

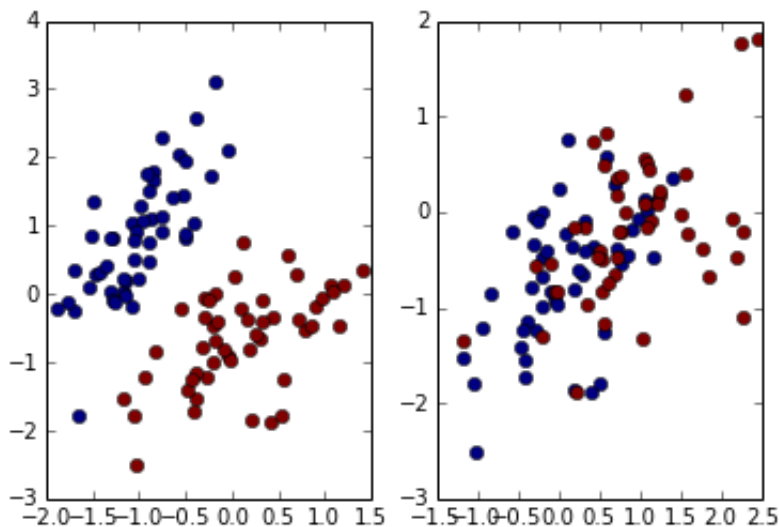
# Ian Schweer

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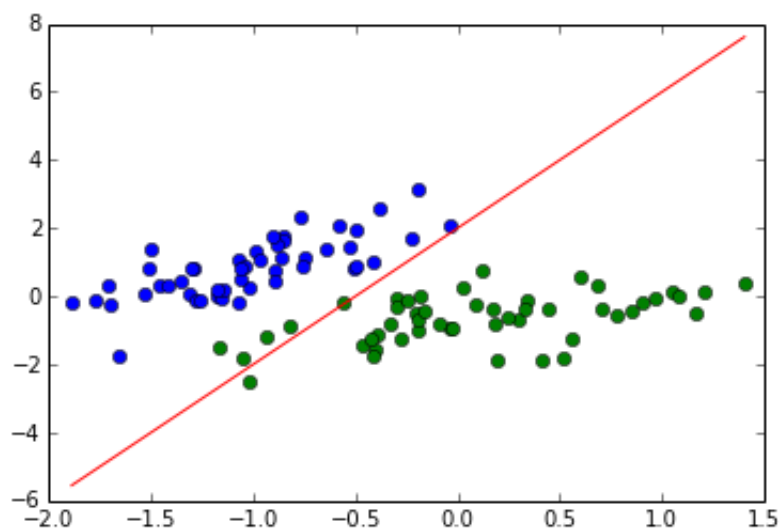
## HW #3

```
In [1]: import matplotlib.pyplot as plt
import mltools as ml
import numpy as np
import mltools.logistic2 as lc2
reload(lc2)
%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
```

```
In [2]: # ensure seperability
fig, ax = plt.subplots(1,2)
ml.plotClassify2D(None, XA[:,[0,1]],YA,axis=ax[0])
ml.plotClassify2D(None, XB[:,[0,1]],YB,axis=ax[1])
plt.show()
```



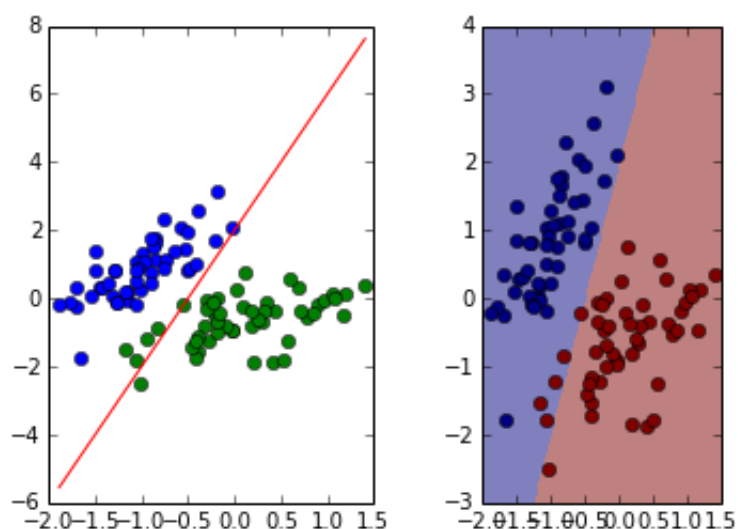
```
In [3]: # Test of plot boundary
learner = lc2.logisticClassify2();
learner.theta=[.5, 1, -.25]
learner.classes=np.unique(YA)
learner.plotBoundary(XA, YA)
plt.show()
print learner.err(XA, YA)
print learner.err(XB, YB)
```



```
0.050505050505051
```

```
0.54545454545455
```

```
In [4]: fig, ax = plt.subplots(1,2)
learner.plotBoundary(XA,YA,axis=ax[0])
ml.plotClassify2D(learner, XA, YA,axis=ax[1])
plt.show()
```

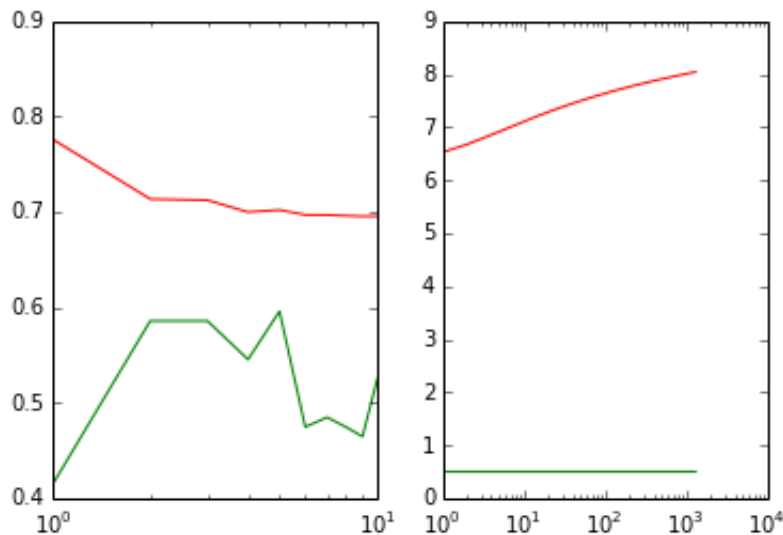


The derivation ended up being:

- (all at j) ::  $-y(1 - \text{sigma}(\text{theta } x)) \text{ xOne} + (1 - y)\text{sigma}(\text{theta } x) \text{ xOne}$

- (all at j) ::  $-y(1 - \sigma(\theta x)) x^2 + (1 - y)\sigma(\theta x) x^2$
- (all at j) ::  $-y(1 - \sigma(\theta x)) + (1 - y)\sigma(\theta x)$

```
In [5]: import mltools.logistic2 as lc2
import matplotlib.pyplot as plt
import mltools as ml
import numpy as np
import mltools.logistic2 as lc2
reload(lc2)
%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
fig, ax = plt.subplots(1, 2)
learner = lc2.logisticClassify2(XA, YA, plot=ax[0])
learner = lc2.logisticClassify2(XB, YB, plot=ax[1])
plt.show()
```



```
In [12]: #Demonstrating L2 penalization.
import matplotlib.pyplot as plt
import mltools as ml
import numpy as np
import mltools.logistic2 as lc2
reload(lc2)
%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

learner = lc2.logisticClassify2(XA, YA)
print learner.err(XB,YB)
learner = lc2.logisticClassify2(XA, YA, alpha=2)
print learner.err(XB,YB)

0.0606060606
0.1818181818
```

## part two

- a.) Can shatter a, b but not c or d. There is no way to make points (2,2) and (8,7) in the same class
- b.) Most points can be shatter. Since c can skew the origin point, you can scatter each point in c, but not in d.
- c.) Can up to d. You can not put point (2,2) and 8,7 in the same class with 4,8 and 6,4 in the same class.