

# Machine Learning

## Assignment 1

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# Q1: Linear Regression

a.)

Batch Gradient Descent.

Learning Rate = 0.001

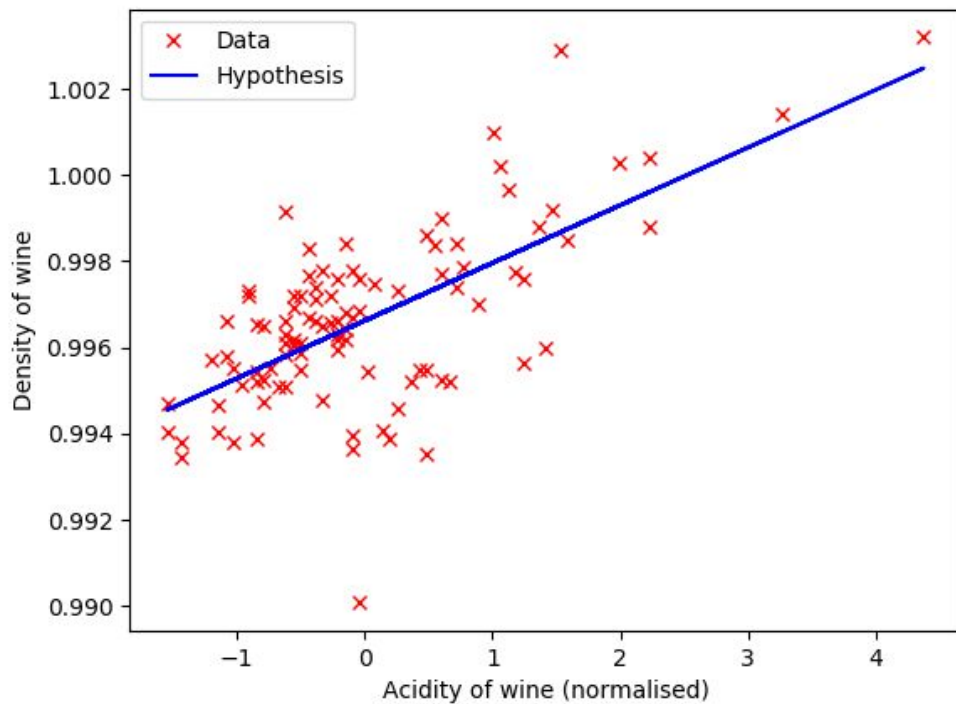
Stopping Criteria =  $\text{abs}(J_{\text{old}} - J_{\text{new}}) < 10^{-15}$

Final Parameters = [ 0.99662009 0.0013402 ]

Number of iterations taken = 176

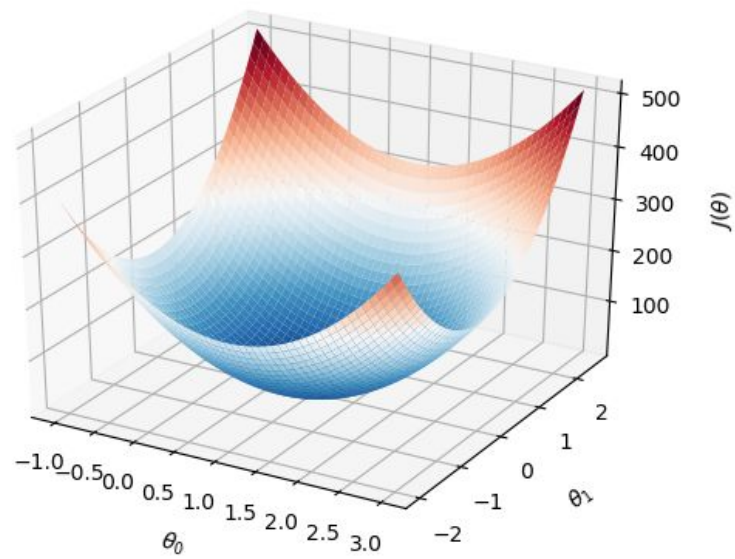
b.)

Plot of the hypothesis function learned:

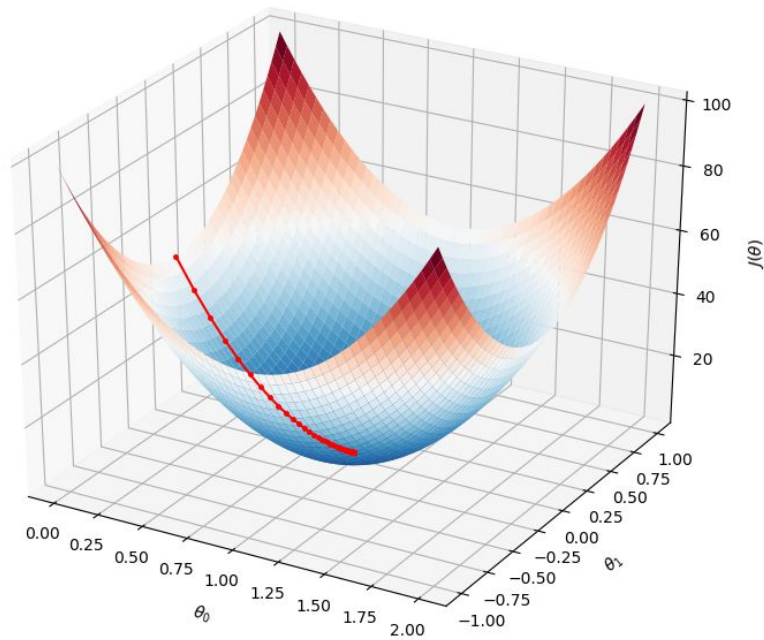


c.)

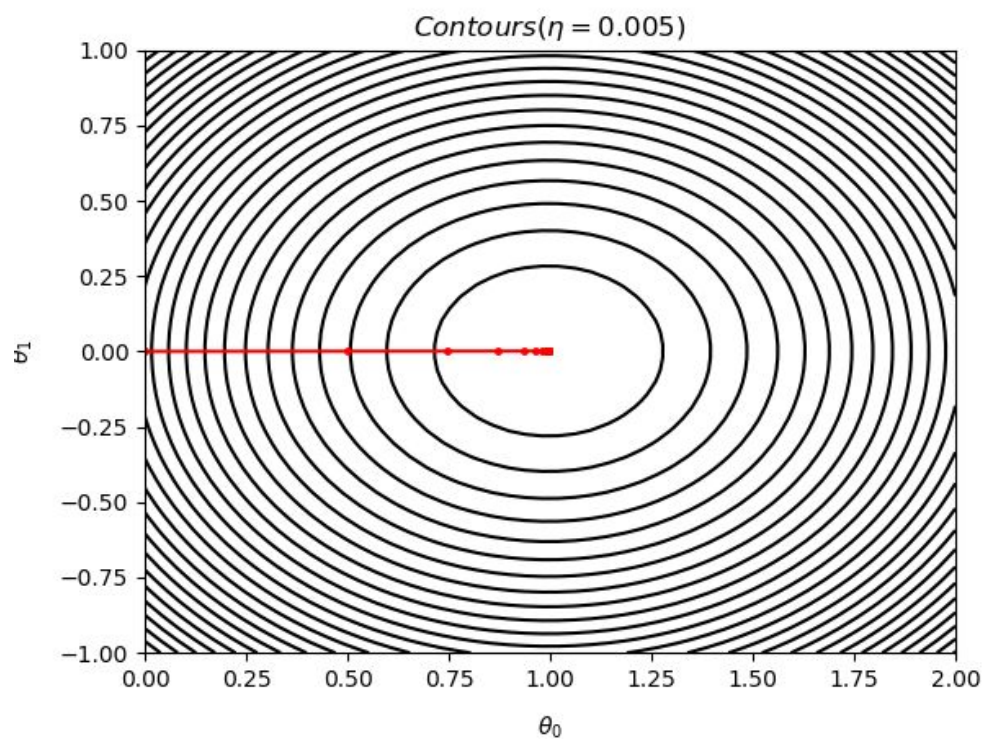
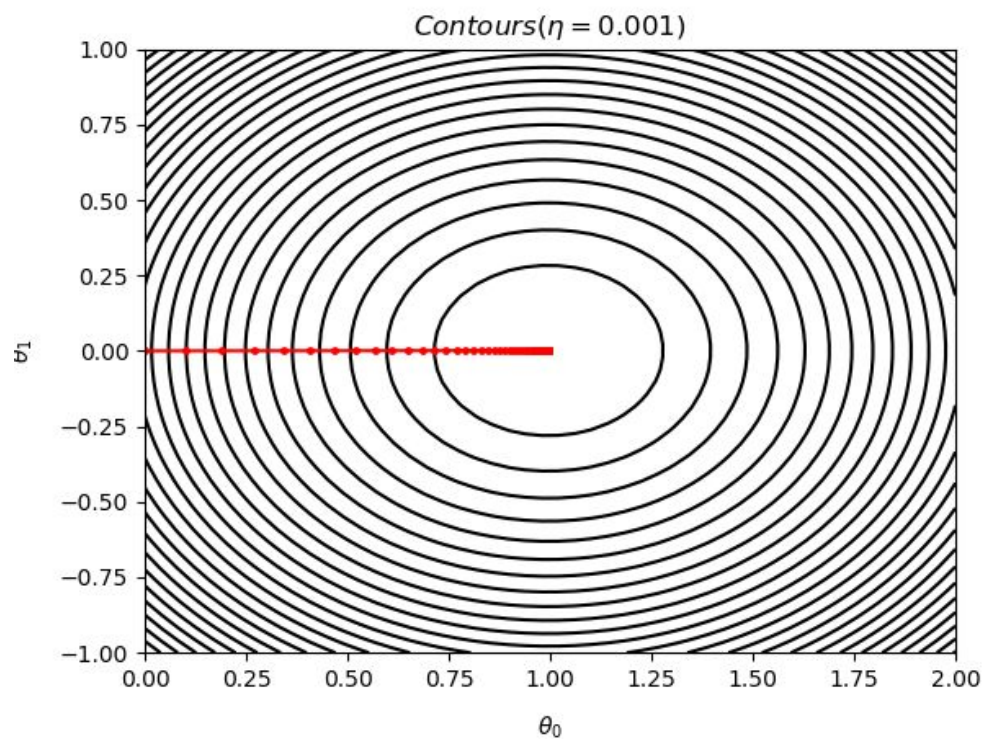
3D Plot of Error Function (  $J(\theta)$  )

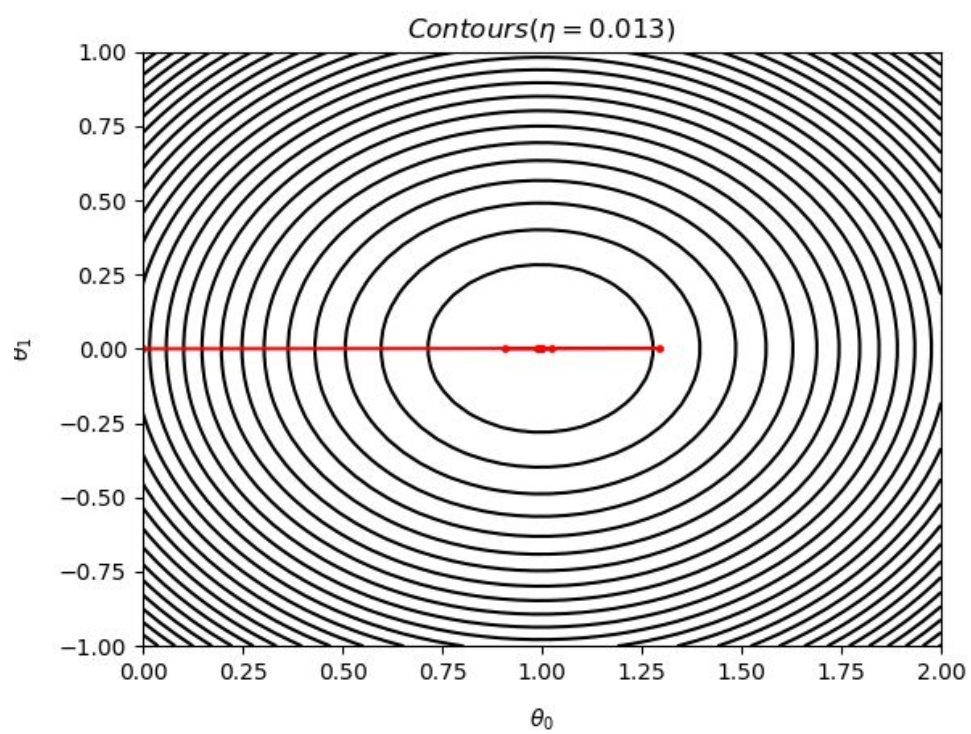
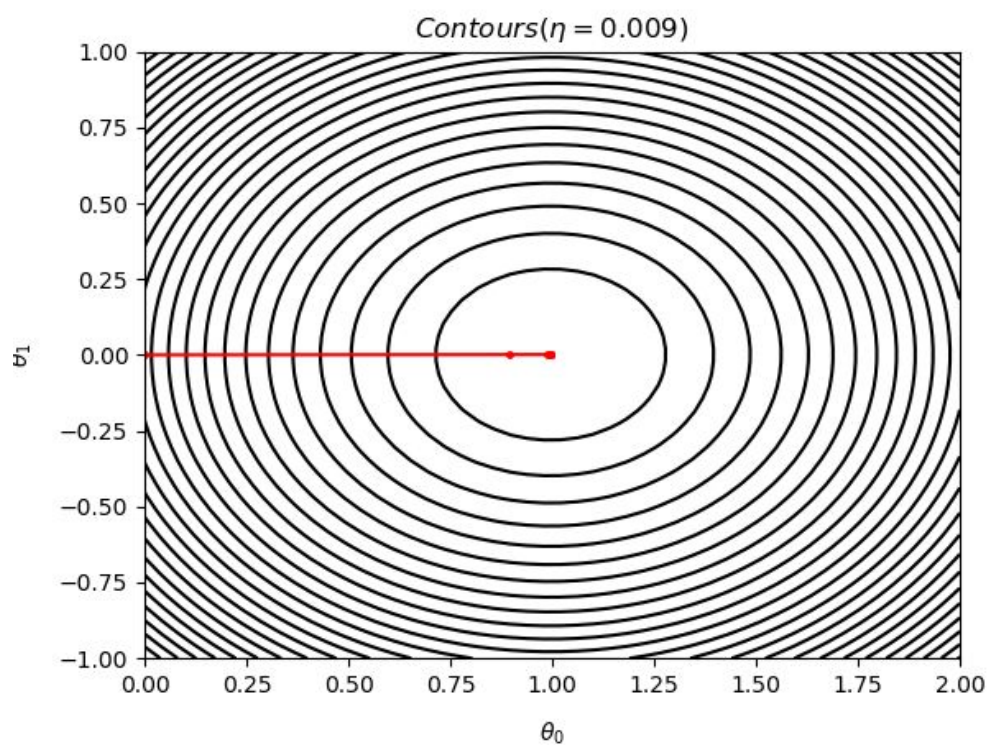


3D Plot with error values traced out:

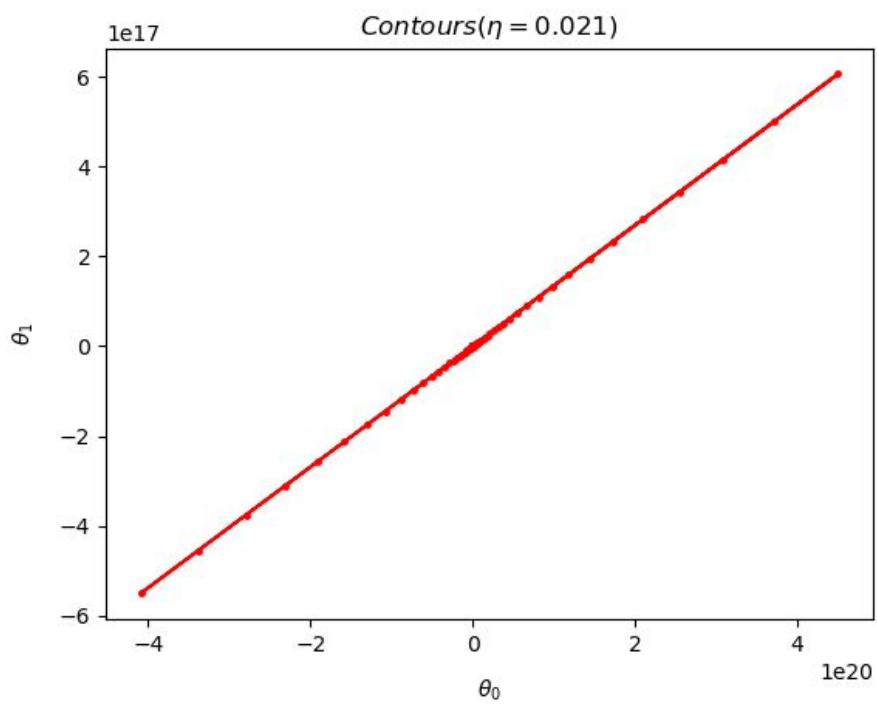
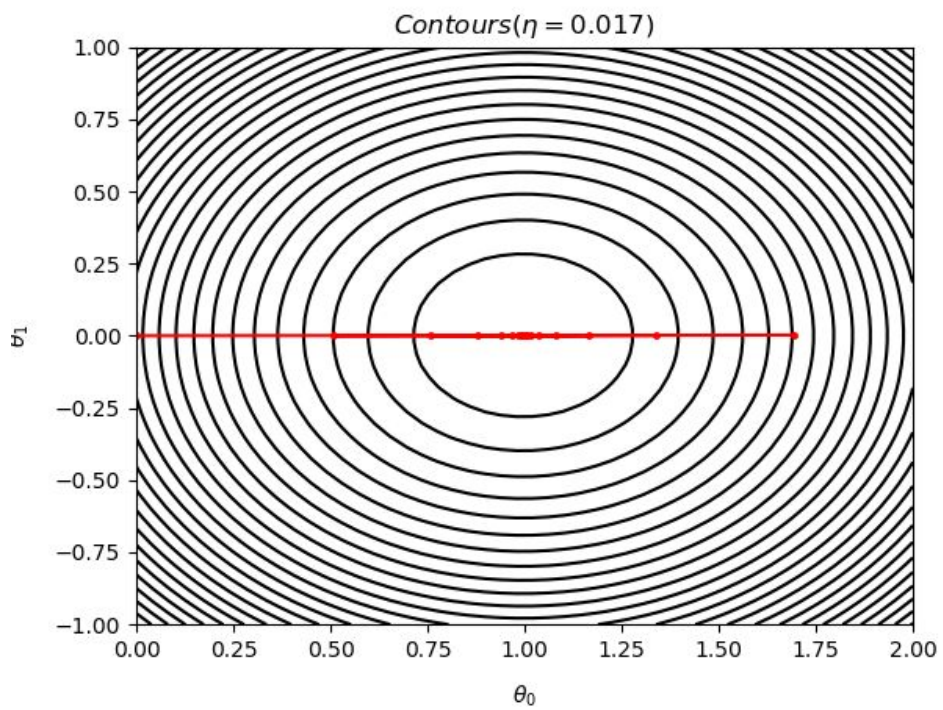


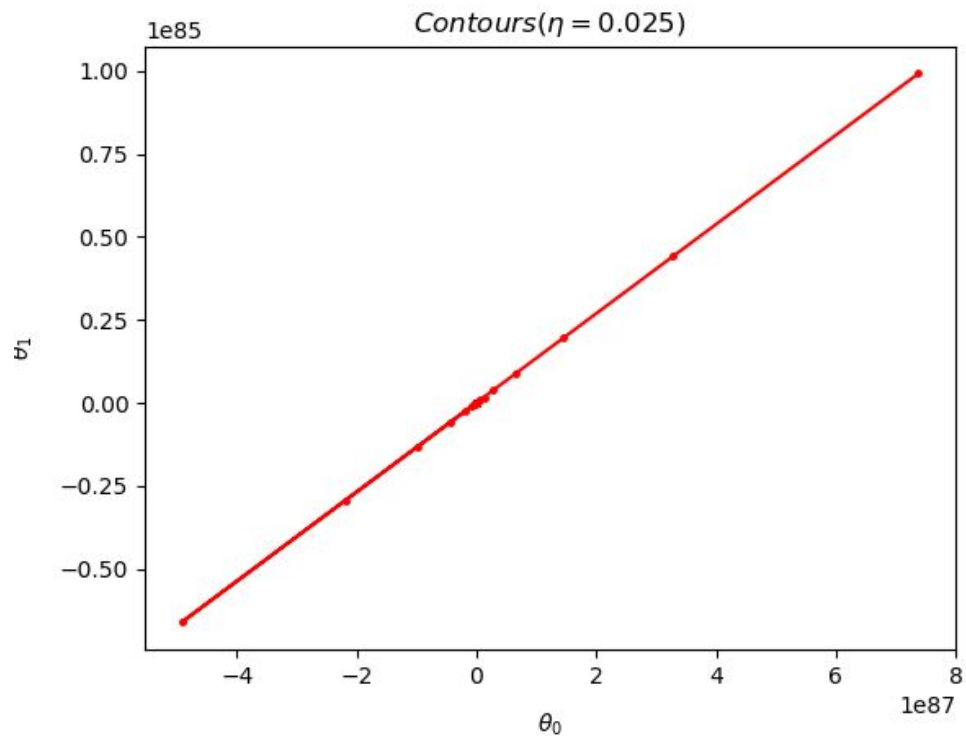
e.)











As eta increases the number of iterations required by the algorithm decrease so it converges faster (which is shown by lesser number of points on the graph - around eta = 0.09) this seems to be the best of the given values.

But then, when eta is increased further the error function oscillates around the minima (can be observed for eta 0.013 & 0.017)

Further increasing eta values results in divergence so the contours hide from view.

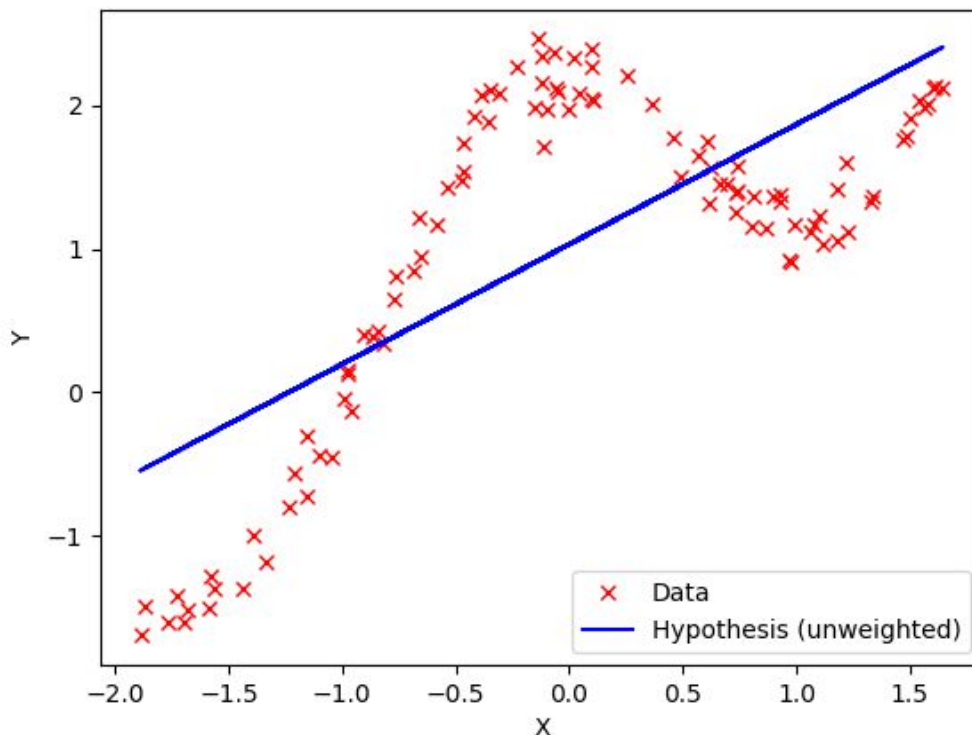
## Q2: Locally Weighted Linear Regression

a.)

Unweighted Linear Regression using Normal Equations

Final Parameters = [ 1.03128116, 0.83519315]

Plot of the Hypothesis function learnt:



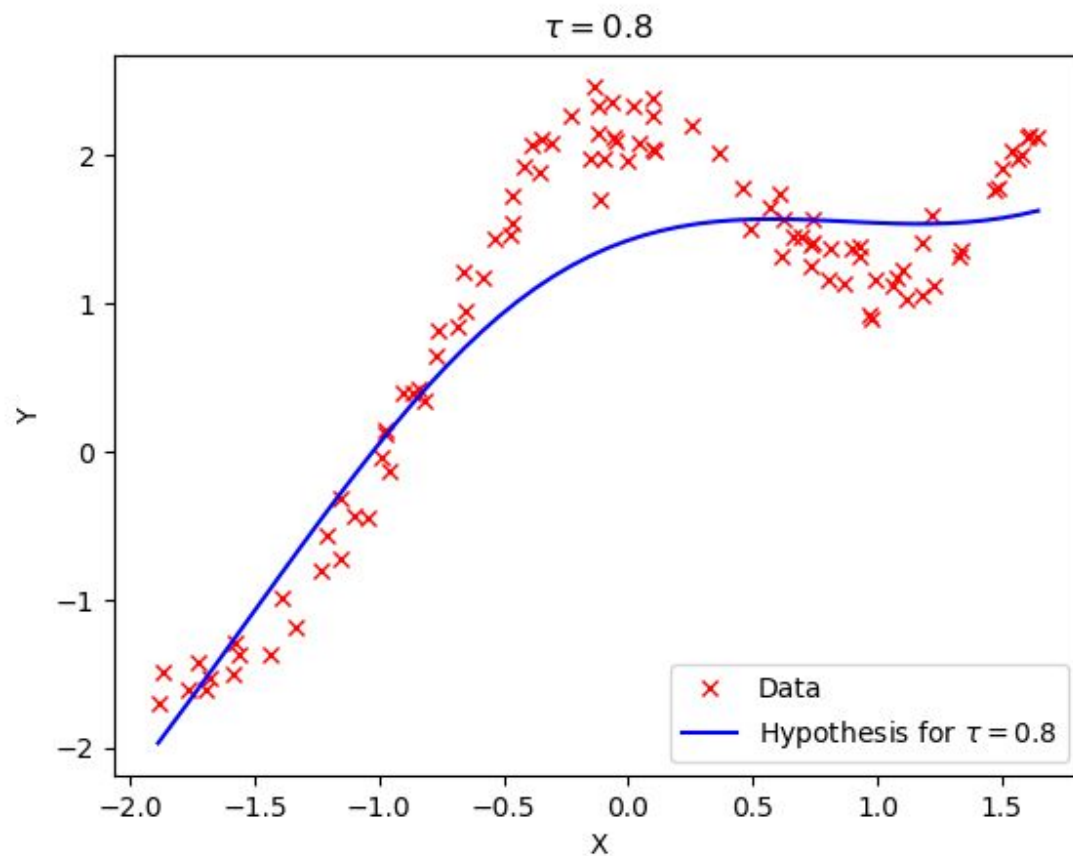
As can be observed, a simple unweighted linear regression is not able to fit the data properly, because the data is inherently non linear.



b.)

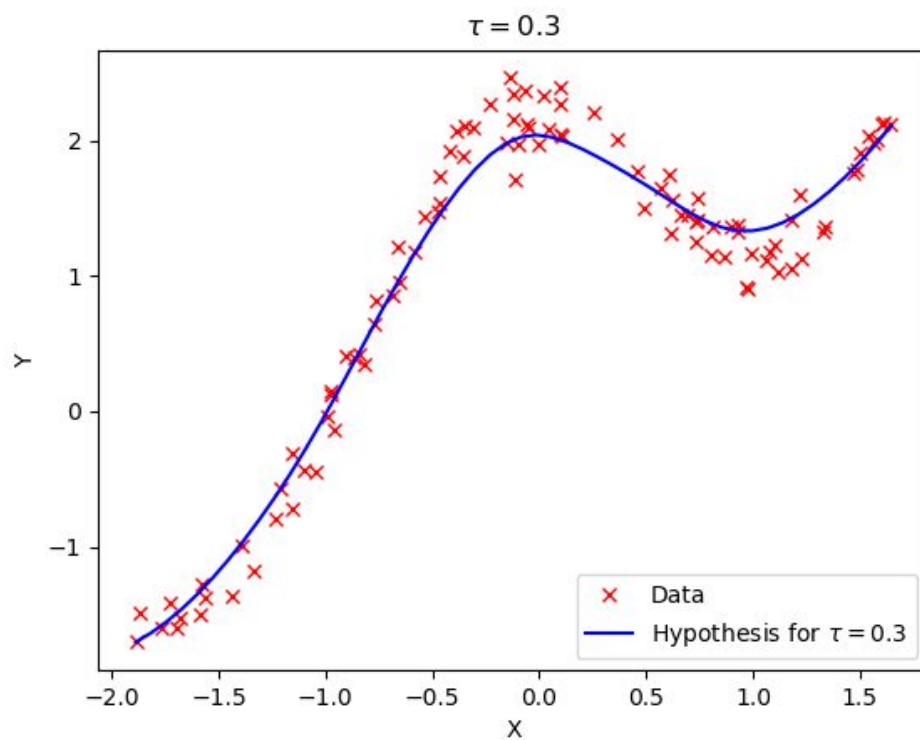
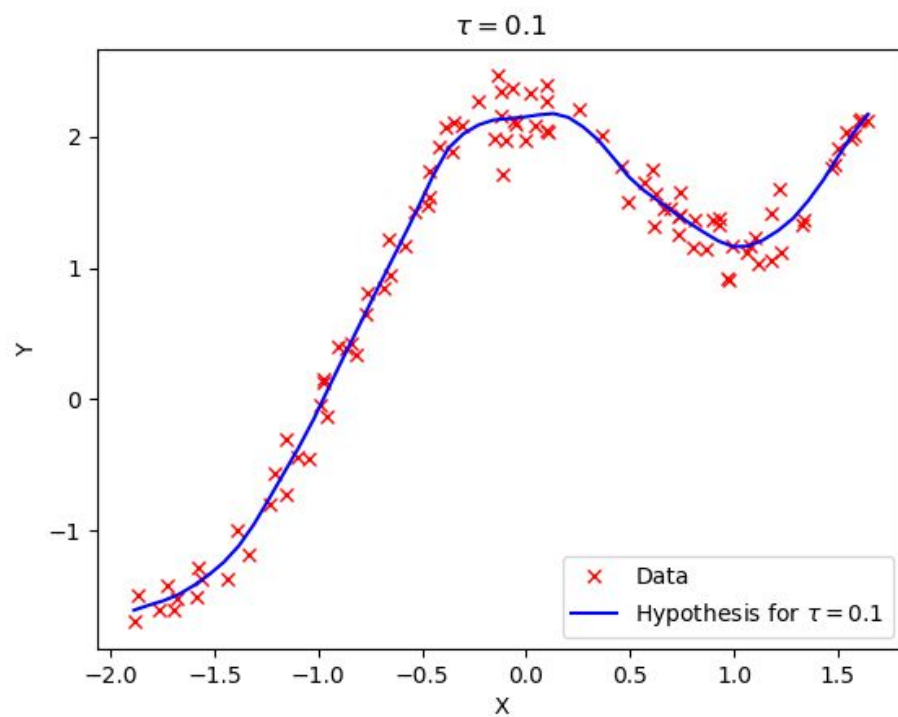
### Weighted Linear Regression using Normal Equations

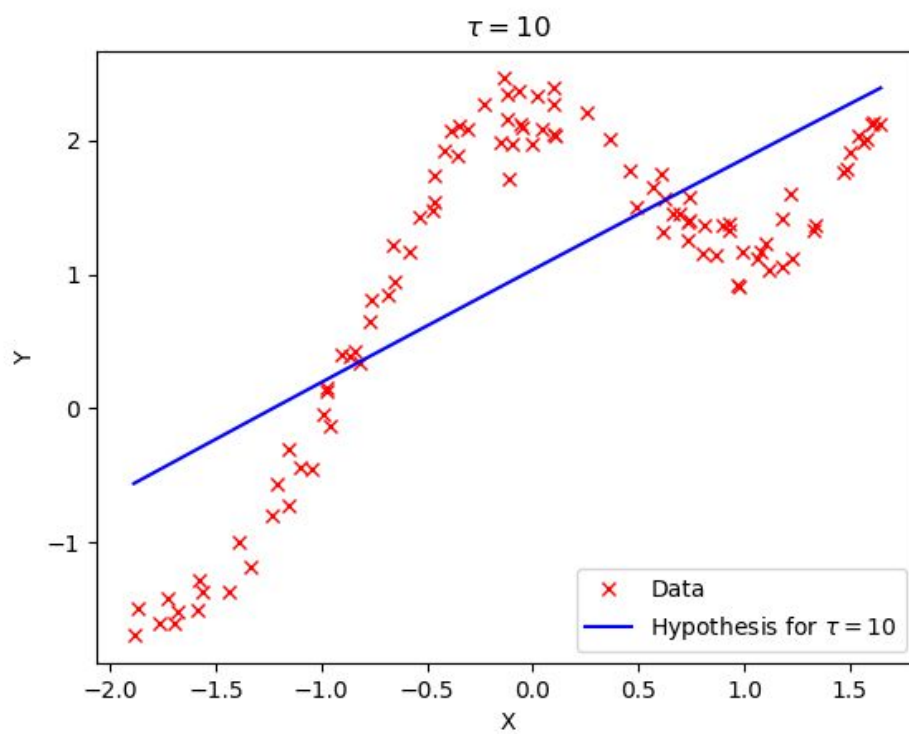
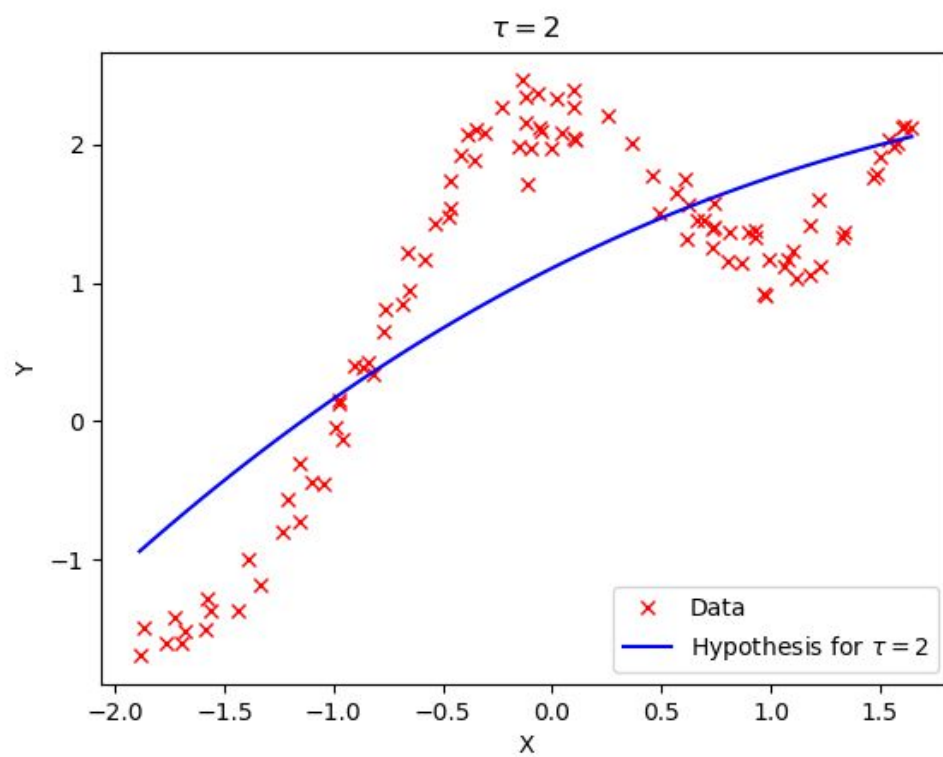
Plot of the Hypothesis function learnt when  $\tau = 0.8$ :



c.)

### Effect of values of Tau





As can be observed from the plots the value of  $\text{Tau} = 0.3$  works the best.

As  $\text{Tau}$  gets larger, the curve becomes a straight line as all weights get close to 1 and the process reduces to that of the unweighted regression.

As  $\text{Tau}$  gets smaller, the curve tries to pass through every data point. Since this is overfitting the data, it won't work well on new test data.

## Q3: Logistic Regression

a.)

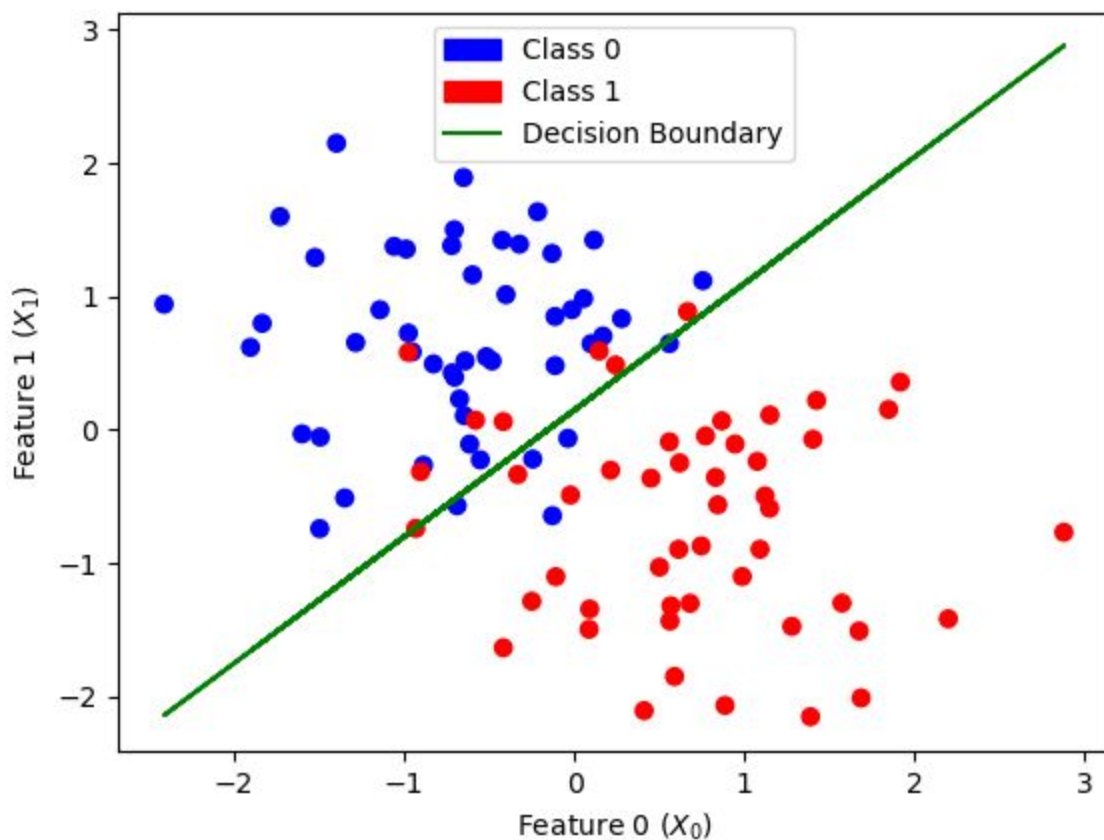
Logistic Regression using Newton's Method

Final Parameters = [ 0.40125316, 2.5885477 , -2.72558849]

Number of iterations = 8

b.)

Plot of the training data and decision boundary learnt:



# Q4: Gaussian Discriminant Analysis

a.)

GDA using Closed form equations.

$$\phi = 0.5$$

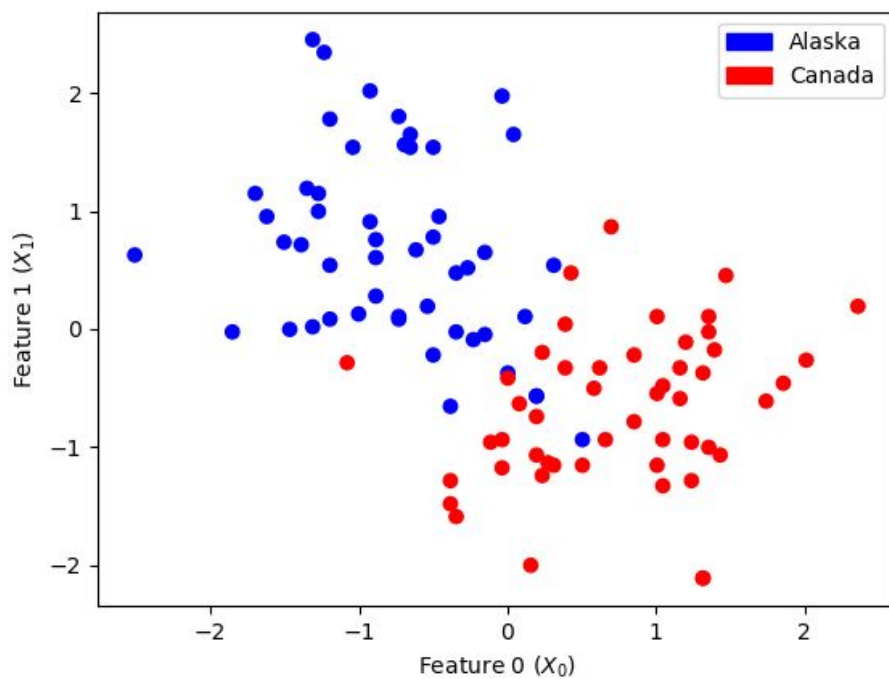
$$\mu_0 = [-0.75529433 \ 0.68509431]$$

$$\mu_1 = [0.75529433 \ -0.68509431]$$

$$\Sigma = \begin{bmatrix} 0.42953048 & -0.02247228 \\ -0.02247228 & 0.53064579 \end{bmatrix}$$

b.)

Plot of Training Data:





c.)

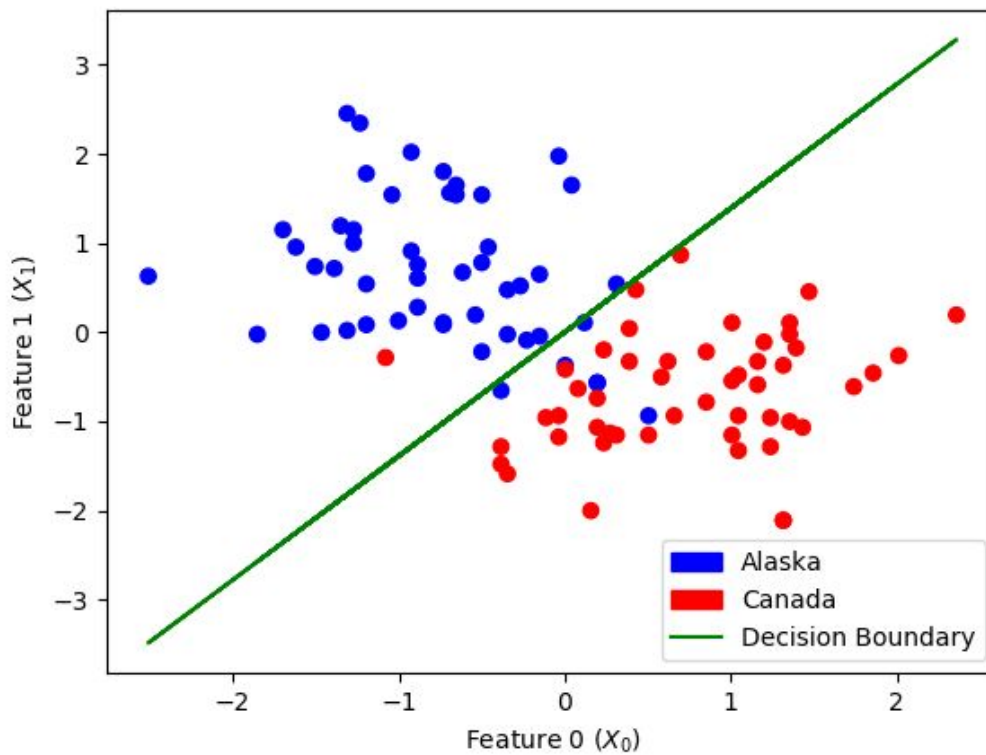
Equation of Linear Boundary:

Linear boundary can be expressed as :  $A X = B$

Where  $A = 2 * ( \mu_0^T \Sigma^{-1} - \mu_1^T \Sigma^{-1} )$

$B = ( \mu_0^T \Sigma_0^{-1} \mu_0 - \mu_1^T \Sigma_1^{-1} \mu_1 - 2 * \log ( ((1/\phi) - 1) ) )$

Plot of Decision Boundary:



**d.)**

GDA with different covariance matrices.

$$\mu_0 = [ -0.75529433, 0.68509431 ]$$

$$\mu_1 = [ 0.75529433, -0.68509431 ]$$

$$\Sigma_0 = [ [ 0.38158978, -0.15486516 ], \\ [-0.15486516, 0.64773717] ]$$

$$\Sigma_1 = [ [ 0.47747117, 0.1099206 ], \\ [ 0.1099206, 0.41355441] ]$$

**e.)**

Equation for Quadratic Decision Boundary:

The general decision boundary can be written as:

$$X^T A X + B X + C = 0$$

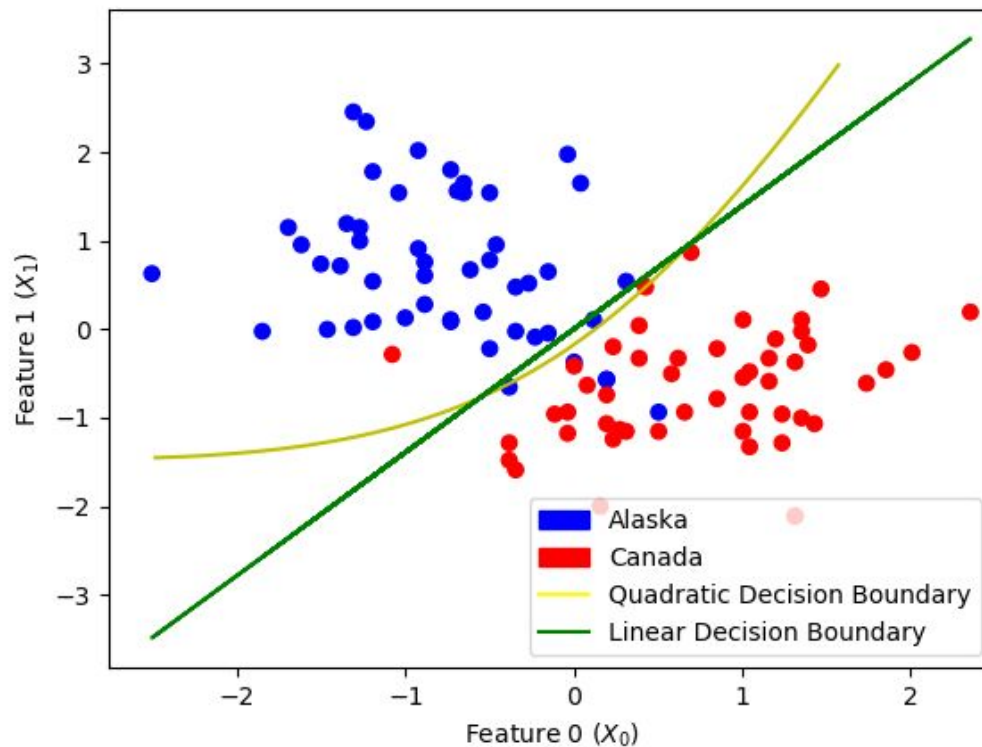
Where

$$A = \Sigma_0^{-1} - \Sigma_1^{-1}$$

$$B = -2 * ( \mu_0^T \Sigma_0^{-1} - \mu_1^T \Sigma_1^{-1} )$$

$$C = ( \mu_0^T \Sigma_0^{-1} \mu_0 - \mu_1^T \Sigma_1^{-1} \mu_1 - 2 * \log ( ((1/\phi) - 1) * (|\Sigma_1| / \Sigma_0) )$$

## Plot of Quadratic & Linear Decision Boundaries:



f.)

### Analysis/Comment on Decision Boundaries

As we can see from the last figure, the quadratic classifier separates the classes a bit better. Some of the Alaskan fishes that were being incorrectly classified are now classified correctly.

Zooming out on the same graph, we see that the curve is actually a hyperbola!

