

Example Template for HW3

This notebook contains the same template code as "logisticClassify2.py", but reorganized to make it simpler to edit and solve in iPython. Feel free to use this for your homework, or do it another way, as you prefer.

```
In [1]: 1 from __future__ import division
2
3 import numpy as np
4 np.random.seed(0)
5
6 import mltools as ml
7 import sys
8 sys.path.append('code')
9
10 import matplotlib.pyplot as plt # use matplotlib for plotting with in
11 plt.set_cmap('jet');
12 %matplotlib inline
13 import warnings
14 warnings.filterwarnings('ignore'); # for deprecated matplotlib function
15
16 import mltools as ml
17 from logisticClassify2 import *
18
```

Problem 1

```
In [2]: 1 iris = np.genfromtxt("data/iris.txt", delimiter=None)
2 X, Y = iris[:,0:2], iris[:, -1] # get first two features & target
3
4 X, Y = ml.shuffleData(X, Y) # reorder randomly rather than by class
5
6 X, _ = ml.transforms.rescale(X) # rescale to improve numerical stability
7
8 XA, YA = X[Y<2, :], Y[Y<2] # Dataset A: class 0 vs class 1
9 XB, YB = X[Y>0, :], Y[Y>0] # Dataset B: class 1 vs class 2
10
11
```

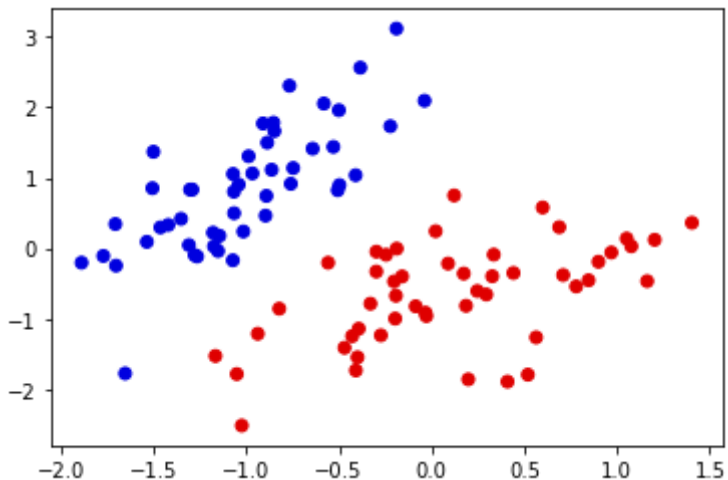
P1.1

For each of the two datasets, create a separate scatter plot in which the training data from the two classes is plotted in different colors. Which of the two datasets is linearly separable?

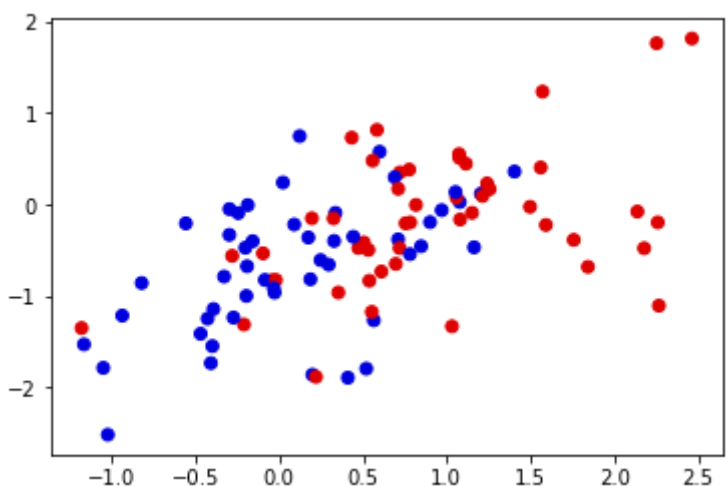
P1.1 Answer : dataset set A can linearly

separable. But some of data in set B is overlapping so too hard to be linearly separable

```
In [3]: 1 ml.plotClassify2D( None, XA, YA)
        2 plt.show()
```



```
In [4]: 1 ml.plotClassify2D( None, XB, YB)
        2 plt.show()
```



P1.2

Write (fill in) the function `plotBoundary` in `logisticClassify2.py` to compute the points on the decision boundary. In particular, you only need to make sure `x2b` is set correctly using `self.theta`. This will plot the data & boundary quickly, which is useful for visualizing the model during training. To demonstrate your function, plot the decision boundary corresponding to the classifier

$$\text{sign}(2 + 6 \cdot X_1 - 1 \cdot X_2)$$

along with dataset A, and again with dataset B. These fixed parameters should lead to an OK classifier on one data set, but a poor classifier on the other. You can create a “blank” learner and set the weights as follows:

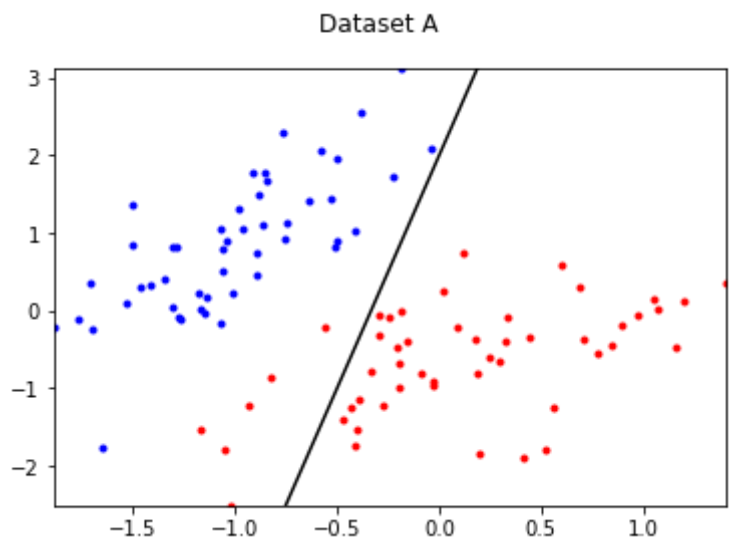
set the weights as follows:

```

In [5]: 1 def myPlotBoundary(self, X,Y):
2
3
4
5
6     """ Plot the (linear) decision boundary of the classifier, along with
7     if len(self.theta) != 3: raise ValueError('Data & model must be 2D')
8     ax = X.min(0),X.max(0);
9     ax = (ax[0][0],ax[1][0],ax[0][1],ax[1][1]);
10
11     ## TODO: find points on decision boundary defined by theta0 + theta1x1 + theta2x2 = 0
12     x1b = np.array([ax[0],ax[1]]); # at X1 = points in x1b # HW3 given
13
14     # TODO find x2 values as a function of x1's values
15     # x2b = np.array([-self.theta[0]+self.theta[1]*x1b[0])/self.theta[2],
16     x2b = (-self.theta[0]-self.theta[1]*x1b)/self.theta[2]
17
18     ## Now plot the data and the resulting boundary:
19     A = Y==self.classes[0]; # and plot it: # HW3 given code
20     plt.plot(X[A,0],X[A,1], 'b.', X[-A,0],X[-A,1], 'r.', x1b,x2b, 'k-'); # H
21     plt.axis(ax);
22     plt.draw();
23
24     # Create a shell classifier
25     class logisticClassify2(ml.classifier):
26         classes = []
27         theta = np.array( [-1, 0, 0] ) # initialize theta to something #
28         plotBoundary = myPlotBoundary
29         predict = None # these functions will be implemented
30         train = None

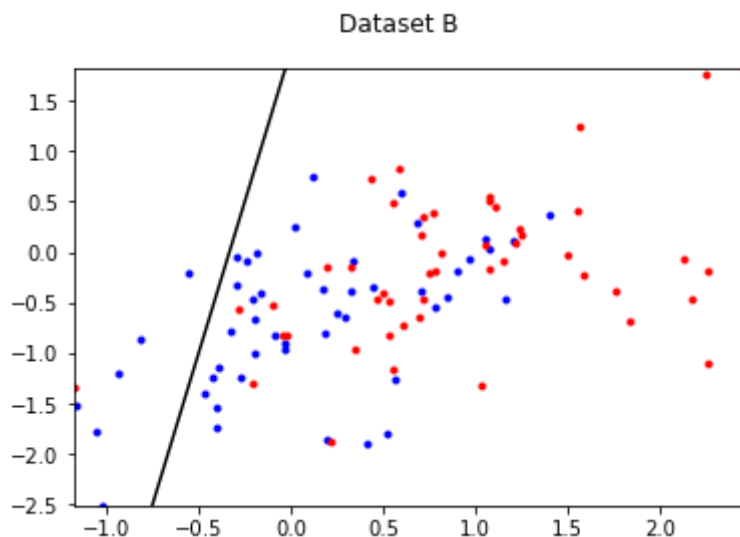
```

```
In [6]: 1 learnerA = logisticClassify2()  
2 learnerA.classes = np.unique(YA)           # store the class values for thi  
3 learnerA.theta = np.array([2,6,-1]);        # TODO: insert hard-coded values  
4 learnerA.plotBoundary(XA,YA)  
5  
6 plt.suptitle('Dataset A')  
7 plt.figure(figsize=(10,5))  
8 plt.show()
```



<Figure size 720x360 with 0 Axes>

```
In [7]: 1 learnerA = logisticClassify2()# HW3 given code
2 learnerA.classes = np.unique(YB) # store the class values for thi
3 learnerA.theta = np.array([2,6,-1]); # TODO: insert hard-coded values
4 learnerA.plotBoundary(XB,YB)
5
6 plt.suptitle('Dataset B')
7 plt.figure(figsize=(10,5))
8 plt.show()
```



```
In [36]: 1 # ...
2
```

P1.3 : predict function and error rate

```

In [34]: 1 # Should go in your logistic2 class:
2 def myPredict(self,X):
3     """ Return the predicted class of each data point in X"""
4     """
5     raise NotImplementedError
6
7     ## TODO: compute linear response  $r[i] = \theta_0 + \theta_1 X[i,1] + \theta_2 X[i,2]$ 
8
9     ##         else predict class 0:  $\hat{Y}[i] = \text{self.classes}[0]$ 
10    """
11    leng = len(X)
12
13    errRate = np.zeros(leng)
14    Yhat = np.zeros(leng)
15
16    ## TODO: compute linear response  $r[i] = \theta_0 + \theta_1 X[i,1] + \theta_2 X[i,2]$ 
17    for i in range ( leng ):
18        errRate[i] = self.theta[0] + self.theta[1]*X[i,0] + self.theta[2]*X[i,1]
19
20        ## TODO: if  $r[i] > 0$ , predict class 1:  $\hat{Y}[i] = \text{self.classes}[1]$ 
21        if (errRate[i] > 0):
22            Yhat[i] = self.classes[1]
23        ## TODO: else predict class 0:  $\hat{Y}[i] = \text{self.classes}[0]$ 
24        else:
25            Yhat[i] = self.classes[0]
26    return Yhat
27
28
29 # Update our shell classifier definition
30 class logisticClassify2(ml.classifier):
31     classes = [] # HW3 given code
32     theta = np.array( [-1, 0, 0] ) # initialize theta to something# HW3 given code
33     plotBoundary = myPlotBoundary
34     predict = myPredict
35     train = None# HW3 given code
36
37
38
39 # ...

```

```

In [35]: 1 learnerA = logisticClassify2()
2 learnerA.classes = np.unique(YA) # store the class values for the dataset
3 learnerA.theta = [2,6,-1]; # TODO: insert hard-coded values# HW3 given code
4
5 print ( "For Dataset A ")
6 print( "Error: ", learnerA.err(XA,YA) )

```

For Dataset A
Error: 0.06060606060606061

```
In [36]: 1 learnerA = logisticClassify2()  
2 learnerA.classes = np.unique(YB) # store the class values for th  
3 learnerA.theta = [2,6,-1]; # TODO: insert hard-coded values# HW3 give  
4  
5 print ( "For Dataset B "  
6 print( "Error: ", learnerA.err(XB,YB) )
```

For Dataset B

Error: 0.45454545454545453

If predict is implemented, then the inherited 2D visualization function should work; you can verify your decision boundary from P1.2:

1.4

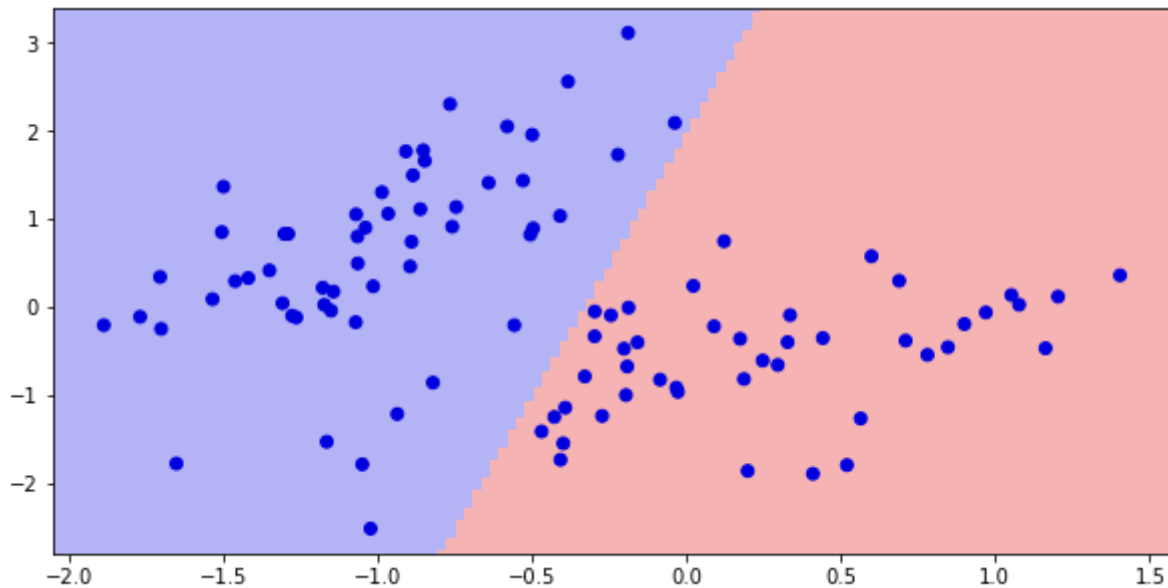
Verify that your predict and plotBoundary implementations are consistent by using plotClassify2D with your manually constructed learner on each dataset. This will call predict on a dense grid of points, and you should find that the resulting decision boundary matches the one you plotted previously. (5 points)

- plotBoundary

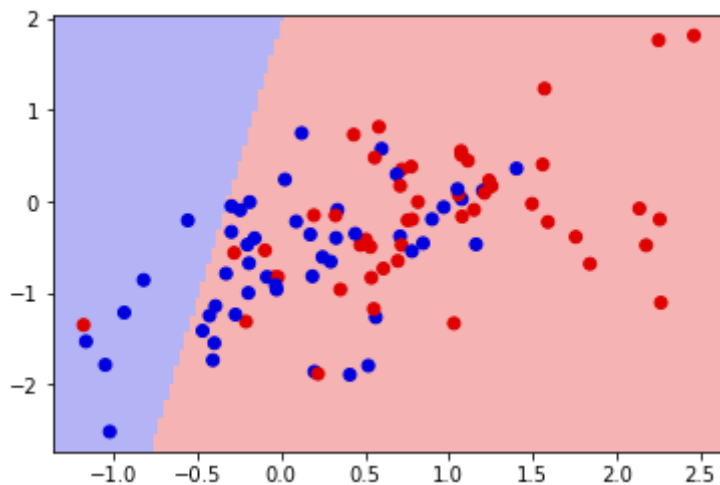
1.4 answer

- Although some of the points in Dataset A have crossed the decision boundary, generally given theta are well applied to Dataset A.
- In Dataset B, the decision boundary does not function properly. Given thetaes do not apply well to B

```
In [37]: 1 ml.plotClassify2D(learnerA,XA,YA)
          2 plt.show()
```



```
In [12]: 1 ml.plotClassify2D(learnerA,XB,YB)
          2 plt.show()
```



...

Here is an example of latex equations that may be useful for expressing the gradient:

1.5 Gradient of NLL

Our negative log-likelihood loss is:

$$J_j(\theta) = - \begin{cases} \log(\sigma(x^{(i)} \cdot \theta)) & \text{if } y^{(i)} = 1 \\ \log(1 - \sigma(x^{(i)} \cdot \theta)) & \text{if } y^{(i)} = 0 \end{cases}$$

Thus, its gradient is:

$$\nabla J_j(\theta) = (\text{something})$$

$$\checkmark J_j(\theta) = -y^{(j)} \log \alpha(x^{(j)} \cdot \theta) - (1 - y^{(j)}) \cdot \log(1 - \alpha(x^{(j)} \cdot \theta))$$

$$\checkmark \nabla J_j = (\alpha(x^{(j)} \cdot \theta) - y^{(j)}) x^{(j)}$$

$$\checkmark \alpha'(r) = \alpha(r) \cdot (1 - \alpha(r))$$

$$\begin{aligned} \nabla J_i(\theta) &= -y^{(i)} \cdot (1 - s^i) \cdot x^i + (1 - y^i) \cdot s^i \cdot x^i \\ &= -y^i \cdot x^i + y^i \cdot s^i \cdot x^i + s^i \cdot x^i - y^i \cdot s^i \cdot x^i \\ &= -y^i \cdot x^i + s^i \cdot x^i = (-y^i + s^i) x^i \end{aligned}$$

1.6

Now define the train function and complete its missing code.

```

In [52]: 1 def myTrain(self, X, Y, initStep=1.0, stopTol=1e-4, stopEpochs=5000, pl
2         """ Train the logistic regression using stochastic gradient descent
3         from IPython import display
4         M,N = X.shape; # initialize the model if necess
5         self.classes = np.unique(Y); # Y may have two classes, any va
6         XX = np.hstack((np.ones((M,1)),X)) # XX is X, but with an extra col
7         YY = ml.toIndex(Y,self.classes); # YY is Y, but with canonical va
8         if len(self.theta)!=N+1: self.theta=np.random.rand(N+1);
9         # init loop variables:
10        epoch=0; done=False; Jnll=[]; J01=[];
11        while not done:
12            stepsize, epoch = initStep*2.0/(2.0+epoch), epoch+1; # update s
13            # Do an SGD pass through the entire data set:
14
15            """
16            # TODO: compute linear response r(x)
17            # TODO: compute gradient of NLL loss
18            # take a gradient step
19            """
20            for i in np.random.permutation(M):
21                ri = XX[i].dot(self.theta)
22                si = 1/ ( 1+np.exp(-ri)); # TODO: compute linear resp
23
24                gradi = (si - YY[i])*XX[i]; # TODO: compute gradient of
25                self.theta -= stepsize * gradi; # take a gradient step
26
27            J01.append( self.err(X,Y) ) # evaluate the current error rate
28
29            """
30            ## TODO: compute surrogate loss (logistic negative log-likeliho
31            ## Jsurr = - sum_i [ (log si) if yi==1 else (log(1-si)) ]
32            """
33            Jsurr = 0;
34            for i in range (M):
35
36                if ( YY[i] == 1):
37                    Jsurr = Jsurr + np.log(si)
38                else:
39                    Jsurr = Jsurr + np.log(1-si)
40
41            J = np.mean(Jsurr)
42
43
44            Jnll.append( J ) # TODO evaluate the current NLL loss
45            display.clear_output(wait=True);
46            plt.subplot(1,2,1);
47            plt.cla();
48            plt.plot(Jnll,'b-',J01,'r-'); # plot losses
49            if N==2: plt.subplot(1,2,2); plt.cla(); self.plotBoundary(X,Y);
50            plt.pause(.01); # let OS draw the plot
51
52            """
53            ## For debugging: you may want to print current parameters & lo
54            # print self.theta, ' => ', Jnll[-1], ' / ', J01[-1]
55            # raw_input() # pause for keystroke
56

```

```

57         # TODO check stopping criteria: exit if exceeded # of epochs (
58         """
59     #         done = NotImplementedError; # or if Jnll not changing between
60     done = epoch>=stopEpochs or (epoch>1 and abs(Jnll[-1]-Jnll[-2]))

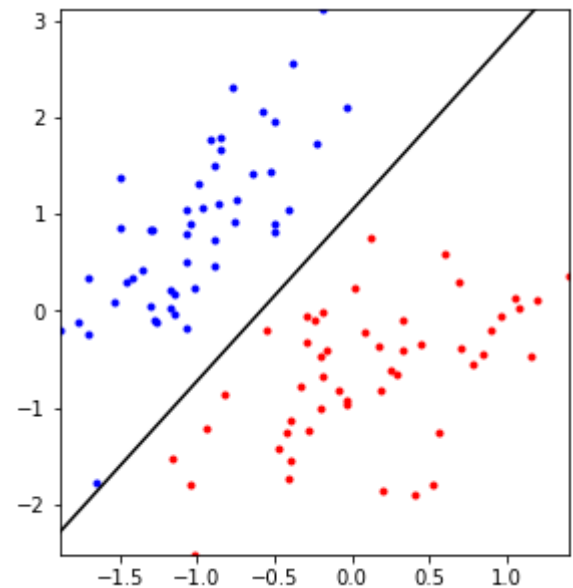
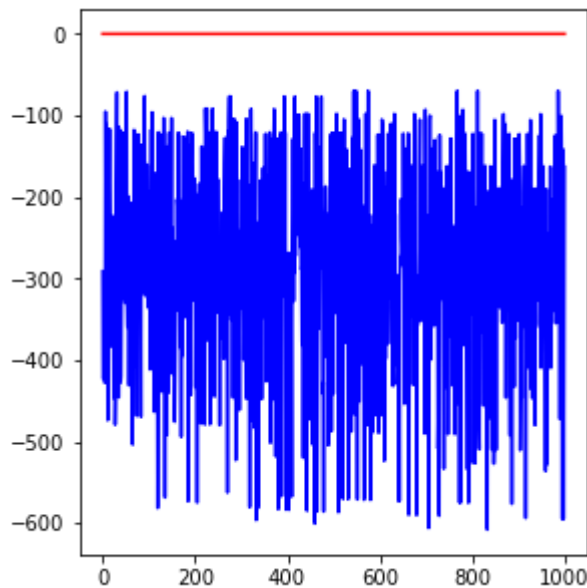
```

1.7

```

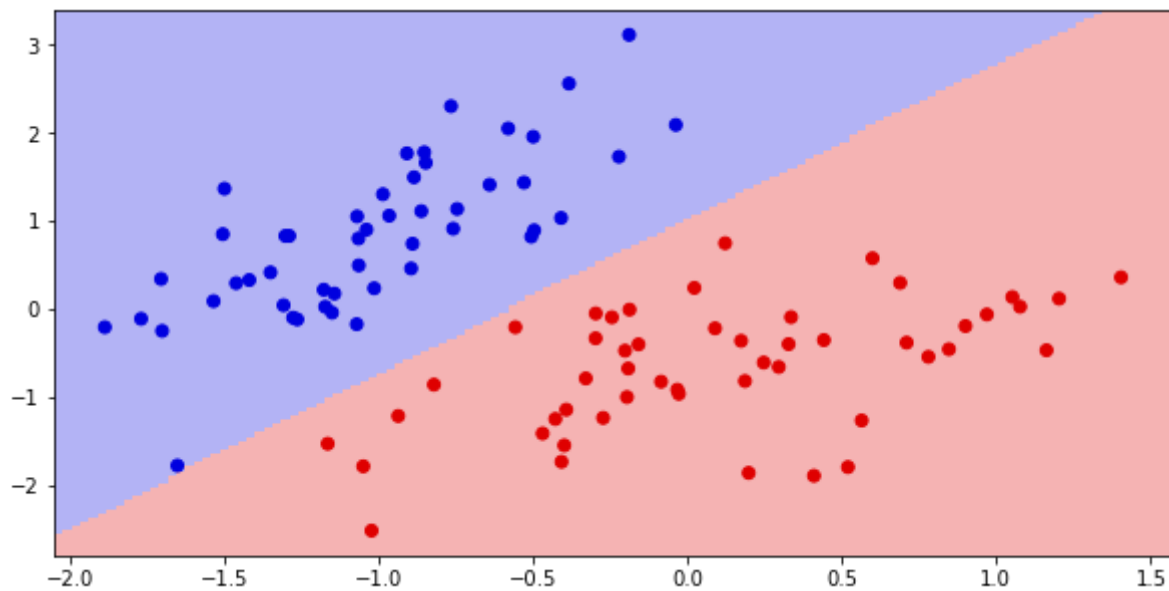
In [53]: 1 # Update our shell classifier definition
          2 class logisticClassify2(ml.classifier):
          3     classes = []
          4     theta = np.array( [-1, 0, 0] ) # initialize theta to something
          5     plotBoundary = myPlotBoundary #
          6     predict = myPredict # Now all parts are implemented
          7     train = myTrain
          8
          9 plt.rcParams['figure.figsize'] = (10,5) # make a wide figure, for tw
         10
         11 learnerA = logisticClassify2()
         12 #learnerA.theta = np.array([0.,0.,0.]);
         13 learnerA.theta = np.array([2, 6, -1.]);
         14 learnerA.train(XA,YA,initStep=1e-1,stopEpochs=1000,stopTol=1e-5);
         15

```

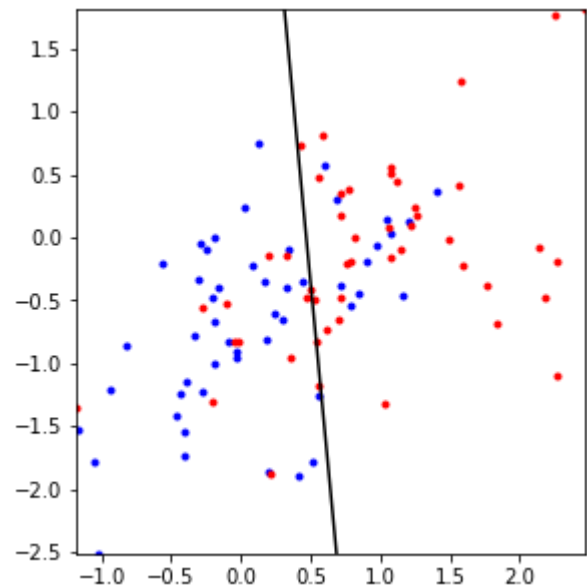
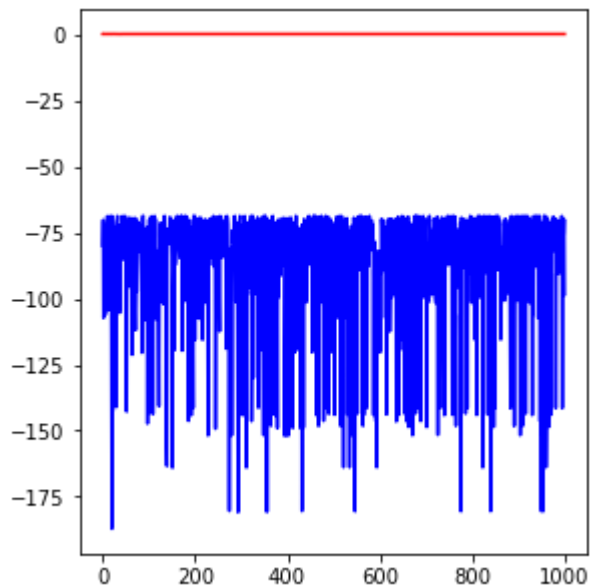


```
In [18]: 1 ml.plotClassify2D(learnerA,XA,YA)
          2 print("Training error rate: ",learnerA.err(XA,YA))
          3
          4 plt.show()
```

Training error rate: 0.0



```
In [59]: 1
2 plt.rcParams['figure.figsize'] = (10,5)
3 learnerB = logisticClassify2()
4 learnerB.theta = np.array([2, 6, -1.]);
5 learnerB.train(XB,YB,initStep=1.,stopEpochs=1000,stopTol=1e-5);
6
7
8
9
10
```



```
In [65]: 1 ml.plotClassify2D(learnerB,XB,XB)
          2 print("Training error rate: ",learnerB.err(XB,XB))
          3
          4 plt.show()
```

```
-----
--
ValueError                                Traceback (most recent call las
t)
~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/axes/_axes.py in _
parse_scatter_color_args(c, edgecolors, kwargs, xsize, get_next_color_fun
c)
    4238             try: # Is 'c' acceptable as PathCollection facecolor
s?
-> 4239                 colors = mcolors.to_rgba_array(c)
    4240             except ValueError:

~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/colors.py in to_rg
ba_array(c, alpha)
    306         if np.any((result < 0) | (result > 1)):
--> 307             raise ValueError("RGBA values should be within 0-1 ra
nge")
    308         return result
```

ValueError: RGBA values should be within 0-1 range

During handling of the above exception, another exception occurred:

```
ValueError                                Traceback (most recent call las
t)
<ipython-input-65-cc055c138595> in <module>
----> 1 ml.plotClassify2D(learnerB,XB,XB)
      2 print("Training error rate: ",learnerB.err(XB,XB))
      3
      4 plt.show()

~/CS178/178-hw3-code/mltools/plot.py in plotClassify2D(learner, X, Y, pr
e, ax, nGrid, cm, bgamma, soft, **kwargs)
    72         if len(Y.shape)==1 or Y.shape[1]==1: data_colors = classcolor
[np.searchsorted(classes,Y)]; # use colors if Y is discrete class
    73         else: data_colors = Y.dot(classcolor); data_colors[data_color
s>1]=1; # blend colors if Y is a soft confidence
--> 74         ax.scatter(X[:,0],X[:,1], c=data_colors, **kwargs);
    75
    76         #for i,c in enumerate(classes): # old code: us
ed plot instead of scatter

~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/__init__.py in inn
er(ax, data, *args, **kwargs)
    1563     def inner(ax, *args, data=None, **kwargs):
    1564         if data is None:
-> 1565             return func(ax, *map(sanitize_sequence, args), **kwar
gs)
    1566
    1567         bound = new_sig.bind(ax, *args, **kwargs)
```

```
~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/cbook/deprecation.
```

```

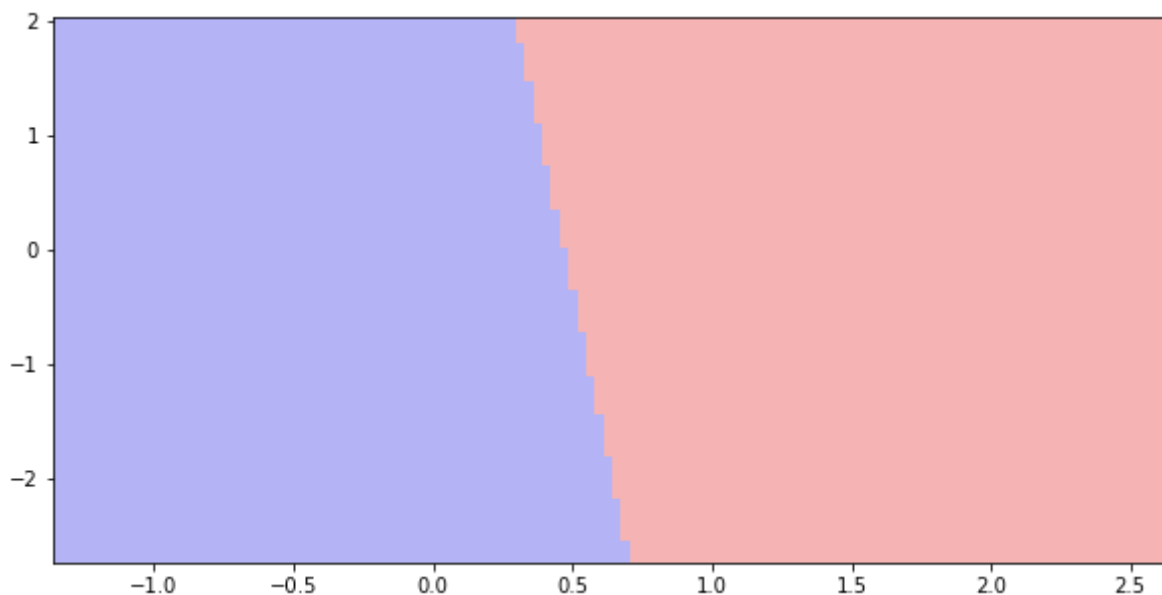
py in wrapper(*args, **kwargs)
    356             f"%(removal)s.  If any parameter follows {name!
r}, they "
    357             f"should be pass as keyword, not positionally.")
--> 358         return func(*args, **kwargs)
    359
    360     return wrapper

~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/axes/_axes.py in s
catter(self, x, y, s, c, marker, cmap, norm, vmin, vmax, alpha, linewidth
s, verts, edgecolors, plotnonfinite, **kwargs)
    4399
    4400         c, colors, edgecolors = \
-> 4401             self._parse_scatter_color_args(
    4402                 c, edgecolors, kwargs, x.size,
    4403                 get_next_color_func=self._get_patches_for_fill.ge
t_next_color)

~/opt/anaconda3/lib/python3.8/site-packages/matplotlib/axes/_axes.py in _
parse_scatter_color_args(c, edgecolors, kwargs, xsize, get_next_color_fun
c)
    4240         except ValueError:
    4241             if not valid_shape:
-> 4242                 raise invalid_shape_exception(c.size, xsize)
    4243             # Both the mapping *and* the RGBA conversion fail
ed: pretty
    4244             # severe failure => one may appreciate a verbose
feedback.

ValueError: 'c' argument has 396 elements, which is inconsistent with 'x'
and 'y' with size 99.

```



In []:

1

Problem 3: Statement of Collaboration (5 points)

1	Gwenth : discuss , Shattering and VC Dimension
2	Piazza : 359
3	Park : discuss regression

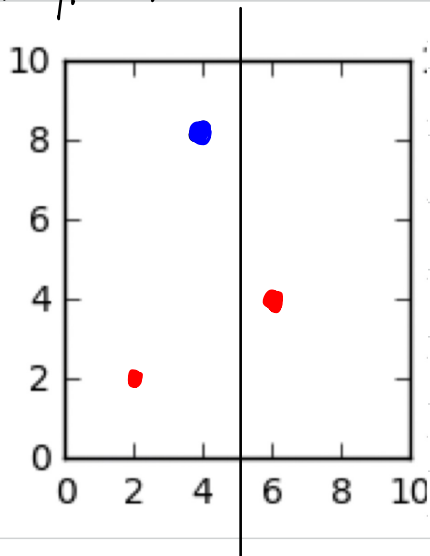
■ ■ ■ ■ ■

HW3 Part 2

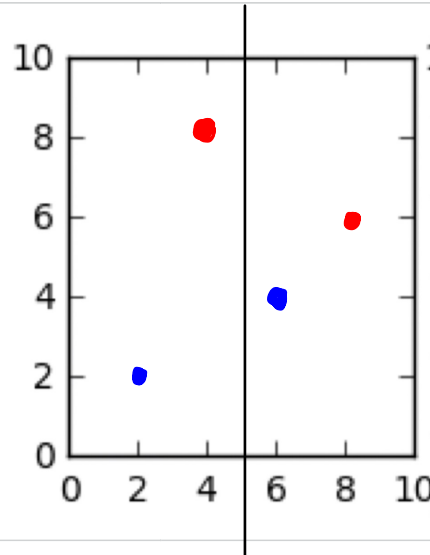
1. $T(a + b \cdot x_1)$

- ~ perceptron
- ~ Two parameter and one feature (b)
- ~ This learner can shattered dataset (a) & (b).
- ~ This learner can't shattered dataset (c) & (d), if point $h \geq 3$

example c)



Decision Boundary line.

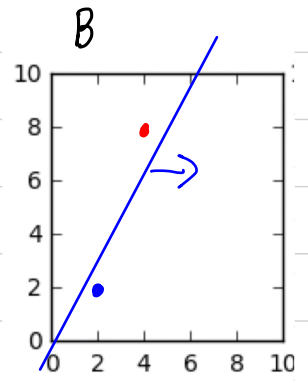
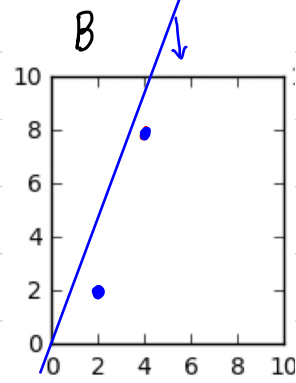
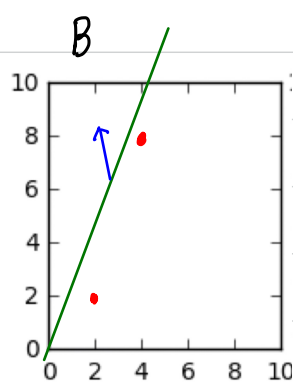
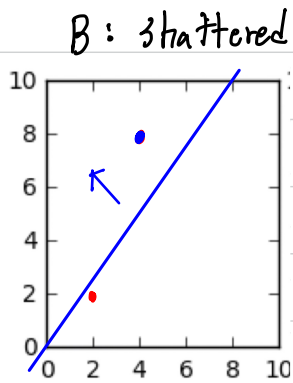


Decision Boundary line

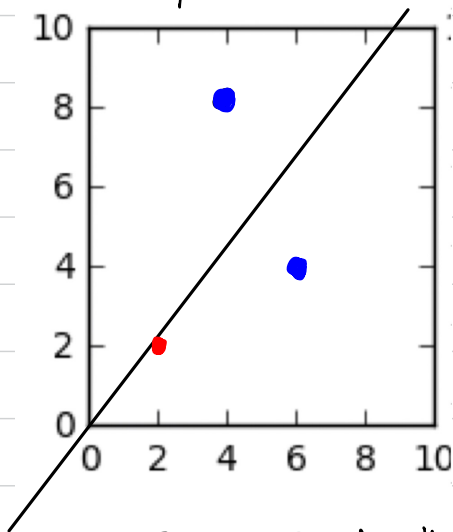
$VCdim = 2$: Can arrange two points, can't arrange more than two

$$2. T((a \times b)x_1 + (c/a)x_2)$$

- ~ perceptron
- ~ Three parameter (a, b, c) and two feature $(a \times b)$ & (c/a)
- ~ No constant \rightarrow Pass the original point $(0, 0)$
- ~ This learner can shattered dataset (a) & (b) .
- ~ This learner can't shattered dataset (c) & (D) , if point $n \geq 3$

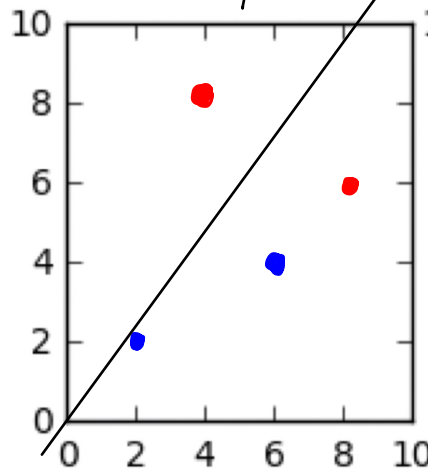


count example of D



Decision Boundary line

Count example of D



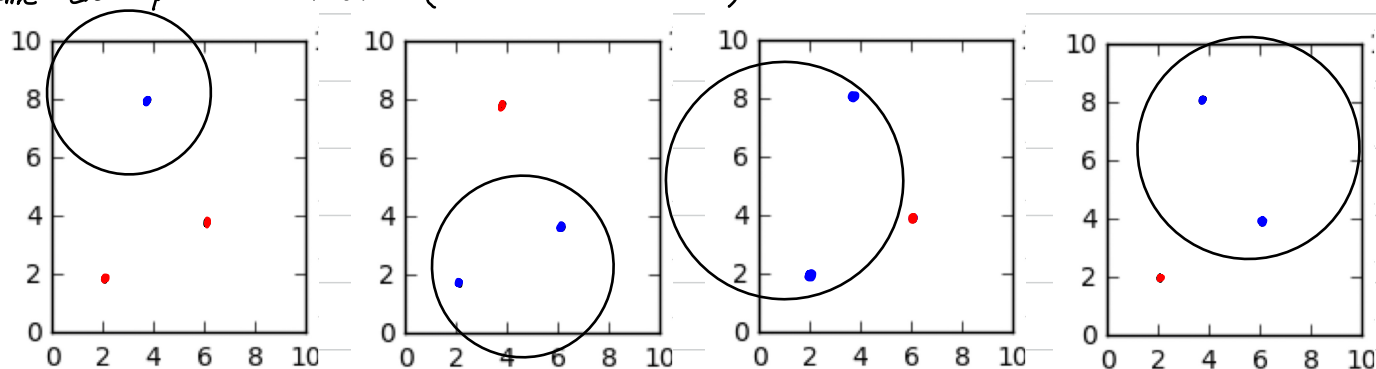
Decision Boundary line

VCdim = 2 : Can arrange two points, can't arrange more than two

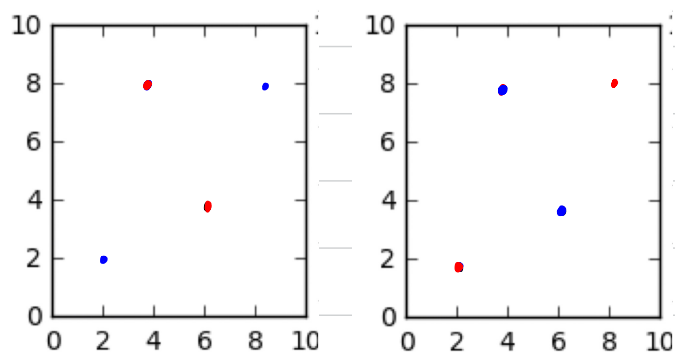
3. $T((x_1 - a)^2 + (x_2 - b)^2 + c)$

- three parameter, two features, one constant
- Circle type \rightarrow center (a, b)

- Some example C : learner $((x_1 - a)^2 + (x_2 - b)^2 + c)$ can shatter dataset C .



- Example this learner can't shatter dataset D



\rightarrow These two examples show this learner can't shatter dataset D .

VCdim = 2 : Can arrange 2 points, can't arrange more than 3.

4. $T(a + bx_1 + cx_2) \times T(d + bx_1 + cx_2)$

VC Dimension = 3

- Total 4 parameters (a, b, c, d) and two features (b, c)
- there are two different constants (a) and (d).
- (a), (b), and (c) are shattered all of them
 "one more line than (b) so VC dimension should be bigger than 2.
- this learner can shatter (d)

