

## 7 Lecture 7: Bayesian Prospective of MRIE

Motivating example: location invariant estimator

Suppose the p.d.f. of  $X$  satisfies  $f(x - \theta)$ ,  $\theta \in \mathbb{R}$ ,  $x \in \mathbb{R}$ , under loss function  $L(\theta, a) = (\theta - a)^2$ .

Our goal is to estimate  $\theta$ .

Consider  $\delta_0(x) = x$ , then  $\delta(x)$  is invariant if and only if  $\delta(x) = \delta_0(x) - u = x - u$ .

$\delta^*(x) = x - u^*$  is MRIE if and only if

$$\delta^*(x) = \arg \min_{\delta \in \mathbb{A}} R(\theta, \delta) = \arg \min_{\delta \in \mathbb{A}} E_{\theta}[(x - u)^2] = \arg \min E_0[(x - u)^2].$$

So  $\delta^* = E(x|\theta) = E_{\theta=0}(x) = 0$ . Let's look at the function to be minimized.

$$\begin{aligned} E_0[(x - u)^2] &= \int (x' - u)^2 f_0(x') dx' = \int (x' + \delta(x) - x)^2 f_0(x') dx', \quad \text{let } x' = x - \theta, \\ &= \int (x - \theta + \delta(x) - x)^2 f_0(x - \theta) d\theta \\ &= \int (\delta(x) - \theta)^2 f_0(x - \theta) d\theta \\ &= \int (\delta(x) - \theta)^2 \Pi(\theta|x) d\theta \\ &\propto r(\Pi, \delta), \quad \text{Bayes risk w.r.t. } \Pi. \end{aligned}$$

where  $\Pi$  is the generalized Bayes posterior under uniform prior on  $\mathbb{R}$  (improper prior),

$$\Pi(\theta|x) = \frac{\Pi(\theta) f(x|\theta)}{\int \Pi(\theta) f(x|\theta) d\theta} = \frac{f(x|\theta)}{\int f(x|\theta) d\theta} = \frac{f_0(x - \theta)}{\int f_0(x - \theta) d\theta} f_0(x - \theta).$$

Hence the generalized bayes rule that minimizes the above Bayes risk is

$$\begin{aligned} \delta^*(x) &= E(\theta|x) = \int \theta \Pi(\theta|x) d\theta \\ &= \int \theta f_0(x - \theta) d\theta, \quad \text{let } x' = x - \theta, \\ &= \int (x - x') f_0(x') dx' \\ &= x \int f_0(x') dx' - \int x' f_0(x') dx' \\ &= x - E(x|\theta = 0) = x \end{aligned}$$

The generalized Bayes rule w.r.t. uniform prior is same as MRIE.

**Theorem 7.1** (Eaton 1989). *If  $\bar{G}$  acts transitive on  $\Theta$ , the MRIE is given by*

$$\delta^*(x) = \arg \min_{\delta \in \mathbb{A}} \int_{\bar{G}} L(\bar{g}\theta, \delta) f(x|\bar{g}\theta_0) d\mu_r(\bar{g}),$$

where  $\mu_r$  is the right-invariant measure on  $\bar{G}$  and  $\theta_0$  is any point in  $\Theta$ .

(Note: as  $\bar{g}$  ranges over  $\bar{G}$ ,  $\bar{g}\theta_0$  ranges over entire  $\Theta$ .)

**Definition** Right-invariant prior corresponding to  $\bar{G}$  on  $\Theta$  is

$$\forall A \in \sigma(\Theta), \quad \Pi_r(A) = \mu_r\{\bar{g} : \bar{g}\theta_0 \in A\} = \int \mathbf{1}(\bar{g}\theta_0 \in A) d\mu_r(\bar{g}),$$

where  $\theta_0$  is any point in  $\Theta$ ,  $\mu_r$  is the right-invariant measure on  $\bar{G}$ .

Interpretation:  $\Pi_r$  is the distribution of  $\bar{g}\theta_0$ , where  $\bar{g}$  is randomly selected from  $\bar{G}$ .

**Corollary 7.2.** *If  $\bar{G}$  is transitive. The MRIE is given by*

$$\delta^*(x) = \arg \min_{\delta \in \mathbb{A}} \int_{\Theta} L(\theta, \delta) d\Pi_r(\theta|x),$$

where  $\Pi_r(\theta|x)$  is the posterior of  $\theta$  with p.d.f (w.r.t  $\Pi_r(\theta)$ )

$$\frac{d\Pi_r(\theta|x)}{d\Pi_r(\theta)} = \frac{f(x|\theta)}{\int f(x|\theta) d\Pi_r(\theta)}$$

$$(d\Pi_r(\theta|x) = \frac{f(x|\theta) d\Pi_r(\theta)}{\int f(x|\theta) d\Pi_r(\theta)})$$

**Remarks:** This corollary shows that the MRIE  $\delta^*$  can be viewed as a generalized Bayes estimator w.r.t prior  $\Pi_r$ , since

$$\int_{\Theta} L(\theta, \delta) d\Pi_r(\theta|x) = \frac{1}{C_x} \int_{\Theta} L(\theta, \delta) f(x|\theta) d\Pi_r(\theta) = \frac{1}{C_x} r(\Pi_r, \delta),$$

where  $C_x = \int f(x|\theta) d\Pi_r(\theta)$  is independent of  $\theta$ .

**Finding the Right-invariant Measure  $\mu_r$  on  $\bar{G}$**

A measure  $\mu_r$  is right-invariant iff  $\forall \bar{g}_0 \in \bar{G}$  and measurable  $A \subset \bar{G}$ ,

$$\mu_r(A\bar{g}_0^{-1}) = \mu_r(A)$$

In other words, if view  $\mu_r$  as a probability measure

$$P(\bar{g} \in A) = P(\bar{g} \circ \bar{g}_0 \in A)$$

**Examples:**

1. Additive groups:  $\bar{G} = \{\bar{g} : \bar{g}(\theta) = \theta + c, c \in \mathbb{R}\}$ .

$\bar{g}_0(\theta) = \theta + c_0$ , then  $\bar{g} \circ \bar{g}_0 = \theta + (c + c_0)$ .  $\mu_r$  is right-invariant if  $\mu_r(A - c_0) = \mu_r(A)$ ,  $\forall c_0 \in \mathbb{R}, \forall A \in \mathcal{B}_{\mathbb{R}}$

Lebesgue measure is invariant on  $\mathbb{R}$ . The induced prior is given by the distribution of  $\theta_0 + c$ , where  $c \sim \mu_r = \mu_L$  (lebesgue measure)

$\therefore \Pi_r = \mu_r = \mu_L$

2. Multiplicative group:  $\bar{G} = \{\bar{g} : \bar{g}(\theta) = c\theta, c > 0\}$ .  
 $\bar{g}_0(\theta) = c_0\theta$ , then  $\bar{g} \circ \bar{g}_0 = c \cdot c_0\theta$ .  $\bar{G}$  is isomorphic on  $\mathbb{R}^+$ .  $\mu_r$  is right-invariant if

$$\mu_r(A/c_0) = \mu_r(A), \forall c_0 \in \mathbb{R}^+, \forall A \subset \mathcal{B}_{\mathbb{R}^+}$$

Lebesgue measure on  $\mathbb{R}^+$  is not right-invariant. Consider the measure  $\mu_r$  with the density  $1/c$  w.r.t lebesgue measure  $\mu_L$ .  $\forall B = (b_1, b_2) \in \mathbb{R}^+$ , let  $c' = c \cdot c_0$ . Then

$$\mu_r(B/c_0) = \int_{b_1/c_0}^{b_2/c_0} \frac{1}{c} d\mu_L(c) = \int_{b_1}^{b_2} \frac{c_0}{c'} d\mu_L\left(\frac{c'}{c_0}\right) = \int_{b_1}^{b_2} \frac{1}{c'} d\mu_L(c') = \mu_r(B)$$

$\therefore \mu_r$  is the right-invariant measure. The induced right-invariant prior  $\Pi_r = \mu_r$

## 7.1 Related Reading

1. Sh P253-255
2. LC Chapter 4