Lab3

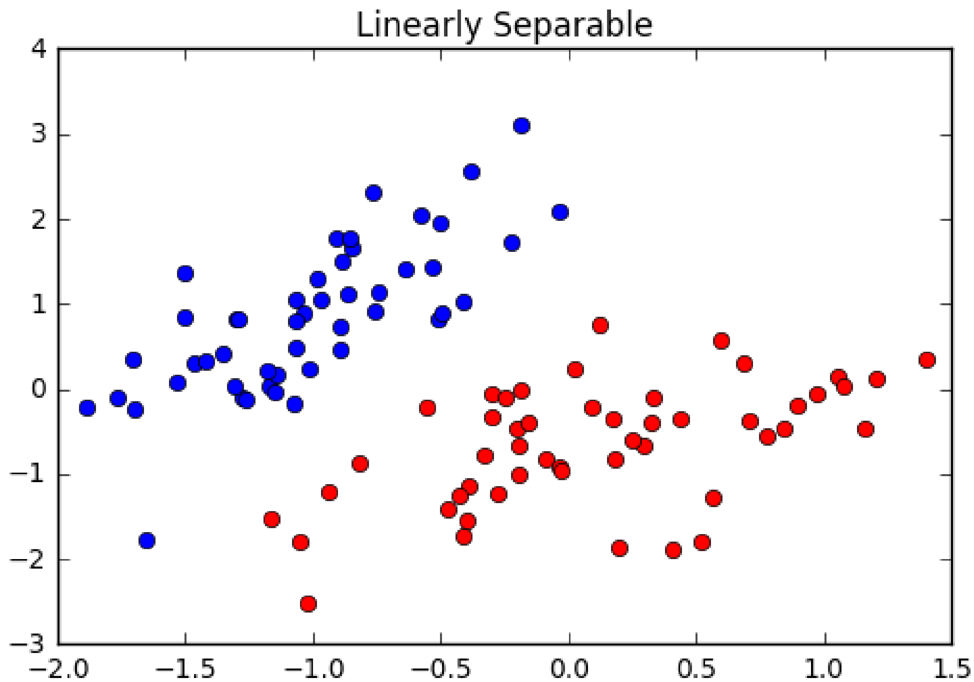
February 8, 2017

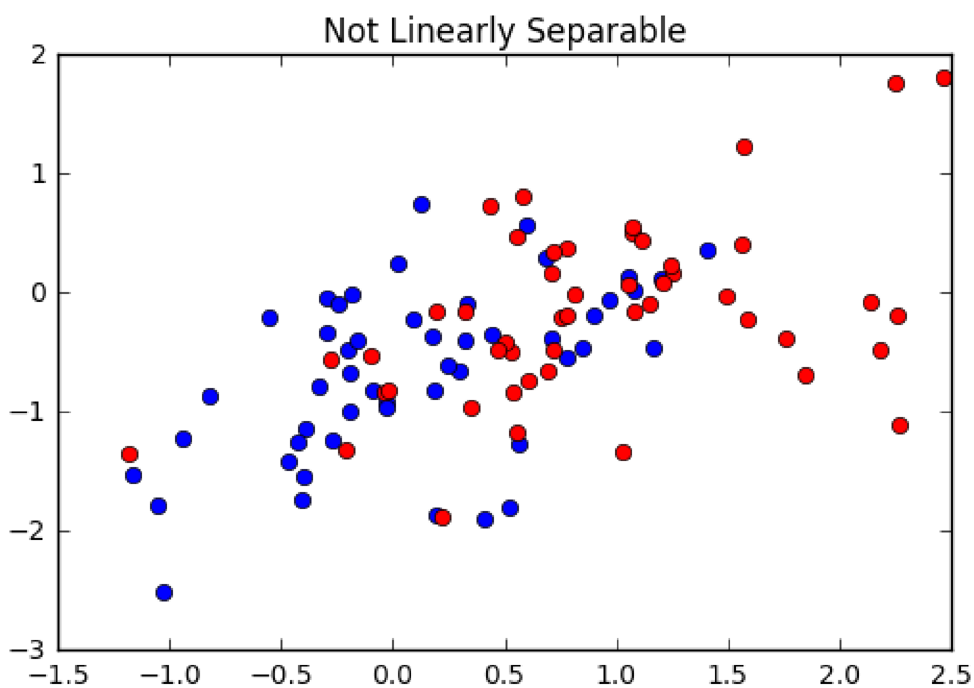
1 CS178 LAB 3 WINTER 2017

2 KODY CHEUNG 85737824

2.0.1 Problem 1A

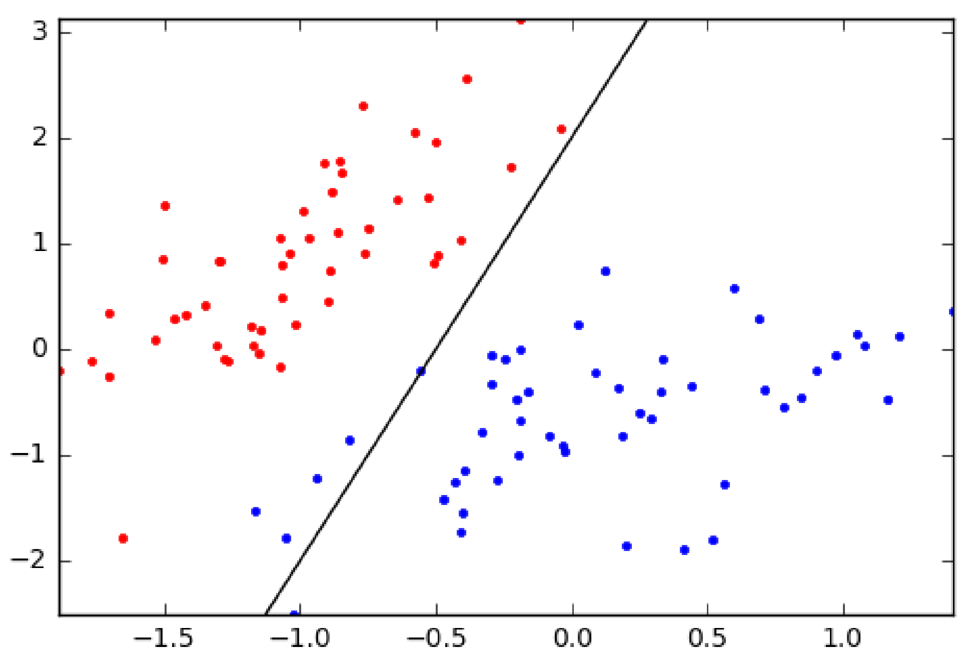
In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import mltools as ml

iris = np.genfromtxt("C:\Python35\CS178\Lab3\data\iris.txt",delimiter=None)

X, Y = iris[:,0:2], iris[:,-1]  #get first two features & targett
X, Y = ml.shuffleData(X,Y)
X,_  = ml.transforms.rescale(X)

XA, YA = X[Y<2,:], Y[Y<2]        #get class 0 vs 1 Y[Y<2] = Y[0]
XB, YB = X[Y>0,:], Y[Y>0]        #get clsas 1 vs 2 Y[Y>0] = Y[1]

colors = ['b','r']
for c in np.unique(YA):
    plt.plot(XA[YA==c, 0], XA[YA==c, 1], 'o', color = colors[int(c)])
plt.title("Linearly Separable")
plt.show()


for c in np.unique(YB):
    plt.plot(XB[YB==c, 0], XB[YB==c, 1], 'o', color = colors[int(c)-1])
plt.title("Not Linearly Separable")
plt.show()
```

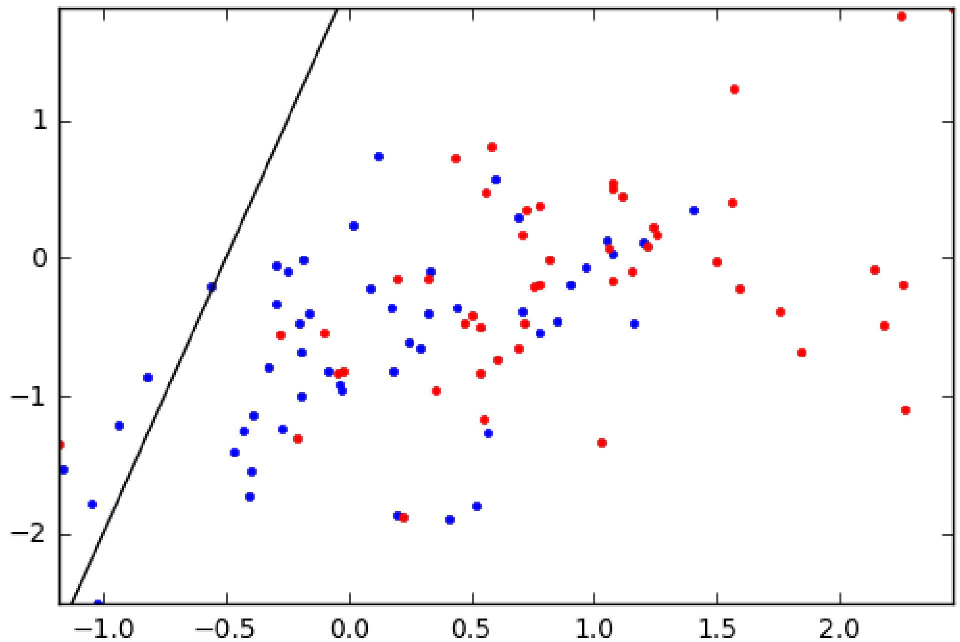

Linearly Separable
4
3
2
1
0
−1
−2
−3
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Not Linearly Separable
2
1
0
−1
−2
−3
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

2.0.2 Problem 1B

In [2]:
```
from logisticClassify2 import *

# data A
learnerA = logisticClassify2(); # create "blank" learner
learnerA.classes = np.unique(YA) # define class labels using YA or YB

wts = np.array([0.5,1,-.25]);  # set theta0, theta1, and theta2
learnerA.theta = wts; # set the learner's parameters

learnerA.plotBoundary(XA,YA)
plt.show()


# data B
learnerB = logisticClassify2(); # create "blank" learner
learnerB.classes = np.unique(YB) # define class labels using YA or YB

wts = np.array([0.5,1,-.25]);  # set theta0, theta1, and theta2
learnerB.theta = wts; # set the learner's parameters


learnerB.plotBoundary(XB,YB)
plt.show()
```





2.0.3 Problem 1C

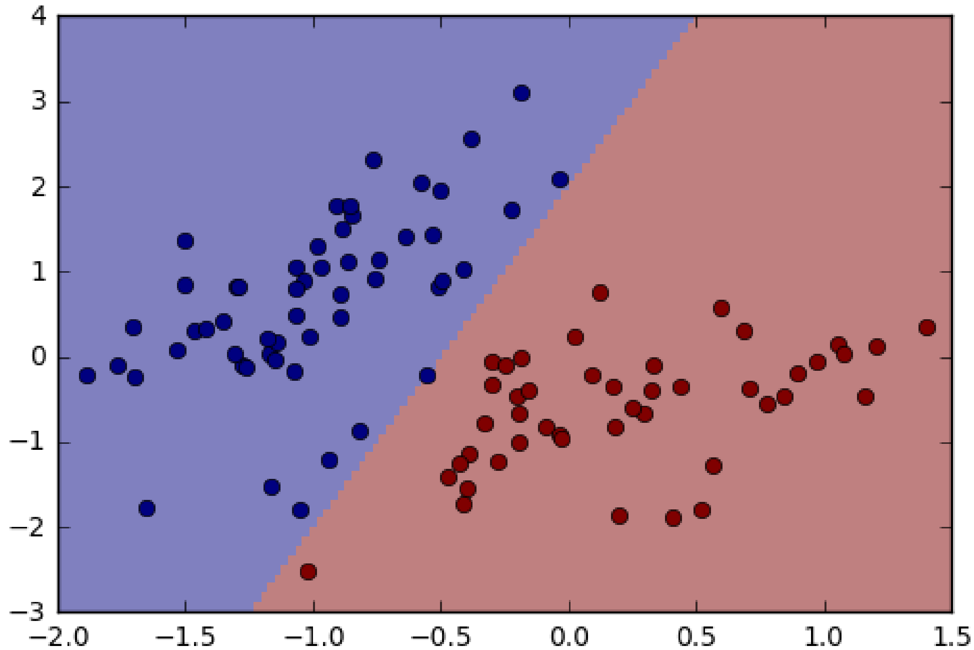
```
In [3]: from sklearn.metrics import mean_squared_error


        YAhat = learnerA.predict(XA)

        mse = mean_squared_error(YA, YAhat)
        print("Error rate on data set A: {}\n".format(mse))


        YBhat = learnerB.predict(XB)

        mseB = mean_squared_error(YB, YBhat)
        print("Error rate on data set B: {}".format(mseB))
```

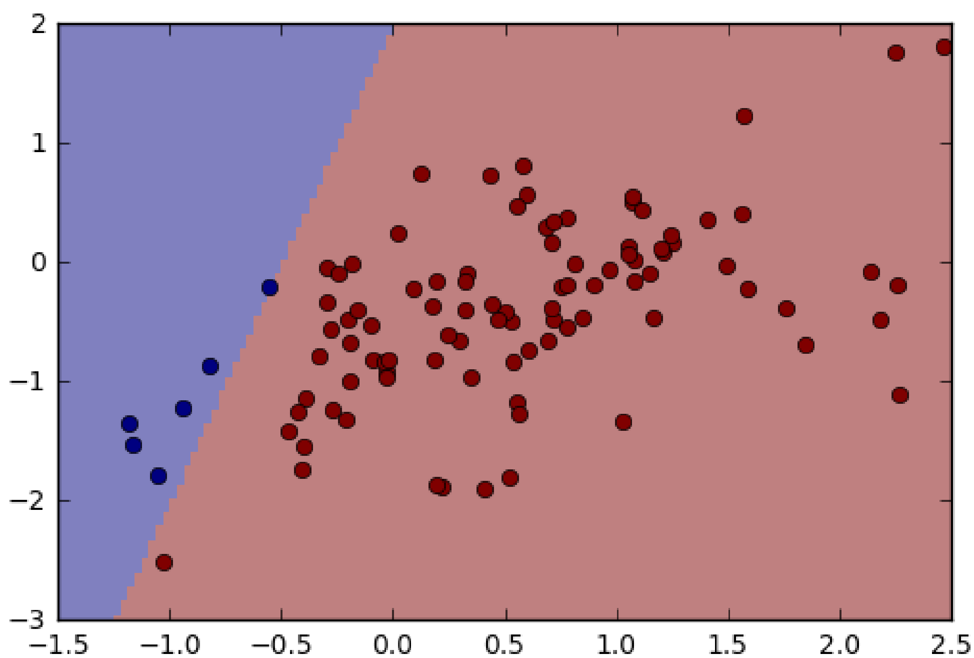
```
Error rate on data set A: 0.050505050505050504

Error rate on data set B: 0.4646464646464646
```

2.0.4 Problem 1D

```
In [4]: ml.plotClassify2D(learnerA, XA, YAhat)
        plt.show()
```

```
ml.plotClassify2D(learnerB, XB, YBhat)
plt.show()
```





2.0.5 Problem 1E

3 Derivation of the gradient of the negative log likelihood J for logistic regression

Code:
ri = XX[i].dot(self.theta.T); #linear response
sigmoid = 1/(1 + math.exp(-ri)); #sigma function
gradi = XX[i].dot(sigmoid-YY[i]); #derivative of negative log likelihood loss
J'(theta) = X(sigmoid(X.dot(theta.T) - Y)

3.0.1 Problem 1F

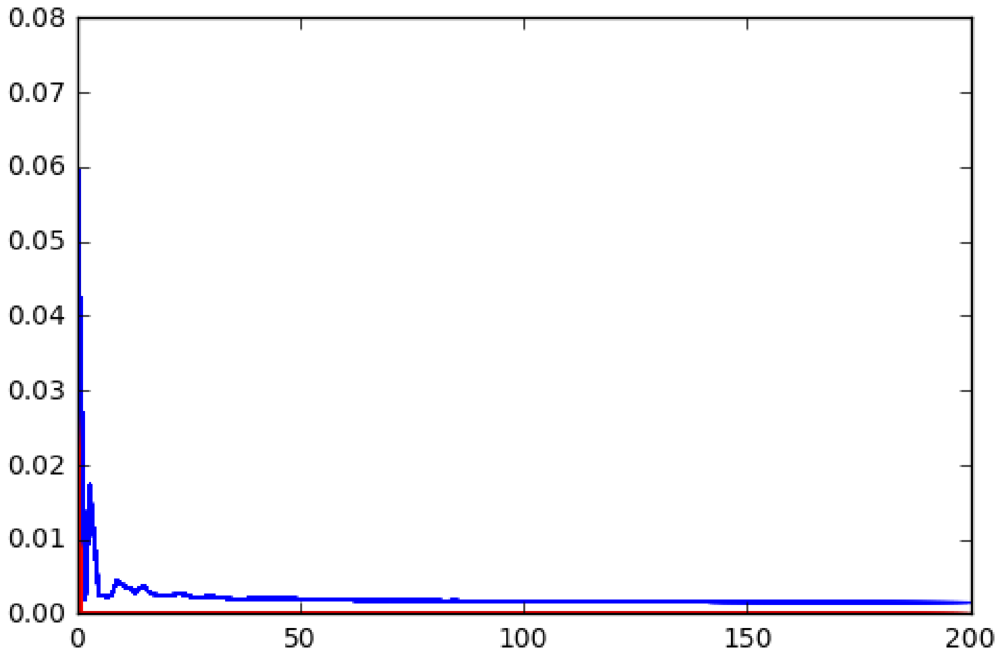
```
In [5]: # #Train function in logisticClassify2

        # def train(self, X, Y, initStep=.1, stopTol=1e-4, stopEpochs=200, plot=Non
        #     """ Train the logistic regression using stochastic gradient descent "
        #     M,N = X.shape;                     # initialize the model if necessar
        #     self.classes = np.unique(Y);       # Y may have two classes, any valu
        #     XX = np.hstack(((np.ones((M,1))),X)); # XX is X, but with an extra co
        #     YY = ml.toIndex(Y,self.classes);   # YY is Y, but with canonical valu

        #     ##        print(XX)
        #     ##        print(YY)

        #     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 = (initStep*2.0)/(2.0+epoch)
        #         epoch = epoch+1; # update stepsize

        #         # Do an SGD pass through the entire data set:
        #         for i in np.random.permutation(M):
        #             ri    = XX[i].dot(self.theta.T);     # TODO: compute linear r
        #             sigmoid = 1/(1 + math.exp(-ri))
        #             gradi = XX[i].dot(sigmoid-YY[i])#XX[i].dot XX[i].dot(ri - YY[
        #             self.theta -= stepsize * gradi;  # take a gradient step

        #         J01.append( self.err(X,Y) )  # evaluate the current error rate

        #         ## TODO: compute surrogate loss (logistic negative log-likelihood
        #         ##  Jsur = sum_i [ (log si) if yi==1 else (log(1-si)) ] / M

        #         sigma = 1/(1 + np.exp(-(XX.dot(self.theta.T))))
```

```
#           #print(sigma)
#           Jsur = (-np.mean(YY * np.log(sigma) + (1-YY)*np.log(1-sigma)))
#           #print(Jsur)
#           Jnll.append( Jsur ) # TODO evaluate the current NLL loss
#           plt.figure(1); plt.plot(Jnll,'b-',J01,'r-'); plt.draw();    # plo
#           if N==2: plt.figure(2); self.plotBoundary(X,Y); plt.draw(); # & p
#           plt.pause(.01);                          # let OS draw the plot

#           #print(epoch)
#           #plt.show()
#           plt.gcf().clear()
#           ## For debugging: you may want to print current parameters & loss
#           #print (self.theta, ' => ', Jsur[-1], ' / ', J01[-1]  )
#           ##              print(self.theta)
#           ##              if (epoch > 2):
#           ##                  print(abs(Jnll[-2]-Jsur))
#           # raw_input()    # pause for keystroke

#           # TODO check stopping criteria: exit if exceeded # of epochs ( >
#           if (epoch > stopEpochs):#or abs(Jnll[-2] - Jnll[-1]) < stopTol):
#               done = True;    # or if Jnll not changing between epochs ( < s
```

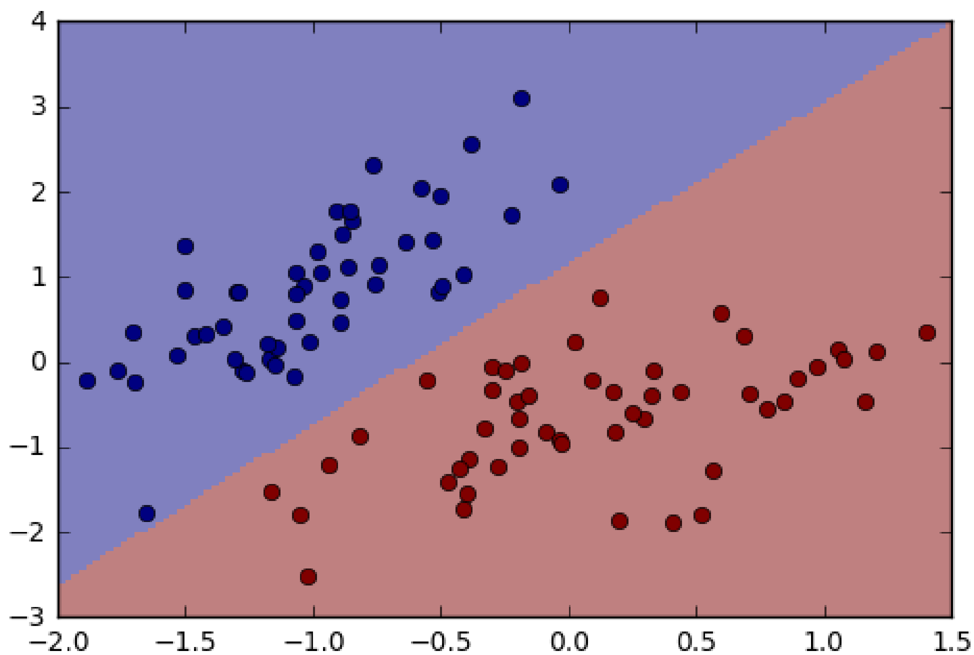
3.0.2 Problem 1G

In [6]:
```
# I chose 200 epochs so it wouldn't load too long but show the convergence
# I used a stepsize of 1 to create an accurate fit, even though the first c
#       had negative surrogate losses

print("Data Set A")
print("Blue: Surrogate Loss")
print("Red: 0-1 Loss")
learnerA.train(XA,YA)


ml.plotClassify2D(learnerA, XA, YA)
plt.show()


print("Data Set B")
print("Blue: Surrogate Loss")
print("Red: 0-1 Loss")
learnerB.train(XB,YB)



ml.plotClassify2D(learnerB, XB, YB)
plt.show()
```

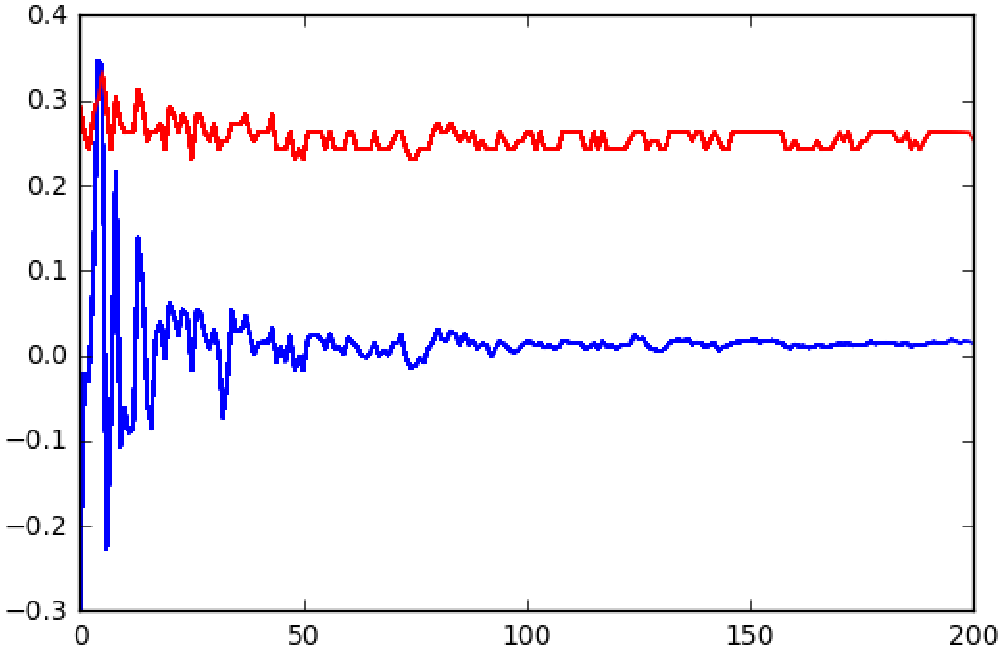
```
Data Set A
Blue: Surrogate Loss
Red: 0-1 Loss
```



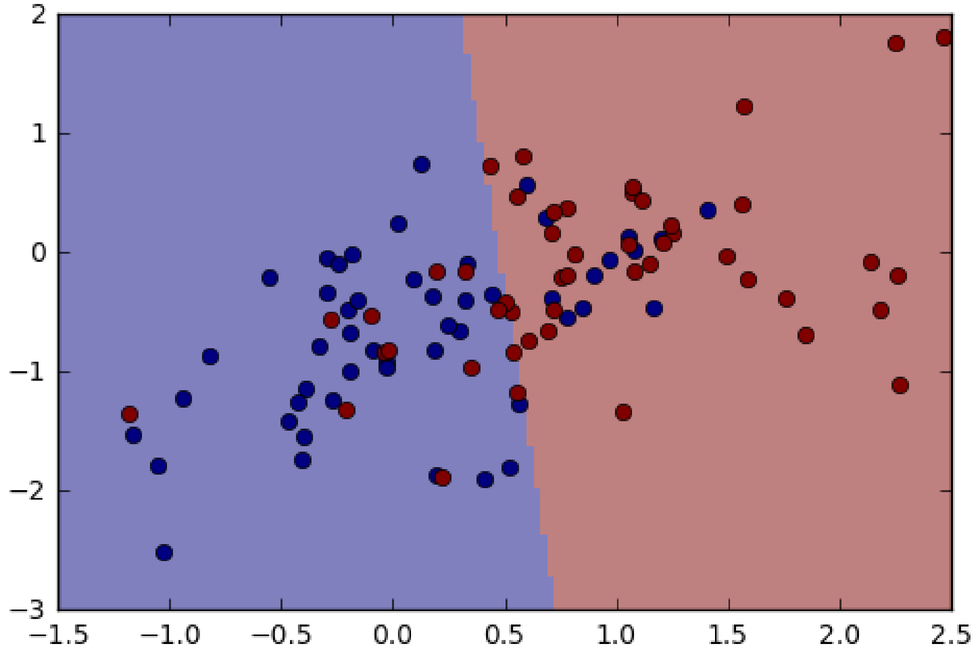

```
<matplotlib.figure.Figure at 0x1bb71168780>
```



```
Data Set B
Blue: Surrogate Loss
Red: 0-1 Loss
```




```
&lt;matplotlib.figure.Figure at 0x1bb71739f28&gt;
```



3.0.3 Problem 2

a) T(a+bx)

This function can shatter graphs 1, 2, and 3, but not 4. Suppose the points were red, blue, blue, red, from right to left. No straight line could split the red from blue.
VC <= 3

b) T((x1 - a)2 + (x1 - b)2 + c)

This function can shatter 1, but not the rest, because if a class 1 point is closer to the center of a class 0 circle, then it would not be able to shatter the points.
VC = 1

c) T((a * b)x1 + (c / a)x2)

This function can shatter 1, 2 and 3, but not 4. This also a straight line so it cannot cross 2 points just like the learner in part a.
VC <= 3