

## 1. Bayesian Inference

$$p(\Lambda | X) \propto \left( p(\Lambda) \prod_{n=1}^{N-1} p(x_n | \Lambda) \right) \cdot p(x_N | \Lambda)$$

$$= p(\Lambda) \cdot p(x_1 | \Lambda) \cdot p(x_2 | \Lambda) \cdots p(x_N | \Lambda)$$

$$= p(\Lambda) \cdot \prod_{n=1}^N p(x_n | \Lambda)$$

$$= p(\Lambda) \cdot \prod_{n=1}^N \mathcal{N}(x_n | \mu, \Sigma)$$

$$\propto \underline{p(\Lambda)} \cdot \Lambda^{\frac{N}{2}} \cdot e^{-\frac{1}{2} \sum_{n=1}^N (x_n - \mu)^T \Lambda (x_n - \mu)}$$

$$= \underline{W(\Lambda | w_0, v_0)} \cdot \Lambda^{\frac{N}{2}} \cdot e^{-\frac{1}{2} \sum_{n=1}^N (x_n - \mu)^T \Lambda (x_n - \mu)}$$

$$= (B \cdot |\Lambda|^{\frac{v_0 + N - D - 1}{2}} \cdot e^{-\frac{1}{2} \text{Tr}(w_0^{-1} \Lambda)}) \cdot \Lambda^{\frac{N}{2}} \cdot e^{-\frac{1}{2} \sum_{n=1}^N (x_n - \mu)^T \Lambda (x_n - \mu)}$$

$$= B \cdot |\Lambda|^{\frac{v_0 + N - D - 1}{2}} \cdot e^{-\frac{1}{2} \text{Tr}(w_0^{-1} \Lambda) + \frac{1}{2} \sum_{n=1}^N (x_n - \mu)^T \Lambda (x_n - \mu)}$$

$$\text{A: } \sum_{n=1}^N (x_n - \mu)^T \Lambda (x_n - \mu)$$

$$= \sum_{n=1}^N [x_{n1} - \mu_1, x_{n2} - \mu_2, \dots, x_{nD} - \mu_D]_{1 \times D} \cdot \Lambda_{D \times D} \cdot \begin{bmatrix} x_{n1} - \mu_1 \\ x_{n2} - \mu_2 \\ \vdots \\ x_{nD} - \mu_D \end{bmatrix}_{D \times 1}$$

which D is the dimension of x-vector.

$$= \sum_{n=1}^N [(x_{n1} - \mu_1) \Lambda_{11}, (x_{n2} - \mu_2) \Lambda_{22}, \dots, (x_{nD} - \mu_D) \Lambda_{DD}]_{1 \times D} \cdot \begin{bmatrix} \vdots \end{bmatrix}_{D \times 1}$$

suppose  $x_{ni}, x_{nj}$  is independent,

$$= \sum_{n=1}^N \left( (x_{n1} - \mu_1)(x_{n1} - \mu_1) \Lambda_{11} + (x_{n2} - \mu_2)(x_{n2} - \mu_2) \Lambda_{22} + \dots + (x_{nD} - \mu_D)(x_{nD} - \mu_D) \Lambda_{DD} \right)$$

$\forall i \neq j, i, j \in D$

$$= \sum_{n=1}^N \text{Tr}(K \cdot \Lambda), \text{ which } K = \begin{bmatrix} (x_{n1} - \mu_1)(x_{n1} - \mu_1) & 0 & \dots & 0 \\ 0 & (x_{n2} - \mu_2)(x_{n2} - \mu_2) & & \\ \vdots & & \ddots & \\ 0 & & & (x_{nD} - \mu_D)(x_{nD} - \mu_D) \end{bmatrix}_{D \times D}$$

$$\therefore p(\Lambda | X) \propto B \cdot |\Lambda|^{\frac{(v_0 + N) - D - 1}{2}} \cdot e^{-\frac{1}{2} \text{Tr}(w_0^{-1} \Lambda) + \frac{1}{2} \sum_{n=1}^N \text{Tr}(K \cdot \Lambda)}$$

$$= B \cdot |\Lambda|^{\frac{v_0 + N - D - 1}{2}} \cdot e^{-\frac{1}{2} \text{Tr}(w_0^{-1} \Lambda + \sum_{n=1}^N K \cdot \Lambda)}$$

$\Theta \Lambda$  is not relate to  $n \#$

$$= B \cdot |\Lambda|^{\frac{(D_0+N)-D-1}{2}} \cdot e^{-\frac{1}{2} \text{Tr} (W_0^{-1} \Lambda + |K| \Lambda)}, \text{ which } |K| = \sum_{n=1}^N K_n \#$$

$$= \mathcal{N}(\Lambda | W_\Lambda, V_\Lambda), \text{ which}$$

$$\begin{cases} W_\Lambda = W_0^{-1} + |K| \\ V_\Lambda = V_0 + N \end{cases}$$