

# H W #5

$$1. L(w) = w_1^2 + 2w_2^2 + w_3^2 + w_4^2 - 2w_3w_4 + w_1^2 + 2w_1 - 4w_2^2 + 4$$

$$d. \frac{dL}{dw_1} \text{ or } \frac{dL}{dw_2} = 2w_1 + 2$$

$$\frac{dL}{dw_2} = 4w_2 - 4$$

$$\frac{dL}{dw_3} = 2w_3 - 2w_4$$

$$\frac{dL}{dw_4} = -2w_3 + 2w_4$$

$$b. \nabla L(w) = \begin{bmatrix} 2w_1+2 \\ 4w_2-4 \\ 2w_3-2w_4 \\ -2w_3+2w_4 \end{bmatrix} \quad \begin{array}{l} \frac{dL}{dw_1} \\ \frac{dL}{dw_2} \\ \frac{dL}{dw_3} \\ \frac{dL}{dw_4} \end{array}$$

$$c. w_{t+1} = w_t - \eta \nabla L(w_t)$$

$$\begin{aligned} w_{t+1} &= (0 - 0.1) \begin{bmatrix} 2(0) + 2 \\ 4(0) - 4 \\ 2(0) - 2(0) \\ -2(0) + 2(0) \end{bmatrix} = \begin{bmatrix} -0.2 \\ -0.4 \\ 0 \\ 0 \end{bmatrix} \\ &= \boxed{\begin{bmatrix} -0.2 \\ -0.4 \\ 0 \\ 0 \end{bmatrix}} \end{aligned}$$

$$d. \min(L(w))$$

$$\nabla L(w) = 0 \quad \begin{bmatrix} 2w_1+2 \\ 4w_2-4 \\ 2w_3-2w_4 \\ -2w_3+2w_4 \end{bmatrix} = \boxed{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}$$

$$w_1 = -1 \quad w_2 = 1 \quad w_3 = w_4 \quad w_3 = w_4 = \cancel{x} \times$$

$$L(w) = (-1)^2 + 2(1)^2 + x^2 - 2x^2 + x^2 + 2(-1) - 4(1) + 4$$

$$= \boxed{1}$$

e. No, there are infinitely many solutions with the form

$$\begin{bmatrix} -1 \\ x \\ x \\ x \end{bmatrix} \quad \forall x \in \mathbb{R}$$

when  $w_3 = w_4$ .

2.  $x^{(1)}, \dots, x^{(n)} \in \mathbb{R}^d$  find  $w \in \mathbb{R}^d$  that minimizes  $L(w) = \sum_{i=1}^n (w \cdot x^{(i)}) + \frac{1}{2} C \|w\|^2$

$$a. \frac{\partial L}{\partial w_j} = \sum_{i=1}^n x_j^{(i)} + \frac{1}{2} C \frac{\partial L}{\partial w_j} \|w\|^2$$

$$= \underbrace{Cw_j}_{\sum_{i=1}^n x_j^{(i)} + Cw_j}$$

$$b. \nabla L(w) = \begin{bmatrix} \sum_{i=1}^n x_1^{(i)} + Cw_1 \\ \sum_{i=1}^n x_2^{(i)} + Cw_2 \\ \vdots \\ \sum_{i=1}^n x_d^{(i)} + Cw_d \end{bmatrix}$$

$$= \sum_{i=1}^n x^{(i)} + Cw$$

$$c. \nabla L(w) = 0$$

$$\sum_{i=1}^n x^{(i)} + Cw = 0$$

$$w = -\frac{\sum_{i=1}^n x^{(i)}}{C} = \boxed{-\frac{1}{C} \sum_{i=1}^n x^{(i)}}$$

~~$\beta. a. L(w) = \sum_{i=1}^n (y^{(i)} - w \cdot x^{(i)})^2 + \lambda \|w\|^2$~~

~~$\nabla L(w) = \sum_{i=1}^n -2(y^{(i)} - w \cdot x^{(i)})x^{(i)} + 2\lambda w$~~

~~$\nabla L(w) = \boxed{2 \sum_{i=1}^n w_i \cdot x^{(i)} - 2 \sum_{i=1}^n y^{(i)} x^{(i)}}$~~

ignoring intercept form

~~$L(w) = \boxed{2 \left( \sum_{i=1}^n w_i \cdot x^{(i)} - y^{(i)} x^{(i)} \right)}$~~ 
 ~~$= \boxed{2 \sum_{i=1}^n w_i \cdot x^{(i)} - 2 \sum_{i=1}^n y^{(i)} x^{(i)}}$~~ 
 ~~$= \boxed{2 \sum_{i=1}^n w \cdot x^{(i)} - 2 \sum_{i=1}^n y^{(i)} x^{(i)}}$~~

3. a.  $L(w) = \sum_{i=1}^n (y^{(i)} - w \cdot x^{(i)})^2 + \lambda \|w\|^2$

$$\frac{\partial L}{\partial w_j} = \sum_{i=1}^n (-2y^{(i)} + 2w \cdot x^{(i)}) x_j^{(i)} + 2\lambda w_j$$

$$\nabla L(w) = 2 \sum_{i=1}^n (w \cdot x^{(i)} - y^{(i)}) x^{(i)} + 2\lambda w$$

b.  $\underbrace{w_{t+1} = w_t + \eta \nabla L(w_t)}_{w_{t+1} = w_t + \eta \sum_{i=1}^n (w_t \cdot x^{(i)} - y^{(i)}) x^{(i)} - 2\eta \lambda w_t}$

- c.
- set  $w_0 = 0$
  - for  $t = 0, 1, 2, \dots$ , until convergence or fixed iterations
  - randomly select a data point  $(x^{(i)}, y^{(i)})$  from the dataset
  - $w_{t+1} = w_t + \eta (\sum_{i=1}^n w_t \cdot x^{(i)} - y^{(i)}) x^{(i)} - 2\eta \lambda w_t$ 
    - update  $w$  using gradient descent based off the one point
  - get final vector  $w$

4. a.  $f''(x) = 2 > 0$  [convex]
- b.  $f(x) = -2 < 0$  [concave]
- c.  $f'(x) = 2 > 0$  [convex]
- d.  $f''(x) = 0$  [neither] [both]
- e.  $f(x) = 6x$  [neither]
- f.  $f''(x) = 12x^2 \geq 0$  [convex]
- g.  $f'' = -\frac{1}{x^2} < 0$  [concave]