Robotics

Estimation and Learning with Dan Lee

Supplementary Notes on MLE for Multivariate Gaussian



Objective

Estimate the mean and the variance given observed data

$$\widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}} = \arg\max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} p(\{\mathbf{x}_i\} | \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Assuming independence of observations,

$$\widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}} = \arg\max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} \prod_{i=1}^{N} p(\mathbf{x}_i | \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

• To obtain $\widehat{\mu}$, $\widehat{\Sigma} = \arg\max_{\mu,\Sigma} \prod_{i=1}^{n} p(\mathbf{x}_i | \mu, \Sigma)$

(1)
$$\arg \max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} \prod_{i=1}^{N} p(\mathbf{x}_i | \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \arg \max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} \sum_{i=1}^{N} \ln p(\mathbf{x}_i | \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

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

$$\widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}} = \arg\max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} \prod_{i=1}^{N} p(\mathbf{x}_{i} | \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

$$= \arg\max_{\boldsymbol{\mu}, \boldsymbol{\sigma}} \sum_{i=1}^{N} \ln p(\mathbf{x}_{i} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) \qquad \text{from (1)}$$

$$= \arg\max_{\boldsymbol{\mu}, \boldsymbol{\sigma}} \sum_{i=1}^{N} \left\{ -\frac{1}{2} (\mathbf{x}_{i} - \boldsymbol{\mu})^{T} \boldsymbol{\Sigma}^{-1} (\mathbf{x}_{i} - \boldsymbol{\mu}) - \frac{1}{2} \ln|\boldsymbol{\Sigma}| + c \right\}$$
from (2)
$$= \arg\min_{\boldsymbol{\mu}, \boldsymbol{\sigma}} \sum_{i=1}^{N} \left\{ \frac{1}{2} (\mathbf{x}_{i} - \boldsymbol{\mu})^{T} \boldsymbol{\Sigma}^{-1} (\mathbf{x}_{i} - \boldsymbol{\mu}) + \frac{1}{2} \ln|\boldsymbol{\Sigma}| \right\}$$

Let
$$J(\mu, \Sigma) = \sum_{i=1}^{N} \left\{ \frac{1}{2} (\mathbf{x}_i - \mu)^T \Sigma^{-1} (\mathbf{x}_i - \mu) + \frac{1}{2} \ln|\Sigma| \right\}$$

Then
$$\widehat{\mu}$$
, $\widehat{\Sigma} = \arg\min_{\mu,\Sigma} J(\mu, \Sigma)$

①
$$\frac{\partial J}{\partial \mu} = \mathbf{0} \longrightarrow \widehat{\mu}$$
 ② $\frac{\partial J(\widehat{\mu}, \Sigma)}{\partial \Sigma} = 0 \longrightarrow \widehat{\Sigma}$

$$\frac{\partial J}{\partial \boldsymbol{\mu}} = \frac{\partial}{\partial \boldsymbol{\mu}} \sum_{i=1}^{N} \left\{ \frac{1}{2} (\mathbf{x}_{i} - \boldsymbol{\mu})^{T} \boldsymbol{\Sigma}^{-1} (\mathbf{x}_{i} - \boldsymbol{\mu}) + \frac{1}{2} |\boldsymbol{\Sigma}| \right\}$$

$$= \frac{\partial}{\partial \boldsymbol{\mu}} \sum_{i=1}^{N} \left\{ \frac{1}{2} \boldsymbol{\mu}^{T} \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu} - \boldsymbol{\mu}^{T} \boldsymbol{\Sigma}^{-1} \mathbf{x}_{i} \right\}$$

$$= \boldsymbol{\Sigma}^{-1} \sum_{i=1}^{N} \{ \boldsymbol{\mu} - \mathbf{x}_{i} \} = \mathbf{0} \qquad \widehat{\boldsymbol{\mu}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}_{i}$$

$$\widehat{\Sigma} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}})^{\mathsf{T}} \\
\frac{\partial J}{\partial \Sigma} = \frac{\partial}{\partial \Sigma} \sum_{i=1}^{N} \left\{ \frac{1}{2} (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}})^{\mathsf{T}} \Sigma^{-1} (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}}) + \frac{1}{2} \ln|\Sigma| \right\} \\
= \frac{1}{2} \sum_{i=1}^{N} \left\{ -\Sigma^{-1} (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}}) (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}})^{\mathsf{T}} \Sigma^{-1} + \Sigma^{-1} \right\} \\
= \frac{1}{2} \Sigma^{-1} \left[-\left\{ \sum_{i=1}^{N} (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}}) (\mathbf{x}_{i} - \widehat{\boldsymbol{\mu}})^{\mathsf{T}} \right\} \Sigma^{-1} + N \cdot \mathbf{I} \right] = 0$$

In summary, we have

$$\widehat{\mathbf{\mu}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}_{i}$$

$$\widehat{\Sigma} = \frac{1}{N} \sum_{i=1}^{N} (\mathbf{x}_i - \widehat{\boldsymbol{\mu}}) (\mathbf{x}_i - \widehat{\boldsymbol{\mu}})^{\mathsf{T}}$$