

**Homework 1**

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- **Acknowledgments:** For Problem 1.2(b), I refer to some answer on StackExchange <https://math.stackexchange.com/a/108303>
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  - *I certify that all solutions are entirely in my words and that I have not looked at another student's solutions. I have credited all external sources in this write up.*

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1.1. *Mathematical Expectation, Variance, and Covariance Matrix*

(a) i.  $\mathbb{E}[x|y] = \mathbb{E}[\mathbb{E}[x|yz]|y]$

*Proof.*

$$\mathbb{E}[x|yz] = \sum_x x P_{X|YZ}(x|yz) \quad (1)$$

Denote  $\mathbb{E}[x|yz]$  as  $g(y, z)$

$$\begin{aligned} E[g(y, z)|y] &= \sum_z g(y, z) P_{Z|Y}(z|y) \\ &= \sum_z \left( \sum_x x P_{X|YZ}(x|yz) \right) P_{Z|Y}(z|y) \\ &= \sum_{x,z} x f_{X|YZ}(x|yz) P_{Z|Y}(z|y) \\ &= \sum_{x,z} x P_{X,Z|Y}(x, z|y) \\ &= \sum_x x P_{X|Y}(x|y) \\ &= \mathbb{E}[x|y] \end{aligned} \quad (2)$$

So we have  $\mathbb{E}[x|y] = \mathbb{E}[\mathbb{E}[x|yz]|y]$  □

ii.  $\mathbb{E}[xg(y)|y] = g(y)\mathbb{E}[x|y]$

*Proof.*

$$\begin{aligned}
\mathbb{E}[xg(y)|y] &= \sum_x xg(y)P_{X|Y}(x|y) \\
&= g(y) \sum_x xP_{X|Y}(x|y) \quad (g(y) \text{ is constant with } y \text{ fixed}) \\
&= g(y)\mathbb{E}[x|y]
\end{aligned} \tag{3}$$

□

iii.  $\mathbb{E}[x\mathbb{E}[x|y]] = \mathbb{E}[(\mathbb{E}[x|y])^2]$

*Proof.* Denote  $\mathbb{E}[x|y]$  as  $g(y)$ , using the conclusion from Equation [3], considering the following expression  $\mathbb{E}[xg(y)|y]$

$$\mathbb{E}[xg(y)|y] = g(y)\mathbb{E}[x|y] = (\mathbb{E}[x|y])^2 \tag{4}$$

Considering the expectation of each side in the above equation,

$$\begin{aligned}
\mathbb{E}[\mathbb{E}[xg(y)|y]] &= \mathbb{E}[xg(y)] \quad (\text{Total Expectation Rule}) \\
&= \mathbb{E}[x\mathbb{E}[x|y]] \\
&= \mathbb{E}[(\mathbb{E}[x|y])^2]
\end{aligned} \tag{5}$$

□

iv.  $\text{var}(x) = \mathbb{E}[\text{var}(x|y)] + \text{var}(\mathbb{E}[x|y])$

*Proof.* Because

$$\text{var}(x|y) = \mathbb{E}[(x - \mathbb{E}[x|y])^2|y] = \mathbb{E}[x^2|y] - (\mathbb{E}[x|y])^2,$$

$$\begin{aligned}
\mathbb{E}[\text{var}(x|y)] &= \mathbb{E}[\mathbb{E}[x^2|y] - (\mathbb{E}[x|y])^2] \\
&= \mathbb{E}[x^2] - \mathbb{E}[(\mathbb{E}[x|y])^2]
\end{aligned} \tag{6}$$

Meanwhile,

$$\begin{aligned}
\text{var}(\mathbb{E}[x|y]) &= \mathbb{E}[(\mathbb{E}[x|y])^2] - (\mathbb{E}[\mathbb{E}[x|y]])^2 \\
&= \mathbb{E}[(\mathbb{E}[x|y])^2] - (\mathbb{E}[x])^2
\end{aligned} \tag{7}$$

Therefore,

$$\begin{aligned}
\mathbb{E}[\text{var}(x|y)] + \text{var}(\mathbb{E}[x|y]) &= \mathbb{E}[x^2] - \mathbb{E}[(\mathbb{E}[x|y])^2] \\
&\quad + \mathbb{E}[(\mathbb{E}[x|y])^2] - (\mathbb{E}[x])^2 \\
&= \mathbb{E}[x^2] - (\mathbb{E}[x])^2 \\
&= \text{var}(x)
\end{aligned} \tag{8}$$

□

(b) i.  $\text{cov}(\underline{x}) = \mathbb{E}[\text{cov}(\underline{x}|y)] + \text{cov}(\mathbb{E}[\underline{x}|y])$

*Proof.* Because  $\text{cov}(\underline{x}|y) = \mathbb{E}[\underline{x} \cdot \underline{x}^T|y] - \mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T$ ,

$$\begin{aligned}
\mathbb{E}[\text{cov}(\underline{x}|y)] &= \mathbb{E}[\mathbb{E}[\underline{x} \cdot \underline{x}^T|y] - \mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T] \\
&= \mathbb{E}[\underline{x} \cdot \underline{x}^T] - \mathbb{E}[\mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T]
\end{aligned} \tag{9}$$

Meanwhile,

$$\begin{aligned}\text{cov}(\mathbb{E}[\underline{x}|y]) &= \mathbb{E}[\mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T] - \mathbb{E}[\mathbb{E}[\underline{x}|y]] \cdot (\mathbb{E}[\mathbb{E}[\underline{x}|y]])^T \\ &= \mathbb{E}[\mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T] - \mathbb{E}[\underline{x}] \cdot (\mathbb{E}[\underline{x}])^T\end{aligned}\quad (10)$$

Therefore,

$$\begin{aligned}\mathbb{E}[\text{cov}(\underline{x}|y)] + \text{cov}(\mathbb{E}[\underline{x}|y]) &= \mathbb{E}[\underline{x} \cdot \underline{x}^T] - \mathbb{E}[\mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T] \\ &\quad + \mathbb{E}[\mathbb{E}[\underline{x}|y] \cdot (\mathbb{E}[\underline{x}|y])^T] - \mathbb{E}[\underline{x}] \cdot (\mathbb{E}[\underline{x}])^T \\ &= \mathbb{E}[\underline{x} \cdot \underline{x}^T] - \mathbb{E}[\underline{x}] \cdot (\mathbb{E}[\underline{x}])^T \\ &= \text{cov}(\underline{x})\end{aligned}\quad (11)$$

□

ii. *Proof.* Denote  $\Sigma = \text{cov}(\underline{x}) = \mathbb{E}[(\underline{x} - \underline{\mu})(\underline{x} - \underline{\mu})^T]$ ,  $\underline{\mu} = \mathbb{E}[\underline{x}]$ , then

$$\det(\Sigma) = 0 \iff \exists \underline{b} \in \mathbb{R}^k \setminus \{0\} \text{ such that } \Sigma \underline{b} = 0 \quad (12)$$

" $\implies$ ":

Denote  $\underline{\alpha} = \underline{x} - \underline{\mu}$ ,

$$\Sigma \underline{b} = \mathbb{E}[\underline{\alpha} \underline{\alpha}^T] \underline{b} = \mathbb{E}[\underline{\alpha} \underline{\alpha}^T \underline{b}] = 0 \quad (13)$$

Mutiplied by  $\underline{b}^T$ , and denote  $\underline{\beta} = \underline{b}^T \underline{\alpha}$ , we have

$$\mathbb{E}[\underline{b}^T \underline{\alpha} \underline{\alpha}^T \underline{b}] = \mathbb{E}[\underline{\beta} \underline{\beta}^T] = 0 \quad (14)$$

Suppose  $\underline{\beta} = (\beta_1, \beta_2, \dots, \beta_k)^T$ , considering the diagonal elements of  $\underline{\beta} \underline{\beta}^T$ , the  $i$ -th diagonal element is  $\beta_i^2 \geq 0$ , so  $\mathbb{E}[\beta_i^2] \geq 0$ , but  $\mathbb{E}[\underline{\beta} \underline{\beta}^T] = 0$ , which means  $\beta_i = 0$  and  $\underline{\beta} = \underline{0}$ .

$$\underline{b}^T (\underline{x} - \underline{\mu}) = 0 \iff \underline{b}^T \underline{x} = \underline{b}^T \underline{\mu} \quad (15)$$

So  $\exists \underline{c} = \underline{b} \in \mathbb{R}^k \setminus \{0\}$  such that  $\underline{c}^T \underline{x} = \underline{b}^T \underline{\mu}$  is a constant.

" $\impliedby$ ":

Because  $\underline{c}^T \underline{x}$  is a constant,

$$\underline{c}^T \underline{x} = \mathbb{E}[\underline{c}^T \underline{x}] = \underline{c}^T \mathbb{E}[\underline{x}] = \underline{c}^T \underline{\mu} \quad (16)$$

That is,  $\underline{c}^T (\underline{x} - \underline{\mu}) = 0$ , so  $\underline{c}^T (\underline{x} - \underline{\mu})(\underline{x} - \underline{\mu})^T = 0$ ,

$$\mathbb{E}[\underline{c}^T (\underline{x} - \underline{\mu})(\underline{x} - \underline{\mu})^T] = \underline{c}^T \mathbb{E}[(\underline{x} - \underline{\mu})(\underline{x} - \underline{\mu})^T] = \underline{c}^T \Sigma = 0 \quad (17)$$

So  $\det(\Sigma) = 0$

□

1.2. (a) *Proof.* To minimize

$$L = \mathbb{E}[(y - ax - b)^2] = \mathbb{E}[y^2] + a^2 \mathbb{E}[x^2] + b^2 - 2a \mathbb{E}[xy] + 2ab \mathbb{E}[x] - 2b \mathbb{E}[y],$$

let the partial derivative equals 0.

$$\begin{cases} \frac{\partial L}{\partial a} = 2a\mathbb{E}[x^2] - 2\mathbb{E}[xy] + 2b\mathbb{E}[x] = 0 \\ \frac{\partial L}{\partial b} = 2b + 2a\mathbb{E}[x] - 2\mathbb{E}[y] = 0 \end{cases} \quad (18)$$

Solve the equation, we have

$$a^* = \frac{\mathbb{E}[xy] - \mathbb{E}[x]\mathbb{E}[y]}{\mathbb{E}[x^2] - (\mathbb{E}[x])^2} = \frac{\mathbb{E}[(x - \mathbb{E}[x])(y - \mathbb{E}[y])]}{\text{var}(x)} \quad (19)$$

When  $\text{var}(x) = \text{var}(y)$  we have  $\rho(x, y) = a^*$   $\square$

- (b) *Proof.*  $x$  and  $y$  is independent means  $P_{X,Y}(x, y) = P_X(x)P_Y(y)$ ,  
and  $\rho(f(x), g(y)) = 0$  means  $\mathbb{E}[f(x)]\mathbb{E}[g(y)] = \mathbb{E}[f(x)g(y)]$   
" $\implies$ ":

Suppose  $P_{X,Y}(x, y) = P_X(x)P_Y(y)$ , for  $\forall f, g$

$$\begin{aligned} \mathbb{E}[f(x)g(y)] &= \sum_{x,y} f(x)g(y)P_{X,Y}(x, y) \\ &= \sum_{x,y} f(x)g(y)P_X(x)P_Y(y)dxdy \\ &= \sum_x f(x)P_X(x) \sum_y g(y)P_Y(y) \\ &= \mathbb{E}[f(x)]\mathbb{E}[g(y)] \end{aligned} \quad (20)$$

" $\longleftarrow$ ":

Suppose  $\mathbb{E}[f(x)]\mathbb{E}[g(y)] = \mathbb{E}[f(x)g(y)]$ , for all  $A, B \in \mathbb{R}$  Let  $f(x)$  be the indicator random variable  $f(x) = \mathbb{I}(x \in A)$ ,  $g(y) = \mathbb{I}(y \in B)$

$$\begin{aligned} P(x \in A, y \in B) &= \mathbb{E}[\mathbb{I}(x \in A)\mathbb{I}(y \in B)] = \mathbb{E}[f(x)g(y)] \\ &= \mathbb{E}[f(x)]\mathbb{E}[g(y)] = \mathbb{E}[\mathbb{I}(x \in A)]\mathbb{E}[\mathbb{I}(y \in B)] \\ &= P(x \in A)P(y \in B) \end{aligned} \quad (21)$$

So  $P_{X,Y}(x, y) = P_X(x)P_Y(y)$  which means  $X, Y$  are independent.  $\square$

- 1.3. Let  $X \sim N(0, 1)$ , the pdf of  $X$  is  $f_X(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}x^2}$ , denote the cumulative distribution function  $\Phi(x) = P(X \leq x)$  and  $\Phi'(x) = f_X(x)$ .  
Suppose  $Y = \exp(X)$ , we try to find the cumulative distribution function  $P(Y \leq y)$ ,

$$P(Y \leq y) = P(X \leq \ln y) = \Phi(\ln y) \quad (22)$$

Therefore, the pdf of  $Y$  is,

$$f_Y(y) = \frac{d\Phi(\ln y)}{dy} = f_X(\ln y) \frac{1}{y} = \frac{1}{\sqrt{2\pi}y} e^{-\frac{1}{2}(\ln y)^2} \quad (23)$$