

# Lec 2: Consistency

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(\*) Suggested reading: Newey and McFadden (1994), Section 2

## 1 Consistency

**Motivation.** We know  $\hat{Q}_n(\theta) \xrightarrow{p} Q_0(\theta)$  *pointwise* in  $\theta$  by WLLN. But does it sufficiently imply  $\hat{\theta} \xrightarrow{p} \theta_0$ ? The answer is **NO!** We need  $\sup_{\theta \in \Theta} |\hat{Q}_n(\theta) - Q_0(\theta)| \xrightarrow{p} 0$  (uniform consistency in  $\theta$ ) + "regularity conditions". Thus, let's begin by showing **Consistency Theorem**.

**Theorem 1.1 (Consistency of  $\hat{\theta}$ ).**  $\hat{\theta} \xrightarrow{p} \theta_0$  if:

- (i)  $\theta_0$  is **unique** maximizer for  $Q_0$  (*identification*),
- (ii)  $\Theta$  is compact,
- (iii)  $Q_0$  is continuous in  $\theta$  (parameter of interest), and
- (iv)  $\hat{Q}_n$  is **uniformly consistent** for  $Q_0$ .

*Proof.* For any  $\varepsilon > 0$ , we know  $\hat{Q}_n(\hat{\theta}) \geq \hat{Q}_n(\theta_0) > \hat{Q}_n(\theta_0) - \varepsilon$ , since  $\hat{\theta}$  is maximizer of  $\hat{Q}_n$ . By (iv), as  $n \rightarrow \infty$ , for any  $\theta \in \Theta$ , we have  $|\hat{Q}_n(\theta) - Q_0(\theta)| < \varepsilon$  with probability 1.

$$\Rightarrow \begin{cases} \hat{Q}_n(\hat{\theta}) - Q_0(\hat{\theta}) < \varepsilon & \Rightarrow Q_0(\hat{\theta}) > \hat{Q}_n(\hat{\theta}) - \varepsilon \\ Q_0(\theta_0) - \hat{Q}_n(\theta_0) < \varepsilon & \Rightarrow \hat{Q}_n(\theta_0) > Q_0(\theta_0) - \varepsilon \end{cases} \quad (1.1)$$

Then, as  $n \rightarrow \infty$ , we have:

$$Q_0(\hat{\theta}) > \hat{Q}_n(\hat{\theta}) - \varepsilon > (\hat{Q}_n(\theta_0) - \varepsilon) - \varepsilon \quad (1.2)$$

$$> (Q_0(\theta_0) - \varepsilon) - 2\varepsilon = Q_0(\theta_0) - 3\varepsilon, \text{ with probability 1} \quad (1.3)$$

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Let  $\mathcal{N}$  be open set s.t.  $\theta_0 \in \mathcal{N} \subseteq \Theta$ , then  $\mathcal{N}^c := \Theta \cap \mathcal{N}^c$  is compact by (ii) (closed subset of a compact set). Therefore,

$$\exists \theta^* \in \mathcal{N}^c \text{ s.t. } \sup_{\theta \in \Theta} \mathbf{Q}_0(\theta) = \mathbf{Q}_0(\theta^*) \longleftarrow \text{by (iii) continuity} \quad (1.4)$$

$$< \mathbf{Q}_0(\theta_0) \longleftarrow \text{by } \theta_0 = \arg \max \mathbf{Q}_0 \quad (1.5)$$

We now can pick our  $\varepsilon = \frac{1}{3} [\mathbf{Q}_0(\theta_0) - \mathbf{Q}_0(\theta^*)]$  ( $> 0$ ) so that, as  $n \rightarrow \infty$ , equation (4) yields  $\mathbf{Q}_0(\hat{\theta}) > \mathbf{Q}_0(\theta^*)$  with probability 1, i.e.,  $\hat{\theta} \notin \mathcal{N}^c$  w.p.1  $\implies \hat{\theta} \in \mathcal{N}$  w.p.1  $\implies \hat{\theta} \xrightarrow{p} \theta_0$ .  $\square$

**Remark.** Only Condition (i) *uniqueness of maximizer*  $\theta_0$  is required. This makes sure that our estimator  $\hat{\theta}$  is centering at the true maximizer  $\theta_0$  (and therefore *consistent*), not multiple  $\hat{\theta}$  and being inconsistent.

**Question.** How do we check the Consistency conditions?

**Answer.** (i) depends case-by-case; (ii) holds normally by assumption; (iii) & (iv) jointly implied by **Uniform LLN (ULLN)**

## 2 ULLN

**Motivation.** We rely on **ULLN** to determine Condition (iii) & (iv) in **Consistency Theorem** so that we make sure our estimator  $\hat{\theta}$  is consistent for  $\theta_0$ .

**Theorem 2.1 (ULLN).** Suppose  $(Z_i)_{i=1}^n \stackrel{iid}{\sim} Z$  and  $\Theta$  compact. If:

(i)  $\theta \mapsto g(Z; \theta)$  is continuous (a.e.)  $\forall \theta \in \Theta$ , and

(ii)  $\exists$  a function  $\zeta \mapsto h(\zeta)$  s.t.  $\begin{cases} |g(\zeta; \theta)| \leq h(\zeta) \quad \forall \theta \in \Theta, \text{ (i.e., } h(\zeta) \text{ dominating func w/o param)} \\ \mathbb{E}[h(Z)] < \infty \end{cases}$

Then,

①  $\theta \mapsto \mathbb{E}[g(Z; \theta)]$  is continuous in  $\theta$  ( $\longleftarrow$  Condition (iii)  $\checkmark$ )

②  $\sup_{\theta \in \Theta} \left| \frac{1}{n} \sum_{i=1}^n g(Z_i; \theta) - \mathbb{E}[g(Z; \theta)] \right| \xrightarrow{p} 0$  ( $\longleftarrow$  Condition (iv)  $\checkmark$ )

*Proof.* (Harold: "Take ECON715")  $\square$

**Remark.** Recall, [Lec 1] *uniform consistency* tells us  $\sup_{\theta \in \Theta} |\hat{\mathbf{Q}}_n(\theta) - \mathbf{Q}_0(\theta)| \xrightarrow{p} 0 \rightsquigarrow o_p(1)$ .

Here, we use  $\frac{1}{n} \sum_{i=1}^n g(Z_i; \theta)$  as  $\hat{\mathbf{Q}}_n(\theta)$  and use  $\mathbb{E}[g(Z; \theta)]$  as true objective function  $\mathbf{Q}_0(\theta)$ .

**Example 2.1 (NLS ✓).** Consider  $\mathbf{Q}_0(\theta) = -\mathbb{E}[(Y - \mu(x; \theta))^2] =: \mathbb{E}[g(Z; \theta)]$ , then ULLN is applicable if  $\mu$  satisfies ULLN (i) & (ii).

**Example 2.2 (MLE ✓).** Consider  $\mathbf{Q}_0(\theta) = \mathbb{E}[\ln f(Z; \theta)] =: \mathbb{E}[g(Z; \theta)]$ , where  $Z \sim^d f(Z; \theta)$  and  $f$  is known up to  $\theta$  (pdf).

**Example 2.3 (GMM ×).** Goal:  $\mathbb{E}[g(Z; \theta_0)] = 0$   
 $\implies$  Consider  $\mathbf{Q}_0(\theta) = -\mathbb{E}[g(Z; \theta)]' \mathbf{W} \mathbb{E}[g(Z; \theta)]$ , which is a *quadratic* form of  $\mathbb{E}[g(Z; \theta)]$   
 $\implies$  *Cannot directly apply ULLN!*

**Summary.** Therefore, we can categorize above discussion into:

- MLE-type (★)
- GMM-type ("minimum distance"): collapse to MLE-type when Just-ID case.

### 3 Consistency of MLE

**Theorem 3.1 (Consistency; MLE).** Suppose  $(Z_i)_{i=1}^n \stackrel{iid}{\sim} f(\zeta; \theta)$ , where  $f$ : known pdf given  $\theta \in \Theta$ , then  $\hat{\theta} \xrightarrow{P} \theta_0$  if:

- ①  $\theta \neq \theta_0 \implies f(Z; \theta) \neq f(Z; \theta_0)$  (i.e., different density),
- ②  $\Theta$  is compact,
- ③  $\theta \mapsto \ln f(Z; \theta)$  is continuous (a.e.)  $\forall \theta \in \Theta$  and  $Z_i$ , and
- ④  $\mathbb{E} \left[ \sup_{\theta \in \Theta} |\ln f(Z; \theta)| \right] < \infty$ .

*Proof.* Since Theorem 1.1 (Consistency) condition (ii) is checked by ②, we now need to verify condition (i): unique maximizer [Spring 2023 Final Q1].

Recall that  $\mathbf{Q}_0 := \mathbb{E}[\ln f(Z; \theta)]$  for MLE.

$\implies$  **WTS.**  $\mathbf{Q}_0(\theta_0) > \mathbf{Q}_0(\theta) \forall \theta \neq \theta_0$  (\* intuition:  $\theta_0 = \arg \max_{\theta} \mathbf{Q}_0$ )

$$\mathbf{Q}_0(\theta) - \mathbf{Q}_0(\theta_0) = \mathbb{E}[\ln f(Z; \theta) - \ln f(Z; \theta_0)] = \mathbb{E} \left[ \ln \left( \frac{f(Z; \theta)}{f(Z; \theta_0)} \right) \right] \quad (3.1)$$

$$< \ln \mathbb{E} \left[ \frac{f(Z; \theta)}{f(Z; \theta_0)} \right] \leftarrow "<" \text{ holds by Jensen's Ineq \& ① diff density } \forall \theta \neq \theta_0 \quad (3.2)$$

$$= \ln \int \frac{f(\zeta; \theta)}{\underbrace{f(\zeta; \theta_0)}_{\text{true pdf}}} d\zeta = \ln \int f(\zeta; \theta) d\zeta = \ln 1 = 0 \quad (3.3)$$

Thus, we verify  $Q_0(\theta_0) > Q_0(\theta) \forall \theta \neq \theta_0$ , i.e.,  $\theta_0$  is unique maximizer & condition (i) (✓). We now use ③ & ④ to check if ULLN is applicable so that Consistency condition (iii) & (iv) will be jointly satisfied.

- Define  $g(\zeta; \theta) := \ell n f(\zeta; \theta)$ , then by ③ we note  $g(Z; \theta)$  is conti.  $\forall \theta \in \Theta$  &  $Z$  w.p.1.
- Let  $h(\zeta) = \sup_{\theta \in \Theta} |\ell n f(\zeta; \theta)|$ , then 
$$\begin{cases} |g(\zeta; \theta)| = |\ell n f(\zeta; \theta)| \leq \sup_{\theta \in \Theta} |\ell n f(\zeta; \theta)| = h(\zeta; \theta) \forall \theta \in \Theta \\ \mathbb{E}[h(Z)] = \mathbb{E} \left[ \sup_{\theta \in \Theta} |\ell n f(Z; \theta)| \right] < \infty \leftarrow \text{by ④} \end{cases}$$

So, ULLN is satisfied, and by ULLN we know Consistency condition (iii) & (iv) (✓).

Ultimately, by Theorem 1.1, we conclude MLE is consistent.  $\square$

## 4 Exercise from DIS SEC

**Exercise 4.1** (Spring24 TA Handout7 Ex3). Consider the simple linear model  $Y_i = \beta_0 X_i + e_i$  where  $\mathbb{E}[e_i | X_i] = 0$ . Here  $Y_i$  and  $X_i$  are scalars with  $\mathbb{E}[Y_i^4] < \infty$  and  $\mathbb{E}[X_i^4] < \infty$ . Take the parameter space  $\Theta = [-1, 1]$  and assume  $\beta_0 \in \text{int}(\Theta)$ . Then, we define an M-estimator for  $\beta$  as follows:

$$\hat{\beta} = \underset{\beta \in [-1, 1]}{\text{argmin}} S_n(\beta) \text{ where } S_n(\beta) = \frac{1}{n} \sum_{i=1}^n (Y_i - \beta X_i)^2 \quad (4.1)$$

(a) Show that  $\sup_{\beta \in [-1, 1]} |S_n(\beta) - S(\beta)| \xrightarrow{p} 0$  where  $S(\beta) = \mathbb{E}[(Y_i - \beta X_i)^2]$ .

(b) Show that  $\hat{\beta} \xrightarrow{p} \beta_0$ .

**Solution (a).** Essentially, we want to invoke **ULLN**. For ULLN (i): *continuous in parameter*, we see that  $(Y_i - \beta X_i)^2$  is continuous in  $\beta$  (✓). To check ULLN (ii) *dominating function w/o parameter*, we define  $g(Y_i, X_i; \beta) = (Y_i - \beta X_i)^2$  and find that:

$$|g(Y_i, X_i; \beta)| = |(Y_i - \beta X_i)^2| = (Y_i - \beta X_i)^2 \quad (4.2)$$

$$\leq 2(Y_i^2 + \beta^2 X_i^2) \leftarrow \text{by CR Ineq.} \quad (4.3)$$

$$\leq 2(Y_i^2 + 1^2 X_i^2) \leftarrow \text{by } \beta \in [-1, 1] \Rightarrow \beta^2 \in [0, 1]. \quad (4.4)$$

So, we can let  $h(Y_i, X_i) = 2(Y_i^2 + X_i^2)$  and that ULLN (ii) is satisfied by  $|g(Y_i, X_i; \beta)| \leq h(Y_i, X_i)$ , with  $\mathbb{E}[h(Y_i, X_i)] = 2(\mathbb{E}[Y_i^2] + \mathbb{E}[X_i^2]) < \infty$  (since 4<sup>th</sup> moments exist). By Theorem 2.1 (ULLN), the statement is true.

**Solution (b).** Since  $\Theta = [-1, 1] \subset \mathbb{R}$  is closed and bounded, by Heine-Borel Theorem we know  $\Theta$  is compact. We now only need to check Theorem 1.1 (Consistency) (i):  $\beta_0$  being

unique minimizer for  $S(\beta)$ <sup>1</sup>. First note that  $S(\beta_0) = \mathbb{E}[(Y_i - \beta_0 X_i)^2] = \mathbb{E}[e_i^2]$ . Then, as we take any  $\tilde{\beta} \neq \beta_0$ , we find that:

$$S(\tilde{\beta}) = \mathbb{E}[(Y_i - \tilde{\beta} X_i)^2] \quad (4.5)$$

$$= \mathbb{E}[(\beta_0 X_i + e_i - \tilde{\beta} X_i)^2] \leftarrow \text{plugging in } Y_i. \quad (4.6)$$

$$= \mathbb{E}[(\beta_0 - \tilde{\beta}) X_i + e_i]^2 \quad (4.7)$$

$$= (\beta_0 - \tilde{\beta})^2 \mathbb{E}[X_i^2] + \mathbb{E}[e_i^2] + \underbrace{2(\beta_0 - \tilde{\beta}) \mathbb{E}[X_i e_i]}_{= 0 \text{ by } \mathbb{E}[e_i | X_i] = 0} \quad (4.8)$$

$$= (\beta_0 - \tilde{\beta})^2 \mathbb{E}[X_i^2] + \mathbb{E}[e_i^2] \quad (4.9)$$

$$> \mathbb{E}[e_i^2] = S(\beta_0) \quad (4.10)$$

So, we verify that  $\beta_0$  is unique minimizer of  $S(\beta)$ . By Theorem 1.1 (Consistency),  $\hat{\beta} \xrightarrow{p} \beta_0$ .

## References

Newey, W. K., & McFadden, D. (1994). Chapter 36 large sample estimation and hypothesis testing. Elsevier. [https://doi.org/10.1016/S1573-4412\(05\)80005-4](https://doi.org/10.1016/S1573-4412(05)80005-4)

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<sup>1</sup>Here, we construct  $\hat{\beta} = \arg \min S_n(\beta)$  rather than  $\arg \max$ , so we need to verify unique MINIMIZER.