

Homework3

November 1, 2018

1 Homework3

1.1 Problem 1: Logistic Regression

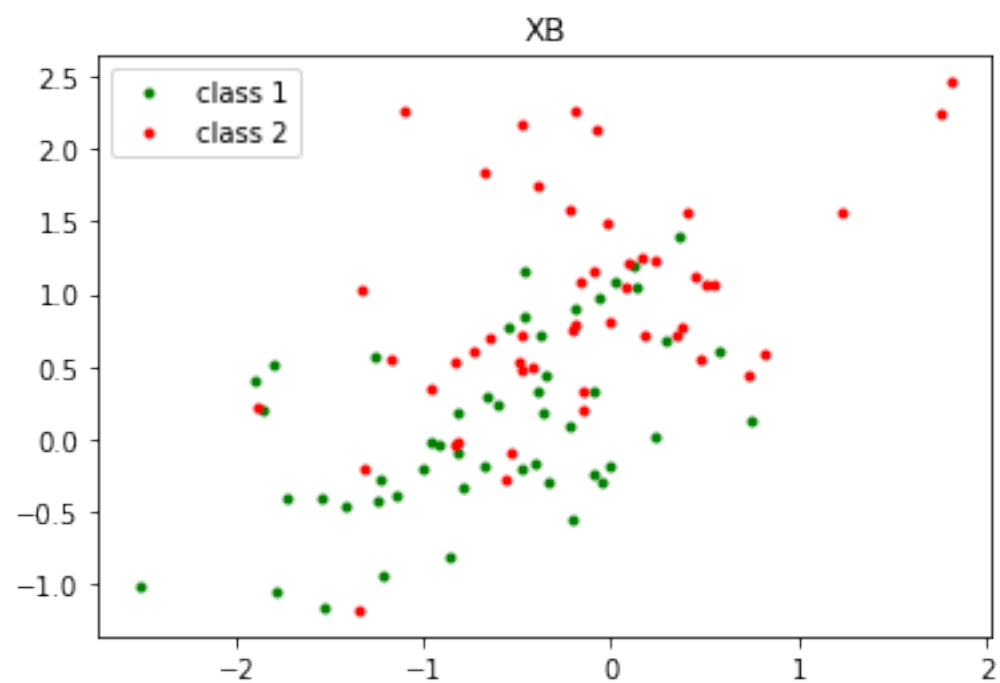
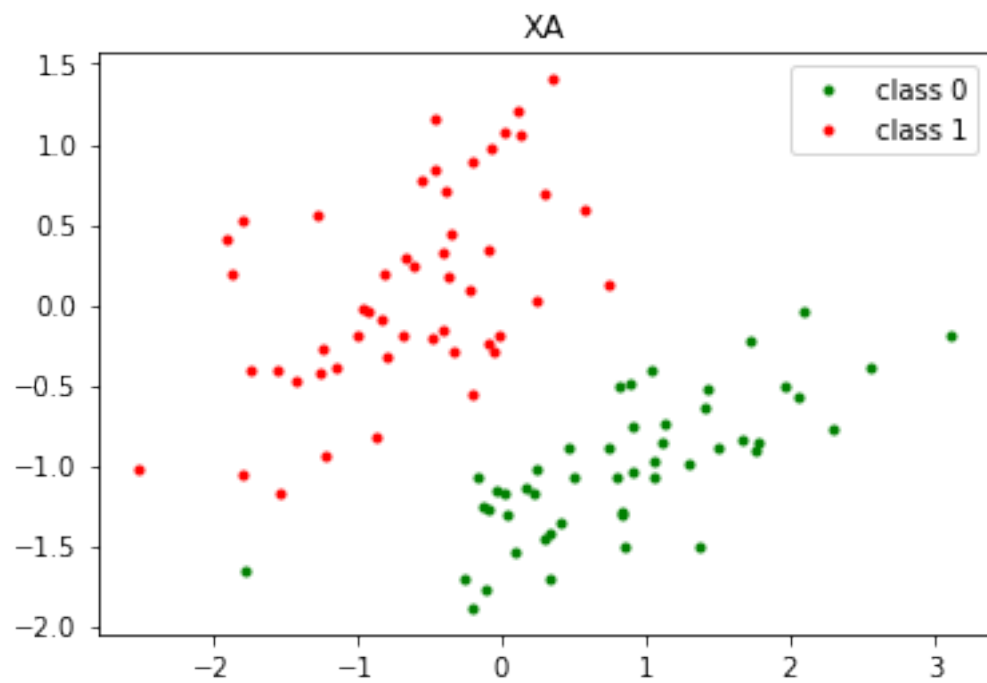
1.1.1 1

```
In [2]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml

iris = np.genfromtxt("data/iris.txt",delimiter=None)
X, Y = iris[:,0:2], iris[:, -1]
X,Y = ml.shuffleData(X,Y)
X,_ = ml.rescale(X)

XA, YA = X[Y < 2, :], Y[Y < 2]
XB, YB = X[Y > 0, :], Y[Y > 0]

plt.plot(XA[YA==0,0],XA[YA==0,1],'.',color='g',label = 'class 0')
plt.legend()
plt.plot(XA[YA==1,0],XA[YA==1,1],'.',color='r',label='class 1')
plt.legend()
plt.title('XA')
plt.show()
plt.plot(XB[YB==1,0],XB[YB==1,1],'.',color='g',label='class 1')
plt.legend()
plt.plot(XB[YB==2,0],XB[YB==2,1],'.',color='r',label='class 2')
plt.legend()
plt.title('XB')
plt.show()
```



1.1.2 2

```
In [3]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
from logisticClassify2 import *
iris = np.genfromtxt("data/iris.txt", delimiter = None)

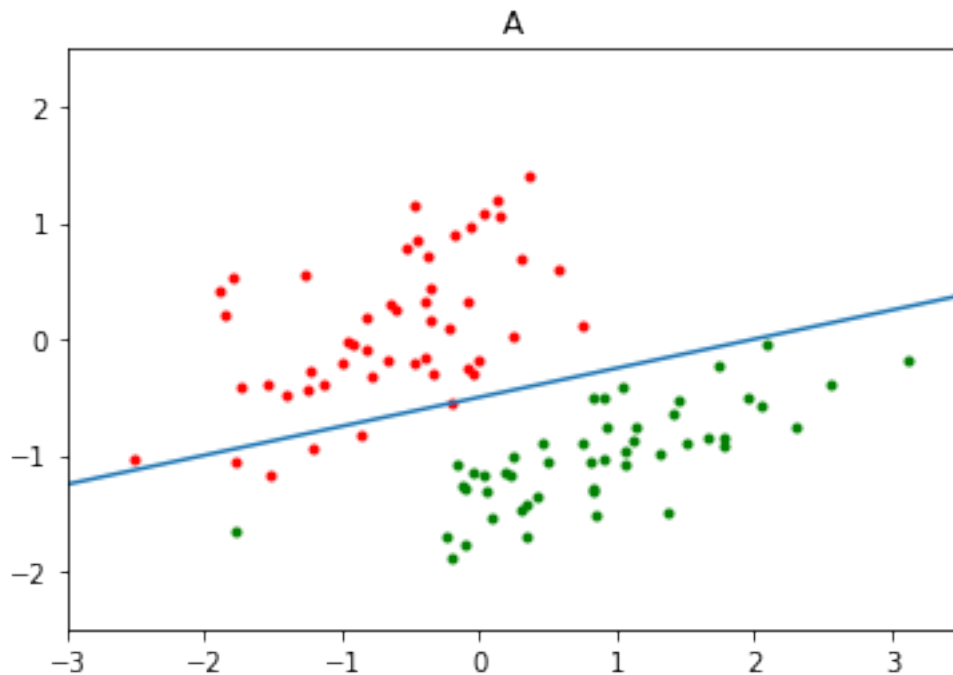
X, Y = iris[:,0:2], iris[:, -1]
X,Y = ml.shuffleData(X,Y)
X,_ = ml.rescale(X)

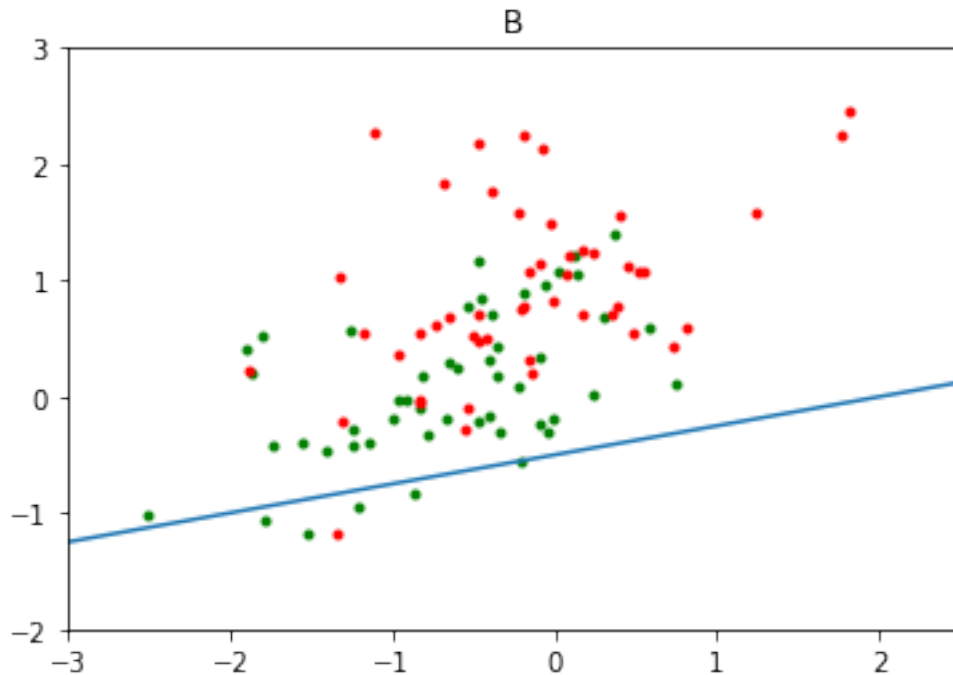
XA, YA = X[Y < 2, :], Y[Y < 2]
XB, YB = X[Y > 0, :], Y[Y > 0]

learner = logisticClassify2()
wts =np.array( [0.5,-0.25,1])
learner.theta = wts

learner.plotBoundary(XA, YA)
plt.axis([-3,3.5,-2.5,2.5])
plt.title('A')
plt.show()

learner.plotBoundary(XB, YB)
plt.axis([-3,2.5,-2,3])
plt.title('B')
plt.show()
```





```
In [2]: def plotBoundary(self,X,Y):
        if len(self.theta) != 3: raise ValueError('Data & model must be 2D');
        K = np.unique(Y)
        X1 = np.linspace(min(X[:,0]), max(X[:,0]), 200)
        Y1 = -(self.theta[1]/self.theta[2])*X1-self.theta[0]/self.theta[2]
        plt.plot(X[Y==K[0],0],X[Y==K[0],1],'.',color='g')
        plt.plot(X[Y==K[1],0],X[Y==K[1],1],'.',color='r')
        plt.plot(X1, Y1)
```

1.1.3 3

```
In [11]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
from logisticClassify2 import *
iris = np.genfromtxt("data/iris.txt", delimiter = None)

X, Y = iris[:,0:2], iris[:, -1]
X,Y = ml.shuffleData(X,Y)
X,_ = ml.rescale(X)

XA, YA = X[Y < 2, :], Y[Y < 2]
```

```

XB, YB = X[Y > 0, :], Y[Y > 0]

learner = logisticClassify2()
learner.classes = np.unique(YA)
wts = np.array([0.5,-0.25,1])
learner.theta = wts;

print("error rate for A = ",learner.err(XA, YA))

learner.classes = np.unique(YB)
print("error rate for B = ",learner.err(XB, YB))

error rate for A = 0.050505050505050504
error rate for B = 0.46464646464646464

In [12]: def predict(self, X):
        """ Return the predicted class of each data point in X"""
        Yhat = np.zeros(X.shape[0]);
        for i in range(X.shape[0]):
            r = self.theta[0] + self.theta[1]*X[i,0]+ self.theta[2]*X[i,1]
            if r > 0:
                Yhat[i] = self.classes[1]
            else:
                Yhat[i] = self.classes[0]
        return Yhat

```

1.1.4 4

```

In [4]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
from logisticClassify2 import *
iris = np.genfromtxt("data/iris.txt", delimiter = None)

Y = iris[:, -1]
X = iris[:, 0: 2]
X,Y = ml.shuffleData(X, Y)
X, _ = ml.transforms.rescale(X)
XA, YA = X[Y < 2, :], Y[Y < 2]
XB, YB = X[Y > 0, :], Y[Y > 0]

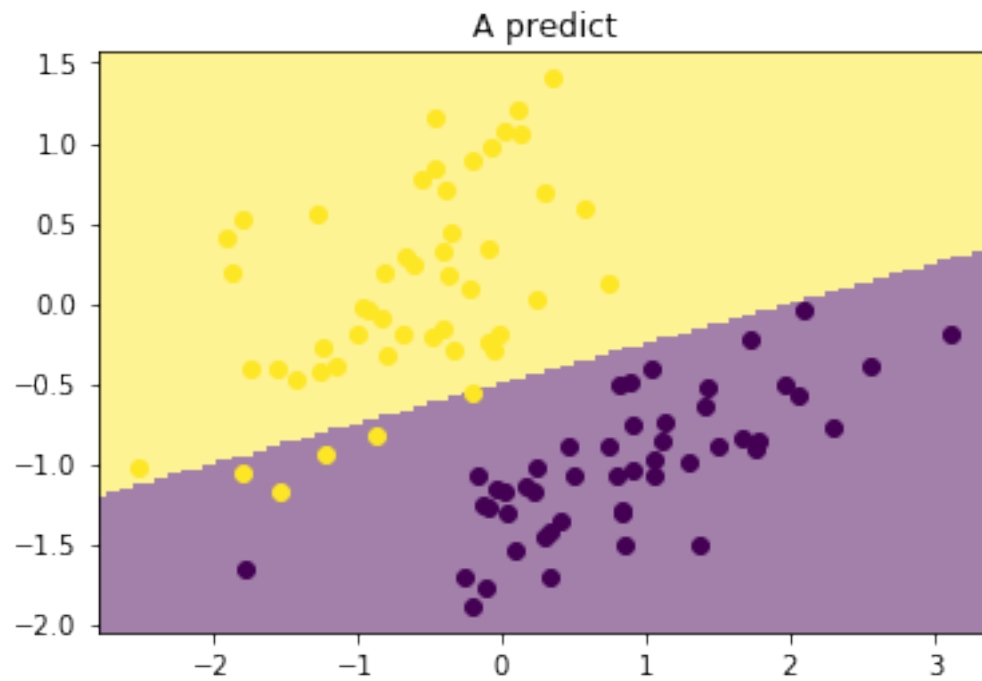
learner = logisticClassify2()
wts =[0.5,-0.25,1]
learner.theta = wts

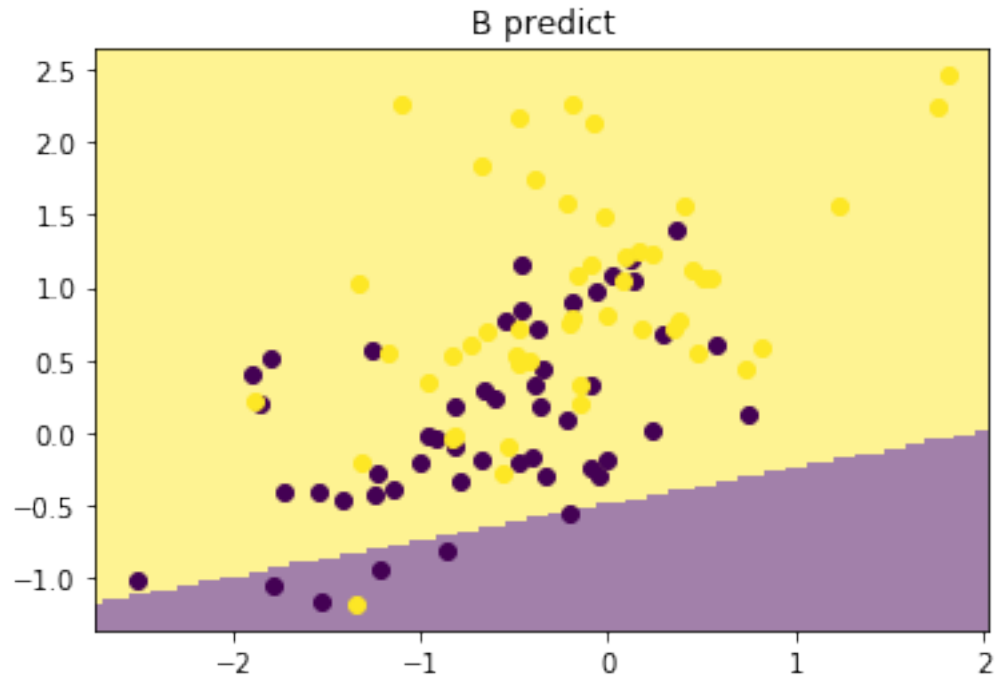
learner.classes = np.unique(YA)
ml.plotClassify2D(learner, XA, YA)

```

```
plt.title('A predict')
plt.show()

learner.classes = np.unique(YB)
ml.plotClassify2D(learner, XB, YB)
plt.title('B predict')
plt.show()
```





1.1.5 5

```
In [3]: from PIL import Image
        im = Image.open("c.jpg")
        im
```

Out [3]:

$$\begin{aligned}
 \sigma(r) &= \frac{1}{1+e^{-r}} \quad \frac{\partial \sigma(r)}{\partial \theta} = \frac{\partial \sigma(r)}{\partial r} \frac{\partial r}{\partial \theta} \\
 \because r &= x^{(j)} \theta^T \quad \frac{\partial r}{\partial \theta} = x^{(j)} \\
 \therefore \frac{\partial \sigma(r)}{\partial \theta} &= [\sigma(r)^2 - \sigma(r)] x^{(j)} \\
 \frac{\partial J}{\partial \theta} &= - \left[\frac{y}{\sigma(r)} - \frac{(1-y)}{1-\sigma(r)} \right] \frac{\partial \sigma(r)}{\partial \theta} \\
 &= - \left[\frac{y}{\frac{1}{1+e^{-r}}} - \frac{1-y}{1-\frac{1}{1+e^{-r}}} \right] [\sigma(r)^2 - \sigma(r)] x^{(j)} \\
 &= (-y^{(j)} + \sigma(x^{(j)} \theta^T)) x_2
 \end{aligned}$$

1.1.6 6

```
In [ ]: def train(self, X, Y, initStep=1.0, stopTol=1e-4, stopEpochs=5000, plot=None):
    """ Train the logistic regression using stochastic gradient descent """
    M,N = X.shape; # initialize the model if necessary:
    self.classes = np.unique(Y); # Y may have two classes, any values
    XX = np.hstack((np.ones((M,1)),X)) # XX is X, but with an extra column of ones
    YY = ml.toIndex(Y,self.classes); # YY is Y, but with canonical values 0 or 1
    if len(self.theta)!=N+1: self.theta=np.random.rand(N+1);
    # init loop variables:
    epoch=0; done=False; Jnll=[]; J01=[];
    while not done:
        stepsize, epoch = initStep*2.0/(2.0+epoch), epoch+1; # update stepsize
        # Do an SGD pass through the entire data set:
        for i in np.random.permutation(M):
            ri = np.dot(self.theta,XX[i,:]); # TODO: compute linear response r
            gradi = (-YY[i]+1/(1+np.exp(-ri)))*XX[i,:]; # TODO: compute gradient
            self.theta -= stepsize * gradi; # take a gradient step

        J01.append( self.err(X,Y) ) # evaluate the current error rate
        j = 0
        for i in np.random.permutation(M):
            j += -YY[i]*np.log(1/(1+np.exp(-np.dot(self.theta, XX[i,:]))))- \
                (1-YY[i])*np.log(1-1/(1+np.exp(np.dot(self.theta, XX[i,:]))))
        ## TODO: compute surrogate loss (logistic negative log-likelihood)
        Jsurr = j/M
        Jnll.append( Jsurr ) # TODO evaluate the current NLL loss

        ## For debugging: you may want to print current parameters & losses
        # print self.theta, ' => ', Jnll[-1], ' / ', J01[-1]
        # raw_input() # pause for keystroke
        if epoch > stopEpochs or ((epoch>1) and np.abs(Jnll[-2] - Jnll[-1]) < stopTol):
            done = True
        # TODO check stopping criteria: exit if exceeded # of epochs ( > stopEpochs )
        # or if Jnll not changing between epochs ( < stopTol )

    plt.figure(1)
    plt.plot(Jnll,'b-',label='loss')
    plt.legend()
    plt.plot(J01,'r-',label='error')
    plt.legend()
    plt.figure(2)
    self.plotBoundary(X,Y)
    plt.show()
```

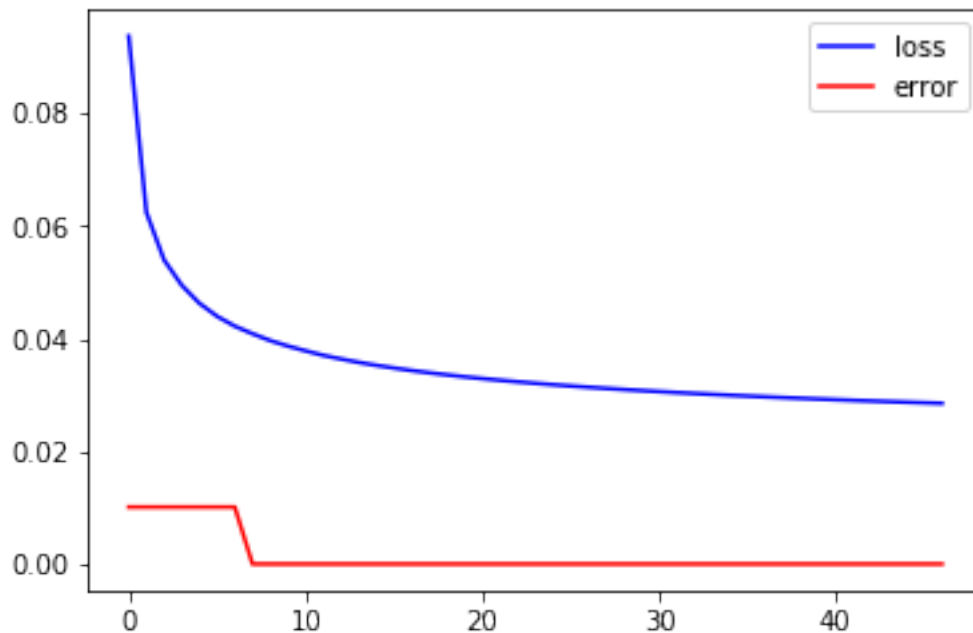

1.1.7 7

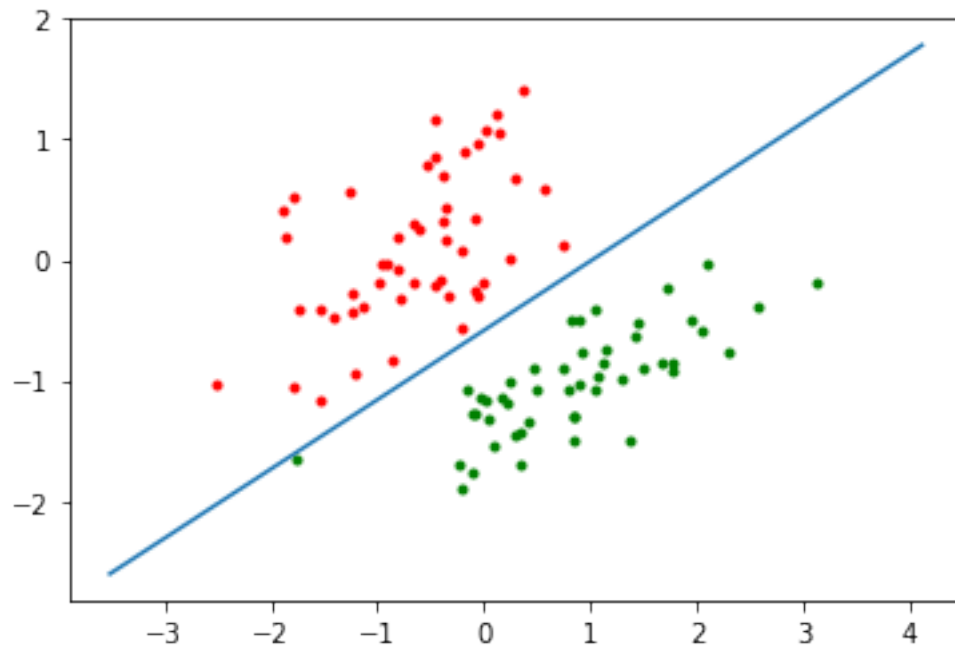
```
In [4]: import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
from logisticClassify2 import *
iris = np.genfromtxt("data/iris.txt", delimiter = None)

Y = iris[:, -1]
X = iris[:, 0: 2]
X,Y = ml.shuffleData(X, Y)
X, _ = ml.transforms.rescale(X)
XA, YA = X[Y < 2, :], Y[Y < 2]
XB, YB = X[Y > 0, :], Y[Y > 0]

wts = np.array([0.5,-0.25,1])
learner = logisticClassify2()
learner.theta = wts;

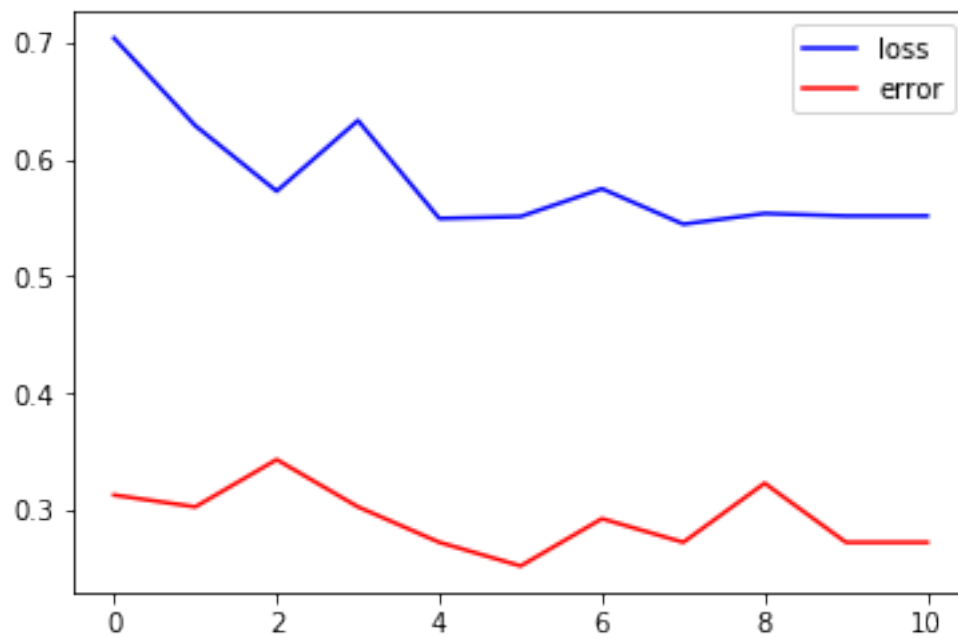
learner.train(XA,YA,initStep=0.5)
print("dataset A theta = ", learner.theta)
```

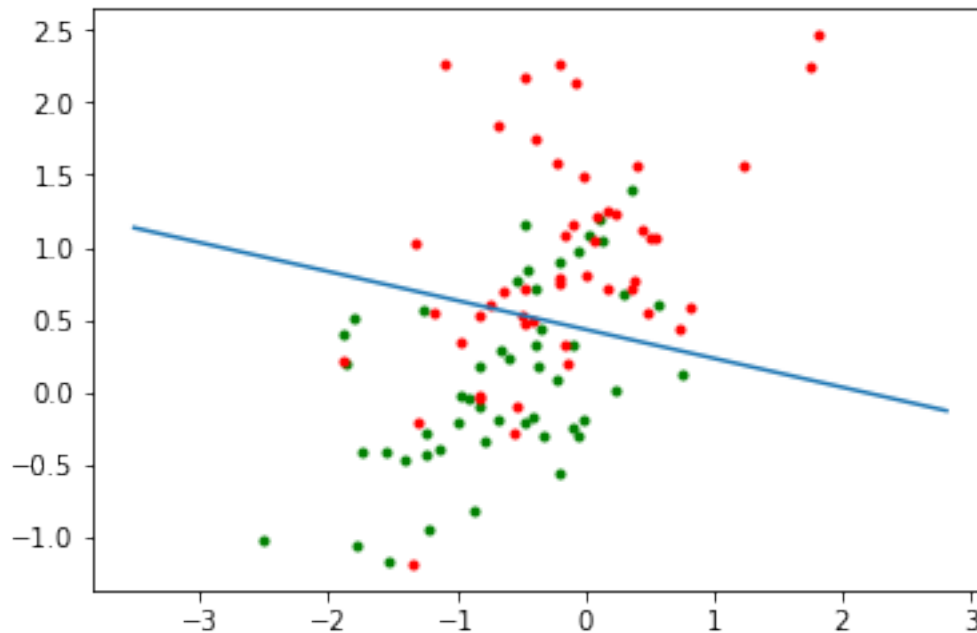




dataset A theta = [3.5100365 -3.45604098 6.01391604]

```
In [5]: learner.train(XB,YB,initStep=1)
print("dataset B theta = ",learner.theta)
```





dataset B theta = [-0.85447936 0.39042084 1.9604496]

1.2 Problem 2: Shattering and VC Dimension

(1) $T(a + bx_1)$ is a line parallel to axis x_2

Since there are only one point in the dataset, so (a) can be shattered. There are only two points with different x_1 in dataset(b), it can also be shattered. VC dim =2. (c)(d) can't be shattered.

(2) $T((ab)x_1 + (c/a)x_2)$ is a line with angle crossing the original point

It can shattered dataset(a)(b). It can not shatter point(2,2) from others in dataset (c)(d). VC dim =2.

(3) $T((x_1a)^2 + (x_2b)^2 + c)$ is a circle, which center and R can be changed.

It can shatter dataset (a)(b)(c). For dataset (d), a cricle can not shatter if the combined lines for each two points with different color is arossed.VC dim =3.

(4) $T(a + bx_1 + cx_2)T(d + bx_1 + cx_2)$ is two parallel line, between them is $z < 0$. It can shattered dataset(a)(b)(c)(d) with two parallel lines in different angle, but it can shatter 5 points if it is divided into class with 3 points and 2 points and the 2 points with one outside the middle area, so its VC dim = 4.

2 Statement of Collaboration

I obey all the rules of UCI academic integrity and finish the project only by my own. Ziyang Zhang
1/11/2018