# Machine Learning

#### Answer Sheet for Homework 4

# Da-Min HUANG

#### R04942045

Graduate Institute of Communication Engineering, National Taiwan University

### November 7, 2015

# Problem 1

Deterministic error is the difference between best  $h^* \in H$  and f. If  $H' \subset H$ , then the complexity of H' is lower than H in general. Hence, in general, the deterministic error increases.

#### Problem 2

1.

$$H(10,0,3) \cap H(10,0,4) = \left\{ \sum_{i=0}^{2} w_q L_q(x) \right\} \cap \left\{ \sum_{i=0}^{3} w_q L_q(x) \right\}$$
(1)

$$= \left\{ \sum_{i=0}^{2} w_q L_q(x) \right\} = H_2 \tag{2}$$

2.

$$H(10,0,3) \cup H(10,1,4) = \left\{ \sum_{i=0}^{2} w_{q} L_{q}(x) \right\} \cup \left\{ \sum_{i=0}^{3} w_{q} L_{q}(x) + \sum_{i=4}^{10} L_{q}(x) \right\}$$
(3)
$$= \left\{ \sum_{i=0}^{3} w_{q} L_{q}(x) + \sum_{i=4}^{10} L_{q}(x) \right\}$$
(4)

3.

$$H(10,1,3) \cap H(10,1,4) = \left\{ \sum_{i=0}^{2} w_{q} L_{q}(x) + \sum_{i=3}^{10} L_{q}(x) \right\} \cap \left\{ \sum_{i=0}^{3} w_{q} L_{q}(x) + \sum_{i=4}^{10} L_{q}(x) \right\}$$
(5)

$$= \left\{ \sum_{i=0}^{2} w_q L_q(x) + \sum_{i=4}^{10} L_q(x) \right\}$$
 (6)

4.

$$H(10,0,3) \cup H(10,0,4) = \left\{ \sum_{i=0}^{2} w_q L_q(x) \right\} \cup \left\{ \sum_{i=0}^{3} w_q L_q(x) \right\}$$
 (7)

$$= \left\{ \sum_{i=0}^{3} w_q L_q(x) \right\} = H_3 \tag{8}$$

#### Problem 3

We have

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \eta \nabla E_{\text{aug}} \left( \mathbf{w}_t \right) \tag{9}$$

where  $\nabla E_{\text{aug}}(\mathbf{w}_t)$  is

$$\nabla E_{\text{aug}}\left(\mathbf{w}_{t}\right) = \frac{\partial}{\partial \mathbf{w}_{t}^{T}} \left( E_{\text{in}}\left(\mathbf{w}_{t}\right) + \frac{\lambda}{N} \mathbf{w}_{t}^{T} \mathbf{w}_{t} \right) = \frac{\partial E_{\text{in}}\left(\mathbf{w}_{t}\right)}{\partial \mathbf{w}_{t}^{T}} + \frac{2\lambda}{N} \mathbf{w}_{t}$$
(10)

Hence, we have

$$\mathbf{w}_{t+1} \leftarrow \left(1 - \frac{2\eta\lambda}{N}\right) \mathbf{w}_t - \eta \nabla E_{\text{in}}\left(\mathbf{w}_t\right) \tag{11}$$

# Problem 4

Since  $\mathbf{w}_{\mathrm{lin}}$  is the optimal solution for the plain-vanilla linear regression, we have

$$E_{\rm in}\left(\mathbf{w}_{\rm lin}\right) \le E_{\rm in}\left(\mathbf{w}_{\rm reg}\left(\lambda\right)\right)$$
 (12)

Also,  $\mathbf{w}_{\text{reg}}(\lambda)$  is the optimal solution for  $E_{\text{aug}}(\mathbf{w})$ , we have

$$E_{\text{aug}}\left(\mathbf{w}_{\text{reg}}\left(\lambda\right)\right) \le E_{\text{aug}}\left(\mathbf{w}_{\text{lin}}\right)$$
 (13)

So, we have

$$E_{\text{in}}\left(\mathbf{w}_{\text{reg}}\left(\lambda\right)\right) + \frac{\lambda}{N}\mathbf{w}_{\text{reg}}^{T}\left(\lambda\right)\mathbf{w}_{\text{reg}}\left(\lambda\right) \le E_{\text{in}}\left(\mathbf{w}_{\text{lin}}\right) + \frac{\lambda}{N}\mathbf{w}_{\text{lin}}^{T}\mathbf{w}_{\text{lin}}$$
(14)

$$0 \le E_{\text{in}}\left(\mathbf{w}_{\text{reg}}\left(\lambda\right)\right) - E_{\text{in}}\left(\mathbf{w}_{\text{lin}}\right) \le \frac{\lambda}{N} \left(\|\mathbf{w}_{\text{lin}}\|^2 - \|\mathbf{w}_{\text{reg}}\left(\lambda\right)\|^2\right), \ \forall \lambda$$
 (15)

Hence, we have  $\|\mathbf{w}_{\text{lin}}\| \ge \|\mathbf{w}_{\text{reg}}(\lambda)\|$  if  $\lambda > 0$ .

Since this inequality holds for all  $\lambda$  and  $\|\mathbf{w}_{lin}\|$  is not a function of  $\lambda$ . We know that  $\|\mathbf{w}_{reg}(\lambda)\|$  is a non-increasing function of  $\lambda$  for  $\lambda \geq 0$ .

#### Problem 5

For constant model with three points A(-1,0),  $B(\rho,1)$  and C(1,0).

$$\frac{1}{3} \left( \underbrace{\left(0 - \frac{1}{2}\right)^2}_{\text{leave } A} + \underbrace{\left(1 - 0\right)^2}_{\text{leave } B} + \underbrace{\left(0 - \frac{1}{2}\right)^2}_{\text{leave } C} \right) = \frac{1}{2}$$
 (16)

For linear model. Leave A, we get line  $y = \frac{1}{\rho - 1}(x - 1)$ ; leave B, we get line y = 0; leave C, we get line  $y = \frac{1}{\rho + 1}(x + 1)$ . So the error is

$$\frac{1}{3} \left( \left( 0 - \left( \frac{-2}{\rho - 1} \right) \right)^2 + (1 - 0)^2 + \left( 0 - \frac{2}{\rho + 1} \right)^2 \right) \tag{17}$$

Then we have

$$\frac{1}{3} \left( \frac{4}{\rho^2 - 2\rho + 1} + 1 + \frac{4}{\rho^2 + 2\rho + 1} \right) = \frac{1}{2} \Rightarrow \rho = \pm \sqrt{9 + 4\sqrt{6}}$$
 (18)

Since  $\rho > 0$ , we have  $\rho = \sqrt{9 + 4\sqrt{6}}$ .

#### Problem 6

If the sender wants to make sure at least one person receives correct predictions on all 5 games. Then he should target at least 32 people at first game since there are half the number of people receive wrong prediction after each game and the sender can just ignore people who receives wrong prediction.

The sender sends

$$32 + 16 + 8 + 4 + 2 + 1 = 63$$
 letters (19)

# Problem 7

From the conclusion above, we have

$$1000 - 63 \times 10 = 370 \tag{20}$$

#### Problem 8

The mathematical derivations can just generate hypothesis set with size 1.

# Problem 9

The Hoeffding bound is

$$2M \exp(-2\epsilon^2 N) = 2 \exp(-20000 \times (0.01)^2) = 2e^{-2} \approx 0.271$$
 (21)

# Problem 10

The computation of Hoeffding bound is computated with data verified by  $a(\mathbf{x})$ . To improve the performance of  $g(\mathbf{x})$ , we should only give data sampled by  $a(\mathbf{x})$ .

Hence,  $a(\mathbf{x})$  AND  $g(\mathbf{x})$  can improve the system.

# Problem 11

Problem 12	
Problem 13	
Problem 14	
Problem 15	
Problem 16	
Problem 17	
Problem 18	
Problem 19	

# Problem 20

# Reference

[1] Lecture Notes by Hsuan-Tien LIN, Department of Computer Science and Information Engineering, National Taiwan University, Taipei 106, Taiwan.