
Machine Learning

Answer Sheet for Homework 6

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Problem 1

With the definition of z_n , rewrite the equation

$$\min_{A,B} F(A, B) = \frac{1}{N} \sum_{n=1}^N \ln(1 + \exp(-y_n(Az_n + B))) \quad (1)$$

So

$$\frac{\partial F}{\partial A} = \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{\exp(-y_n(Az_n + B))}{1 + \exp(-y_n(Az_n + B))} \right)^T z_n = \frac{1}{N} \sum_{n=1}^N -y_n p_n^T z_n \quad (2)$$

$$\frac{\partial F}{\partial B} = \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{\exp(-y_n(Az_n + B))}{1 + \exp(-y_n(Az_n + B))} \right)^T = \frac{1}{N} \sum_{n=1}^N -y_n p_n^T \quad (3)$$

Hence

$$\nabla F(A, B) = \frac{1}{N} \sum_{n=1}^N [-y_n z_n p_n, -y_n p_n]^T \quad (4)$$

□

Problem 2

Use the result of Problem 1 and define $\exp(-y_n(Az_n + B)) = \exp(\xi_n)$, we have

$$\frac{\partial^2 F}{\partial A^2} = \frac{\partial}{\partial A} \left(\frac{1}{N} \sum_{n=1}^N -y_n p_n^T z_n \right) \quad (5)$$

$$= \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{-y_n \exp(\xi_n) (1 + \exp(\xi_n)) z_n - y_n (\exp(\xi_n))^2 z_n}{(1 + \exp(\xi_n))^2} \right) z_n \quad (6)$$

$$= \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{-y_n \exp(\xi_n) z_n}{(1 + \exp(\xi_n))^2} \right) z_n \quad (7)$$

$$= \frac{1}{N} \sum_{n=1}^N (y_n)^2 \left(\frac{\exp(\xi_n)}{1 + \exp(\xi_n)} \left(1 - \frac{\exp(\xi_n)}{1 + \exp(\xi_n)} \right) \right) z_n^2 \quad (8)$$

$$= \frac{1}{N} \sum_{n=1}^N z_n^2 p_n (1 - p_n) \quad (9)$$

where $y_n^2 = 1$ since $y_n \in \{-1, +1\}$.

The other term is

$$\frac{\partial^2 F}{\partial A \partial B} = \frac{\partial}{\partial A} \left(\frac{1}{N} \sum_{n=1}^N -y_n p_n^T \right) = \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{-y_n \exp(\xi_n) z_n}{(1 + \exp(\xi_n))^2} \right) \quad (10)$$

$$= \frac{1}{N} \sum_{n=1}^N z_n p_n (1 - p_n) \quad (11)$$

$$\frac{\partial^2 F}{\partial B \partial A} = \frac{\partial}{\partial B} \left(\frac{1}{N} \sum_{n=1}^N -y_n p_n^T z_n \right) = \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{-y_n \exp(\xi_n)}{(1 + \exp(\xi_n))^2} \right) z_n \quad (12)$$

$$= \frac{1}{N} \sum_{n=1}^N z_n p_n (1 - p_n) \quad (13)$$

$$\frac{\partial^2 F}{\partial B^2} = \frac{\partial}{\partial B} \left(\frac{1}{N} \sum_{n=1}^N -y_n p_n^T \right) = \frac{1}{N} \sum_{n=1}^N -y_n \left(\frac{-y_n \exp(\xi_n)}{(1 + \exp(\xi_n))^2} \right) \quad (14)$$

$$= \frac{1}{N} \sum_{n=1}^N p_n (1 - p_n) \quad (15)$$

Hence, we have

$$H(F) = \frac{1}{N} \sum_{n=1}^N \begin{bmatrix} z_n^2 p_n (1 - p_n) & z_n p_n (1 - p_n) \\ z_n p_n (1 - p_n) & p_n (1 - p_n) \end{bmatrix} \quad (16)$$

□

Problem 3

As $\gamma \rightarrow \infty$, we have

$$\lim_{\gamma \rightarrow \infty} \exp(-\gamma \|\mathbf{x}_n - \mathbf{x}_m\|^2) = 0 \quad (17)$$

So K should be a zero matrix with size $N \times N$, which is $\mathbf{0}_{N \times N}$.

And β is

$$\beta = (\lambda I + K)^{-1} \mathbf{y} = \lambda^{-1} \mathbf{y} \quad (18)$$

□

Problem 4

If $|y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| \geq \epsilon$, then

$$\begin{cases} |y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| - \epsilon = \xi_n^\wedge \text{ and } \xi_n^\vee = 0, & \text{if } y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b > 0 \\ |y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| - \epsilon = \xi_n^\vee \text{ and } \xi_n^\wedge = 0, & \text{if } y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b < 0 \end{cases} \quad (19)$$

and if $|y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| < \epsilon$, then $\xi_n^\wedge = 0$ and $\xi_n^\vee = 0$. Hence, we have

$$(\xi_n^\wedge)^2 + (\xi_n^\vee)^2 = (\max(0, |y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| - \epsilon))^2 \quad (20)$$

So P_2 is equivalent to

$$\min_{b, \mathbf{w}} \left(\frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{n=1}^N (\max(0, |y_n - \mathbf{w}^T \phi(\mathbf{x}_n) - b| - \epsilon))^2 \right) \quad (21)$$

with no constraints.

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Problem 5

The first term is of course

$$\frac{\partial}{\partial \beta_m} \left(\frac{1}{2} \sum_{m=1}^N \sum_{n=1}^N \beta_n \beta_m K(\mathbf{x}_n, \mathbf{x}_m) \right) = \sum_{n=1}^N \beta_n K(\mathbf{x}_n, \mathbf{x}_m) \quad (22)$$

With \mathbf{w}_* , rewrite the result of Problem 4,

$$\text{something} = C \sum_{n=1}^N \left(\max \left(0, \left| y_n - \sum_{m=1}^N \beta_m K(\mathbf{x}_n, \mathbf{x}_m) - b \right| - \epsilon \right) \right)^2 \quad (23)$$

$$= C \sum_{n=1}^N (\max(0, |y_n - s_n| - \epsilon))^2 \quad (24)$$

Consider the following cases.

$$1. |y_n - s_n| \geq \epsilon.$$

Then we have

$$\frac{\partial}{\partial \beta_m} (\text{something}) = \frac{\partial}{\partial \beta_m} (C (|y_n - s_n| - \epsilon)^2) \quad (25)$$

$$= (2C (|y_n - s_n| - \epsilon)) \frac{\partial}{\partial \beta_m} |y_n - s_n| \quad (26)$$

$$= -2C (|y_n - s_n| - \epsilon) \text{sign} (y_n - s_n) \frac{\partial s_n}{\partial \beta_m} \quad (27)$$

$$= -2C (|y_n - s_n| - \epsilon) \text{sign} (y_n - s_n) K (\mathbf{x}_n, \mathbf{x}_m) \quad (28)$$

$$2. |y_n - s_n| < \epsilon.$$

Then we have

$$\frac{\partial}{\partial \beta_m} (\text{something}) = 0 \quad (29)$$

So we have

$$\frac{\partial F(b, \boldsymbol{\beta})}{\partial \beta_m} = \sum_{n=1}^N \beta_n K (\mathbf{x}_n, \mathbf{x}_m) - 2C \sum_{n=1}^N \mathbb{I} [|y_n - s_n| \geq \epsilon] (|y_n - s_n| - \epsilon) \text{sign} (y_n - s_n) K (\mathbf{x}_n, \mathbf{x}_m) \quad (30)$$

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Problem 6

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Problem 7

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Problem 8

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Problem 9

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Problem 10

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Problem 11

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Problem 12

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Problem 13

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Problem 14

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Problem 15

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Problem 16

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Problem 17

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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.