

# MLFoundation HW4

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1.

此課程: 機器學習基石下 (Machine Learning Foundations)---Algorithmic Foundations

測驗

## 作業四

20 個問題

您的分數

100.00%

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2.

gradient descent :  $w_{t+1} \leftarrow w_t - \eta \nabla E_{in}$

augmented error gradient descent :  $w_{t+1} \leftarrow w_t - \eta \nabla E_{aug}$

$$\because E_{aug} = E_{in} + \frac{\lambda}{N} w^T w \quad \therefore \nabla E_{aug} = \nabla E_{in} + \frac{\partial}{\partial w} \frac{\lambda}{N} w^T w = \nabla E_{in} + \frac{2\lambda}{N} w$$

因此得  $w_{t+1} \leftarrow w_t - \eta \nabla E_{aug} = w_t - \eta (\nabla E_{in} + \frac{2\lambda}{N} w_t) = (1 - \frac{2\eta\lambda}{N}) w_t - \eta \nabla E_{in}(w_t)$

3.

$(-1,0), (\rho,1), (1,0)$  三點一次取出一點當作LOO則會得三條線：

$(-1,0), (1,0) : h_1(x) = 0$

$(-1,0), (\rho,1) : h_1(x) = \frac{1}{\rho+1}x + \frac{1}{\rho+1}$

$(1,0), (\rho,1) : h_1(x) = \frac{1}{\rho-1}x + \frac{1}{1-\rho}$

可得

$$\begin{aligned} E_{loo} &= \frac{1}{3} \left( \left( \frac{-1}{\rho-1} + \frac{1}{1-\rho} \right)^2 + \left( \frac{1}{\rho+1} + \frac{1}{\rho+1} \right)^2 + 1 \right) = \frac{1}{3} \left( 4 \left( \frac{1}{\rho-1} \right)^2 + 4 \left( \frac{1}{\rho+1} \right)^2 + 1 \right) = \frac{1}{3} \left( 4 \frac{2\rho^2+2}{(\rho^2-1)^2} + 1 \right) \\ &= \frac{1}{3} \left( \frac{\rho^4 + 6\rho^2 + 9}{\rho^4 - 2\rho^2 + 1} \right) \end{aligned}$$

4.

SGD on original & virtual samples

$X = [x_1, x_2, \dots]^T$ ,  $Y$  為 original samples

$\tilde{X} = \sqrt{\lambda}I = [[\sqrt{\lambda}, 0, \dots], [0, \sqrt{\lambda}, 0, \dots], \dots]$ ,  $\tilde{Y} = [0, 0, \dots]$  為 virtual samples

for  $i$  in iterations

random pick a sample from  $X$ ,  $\tilde{X}$  with its label in  $Y$ ,  $\tilde{Y}$

calculate the gradient  $\nabla E_{in}$  with Squared Error function

update  $w$  with rule  $w_{t+1} \leftarrow w_t - \eta \nabla E_{in}(w_t)$

Augmented gradient descent

$$w_{t+1} \leftarrow (1 - \frac{2\eta\lambda}{N})w_t - \eta \nabla E_{in}(w_t)$$

使用  $N+K$  筆資料是透過加入的 virtual samples 調整梯度來控制  $\|w\|^2$  的成長

使用 Augmented 的 GD 是透過每個 iteration 都削減原本的 weight 來控制  $\|w\|^2$

5.

$$\text{error} = |\sin(ax) - wx| = \sqrt{(\sin(ax) - wx)^2} = \sqrt{\sin^2(ax) + (wx)^2 - 2wx \sin(ax)}$$

$$\text{if } w \neq 0 \text{ then } \lim_{x \rightarrow \infty} (wx)^2 - 2wx \sin(ax) = \infty \text{ and then error} \rightarrow \infty$$

$$\text{if } w = 0 \text{ then } \lim_{x \rightarrow \infty} (0x)^2 - 2 \times 0x \sin(ax) = 0 \text{ and then error} = |\sin(ax)|$$

而 deterministic noise 是  $f$  與 best hypothesis  $h^*$  間的誤差，得

$$\text{deterministic noise} = |\sin(ax)|$$