

Statistical Learning

Homework 1

Part 1: Conceptual Questions

Problem 1. Let (X, Y) be a pair of random variables. Show that if $E[Y | X] = E[Y]$, then $\text{Cov}[X, Y] = 0$.

Problem 2. Let (X, Y) be a pair of random variables. Denote $f(X) = E[Y | X]$. Show that for any function g ,

$$E[(Y - f(X))^2 | X] \leq E[(Y - g(X))^2 | X].$$

Hint: write

$$E[(Y - g(X))^2 | X] = E[(Y - f(X) + f(X) - g(X))^2 | X]$$

and use the law of iterated expectations (LIE).

Problem 3. Given training data $\text{Tr} = \{(X_1, Y_1), \dots, (X_n, Y_n)\}$ and a predictor $\hat{f}(x)$ which depends on Tr for any x , we have a new observation (X_0, Y_0) that is independent from Tr . Suppose that (X_0, Y_0) is generated by the model $Y_0 = f(X_0) + \epsilon_0$ with ϵ_0 being a new error term that is independent from (X_0, Tr) . Show that the conditional expected test MSE can be decomposed into

$$E\left[\left(Y_0 - \hat{f}(X_0)\right)^2 | X_0\right] = \text{Var}[\epsilon] + \text{Bias}(X_0)^2 + \text{Variance}(X_0)$$

where $\text{Bias}(X_0) = E[\hat{f}(X_0) | X_0] - f(X_0)$ and

$$\text{Variance}(X_0) = \text{Var}\left[\hat{f}(X_0) | X_0\right] = E\left[\left(\hat{f}(X_0) - E[\hat{f}(X_0) | X_0]\right)^2 | X_0\right].$$

Hint: by LIE, write

$$\begin{aligned} E\left[\left(Y_0 - \hat{f}(X_0)\right)^2 | X_0\right] &= E\left[E\left[\left(Y_0 - \hat{f}(X_0)\right)^2 | X_0, \text{Tr}\right] | X_0\right] \\ &= E\left[E\left[\left(Y_0 - f(X_0) + f(X_0) - \hat{f}(X_0)\right)^2 | X_0, \text{Tr}\right] | X_0\right]. \end{aligned}$$

You may use the result $E[Y_0 | \text{Tr}, X_0] = E[Y_0 | X_0]$ without proving it.

Problem 4. Suppose that Y is a binary response variable. The range of values taken by Y is $\{0, 1\}$. The goal is to predict Y given another random variable X . When we observe a new X , we predict Y to be $h(X)$, where $h : \mathbb{R} \rightarrow \{0, 1\}$ is a function that takes 0 or 1. We call h a classification rule. The “classification risk” of h is

$$R(h) = \Pr(Y \neq h(X)).$$

Let $m(x) = \mathbb{E}[Y \mid X = x]$. Since Y is binary,

$$\mathbb{E}[Y \mid X = x] = 1 \times \Pr(Y = 1 \mid X = x) + 0 \times \Pr(Y = 0 \mid X = x) = \Pr(Y = 1 \mid X = x).$$

(You may assume X is discrete if you have difficulty making sense of “ $\Pr(Y = 1 \mid X = x)$ ”. This is like $\Pr(A \mid B)$ with A being the event “ $Y = 1$ ” and B being the event $X = x$). Show that the rule that minimizes $R(h)$ is

$$h^*(x) = \begin{cases} 1 & \text{if } m(x) > \frac{1}{2} \\ 0 & \text{otherwise.} \end{cases}$$

Hint: Note that

$$R(h) = \Pr(Y \neq h(X)) = \int \Pr(Y \neq h(x) \mid X = x) f_X(x) dx,$$

where the second equality follows from LIE. It suffices to show that

$$\Pr(Y \neq h(x) \mid X = x) - \Pr(Y \neq h^*(x) \mid X = x) \geq 0 \text{ for all } x.$$

Use $\Pr(Y \neq h(x) \mid X = x) = 1 - \Pr(Y = h(x) \mid X = x)$ and

$$\Pr(Y = h(x) \mid X = x) = h(x) \Pr(Y = 1 \mid X = x) + (1 - h(x)) \Pr(Y = 0 \mid X = x).$$

Problem 5. Let $\{x_i : i = 1, \dots, n\}$ and $\{y_i : i = 1, \dots, n\}$ be two sequences. Define the averages

$$\begin{aligned} \bar{x} &= \frac{1}{n} \sum_{i=1}^n x_i, \\ \bar{y} &= \frac{1}{n} \sum_{i=1}^n y_i. \end{aligned}$$

1. Show that $\sum_{i=1}^n (x_i - \bar{x}) = 0$.
2. Using the result in part (1), show that

$$\begin{aligned} \sum_{i=1}^n (x_i - \bar{x})^2 &= \sum_{i=1}^n x_i (x_i - \bar{x}), \text{ and} \\ \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) &= \sum_{i=1}^n y_i (x_i - \bar{x}) = \sum_{i=1}^n x_i (y_i - \bar{y}). \end{aligned}$$

Problem 6. Given training data $\text{Tr} = \{(X_1, Y_1), \dots, (X_n, Y_n)\}$, suppose that $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$ where ϵ_i is the error term. The simple regression coefficient presented in class is

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (Y_i - \bar{Y}) (X_i - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

Denote $X_1^n = (X_1, \dots, X_n)$ for notational simplicity. Assume that $E[\epsilon_i | X_1^n] = 0$, $E[\epsilon_i^2 | X_1^n] = \sigma^2$ (for some $\sigma^2 > 0$) and $E[\epsilon_i \epsilon_j | X_1^n] = 0$, $\forall i$ and $\forall j \neq i$.

1. Use the result in the last problem, show that

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (X_i - \bar{X}) Y_i}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

2. Show that $E[\hat{\beta}_1 | X_1^n] = \beta_1$ and $\text{Var}[\hat{\beta}_1 | X_1^n] = \sigma^2 / \sum_{i=1}^n (X_i - \bar{X})^2$, where $\bar{X} = n^{-1} \sum_{i=1}^n X_i$.
3. Assume that the conditional distribution of ϵ_i given X_1^n is $N(0, \sigma^2)$. What is the conditional distribution of Y_i given X_1^n ?
4. What is the conditional distribution of $\hat{\beta}_1$ given X_1^n ?
5. What is the unconditional distribution of the z -statistic:

$$\frac{\hat{\beta}_1 - \beta_1}{\sqrt{\sigma^2 / \sum_{i=1}^n (X_i - \bar{X})^2}}?$$

Problem 7. ISL (2nd edition) Question 7 on Page 54.

Part 2: Applied Questions

Write your answer in an RMarkdown report, print your report and hand in.

Problem 8. ISL (2nd edition) Question 8. Give answers to Parts a, b and c(i-iv).

Problem 9. ISL (2nd edition) Question 9. Give answers to Parts a, b, c and d.