

模式识别：作业 #2

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Question 1

(a)

$$\begin{aligned}
\sigma_{ij} &= E[(x_i - \mu_i)(x_j - \mu_j)] \\
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x_i, x_j)(x_i - \mu_i)(x_j - \mu_j) dx_i dx_j \\
&= \int_{-\infty}^{\infty} p(x_i)(x_i - \mu_i) dx_i \int_{-\infty}^{\infty} p(x_j)(x_j - \mu_j) dx_j \\
&= \left[\int_{-\infty}^{\infty} x_i p(x_i) dx_i - \mu_i \int_{-\infty}^{\infty} p(x_i) dx_i \right] \left[\int_{-\infty}^{\infty} x_j p(x_j) dx_j - \mu_j \int_{-\infty}^{\infty} p(x_j) dx_j \right] \\
&= (\mu_i - \mu_i)(\mu_j - \mu_j) \\
&= 0
\end{aligned}$$

(b)

设有一个 d 维的高斯分布 $\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$

$$\text{其中, } \mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix}, \boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_d \end{bmatrix}, \boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2 & \cdots & \sigma_1\sigma_d \\ \sigma_2\sigma_1 & \sigma_2^2 & \cdots & \sigma_2\sigma_d \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_d\sigma_1 & \sigma_d\sigma_2 & \cdots & \sigma_d^2 \end{bmatrix}$$

因为 $\sigma_{ij} = 0$, 所以 $|\boldsymbol{\Sigma}| = \sigma_1^2 \sigma_2^2 \cdots \sigma_d^2$, $\boldsymbol{\Sigma}^{-1} = \text{diag}\left(\frac{1}{\sigma_1^2}, \frac{1}{\sigma_2^2}, \cdots, \frac{1}{\sigma_d^2}\right)$

$$\begin{aligned}
p(x_1 - \mu_1, x_2 - \mu_2, \cdots, x_d - \mu_d) &= p(\mathbf{x} - \boldsymbol{\mu}) = \frac{1}{(2\pi)^{d/2} |\boldsymbol{\Sigma}|^{1/2}} \exp\left[-\frac{1}{2} \mathbf{x}^t \boldsymbol{\Sigma}^{-1} \mathbf{x}\right] \\
&= \frac{1}{(2\pi)^{d/2} \sigma_1 \sigma_2 \cdots \sigma_d} \exp\left[-\frac{1}{2} \sum_{i=1}^d \frac{x_i^2}{\sigma_i^2}\right] \\
&= \prod_{i=1}^d \frac{1}{\sqrt{2\pi} \sigma_i} \exp\left[-\frac{1}{2} \left(\frac{x_i}{\sigma_i}\right)^2\right] \\
&= \prod_{i=1}^d p(x_i - \mu_i)
\end{aligned}$$

根据上式容易知, 对于高斯分布, 如果 $\sigma_{ij} = 0$, 那么 $x_i - \mu_i$ 和 $x_j - \mu_j$ 是统计独立的 ($i \neq j$)。

Question 2

(a)

$$P[z_{ik} = 1 | P(\omega_i)] = P(\omega_i)$$

$$P[z_{ik} = 0|P(\omega_i)] = 1 - P(\omega_i)$$

因此, $P[z_{ik}|P(\omega_i)] = P(\omega_i)^{z_{ik}}[1 - P(\omega_i)]^{1-z_{ik}}$
 对于独立随机变量, 有

$$\begin{aligned} P[z_{i1}, \dots, z_{in}|P(\omega_i)] &= \prod_{k=1}^n P[z_{ik}|P(\omega_i)] \\ &= \prod_{k=1}^n P(\omega_i)^{z_{ik}}[1 - P(\omega_i)]^{1-z_{ik}} \end{aligned}$$

(b)

对数似然函数

$$\begin{aligned} l(P(\omega_i)) &= \ln P[z_{i1}, \dots, z_{in}|P(\omega_i)] \\ &= \ln \left\{ \prod_{k=1}^n P(\omega_i)^{z_{ik}}[1 - P(\omega_i)]^{1-z_{ik}} \right\} \\ &= \sum_{k=1}^n [z_{ik} \ln P(\omega_i) + (1 - z_{ik}) \ln [1 - P(\omega_i)]] \end{aligned}$$

求梯度,

$$\nabla_{P(\omega_i)} l(P(\omega_i)) = \frac{1}{P(\omega_i)} \sum_{k=1}^n z_{ik} - \frac{1}{1 - P(\omega_i)} \sum_{k=1}^n (1 - z_{ik})$$

令 $\nabla_{P(\omega_i)} l(P(\omega_i)) = 0$, 有

$$\begin{aligned} (1 - \hat{P}(\omega_i)) \sum_{k=1}^n z_{ik} &= \hat{P}(\omega_i) \sum_{k=1}^n (1 - z_{ik}) \\ \sum_{k=1}^n z_{ik} - \hat{P}(\omega_i) \sum_{k=1}^n z_{ik} &= n\hat{P}(\omega_i) - \hat{P}(\omega_i) \sum_{k=1}^n z_{ik} \\ \hat{P}(\omega_i) &= \frac{1}{n} \sum_{k=1}^n z_{ik} \end{aligned}$$

Question 3

$p_1(\mathbf{x}) \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$,
 $p_2(\mathbf{x})$ 是任意分布。

$$\begin{aligned} D_{KL}(p_2, p_1) &= \int p_2(\mathbf{x}) \ln \frac{p_2(\mathbf{x})}{p_1(\mathbf{x})} d\mathbf{x} \\ &= \int p_2(\mathbf{x}) \ln p_2(\mathbf{x}) d\mathbf{x} + \frac{1}{2} \int p_2(\mathbf{x}) [d \ln(2\pi) + \ln |\boldsymbol{\Sigma}| + (\mathbf{x} - \boldsymbol{\mu})^t \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu})] d\mathbf{x} \end{aligned}$$

分别对 $\boldsymbol{\mu}$, $\boldsymbol{\Sigma}$ 求导有,

$$\frac{\partial D_{KL}(p_2, p_1)}{\partial \boldsymbol{\mu}} = - \int p_2(\mathbf{x}) \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) d\mathbf{x}$$

$$\begin{aligned} \frac{\partial D_{KL}(p_2, p_1)}{\partial \boldsymbol{\Sigma}} &= \frac{\partial \boldsymbol{\Sigma}^{-1}}{\partial \boldsymbol{\Sigma}} \times \frac{\partial D_{KL}(p_2, p_1)}{\partial \boldsymbol{\Sigma}^{-1}} \\ &= \frac{\partial \boldsymbol{\Sigma}^{-1}}{\partial \boldsymbol{\Sigma}} \times \frac{1}{2} \int p_2(\mathbf{x}) \frac{\partial}{\partial \boldsymbol{\Sigma}^{-1}} (\ln |\boldsymbol{\Sigma}| + (\mathbf{x} - \boldsymbol{\mu})^t \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu})) d\mathbf{x} \\ &= \frac{1}{-\boldsymbol{\Sigma}^2} \times \frac{1}{2} \int p_2(\mathbf{x}) (-\boldsymbol{\Sigma} + (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^t) d\mathbf{x} \end{aligned}$$

令 $\frac{\partial D_{KL}(p_2, p_1)}{\partial \boldsymbol{\mu}} = 0$, 得

$$\int p_2(\mathbf{x}) (\mathbf{x} - \boldsymbol{\mu}) d\mathbf{x} = 0$$

即,

$$E_2[\mathbf{x} - \boldsymbol{\mu}] = 0$$

$$\boldsymbol{\mu} = E_2(\mathbf{x})$$

令 $\frac{\partial D_{KL}(p_2, p_1)}{\partial \boldsymbol{\Sigma}} = 0$, 得

$$\int p_2(\mathbf{x}) [-\boldsymbol{\Sigma} + (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^t] d\mathbf{x} = 0$$

即,

$$E_2[-\boldsymbol{\Sigma} + (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^t] = 0$$

$$\boldsymbol{\Sigma} = E_2[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^t]$$

Question 4

(a)

$$\begin{aligned} \hat{\boldsymbol{\mu}}_{n+1} &= \frac{1}{n+1} \sum_{k=1}^{n+1} \mathbf{x}_k \\ &= \frac{1}{n+1} \left(\sum_{k=1}^n \mathbf{x}_k + \mathbf{x}_{n+1} \right) \\ &= \frac{1}{n+1} (n\hat{\boldsymbol{\mu}}_n + \mathbf{x}_{n+1}) \\ &= \frac{n}{n+1} \hat{\boldsymbol{\mu}}_n + \frac{1}{n+1} \mathbf{x}_{n+1} \\ &= \hat{\boldsymbol{\mu}}_n - \frac{1}{n+1} (\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1}) \\ &= \hat{\boldsymbol{\mu}}_n + \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) \end{aligned}$$

$$\begin{aligned}
\mathbf{C}_{n+1} &= \frac{1}{n} \sum_{k=1}^{n+1} (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1})^t \\
&= \frac{1}{n} \left[\sum_{k=1}^n (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1})^t + (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1})^t \right]
\end{aligned}$$

其中,

$$\begin{aligned}
\sum_{k=1}^n (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1})^t &= \sum_{k=1}^n \left[\left(\mathbf{x}_k - \frac{1}{n+1} \sum_{k=1}^{n+1} \mathbf{x}_k \right) \left(\mathbf{x}_k - \frac{1}{n+1} \sum_{k=1}^{n+1} \mathbf{x}_k \right)^t \right] \\
&= \sum_{k=1}^n \left[\left(\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n + \frac{\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1}}{n+1} \right) \left(\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n + \frac{\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1}}{n+1} \right)^t \right] \\
&= \sum_{k=1}^n \left[(\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n)^t + \frac{1}{(n+1)^2} (\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1}) (\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1})^t \right] \\
&= \sum_{k=1}^n (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_n)^t + \frac{n}{(n+1)^2} (\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1}) (\hat{\boldsymbol{\mu}}_n - \mathbf{x}_{n+1})^t \\
&= (n-1) \mathbf{C}_n + \frac{n}{(n+1)^2} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t
\end{aligned}$$

$$\begin{aligned}
(\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1})^t &= \left(\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n - \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) \right) \left(\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n - \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) \right)^t \\
&= \left(\frac{n}{n+1} \right)^2 (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t
\end{aligned}$$

因而,

$$\begin{aligned}
\mathbf{C}_{n+1} &= \frac{1}{n} \left[\sum_{k=1}^n (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_k - \hat{\boldsymbol{\mu}}_{n+1})^t + (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1}) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_{n+1})^t \right] \\
&= \frac{n-1}{n} \mathbf{C}_n + \frac{1}{(n+1)^2} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t + \frac{n}{(n+1)^2} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t \\
&= \frac{n-1}{n} \mathbf{C}_n + \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t
\end{aligned}$$

(b)

$\hat{\boldsymbol{\mu}}_n = \frac{1}{n} \sum_{k=1}^n \mathbf{x}_k$ 的时间复杂度为 $O(dn)$, $\hat{\boldsymbol{\mu}}_{n+1} = \hat{\boldsymbol{\mu}}_n + \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)$ 所需的时间复杂度为 $O(d)$, 因此计算 $\hat{\boldsymbol{\mu}}_n$ 的时间复杂度为 $O(dn)$ 。

在 $\mathbf{C}_{n+1} = \frac{n-1}{n} \mathbf{C}_n + \frac{1}{n+1} (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n) (\mathbf{x}_{n+1} - \hat{\boldsymbol{\mu}}_n)^t$ 中, 在已知 $\mathbf{C}_n, \hat{\boldsymbol{\mu}}, \mathbf{x}_n$ 的情况下, 计算该式需要时间复杂度 $O(d^2)$ 。且计算 \mathbf{C}_n 需要 $O(d^2n)$, 计算 $\hat{\boldsymbol{\mu}}_n$ 需要 $O(dn)$, 因此计算 \mathbf{C}_n 的时间复杂度为 $O(d^2n)$ 。

Question 5

(a)

$$\boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}, \quad \boldsymbol{\theta}^0 = \begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

$$\begin{aligned} Q(\boldsymbol{\theta}; \boldsymbol{\theta}^0) &= \varepsilon_{x_{32}} [\ln p(\mathbf{x}_g, \mathbf{x}_b; \boldsymbol{\theta}) | \boldsymbol{\theta}^0; D_g] \\ &= \ln p(x_1 | \boldsymbol{\theta}) + \ln p(x_2 | \boldsymbol{\theta}) + \int_{-\infty}^{\infty} \ln p(x_{32} | \boldsymbol{\theta}) p(x_{32} | \boldsymbol{\theta}^0, x_{31} = 2) dx_{32} \\ &= \ln p(x_1 | \boldsymbol{\theta}) + \ln p(x_2 | \boldsymbol{\theta}) + \int_{-\infty}^{\infty} \ln p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}\right) \frac{p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}^0\right)}{\int_{-\infty}^{\infty} p\left(\begin{pmatrix} 2 \\ x'_{32} \end{pmatrix} | \boldsymbol{\theta}^0\right) dx'_{32}} dx_{32} \\ &= \ln p(x_1 | \boldsymbol{\theta}) + \ln p(x_2 | \boldsymbol{\theta}) + 2e^4 \int_{-\infty}^{\infty} \ln p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}\right) p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}^0\right) dx_{32} \end{aligned}$$

设

$$\begin{aligned} K &= 2e^4 \int_{-\infty}^{\infty} \ln p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}\right) p\left(\begin{pmatrix} 2 \\ x_{32} \end{pmatrix} | \boldsymbol{\theta}^0\right) dx_{32} \\ &= \int_{-\infty}^{\infty} \ln [p(2 | \theta_1) p(x_{32} | \theta_2)] p(x_{32} | \theta_2 = 4) dx_{32} \\ &= \frac{1}{4} \int_0^4 \ln \left[\frac{1}{\theta_1} e^{-2\theta_1} p(x_{32} | \theta_2) \right] dx_{32} \end{aligned}$$

由于 $p(x_2) \sim U(0, \theta_2)$, 且存在样本 $x_{22} = 3$, 因此 $\theta_2 \geq 3$ 当 $3 \leq \theta_2 \leq 4$ 时,

$$\begin{aligned} K &= \frac{1}{4} \int_0^{\theta_2} \ln \left[\frac{1}{\theta_1} e^{-2\theta_1} \frac{1}{\theta_2} \right] dx_{32} \\ &= \frac{1}{4} \theta_2 \ln \left(\frac{1}{\theta_1} e^{-2\theta_1} \frac{1}{\theta_2} \right) \\ &= -\frac{1}{2} \theta_1 \theta_2 - \frac{1}{4} \theta_2 \ln(\theta_1 \theta_2) \end{aligned}$$

当 $\theta_2 > 4$ 时,

$$\begin{aligned} K &= \frac{1}{4} \int_0^4 \ln \left(\frac{1}{\theta_1} e^{-2\theta_1} \frac{1}{\theta_2} \right) dx_{32} \\ &= \ln \left(\frac{1}{\theta_1} e^{-2\theta_1} \frac{1}{\theta_2} \right) \\ &= -2\theta_1 - \ln(\theta_1 \theta_2) \end{aligned}$$

$$Q(\boldsymbol{\theta}; \boldsymbol{\theta}^0) = \begin{cases} \ln p(x_1 | \boldsymbol{\theta}) + \ln p(x_2 | \boldsymbol{\theta}) + -\frac{1}{2} \theta_1 \theta_2 - \frac{1}{4} \theta_2 \ln(\theta_1 \theta_2), & 3 \leq \theta_2 \leq 4 \\ \ln p(x_1 | \boldsymbol{\theta}) + \ln p(x_2 | \boldsymbol{\theta}) - 2\theta_1 - \ln(\theta_1 \theta_2), & \theta_2 > 4 \end{cases}$$

(b)

由于 $\int_{-\infty}^{\infty} p(x_1) dx_1 = \int_{-\infty}^{\infty} \frac{1}{\theta_1} e^{-\theta_1 x_1} dx_1 = 1$, 因此 $\theta_1 = 1$ 。
 当 $3 \leq \theta_2 \leq 4$ 时,

$$Q(\boldsymbol{\theta}; \boldsymbol{\theta}^0) = -4 - 2 \ln \theta_2 - \frac{1}{2} \theta_2 - \frac{1}{4} \theta_2 \ln \theta_2$$

由于 $\frac{\partial Q}{\partial \theta_2} = -\frac{2}{\theta_2} - \frac{1}{4} \ln \theta_2 - \frac{3}{4} < 0$, 所以 $\theta_2 = 3$ 时取最大。
 当 $\theta_2 > 4$ 时,

$$Q(\boldsymbol{\theta}; \boldsymbol{\theta}^0) = -6 - 3 \ln \theta_2$$

由于 $\frac{\partial Q}{\partial \theta_2} = -\frac{3}{\theta_2} < 0$, 所以 $\theta_2 = 4$ 时取最大。

综上, 又由于两种情况在 $\theta_2 = 4$ 时取值相同, 因而使 Q 最大的 $\boldsymbol{\theta} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$

Question 6

$$\gamma_{ij}(t) = \frac{\alpha_i(t-1) a_{ij} b_{ij} \beta_i(t)}{P(\mathbf{V}^T | \boldsymbol{\theta})}$$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^T \gamma_{ij}(t)}{\sum_{t=1}^T \sum_{k=1}^c \gamma_{ik}(t)}$$

$$\hat{b}_{jk} = \frac{\sum_{k=1}^c \gamma_{jk}(t)}{\sum_{t=1}^T \gamma_{jk}(t)}$$

要计算 $\gamma_{ij}(t)$, 通过前向算法可以计算出 $P(\mathbf{V}^T | \boldsymbol{\theta})$ 和 $\alpha_i(t)$, 时间复杂度为 $O(c^2T)$, 后向算法可以算出 $\beta_i(t)$, 时间复杂度同样为 $O(c^2T)$ 。因此, 计算 \hat{a}_{ij} 和 \hat{b}_{jk} 时, 计算 $\gamma_{ij}(t)$ 的累加也需要 $O(c^2T)$ 。综合起来所需的时间复杂度为 $O(c^2T)$ 。