

CMPS 142 HW 2

Isaiah Solomon

February 2017

1 Question 1

i)

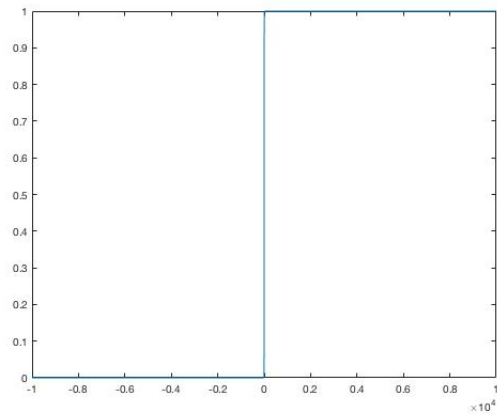
First, we will derive $\frac{d\sigma(z)}{dz} = \sigma(z)(1 - \sigma(z))$:

$$\begin{aligned}\frac{d\sigma(z)}{dz} &= \sigma(z)(1 - \sigma(z)) \\ \sigma(z) &= \frac{1}{1 + e^{-z}} \\ \frac{d\sigma(z)}{dz} &= \frac{e^{-z}}{(1 + e^{-z})^2} \\ &= \sigma(z)(1 - \sigma(z))\end{aligned}$$

Next, we will find the gradient of total loss function w.r.t.:

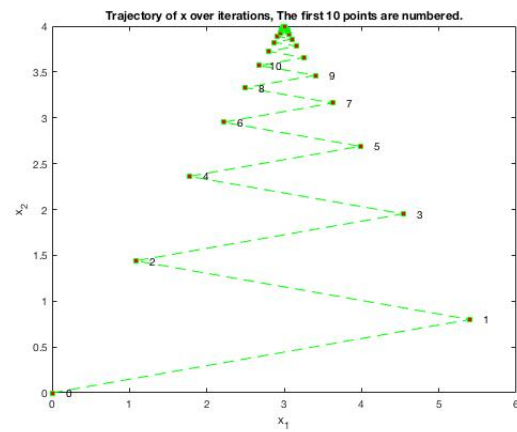
$$\begin{aligned}\nabla_w l &= X^T(\hat{y} - y) \\ l &= \sum_{i=1}^t L(\hat{y}_i, y_i) \\ \nabla_w l &= \nabla_w \left(\sum_{i=1}^t L(\hat{y}_i, y_i) \right) \\ &= \sum_{i=1}^t \frac{\delta L(\hat{y}, y)}{\partial \sigma(z_i)} \frac{\partial \sigma(z_i)}{\partial z_i} \frac{\partial z_i}{\partial w} \\ &= (X^T)(\sigma(z)(1 - z)) \left(\frac{\hat{y} - y}{\hat{y} - \hat{y}^2} \right) \\ &= X^T(\hat{y}(1 - \hat{y})) \frac{\hat{y} - y}{\hat{y}(1 - \hat{y})} \\ &= X^T(\hat{y} - y)\end{aligned}$$

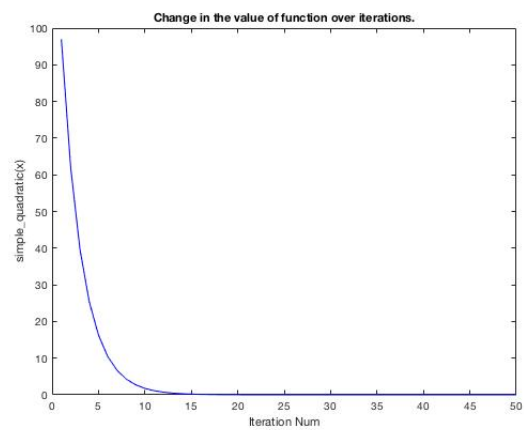
ii)



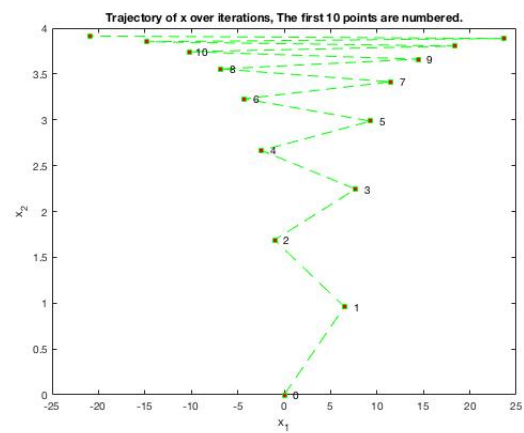
2 Question 2

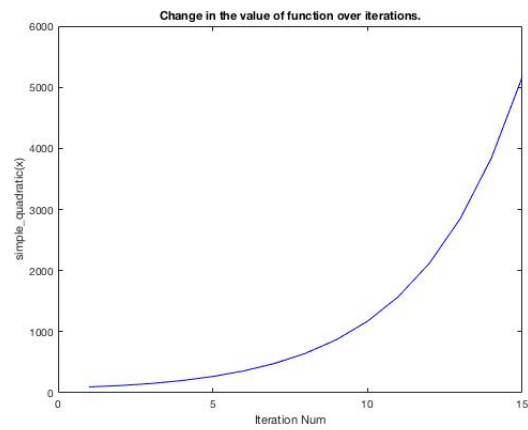
c)





d)





x_2 is converging to the optimal value; however, x_1 is diverging further away. This is due to the step size being larger and fluctuates at a faster pace, thus ends up diverging