Homework3

February 7, 2024

1 Problem1

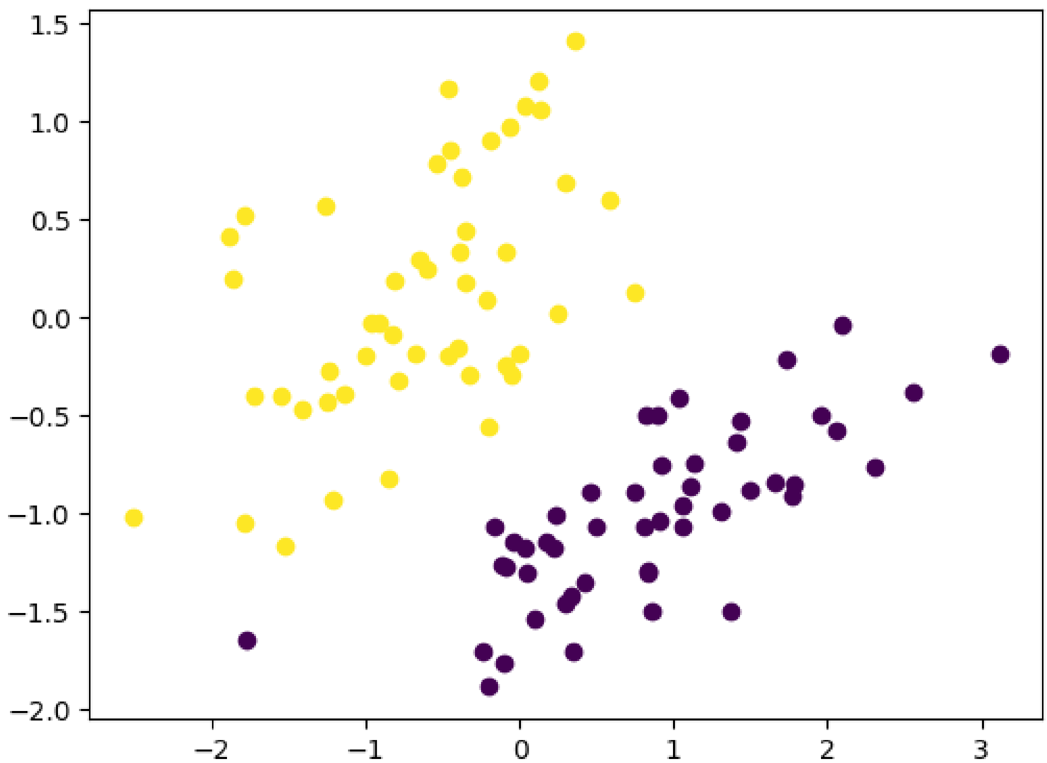
[19]:
```
from __future__ import division
import numpy as np
np.random.seed(0)
import mltools as ml
import matplotlib.pyplot as plt
from IPython.display import clear_output
%matplotlib inline

iris = np.genfromtxt("data/iris.txt",delimiter=None)
X, Y = iris[:,0:2], iris[:,-1] # get first two features & target
X,Y  = ml.shuffleData(X,Y)  # reorder randomly (important later)
X,_  = ml.transforms.rescale(X)   # works much better on rescaled data
XA, YA = X[Y<2,:], Y[Y<2]   # get class 0 vs 1
XB, YB = X[Y>0,:], Y[Y>0]   # get class 1 vs 2
```

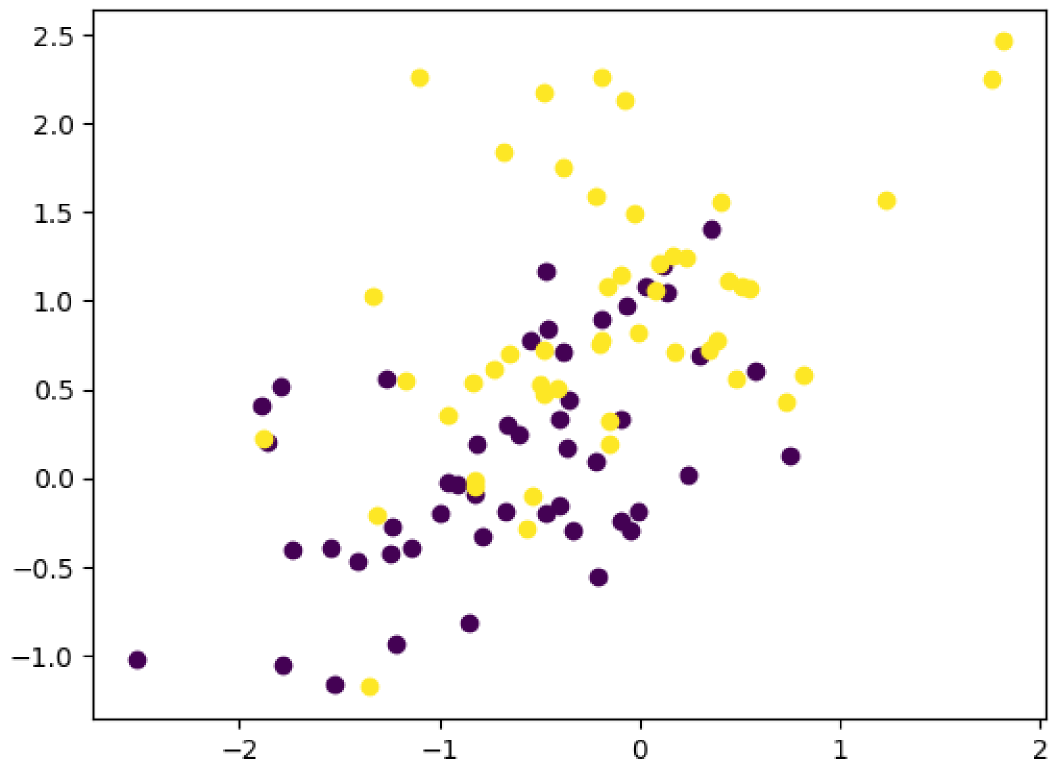
1.1 Problem 1.1

[20]:
```
ml.plotClassify2D(None,XA,YA)
plt.show()
```

```
/Users/huangjiayi/Documents/003UCI/learn/2024Winter/273p_ML/hw/hw3/mltools/plot.
py:61: UserWarning: color is redundantly defined by the 'color' keyword argument
and the fmt string "ko" (-> color='k'). The keyword argument will take
precedence.
  axis.plot( X[Y==c,0],X[Y==c,1], 'ko', color=cmap(cvals[i]), **kwargs )
```

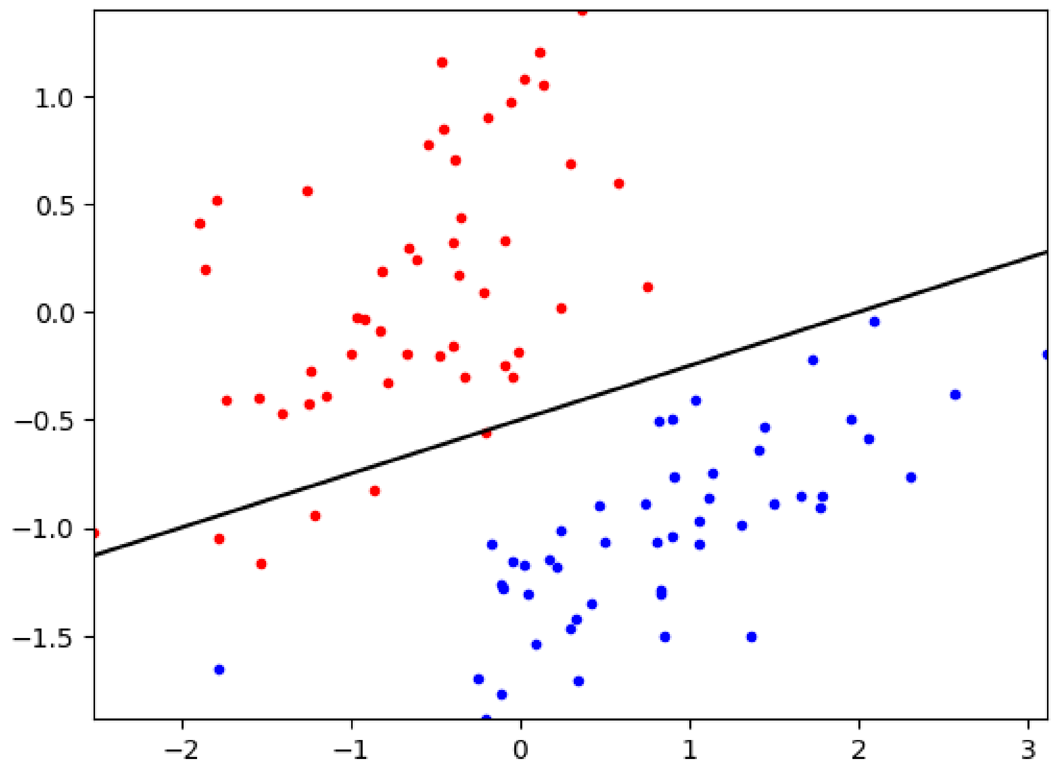


[21]:
```
ml.plotClassify2D(None,XB,YB)
plt.show()
```

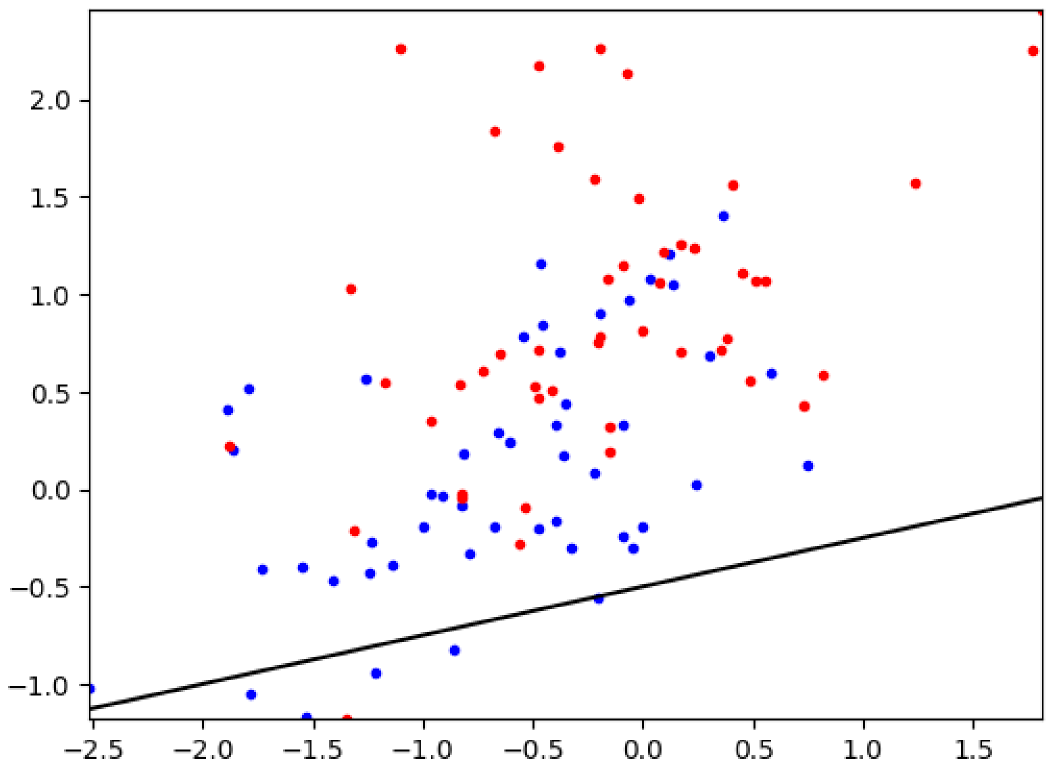


1.2 Problem 1.2

[22]:
```
import mltools as ml
from logisticClassify2 import *
learnerA = logisticClassify2(); # create "blank" learner
learnerA.classes = np.unique(YA) # define class labels using YA or YB
wts = np.array([0.5,-0.25,1]); # TODO: fill in values
learnerA.theta = wts; # set the learner's parameters
learnerA.plotBoundary(XA,YA)
```



[23]:
```
learnerB=logisticClassify2()
learnerB.classes=np.unique(YB)
wts=np.array([0.5,-0.25,1])
learnerB.theta=wts
learnerB.plotBoundary(XB,YB)
```



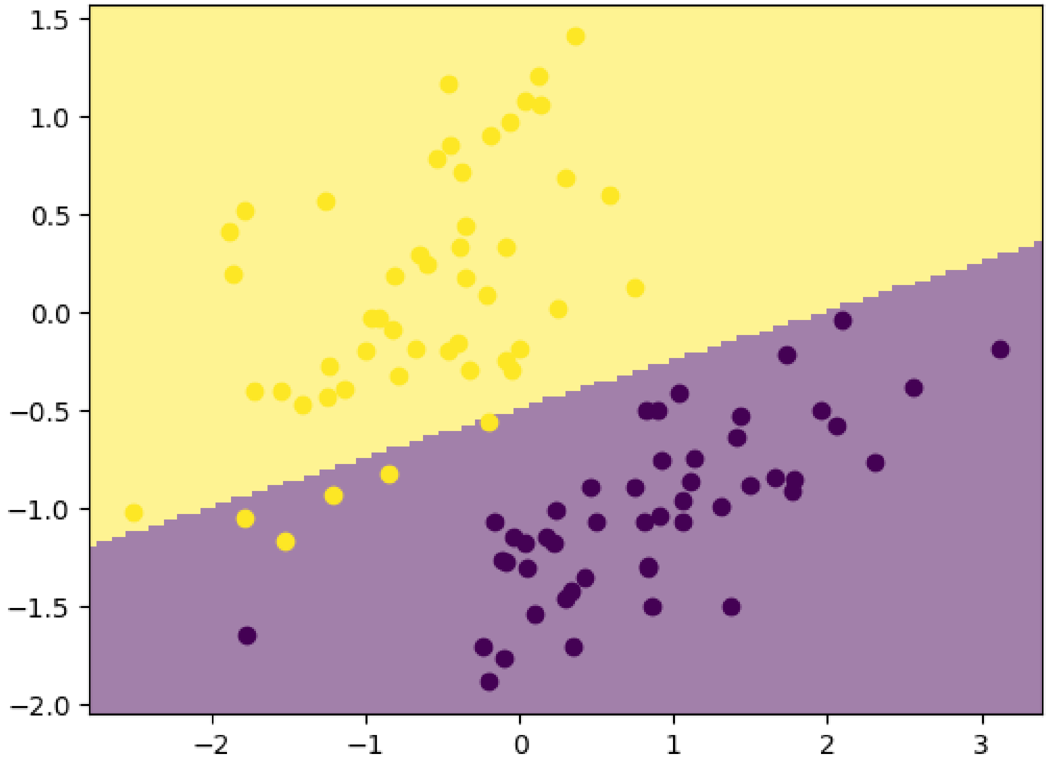
1.3 Problem 1.3

[24]:
```python
YAhat=learnerA.predict(XA)
YBhat=learnerA.predict(XB)
print('Error Data set A: ',learnerA.err(XA,YA))
print('Error Data set B: ',learnerA.err(XB,YB))
```

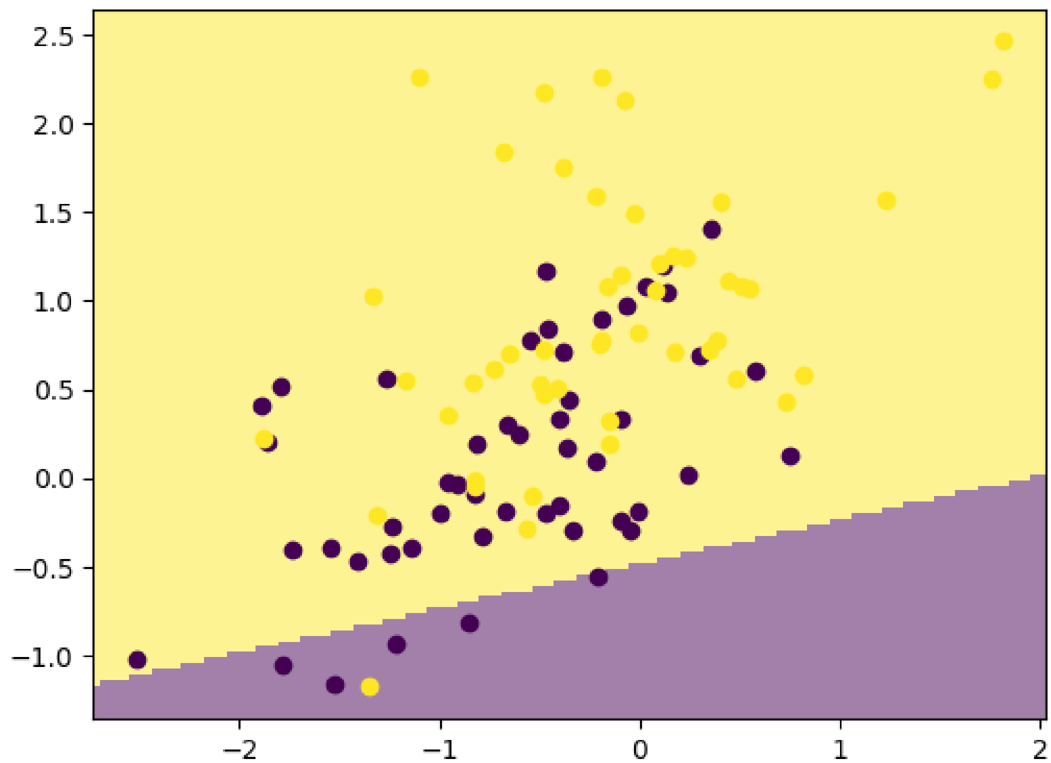
```
Error Data set A:  0.050505050505050504
Error Data set B:  0.5454545454545454
```

1.4 Problem 1.4

[25]:
```python
ml.plotClassify2D(learnerA,XA,YA)
```



[26]:
```
ml.plotClassify2D(learnerB,XB,YB)
```



1.5 Problem 1.5

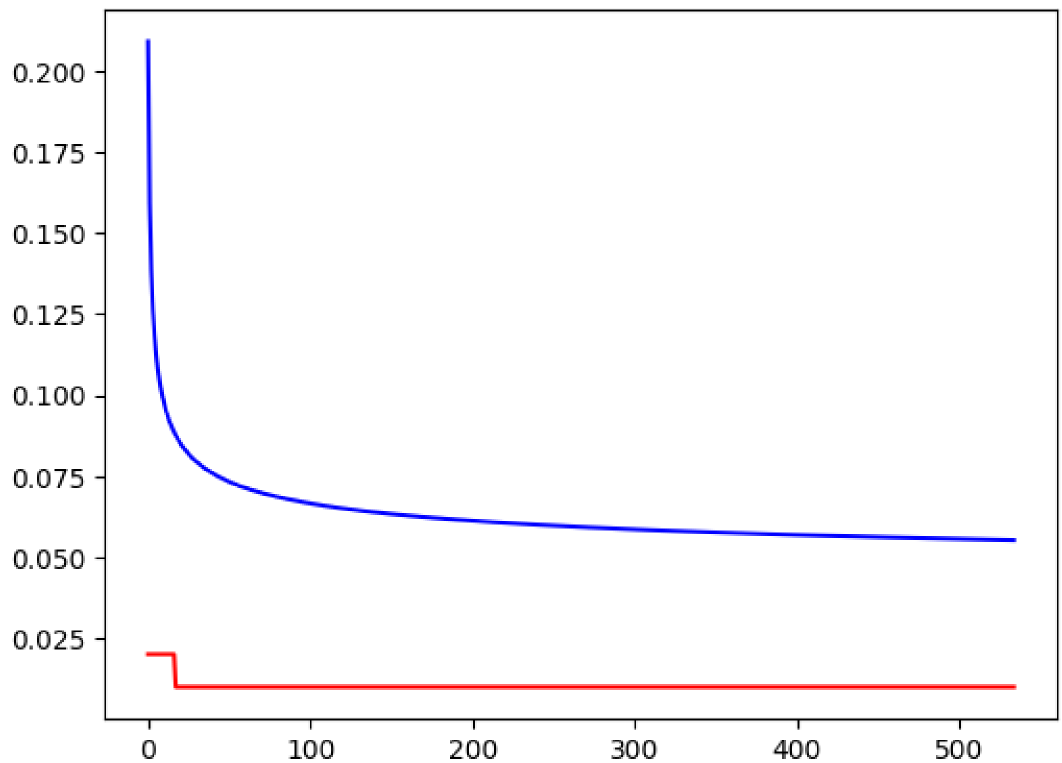
$$\frac{\partial J_j}{\partial \theta_0} = x_0(\sigma - y^{(j)})$$

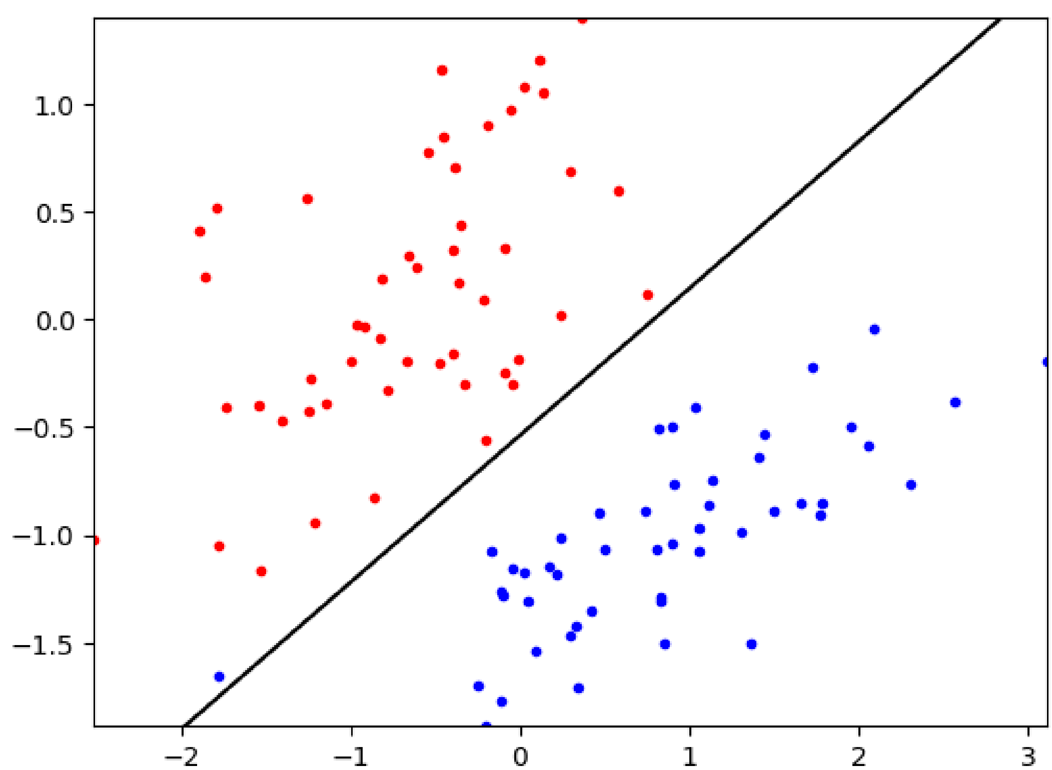
$$\frac{\partial J_j}{\partial \theta_1} = x_1(\sigma - y^{(j)})$$

$$\frac{\partial J_j}{\partial \theta_2} = x_2(\sigma - y^{(j)})$$

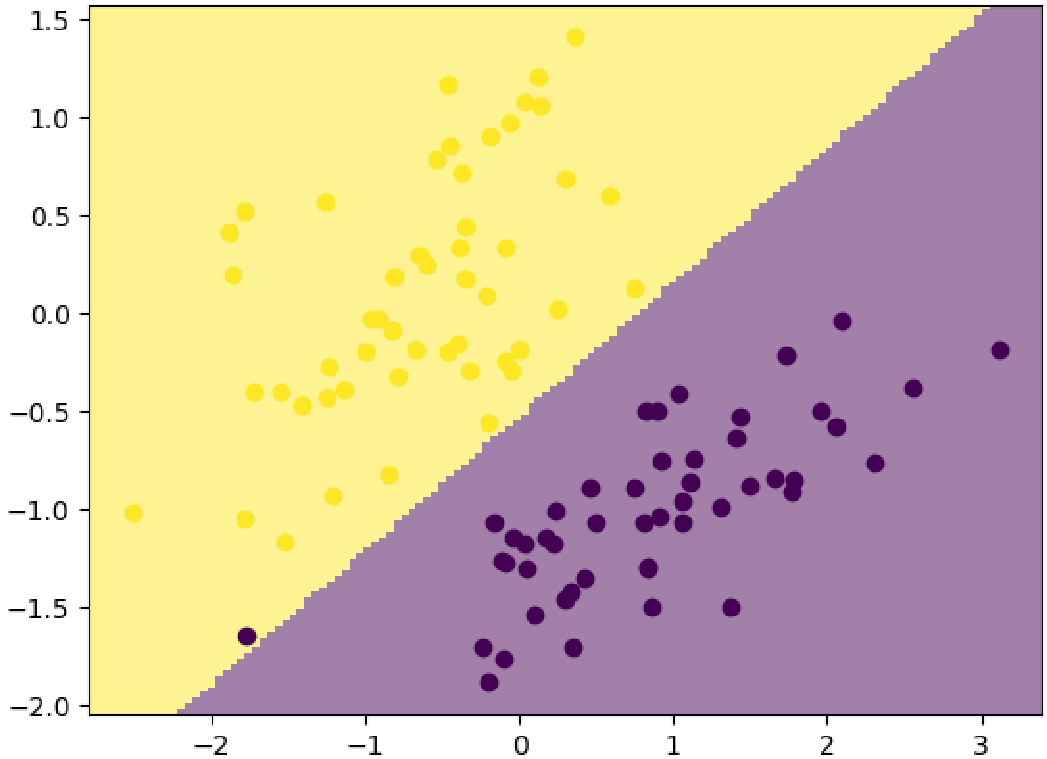
1.6 Problem 1.6/1.7

[27]:
```
learnerA.theta = np.array([0.,0.,0.])
learnerA.train(XA,YA,initStep=1e-1,stopEpochs=1000,stopTol=1e-5)
plt.show()
ml.plotClassify2D(learnerA,XA,YA)
print("Training error rate: ",learnerA.err(XA,YA))
```

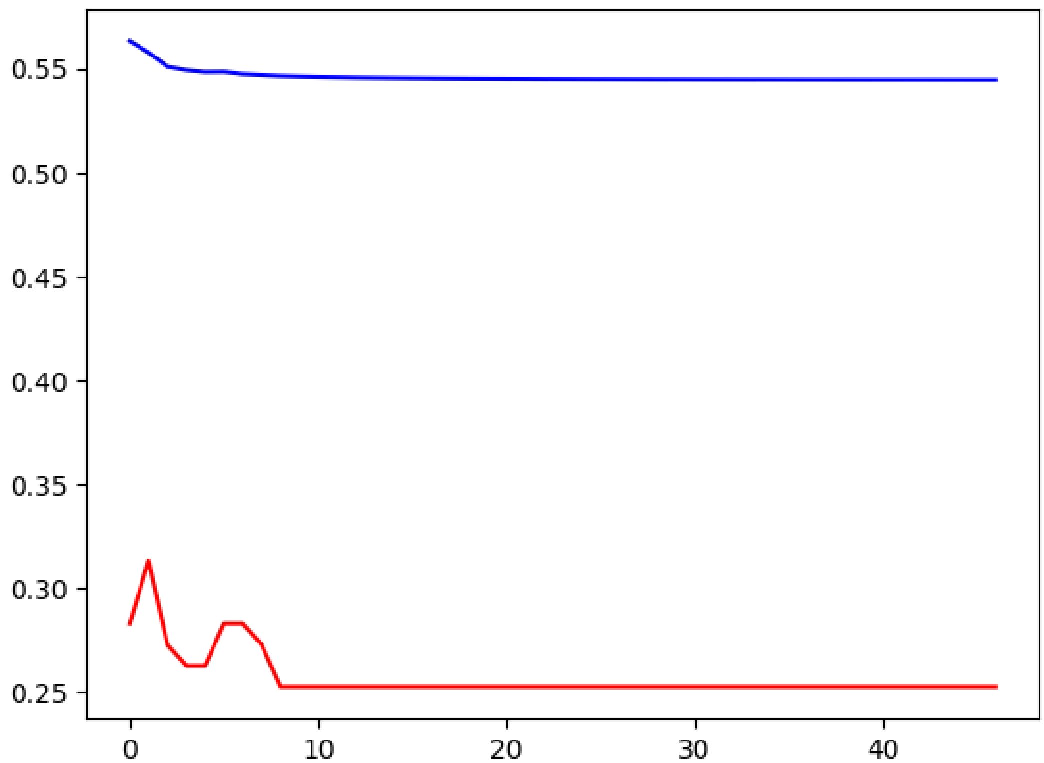

0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0
100
200
300
400
500

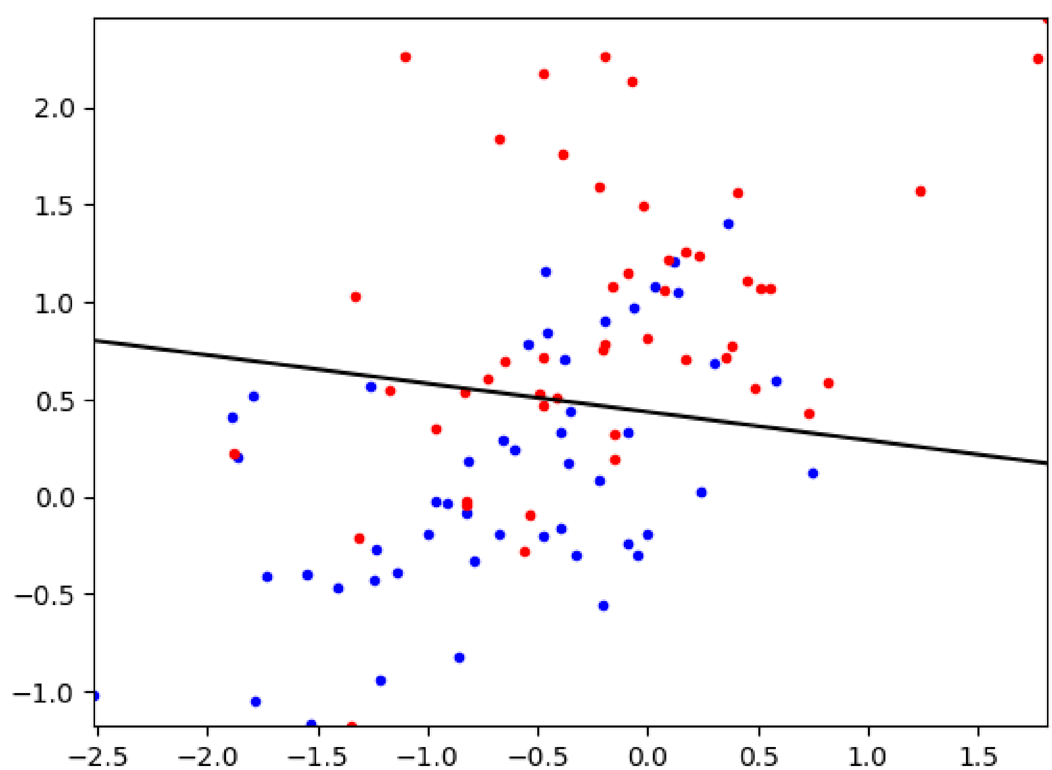

1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2
3

```
Training error rate:  0.010101010101010102
```

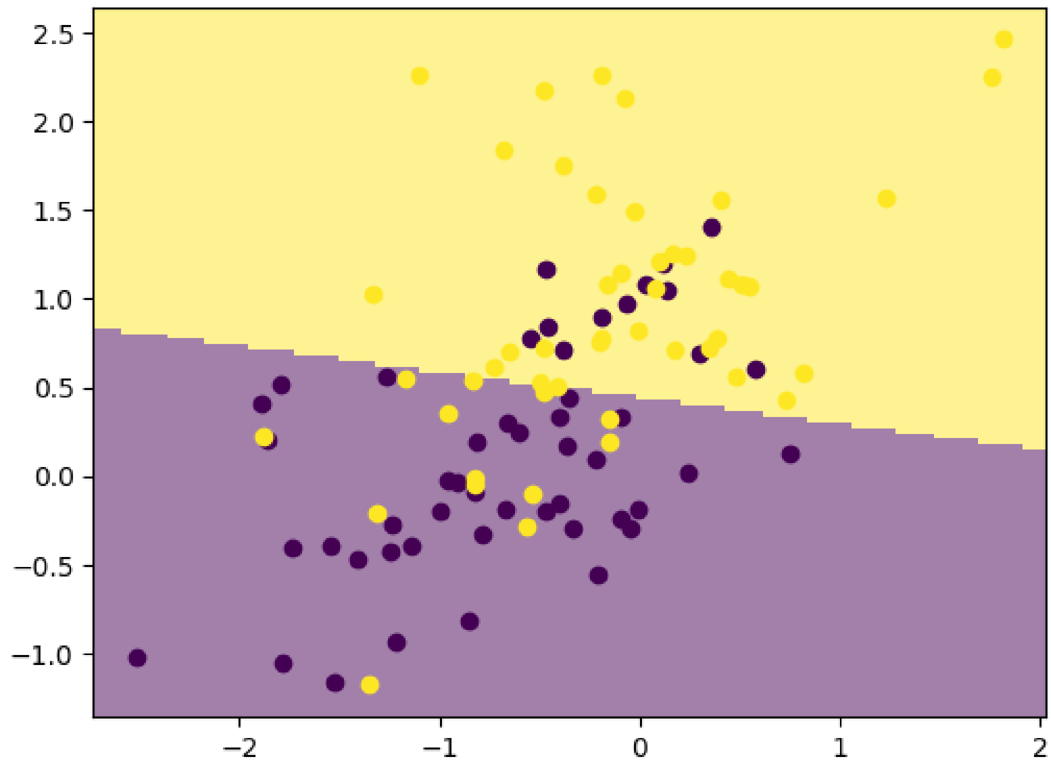



```
[28]: learnerB.theta = np.array([0.,0.,0.])
      learnerB.train(XB,YB,initStep=1e-1,stopEpochs=1000,stopTol=1e-5)
      plt.show()
      ml.plotClassify2D(learnerB,XB,YB)
      print("Training error rate: ",learnerB.err(XB,YB))
```


0.55
0.50
0.45
0.40
0.35
0.30
0.25
0
10
20
30
40


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

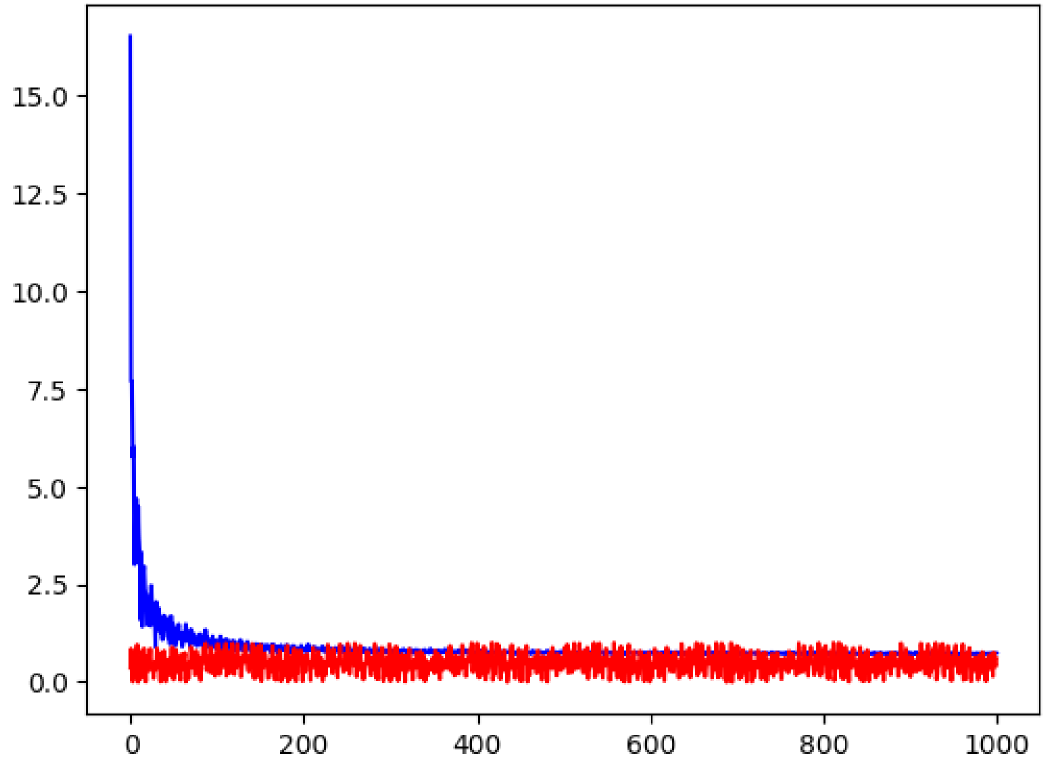
```
Training error rate:  0.25252525252525254
```

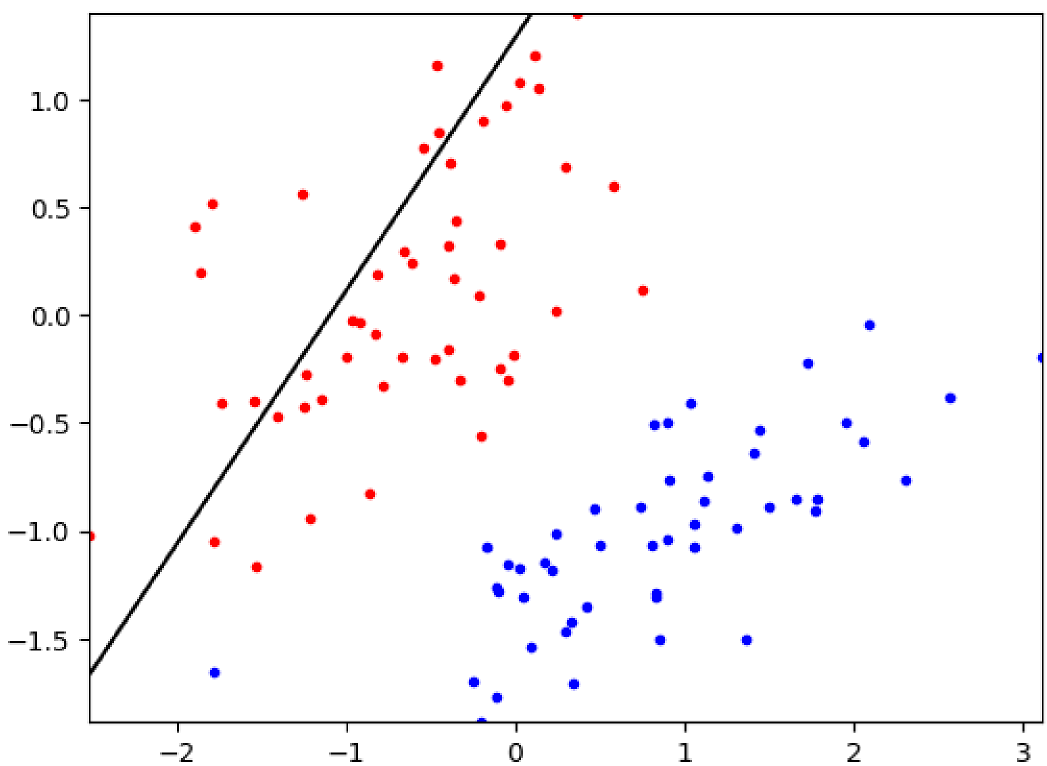


1.7 Problem 1.8

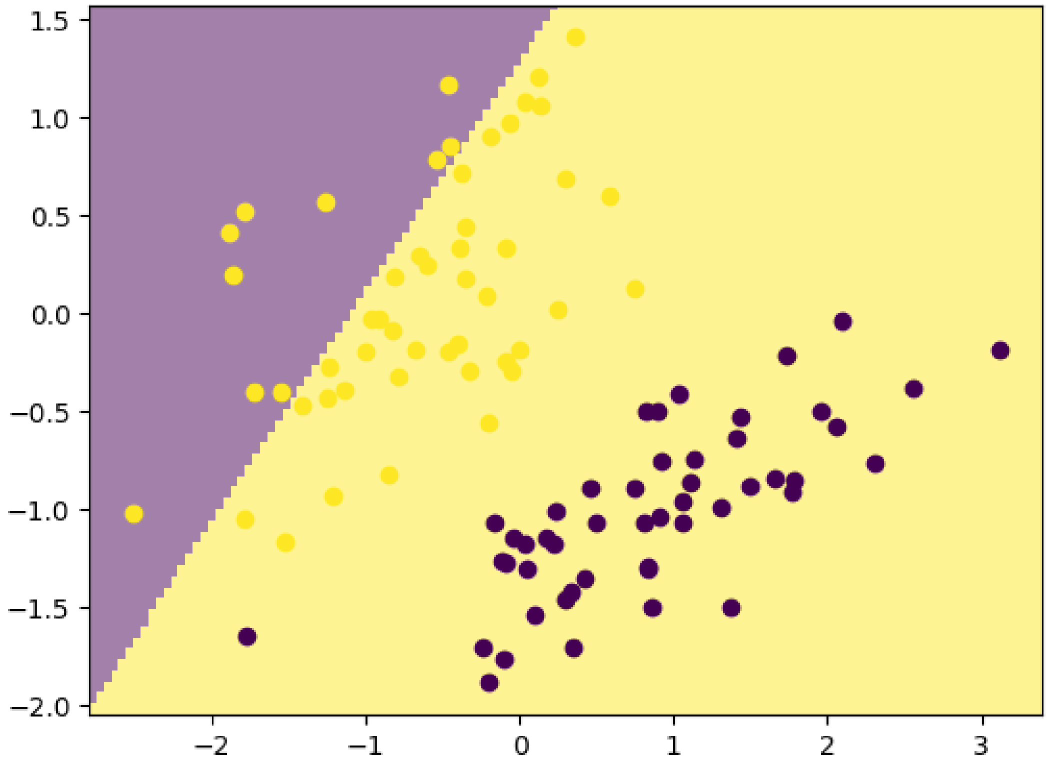
[29]:

```
L1_alpha = 10
learnerAL1 = logisticClassify2();
learnerAL1.theta = np.array([0.,0.,0.])
learnerAL1.
  ↪regTrainL1(XA,YA,initStep=1e-1,stopEpochs=1000,stopTol=1e-5,alpha=L1_alpha)
plt.show()
ml.plotClassify2D(learnerAL1,XA,YA)
print("Training error rate: ",learnerAL1.err(XA,YA))
```

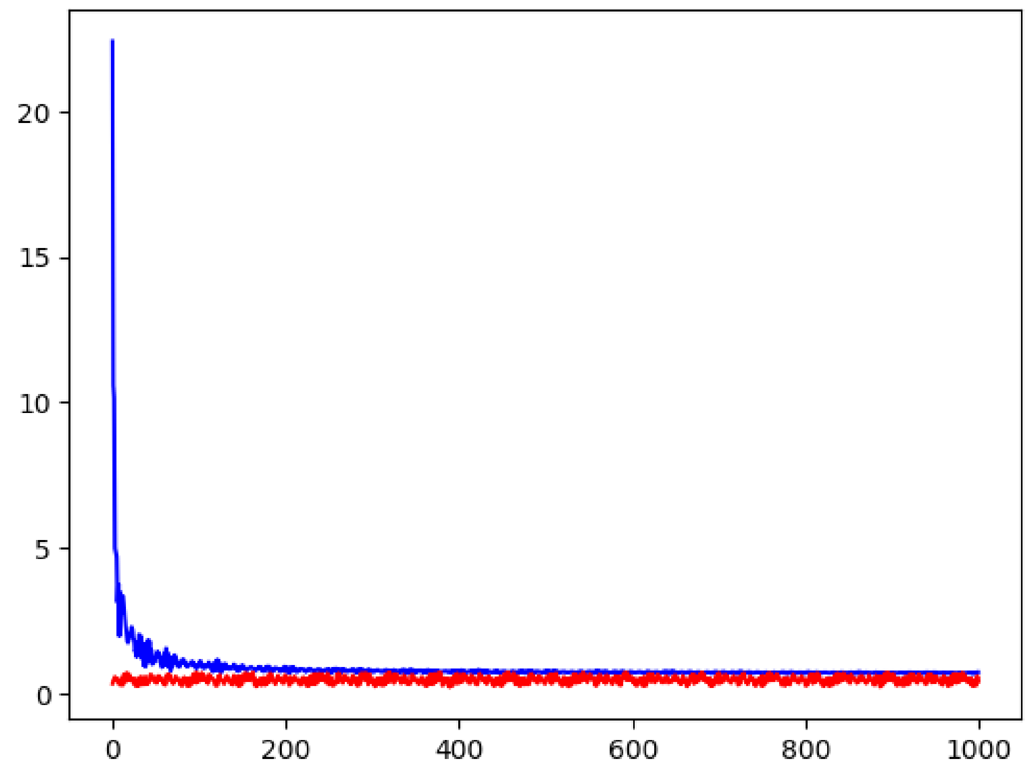

15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
200
400
600
800
1000


1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2
3

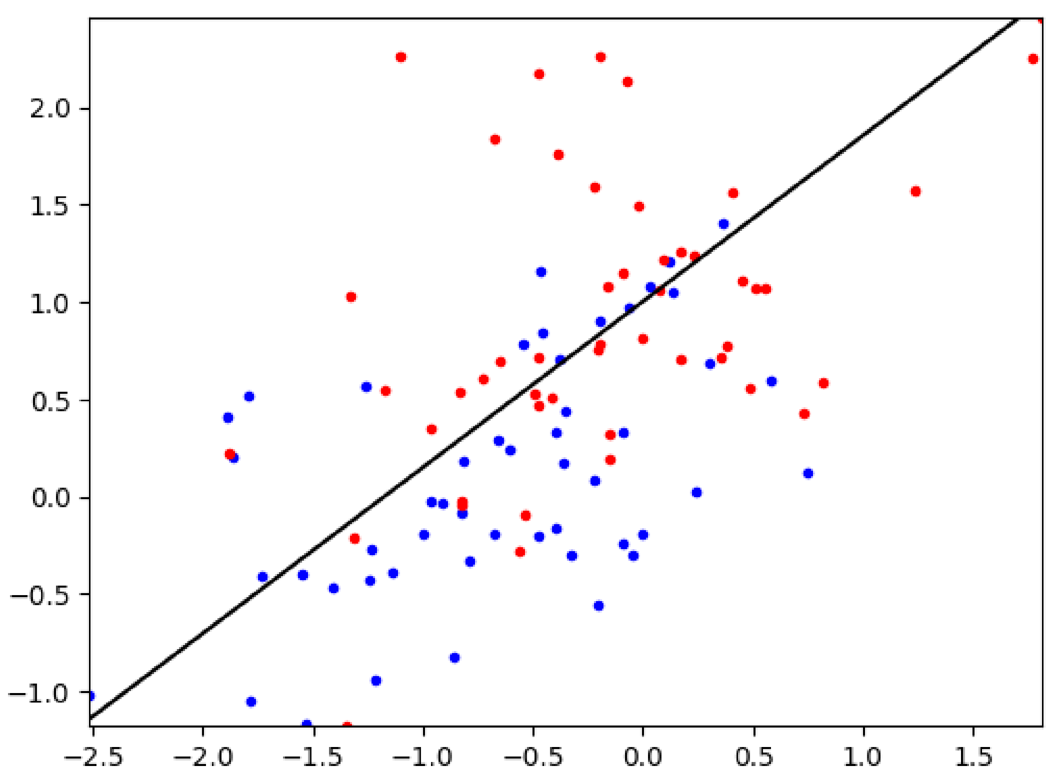
```
Training error rate:  0.5959595959595959
```



[30]:
```
learnerBL1 = logisticClassify2();
learnerBL1.theta = np.array([0.,0.,0.])
learnerBL1.
 ↪regTrainL1(XB,YB,initStep=1e-1,stopEpochs=1000,stopTol=1e-5,alpha=L1_alpha)
plt.show()
ml.plotClassify2D(learnerBL1,XB,YB)
print("Training error rate: ",learnerBL1.err(XB,YB))
```

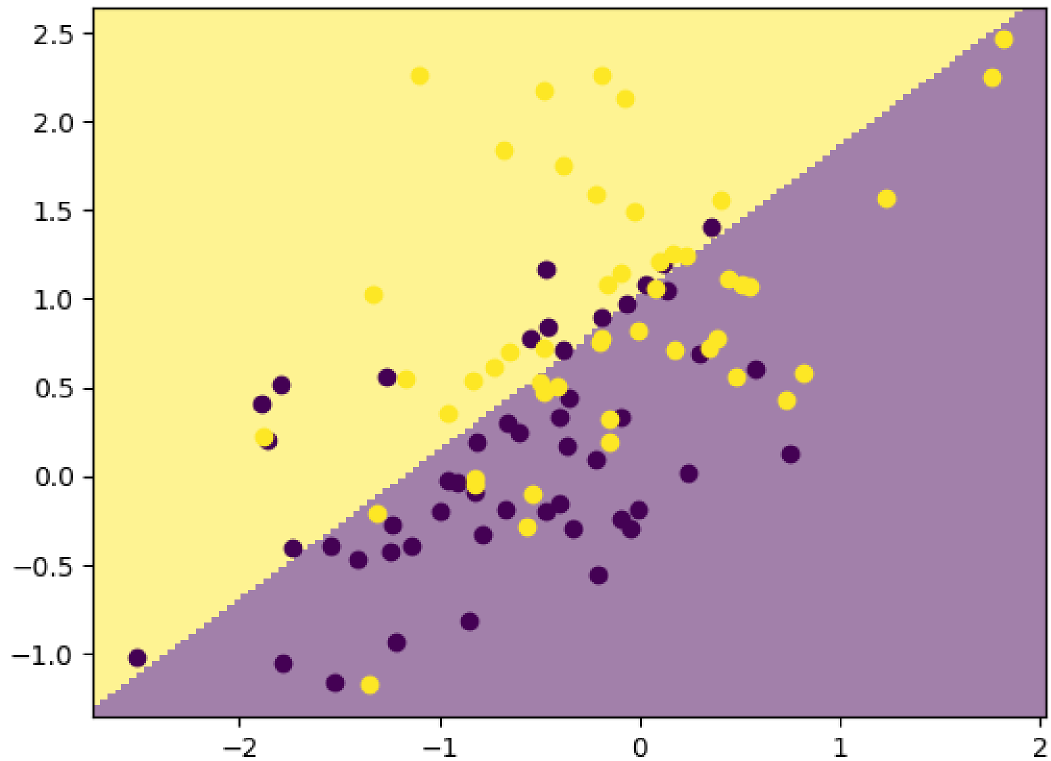


0
5
10
15
20
0
200
400
600
800
1000



−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

```
Training error rate:  0.42424242424242425
```



[31]:
```
print(learnerA.theta,learnerAL1.theta)
print(learnerA.err(XA,YA),learnerAL1.err(XA,YA))
```

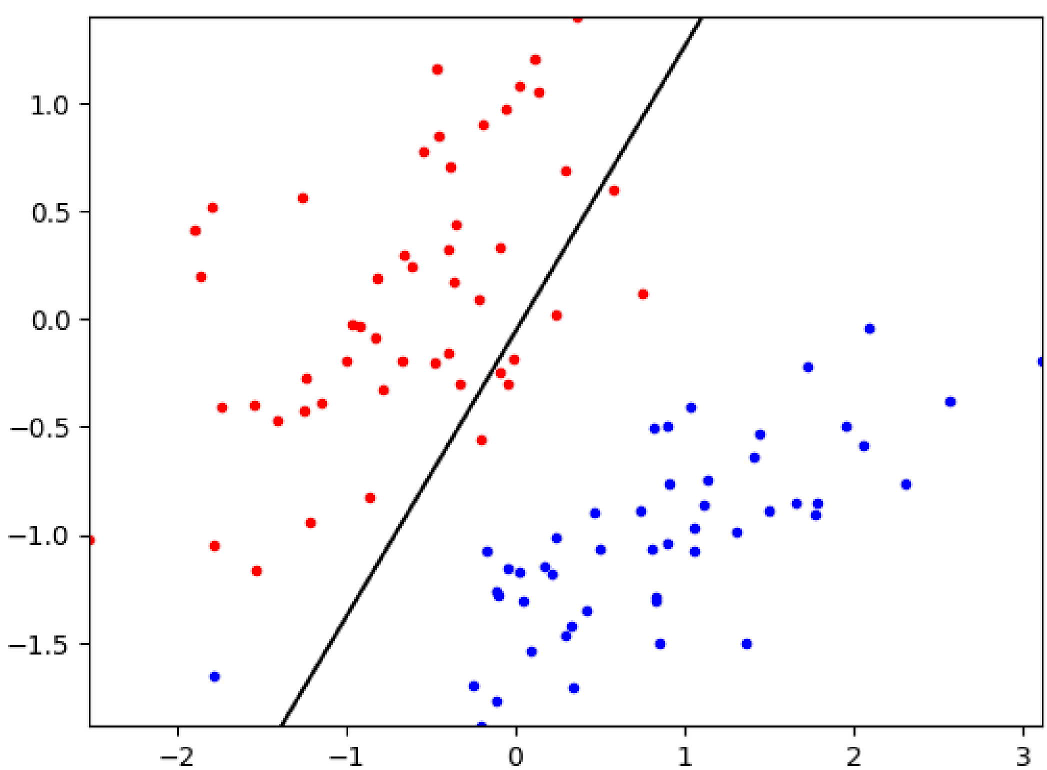
```
[ 2.17599611 -2.75794635  4.04441023] [ 0.00158393  0.0014462  -0.001231  ]
0.010101010101010102 0.5959595959595959
```

The value of theta have dropped and error has increased due to L1 regularization term.

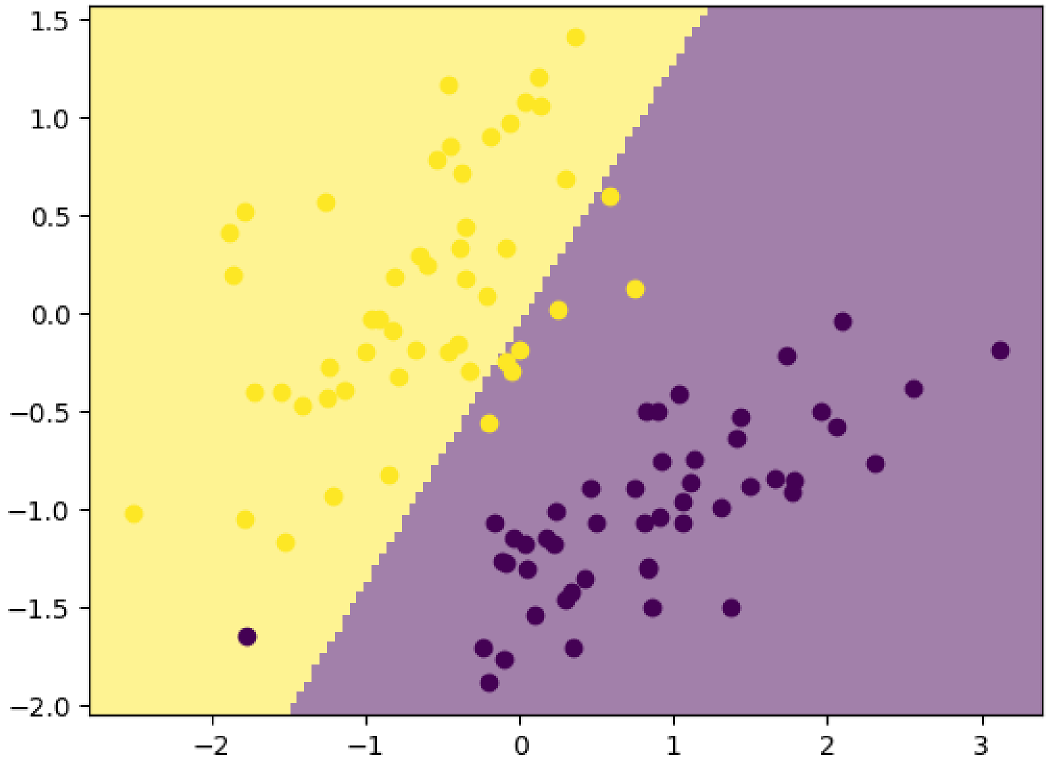
1.8 Problem 1.9

[32]:
```
L2_alpha = 2
learnerAL2 = logisticClassify2();
learnerAL2.theta = np.array([0.,0.,0.])
learnerAL2.
  ↪regTrainL2(XA,YA,initStep=1e-1,stopEpochs=1000,stopTol=1e-5,alpha=L2_alpha)
plt.show()
ml.plotClassify2D(learnerAL2,XA,YA)
print("Training error rate: ",learnerAL2.err(XA,YA))
```

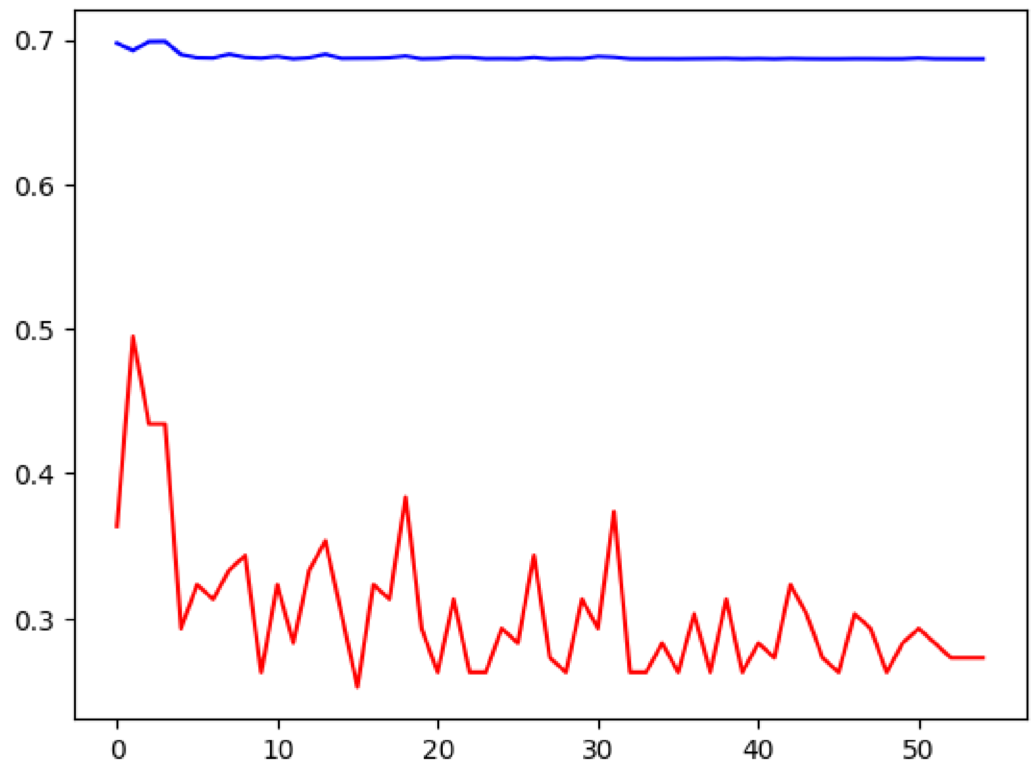

0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
10
20
30
40

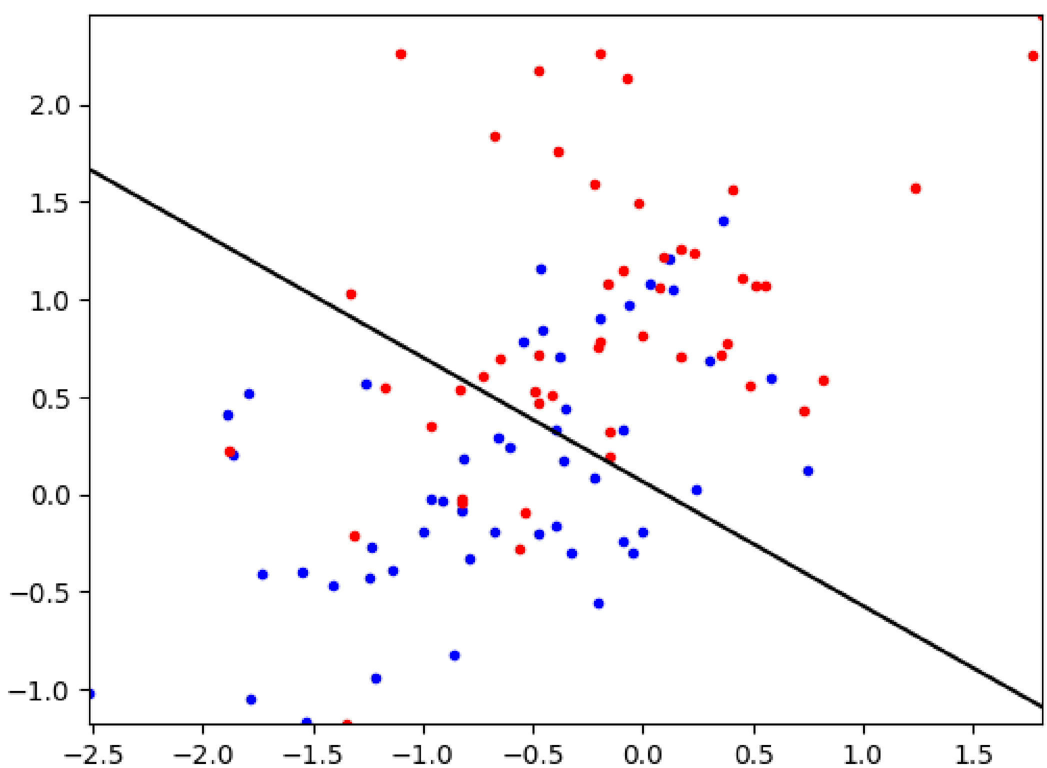

1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2
3

```
Training error rate:  0.08080808080808081
```

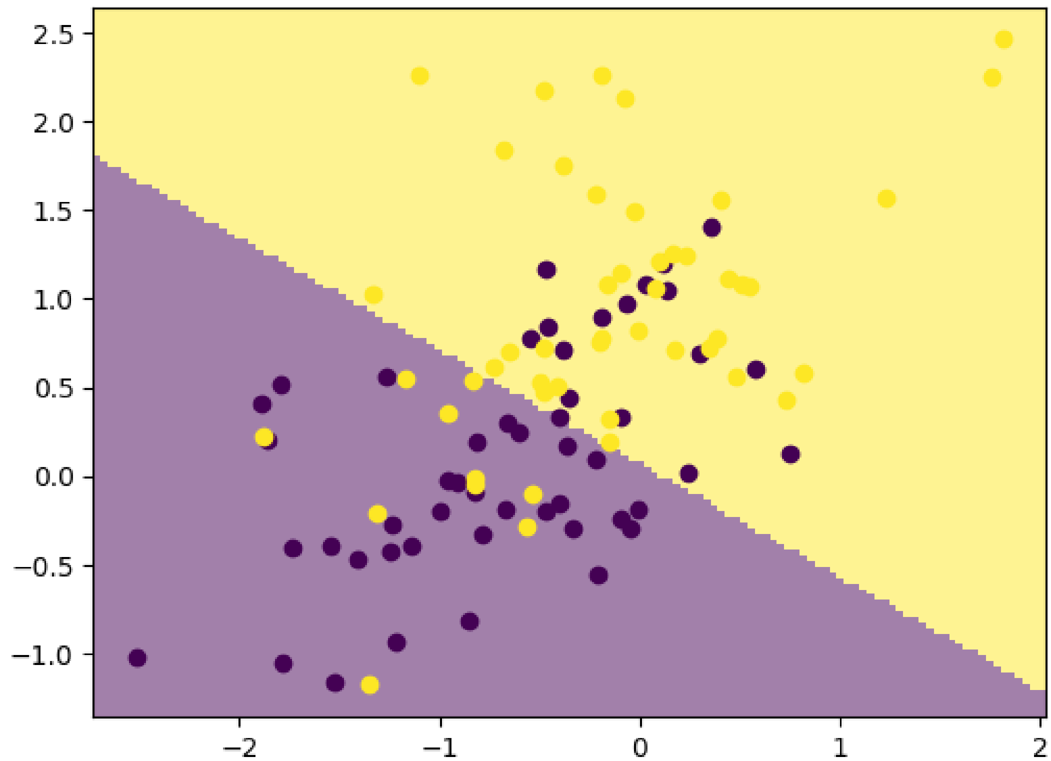



```
[33]: learnerBL2 = logisticClassify2();
      learnerBL2.theta = np.array([0.,0.,0.])
      learnerBL2.
       ↪regTrainL2(XB,YB,initStep=1e-1,stopEpochs=1000,stopTol=1e-5,alpha=L2_alpha)
      plt.show()
      ml.plotClassify2D(learnerBL2,XB,YB)
      print("Training error rate: ",learnerBL2.err(XB,YB))
```


0.7
0.6
0.5
0.4
0.3
0
10
20
30
40
50


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

```
Training error rate:  0.2727272727272727
```



[34]:
```python
print(learnerAL1.theta,learnerAL2.theta)
print(learnerAL1.err(XA,YA),learnerAL2.err(XA,YA))
```

```
[ 0.00158393  0.0014462  -0.001231  ] [ 0.00388709 -0.08433112  0.06375112]
0.5959595959595959 0.08080808080808081
```

Compared with L1 regularization, the value of theta have dropped, and the error has decresedd due to L2 regularization term.

1.9 Problem 1.10

For L1 regularization, the loss fuction + || || , and the gradient + sign( ).
For L2 regularization, the loss fuction + || ||^2 , and the gradient +2 .
L2 regularization is the better one.

2 Statement of Collaboration

I do it by myself