

EE702: Lec-13 (21 Feb)

Statistical Parameter Estimation

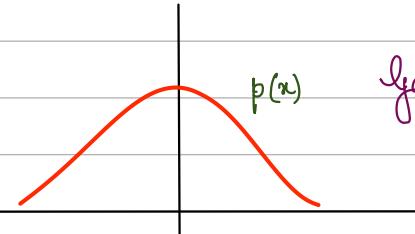
$$\hat{\theta}_{ML} = \min_{\theta} \|y - H\theta\|^2 + \lambda f(\theta)$$

$$H_s e_g = -1 \Rightarrow \hat{e}_g = (H_s^T H_s)^{-1} H_s^T (-1) \rightarrow \hat{\eta}_{\text{obs}} \rightarrow H_s \hat{\theta}_s$$

$$y + s_H = (H + \delta H)\theta \Rightarrow H_g e_g = 0 \Rightarrow U \tilde{V}^T e_g \rightarrow U \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \\ \vdots & \vdots \end{bmatrix} V^T \rightarrow \delta H = U (\tilde{z} - \hat{z}) V^T$$

$$|\theta_0| = 1$$

compressed sensing



Gaussian \rightarrow Symmetric
 \rightarrow Unimodal

What if $\int_{\text{mode} \pm \epsilon} p(x) \geq \inf()$? Think.

Consider $p(x) = \alpha \mathcal{N}(m_1, \sigma_1^2) + (1-\alpha) \mathcal{N}(m_2, \sigma_2^2)$

mixture density fn

Model: $y_i = h + \eta_i$ [Additive]

$$\theta \sim \mathcal{N}(m_\theta, \sigma_\theta^2)$$

$$\eta_i \text{ (measurement error)} \sim \mathcal{N}(0, \sigma_n^2)$$

$$\text{ML} \rightarrow \max \ln(p(y|\theta))$$

$$\text{MAP} \rightarrow \max p(\theta|y) = \frac{\max p(\theta, y)}{p(y)}$$

$$= \max \left(\frac{p(y|\theta) p(\theta)}{p(y)} \right) \Rightarrow \max p(y|\theta) p(\theta)$$

$$= \max \left[\underbrace{\ln(p(y|\theta))}_{\text{ML}} + \underbrace{\ln p(\theta)}_{\text{prior}} \right]$$

$$= \max \left[\ln \left(\exp \left(- \sum_{i=1}^m (y_i - \theta)^2 / 2\sigma_n^2 \right) \right) + \frac{\ln}{\sqrt{}} \left(\exp \left(- (\theta - m\bar{\theta})^2 / 2\sigma_\theta^2 \right) \right) \right]$$

$$= \min_{\theta} \left[\sum_{i=1}^m (y_i - \theta)^2 / 2\sigma_n^2 + (\theta - m\bar{\theta})^2 / 2\sigma_\theta^2 \right]$$

using $\sum y_c = M\bar{m}$,

$$\hat{\theta}_{MAP} = \frac{\frac{M\bar{m}}{\sigma_n^2} + \frac{m\bar{\theta}}{\sigma_\theta^2}}{\frac{M}{\sigma_n^2} + \frac{1}{\sigma_\theta^2}}$$

Properties of Estimator

* Sorenson

$$T(\theta)$$

$\hat{\theta} \rightarrow \text{r.v or not? } \checkmark \text{ r.v}$

Dbiased? $p(\hat{\theta}) = ?$

or unbiased? $E[\hat{\theta}] = ?$

* $\hat{\theta}_m \sim N(0, \frac{\sigma^2}{N})$ or $\hat{\theta}_{10} \sim N(0, \sigma^2)$? What would you prefer?

$$\checkmark \hat{\theta}_m \sim N(0, \frac{\sigma^2}{N})$$

$$E[\hat{\theta}] = \theta \quad \text{"unbiased"} \quad \text{As } N \rightarrow \infty, \text{ bias} \rightarrow 0$$

$$\text{bias} \rightarrow E[\hat{\theta}] - \theta$$

"Asymptotically unbiased"

$$\Rightarrow E[(\hat{\theta} - \theta)]^2 \rightarrow 0 \quad \text{as } N \rightarrow \infty$$

variance ↙

"unbiased"

→ "consistent"

$$\sigma = \sqrt{\frac{\sum (x_i - \bar{x})^2}{N-1}} \quad \text{or} \quad \sqrt{\frac{\sum (x_i - \bar{x})^2}{N}} ?$$

Ans:

↓
correct if \bar{x}
calculated from
given x_i 's

↓
correct only when \bar{x}
is separately given.

σ^2 goes like $\frac{1}{N}$

* variance of median
goes like $N^{-1/3}$.