

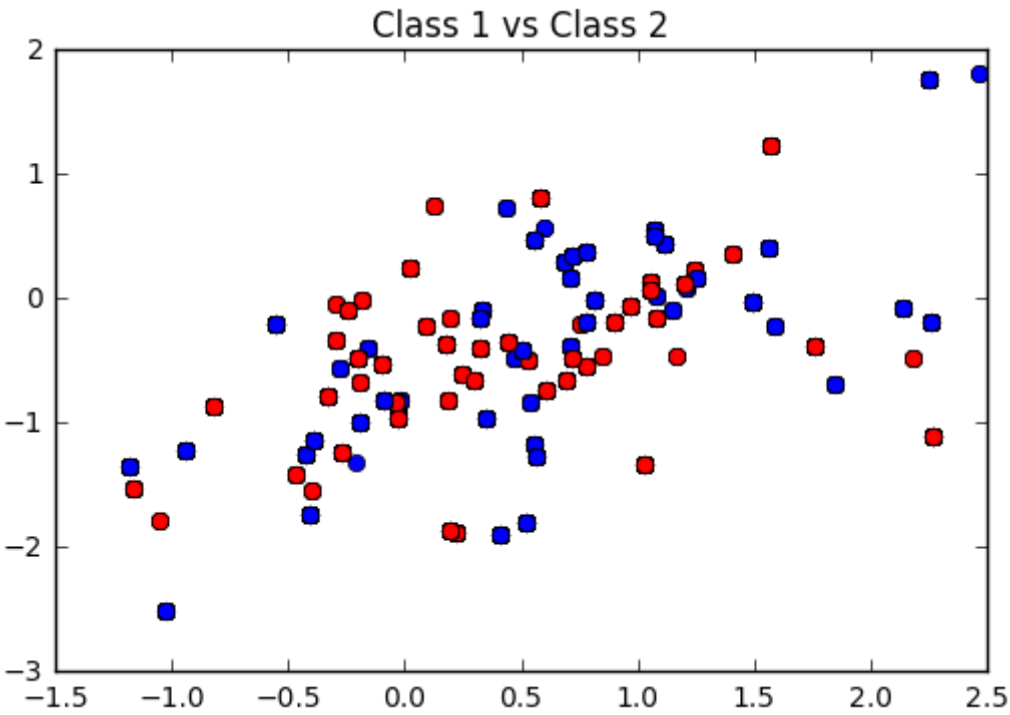
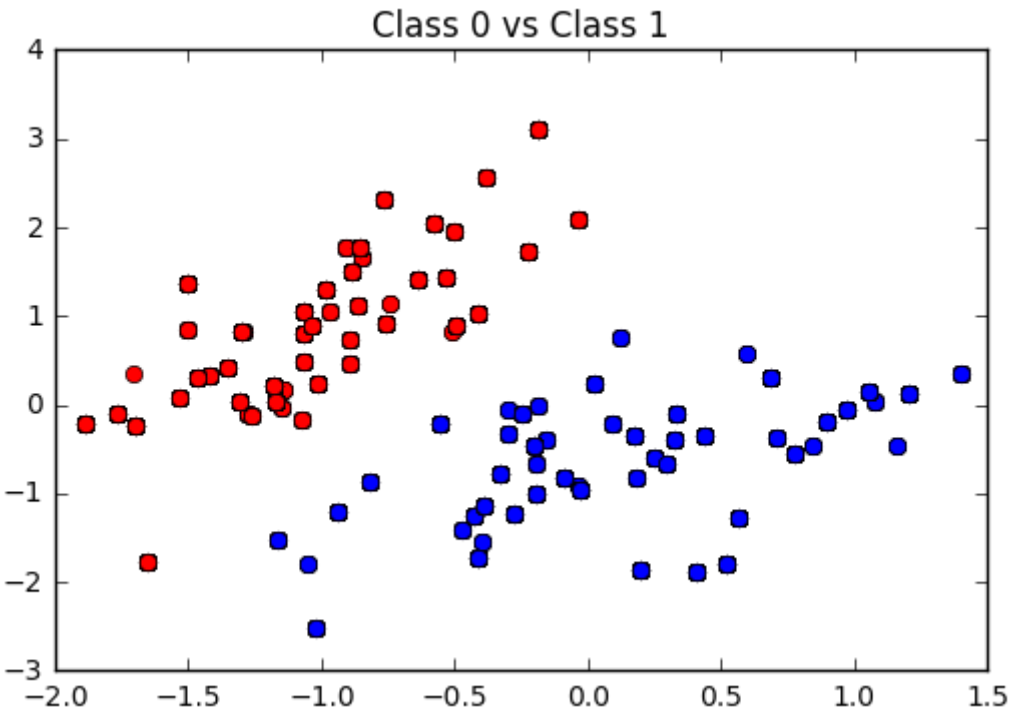
In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import mltools as ml
import mltools.logistic2 as lc2
import importlib

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]

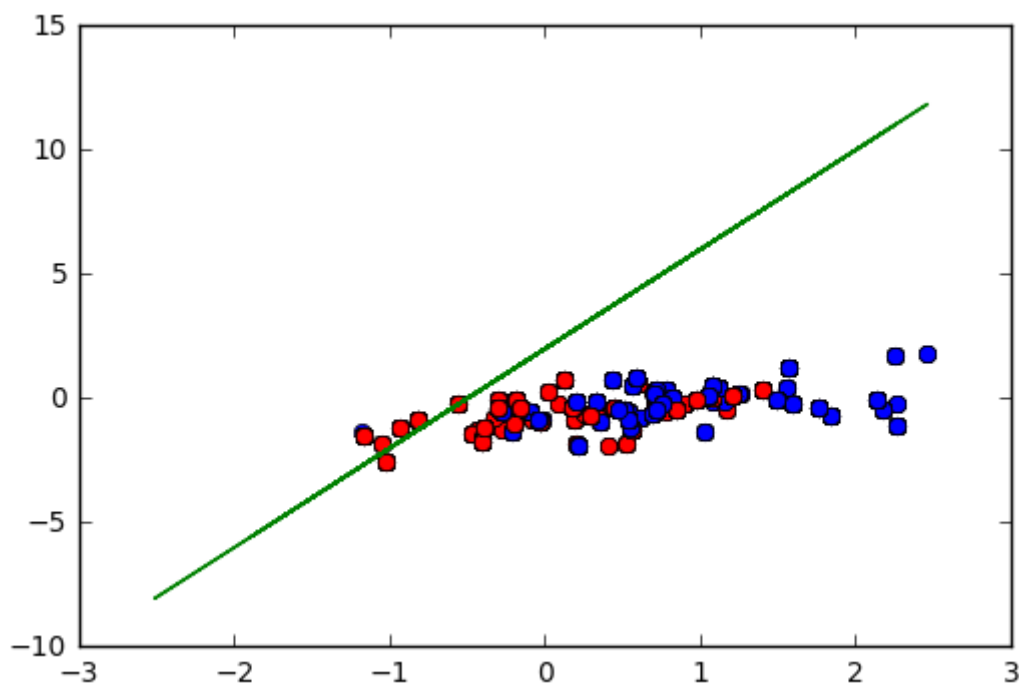
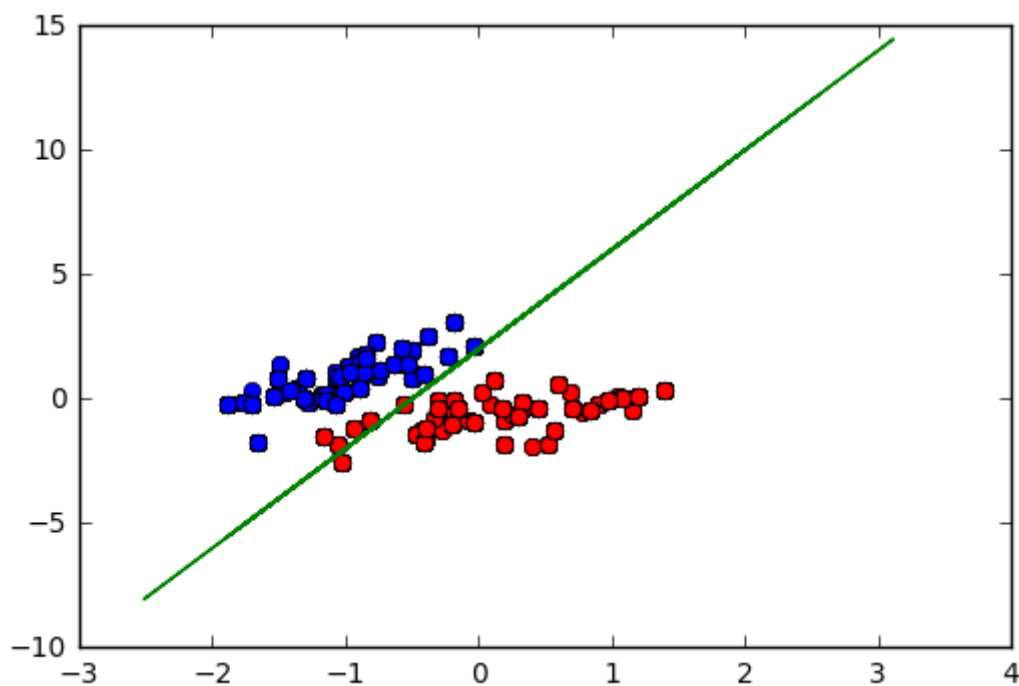
#print(len(XA[:,0]))
#print(len(YA))
#print(YB)
plt.clf()
for i in range(len(YA)):
    if YA[i] == 0:
        plt.plot(XA[i,0], XA[i,1], 'ro', color='red')
    else:
        plt.plot(XA[i,0], XA[i,1], 'ro', color='blue')
plt.title("Class 0 vs Class 1")
plt.show()

plt.clf()
for i in range(len(YA)):
    if YA[i] == 1:
        plt.plot(XB[i,0], XB[i,1], 'ro', color='red')
    else:
        plt.plot(XB[i,0], XB[i,1], 'ro', color='blue')
plt.title("Class 1 vs Class 2")
plt.show()
```



In [67]:

```
reload(lc2)
learner = lc2.logisticClassify2()
learner.classes = np.unique(YA)
theta0 = 0.5
theta1 = 1
theta2 = -0.25
YAhat = [None] * len(XA)
YBhat = [None] * len(XB)
wts = [theta0, theta1, theta2]
learner.theta = wts
learner.plotBoundary(XA, YA)
plt.show()
learner.plotBoundary(XB, YB)
plt.show()
```



In [68]:

```
YAhat = learner.predict(XA)
YBhat = learner.predict(XB)
Aerr = 0
Berr = 0

for i in range(len(XA)):
    Aerr += ((YA[i] - YAhat[i])**2)
Aerr /= len(XA);
for i in range(len(XB)):
    Berr += ((YB[i] - YBhat[i])**2)
Berr /= len(XB);

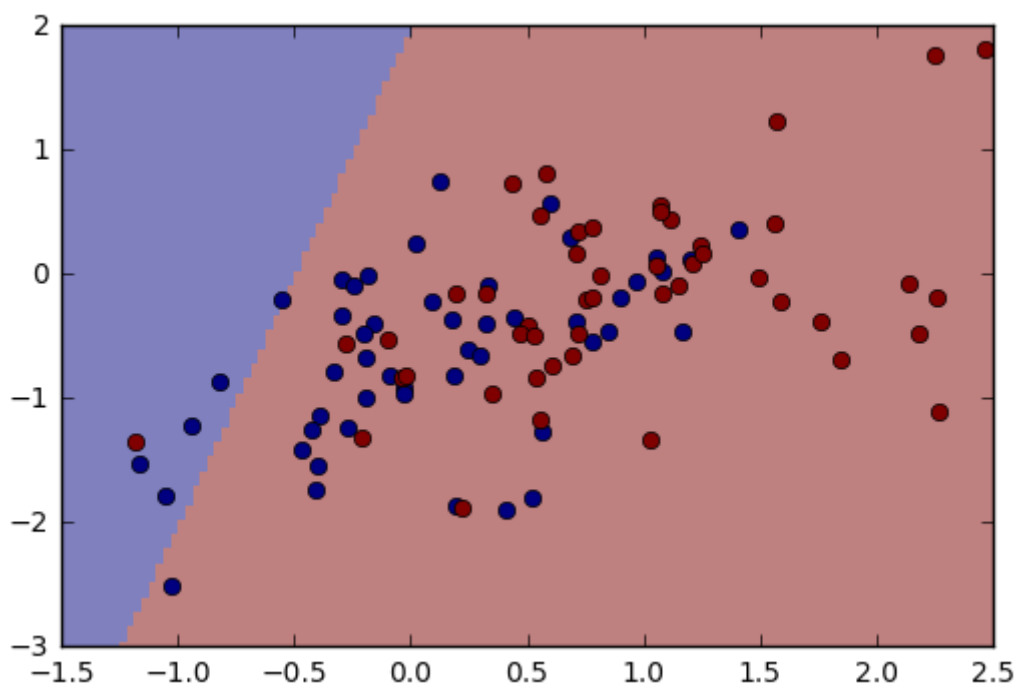
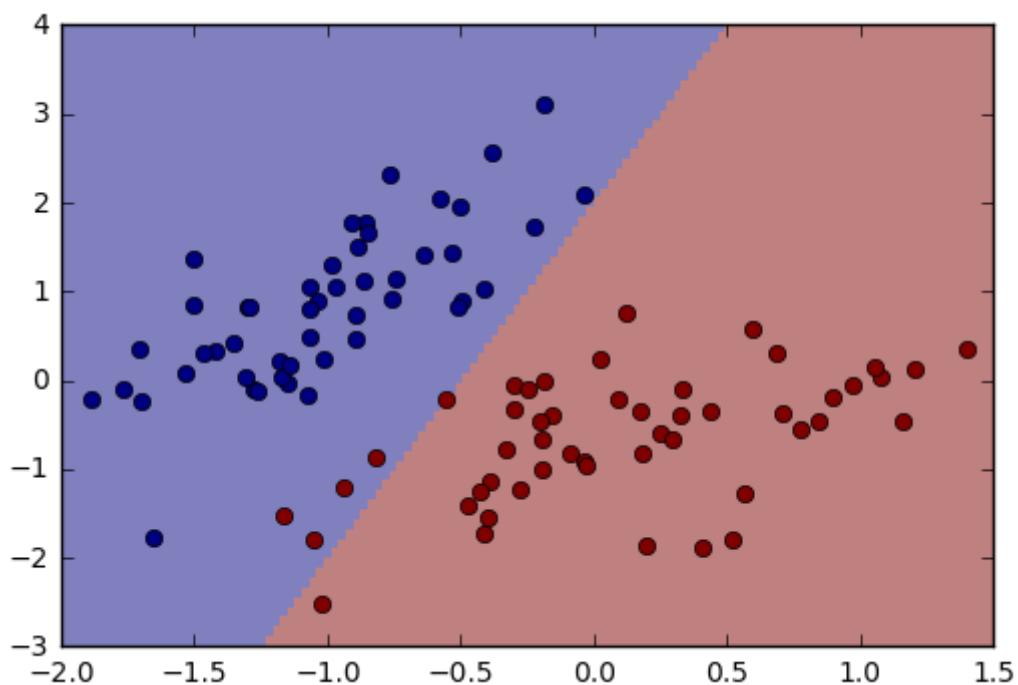
print(Aerr)
print(Berr)
```

0.050505050505051

0.57575757575758

In [34]:

```
#plt.clf()
ml.plot.plotClassify2D(learner,XA,YA)
plt.show()
#learner.plotBoundary(XA,YA)
ml.plot.plotClassify2D(learner,XB,YB)
plt.show()
#Learner.plotBoundary(XB,YBhat)
```



In [3]:

```
#num iterations = 5000 & step size = 1

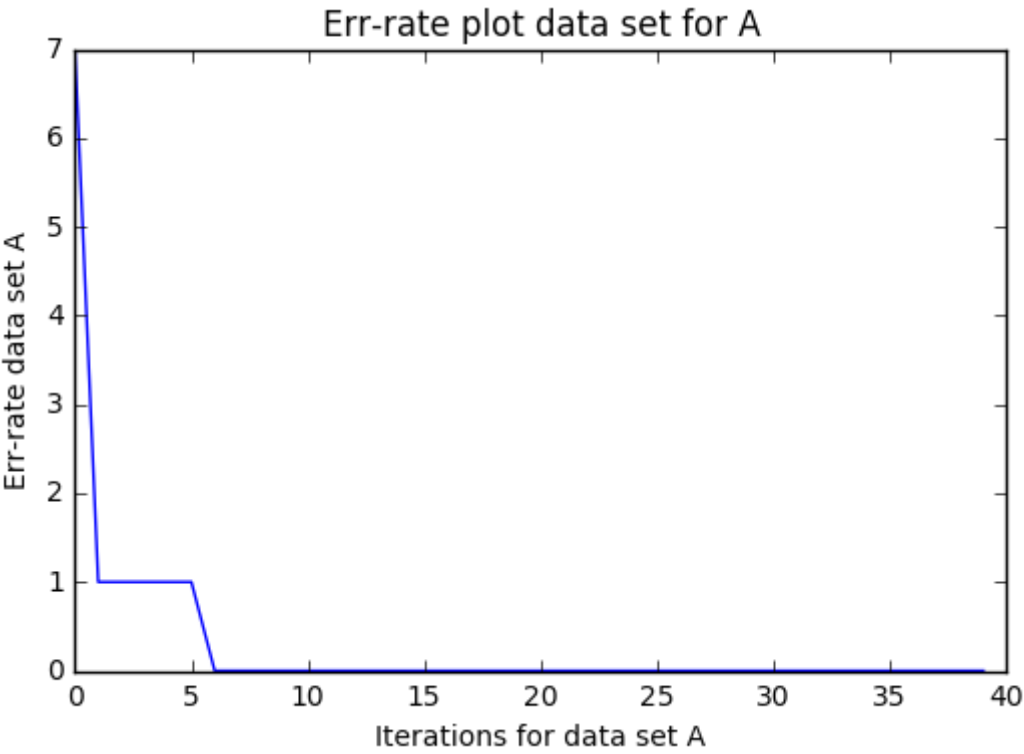
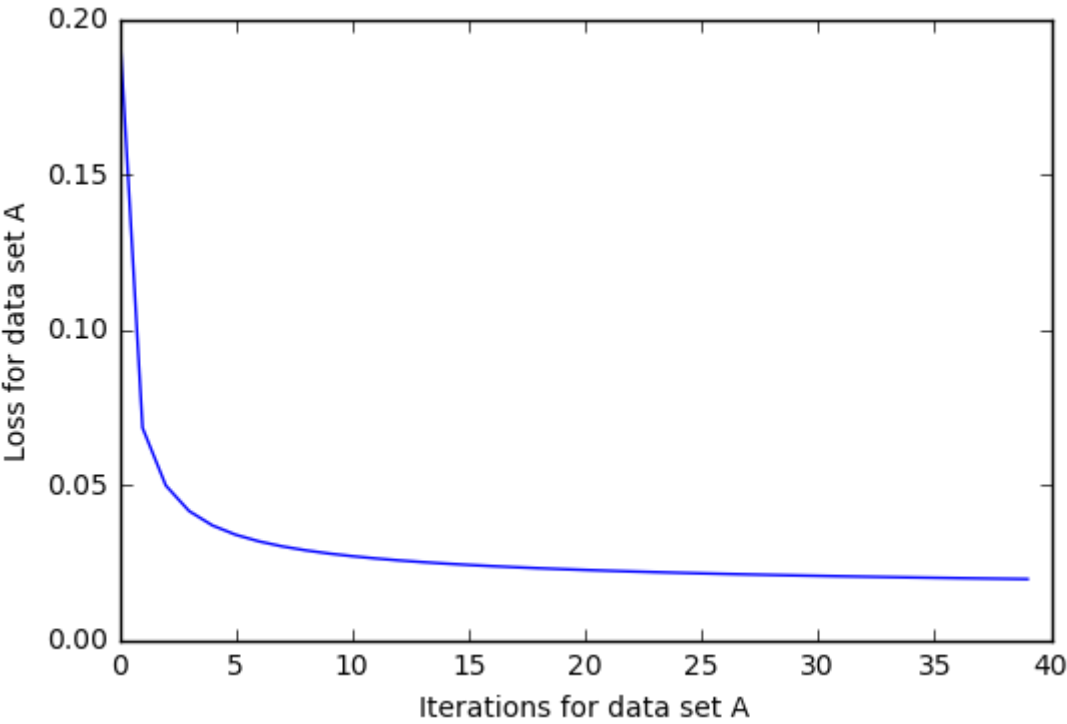
plt.clf()
reload(lc2)
learner=lc2.logisticClassify2();
learner.train(XA,YA,stopIter=5000,initStep=1.0)
plt.plot(learner.loss)
plt.xlabel("Iterations for data set A")
plt.ylabel("Loss for data set A")
plt.show()

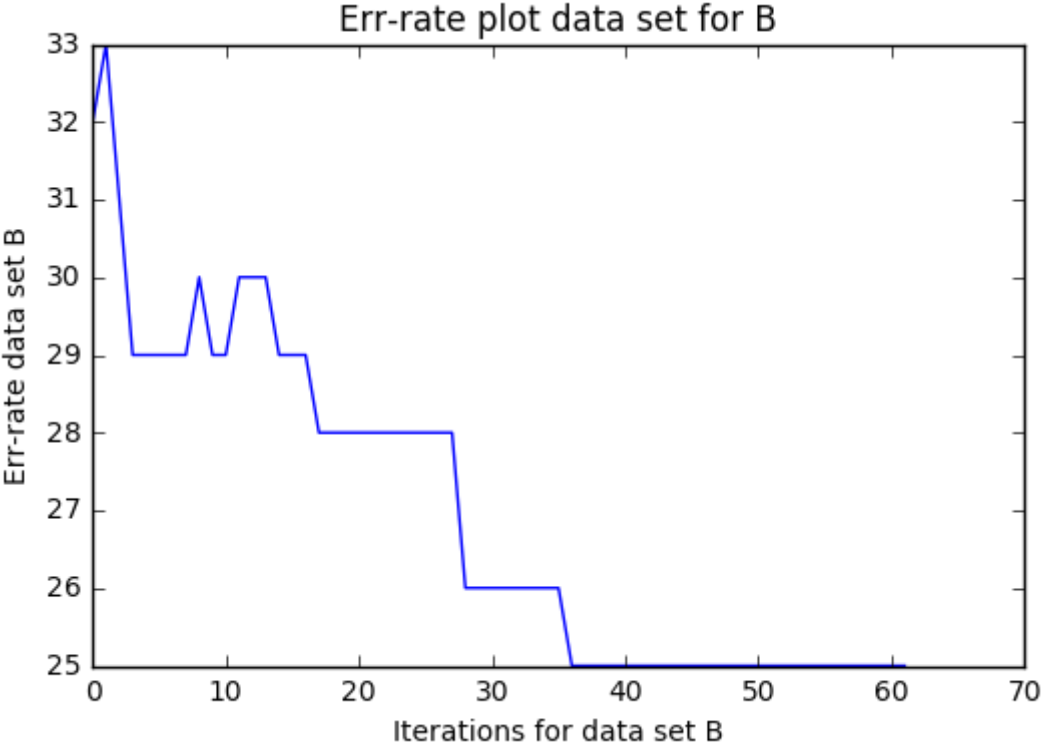
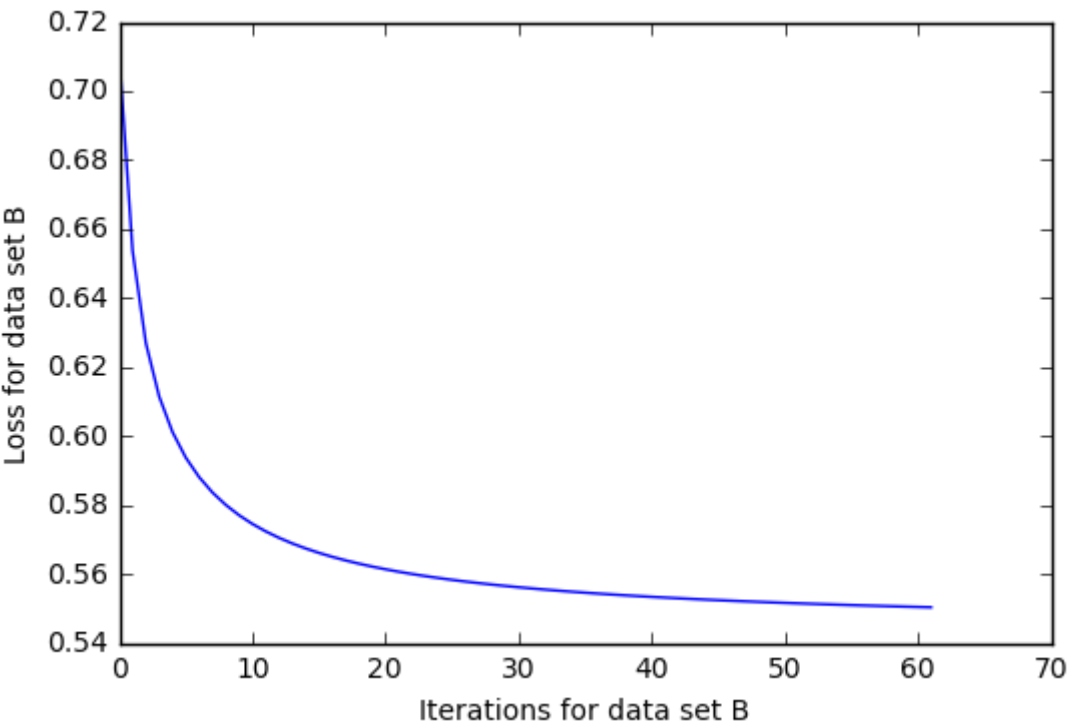
plt.title("Err-rate plot data set for A")
plt.plot(learner.error)
plt.xlabel("Iterations for data set A")
plt.ylabel("Err-rate data set A")
plt.show()

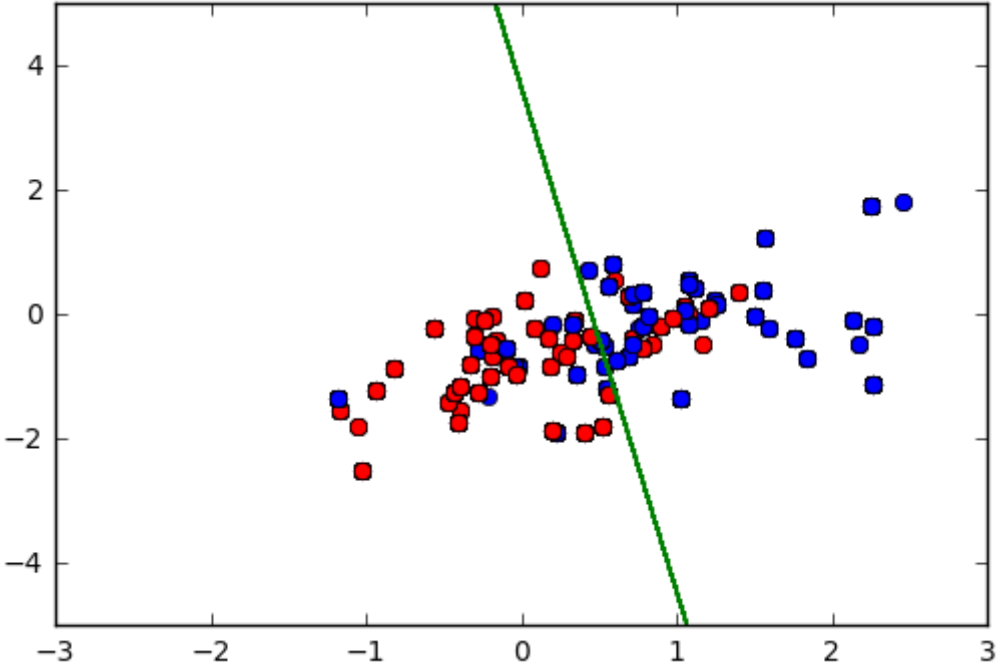
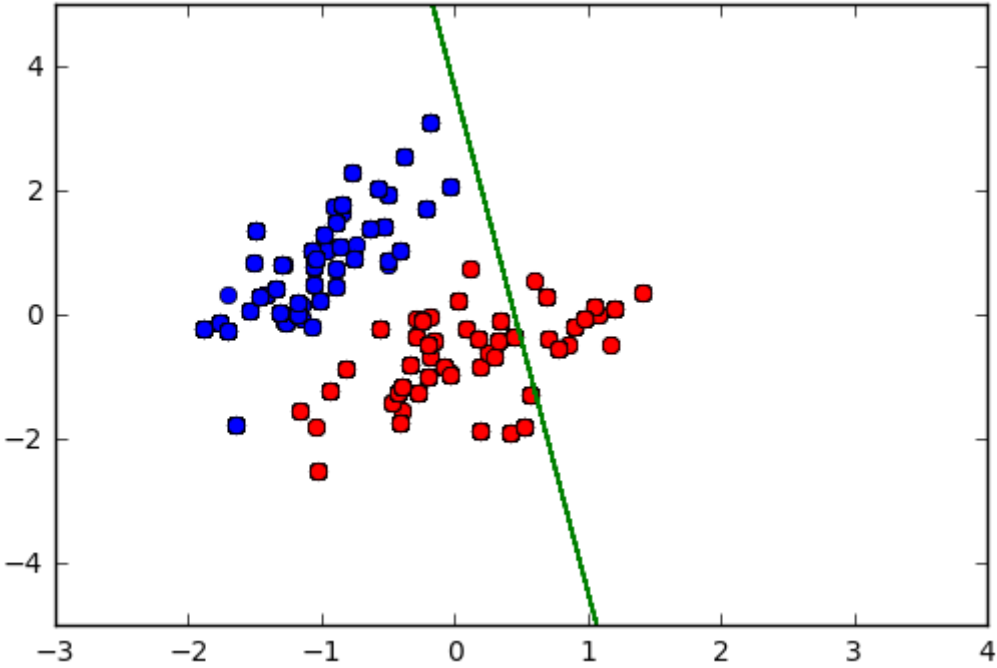
plt.clf()
reload(lc2)
learner=lc2.logisticClassify2();
learner.train(XB,YB,stopIter=5000,initStep=1.0)
plt.plot(learner.loss)
plt.xlabel("Iterations for data set B")
plt.ylabel("Loss for data set B")
plt.show()

plt.title("Err-rate plot data set for B")
plt.plot(learner.error)
plt.xlabel("Iterations for data set B")
plt.ylabel("Err-rate data set B")
plt.show()

plt.title("final converged classifier data set A")
learner.plotBoundary(XA,YA)
plt.ylim(-5,5)
plt.show()
plt.title("final converged classifier data set B")
learner.plotBoundary(XB,YB)
plt.ylim(-5,5)
#plt.ylim(max(YB),min(YB))
plt.show()
```







In []:

2.a) **for** the case $T(a+bx_1)$ the decision boundary will be a line parallel to the x_2 axis.

this will shatter the figures a,b

in case c,d when the (2,2)&(6,4) are of same **class** **this** will **not** be shattered.

2.b) **for** $T((x_1-a)^2 + (x_2-b)^2 + c)$ the decision boundary will be a circle centered at a,

this will shatter the cases a,b

but in the case of c & d if we look at the points A(2,2) & B(4,8) when they are in the same **class**

and C(6,4) is different **class**

then there is no possible way to draw a circle containing A,B which will **not** encompass the C(6,4)

as (6,4) point is exactly half the distance of (AB) from the midpoint of AB segment (3,5).

2.c) **for** $T((a*b)x_1 + (c/a)x_2)$ the decision boundary will be a plane passing through origin.

in the cases a,b it will shatter.

but in the case c,d when the (4,8) & (6,4) are of same **class** & (2,2) is in different **class** then

using this decision boundary we cannot shatter.

As the slope of the point (2,2) lies between slope of (4,8) and slope (6,4).

$$z = x^{(j)} \cdot \theta^T$$

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

$$J_j(\theta) = y^{(j)} \log \left[\frac{1}{1+e^{-z}} \right] - (1-y^{(j)}) \log \left[1 - \frac{1}{1+e^{-z}} \right]$$

$$= -y^{(j)} \log [\sigma(z)] - (1-y^{(j)}) \log [1-\sigma(z)]$$

$$\frac{\partial J_j(\theta)}{\partial \theta_j} = \left[+y^{(j)} \frac{1}{\sigma(z)} - (1-y^{(j)}) \frac{1}{1-\sigma(z)} \right] \frac{\partial \sigma(z)}{\partial \theta_j}$$

$$= \left[\frac{+y^{(j)}}{\sigma(z)} - \frac{(1-y^{(j)})}{1-\sigma(z)} \right] \frac{\partial \left(\frac{1}{1+e^{-z}} \right)}{\partial \theta_j} \quad \left[\because \text{Substituting } \sigma(z) \right]$$

$$= \left[\frac{+y^{(j)}}{\sigma(z)} - \frac{(1-y^{(j)})}{1-\sigma(z)} \right] \left[\frac{e^{-z}}{(1+e^{-z})^2} \right] \times \frac{\partial z}{\partial \theta_j} \quad \left(\text{as } \frac{\partial \sigma(z)}{\partial \theta_j} = \frac{\partial \sigma(z)}{\partial z} \times \frac{\partial z}{\partial \theta_j} \right)$$

$$= \left[\frac{+y^{(j)}}{\sigma(z)} - \frac{(1-y^{(j)})}{1-\sigma(z)} \right] \left[1 - \frac{1}{1+e^{-z}} \right] \left[\frac{1}{1+e^{-z}} \right] x_j$$

$$\quad \left[\text{as } \frac{\partial z}{\partial \theta_j} = x_j \right]$$

$$= \left[\frac{+y^{(j)}}{\sigma(z)} - \frac{(1-y^{(j)})}{1-\sigma(z)} \right] \left[(1-\sigma(z)) \times \sigma(z) \right] x_j$$

$$= \left[+y^{(j)} \times (1-\sigma(z)) - (1-y^{(j)}) \sigma(z) \right] x_j$$

$$= (y^{(j)} - \sigma(z)) x_j$$