

数学基础 7<sup>th</sup>

$$\begin{aligned}
 f(\theta) &= \frac{1}{2} \|Ax + b - y\|_2^2 \\
 &= \frac{1}{2} \left( (Ax + b - y)^T (Ax + b - y) \right) \\
 &= \frac{1}{2} (x^T A^T + (b - y)^T) (Ax + b - y) \\
 &= \frac{1}{2} (x^T A^T Ax + x^T A^T (b - y) + (b - y)^T Ax + (b - y)^T (b - y))
 \end{aligned}$$

$$x^T \cdot A^T (b - y) = 1 \times 1$$

$$1 \times n \quad n \times m \quad m \times 1$$

$$\therefore x^T \cdot A^T (b - y) = (x^T A^T (b - y))^T = (b - y)^T Ax$$

$$= \frac{1}{2} (x^T A^T Ax + 2(b - y)^T Ax + (b - y)^T (b - y))$$

$$f(\theta) = \frac{1}{2} x^T A^T Ax + (b - y)^T Ax + \frac{1}{2} (b - y)^T (b - y)$$

$$\frac{\partial f}{\partial x} = \frac{1}{2} (Ax x^T + Ax x^T) + (b - y) x^T = Ax x^T + (b - y) x^T$$

$$\frac{\partial f}{\partial x} = \frac{1}{2} A^T Ax + \frac{1}{2} A^T Ax + A^T (b - y) = A^T Ax + A^T (b - y)$$

$$2. \quad \frac{\partial x^T Ax}{\partial x} = Ax + \frac{\partial (Ax)^T}{\partial x} x = Ax + \frac{\partial x^T A^T}{\partial x} x = Ax + A^T x = (A + A^T)x$$

$$\frac{\partial x^T Ax}{\partial x} = x x^T \quad \therefore \frac{\partial x^T Ax}{\partial x} = (x_i x_j)_{m \times m}$$

$$x^T Ax = \sum_{j=1}^m \sum_{i=1}^m a_{ij} x_i x_j$$



$$3. \quad 0 = dI = d(WW^{-1}) = dW W^{-1} + W dW^{-1}$$

$$W dW^{-1} = -dW W^{-1}$$

$$dW^{-1} = -W^{-1} dW W^{-1}$$

$$\frac{d \operatorname{Tr}(W^{-1})}{dW}$$

$$\begin{aligned} d \operatorname{Tr}(W^{-1}) &= \operatorname{Tr}(dW^{-1}) = \operatorname{Tr}(-W^{-1} dW W^{-1}) \\ &= \operatorname{Tr}(-(W^{-1})^2 dW) \end{aligned}$$

$$\frac{d \operatorname{Tr}(W^{-1})}{dW} = \frac{d \operatorname{Tr}(-(W^{-1})^2 dW)}{dW} = -(W^{-1})^2$$



$$4. \quad (1) \quad f(z) = \frac{\exp(z)}{1^T \exp(z)} \quad q = f(z), \quad J = -P^T \log(q) = -P^T \log(f(z))$$

$$f(z) = \left( \frac{e^{z_1}}{\sum_{i=1}^n e^{z_i}}, \dots, \frac{e^{z_n}}{\sum_{i=1}^n e^{z_i}} \right)^T$$

$$\log(f(z)) = \log(\exp(z)) - \log(1^T \exp(z))$$

$$J = -P^T [\log(\exp(z)) - 1 \cdot \log(1^T \exp(z))] = -P^T (z - 1 \cdot \log(1^T \exp(z)))$$

$$J = -P^T z + P^T 1 \cdot \log(1^T \exp(z))$$

$$\begin{aligned} \frac{dJ}{dz} &= -P + P^T 1 \cdot \frac{\exp(z)}{1^T \exp(z)} & P^T 1 &= \text{概率之和} = 1 \\ &= -P + \frac{\exp(z)}{1^T \exp(z)} = -P + f(z) = -P + q \end{aligned}$$

$$(2) \quad dJ = \text{tr} \left( \frac{dJ}{dz^T} dz \right) = \text{tr} \left( (q - p)^T dz \right)$$

$$z = wX \quad dz = d(wX) = dwX + w dX = dwX$$

$$dJ = \text{tr} \left( (q - p)^T dwX \right) = \text{tr} \left( X(q - p)^T dw \right)$$

$$\frac{dJ}{dw} = (q - p) X^T$$





5.

(1) 求  $\frac{\partial L}{\partial \mu}$  中与  $\mu$  有关的项  $-\frac{1}{2} \bar{\Sigma}_t (X_t - \mu)^T \bar{\Sigma}_t^{-1} (X_t - \mu)$

$$\frac{\partial L}{\partial \mu} = -\frac{1}{2} \bar{\Sigma}_t \frac{\partial (X_t - \mu)^T \bar{\Sigma}_t^{-1} (X_t - \mu)}{\partial \mu}$$

$$\begin{aligned} (X_t - \mu)^T \bar{\Sigma}_t^{-1} (X_t - \mu) &= X_t^T \bar{\Sigma}_t^{-1} X_t - X_t^T \bar{\Sigma}_t^{-1} \mu - \mu^T \bar{\Sigma}_t^{-1} X_t + \mu^T \bar{\Sigma}_t^{-1} \mu \\ &= X_t^T \bar{\Sigma}_t^{-1} X_t - 2 X_t^T \bar{\Sigma}_t^{-1} \mu + \mu^T \bar{\Sigma}_t^{-1} \mu \end{aligned}$$

$$\frac{\partial L}{\partial \mu} = -\frac{1}{2} \bar{\Sigma}_t \frac{\partial [\mu^T \bar{\Sigma}_t^{-1} \mu - 2 X_t^T \bar{\Sigma}_t^{-1} \mu]}{\partial \mu}$$

$$= -\frac{1}{2} \bar{\Sigma}_t \left( (\bar{\Sigma}_t^{-1} + \bar{\Sigma}_t^{-T}) \mu - 2 \bar{\Sigma}_t^{-T} X_t \right) \quad \bar{\Sigma}_t^{-1} \text{ 是对称的}$$

$$= -\frac{1}{2} \bar{\Sigma}_t (2 \bar{\Sigma}_t^{-1} \mu - 2 \bar{\Sigma}_t^{-1} X_t)$$

$$= \bar{\Sigma}_t (\bar{\Sigma}_t^{-1} X_t - \bar{\Sigma}_t^{-1} \mu)$$

$$= \bar{\Sigma}_t \bar{\Sigma}_t^{-1} (X_t - \mu)$$

(2)  $\frac{\partial L}{\partial \Sigma} \quad d\left(\frac{n}{2} \ln |\bar{\Sigma}|\right) = \frac{n}{2} d(\ln |\bar{\Sigma}|) = \frac{n}{2} \frac{1}{|\bar{\Sigma}|} d|\bar{\Sigma}| = \frac{n}{2} \frac{1}{|\bar{\Sigma}|} \bar{\Sigma}^* d\bar{\Sigma}$

$$\bar{\Sigma}^{-1} = \frac{\bar{\Sigma}^*}{|\bar{\Sigma}|} \quad |\bar{\Sigma}| = \frac{\bar{\Sigma}^*}{\bar{\Sigma}^{-1}}$$

$$\therefore d\left(\frac{n}{2} \ln |\bar{\Sigma}|\right) = \frac{n}{2} \frac{1}{|\bar{\Sigma}|} \bar{\Sigma}^{-1} d\bar{\Sigma} = \frac{n}{2} \bar{\Sigma}^{-1} d\bar{\Sigma}$$

$$\begin{aligned} d\left(-\frac{1}{2} \bar{\Sigma}_t (X_t - \mu)^T \bar{\Sigma}_t^{-1} (X_t - \mu)\right) &= -\frac{1}{2} \bar{\Sigma}_t d\left((X_t - \mu)^T \bar{\Sigma}_t^{-1} (X_t - \mu)\right) \\ &= -\frac{1}{2} \bar{\Sigma}_t (X_t - \mu) (X_t - \mu)^T d\bar{\Sigma}_t^{-1} \end{aligned}$$

$$d\bar{\Sigma}_t^{-1} = -\bar{\Sigma}_t^{-1} d\bar{\Sigma}_t \bar{\Sigma}_t^{-1}$$

$$\therefore \frac{\partial L}{\partial \Sigma} = -\frac{n}{2} \bar{\Sigma}^{-1} + \frac{1}{2} \bar{\Sigma}_t (\bar{\Sigma}_t^{-1}) (X_t - \mu) (X_t - \mu)^T (\bar{\Sigma}_t^{-1})$$



$$\frac{\partial L}{\partial \Sigma} = 0 \quad -\frac{N}{2} \bar{\Sigma}^{-1} + \frac{1}{2} \bar{\Sigma}^{-1} \bar{\Sigma}_t (X_t - \mu)(X_t - \mu)^T \bar{\Sigma}^{-1} = 0$$

$$\cancel{\frac{1}{2} \bar{\Sigma}^{-1}} \bar{\Sigma}_t (X_t - \mu)(X_t - \mu)^T \bar{\Sigma}^{-1} = \cancel{\frac{N}{2} \bar{\Sigma}^{-1}}$$

$$\bar{\Sigma}_t (X_t - \mu)(X_t - \mu)^T \bar{\Sigma}^{-1} = N$$

$$\bar{\Sigma}_t (X_t - \mu)(X_t - \mu)^T = N \bar{\Sigma}$$

$$\bar{\Sigma} = \frac{\bar{\Sigma}_t (X_t - \mu)(X_t - \mu)^T}{N}$$

$$\mu = \frac{1}{N} \bar{\Sigma}_t X_t$$

$$\bar{\Sigma} = \frac{\bar{\Sigma}_t (X_t - \frac{\bar{\Sigma}_t X_t}{N}) (X_t - \frac{\bar{\Sigma}_t X_t}{N})^T}{N}$$



$$6. \quad \frac{d |X^k|}{dX} \quad X \in \mathbb{R}^{m \times m} \quad |X| \neq 0$$

$$|X^k| = |X|^k \quad \frac{d|X|}{dX} = |X| (X^{-1})^T$$

$$\begin{aligned} d|X^k| &= \text{Tr} (|X^k| (X^k)^{-1} d(X^k)) = \text{Tr} (|X^k| (X^k)^{-1} (k(X^{k-1}) dX)) \\ &= \text{Tr} (k|X^k| (X^{1-k} X^k)^{-1} dX) \\ &= \text{Tr} (k|X^k| (X)^{-1} dX) \end{aligned}$$

$$\frac{d|X^k|}{dX} = k|X^k| (X^{-1})^T$$





$$7. \quad \frac{\partial \text{Tr}(AXBX^TC)}{\partial X} \quad \partial \text{Tr}(AXBX^TC) = \partial \text{Tr}(C^T X B^T X^T A^T)$$

$$= \text{Tr}(\partial(C^T X B^T X^T A^T)) = \text{Tr}(C^T dX B^T X^T A^T + C^T X B^T dX^T A^T)$$

$$= \text{Tr}(C^T dX B^T X^T A^T) + \text{Tr}(C^T X B^T dX^T A^T)$$

$$= \text{Tr}(B^T X^T A^T C^T dX) + \text{Tr}((dX)^T A^T C^T X B^T)$$

$$= \text{Tr}(B^T X^T A^T C^T dX) + \text{Tr}(B X^T C A dX)$$

$$= \text{Tr}((B^T X^T A^T C^T + B X^T C A) dX)$$

$$\therefore \frac{\partial \text{Tr}(AXBX^TC)}{\partial X} = CA^T B + A^T C^T X B^T$$

