

## 极大似然估计

• Data:  $X = (x_1, x_2, \dots, x_N)^T = \begin{pmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_N^T \end{pmatrix}_{N \times p}$

$$x_i \in \mathbb{R}^p$$

$$x_i \stackrel{iid}{\sim} N(\mu, \Sigma)$$

$$\theta = (\mu, \Sigma)$$

点估计

• MLE:  $\theta_{MLE} = \arg \max_{\theta} P(x|\theta)$   $\begin{cases} P(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \\ P(x) = \frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)} \end{cases}$

$\Sigma = I \quad \theta = (\mu, \sigma^2)$

$$\log P(x|\theta) = \log \prod_{i=1}^N P(x_i|\theta) = \sum_{i=1}^N \log P(x_i|\theta)$$

$$= \sum_{i=1}^N \log \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}$$

$$= \sum_{i=1}^N \left[ \log \frac{1}{\sqrt{2\pi}} - \frac{(x_i-\mu)^2}{2\sigma^2} + \log \frac{1}{\sigma} \right]$$

①  $\mu_{MLE} = \arg \max_{\mu} \log P(x|\theta)$

$$= \arg \max_{\mu} \sum \frac{(x_i - \mu)^2}{2\sigma^2}$$

$$= \arg \max_{\mu} \sum (x_i - \mu)^2$$

$$\frac{\partial \sum (x_i - \mu)^2}{\partial \mu} = \sum 2(x_i - \mu)(-1) = 0$$

$$\sum (x_i - \mu) = 0 \Rightarrow \sum x_i - \sum \mu = 0$$

$$\mu_{MLE} = \frac{1}{N} \sum_{i=1}^N x_i$$

无偏  $E[\mu_{MLE}] = \frac{1}{N} \sum E[x_i]$

$$= \frac{1}{N} \sum E[x_i] = \frac{1}{N} \sum \mu = \mu$$

$$\text{Var}[\mu_{MLE}] = \text{Var}\left[\frac{1}{N} \sum x_i\right] = \frac{1}{N^2} \text{Var}(\sum x_i^2) = \frac{1}{N^2} \sum \sigma^2 = \frac{1}{N} \sigma^2$$

$$② \hat{\sigma}_{MLE}^2 = \arg \max_{\sigma^2} P(\mathbf{d}|\theta)$$

$$= \arg \max_{\sigma^2} \left[ \log \frac{1}{\sigma^2} - \frac{(\mathbf{d}-\mu)^2}{2\sigma^2} \right]$$

$$= \arg \max_{\sigma^2} \left[ -\log \sigma^2 - \frac{(\mathbf{d}-\mu)^2}{2\sigma^2} \right]$$

$L$

$$\frac{\partial L}{\partial \sigma^2} = \left[ \frac{-1}{\sigma^2} + (\mathbf{d}_i - \mu)^2 \sigma^{-3} \right] = 0$$

$$\sum \left[ -\sigma^2 + (\mathbf{d}_i - \mu)^2 \right] = 0$$

$$N \sigma^2 = \sum (\mathbf{d}_i - \mu)^2$$

$$\boxed{\hat{\sigma}_{MLE}^2 = \frac{1}{N} \sum (\mathbf{d}_i - \mu)^2} \rightarrow \text{有偏估计}$$

$$E[\hat{\sigma}_{MLE}^2] = \frac{N-1}{N} \sigma^2 < \text{真实的参数}$$

$$\text{无偏: } \hat{\sigma}^2 = \frac{1}{N-1} \sum (\mathbf{d}_i - \mu_{MLE})^2$$

$$E[\hat{\sigma}_{MLE}^2] = E\left[\frac{1}{N} \sum \mathbf{d}_i^2 - \mu_{MLE}^2\right]$$

$$= E\left[\frac{1}{N} \sum \mathbf{d}_i^2 - \mu^2 - (\mu_{MLE}^2 - \mu^2)\right]$$

$$= E\left[\frac{1}{N} \sum \mathbf{d}_i^2 - \mu^2\right] - E[\mu_{MLE}^2 - \mu^2]$$

$$= E\left[\frac{1}{N} \sum (\mathbf{d}_i^2 - \mu^2)\right] - [E[\mu_{MLE}^2] - E(\mu^2)]$$

$$= \frac{1}{N} \sum E(\mathbf{d}_i^2 - \mu^2) - [E(\mu_{MLE}^2) - \mu^2]$$

$$= \frac{1}{N} \sum [E[\mathbf{d}_i^2] - \mu^2] - \text{Var}[\mu_{MLE}]$$

$$= \frac{1}{N} \sum \text{Var}(\mathbf{d}_i) - \frac{1}{N} \sigma^2$$

$$= \sigma^2 - \frac{1}{N} \sigma^2$$

$$= \boxed{\frac{N-1}{N}} \sigma^2 \text{ 有偏: 比真实的小. (估计值)} \quad \text{有偏: 比真实的小. (估计值)}$$

