000, 0.01, 0)
              elapsed_time = tm.time() - start_time
              y_pred = NN.predict(X)
              display_mat[i,0] = i+1
              display_mat[i,1] = (np.sum(y_pred==y))*1. / len(y_pred)
              display_mat[i,2] = NN.compute_cost(X,y)
              display_mat[i,3] = elapsed_time
              display_mat[i,4] = count_upd
In [150]: #export matrix to csv
          pd.set_option('display.precision',5)
          df =pd.DataFrame(display_mat)
          df.columns = ['#Nodes','Accuracy','CostFunction','TimeElapsed','#Updates']
          df.style
          print(df)
          df.to_csv('/Users/pavithraraghavan/Documents/BU/2nd_sem/AI/P1/Plots/NodesNum.csv', e:
    #Nodes Accuracy CostFunction TimeElapsed #Updates
0
       1.0
               0.871
                           0.32527
                                         0.61274
                                                       7.0
                                                      12.0
1
       2.0
               0.887
                           0.32277
                                         1.04259
2
       3.0
               0.881
                           0.31302
                                         0.89794
                                                      17.0
3
       4.0
               0.965
                           0.08812
                                                      22.0
                                         0.85636
4
                                                      27.0
       5.0
               0.949
                           0.13034
                                         0.59349
5
       6.0
                           0.08321
                                                      32.0
               0.967
                                         0.61423
6
       7.0
                                                      37.0
               0.970
                           0.08226
                                         0.89329
7
       8.0
               0.965
                           0.08770
                                         0.79272
                                                      42.0
                                                      47.0
8
       9.0
               0.966
                           0.08741
                                         0.65206
9
      10.0
                                                      52.0
               0.969
                           0.07930
                                         0.70333
10
      11.0
               0.969
                           0.07901
                                         0.69074
                                                      57.0
11
     12.0
                                                      62.0
               0.966
                           0.08566
                                         0.85673
12
     13.0
               0.967
                           0.07928
                                         0.99102
                                                      67.0
13
      14.0
                           0.07828
                                         0.77222
                                                      72.0
               0.967
14
                                                      77.0
      15.0
               0.968
                           0.07905
                                         0.75163
```

15	16.0	0.965	0.08733	0.76503	82.0
16	17.0	0.968	0.07993	0.89266	87.0
17	18.0	0.969	0.07796	0.90861	92.0
18	19.0	0.966	0.08168	0.93453	97.0
19	20.0	0.967	0.07899	0.96632	102.0

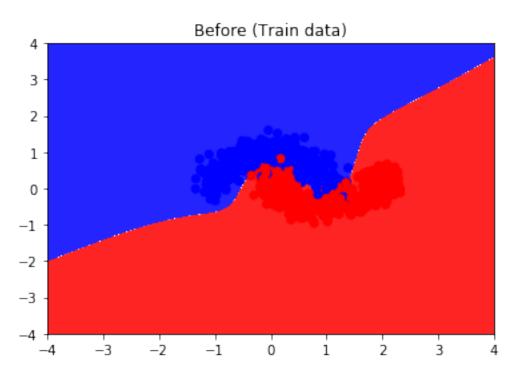
6 8) L2 Regularization

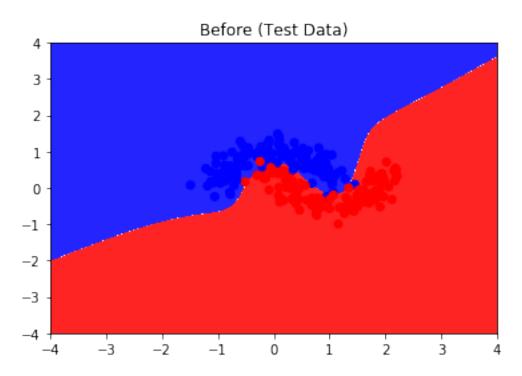
NN = NeuralNetwork_3layer(input_dim, hidden_dim, output_dim)
NN_L2 = cpy.deepcopy(NN)

In [131]: NN.fit(Xtrain,ytrain,1000,alpha=0.01, lambda1=0)

Out[131]: 102

In [132]: #Plot decision boundary after training plot_decision_boundary(NN, Xtrain, ytrain, 'Before (Train data)', '/Users/pavithrarag



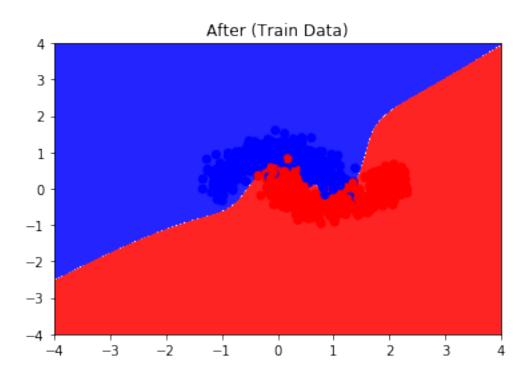


Training accuracy: 0.9627 Testing accuracy: 0.9800

In [135]: NN_L2.fit(Xtrain,ytrain,1000,alpha=0.01, lambda1=0.03)

Out[135]: 102

In [136]: #Plot decision boundary after training plot_decision_boundary(NN_L2, Xtrain, ytrain, 'After (Train Data)', '/Users/pavithrare





Training accuracy: 0.9733
Testing accuracy: 0.9520