



中国科学院大学

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Lecture 11

Bayes估计

LECTURE10

- 随机参量信号检测

- 有PD：复合假设检验，计算平均似然函数/似然比
- 无PDF：估计+检测（广义似然比）或条件似然比

- 随机信号检测（高斯）

白信号：能量检测器 $T(Y) = \sum_{i=1}^M y_i^2 \stackrel{H_1}{\geq} th'$

有色噪声：估计-检测器 $T(Y) = Y^T \hat{S} = Y^T C_s (C_s + \sigma^2 I)^{-1} Y$



估计背景

- 参量估计
- 理论框架
- 估计性能
- 参量随机/非随机





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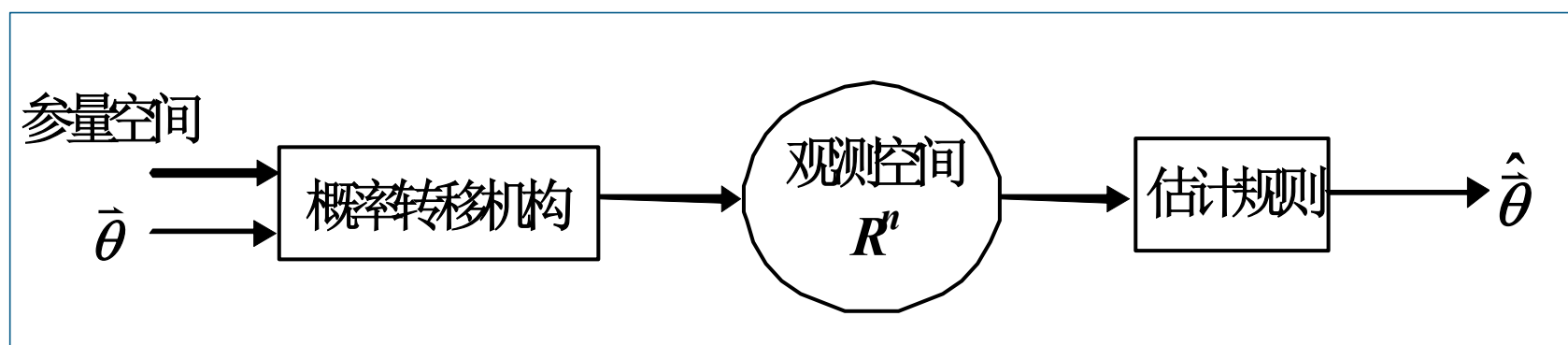
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最小均方误差估计

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估计模型

- 参量空间
- 概率映射
- 观测空间
- 估计规则



估计性能

- 数学期望（无偏性）

$$E\{\hat{\theta}\} = E\{\theta\}$$

- 方差（有效性）
- 均方误差矩阵
- 充分性





重复上节例题

$H_1: Y=A+N; H_0: Y=N$ 。 A 未知。 高斯白噪声。 求检验准则。

$$f(\vec{Y} \mid A) = \left(\prod_{k=1}^N \frac{1}{\sqrt{2\pi}\sigma_n} \right) \exp \left\{ \sum_{k=1}^N -\frac{1}{2\sigma_n^2} (y_k - A)^2 \right\}$$

$$ML \text{ 方程: } \frac{\partial}{\partial A} \ln f(\vec{Y} \mid A) \Big| = 0, \text{ 即 } \sum_{k=1}^N \frac{1}{\sigma_n^2} (y_k - A) \Big| = 0 \Rightarrow \hat{A} = \frac{1}{N} \sum_{k=1}^N y_k$$

$$E(\hat{A}) = E \left[\frac{1}{N} \sum_{k=1}^N (A + n_k) \right] = A$$

$$E \left[(A - \hat{A})^2 \right] = E \left[\left(\frac{1}{N} \sum_{k=1}^N n_k \right)^2 \right] = \frac{\sigma_n^2}{N}$$





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Bayes估计

- 每次估计的条件风险代价

$$R(\theta) = \int C(\hat{\theta}(Y), \theta) f(Y|\theta) dY$$

- 平均风险代价

$$\bar{C} = \int R(\theta) f(\theta) d\theta = \int f(Y) dY \int C(\hat{\theta}(Y), \theta) f(\theta|Y) d\theta$$

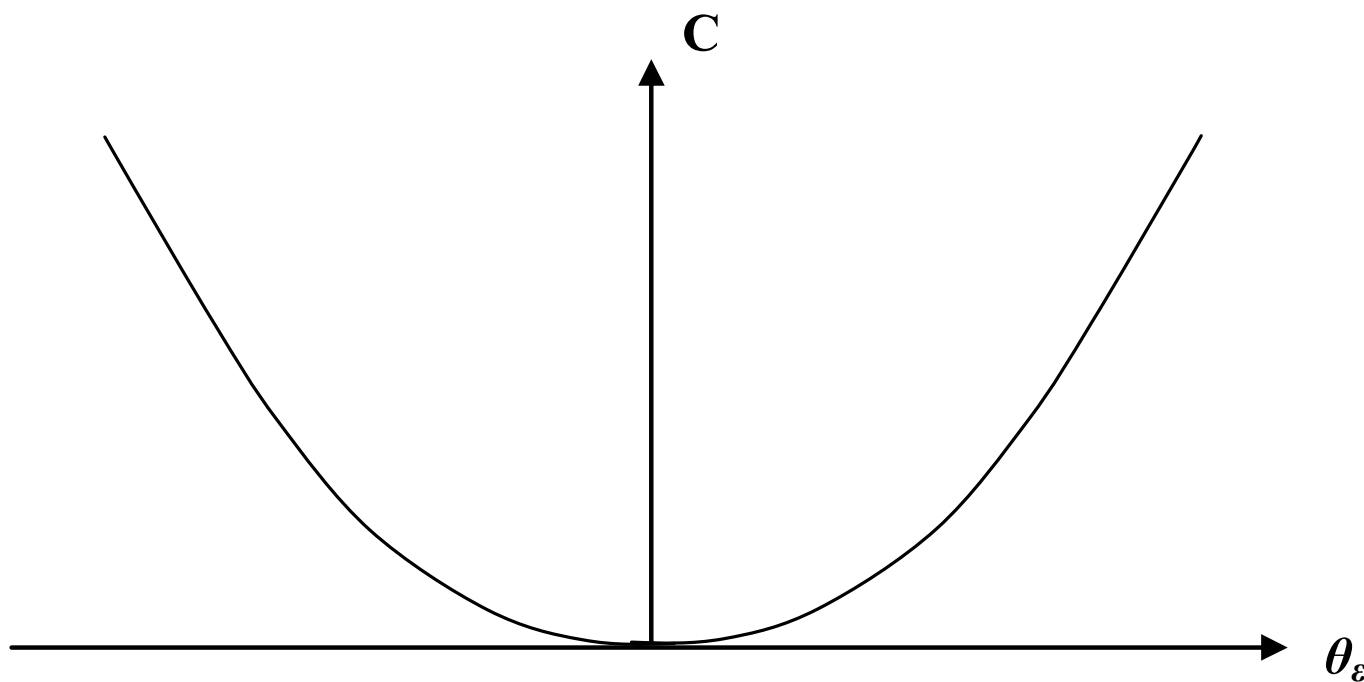
- Bayes估计

$$\hat{\theta} \rightarrow \min \{ \bar{C}(\hat{\theta}, \theta) \}$$



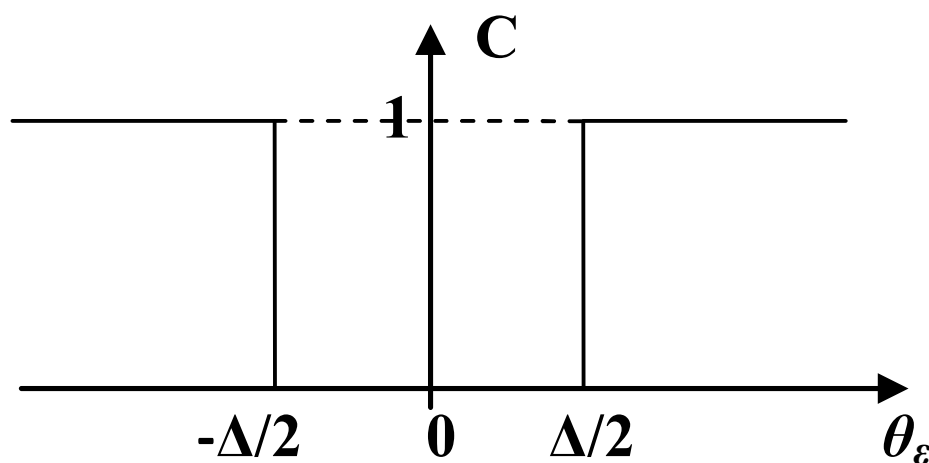
误差平方代价函数

$$c(\hat{\theta}) = c[\theta - \hat{\theta}(y)] = [\theta - \hat{\theta}(y)]^2 = \theta_{\varepsilon}^2$$



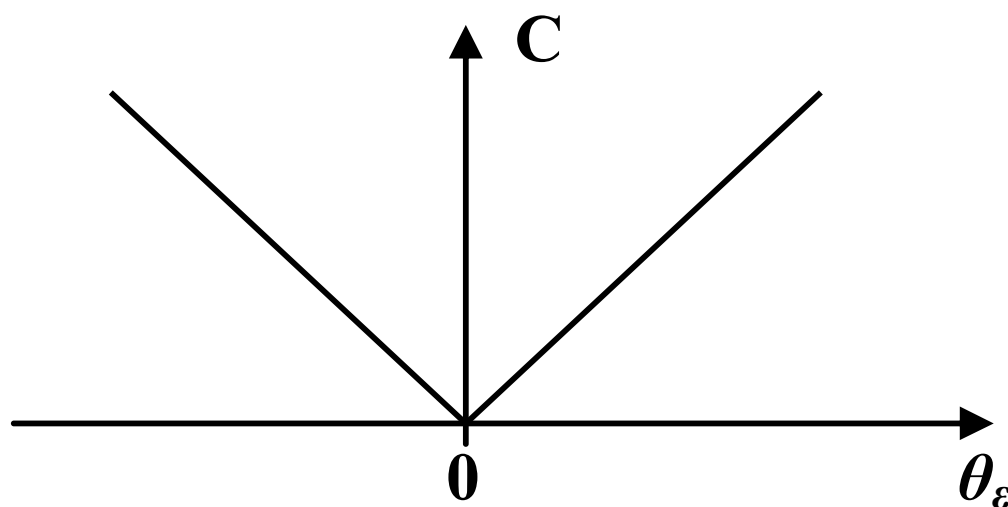
均匀代价函数

$$C(\hat{\theta}) = C[\theta - \hat{\theta}(y)] = \begin{cases} 1, & |\theta - \hat{\theta}(y)| \geq \frac{\Delta}{2} \\ 0, & |\theta - \hat{\theta}(y)| < \frac{\Delta}{2} \end{cases}$$



误差绝对值代价函数

$$C(\hat{\theta}) = C[\theta - \hat{\theta}(y)] = |\theta - \hat{\theta}(y)|$$





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MAP检测到MAP估计

- 离散待估参量 θ
- 多元假设检验 $H_i: \theta=\theta_i$
- MAP检测判决:

$P(H_{i_0} \setminus Y) \geq P(H_i \setminus Y)$ 判 H_{i_0} 为真

- MAP估计:

$$K \rightarrow \infty : f\left(\hat{\theta}_{MAP} \setminus Y\right) = \max_{\theta} f\left(\theta \setminus Y\right)$$



MAP估计(随机待估参量)

- MAP方程:

$$\left. \frac{\partial}{\partial \theta} f(\theta \setminus Y) \right|_{\theta = \hat{\theta}_{MAP}} = 0$$

$$\Leftrightarrow \left. \frac{\partial}{\partial \theta} [\ln f(Y \setminus \theta) + \ln f(\theta)] \right|_{\theta = \hat{\theta}_{MAP}} = 0$$



MAP估计代价

平均代价

$$\bar{C} = \int_{-\infty}^{\infty} f(Y) dY \left[\int_{-\infty}^{\hat{\theta} - \frac{\Delta}{2}} f(\theta | Y) d\theta + \int_{\hat{\theta} + \frac{\Delta}{2}}^{\infty} f(\theta | Y) d\theta \right]$$

$$= \int_{-\infty}^{\infty} f(Y) dY \left[1 - \int_{\hat{\theta} - \frac{\Delta}{2}}^{\hat{\theta} + \frac{\Delta}{2}} f(\theta | Y) d\theta \right]$$

$$\min \bar{C} \Leftrightarrow \max f(\theta | Y) \Rightarrow MAP \text{ 准则}$$



ML方程（非随机参量）

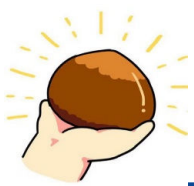
- 最大似然判决准则：

$$\frac{f(Y \setminus H_{i_0})}{f(Y \setminus H_i)} \geq 1, \text{ 判为 } H_{i_0}$$

- 最大似然估计方程：

$$\left. \frac{\partial}{\partial \theta} [\ln f(Y \setminus \theta)] \right|_{\theta = \hat{\theta}_{ML}} = 0$$





观测数据为 $y_k = m + n_k$, $k=1, 2, \dots, N$, m 为待估参量, 均值为零, 方差 σ_θ^2 , 高斯分布; $\{n_k\}$ 为独立于 m 的均值为零、方差 σ_n^2 的高斯噪声。

解:

$$m \text{ 的先验分布 } f(m) = \frac{1}{\sqrt{2\pi}\sigma_\theta} \exp\left\{-\frac{m^2}{2\sigma_\theta^2}\right\}$$

$$\text{观测矢量 } \vec{Y} = [y_1, y_2, \dots, y_N]^T$$

$$\text{似然函数 } f(\vec{Y} | m) = \left(\frac{1}{\sqrt{2\pi}\sigma_n}\right)^N \exp\left\{-\frac{1}{2\sigma_n^2} \sum_{k=1}^N (y_k - m)^2\right\}$$





后验概率

$$f(m|\vec{Y}) = \frac{f(\vec{Y}|m)f(m)}{f(\vec{Y})}$$

$$= \frac{f(\vec{Y}|m)f(m)}{\int_{-\infty}^{\infty} f(\vec{Y}|m)f(m)dm}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_p} \exp \left\{ -\frac{1}{2\sigma_p^2} \left(m - \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_n^2/N} \bar{y} \right)^2 \right\}$$

$$\Rightarrow \hat{m}_{MAP} = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_n^2/N} \bar{y}$$

$$\text{其中} \begin{cases} \sigma_p^2 = \frac{\sigma_\theta^2 \cdot \sigma_n^2}{N\sigma_\theta^2 + \sigma_n^2} \\ \bar{y} = \frac{1}{N} \sum_{k=1}^N y_k \end{cases}$$





雷达测距系统，目标真实距离为 m ，由于噪声的干扰，每次测量的结果为 $y_k = m + n_k$ ， $k=1, 2, \dots, N$ ， n_k 为均值零、方差 σ_n^2 的高斯干扰或噪声。 N 次独立观测。

$$f(\vec{Y} | m) = \left(\prod_{k=1}^N \frac{1}{\sqrt{2\pi}\sigma_k} \right) \exp \left\{ \sum_{k=1}^N -\frac{1}{2\sigma_k^2} (y_k - m)^2 \right\}$$

$$ML \text{ 方程: } \left. \frac{\partial}{\partial m} \ln f(\vec{Y} | m) \right|_{m=\hat{m}_{ML}} = 0, \quad \text{即} \quad \left. \sum_{k=1}^N \frac{1}{2\sigma_k^2} (y_k - m) \right|_{m=\hat{m}_{ML}} = 0$$

$$\Rightarrow \hat{m}_{ML} = \frac{\sum_{k=1}^N \frac{y_k}{\sigma_k^2}}{\sum_{k=1}^N \frac{1}{\sigma_k^2}} \xrightarrow{\text{方差相等}} \frac{1}{N} \sum_{k=1}^N y_k$$



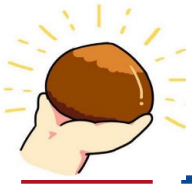
对噪声中正弦序列信号的相位进行估计。设观测为 $y_k = A \cos(k\omega_0 + \varphi) + n_k$, $k=1, 2, \dots, N$, 幅度 A 和频率 f_0 为已知的, 噪声是方差为 σ_n^2 的高斯白噪声。

$$f(Y \setminus \varphi) = \frac{1}{(2\pi\sigma_n^2)^{\frac{N}{2}}} \exp \left\{ \sum_{k=1}^N -\frac{1}{2\sigma_n^2} [y_k - A \cos(2\pi k f_0 + \varphi)]^2 \right\}$$

$$\frac{\partial}{\partial \varphi} \ln f(Y \setminus \varphi) = 0,$$

$$\text{即} \left[2 \sum_{k=1}^N [y_k - A \cos(2\pi k f_0 + \varphi)] A \sin(2\pi k f_0 + \varphi) \right] = 0$$





$$\Rightarrow \sum_{k=1}^N y_k \sin(2\pi k f_0 + \hat{\varphi}) = A \sum_{k=1}^N \sin(4\pi k f_0 + 2\hat{\varphi}) \approx 0$$

$$\Rightarrow \sum_{k=1}^N y_k \sin(2\pi k f_0) \cos \hat{\varphi} = \sum_{k=1}^N y_k \cos(2\pi k f_0) \sin \hat{\varphi}$$

$$\Rightarrow \hat{\varphi} = \arctan \frac{\sum_{k=1}^N y_k \sin(2\pi k f_0)}{\sum_{k=1}^N y_k \cos(2\pi k f_0)}$$





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Minimum Mean Square Error(MMSE)

- 估计误差

$$\theta_{\varepsilon} = \hat{\theta} - \theta$$

- 代价函数

$$C(\hat{\theta}, \theta) = \theta_{\varepsilon}^T \theta_{\varepsilon}$$

- 条件平均风险

$$R(\theta) = \int C(\hat{\theta}(Y), \theta) f(Y|\theta) dY$$



Minimum Mean Square Error(MMSE)

- 平均代价

$$\begin{aligned}\bar{C}_{MS} &= \int R(\theta) f(\theta) d\theta \\ &= \int f(Y) dY \int C(\hat{\theta}(Y), \theta) f(\theta|Y) d\theta \\ &= \int f(Y) dY \int [\hat{\theta}(Y) - \theta]^T [\hat{\theta}(Y) - \theta] f(\theta|Y) d\theta\end{aligned}$$

- MMSE估计方程

$$\frac{\partial}{\partial \hat{\theta}} \bar{C}_{MS} = 0 \Rightarrow \hat{\theta}_{MS}(Y) = \int \theta f(\theta|Y) d\theta$$





雷达测距系统，目标真实距离为 m ，由于噪声的干扰，观测数据为 $y_k = m + n_k$ ， $k=1, 2, \dots, N$ ， m 为待估参量，均值为零，方差 σ_θ^2 ，高斯分布； $\{n_k\}$ 为独立于 m 的均值零、方差 σ_n^2 的高斯噪声。 N 次独立观测。MMSE估计。

解：

$$f(m | \vec{Y}) = \frac{1}{\sqrt{2\pi}\sigma_p} \exp \left\{ -\frac{1}{2\sigma_p^2} \left(m - \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_n^2/N} \bar{y} \right)^2 \right\}$$

$$\Rightarrow \hat{m}_{MMSE} = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_n^2/N} \bar{y} = \hat{m}_{MAP}$$



无偏性

$$\begin{aligned} E\{\hat{\theta}_{MS}(Y)\} &= \int_{(Y)} \left[\int_{(\theta)} \theta f(\theta|Y) d\theta \right] f(Y) dY \\ &= \int_{(\theta)} \theta \int_{(Y)} f(\theta, Y) dY d\theta \\ &= \int_{(\theta)} \theta f(\theta) d\theta \\ &= E\{\theta\} \end{aligned}$$





傅里叶分析。 数据模型表示为 $y_k = a \cos k\omega_0 + b \sin k\omega_0 + n_k$, $k=1 \dots N$, f_0 为 $(1/N)$ 的倍数。 a 和 b 为待估参量, 均值为零, 方差 σ_θ^2 , 高斯分布; $\{n_k\}$ 为独立于 m 的均值零、方差 σ_n^2 的高斯噪声。**N次独立观测。**
MMSE估计。

$$Y = H\theta + N$$
$$H = \begin{bmatrix} \cos \omega_0 & \sin \omega_0 \\ \cos 2\omega_0 & \sin 2\omega_0 \\ \vdots & \vdots \\ \cos N\omega_0 & \sin N\omega_0 \end{bmatrix}$$

$$\theta = [a \quad b]^T$$
$$E\{\theta\} = 0$$
$$C_\theta = \sigma_\theta^2 I$$
$$C_n = \sigma_n^2 I$$





$$f(Y|\theta) \sim N(H\theta, C_n)$$

$$f(\theta) \sim N(0, C_\theta)$$

$$\text{由 } \frac{\partial}{\partial \theta} [\ln f(Y|\theta) + \ln f(\theta)] \Big|_{\theta=\hat{\theta}_{MAP}} = 0$$

$$\text{针对 } \frac{1}{(2\pi)^N |C_n|^{1/2}} \exp \left\{ -\frac{1}{2} [(Y - H\theta)^T C_n^{-1} (Y - H\theta)] \right\} \frac{1}{|C_\theta|^{1/2}} \exp \left\{ -\frac{1}{2} [\theta^T C_\theta^{-1} \theta] \right\}$$

取对数后求导得

$$H^T C_n^{-1} [Y - H\hat{\theta}] = C_\theta^{-1} \hat{\theta} \Rightarrow H^T C_n^{-1} Y = [H^T C_n^{-1} H + C_\theta^{-1}] \hat{\theta}$$





$$\begin{bmatrix} \cos \omega_0 & \cos 2\omega_0 & \cdots & \cos N\omega_0 \\ \sin \omega_0 & \sin 2\omega_0 & \cdots & \sin N\omega_0 \end{bmatrix} \begin{bmatrix} 1/\sigma_n^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1/\sigma_n^2 \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} \\
 = \left\{ \begin{bmatrix} \cos \omega_0 & \cos 2\omega_0 & \cdots & \cos N\omega_0 \\ \sin \omega_0 & \sin 2\omega_0 & \cdots & \sin N\omega_0 \end{bmatrix} \begin{bmatrix} 1/\sigma_n^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1/\sigma_n^2 \end{bmatrix} \begin{bmatrix} \cos \omega_0 & \sin \omega_0 \\ \cos 2\omega_0 & \sin 2\omega_0 \\ \vdots & \vdots \\ \cos N\omega_0 & \sin N\omega_0 \end{bmatrix} + \begin{bmatrix} 1/\sigma_\theta^2 & 0 \\ 0 & 1/\sigma_\theta^2 \end{bmatrix} \right\} \begin{bmatrix} a \\ b \end{bmatrix}$$

由 **DFT** 正交性

$$\begin{cases} \sum_{n=1}^N \cos\left(\frac{2\pi in}{N}\right) \cos\left(\frac{2\pi jn}{N}\right) = \frac{N}{2} \delta_{ij} \\ \sum_{n=1}^N \sin\left(\frac{2\pi in}{N}\right) \sin\left(\frac{2\pi jn}{N}\right) = \frac{N}{2} \delta_{ij} \\ \sum_{n=1}^N \cos\left(\frac{2\pi in}{N}\right) \sin\left(\frac{2\pi jn}{N}\right) = 0 \end{cases}$$





$$\frac{1}{\sigma_n^2} \begin{bmatrix} \sum_{k=1}^N y_k \cos k\omega_0 \\ \sum_{k=1}^N y_k \sin k\omega_0 \end{bmatrix} = \begin{bmatrix} \frac{N}{2\sigma_n^2} + \frac{1}{\sigma_\theta^2} & 0 \\ 0 & \frac{N}{2\sigma_n^2} + \frac{1}{\sigma_\theta^2} \end{bmatrix} \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix}$$

$$\text{其中 } \frac{\frac{1}{\sigma_n^2}}{\frac{N}{2\sigma_n^2} + \frac{1}{\sigma_\theta^2}} = \frac{1}{\frac{N}{2} + \frac{\sigma_n^2}{\sigma_\theta^2}}$$

$$\Rightarrow \hat{\theta} = \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = \frac{\frac{2}{N}}{1 + \frac{2\sigma_n^2/N}{\sigma_\theta^2}} \begin{bmatrix} \sum_{k=1}^N y_k \cos k\omega_0 \\ \sum_{k=1}^N y_k \sin k\omega_0 \end{bmatrix}$$



条件中值估计

误差绝对值代价函数

$$\begin{aligned}\bar{C} &= \int R(\theta) f(\theta) d\theta = \int_{-\infty}^{\infty} f(Y) dY \int |\hat{\theta}(Y) - \theta| f(\theta | Y) d\theta \\ &= \int_{-\infty}^{\hat{\theta}} (\hat{\theta}(Y) - \theta) f(\theta | Y) d\theta + \int_{\hat{\theta}}^{\infty} (\theta - \hat{\theta}(Y)) f(\theta | Y) d\theta\end{aligned}$$

求导等于零，可得

$$\int_{-\infty}^{\hat{\theta}} f(\theta | Y) d\theta = \int_{\hat{\theta}}^{\infty} f(\theta | Y) d\theta$$





线性观测： $x=m+n$ ， m 为待估参量，在 $[-A, A]$ 区间均匀分布； n 为独立于 m 的均值零、方差 σ_n^2 的高斯噪声。**MAP和MMSE估计。**

$$f(x \setminus m) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp \left\{ -\frac{(x-m)^2}{2\sigma_n^2} \right\}$$

$$f(m) = \begin{cases} \frac{1}{2A} & -A \leq m \leq A \\ 0 & \text{其它} \end{cases}$$





$$\hat{\theta}_{MS}(Y) = \int \theta f(\theta | Y) d\theta$$

$$\begin{aligned}\hat{m}_{MS} &= \frac{\int m f(x | m) f(m) dm}{f(x)} = \frac{\int_{-\infty}^{\infty} m f(x | m) f(m) dm}{\int_{-\infty}^{\infty} f(x | m) f(m) dm} \\ &= \frac{\int_{-\infty}^{\infty} m \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(x-m)^2}{2\sigma_n^2}\right] \frac{1}{2A} dm}{\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left[-\frac{(x-m)^2}{2\sigma_n^2}\right] \frac{1}{2A} dm}\end{aligned}$$





$$\begin{aligned}\hat{m}_{MS} &= \frac{\int_{-\infty}^{\infty} m \exp\left[-\frac{(x-m)^2}{2\sigma_n^2}\right] dm}{\int_{-\infty}^{\infty} \exp\left[-\frac{(x-m)^2}{2\sigma_n^2}\right] dm} = x - \frac{\sigma_n \int_{(x/\sigma_n - A/\sigma_n)^2/2}^{(x/\sigma_n + A/\sigma_n)^2/2} \exp(-v) dv}{\sqrt{2\pi} \int_{x/\sigma_n - A/\sigma_n}^{x/\sigma_n + A/\sigma_n} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) du} \\ &= x - \frac{\sigma_n \left\{ \exp\left[-\frac{(x/\sigma_n - A/\sigma_n)^2}{2}\right] - \exp\left[-\frac{(x/\sigma_n + A/\sigma_n)^2}{2}\right] \right\}}{\sqrt{2\pi} \left[Q\left(x/\sigma_n + A/\sigma_n\right) - Q\left(x/\sigma_n - A/\sigma_n\right) \right]}\end{aligned}$$

$$\text{令 } u = \frac{x-m}{\sigma_n}, \quad v = \frac{u^2}{2}$$

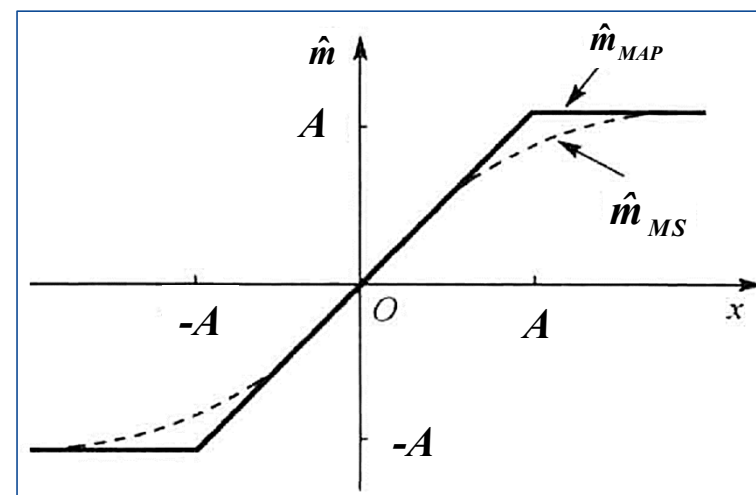




$$\left. \frac{\partial}{\partial \theta} [\ln f(Y \setminus \theta) + \ln f(\theta)] \right|_{\theta = \hat{\theta}_{\text{MAP}}} = 0$$

$$\Rightarrow \frac{x}{\sigma_n^2} - \frac{\hat{m}}{\sigma_n^2} = 0, -A \leq m \leq A$$

$$\Rightarrow \hat{m}_{\text{MAP}} = \begin{cases} x & -A \leq m \leq A \\ -A & m < -A \\ A & m > A \end{cases}$$



summary

- 随机参量，已知PDF：BAYES估计
 - 均匀代价函数：MAP
 - 平方代价函数：MMSE
 - 绝对值代价函数：MED
- 非随机参量：ML估计
- 估计性能评价：一阶矩、二阶矩

Ref: §5.1-5.4(赵版)、第7章、第10章、第11章 (KAY版)



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