

$$\hat{\mu}_{MLE} = \bar{\underline{x}}$$

$$\hat{\Sigma}_{MLE} = S_n$$

Lemma:  $\bar{\underline{x}} \sim N_p(\mu, \Sigma/n)$

→ We can use characteristic function to prove this

Proof:  $\Phi_{\underline{x}_i}(\underline{t}) = \exp \left[ i \underline{t}^T \mu - \frac{1}{2} \underline{t}^T \Sigma \underline{t} \right]$

$$\bar{\underline{x}} = \frac{1}{n} \sum_{i=1}^n \underline{x}_i = \sum_{i=1}^n \frac{1}{n} \underline{x}_i = \sum_{i=1}^n a_i \underline{x}_i$$

Let  $\underline{y} = \sum_{j=1}^n a_j \underline{x}_j$

$$\Phi_{\underline{y}}(\underline{t}) = \prod_{j=1}^n \Phi_{a_j \underline{x}_j}(\underline{t})$$

$$= \prod_{j=1}^n \exp \left[ a_j i \underline{t}^T \mu - \frac{a_j^2}{2} \underline{t}^T \Sigma \underline{t} \right]$$

$$= \exp \left[ \sum_{j=1}^n \left( a_j i \underline{t}^T \mu - \frac{a_j^2}{2} \underline{t}^T \Sigma \underline{t} \right) \right]$$

at  $a_j = \frac{1}{n}$

$$= \exp \left[ i \underline{t}^T \mu - \frac{1}{2} \underline{t}^T (\Sigma/n) \underline{t} \right]$$

Def<sup>n</sup>: Wishart distribution (WD)

Suppose  $\underline{y}_1, \dots, \underline{y}_n$  are i.i.d.  $N_p(\underline{0}, \Sigma)$ ,  $\Sigma > 0$

Then  $A = \sum_{j=1}^n \underline{y}_j \underline{y}_j^T$  is said to follow wishart distribution with parameters  $n$  &  $\Sigma$ , it is denoted by  $A \sim W_p(n, \Sigma)$

→ WD is multivariate generalization of  $\chi^2$  distribution

Result ①: Suppose  $A \sim W_m(n, \Sigma)$  and  $C_{q \times m}$  be a non-random matrix,  $q \leq m$ , then  $CAC^T \sim W_q(n, C\Sigma C^T)$

Result ②: Let  $A_1 \sim W_p(n_1, \Sigma)$  &  $A_2 \sim W_p(n_2, \Sigma)$  are independent then  $A_1 + A_2 \sim W_p(n_1 + n_2, \Sigma)$

Observe:

It is possible that  $x_1 + x_2 \sim N$

but  $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$  is not normal

Eg <sup>H/W</sup>:  $\begin{pmatrix} x \\ y \end{pmatrix} \sim \frac{1}{2} N_2 \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix} \right) + \frac{1}{2} N_2 \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & -0.5 \\ -0.5 & 1 \end{pmatrix} \right)$

Marginal distribution is normal

$$\text{Cov}(x, y) = 0$$

Theorem:  $\underline{X}_1, \dots, \underline{X}_n$  iid  $N_p(\mu, \Sigma)$

(i)  $\bar{\underline{X}} \sim N_p(\mu, \Sigma/n)$

(ii)  $A = (n-1) S_{n-1} \sim W_p(n-1, \Sigma)$  (next class)

(iii)  $\bar{\underline{X}}$  &  $A$  are independent

Proof: (i) Can be done using characteristic function

(ii) next class

(iii)  $A = \sum_{i=1}^n (\underline{X}_i - \bar{\underline{X}})(\underline{X}_i - \bar{\underline{X}})^T$

$$= \sum_{i=1}^n \underline{Y}_i \underline{Y}_i^T, \text{ where } \underline{Y}_i = \underline{X}_i - \bar{\underline{X}}$$

claim: joint dist<sup>n</sup> of  $(\bar{\underline{X}}, \underline{Y}_i)$  is normal

claim:  $\text{Cov}(\bar{\underline{X}}, \underline{Y}_i) = \underline{0}$

$$\Rightarrow \bar{x} \perp y_i \quad \forall i$$

$$\Rightarrow \bar{x} \perp \sum y_i y_i^T = A$$

Consistency:

$$\begin{array}{ccc} \bar{x} & \xrightarrow{p} & \mu \\ s_n & \xrightarrow{p} & \Sigma \end{array}$$

$$\bar{x}_i \xrightarrow{p} \mu_i$$