

无偏估计 刘子源 2023/10/09

11.1, 3, 4, 9, 16

11.4. $p(A) = \begin{cases} \lambda e^{-\lambda A} & A > 0 \\ 0 & \text{其他} \end{cases}$ $x[n] = A + w[n]$ $w[n] \sim \mathcal{N}(0, \sigma^2)$

~~$p(A|x) = \frac{p(A)p(x|A)}{p(x)}$~~

$\hat{A} = \arg \max_A p(A) p(x|A)$

$= \arg \max_A (\ln p(A) + \ln p(x|A)) \triangleq \arg \max_A$

$l(A) = \begin{cases} -\frac{N}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_n (x[n] - A)^2 + \ln \lambda - \lambda A & (A > 0) \\ 0 & (A \leq 0) \end{cases}$

~~$\frac{\partial \ln A}{\partial A}$~~ $\frac{\partial l(A)}{\partial A} = \frac{1}{\sigma^2} \sum_n (x[n] - A) - \lambda = 0$

$\Rightarrow \hat{A} = \begin{cases} \bar{x} - \frac{\sigma^2}{N} \lambda & \hat{A} > 0 \\ 0 & \hat{A} \leq 0 \end{cases}$

即 $\hat{A} = \max\{\bar{x} - \frac{\sigma^2}{N} \lambda, 0\}$

11.1) $p(x[n]|\mu) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2\sigma^2} (x[n] - \mu)^2\right\}$

$\mu \sim \mathcal{N}(\mu_0, \sigma_0^2)$

MUSE: $\hat{\mu}_{MUSE} = \frac{\sigma_0^2}{\sigma_0^2 + \frac{\sigma^2}{N}} \bar{x} + \frac{\frac{\sigma^2}{N}}{\sigma_0^2 + \frac{\sigma^2}{N}} \mu_0$

MAP: 已知先验分布的PDF也是Gaussian的. 则

$\hat{\mu}_{MAP} = \hat{\mu}_{MUSE}$

$\sigma_0^2 \rightarrow 0$ 时 $\hat{\mu} \rightarrow \mu_0$ 先验主导

$\sigma_0^2 \rightarrow \infty$ 时, $\hat{\mu} \rightarrow \bar{x}$ 观测主导

11.3 $p(\theta|x) = \begin{cases} \exp[-(\theta-x)], & \theta > x \\ 0, & \theta < x \end{cases}$

MUSE: $\hat{\theta} = \int_x^\infty \theta e^{-(\theta-x)} d\theta = x + 1$

MAP: $\hat{\theta} = \arg \max_{\theta} p(\theta|x) = x$

$$\theta[n] = \begin{bmatrix} x[n] \\ y[n] \\ v_x \\ v_y \end{bmatrix} = \begin{bmatrix} x[n-1] + v_x \\ y[n-1] + v_y \\ v_x \\ v_y \end{bmatrix}$$

$$\text{因为 } x[n] - x[n-1] = v_x, y[n] - y[n-1] = v_y$$

$$\text{则 } \theta[n] = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x[n-1] \\ y[n-1] \\ v_x \\ v_y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \theta[n-1]$$

$$\text{则 } \hat{\theta}[n] = A^n \hat{\theta}[0], A = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

\hat{A} 得到的益处更多, 因为
 $\sum n^2$ 对 Bmse 造成的衰减比 N 更大

$$11.16 \quad x[n] = A + Bn + w[n], \quad -M \leq n \leq M$$

$$\begin{bmatrix} A \\ B \end{bmatrix} \sim N \left(\begin{bmatrix} A_0 \\ B_0 \end{bmatrix}, \begin{bmatrix} \sigma_A^2 & 0 \\ 0 & \sigma_B^2 \end{bmatrix} \right), w[n] \sim N(0, \sigma^2)$$

由书上 (11.33) 可知

$$\hat{\theta} = \mu_0 + (C_0^{-1} + H^T C_w^{-1} H)^{-1} H^T C_w^{-1} (x - H \mu_0)$$

$$\mu_0 = \begin{bmatrix} A_0 \\ B_0 \end{bmatrix}, C_0 = \begin{bmatrix} \sigma_A^2 & 0 \\ 0 & \sigma_B^2 \end{bmatrix}, H = \begin{bmatrix} 1 & -M \\ 1 & -M+1 \\ \vdots & \vdots \\ 1 & M \end{bmatrix}, C_w = \sigma^2 I$$

$$\text{则 } H^T C_w^{-1} H + C_0^{-1} = \begin{bmatrix} \frac{1}{\sigma_A^2} + \frac{N}{\sigma^2} & 0 \\ 0 & \frac{1}{\sigma_B^2} + \frac{\sum n^2}{\sigma^2} \end{bmatrix}$$

$$(H^T C_w^{-1} H + C_0^{-1})^{-1} = \begin{bmatrix} \frac{1}{\frac{1}{\sigma_A^2} + \frac{N}{\sigma^2}} & 0 \\ 0 & \frac{1}{\frac{1}{\sigma_B^2} + \frac{\sum n^2}{\sigma^2}} \end{bmatrix}$$

$$\hat{A} = A_0 + \frac{\frac{N}{\sigma^2}}{\frac{1}{\sigma_A^2} + \frac{N}{\sigma^2}} (\bar{x} - A_0)$$

$$B_{\text{mse}}(\hat{A}) = 1 / \left(\frac{1}{\sigma_A^2} + \frac{N}{\sigma^2} \right)$$

$$\hat{B} = B_0 + \frac{\frac{\sum n^2}{\sigma^2}}{\frac{1}{\sigma_B^2} + \frac{\sum n^2}{\sigma^2}} \left[\frac{\sum n x[n]}{\sum n^2} - B_0 \right]$$

$$B_{\text{mse}}(\hat{B}) = 1 / \left(\frac{1}{\sigma_B^2} + \frac{\sum n^2}{\sigma^2} \right)$$