

1. Logistic Regression:

1.2.1 Behavior of the algorithm when there is no regularization:

The behavior of the logistic regression with no regularization tries to fit the model as much as possible, given the constraints and thus will have big values for w . The graphs are given below. The corresponding weights are:

Errors when there is no regularization:

Weights on ls data: $\begin{bmatrix} 8.71220966e-04 \\ -5.93699660e+00 \\ 7.03164376e+00 \end{bmatrix}$

Training error in linearly separable data: 9

====Validation=====

Testing error in non-linearly separable data: 19

====Training=====

Weights on nls data: $\begin{bmatrix} 1.87633691 \\ -1.3147047 \\ 2.41428878 \end{bmatrix}$

Training error in non-linearly separable data: 149

====Validation=====

Testing error in non-linearly separable data: 273

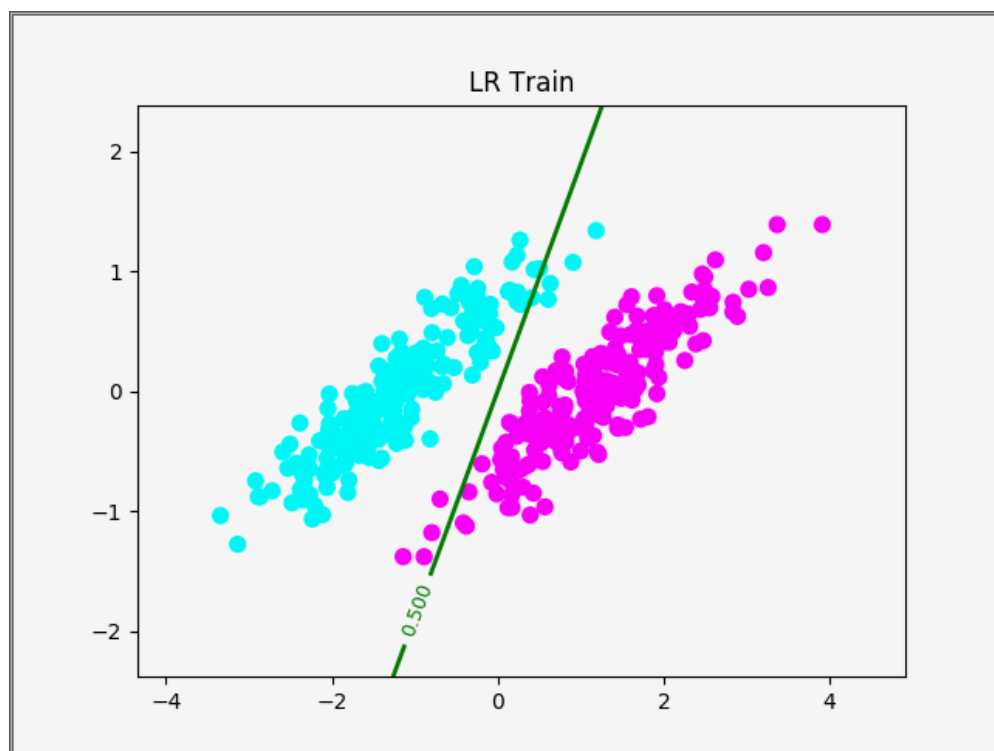
====Training=====

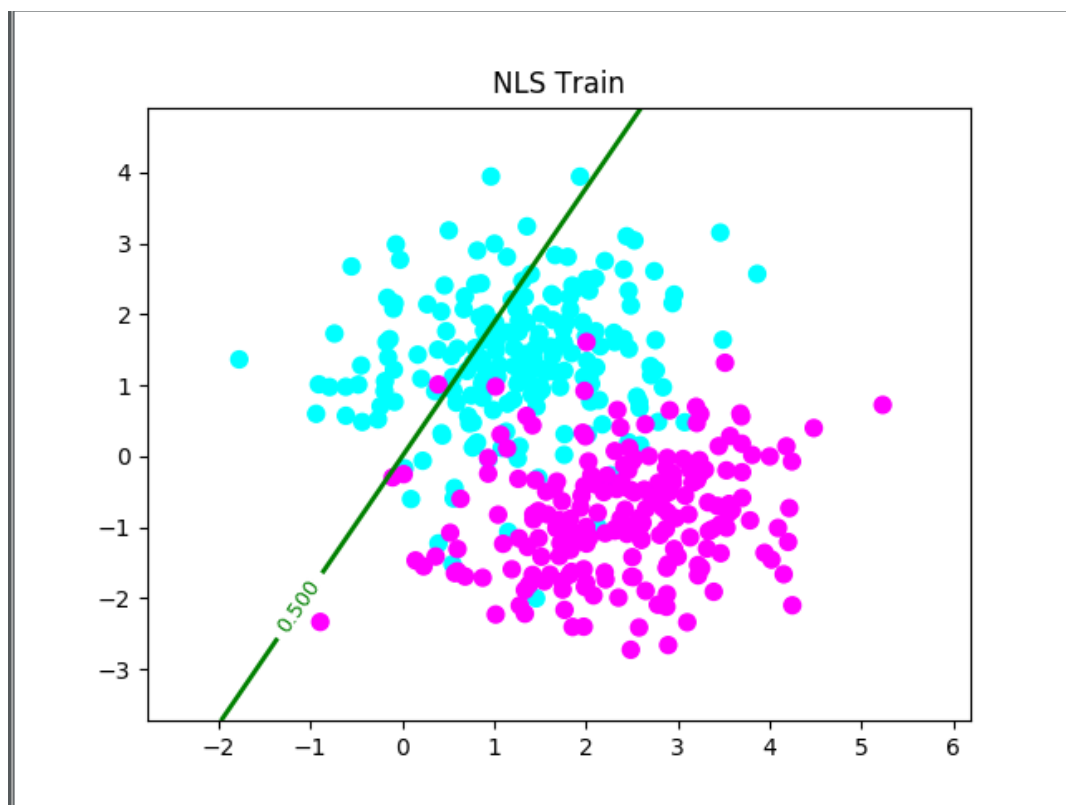
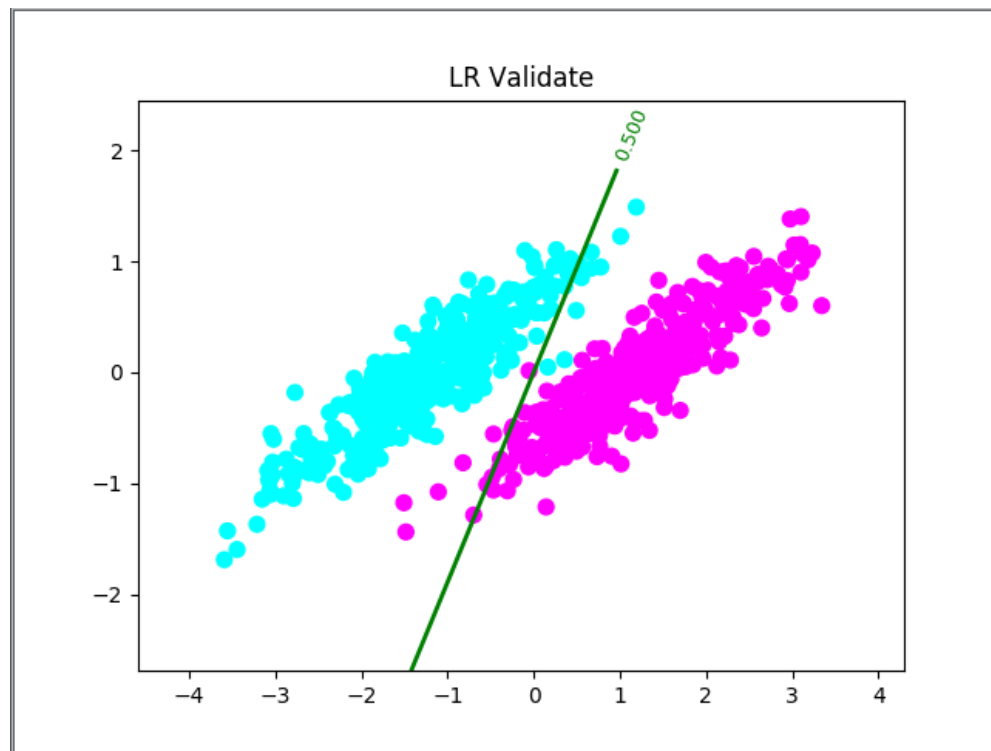
Weights on non-lin data: $\begin{bmatrix} -0.96931637 \\ -0.26522275 \\ -3.23408541 \end{bmatrix}$

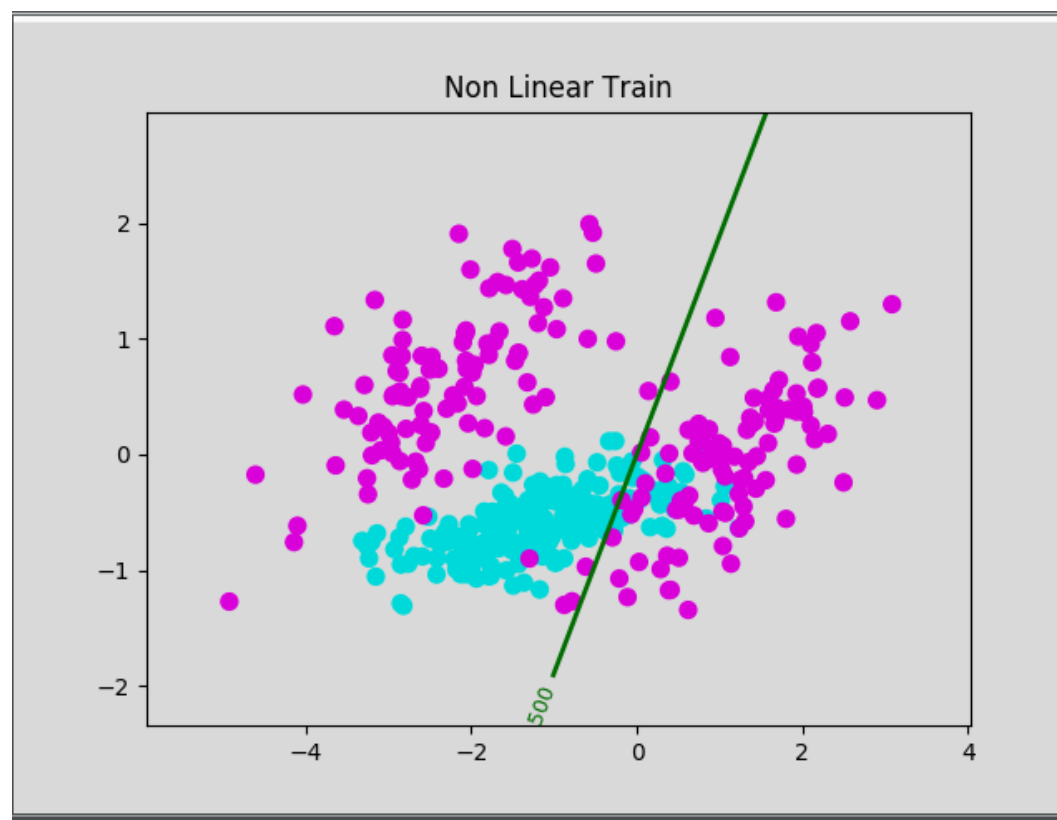
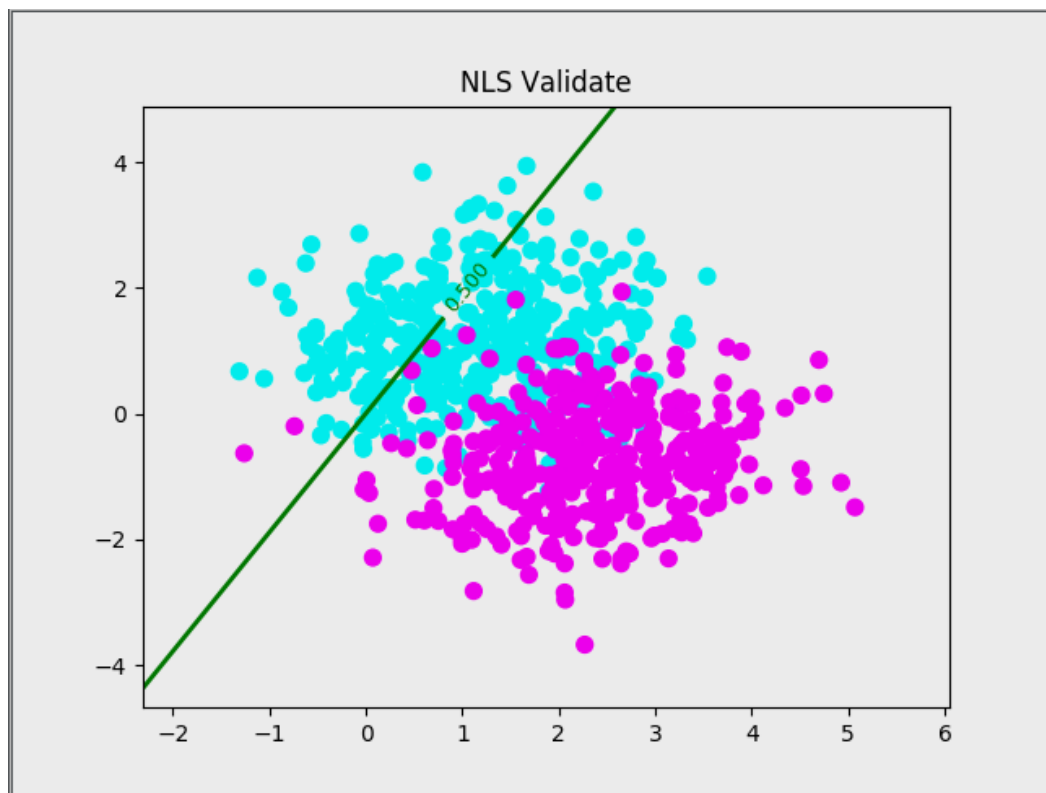
Training error in non-linear data: 136

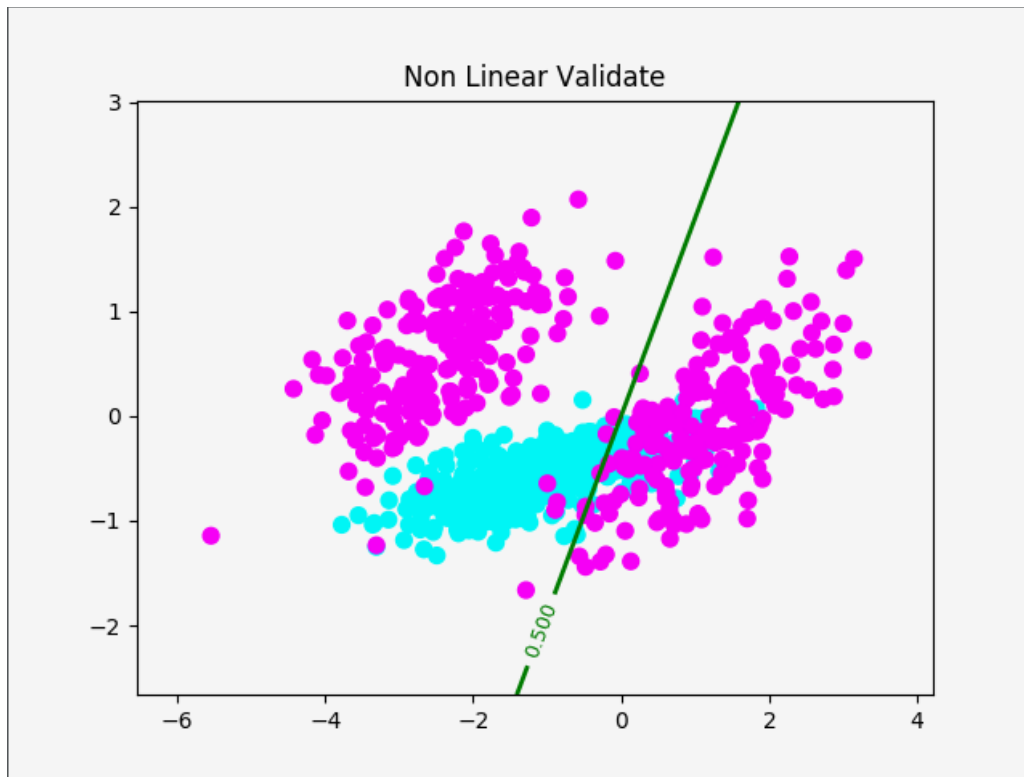
====Validation=====

Testing error in non-linear data: 276



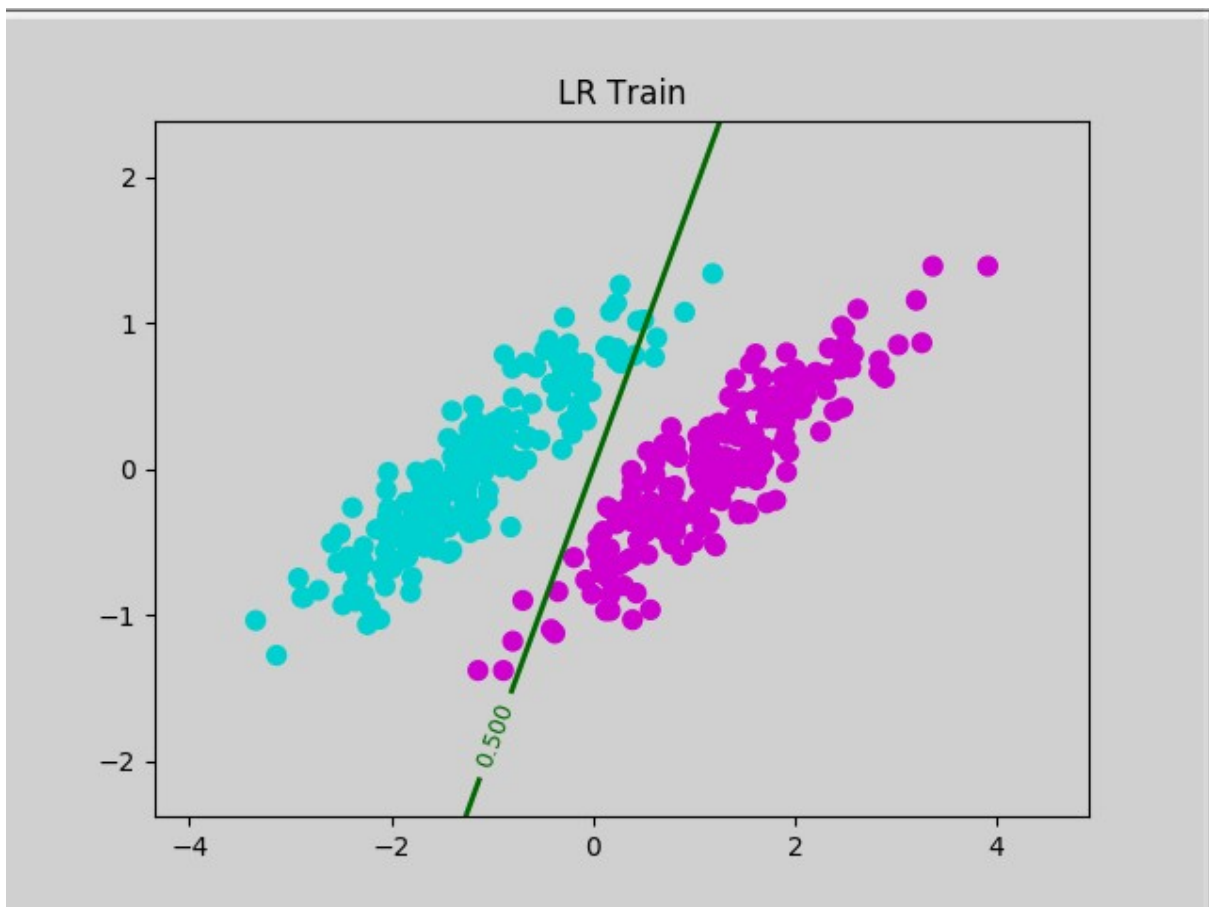


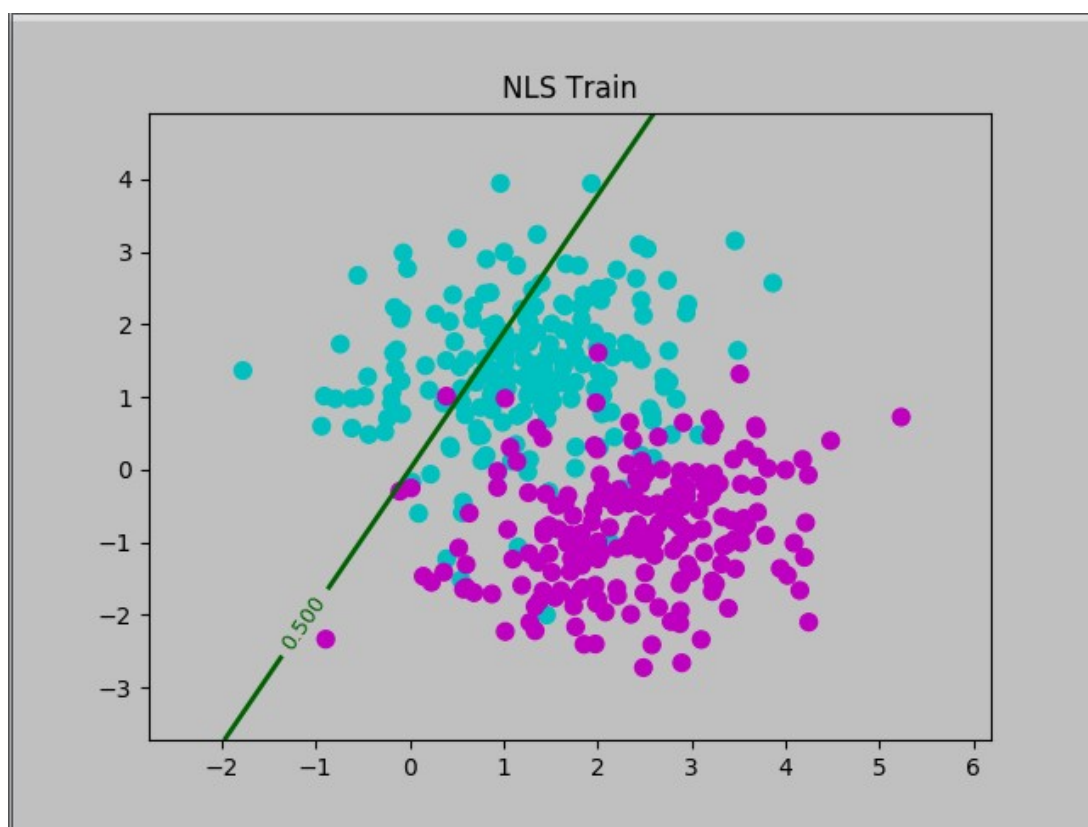
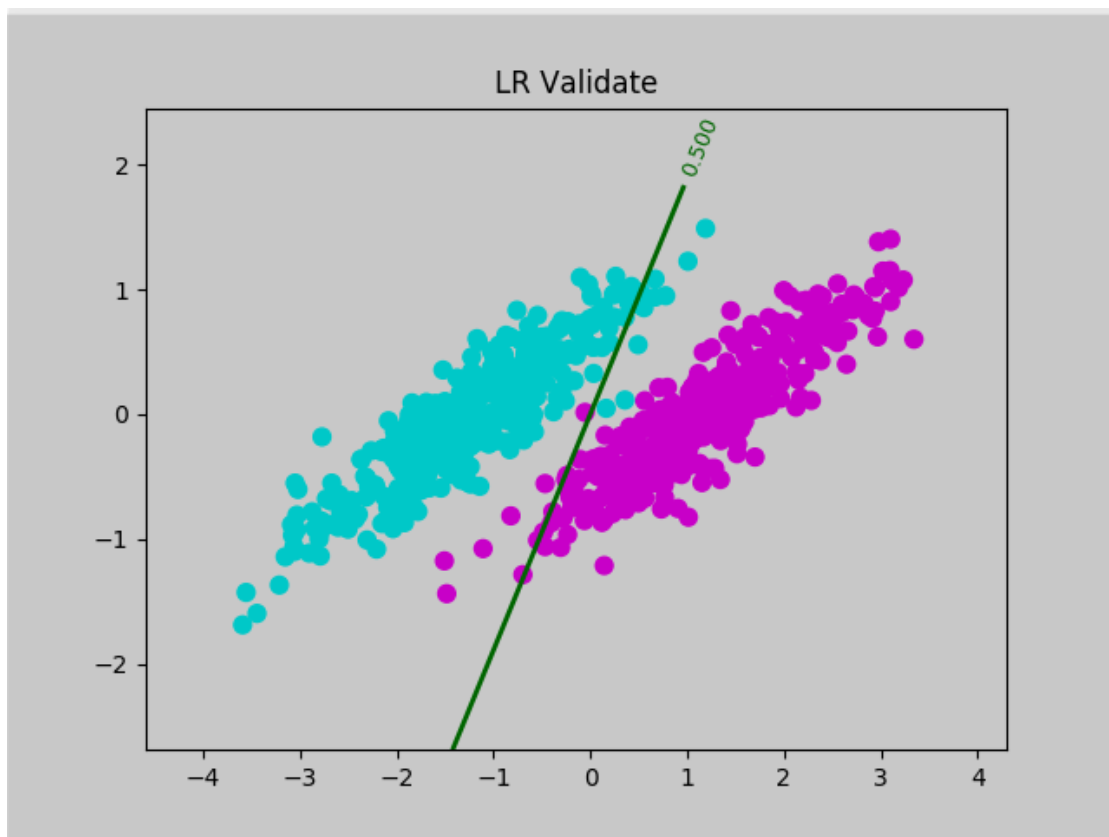


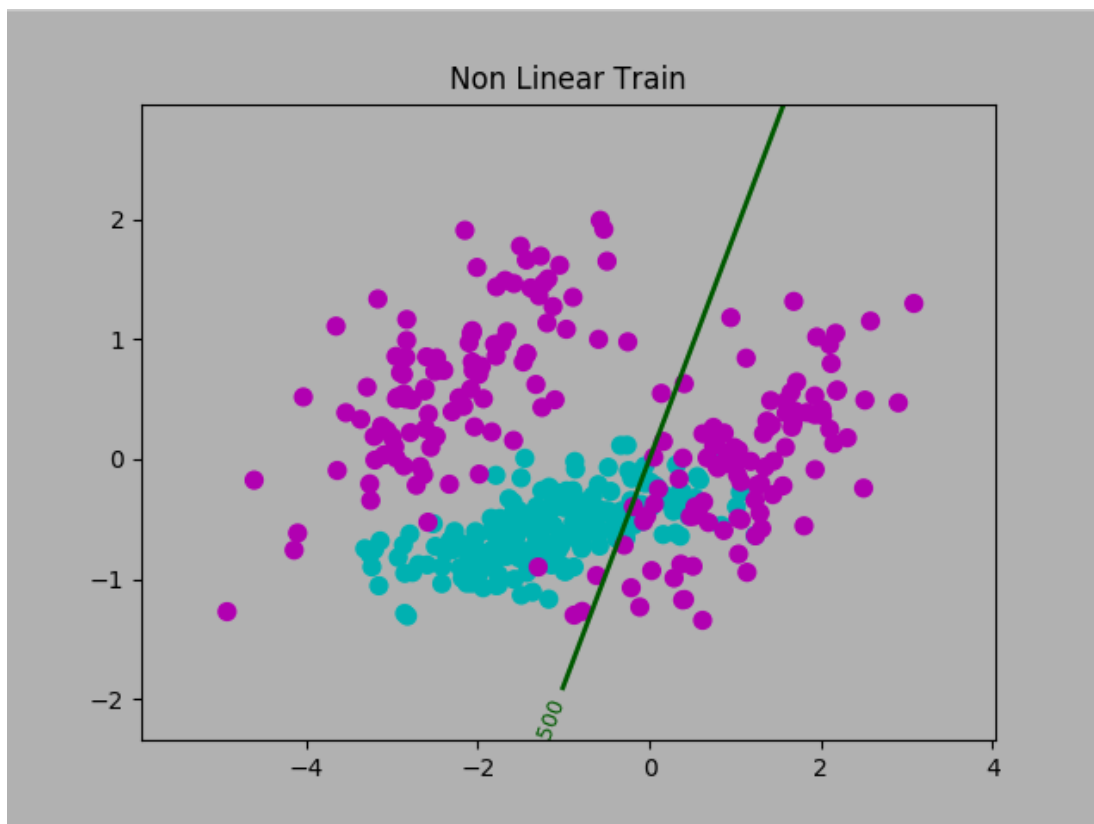
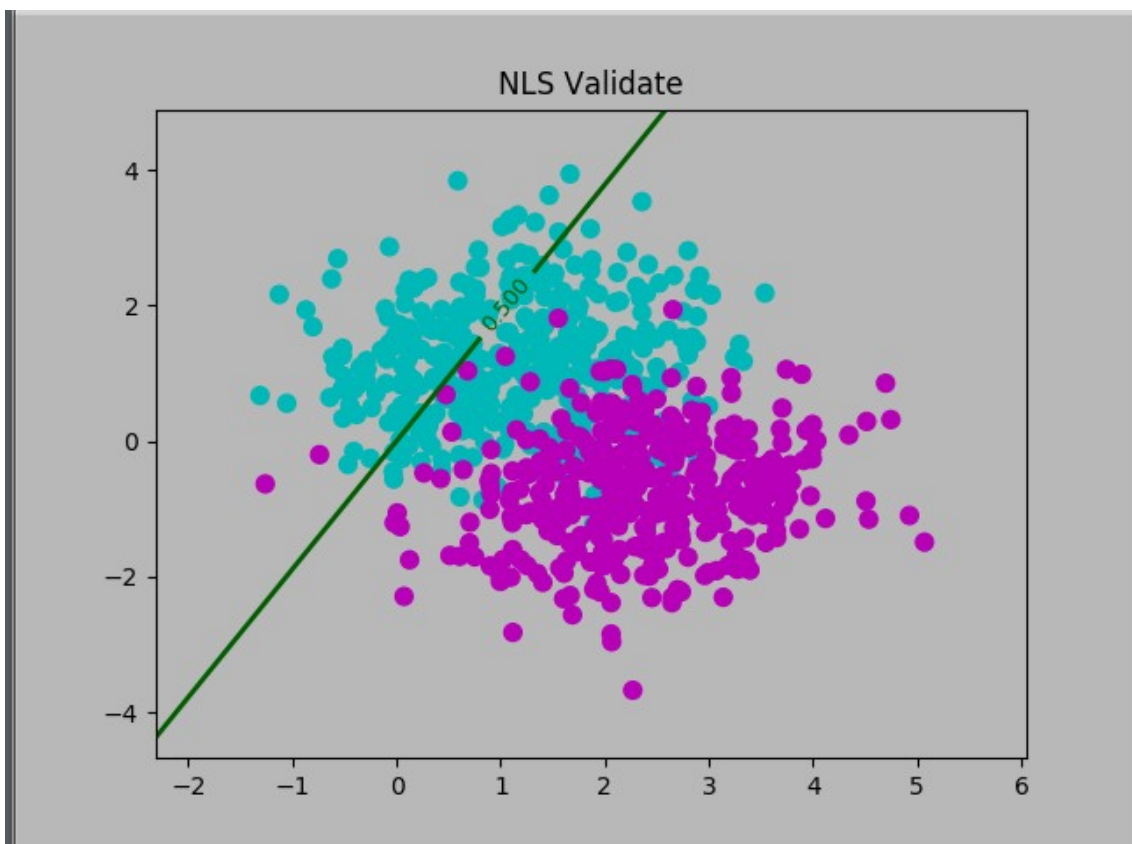


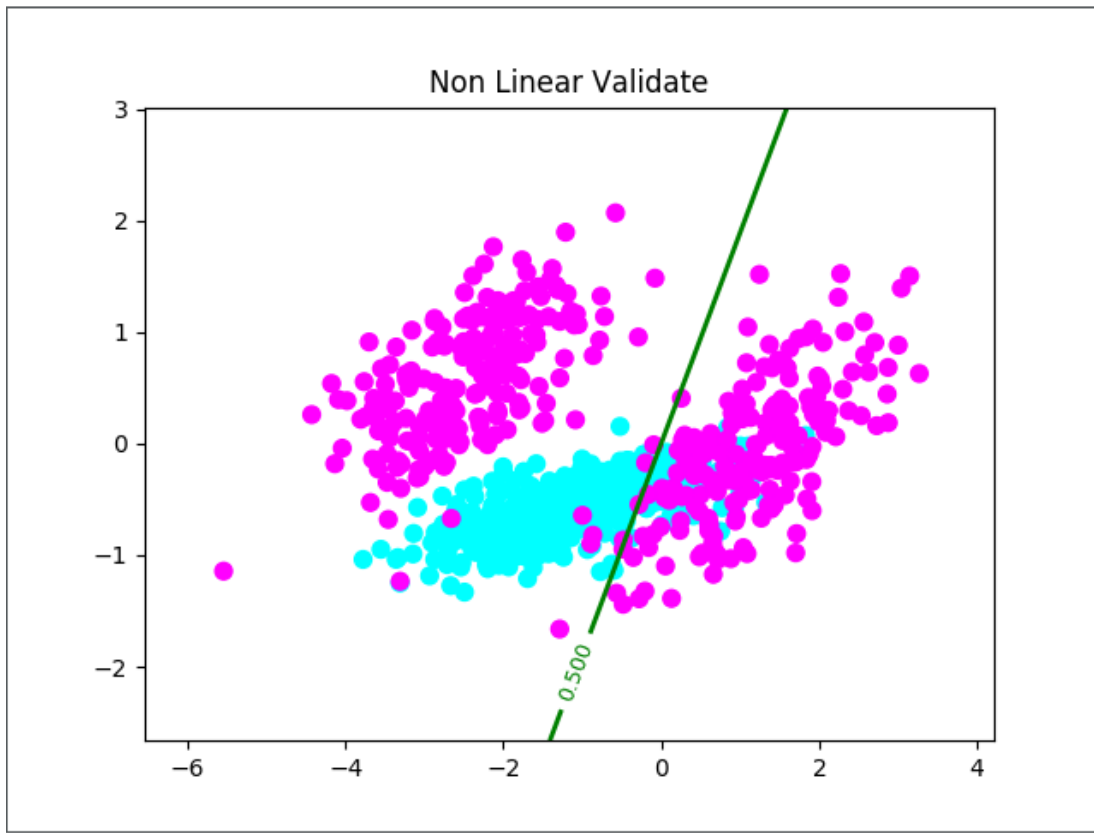
1.2.2 Behavior of the algorithm when lambda increases:

When lambda increases, the model will be regularized and hence the number of errors increases and the weight vector will be smaller. As lambda increases the slope of the decision boundary increases until a point when it becomes parallel to y axis. (w_1 , w_2 will be heavily regularized that they become equal to 0). The graphs representing this is given below: When $L = 10$:

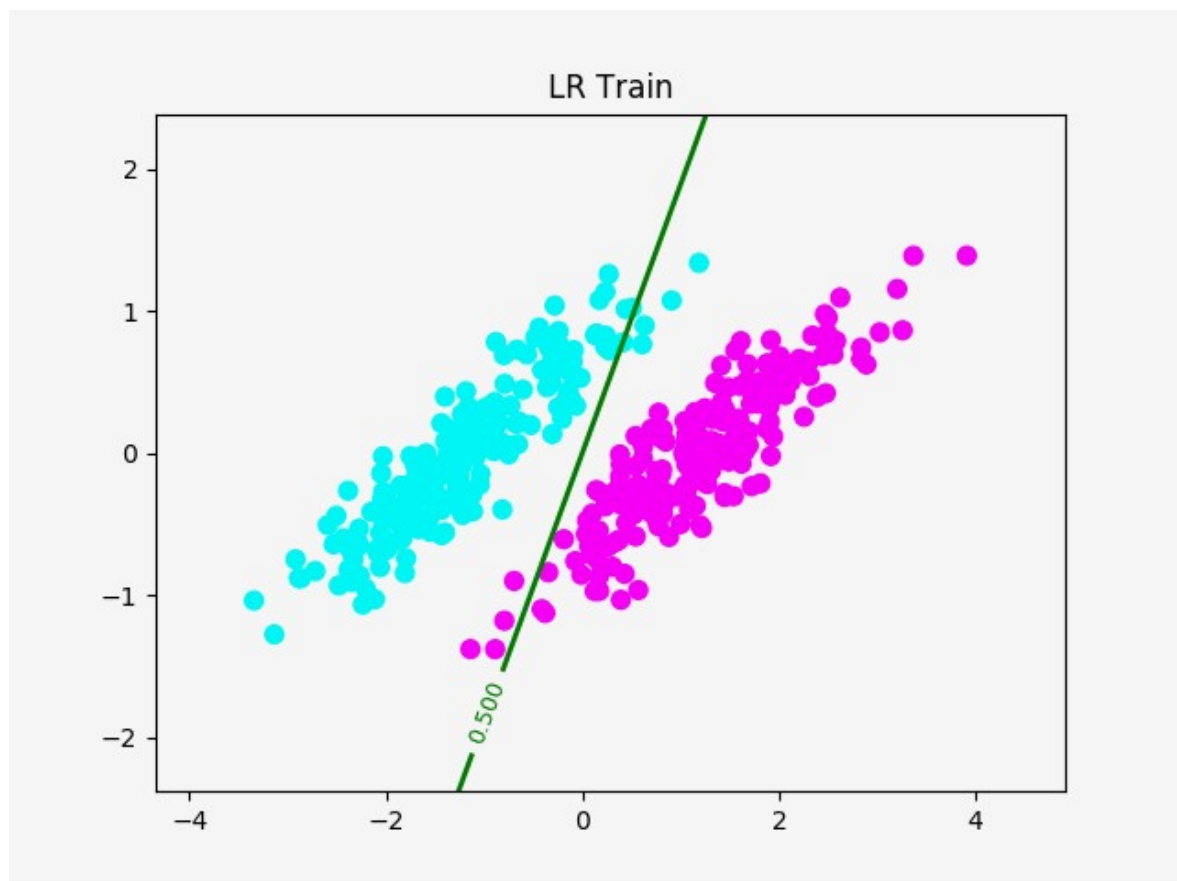


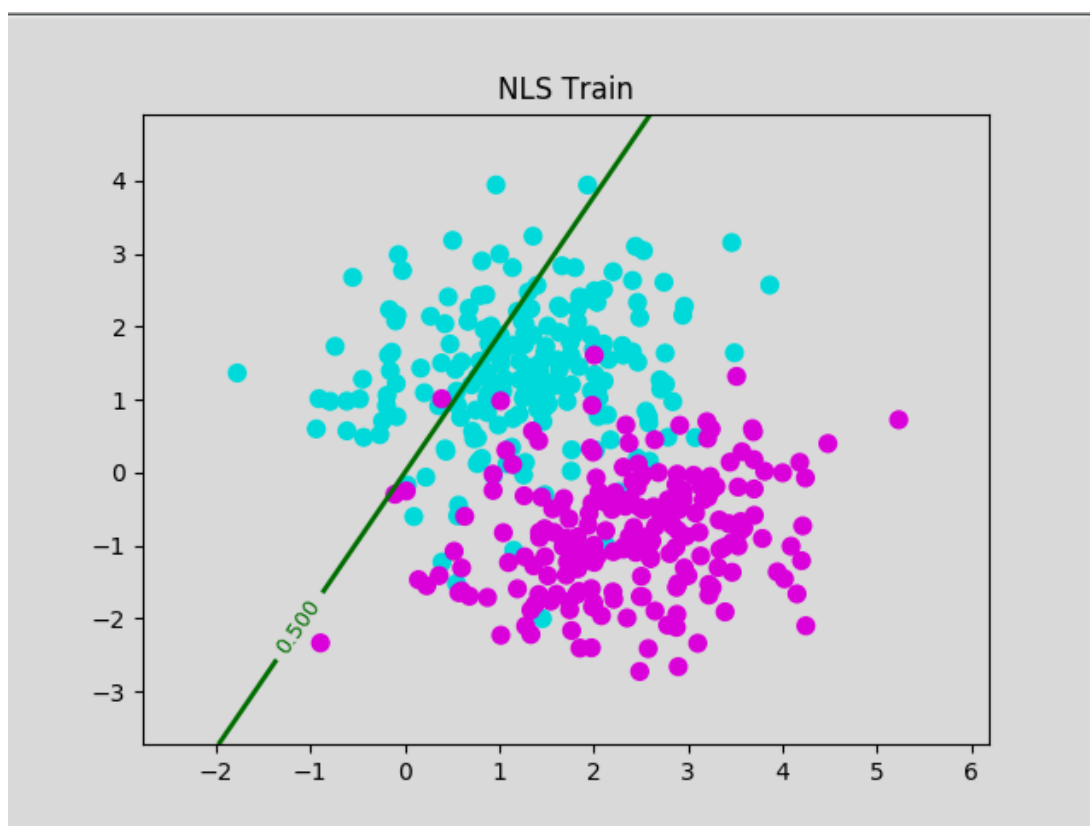
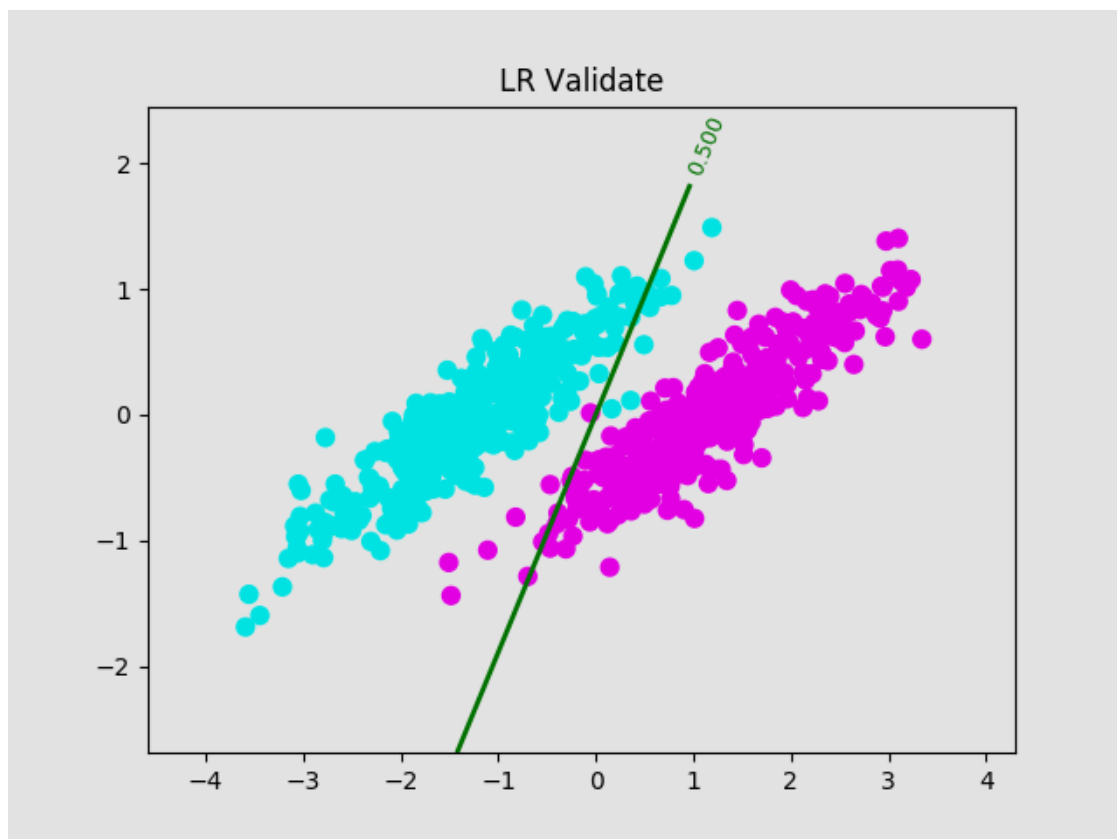


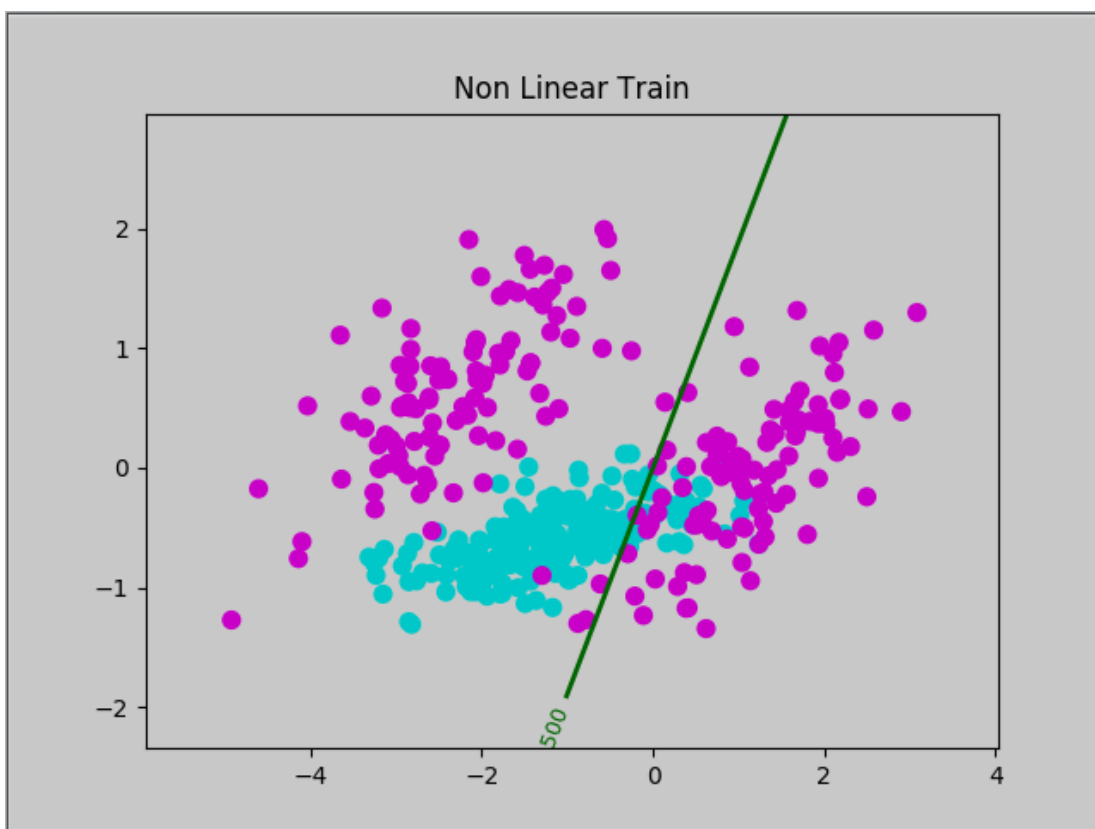
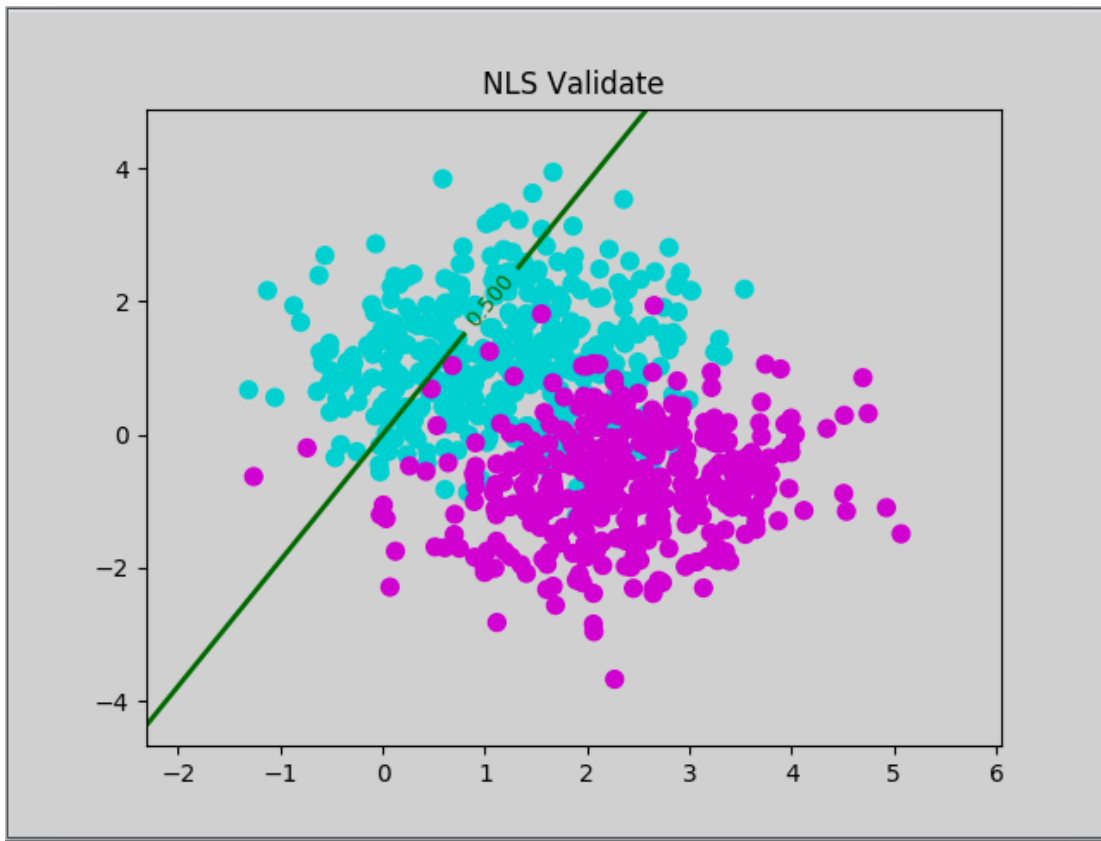


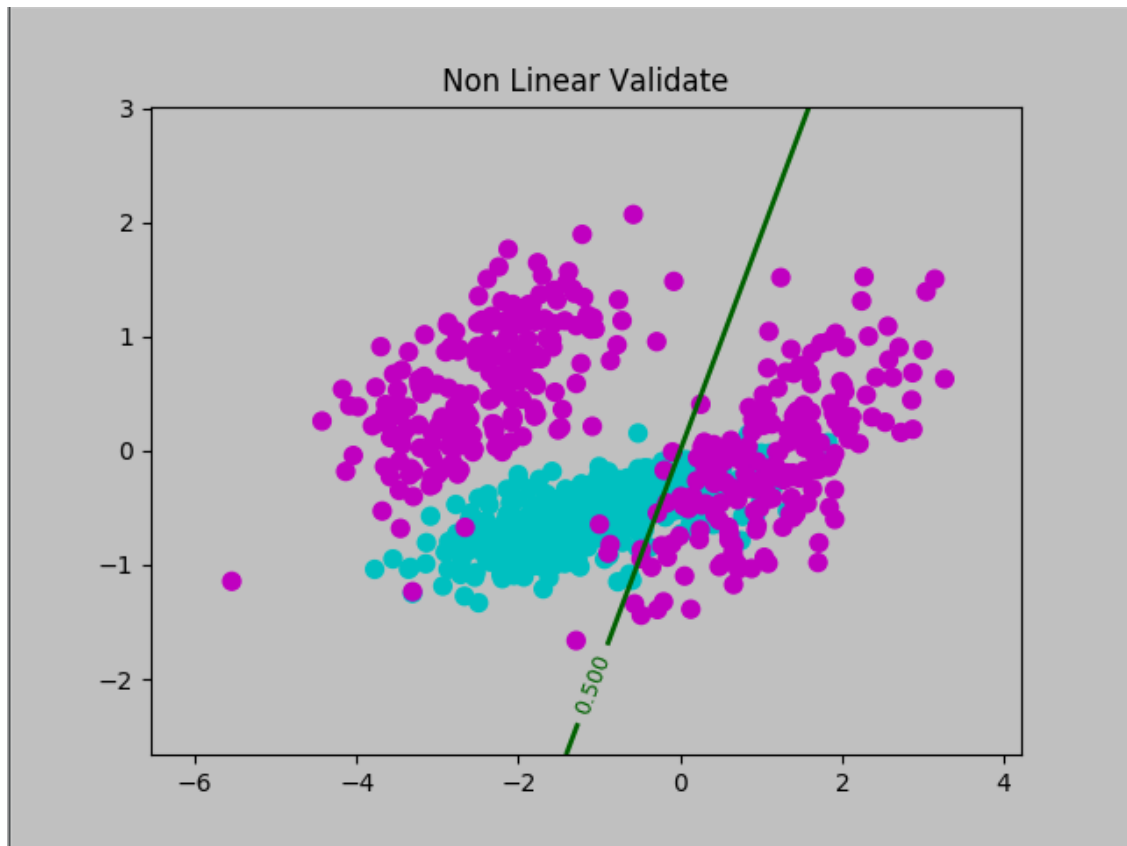


When $\lambda = 100$,









1.2.3 General trends:

Since the regularized logistic regression is for a linearly separable input data, it is not able to accurately classify the data points for non separable data. Hence, the error on non separable data set is very high.

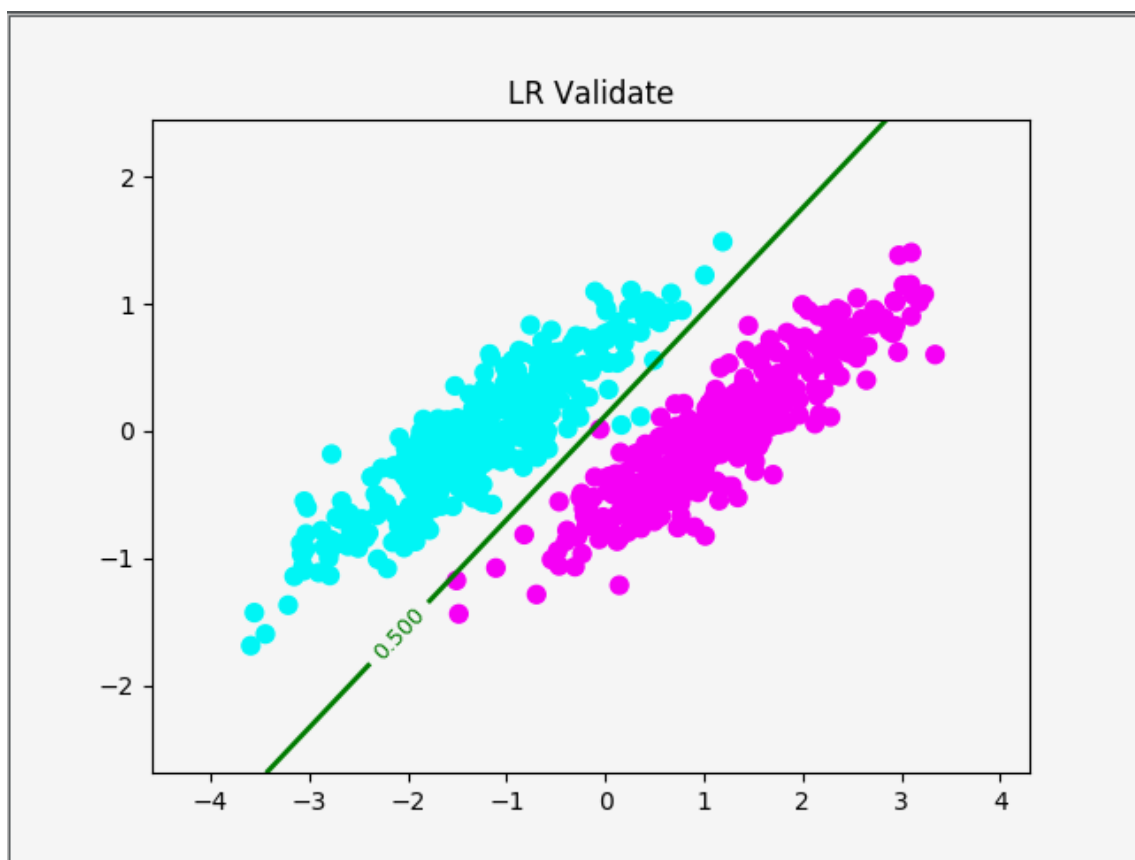
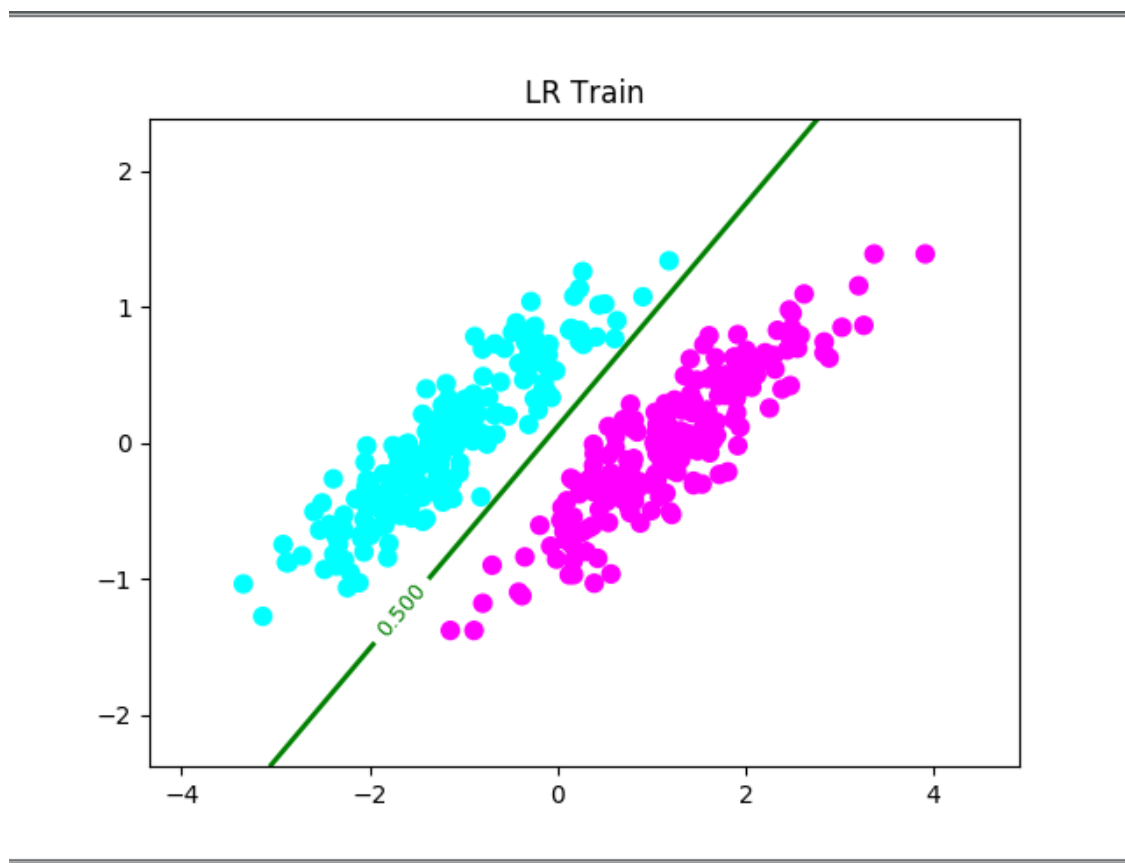
1.3: Regularization on polynomial basis functions:

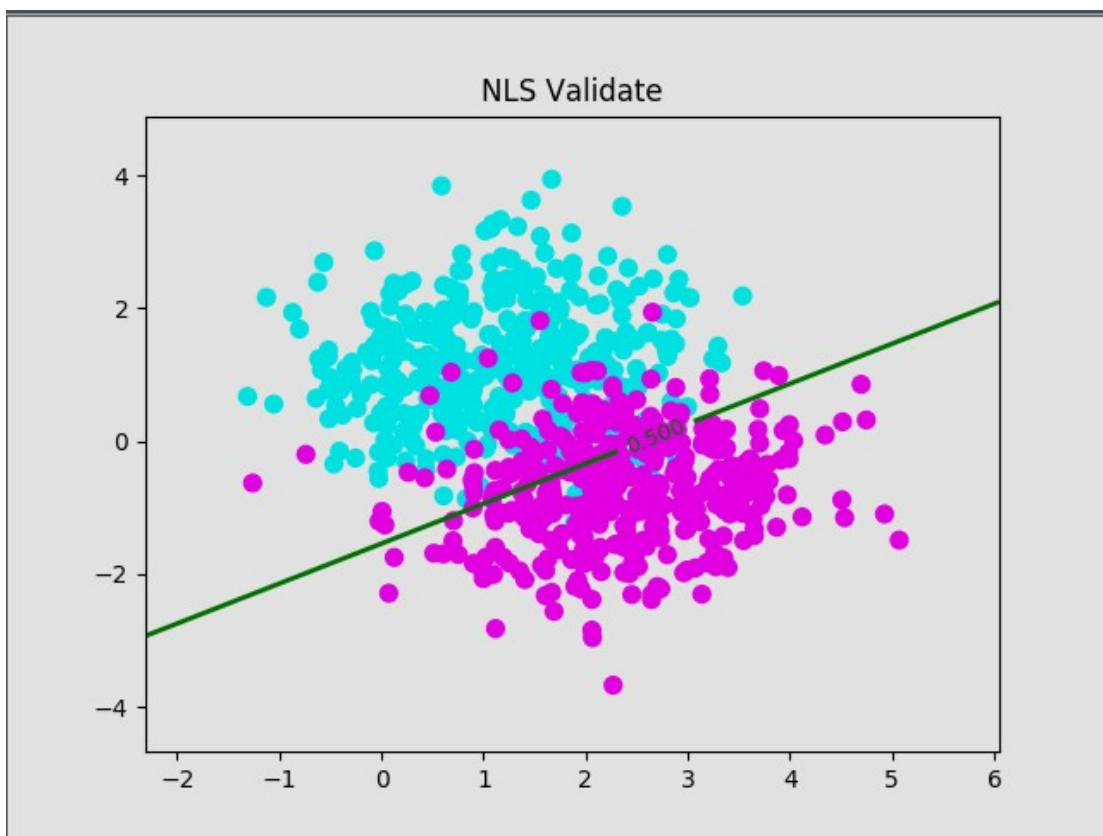
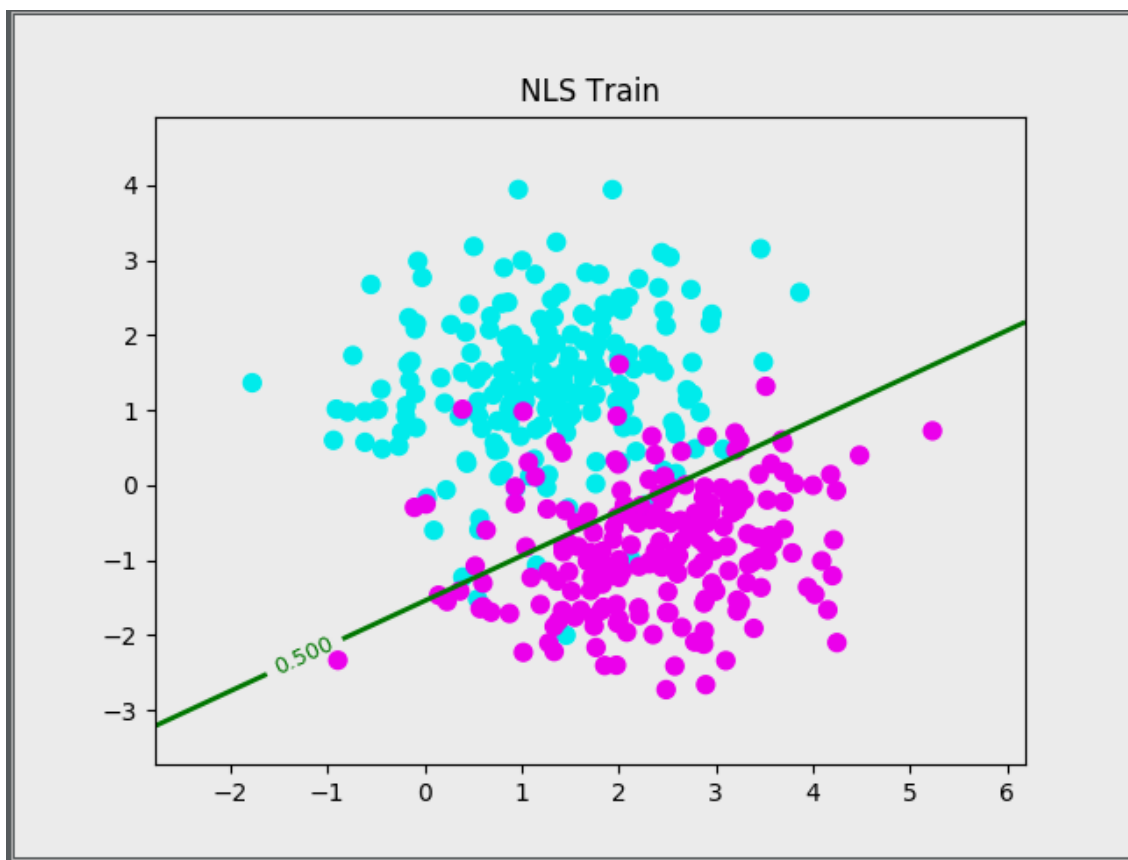
Since we are mapping the input to higher order, it is possible for the logistic regression to handle second order polynomial basis. Hence without regularization, the model overfits. Regularization causes the weights to be small and the weights will be smaller as we increase λ . For non-linear and non separable cases, the error is less since the features are mapped in higher dimensions

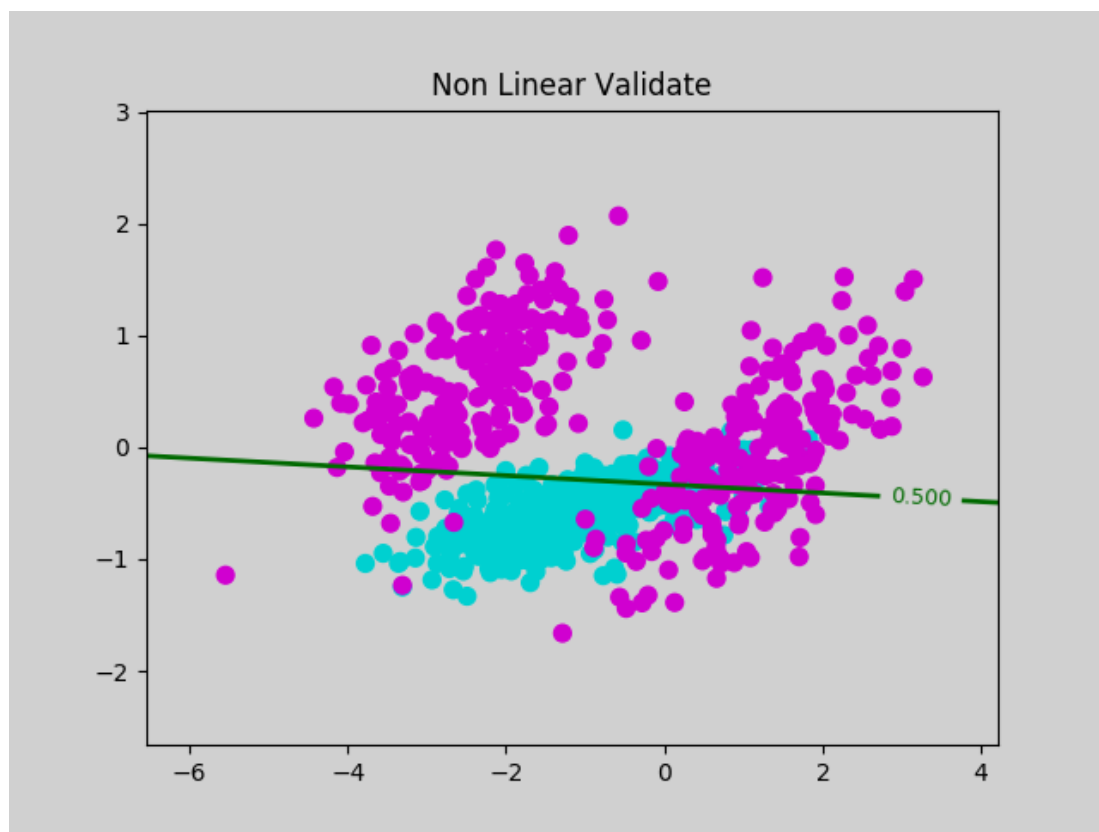
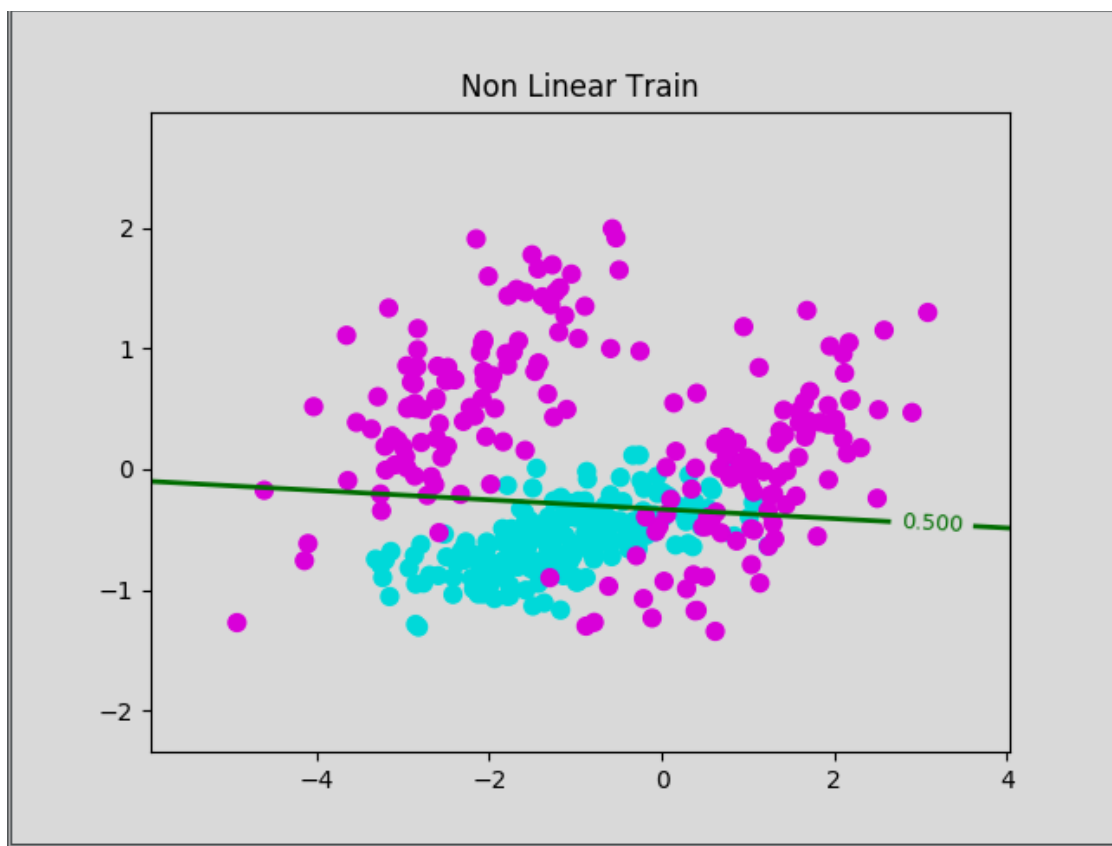
2. Support Vector Machine:

2.2 SVM Implementation report:

The results of implementing SVM is depicted in the graphs below. Since nls and nonlin are not linearly separable, the upper bound of c on α was required to produce a classification. For linearly separable data, it is not required since there is no chance of misclassification. The below graphs are when c is set to 10.

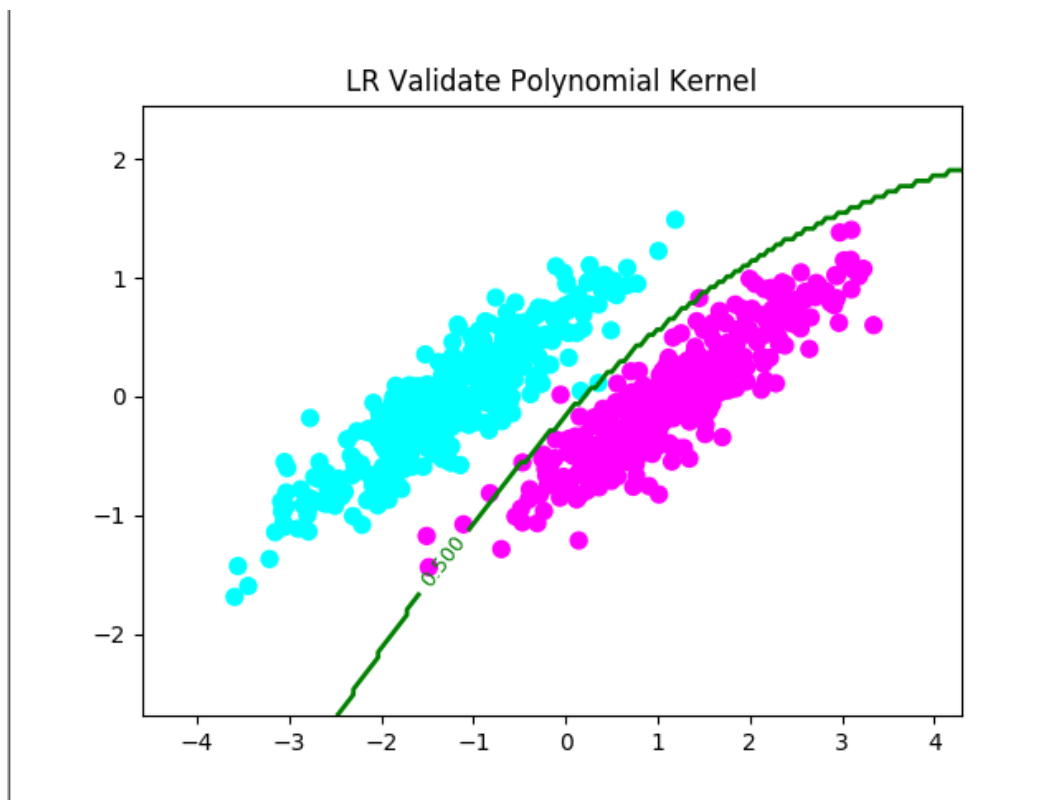
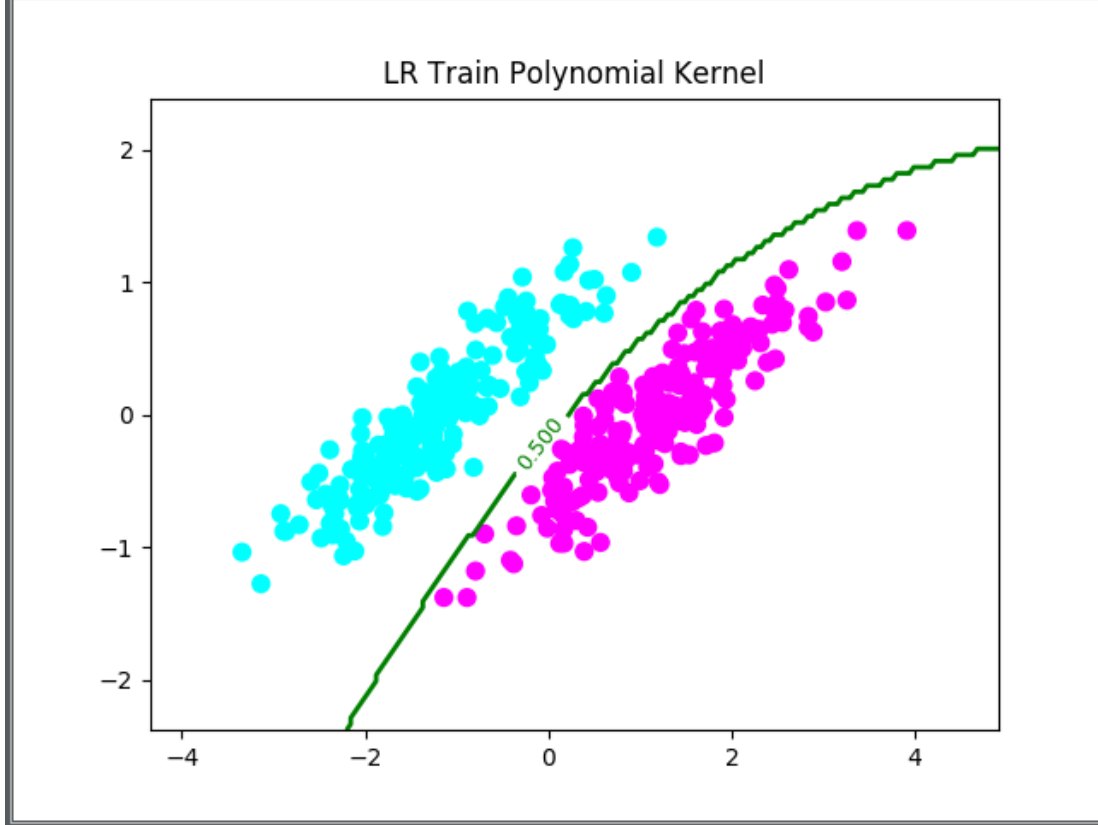


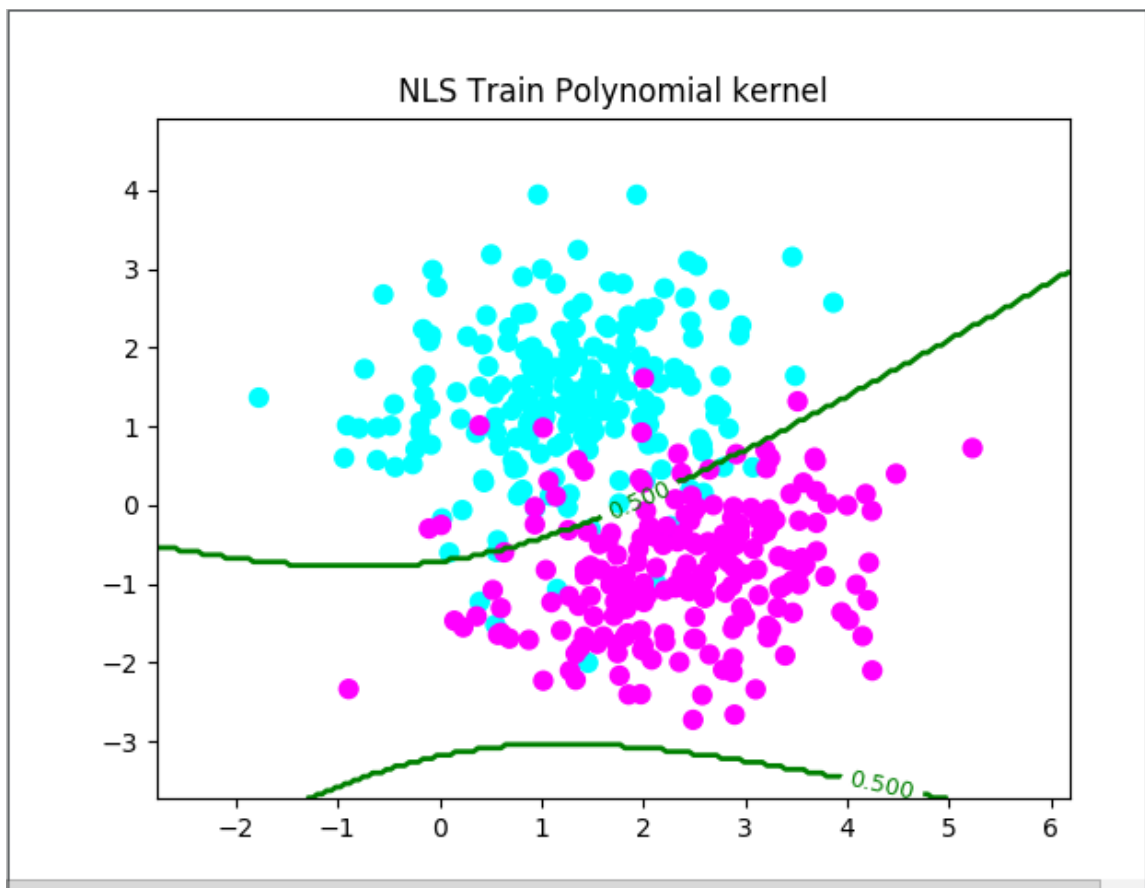




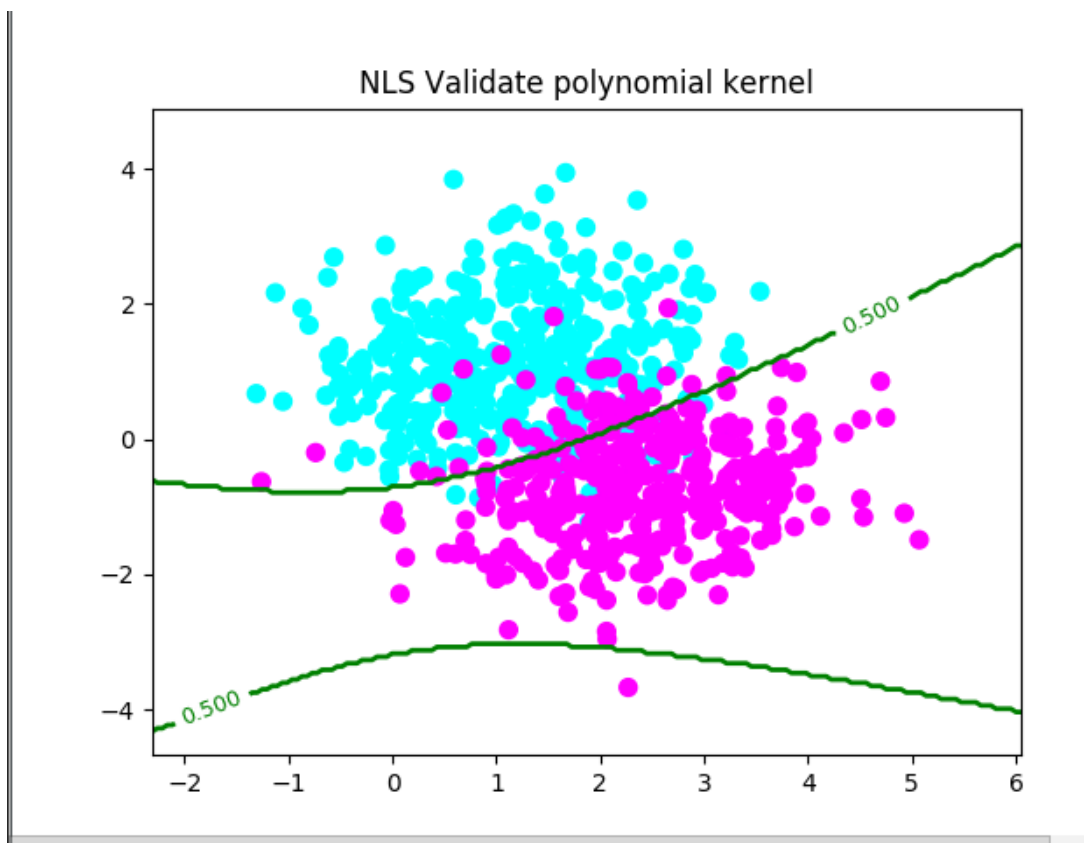
3. Kernel Support Vector Machine:

Some of the graphs obtained by applying a polynomial and Gaussian kernel are given below:





Number of classification errors: 31

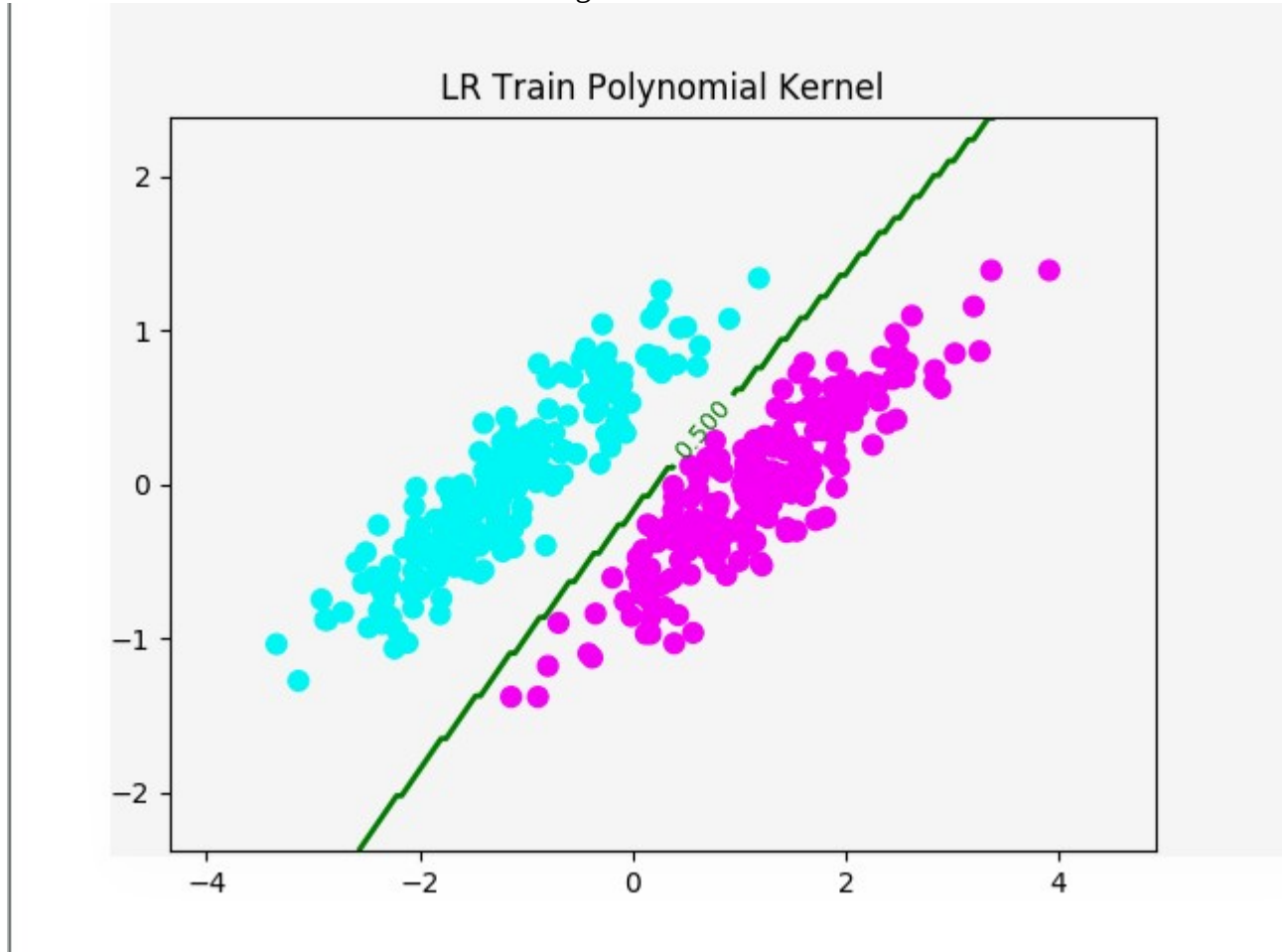


Number of errors: 78

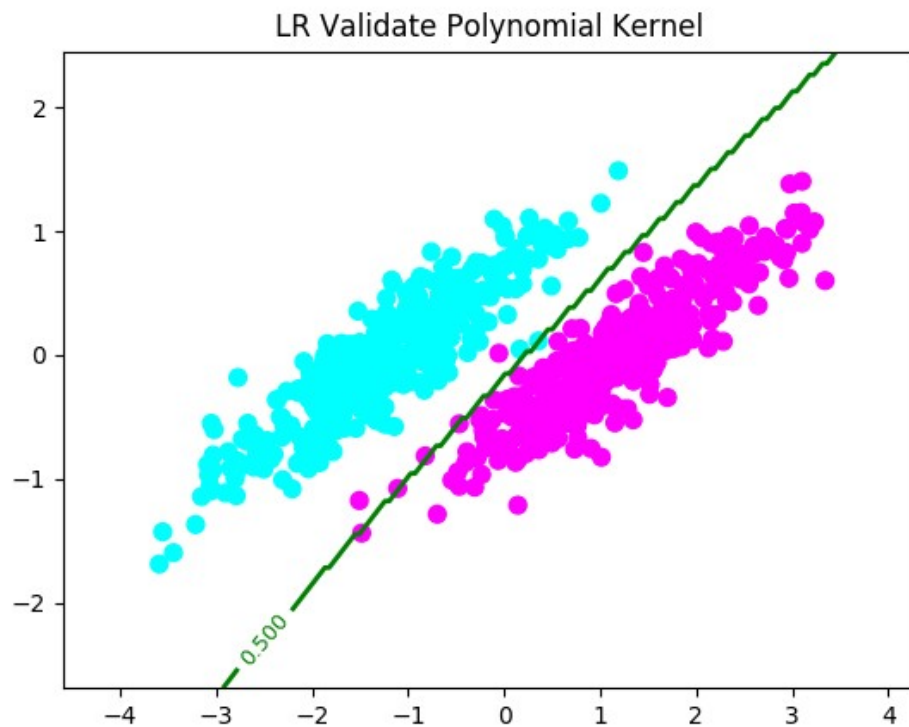
The Gaussian kernel did not produce results for linearly separable and non linearly separable data.

3.1 Effect of C

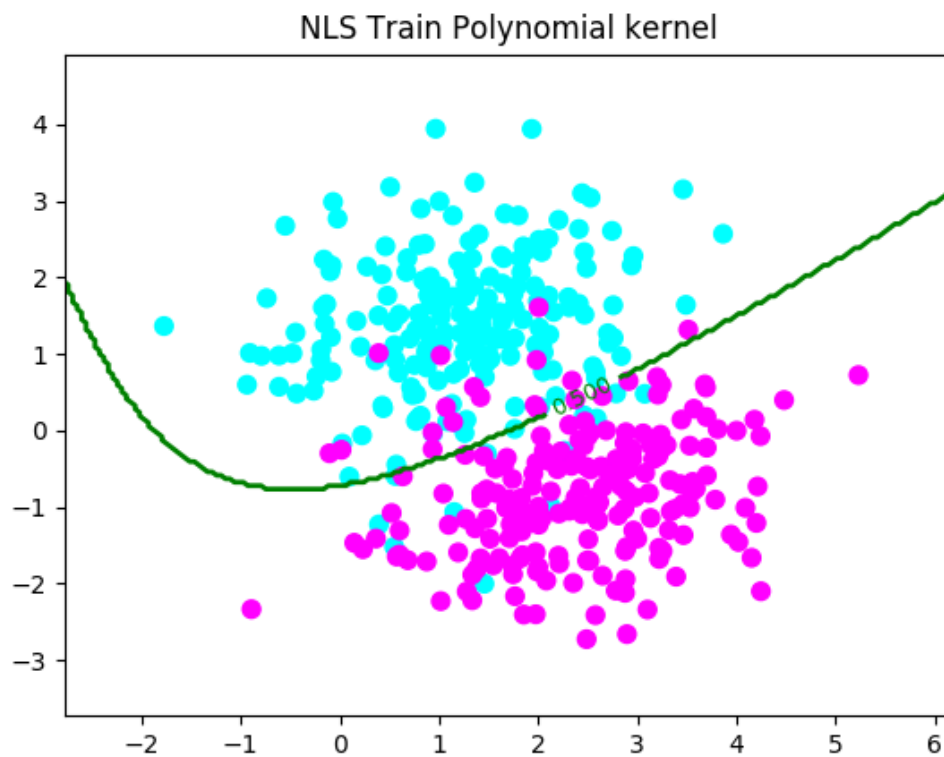
The model is created with $C = 1$. The following result was obtained:



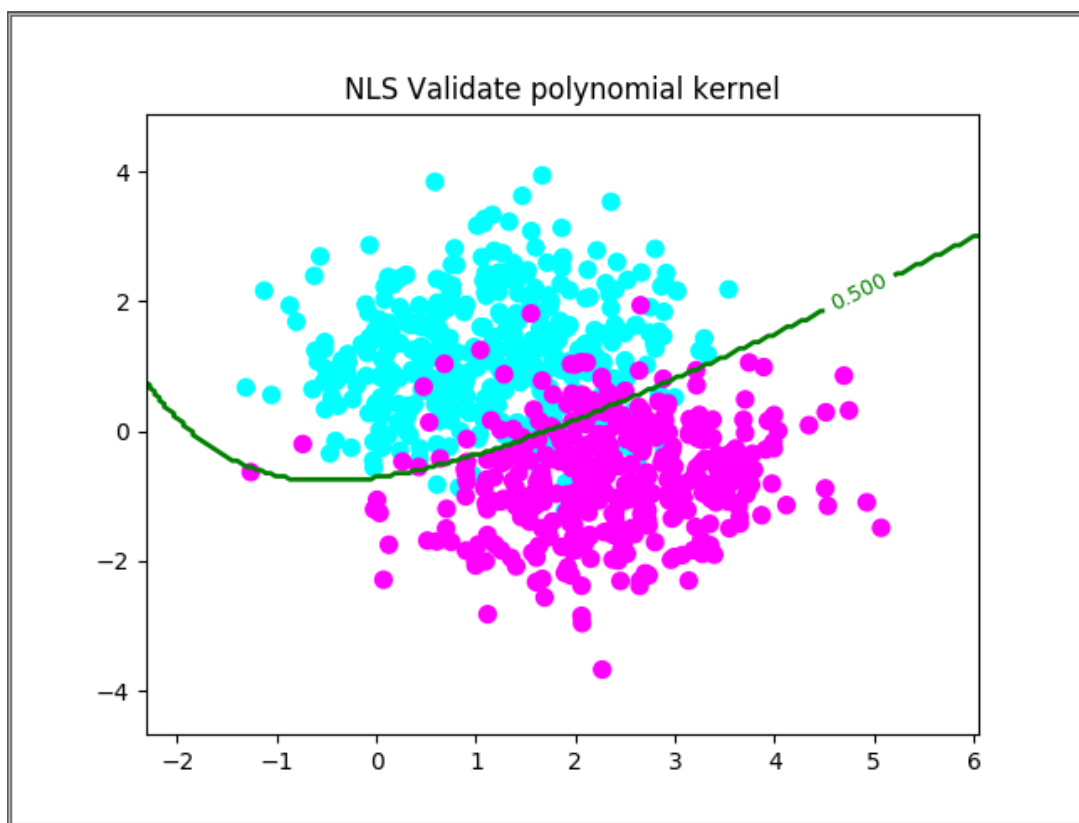
Number of classification errors: 0



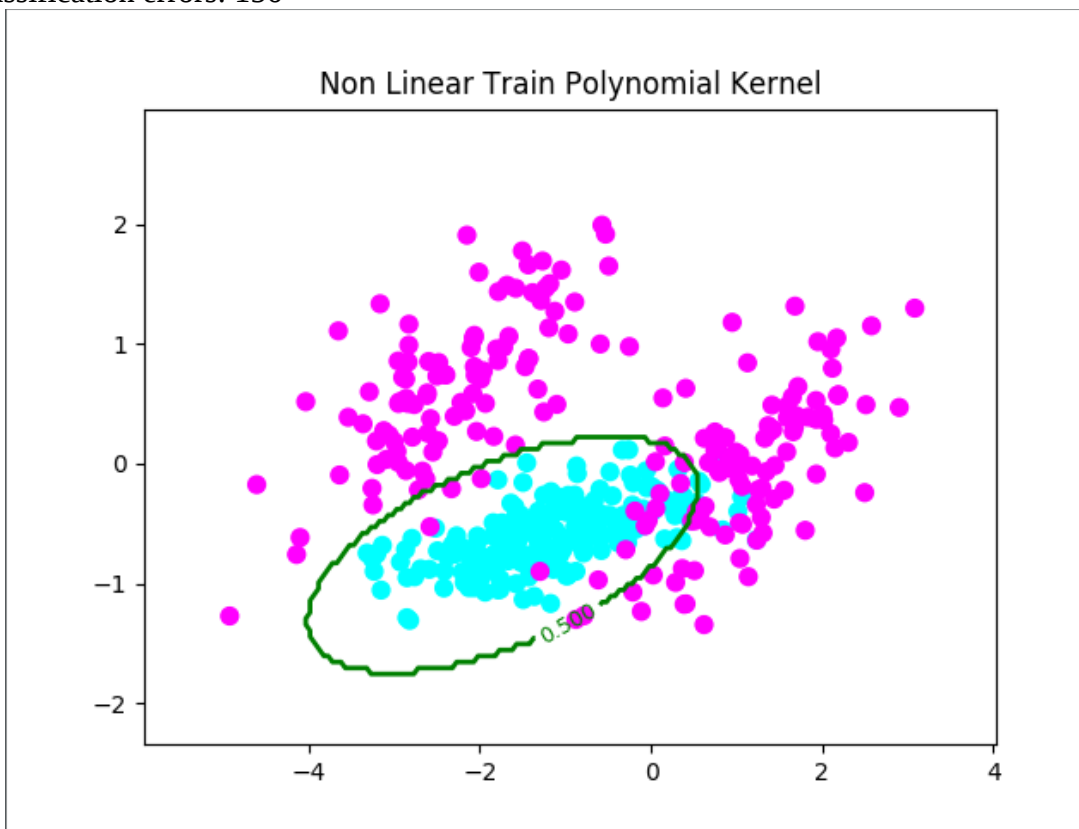
No. of classification errors: 4



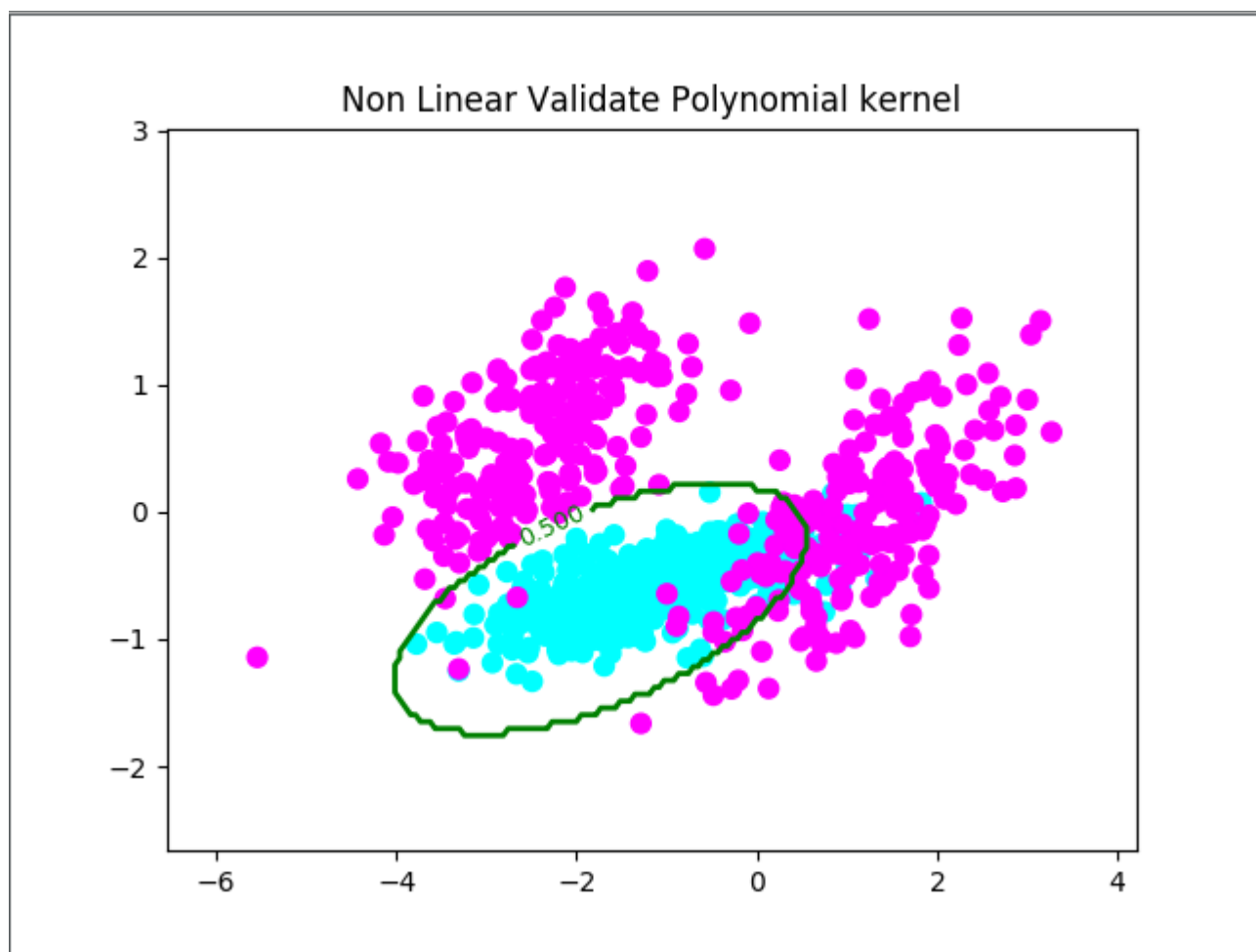
No. of classification errors: 67



No of classification errors: 156



No of classification errors: 67



No of classification errors: 127