Lab 5 - Wyatt Madden & Dan Crowley

March 22, 2020

1 3.

In [1]:
```
import scipy.io as scipy
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import numpy.linalg as lg
from make_cloud import *
#from boosteval import *
from weakeval import *
from weaklearn import *
from boostlearn import *
```

1.1 3.1

In [2]:
```
## adaBOOST model LEARNer
#  Uses the AdaBoost algorithm to train a classifier on data.""
# Inputs
#  X - N x D : Observations
#  t - N x 1 : class labels
#  M - The number of weak learners to include in the ensemble.
# Outputs
#  params - A matrix containing the parameters for the M weak learners.
#  alpha - A vector of weights used to combine the results of the
#    M weak learners.

def boostlearn(X, t, M):
    weights = np.zeros((M + 1, len(t)))
    weights[0, ] = np.repeat(1/np.size(t), np.size(t))
    params = np.zeros((M, np.shape(X)[0] + 1))
    corect = np.zeros(M)
    for i in range(0,M): #changed he range from 1 to 0
        params[i,] = weaklearn(X = X, t = t, v = weights[i, ])
        preds = weakeval(X = X, params = params[i,:])
        pred_correct = (preds == t)
        frac_pred_correct = np.sum(pred_correct) / len(pred_correct)
```

```
            if frac_pred_correct > 0.5:
                epsilon = np.sum(weights[i, pred_correct]) / np.sum(weights[i,]) #the np s
                alpha = np.log((1 - epsilon) / epsilon)
                weights[i + 1, pred_correct] = weights[i, pred_correct] * (np.exp(alpha))
                corect[i] = frac_pred_correct
            if frac_pred_correct < 0.5:

                epsilon = 1 - np.sum(weights[i, pred_correct]) / np.sum(weights[i,]) #the 
                alpha = np.log((1 + epsilon) / epsilon)
                weights[i + 1, pred_correct] = weights[i, pred_correct] * (np.exp(alpha))
                corect[i] = 1 - frac_pred_correct
                params[i,] = params[i,]*-1
        weights = weights[0:M,]
        return params, weights, corect
```

1.2 3.2

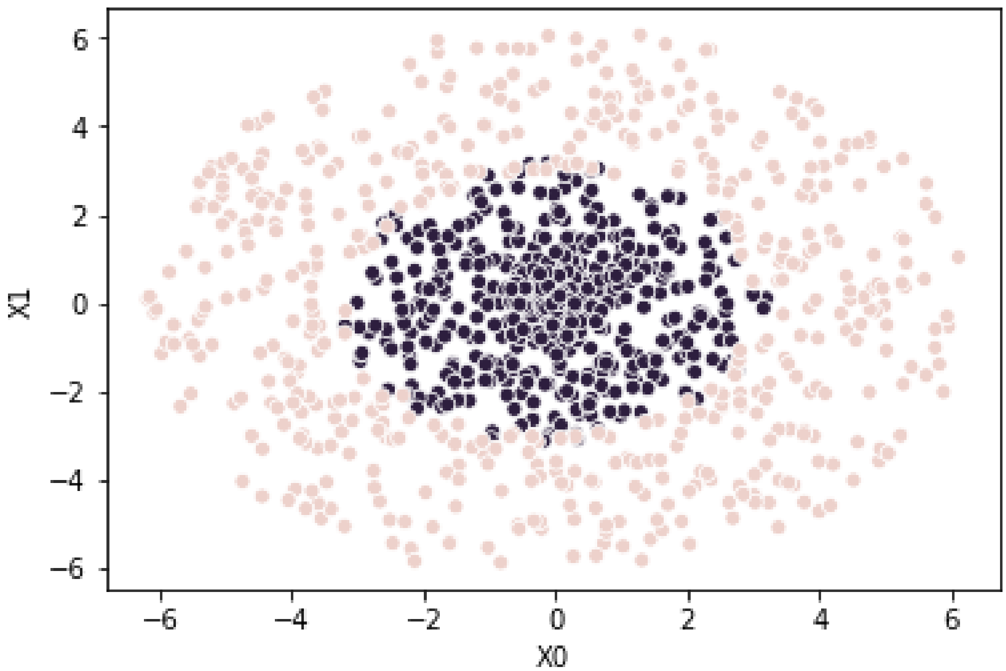
In [3]:
```
# adaBOOST model EVALuator
#  Uses a trained AdaBoost algorithm to classify data.
# Inputs
#  X - Matrix with observations (in columns) to classify.
#  params - Output of boostlearn.m (weak learner parameters).
#  alpha - Output of boostlearn.m (weak learner mixing coefficients).
# Outputs
#  C - A matrix with predicted class labels (-1 or 1) for the input
#    observations in X.

def boosteval(X, params, alpha):

    preds = np.empty((params.shape[0], X.shape[1]))

    for i in range(params.shape[0]):
        preds[i, :] = weakeval(X, params[i,]) * alpha[i, ]

    committee_vote = np.sign(np.sum(preds, axis = 0))

    return(committee_vote)
```

1.3 3.3

In [4]:
```
temp = make_cloud()
dat = pd.DataFrame(np.transpose(temp[0]), columns = ("X0", "X1"))
dat['t'] = temp[1]
```

In [5]:
```
sns.scatterplot(x="X0", y="X1", hue="t",data=dat, legend = False)
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1a174f8e10>

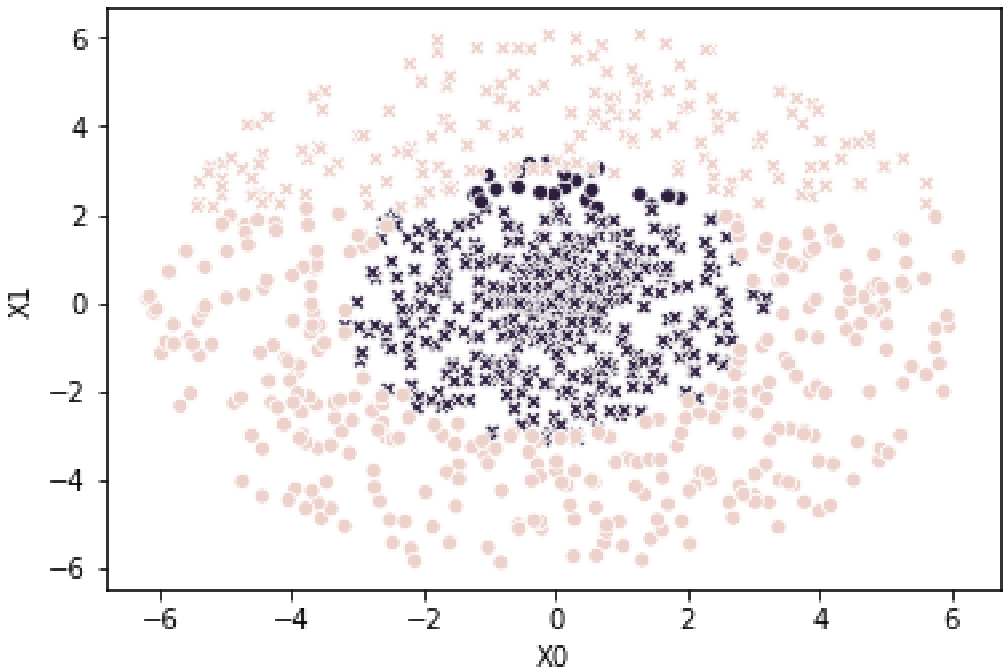


1.4 3.4

```
In [8]: weak_params = weaklearn(temp[0], temp[1])
        dat['t_weak_pred'] = weakeval(temp[0], weak_params)
        dat['correct_class'] = dat['t'] == dat['t_weak_pred']
```

```
In [9]: sns.scatterplot(x="X0", y="X1", hue="t", style = "correct_class", data=dat, legend = Fa
```

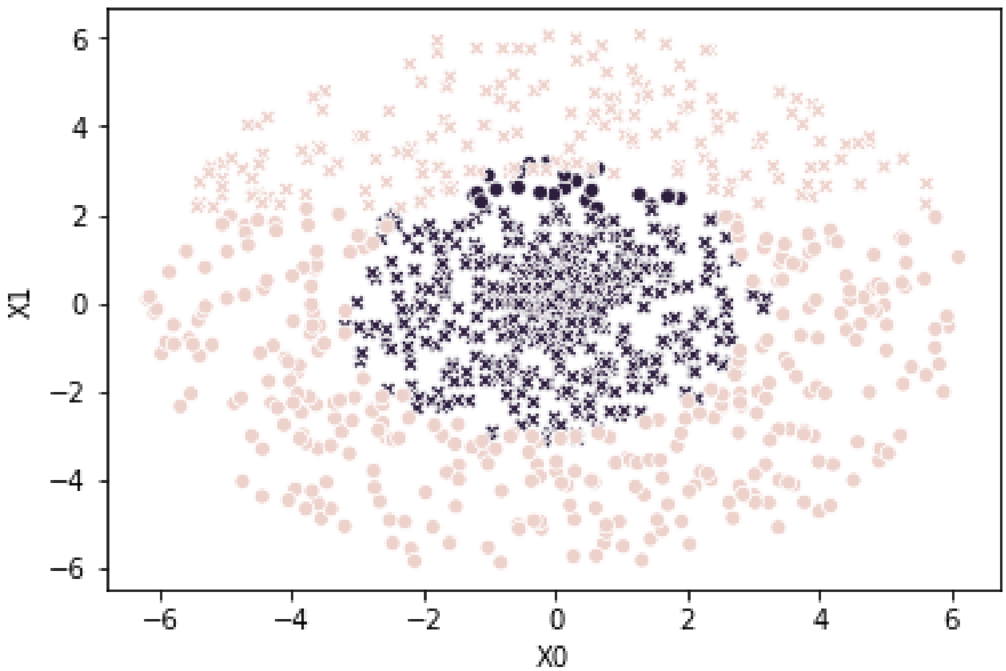
```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22c8ad68>
```



We can see the weak learner classifies according to a horizontal decision boundary. X's are points that are classified correctly, thus the majority of the points within the smaller circle are classified correctly, while a minority of the points in the larger circle are classified correctly.

1.5 3. 5

```
In [17]: temp_boostlearn = boostlearn(X = temp[0], t = temp[1], M = 5)

         dat['t_boost_5'] = boosteval(X = temp[0],
                                      params = temp_boostlearn[0],
                                      alpha = temp_boostlearn[1])
         dat['correct_class_boost_5'] = dat['t'] == dat['t_boost_5']

In [13]: sns.scatterplot(x="X0", y="X1", hue="t", style = "correct_class_boost_5", data=dat, le

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x110de4470>
```

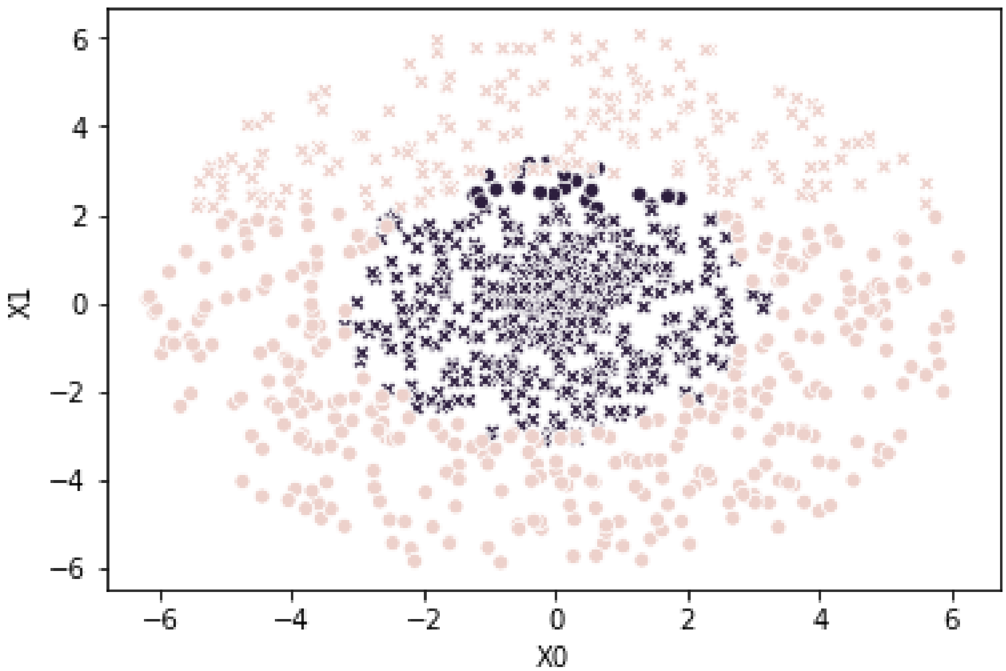


Strangely, the predictions appear to be identical to that of weak learn. This must be due a bug in transfering over the boost_learn function from matlab to python. I will come back to this if I have time..

1.6 3.6

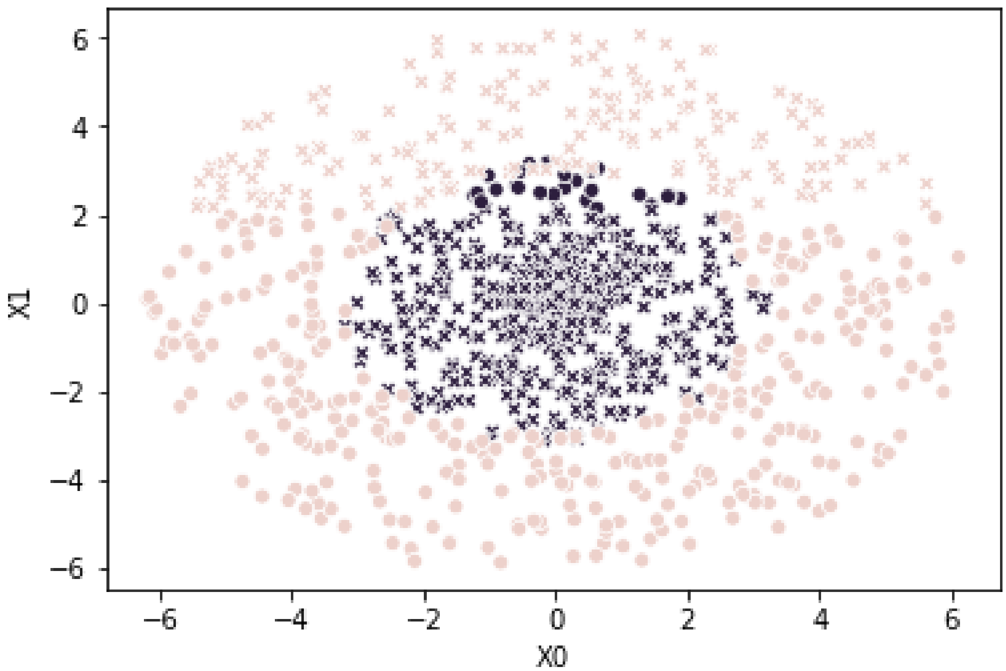
M = 10:

```
In [14]: temp_boostlearn = boostlearn(X = temp[0], t = temp[1], M = 10)

         dat['t_boost_10'] = boosteval(X = temp[0],
                                       params = temp_boostlearn[0],
                                       alpha = temp_boostlearn[1])
         dat['correct_class_boost_10'] = dat['t'] == dat['t_boost_10']

         sns.scatterplot(x="X0", y="X1", hue="t", style = "correct_class_boost_10", data=dat, l

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x110e44908>
```



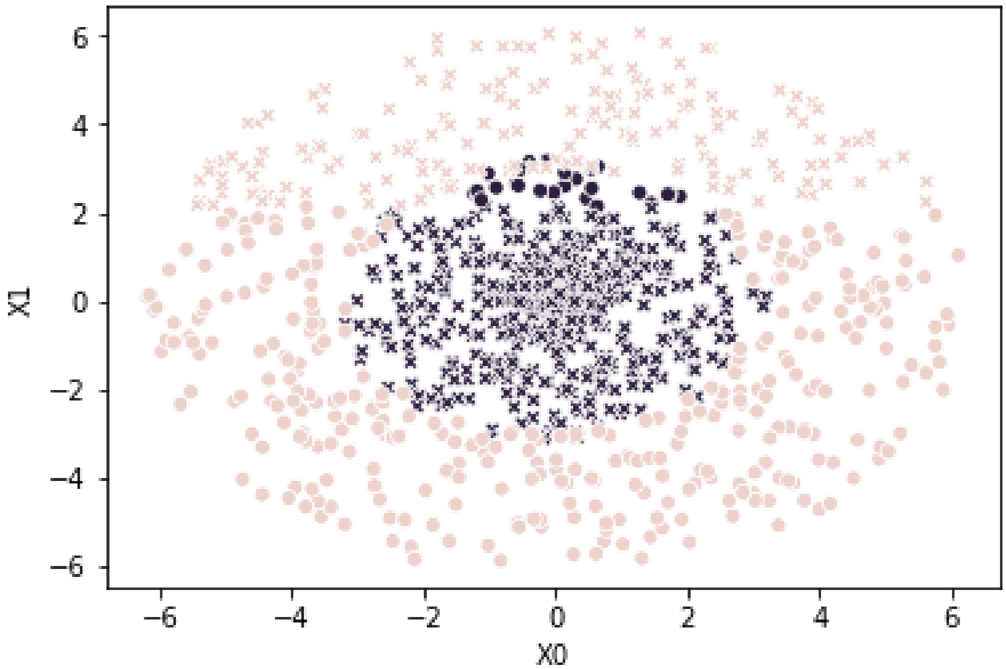
M = 50:

```
In [15]: temp_boostlearn = boostlearn(X = temp[0], t = temp[1], M = 50)

         dat['t_boost_50'] = boosteval(X = temp[0],
                                       params = temp_boostlearn[0],
                                       alpha = temp_boostlearn[1])

         dat['correct_class_boost_50'] = dat['t'] == dat['t_boost_50']

         sns.scatterplot(x="X0", y="X1", hue="t", style = "correct_class_boost_50", data=dat, l

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x110e36b38>
```



M = 100:

```
In [16]: temp_boostlearn = boostlearn(X = temp[0], t = temp[1], M = 100)

         dat['t_boost_100'] = boosteval(X = temp[0],
                                        params = temp_boostlearn[0],
                                        alpha = temp_boostlearn[1])
         dat['correct_class_boost_100'] = dat['t'] == dat['t_boost_100']

         sns.scatterplot(x="X0", y="X1", hue="t", style = "correct_class_boost_100", data=dat,

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23095860>
```



Again, due to the bug in the boost_learn code, the predictions are not changing with M. I would expect to see a gradually decreasing missclassification rate. When the points along the border between the two circles (and overlapping the border) begin to be classified correctly, I would assume that overfitting is ocurring.

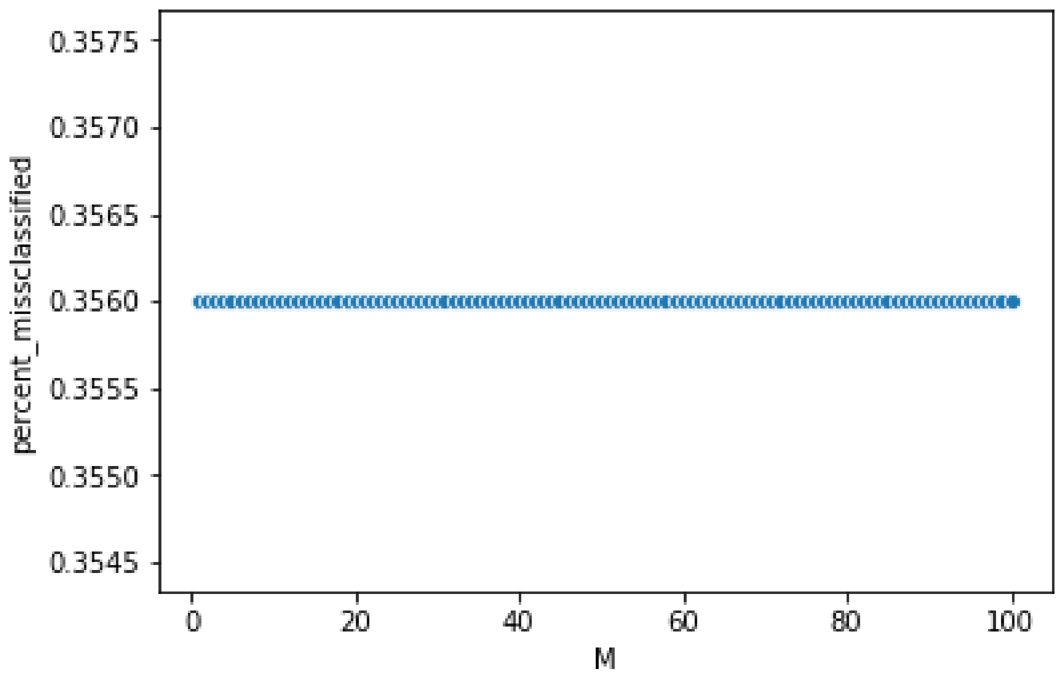
2 3.7

```
In [45]: new_temp = make_cloud()
         new_dat = pd.DataFrame(np.transpose(new_temp[0]), columns = ("X0", "X1"))
         new_dat['t'] = new_temp[1]

         missclass_rate = np.empty((2, 100))

         for i in range(100):
             M = i + 1
             temp_boostlearn = boostlearn(X = temp[0], t = temp[1], M = M)
             temp_boosteval = boosteval(X = new_temp[0],
                                        params = temp_boostlearn[0],
                                        alpha = temp_boostlearn[1])
             missclass_rate[0, i] = M
             missclass_rate[1, i] = sum(new_dat['t'] != temp_boosteval) / temp_boosteval.shape
```

```
In [46]: dat = pd.DataFrame(np.transpose(missclass_rate),
                            columns = ("M", "percent_missclassified"))
```

```
sns.scatterplot(x="M", y="percent_missclassified", data=dat, legend = False)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22e21f60>



Again, the bug is not resolved. The missclassification rate is a constant 0.3560.