

Given  $X = \{x^t\}_{t=1}^N$ ,  $p(x^t | \theta) \sim N_d(\mu, \Sigma)$  (assumed)

$\forall x^t \sim N_d(\mu, \Sigma)$ ,  $\theta = \{\mu, \Sigma\}$ .

To find, estimators for  $\mu$  ( $\hat{\mu}$ ) &  $\Sigma$  ( $\hat{\Sigma}$ ), use MLE.

Now,  $\ell(\theta | X^t) = p(x^t | \theta)$

$$= \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu)\right)$$

$$\ell(\theta | X) = \prod_{t=1}^N \ell(\theta | x^t) \quad (i.i.d.s)$$

$$= \prod_{t=1}^N \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu)\right)$$

$$\mathcal{L}(\theta | X) = \log \ell(\theta | X) = \sum_t \left[ -\frac{d}{2} \log 2\pi - \frac{1}{2} \log |\Sigma| - \frac{1}{2} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

Now, for  $\hat{\mu}$ , find value of  $\mu$  from  $\frac{\partial \mathcal{L}}{\partial \mu} = 0$ .

$$\begin{aligned} 1) \quad \frac{\partial \mathcal{L}}{\partial \mu} &= \sum_t \frac{\partial}{\partial \mu} \left[ -\frac{d}{2} \log 2\pi - \frac{1}{2} \log |\Sigma| - \frac{1}{2} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right] \\ &= \sum_t \left[ 0 + 0 - \frac{1}{2} \times 2 \Sigma^{-1} (x^t - \mu) \right] \quad \left( \because \frac{\partial A^T B A}{\partial A} = 2BA \right) \begin{pmatrix} A = (x^t - \mu) \\ B = \Sigma^{-1} \end{pmatrix} \\ &= \Sigma^{-1} \left[ -\sum_t x^t + \sum_t \mu \right] = \Sigma^{-1} \left[ N\mu - \sum_t x^t \right] \\ \frac{\partial \mathcal{L}}{\partial \mu} = 0 &\Rightarrow \Sigma^{-1} \left[ N\mu - \sum_t x^t \right] = 0 \\ &\Rightarrow N\mu - \sum_t x^t = 0 \\ &\Rightarrow N\mu = \sum_t x^t \Rightarrow \boxed{\hat{\mu}_{MLE} = \frac{\sum_t x^t}{N}} \end{aligned}$$

Now, for  $\Sigma$ , find value of  $\Sigma$  from  $\frac{\partial \mathcal{L}}{\partial \Sigma^{-1}} = 0$ .

$$\begin{aligned} 2) \quad \frac{\partial \mathcal{L}}{\partial \Sigma^{-1}} &= \sum_t \frac{\partial}{\partial \Sigma^{-1}} \left[ -\frac{d}{2} \log 2\pi - \frac{1}{2} \log |\Sigma| - \frac{1}{2} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right] \\ &= \sum_t \left[ \frac{-1}{2} \frac{\partial}{\partial \Sigma^{-1}} \log |\Sigma| - \frac{1}{2} \frac{\partial}{\partial \Sigma^{-1}} [(x^t - \mu)^T \Sigma^{-1} (x^t - \mu)] \right] \end{aligned}$$

Now,  $\frac{\partial}{\partial A} \log |A| = (A^{-1})^T$ , and  $\frac{1}{|A|} = |A|^{-1}$

$$\Rightarrow = \frac{1}{2} \sum_t \left[ \frac{\partial}{\partial \Sigma^{-1}} \log \left( \frac{1}{|\Sigma|} \right) - \frac{\partial}{\partial \Sigma^{-1}} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

$$\Rightarrow = \frac{1}{2} \sum_t \left[ \frac{\partial}{\partial \Sigma^{-1}} \log |\Sigma^{-1}| + \frac{\partial}{\partial \Sigma^{-1}} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

$$= \frac{1}{2} \sum_t \left[ ((\Sigma^{-1})^{-1})^T + \frac{\partial}{\partial \Sigma^{-1}} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

Now,  $\Sigma^T = \Sigma$  ( $\Sigma$  is symmetric)

$$\Rightarrow = \frac{1}{2} \sum_t \left[ \Sigma + \frac{\partial}{\partial \Sigma^{-1}} (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

$$= \frac{1}{2} \sum_t \left[ \Sigma + \frac{\partial}{\partial \Sigma^{-1}} \text{tr}((x^t - \mu)^T \Sigma^{-1} (x^t - \mu)) \right] \quad \text{--- ①}$$

( $\because (x^t - \mu)^T \Sigma^{-1} (x^t - \mu)$  is a scalar, &  
if  $A$  is a  $1 \times 1$  matrix / scalar,  $A = \text{tr}(A)$ ,  
where  $\text{tr}(A) = \text{trace} = \sum_i A_{ii}$  (sum of diagonal values))

$$\text{Now, } \text{tr}(ABC) = \text{tr}(CAB) = \text{tr}(BCA)$$

(trace of product of matrices is invariant to cyclic permutations)

$$\Rightarrow \text{tr}(\underbrace{(x^t - \mu)^T}_A \underbrace{(\Sigma^{-1})}_B \underbrace{(x^t - \mu)}_C) = \text{tr}(\underbrace{(x^t - \mu)}_C \underbrace{(x^t - \mu)^T}_A \underbrace{\Sigma^{-1}}_B)$$

$$= \text{tr}(\underbrace{\Sigma^{-1}}_B \underbrace{(x^t - \mu)}_C \underbrace{(x^t - \mu)^T}_A)$$

$$\text{Now, } \frac{\partial}{\partial A} \text{tr}(AB) = B^T. \text{ Assuming } A = \Sigma^{-1}, B = (x^t - \mu)(x^t - \mu)^T,$$

$$\Rightarrow \frac{\partial}{\partial \Sigma^{-1}} \text{tr}((x^t - \mu)^T \Sigma^{-1} (x^t - \mu)) = [(x^t - \mu)(x^t - \mu)^T]^T$$

$$\text{① } \Rightarrow \frac{\partial \mathcal{L}}{\partial \Sigma^{-1}} = \frac{1}{2} \sum_t \left[ \Sigma - [(x^t - \mu)(x^t - \mu)^T]^T \right]$$

$$= \frac{1}{2} \sum_t \left[ \Sigma + (x^t - \mu)^T (x^t - \mu)^T \right] \quad (\because (AB)^T = B^T A^T)$$

$$= \frac{1}{2} \sum_t \left[ \Sigma - (x^t - \mu)(x^t - \mu)^T \right]$$

$$\frac{\partial \mathcal{L}}{\partial \Sigma^{-1}} = 0 \Rightarrow \sum_t (\Sigma) - \sum_t (x^t - \mu)(x^t - \mu)^T = 0$$

$$\Rightarrow N \Sigma = \sum_t (x^t - \mu)(x^t - \mu)^T$$

$$\Rightarrow \boxed{\hat{\Sigma}_{MLE} = \frac{\sum_t (x^t - \mu)(x^t - \mu)^T}{N}}$$