HW1_NN_Perceptron

September 19, 2019

1 Perceptron training algorithm - Sai Teja Karnati

```
In [331]: import math
          import matplotlib.pyplot  as plt
          import random
          import numpy as np
```

Sections Q3: A-H : Creating Random Weights and preserving using seed so it doesn't change each time

Change N to 10-100-1000 for different data sizes

```
In [332]: n=1000
```

Initialing random Data and preserving using seed

```
In [333]: np.random.seed(3)
          w0 = np.random.uniform(-1/4,1/4)
          w1 = np.random.uniform(-1,1)
          w2 = np.random.uniform(-1,1)
          print("w0,w1,w2 = "+str(w0) +"," + str(w1) +","+str(w2) )
          actualWeights= np.array([w0,w1,w2])
          space= np.random.uniform(-1,1,(2,n))
```

```
w0,w1,w2 = 0.025398951287287752,0.41629564523620965,-0.41819052217411135
```

Initializing some variables to plot positive and negative points

```
In [334]: labels=[]
          pospoints=[]
          negpoints=[]
          positivepointsx=[]
          positivepointsy=[]
          negativepointsx = []
          negativepointsy = []
          epochsAcc = []
```

Q3:i Classifying, recording and plotting the original classifications and points

In [335]:
```
for i in range(100):
    if (w0+w1*space[0][i] + w2*space[1][i])>=0:
        labels.append(1)
        positivepointsx.append(space[0][i])
        positivepointsy.append(space[1][i])
    else:
        labels.append(0)
        negativepointsx.append(space[0][i])
        negativepointsy.append(space[1][i])

pospoints.append(positivepointsx)
pospoints.append(positivepointsy)
negpoints.append(negativepointsx)
negpoints.append(negativepointsy)
xp = pospoints[0]
yp = pospoints[1]
xn = negpoints[0]
yn = negpoints[1]
```

Initializing random Weights to train with Perceptron training algorithm

In [336]:
```
np.random.seed(5)
w01 = np.random.uniform(-1,1)
w11 = np.random.uniform(-1,1)
w21 = np.random.uniform(-1,1)
predictedweights = np.array([w01,w11,w21])
print("w0,w1,w2 = "+str(w01) +"," + str(w11) +","+str(w21))
```

```
w0,w1,w2 = -0.556013657820521,0.7414646123547528,-0.5865616893211472
```

Function to tell us the accuracy of predictions from updated weights compared to the actual weights

In [337]:
```
def accuracy(matrix,weights,actualweights):
    correct=0
    for i in range(len(matrix[0])):
        if weights[0] + weights[1]*matrix[0][i] +weights[2]*matrix[1][i] >=0:
            pred=1
        else:
            pred=0
        if actualweights[0] + actualweights[1]*matrix[0][i] +actualweights[2]*matrix
            actual=1
        else:
            actual=0
        if(actual==pred):
            correct= correct+1
    #print( "correct: "+ str(correct)+", accuracy: "+ str(correct/n))
    return correct/n
```

Q3:i Function to plot graphs for each epoch with updated weights and accuracy along with points and lines

```
In [338]: def plottingline(actualweights,weights,accuracy,epoch):
              fig = plt.figure()
              ax1 = fig.add_subplot(1, 1, 1)
              ax1.scatter(xp,yp, s=10, c='b', marker="s", label='S1')
              ax1.scatter(xn,yn, s=10, c='r', marker="o", label='S0')
              ax1.legend()
              ax1.grid(True)

              x = np.linspace(-1,1,100)
              y = (-actualweights[1]*x+-actualweights[0])/actualweights[2]
              x1 = np.linspace(-1,1,100)
              y1 = (-weights[1]*x1+-weights[0])/weights[2]
              plt.plot(x1, y1, '-r', label= 'Updated line with accuracy:'+str(accuracy))

              plt.plot(x, y, '-g', label= 'Original line')
              plt.title('Graph of training @ epoch: '+str(epoch))
              plt.xlabel('x', color='#1C2833')
              plt.ylabel('y', color='#1C2833')
              plt.legend(loc='upper left')
              plt.grid()
              plt.show()
```

Q4:j - Updating weights using PTA

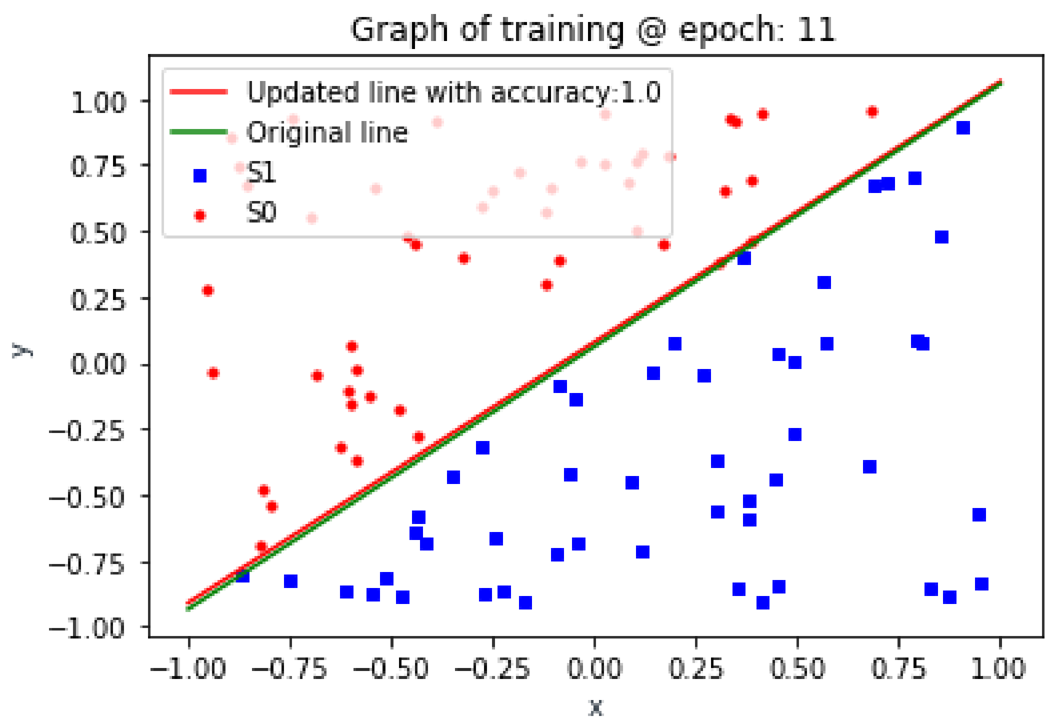
```
In [303]: def trainingWeights(matrix,weights,labels,actualweights,epochs,alpha):
              for e in range(epochs):
                  temp_accuracy = accuracy(matrix,weights,actualweights)
                  #print("Epoch count:"+str(e) + ", Current weights:"+str(weights)+ " Accuracy
                  epochsAcc.append([e,temp_accuracy*100])
                  if temp_accuracy==1:
                      print("Epoch count:"+str(e) + ", Current weights:"+str(weights)+ " Accura
                      plottingline(actualweights,weights,temp_accuracy,e)
                      print("Successful Convergence")
                      break
                  #plottingline(actualweights,weights,temp_accuracy,e)

                  for i in range(len(matrix[0])):
                      if weights[0] + weights[1]*matrix[0][i] +weights[2]*matrix[1][i] >=0:
                          pred=1
                      else:
                          pred=0
                      if actualweights[0] + actualweights[1]*matrix[0][i] +actualweights[2]*ma
                          actual=1
                      else:
                          actual=0
```

```
#print("weights updated from :  ",weights[0],weights[1],weights[2])
error = actual - pred
weights[0]=weights[0] + alpha*error
weights[1]=weights[1] + alpha*error*matrix[0][i]
weights[2]=weights[2] + alpha*error*matrix[1][i]
```

Finally, calling the training functions, we can change the last two hyperparameters:epochs, learning rate alpha respectively

```
In [271]: trainingWeights(space,predictedweights,labels,actualWeights,1000,1)
```

```
Epoch count:11, Current weights:[ 0.44398634  5.64634653 -5.71224446] Accuracy(M,W,AW)1.0
```



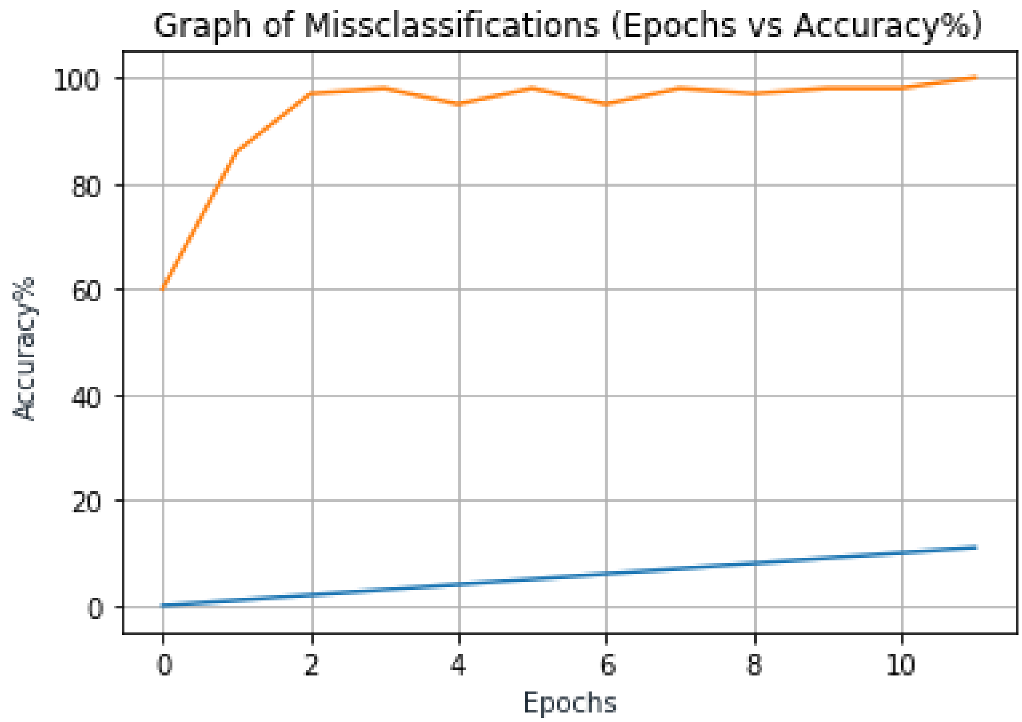

```
Successful Convergence
```

Q3:j:7: The obtained weights and the original weights have similar slope and dispacements as lines. Almost, parallel line but with sparser data, this might not be that true.With denser data, this will be more true.

Q3:k

```
In [272]: plt.plot(epochsAcc,label= '')
          plt.title('Graph of Missclassifications (Epochs vs Accuracy%)')
```

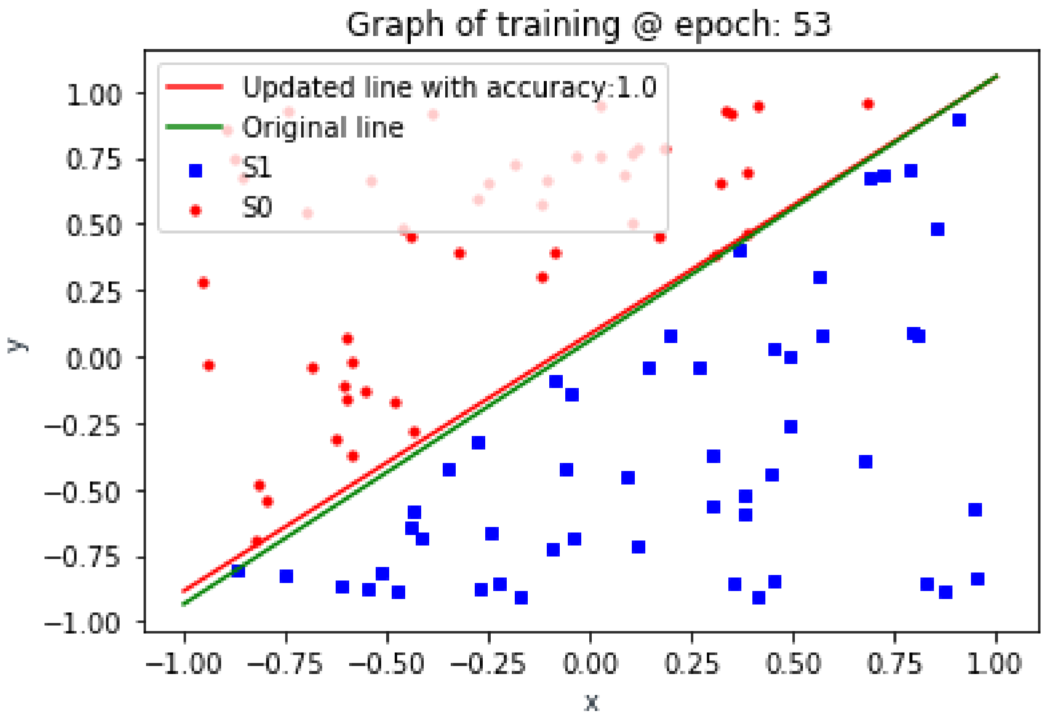
```
plt.xlabel('Epochs', color='#1C2833')
plt.ylabel('Accuracy%', color='#1C2833')
plt.grid()
plt.show()
```



Q3:L - same experiment with Alpha = 10 and Plotting Epoch vs Missclassifications

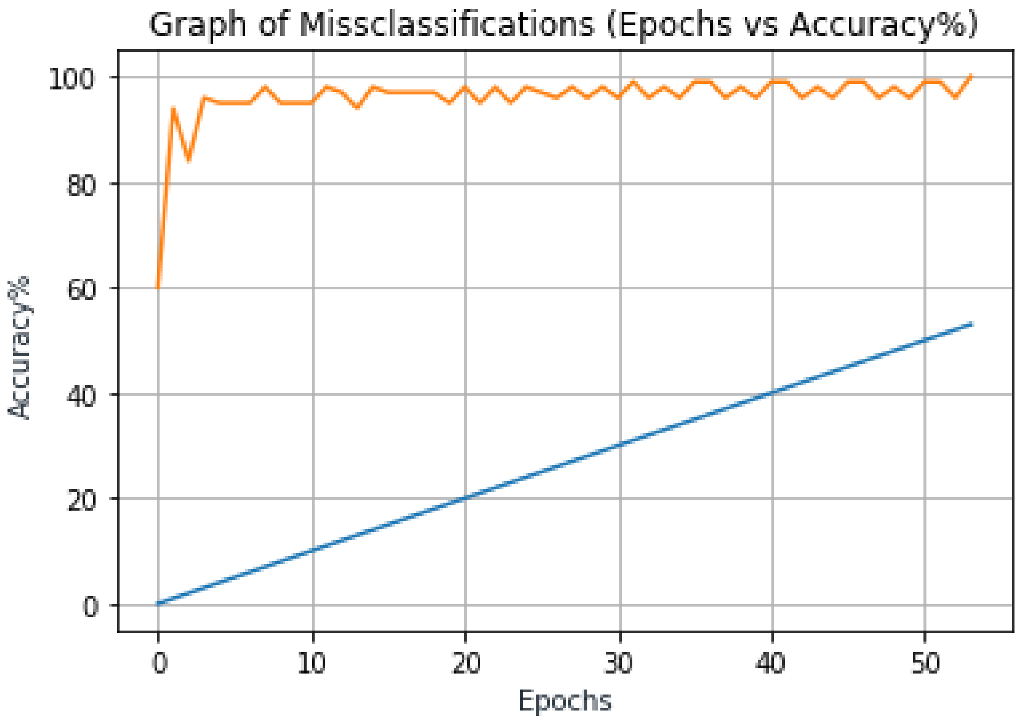
```
In [282]: trainingWeights(space,predictedweights,labels,actualWeights,1000,10)
```

```
Epoch count:53, Current weights:[   9.44398634  107.84480747 -111.1430712 ] Accuracy(M,W,AW)1.(
```



Successful Convergence

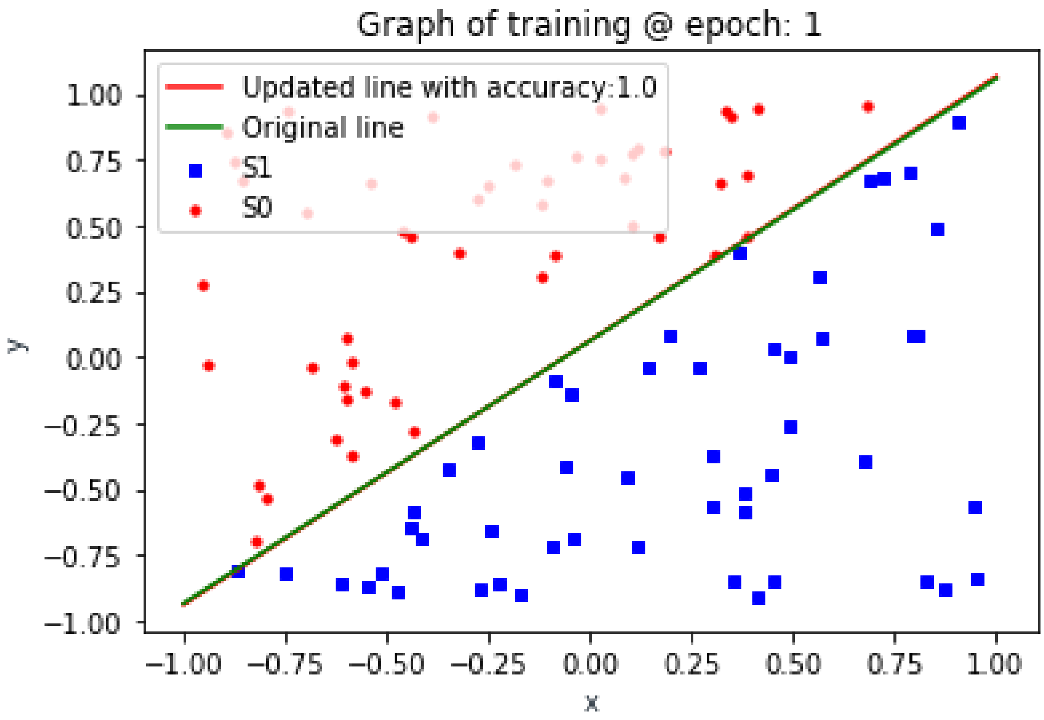
In [283]:
```
plt.plot(epochsAcc,label= '')
plt.title('Graph of Missclassifications (Epochs vs Accuracy%)')
plt.xlabel('Epochs', color='#1C2833')
plt.ylabel('Accuracy%', color='#1C2833')
plt.grid()
plt.show()
```



Q3:M - same experiment with Alpha = 0.1 and Plotting Epoch vs Missclassifications

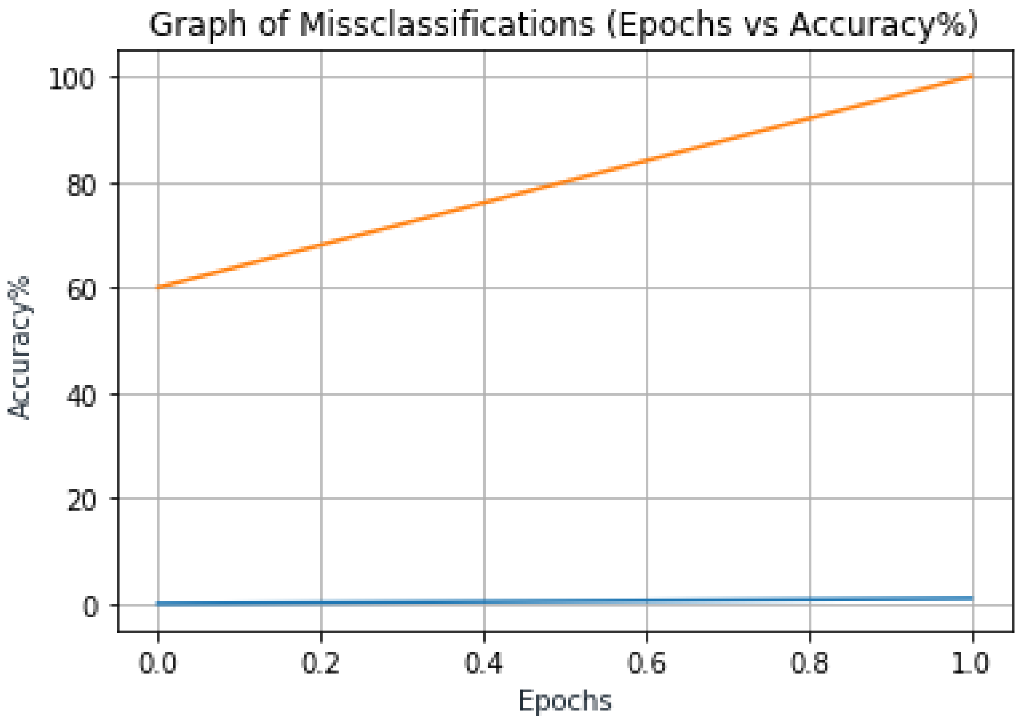
```
In [293]: trainingWeights(space,predictedweights,labels,actualWeights,1000,0.1)
```

```
Epoch count:1, Current weights:[ 0.04398634  0.70743669 -0.70613942] Accuracy(M,W,AW)1.0
```



Successful Convergence

```
In [294]: plt.plot(epochsAcc,label= '')
          plt.title('Graph of Missclassifications (Epochs vs Accuracy%)')
          plt.xlabel('Epochs', color='#1C2833')
          plt.ylabel('Accuracy%', color='#1C2833')
          plt.grid()
          plt.show()
```



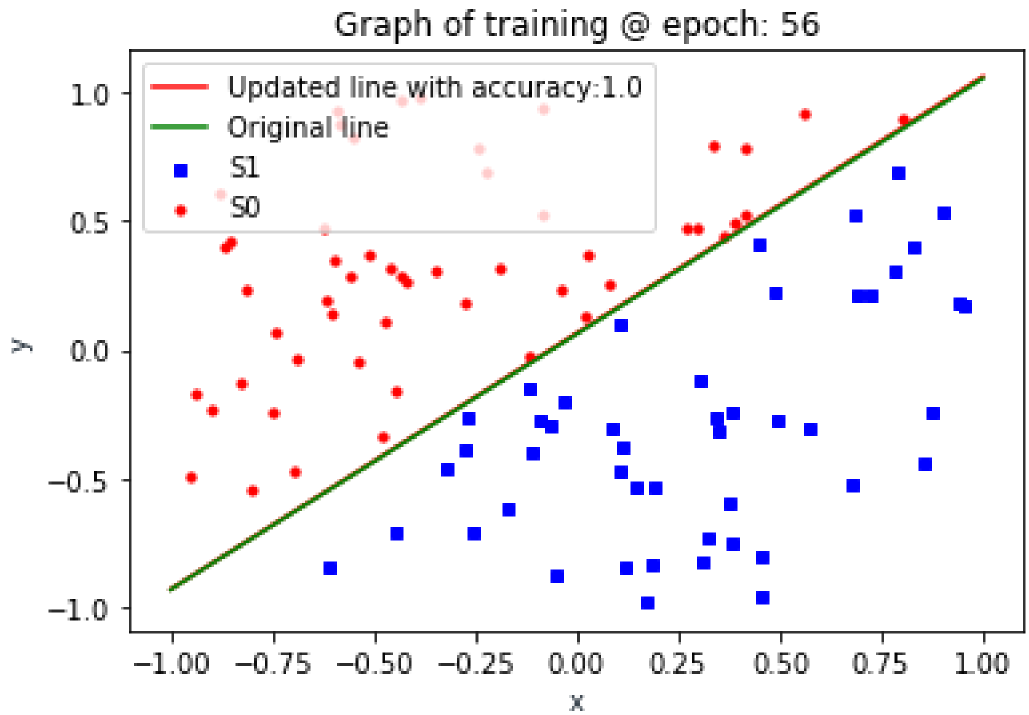
Q3: N : If we take a large alpha(learning rate), the number of epochs increases because of overshooting and if we take a very small alpha(learning rate), the number of epochs increases because of the changes in W being too slow. So, the optimal alpha is somewhere in middle which changes depending on data and initial random weights. For me, my optimal alpha is 0.1 which converges in just 1 epoch while apha=1 takes 11 epochs and alpha =10 takes 53 and alpha =0.01 takes 6 epochs.

Q3:O: I wouldn't have gotten the same results if i started with some other Weights and data. But the effects of overshooting with large alpha(learning rate) increasing the number of epochs and effects of slow learning with small alpha increasing the number of epochs will be similar. Alpha might not 0.1 as in my case but it wouldn't be too far apart like alpha=100 or something.

Q3:P Doing the same experiment with n=1000 for alpha=1,0.1,10,100

```
In [304]: trainingWeights(space,predictedweights,labels,actualWeights,1000,1)
```

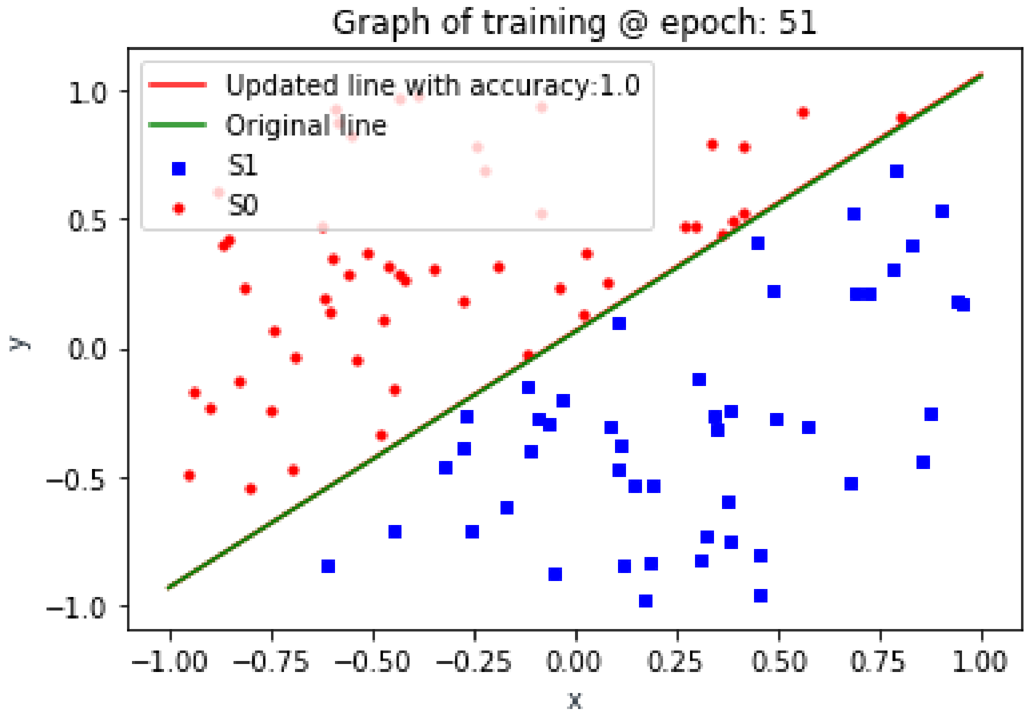
```
Epoch count:56, Current weights:[  1.44398634  22.05859617 -22.0936821 ] Accuracy(M,W,AW)1.0
```




```
Successful Convergence
```

```
In [321]: trainingWeights(space,predictedweights,labels,actualWeights,1000,0.1)
```

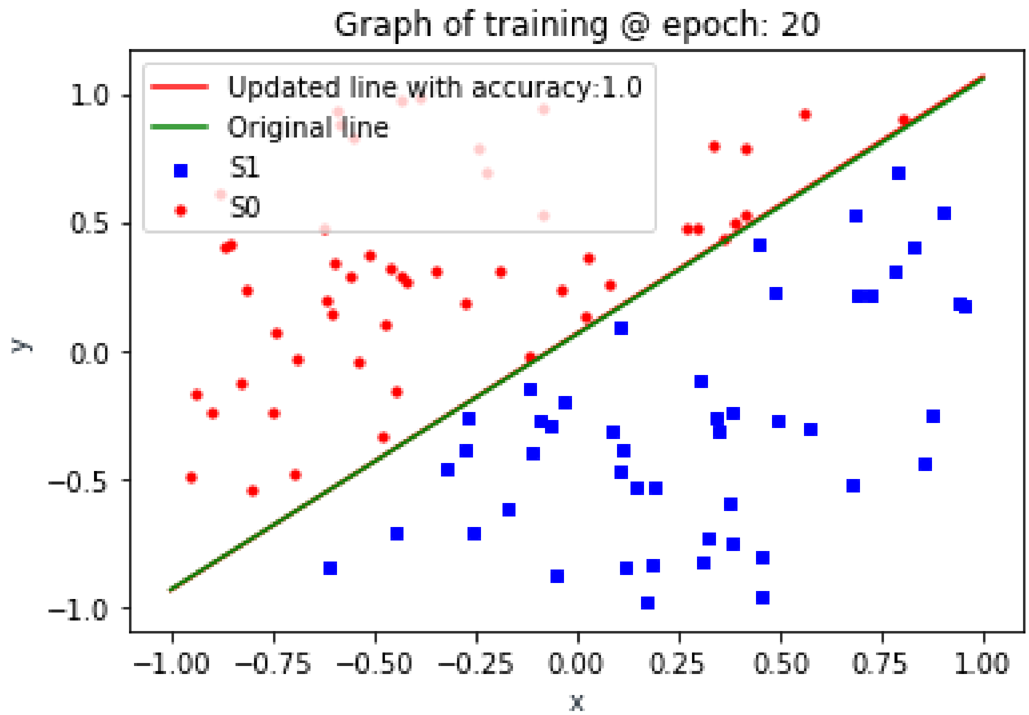
```
Epoch count:51, Current weights:[ 0.14398634  2.22861537 -2.23025595] Accuracy(M,W,AW)1.0
```




```
Successful Convergence
```

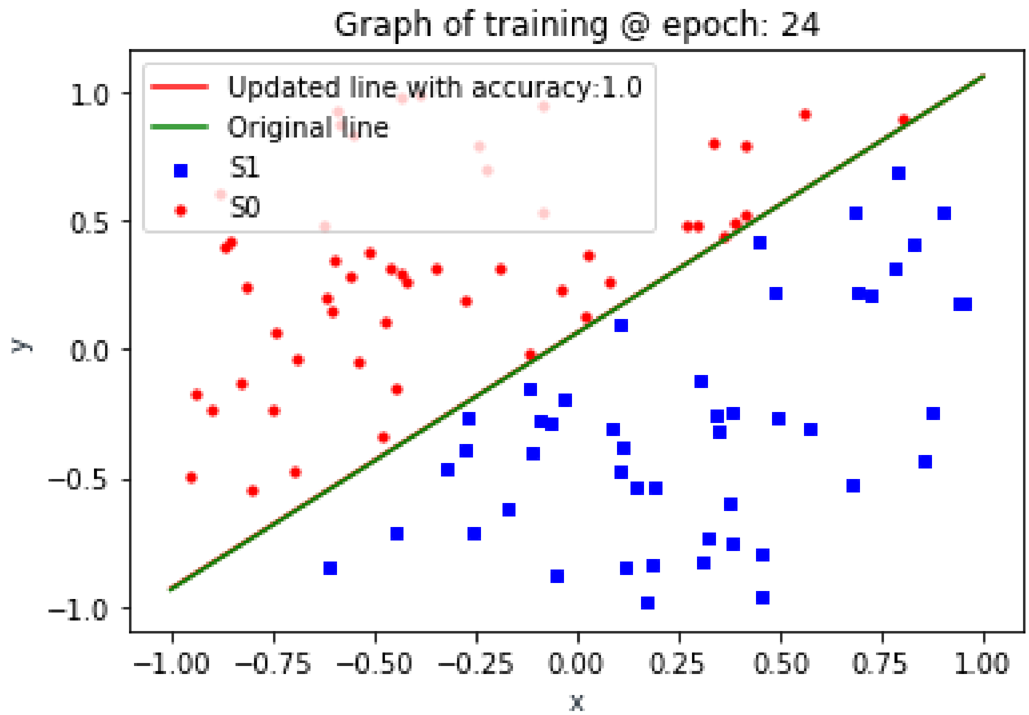
```
In [330]: trainingWeights(space,predictedweights,labels,actualWeights,1000,10)
```

```
Epoch count:20, Current weights:[   9.44398634  146.13091556 -145.95527688] Accuracy(M,W,AW)1.0
```




```
Successful Convergence
```

```
In [339]: trainingWeights(space,predictedweights,labels,actualWeights,1000,100)

Epoch count:24, Current weights:[   99.44398634  1579.2280131  -1588.5921074 ] Accuracy(M,W,AW)
```



`Successful Convergence`

In the case of N=1000, I got convergences at:
alpha = 1 => epoch num 56
alpha = 0.1 => epoch num 51
alpha = 10 => epoch num 20
alpha = 100 => epoch num 24
Therefore, in the case of N=1000, the optimal alpha is 10 with only 20 epochs. Major difference between n=100 and n=1000 is n=1000 needs more time and more epochs for convergence.