

# HW-4

Given the cost function  $J(w_0, w_1) = \frac{1}{2m} \sum_{i=1}^m (w_0 + w_1 x^{(i)} - y_i)^2$ .  
 Determine the definiteness of its  $2m$  Hessian matrix and the convexity of the function. Assume 1-D dataset  $m=1$ . Show your work.

$$\rightarrow J(w_0, w_1) = \frac{1}{2m} \sum_{i=1}^m (w_0 + w_1 x^{(i)} - y_i)^2$$

Assume  $m=1$ , 1-D dataset

$$\frac{dJ(w)}{dw_0} = \frac{1}{m} \sum_{i=1}^m (w_0 + w_1 x^{(i)} - y_i)$$

$$\text{when } m=1 \Rightarrow \frac{dJ(w)}{dw_0} = w_0 + w_1 x - y_1$$

$$\frac{dJ(w)}{dw_1} = \frac{1}{m} \sum_{i=1}^m x^{(i)} (w_0 + w_1 x^{(i)} - y_i)$$

$$\text{when } m=1 \Rightarrow \frac{dJ(w)}{dw_1} = x (w_0 + w_1 x - y_1)$$

$$\frac{d^2 J(w)}{dw_0^2} = \frac{1}{m} \sum_{i=1}^m x^{(i)} (w_0 + w_1 x^{(i)} - y_i)$$

$$\text{when } m=1, \frac{d^2 J(w)}{dw_0^2} = x (w_0 + w_1 x - y_1)$$

$$\frac{d^2 J(w)}{dw_0^2} = 1 \quad \frac{d^2 J(w)}{dw_1^2} = x^* x = x^2$$

$$\frac{d^2 J(w)}{dw_0 dw_1} = \frac{d^2 J(w)}{dw_1 dw_0} = x$$

$$\text{Hessian matrix, } H = \begin{bmatrix} \frac{d^2 J(w)}{dw_0^2} & \frac{d^2 J(w)}{dw_0 dw_1} \\ \frac{d^2 J(w)}{dw_1 dw_0} & \frac{d^2 J(w)}{dw_1^2} \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 1 & x \\ x & x^2 \end{bmatrix}$$



For a square matrix  $H$ ,  $HV = \lambda V$  where

$\lambda = \text{eigen value of } H$

To find the eigen value  $\lambda$ ,  $v = \text{eigen vector associated with } H$   
 $|H - \lambda I| = 0$  ..... where  $I = \text{identity matrix}$

i.e. 
$$\begin{vmatrix} 1-\lambda & x \\ x & x^2-\lambda \end{vmatrix} = 0$$

Calculating the determinant,

$$(1-\lambda)(x^2-\lambda) - x^2 = 0$$

$$x^2 - \lambda - x^2\lambda + \lambda^2 - x^2 = 0$$

$$-\lambda - \lambda(x^2 - \lambda) = 0$$

$$-\lambda [1 + (x^2 - \lambda)] = 0$$

i.e.  $\lambda_1 = 0$  or  $\lambda_2 = 1 + x^2$

$\therefore \lambda_1 = 0$  and  $\lambda_2 > 0$

$\therefore$  given cost function is positive semi-definite.  
(PSD)  $\Rightarrow$  convex.