

Derivations

$$\frac{(x_k - \theta)^2}{2(x_k - \theta)(0-1)}$$

For Unknown mean, θ (u)

$$P(x_k | \theta) = \frac{1}{\sqrt{2\pi}^{d/2} |\Sigma|^{1/2}} \exp \left[-\frac{1}{2} (x_k - \theta)^t \Sigma^{-1} (x_k - \theta) \right]$$

Now, it's easier to maximize if we add \ln :

$$\ln P(x_k | \theta) = -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (x_k - \theta)^t \Sigma^{-1} (x_k - \theta)$$

Now do the partial derivation along with θ ,

$$\nabla_{\theta} P(x_k | \theta) = 0$$

$$\Rightarrow \frac{\partial}{\partial \theta} \left[-\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (x_k - \theta)^t \Sigma^{-1} (x_k - \theta) \right] = 0$$

$$\Rightarrow -\frac{1}{2} \Sigma^{-1} 2(x_k - \theta)(0-1) = 0$$

$$\Rightarrow \Sigma^{-1} (x_k - \theta) = 0$$

$$\Rightarrow \sum_{k=1}^n (x_k - \hat{\theta}) = 0$$

$$\Rightarrow n\hat{\theta} = \sum_{k=1}^n x_k$$

$$\Rightarrow \hat{\theta} = \frac{1}{n} \sum_{k=1}^n x_k$$

$$\begin{aligned} & \frac{\partial}{\partial \theta} \left(-\frac{1}{2} (x_k - \theta)^2 \Sigma^{-1} \right) \\ &= -\frac{1}{2} 2(x_k - \theta)(0-1) \Sigma^{-1} \\ &= (-1)(x_k - \theta)(-1) \Sigma^{-1} \\ &= \Sigma^{-1} (x_k - \theta) \end{aligned}$$

For unknown mean and variance,

$$\text{Let } \theta = [\mu, \sigma^2] \quad \theta_1 = \mu \quad \theta_2 = \sigma^2$$

$$\begin{aligned} \ln P(x_k | \theta) &= -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (x_k - \theta_1)^T \Sigma^{-1} (x_k - \theta_1) \\ &= -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln \theta_2 - \frac{1}{2} (x_k - \theta_1)^T \theta_2^{-1} (x_k - \theta_1) \end{aligned}$$

$$\nabla_{\theta} \ln P(x_k | \theta) = 0$$

$$\text{With respect to } \theta_1 = \frac{1}{\theta_2} (x_k - \theta_1) \quad \text{--- (i)}$$

$$\text{With respect to } \theta_2 = -\frac{1}{2} \theta_2 + \frac{1}{2\theta_2^2} (x_k - \theta_1)^2 \quad \text{--- (ii)}$$

From (i)

$$\sum_{k=1}^n \frac{1}{\theta_2} (x_k - \bar{\theta}_1) = 0$$

$$\Rightarrow \sum_{k=1}^n (x_k - \bar{\theta}_1) = 0$$

$$\Rightarrow n\bar{\theta}_1 = \sum_{k=1}^n x_k$$

$$\boxed{\bar{\theta}_1 = \mu = \frac{1}{n} \sum_{k=1}^n x_k}$$

From (ii)

$$\sum_{k=1}^n -\frac{1}{2\bar{\theta}_2} + \frac{(x_k - \bar{\theta}_1)^2}{2\bar{\theta}_2^2} = 0$$

$$\Rightarrow \sum_{k=1}^n \frac{(x_k - \bar{\theta}_1)^2}{2\bar{\theta}_2^2} = \sum_{k=1}^n \frac{1}{2\bar{\theta}_2}$$

$$\Rightarrow \sum_{k=1}^n (x_k - \bar{\theta}_1)^2 = \sum_{k=1}^n \frac{2\bar{\theta}_2^2}{2\bar{\theta}_2} = \sum_{k=1}^n \bar{\theta}_2$$

$$\sum_{k=1}^n \bar{\theta}_2 = \sum_{k=1}^n (x_k - \bar{\theta}_1)^2$$

$$\Rightarrow n\bar{\theta}_2 = \sum_{k=1}^n (x_k - \mu)^2$$

$$\Rightarrow \bar{\theta}_2 = \frac{1}{n} \sum_{k=1}^n (x_k - \mu)^2$$

$$\boxed{\sigma^2 = \frac{1}{n} \sum_{k=1}^n (x_k - \mu)^2}$$

Proved