

# Homework #2

---

## 1. $\chi_1 | \chi_2$

---

$$f(\chi_1, \chi_2) = \frac{e^{-\frac{1}{2}(\chi - \mu)^T \Sigma^{-1}(\chi - \mu)}}{\sqrt{(2\pi)^d |\Sigma|}}$$

$$\chi = \begin{bmatrix} \chi_1 \\ \chi_2 \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}^T & \Sigma_{22} \end{bmatrix}, d = d_1 + d_2$$

$$f(\chi_2) = \frac{e^{-\frac{1}{2}(\chi_2 - \mu_2)^T \Sigma_{22}^{-1}(\chi_2 - \mu_2)}}{\sqrt{(2\pi)^{d_2} |\Sigma_{22}|}}$$

$$f(\chi_1 | \chi_2) = \frac{e^{-\frac{1}{2}((\chi - \mu)^T \Sigma^{-1}(\chi - \mu) - (\chi_2 - \mu_2)^T \Sigma_{22}^{-1}(\chi_2 - \mu_2))}}{\sqrt{(2\pi)^{d_1} \frac{|\Sigma|}{|\Sigma_{22}|}}}$$

$$\text{Let } M = (\chi - \mu)^T \Sigma^{-1}(\chi - \mu) - (\chi_2 - \mu_2)^T \Sigma_{22}^{-1}(\chi_2 - \mu_2), N = \frac{|\Sigma|}{|\Sigma_{22}|}$$

$$\text{Consider } \Sigma^{-1} = \begin{bmatrix} 0 & 0 \\ 0 & \Sigma_{22} \end{bmatrix} + \begin{bmatrix} I \\ -E \end{bmatrix} \Delta^{-1} \begin{bmatrix} I & -F \end{bmatrix} \text{ by Schur's Inversion Formula, where } E = \Sigma_{22}^{-1} \Sigma_{12}^T, F = \Sigma_{12} \Sigma_{22}^{-1}, \Delta = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T.$$

$$M = (\chi_2 - \mu_2)^T \Sigma_{22}^{-1}(\chi_2 - \mu_2) + ((\chi_1 - \mu_1)^T - (\chi_2 - \mu_2)^T \Sigma_{22}^{-1} \Sigma_{12}^T)(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T)^{-1}((\chi_1 - \mu_1) - \Sigma_{12} \Sigma_{22}^{-1}(\chi_2 - \mu_2)) - (\chi_2 - \mu_2)^T \Sigma_{22}^{-1}(\chi_2 - \mu_2)$$

$$\text{Consider } \Sigma_{22} = \Sigma_{22}^T:$$

$$M = ((\chi_1 - \mu_1) - \Sigma_{12} \Sigma_{22}^{-1}(\chi_2 - \mu_2))^T (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T)^{-1} ((\chi_1 - \mu_1) - \Sigma_{12} \Sigma_{22}^{-1}(\chi_2 - \mu_2))$$

$$\text{Consider } \Sigma_{22} \text{ is invertable.}$$

$$\det(\Sigma) = \det\left(\Sigma \begin{bmatrix} \Sigma_{22} & 0 \\ 0 & \Sigma_{22}^{-1} \end{bmatrix}\right) = \det\left(\begin{bmatrix} \Sigma_{11} \Sigma_{22} & \Sigma_{12} \Sigma_{22}^{-1} \\ \Sigma_{12}^T \Sigma_{22} & I \end{bmatrix}\right) = \det(\Sigma_{22}) \det(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T) \\ N = \det(\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T)$$

$$\text{Denote } \mu_{1|2} = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1}(\chi_2 - \mu_2), \Sigma_{1|2} = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T$$

$$f(\chi_1 | \chi_2) = \frac{e^{-\frac{1}{2}(\chi_1 - \mu_{1|2})^T \Sigma_{1|2}^{-1}(\chi_1 - \mu_{1|2})}}{\sqrt{(2\pi)^{d_1} |\Sigma_{1|2}|}}$$

Therefore,  $\chi_1 | \chi_2 \sim N(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (\chi_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{12}^T)$

## 2. Bernoulli random variable $\chi$

---

### a) The average and the variance of $\chi$

$$E(\chi) = p \times a_1 + (1 - p) \times a_2 = a_2 + p(a_1 - a_2)$$

$$\text{var}(\chi) = p \times (a_1 - E(\chi))^2 + (1 - p) \times (a_2 - E(\chi))^2 = p(1 - p) \times (a_1 - a_2)^2$$

### b) Propose a way to estimate $p = P(\chi = a_1)$

The estimation of  $p$  is the number of realizations that  $\chi = a_1$  divided by the total number of realizations.

$$\hat{p} = \frac{1}{N} \sum_{k=1}^N \mathbb{I}\{x_k = a_1\}, \text{ where } \mathbb{I}\{x_k = a_1\} = \begin{cases} 1 & , x_k = a_1 \\ 0 & , x_k \neq a_1 \end{cases}$$

### c) the mean and variance of estimate.

Notice  $\mathbb{I}\{x = a_1\}$  is a Bernoulli random variable that takes the value 1 with probability  $p$  and the value 0 with probability  $1-p$ .

$$E(\hat{p}) = \frac{1}{N} \sum_{k=1}^N E(\mathbb{I}\{x_k = a_1\}) = p$$

$$\text{var}(\hat{p}) = E((\hat{p} - p)^2) = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N (\mathbb{I}\{x_i = a_1\} - p)(\mathbb{I}\{x_j = a_1\} - p)$$

Notice that when  $i \neq j$ :

$$\sum_{i=1}^N \sum_{j=1}^N (\mathbb{I}\{x_i = a_1\} - p)(\mathbb{I}\{x_j = a_1\} - p) = \left( \sum_{i=1}^N \mathbb{I}\{x_i = a_1\} - Np \right) \left( \sum_{j=1}^N \mathbb{I}\{x_j = a_1\} - Np \right) = 0$$

$$\text{Therefore, } \text{var}(\hat{p}) = \frac{1}{N^2} \sum_{k=1}^N (\mathbb{I}\{x_k = a_1\} - p)^2 = \frac{1}{N} (\mathbb{I}\{x_k = a_1\} - p)^2$$

Notices that  $\mathbb{I}^2\{x_i = a_1\} = \mathbb{I}\{x_i = a_1\}$ :

$$\text{var}(\hat{p}) = \frac{1}{N} (p - 2p + p^2) = \frac{1}{N} (1 - p)p$$

Therefore, when  $N \rightarrow \infty$ , the error of  $\hat{p}$  will be smaller and smaller.

### 3 $X$ is a random vector and there are $K$ different possibilities that can generate realizations of this vector.

---

a)  $f(X) = p_1 f_1(X) + \dots + p_K f_K(X)$ .

$$P(X \leq \chi \leq X + dX) = \sum_{k=1}^K p_k P_k(X \leq \chi \leq X + dX)$$

$$\text{Consider } P(X \leq \chi \leq X + dX) = f_\chi(X) dX$$

$$f(X) dX = \sum_{k=1}^K p_k f_k(X) dX$$

$$f(X) = \sum_{k=1}^K p_k f_k(X)$$

(In case of ambiguity, we can denote  $X \leq \chi$  when each coordinate of  $X$  is smaller than or equal to that of  $\chi$ .)

b) the joint pdf of the two random variables.

$$f_{12}(X_1, X_2) = 0.99 \frac{e^{-\frac{1}{2}(X_1^2 + X_2^2)}}{\sqrt{(2\pi)^2}} + 0.01 \frac{e^{-\frac{1}{2} \frac{X_1^2 + X_2^2}{\sigma^2}}}{\sqrt{(2\pi)^2 \sigma^4}} = 0.99 \frac{e^{-\frac{1}{2}(X_1^2 + X_2^2)}}{2\pi} + 0.01 \frac{e^{-\frac{1}{2} \frac{X_1^2 + X_2^2}{\sigma^2}}}{2\pi \sigma^2}$$

c) independent

$$f_1(X_1) = 0.99 \frac{e^{-\frac{1}{2} X_1^2}}{\sqrt{2\pi}} + 0.01 \frac{e^{-\frac{1}{2} \frac{X_1^2}{\sigma^2}}}{\sqrt{(2\pi)\sigma}}$$

$$f_2(X_2) = 0.99 \frac{e^{-\frac{1}{2} X_2^2}}{\sqrt{2\pi}} + 0.01 \frac{e^{-\frac{1}{2} \frac{X_2^2}{\sigma^2}}}{\sqrt{(2\pi)\sigma}}$$

Because  $f_{12}(X_1, X_2) \neq f_1(X_1) f_2(X_2)$ ,  $\chi_1, \chi_2$  are not independent.

d) uncorrelated but not independent

Consider  $cor(\chi_1, \chi_2) = E(\chi_1 \chi_2) - E(\chi_1) E(\chi_2) = 0 - 0 = 0$ :

Therefore,  $\chi_1, \chi_2$  are 2 random variables that are uncorrelated but not independent.

$$4 \zeta = |\chi + s|.$$


---

**a)  $s$  is a deterministic quantity.**

$$P(\zeta \leq z) = P(-z - s \leq \zeta \leq z - s) = F_\chi(z - s) - F_\chi(-z - s)$$

$$f_\zeta(z) = f_\zeta(z - s) + f_\zeta(-z - s)$$

**b)  $s$  is a random variable independent from  $\chi$ .**

$$P(\zeta \leq z) = P(-z \leq \zeta \leq z | s = 0)P(s = 0) + P(-z - 1 \leq \zeta \leq z - 1 | s = 1)P(s = 1)$$

$$f_\zeta(z) = 0.2(f_\zeta(z) + f_\zeta(-z)) + 0.8(f_\zeta(z - 1) + f_\zeta(-z - 1))$$

**c)  $P(s = 0 | \zeta = z)$**

$$P(s = 0 | \zeta = z) = \frac{P(\zeta=z, s=0)}{P(\zeta=z)} = \frac{0.2(f_\zeta(z) + f_\zeta(-z))}{0.2(f_\zeta(z) + f_\zeta(-z)) + 0.8(f_\zeta(z-1) + f_\zeta(-z-1))}$$

## 5 the space of all scalar random variables

---

**a) a vector space.**

$\chi, \psi, \zeta$  are scalar random variables, and  $m, n, k$  are real numbers.

$$\oplus: \chi \oplus \psi = \chi + \psi$$

**Commutativity:**

$$\chi \oplus \psi = \chi + \psi = \psi + \chi = \psi \oplus \chi$$

**Associativity:**

$$(\chi \oplus \psi) \oplus \zeta = (\chi + \psi) + \zeta = \chi + (\psi + \zeta) = \chi \oplus (\psi \oplus \zeta)$$

**Identity element: 0**

$$\odot: k \odot \chi = k\chi$$

**Associativity:**

$$(mn) \odot \chi = (mn)\chi = m(n\chi) = m \odot (n \odot \chi)$$

**Distributivity:**

$$k \odot (\chi \oplus \psi) = k(\chi + \psi) = k\chi + k\psi = (k \odot \chi) \oplus (k \odot \psi)$$

$$(m + n) \odot \chi = (m + n)\chi = m\chi + n\chi = (m \odot \chi) \oplus (n \odot \chi)$$

**Identity element: 1**

$$\mathbf{b)} \langle \chi, \psi \rangle = E[\chi\psi]$$

**symmetry:**

$$\langle \chi, \psi \rangle = E(\chi\psi) = E(\psi\chi) = \langle \psi, \chi \rangle$$

**Linearity:**

$$\langle k\chi, \psi \rangle = E(k\chi\psi) = kE(\chi\psi) = k \langle \chi, \psi \rangle$$

$$\langle \chi + \psi, \zeta \rangle = E((\chi + \psi)\zeta) = E(\chi\zeta + \psi\zeta) = E(\chi\zeta) + E(\psi\zeta) = \langle \chi, \zeta \rangle + \langle \psi, \zeta \rangle$$

**Positive-definiteness:**

$$\langle \chi, \chi \rangle = E(\chi^2)$$

$$\chi^2 \geq 0, \chi^2 = 0 \Leftrightarrow \chi = 0$$

$$\text{Therefore, } \langle \chi, \chi \rangle = E(\chi^2) \geq 0$$

$$\langle \chi, \chi \rangle = 0 \Leftrightarrow \chi = 0$$

### c) the general Schwarz inequality

$$|\langle \chi, \psi \rangle| \leq \|\chi\| \|\psi\|$$

$$|E(\chi\psi)| \leq \sqrt{E(\chi^2)} \sqrt{E(\psi^2)}$$

### d) random vectors of length d

$$\chi = (\chi_1, \chi_2, \dots, \chi_d)^T$$

$$\psi = (\psi_1, \psi_2, \dots, \psi_d)^T$$

$$\oplus: \chi \oplus \psi = (\chi_1 + \psi_1, \chi_2 + \psi_2, \dots, \chi_d + \psi_d)^T$$

$$\odot: k \odot \chi = (k\chi_1, k\chi_2, \dots, k\chi_d)^T$$

For each coordinate of random vectors, use the previous definition of  $\oplus, \odot$ . It is easy to show the new definition still keeps all the properties.

$$\langle \chi, \psi \rangle = E(\chi^T \psi)$$

**symmetry:**

$$\langle \chi, \psi \rangle = E(\chi^T \psi) = E(\chi_1\psi_1 + \chi_2\psi_2 + \dots + \chi_d\psi_d) = E(\psi^T \chi) = \langle \psi, \chi \rangle$$

**Linearity:**

$$\langle k\chi, \psi \rangle = E(k\chi^T \psi) = kE(\chi^T \psi) = k \langle \chi, \psi \rangle$$

$$\langle \chi + \psi, \zeta \rangle = E((\chi + \psi)^T \zeta) = E((\chi_1 + \psi_1)\zeta_1 + (\chi_2 + \psi_2)\zeta_2 + \dots + (\chi_d + \psi_d)\zeta_d)$$

$$\psi_d)\zeta_2) = E((\chi_1\zeta_1) + (\psi_1\zeta_1) + (\chi_2\zeta_2) + (\psi_2\zeta_2) + \dots + (\chi_d\zeta_d) + (\psi_d\zeta_d)) = \\ E(\chi^T\zeta + \psi^T\zeta) = E(\chi^T\zeta) + E(\psi^T\zeta) = \langle \chi, \zeta \rangle + \langle \psi, \zeta \rangle$$

**Positive-definiteness:**

$$\langle \chi, \chi \rangle = E(\chi^T \chi) = E(\chi_1^2 + \chi_2^2 + \dots + \chi_d^2) = E(\|\chi\|)$$

$$\|\chi\| \geq 0, \chi^2 = 0 \Leftrightarrow \chi = 0$$

$$\text{Therefore, } \langle \chi, \chi \rangle = E(\|\chi\|) \geq 0$$

$$\langle \chi, \chi \rangle = 0 \Leftrightarrow \chi = 0$$

**The Schwartz inequality:**

$$|E(\chi^T \psi)| \leq \sqrt{E(\|\chi\|)} \sqrt{E(\|\psi\|)}$$