

## Lecture 3: February 26

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### 3.1 Example (Discrete Parameter Space)

Let  $\Theta = \{\theta_1, \dots, \theta_K\}$ ,  $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} p_{\theta_j}$ , where  $\theta_j$  is the true parameter. Denote  $p_{\theta_j}(x) = p(x | \theta_j)$  and let  $\pi_j = \pi(\theta = \theta_j)$  be the prior, for  $j = 1, \dots, K$ . Here, we also denote  $X^{(n)} = (X_1, \dots, X_n)$ . We want to show that for  $a \neq j$ ,  $\pi(\theta_a | X^{(n)}) \xrightarrow{\text{a.s.}} 0$ , as this would imply that  $\pi(\theta_a | X^{(n)}) \xrightarrow{\text{a.s.}} 0$  under  $p_{\theta_j}$ . First suppose  $\pi_j = 0$ . Then  $\pi(\theta_j | X^{(n)}) \equiv 0$ . For posterior consistency, we assume that  $\pi_j > 0$  for all  $j = 1, \dots, K$ . Then, for  $a \neq j$ , consider

$$\begin{aligned} \log \frac{\pi(\theta_a | X^{(n)})}{\pi(\theta_j | X^{(n)})} &= \log \frac{\pi_a}{\pi_j} + \log \sum_{i=1}^n \frac{p(X_i | \theta_a)}{p(X_i | \theta_j)} \\ &= n \left( \frac{1}{n} \log \frac{\pi_a}{\pi_j} + \frac{1}{n} \log \sum_{i=1}^n \frac{p(X_i | \theta_a)}{p(X_i | \theta_j)} \right) \end{aligned}$$

Note that under  $p_{\theta_j}$ ,

$$\frac{1}{n} \log \frac{\pi_a}{\pi_j} \rightarrow 0$$

By SLLN,

$$\frac{1}{n} \log \sum_{i=1}^n \frac{p(X_i | \theta_a)}{p(X_i | \theta_j)} \xrightarrow{\text{a.s.}} -D(p_{\theta_j} \| p_{\theta_a})$$

Using these two observations, we have the following

$$\log \frac{\pi(\theta_a | X^{(n)})}{\pi(\theta_j | X^{(n)})} \xrightarrow{\text{a.s.}} -\infty \quad [p_{\theta_j}]$$

and we conclude  $\pi(\theta_j | X^{(n)}) \xrightarrow{\text{a.s.}} 1, [p_{\theta_j}]$ .

#### Remark

1. It is assumed that  $p_{\theta}$  does not depend on  $n$ .
2. If  $\pi_j = 0$ , then there is no posterior consistency.
3. Case of non-identifiability:  $\theta_a \neq \theta_j$  but  $D(p_{\theta_j} \| p_{\theta_a}) = 0$ . Then there is no posterior consistency.
4. The complexity of the parameter space should be sufficiently small.

### 3.2 Some important theorems and concepts

**Theorem 3.1.** (Doob) Let  $(\Omega, \mathcal{A}, p_\theta), \theta \in \Theta$ . Assume  $\theta \mapsto p_\theta$  is 1-1. Let  $X_1 \dots X_n \stackrel{iid}{\sim} p_\theta, \theta \sim \pi$ . Then  $\pi_n(\cdot | X^{(n)})$  is strongly consistent for  $\pi$ -almost  $\theta$ . That is, for  $\Theta_0 \subseteq \Theta$  such that  $\pi(\Theta_0) = 1$ , then  $\pi_n(\cdot | X^{(n)})$  is strongly consistent if  $X_1, \dots, X_n \stackrel{iid}{\sim} p_{\theta_0}, \theta_0 \in \Theta_0$ .

**Remark.** If  $\pi(\{\theta_0\}) = 0$ , or  $\pi$  depends on  $n$ , then the theorem says nothing. The theorem applies for a countable parameter space, provided that  $\theta \mapsto p_\theta$  is 1-1.

**Definition 3.2.** (Kullback–Leibler property and Kullback–Leibler support)

Let  $\mathcal{P}$  be density space and  $p_0 \in \mathcal{P}$ .  $p_0$  is said to have KL property relative to a prior  $\pi$  if

$$\pi\{p : D(p_0 \| p) < \epsilon\} > 0 \text{ for every } \epsilon > 0$$

And KL support,  $KL(\pi)$ , is given by :

$$KL(\pi) = \{p_0 \in \mathcal{P} : p_0 \text{ has KL property}\}$$

**Theorem 3.3.** (Schwartz) If  $p_0 \in KL(\pi)$  and  $\mathcal{U}$  is a neighborhood around  $p_0$  such that there exists a test function  $\phi_n = \phi_n(X_1, \dots, X_n)$ , and  $\mathbb{E}_{p_0} \phi_n \rightarrow 0$  and  $\sup_{p \in \mathcal{U}^c} \mathbb{E}_p(1 - \phi_n) \rightarrow 0$  as  $n \rightarrow \infty$ , then  $\pi_n(\mathcal{U}^c | X^{(n)}) \rightarrow 0$ , a.s.  $[p_0]$

- A typical choice of  $\mathcal{U} = \{p : d(p, p_0) < \epsilon\}$
- If  $\mathcal{U}$  is weak-neighbourhood, then  $\phi_n$  satisfying the above, always exists.

**Definition 3.4.**  $P_n \xrightarrow{w} P$  iff for any bounded continuous function  $\phi$ ,  $\int \phi dP_n \rightarrow \int \phi dP$   
 $\iff P_n(-\infty, x] \rightarrow P(-\infty, x], \forall x$  in continuity points of  $P(-\infty, x]$   
 $\iff P_n(A) \rightarrow P(A) \forall A$  s.t.  $P(\partial A) = 0$

Consider the metric  $(\mathbb{R}, d | x - y |)$ . Then  $\{(-\infty, x] : x \in \mathbb{R}\}$  is called “generating set” or “building block” for open sets in  $\mathcal{B}(\mathbb{R})$ . The following result characterize an open set around  $p_0$ .

**Result :** A generating set of a weak-neighbourhood around  $p_0$  is given by

$$\left\{ \left\{ P : \int \phi dP < \int \phi dP_0 + C \right\}, \phi \text{ is bounded and continuous and } C > 0 \right\}$$

**Definition 3.5.** (Levy metric) Let  $F$  and  $G$  be distribution functions.

$$d(F, G) = \inf\{\epsilon > 0 : F(x - \epsilon) - \epsilon \leq G(x) \leq F(x + \epsilon) + \epsilon, \forall x \in \mathbb{R}\}$$

Let us fix  $\phi$  (bounded and continuous) and  $C > 0$  and define

$$\mathcal{U} = \left\{ P : \int \phi dP < \int \phi dP_0 + C \right\}$$

The goal is to construct  $\phi_n$  based on  $\{X_1, \dots, X_n\}$  such that

$$\mathbb{E}_{p_0} \phi_n \rightarrow 0 \text{ and } \sup_{p \in \mathcal{U}^c} \mathbb{E}_p(1 - \phi_n) \rightarrow 0 \text{ as } n \rightarrow \infty \quad (3.1)$$

Let us start with  $X_1$  and we shall construct an unbiased test based on  $X_1$ .

Without loss of generality, assume  $0 \leq \phi \leq 1$ .

In  $\mathcal{U}^c$  :  $\int \phi(X) dP(X) < \int \phi(X) dP_0(X) + C \implies \phi$  is an unbiased test.

Now, let us define  $\phi_n$  based  $\{X_1, \dots, X_n\}$  as:  $\phi_n = \mathbb{1}\left\{\frac{1}{n} \sum_{i=1}^n \phi(X_i) > \mathbb{E}_{p_0} \phi + \frac{C}{2}\right\}$

It is to be noted that  $\phi_n$  such constructed satisfies (3.1).