

Solutions for Homework 1

TONG ZHOU

PROBLEMS: 2.4, 2.5, 2.16, 2.19.

PROBLEM 2.4

PROOF. Since both X and Y are discrete, just by definition, we have

$$\begin{aligned}\mathbb{E}[Y | X = 0] &= \sum_{y \in \{0,1\}} y \cdot \mathbb{P}(Y = y | X = 0) = 1 \times \frac{0.4}{0.5} = 0.8 \\ \mathbb{E}[Y^2 | X = 0] &= \sum_{y \in \{0,1\}} y^2 \cdot \mathbb{P}(Y = y^2 | X = 0) = 0.8 \\ \text{Var}(Y | X = 0) &= \mathbb{E}[Y^2 | X = 0] - (\mathbb{E}[Y | X = 0])^2 = 0.16.\end{aligned}$$

Similarly when conditional on $X = 1$,

$$\begin{aligned}\mathbb{E}[Y | X = 1] &= 0.6 \\ \mathbb{E}[Y^2 | X = 1] &= 0.6 \\ \text{Var}(Y | X = 1) &= \mathbb{E}[Y^2 | X = 1] - (\mathbb{E}[Y | X = 1])^2 = 0.24.\end{aligned}$$

□

PROBLEM 2.5

PROOF. (a) By definition the mean-squared error of e^2 given X is:

$$\mathbb{E} [e^2 - h(X)]^2.$$

- (b) To predict e^2 , one seeks to find a function h such that the MSE is minimized.
(c) Project e^2 on the space of X , we have

$$e^2 = \mathbb{E} [e^2 | X] + \nu = \sigma^2(X) + \nu,$$

where ν is the projection error.

Then

$$\begin{aligned}\mathbb{E} [e^2 - h(X)] &= \mathbb{E} [\nu + \sigma^2(X) - h(X)]^2 \\ &= \mathbb{E} [\nu^2] + \mathbb{E} [\sigma^2(X) - h(X)]^2 \\ &\geq \mathbb{E} [\nu^2]\end{aligned}$$

where the equality can be attained when $h(X)$ is chosen to be $\sigma^2(X)$.

□

PROBLEM 2.16

PROOF. Following Theorem 2.9 of Hansen's book, we have coefficients of the best linear predictor:

$$(1) \quad \begin{aligned} \begin{pmatrix} \alpha \\ \beta \end{pmatrix} &= \left\{ \mathbb{E} \left[\begin{pmatrix} 1 \\ X \end{pmatrix} (1 \ X) \right] \right\}^{-1} \mathbb{E} \left[\begin{pmatrix} 1 \\ X \end{pmatrix} y \right] \\ &= \begin{bmatrix} 1 & \mathbb{E}(X) \\ \mathbb{E}(X) & \mathbb{E}(X^2) \end{bmatrix}^{-1} \begin{bmatrix} \mathbb{E}(Y) \\ \mathbb{E}(XY) \end{bmatrix} \end{aligned}$$

Since $f(x, y)$ is given, it is not hard to compute $\mathbb{E}(X) = \mathbb{E}(Y) = 5/8$, $\mathbb{E}(X^2) = 7/15$ and $\mathbb{E}(XY) = 3/8$. Plugging those values and computing the inverse of the matrix in Eq. (1), we obtain coefficients:

$$\begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \begin{pmatrix} 55/73 \\ -15/73 \end{pmatrix},$$

and the best linear predictor

$$(2) \quad \mathcal{P}(Y | X = x) = \left(\frac{55}{73} - \frac{15}{73}x \right) \mathbb{1}_{[0,1]}(x),$$

where $\mathbb{1}_A(\cdot)$ denotes the indicator function of x for some set A such that $\mathbb{1}_A(x) = 1$ if $x \in A$.

The conditional mean function $m(x)$ is, by definition

$$m(x) \equiv \mathbb{E}(Y | X = x) = \int_0^1 y f(y | x) dy = \int_0^1 y \cdot \frac{f(x, y)}{f(x)} dy,$$

Note that $f(y | x)$, $f(x, y)$ and $f(x)$ are shorthand for the corresponding conditional, joint and marginal densities involving X and Y , evaluated at $X = x$ and $Y = y$.

The marginal density $f(x)$ then can be obtained by

$$f(x) = \int_0^1 f(x, y) dy = \frac{1}{2} (3x^2 + 1) \mathbb{1}_{[0,1]}(x)$$

Then it is not hard to have

$$(3) \quad m(x) = \left(\frac{6x^2 + 3}{12x^2 + 4} \right) \mathbb{1}_{[0,1]}(x).$$

By Eq. (2) and Eq. (3), it is obvious that $\mathcal{P}(Y | X = x)$ and $m(x)$ do not coincide.

Their discrepancy arises from the fact that the best linear predictor $\mathcal{P}(Y | X = x)$, by construction, places a linear restriction on the relationship between Y and X , implying only their first and second moments matter, whereas the conditional mean function $m(x)$ does not rely on any specific parametric form and thus makes full use of information on the joint distribution of x and y . \square

PROBLEM 2.19

PROOF. By definition, the loss function

$$\begin{aligned} d(\beta) &= \mathbb{E} \left[(m(\mathbf{X}) - \mathbf{X}'\beta)^2 \right] \\ &= \mathbb{E} \left[m^2(\mathbf{X}) \right] + \beta' \mathbb{E} [\mathbf{X}\mathbf{X}'] \beta - 2\beta' \mathbb{E} [\mathbf{X}m(\mathbf{X})]. \end{aligned}$$

FOC w.r.t. β gives

$$\mathbf{0} = \frac{\partial}{\partial \beta} d(\beta) = 2\mathbb{E}[\mathbf{X}\mathbf{X}'] \beta - 2\mathbb{E}[\mathbf{X}m(\mathbf{X})].$$

Therefore,

$$(4) \quad \beta = (\mathbb{E}[\mathbf{X}\mathbf{X}'])^{-1} \mathbb{E} [\mathbf{X}m(\mathbf{X})].$$

By the *law of iterated expectations*, we know

$$\begin{aligned} \mathbb{E}[\mathbf{X}Y] &= \mathbb{E}[\mathbb{E}[\mathbf{X}Y \mid \mathbf{X}]] \\ &= \mathbb{E}[\mathbf{X} \underbrace{\mathbb{E}[Y \mid \mathbf{X}]}_{\equiv m(\mathbf{X})}] \\ &= \mathbb{E}[\mathbf{X}m(\mathbf{X})]. \end{aligned}$$

Plugging the above equality into Eq. (4) yields

$$(5) \quad \beta = (\mathbb{E}[\mathbf{X}\mathbf{X}'])^{-1} \mathbb{E} [\mathbf{X}Y].$$

So, expressions Eq. (4) and Eq. (5) are equivalent. □