

Week 3
Spring 2009

Lecture 3. Bayes estimation, minimaxity and Admissibility (cont.).

Admissibility

Conditions on priors and admissibility: conditions on the prior measure which guarantees that the corresponding generalized Bayes procedure is admissible.

Define

$$J_x(h) = \int h(\theta) \varphi(x - \theta) d\theta.$$

Let $S_1 = \{x \in \mathbb{R}^p : \|x\| \leq 1\}$.

Assumption

Growth Condition:

$$\int_{S_1^c} \frac{g(\theta)}{\|\theta\|^2 \log^2(\|\theta\|)} < \infty$$

Asymptotic flatness condition:

$$\int_{S_1^c} J_x \left\{ \left\| \frac{\nabla g}{g} - \frac{J_x(\nabla g)}{J_x(g)} \right\|^2 g \right\} dx < \infty$$

It can be shown that $\int_{S_1^c} \|\nabla g\|^2 / g dx < \infty$ implies the flatness condition.

Theorem. Let G be a prior satisfying two conditions above. Then δ_G is admissible.

For the normal mean estimation problem with squared error loss,

Blyth's Method. Let δ be an estimator. Let $\{G_j\}$ be a sequence of finite prior measures such that: (i) $r(G_j, \delta) - r(G_j, \delta_{G_j}) \rightarrow 0$ as $j \rightarrow \infty$; (ii) $\inf_j \{G_j(S_1)\} > 0$. Then δ is an admissible estimator.

hint: Let $\delta' = (\delta' + \delta)/2$. If $R(\theta, \delta') \leq R(\theta, \delta)$ for all θ and with strict inequality for some θ , then $R(\theta, \delta') < R(\theta, \delta)$ for all θ . For all j ,

$$\begin{aligned} r(G_j, \delta_{G_j}) &\leq r(G_j, \delta') \leq \int_{S_1} R(\theta, \delta') G_j(d\theta) + \int_{S_1^c} R(\theta, \delta) G_j(d\theta) \\ &= r(G_j, \delta) + \int_{S_1} [R(\theta, \delta') - R(\theta, \delta)] G_j(d\theta) \leq r(G_j, \delta) - \varepsilon \end{aligned}$$

where $\varepsilon = \int_{S_1} [R(\theta, \delta') - R(\theta, \delta)] G_j(d\theta)$. Contradiction!

Example. Let $X \sim N(\theta, 1)$. Let $g_j(x) = \frac{1}{\sqrt{j\pi}} \exp\left(-\frac{x^2}{j}\right)$, and $g_j = dG_j/d\mu$ where μ is the Lebesgue measure. It is easy to show

$$r(G_j, X) = \sqrt{j}, \quad r(G_j, \delta_{G_j}) = \sqrt{j} \frac{j}{j+1}$$

then

$$r(G_i, X) = \frac{\sqrt{j}}{j+1} \rightarrow 0.$$

Proposition.

$$r(G, \delta) - r(G, \delta_C) = \int \|\delta_C - \delta\|^2 g^*(x) dx$$

Proof:

$$\begin{aligned} r(G, \delta) - r(G, \delta_C) &= E_X E \left(\|\theta - \delta_C + \delta_C - \delta\|^2 - \|\theta - \delta_C\|^2 \mid X \right) \\ &= E_X E \left(\|\delta_C - \delta\|^2 \mid X \right) = \int \|\delta_C - \delta\|^2 g^*(x) dx \end{aligned}$$

Proof of the theorem: Please read page 374 of Stein (1961).

Define $g_j = h_j^2 g$ where

$$h_j = \begin{cases} 1 & \|\theta\| \leq 1 \\ 1 - \frac{\log(\|\theta\|)}{\log j} & 1 \leq \|\theta\| \leq j \\ 0 & \|\theta\| > j \end{cases}, j = 2, 3, \dots$$

It is easy to see

$$\delta_{C_j} = \frac{\int \theta h_j^2 g(\theta) \varphi(x - \theta) d\theta}{\int h_j^2 g(\theta) \varphi(x - \theta) d\theta} \rightarrow \delta_C \text{ a.s.}$$

and

$$g_j^*(x) = \int h_j^2 g(\theta) \varphi(x - \theta) d\theta \leq g^*(x).$$

Write

$$\begin{aligned} \delta_C(x) &= x + \frac{\nabla g^*}{g^*} = x + \frac{J_x(\nabla g)}{J_x(g)}, \\ \delta_{C_j}(x) &= x + \frac{\nabla g^*}{g^*} = x + \frac{J_x(h_j^2 \nabla g + g \nabla h_j^2)}{J_x(h_j^2 g)} \end{aligned}$$

where the second equality for each equation follows from integration by parts.

Hence

$$\begin{aligned} & r(G_i, \delta_C) - r(G_i, \delta_{C_j}) \\ &= \int_{S_1^c} \|\delta_C - \delta_{C_j}\|^2 g_j^*(x) dx + \int_{S_1^c} \|\delta_C - \delta_{C_j}\|^2 g_j^*(x) dx \quad (\leftarrow \text{apply DCT, since } g_j^*(x) \leq g^*(x) \text{ finite.}) \\ &\leq 2 \int_{S_1^c} \left\| \frac{J_x(g \nabla h_j^2)}{J_x(g_j)} \right\|^2 g_j^*(x) dx + 2 \int_{S_1^c} \left\| \frac{J_x(\nabla g)}{J_x(g)} - \frac{J_x(h_j^2 \nabla g)}{J_x(g_j)} \right\|^2 g_j^*(x) dx + o(1) \\ &= 2A_j + 2B_j + o(1) \end{aligned}$$

Show $A_j \rightarrow 0$ by DCT:

$$\begin{aligned}
 A_j &= \int_{S_1^+} \left\| \frac{J_x(g \nabla h_j^2)}{J_x(g_i)} \right\|^2 g_j^x(x) dx \\
 &= 4 \int_{S_1^+} \left\| \frac{J_x(g h_j \nabla h_j)}{J_x(g_i)} \right\|^2 g_j^x(x) dx = 4 \int_{S_1^+} \left\| \frac{J_x(g_i^{1/2} \cdot g_i^{1/2} \nabla h_j)}{J_x(g_i)} \right\|^2 g_j^x(x) dx \\
 &\leq 4 \int_{S_1^+} J_x(g \|\nabla h_j\|^2) dx \quad (\text{Cauchy-Schwartz inequality and } g_i \leq g) \\
 &\leq 4 \int_{S_1^+} \|\nabla h_j(\theta)\|^2 g(\theta) d\theta
 \end{aligned}$$

and

$$\|\nabla h_j(\theta)\|^2 = \frac{1}{\|\theta\|^2 \log^2(j)} I_{[1,j]}(\|\theta\|) \leq \frac{1}{\|\theta\|^2 \log^2(\|\theta\| \vee 2)} I_{[1,j]}(\|\theta\|).$$

Show $B_j \rightarrow 0$ by DCT again:

$$\begin{aligned}
 &\left\| \frac{J_x(\nabla g)}{J_x(g)} - \frac{J_x(h_j^2 \nabla g)}{J_x(g_i)} \right\|^2 g_j^x(x) \quad (\text{Note that } h_j^2 \nabla g \text{ is } g_i \frac{\nabla g}{g}) \\
 &= \frac{\left\| J_x \left(g_i \frac{J_x(\nabla g)}{J_x(g)} - h_j^2 \nabla g \right) \right\|^2}{J_x(g_i)} \\
 &= \frac{\left\| J_x \left[g_i \left(\frac{J_x(\nabla g)}{J_x(g)} - \frac{\nabla g}{g} \right) \right] \right\|^2}{J_x(g_i)} \\
 &\leq J_x \left(g_i \left\| \frac{J_x(\nabla g)}{J_x(g)} - \frac{\nabla g}{g} \right\|^2 \right) \quad (\text{Cauchy-Schwartz inequality}) \\
 &\leq J_x \left(g \left\| \frac{J_x(\nabla g)}{J_x(g)} - \frac{\nabla g}{g} \right\|^2 \right).
 \end{aligned}$$

Admissibility of $\delta_0 = \mathcal{X}$ for $p=1, 2$

Let $g(\theta) = 1$, then

$$\int_{S_1^+} \frac{g(\theta)}{\|\theta\|^2 \log^2(\|\theta\|)} = 2\pi \int_2^\infty \frac{1}{r \log^2 r} dr < \infty.$$

Homework problem (you pick one part to work on). Let $X_i \sim \text{Poisson}(\lambda_i)$ be independent, $i = 1, 2, \dots, p$. Denote $\mathcal{X} = (X_1, \dots, X_p)$ and $\lambda = (\lambda_1, \dots, \lambda_p)$. Under the loss $L(\lambda, \delta) = \sum_{i=1}^p (\delta_i - \lambda_i)^2 / \lambda_i$, show that (i) for $p=1$, \mathcal{X} is an admissible estimator of λ using Elyth's method; (2) for $p \geq 2$, \mathcal{X} is not an admissible estimator of λ .