

ULLN

$$\sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n f(X_i) - \mathbb{E}f(X) = o_p(1).$$

(IP_n - IP)_f

$$\mathbb{E} \frac{1}{n} \sup_{f \in \mathcal{F}} \left| \sum_{i=1}^n \varepsilon_i f(X_i) \right| \quad \varepsilon = \begin{cases} 1 & \text{w.p. } \frac{1}{2} \\ -1 & \text{w.p. } \frac{1}{2} \end{cases} \text{ Rad.}$$

For now: \mathcal{F} finite. $\mathcal{F} = \{f_1, \dots, f_N\}$.

$$\mathbb{E} \max_{f \in \{f_1, \dots, f_N\}} X_{f_j} \asymp \sqrt{\log N} \quad \text{union bound.}$$

X_{f_1}, \dots, X_{f_N} indep. "maximal inequality"

$$\{X_f, f \in \mathcal{F}\}.$$

$$\mathcal{F}: \varepsilon\text{-net} \quad \{f_1, \dots, f_{N(\varepsilon)}\}.$$

$$\forall f \in \mathcal{F}. \quad \pi_{\varepsilon}(f) = \operatorname{argmin}_{j \in \{1, \dots, N\}} \|f_j - f\|$$

$$\mathbb{E} \frac{1}{n} \sup_{f \in \mathcal{F}} \left| \sum_{i=1}^n \varepsilon_i f(X_i) \right|$$

$$\leq \mathbb{E} \frac{1}{n} \sup_{f \in \mathcal{F}} \left| \sum_{i=1}^n \varepsilon_i (f(X_i) - \pi_{\varepsilon}(f)(X_i)) \right| + \mathbb{E} \frac{1}{n} \sup_{f \in \mathcal{F}} \left| \sum_{i=1}^n \varepsilon_i \pi_{\varepsilon}(f)(X_i) \right|$$

$\leq \varepsilon.$ maximal inequality

\mathcal{F} : metric entropy condition

$\rightarrow 0.$

Unif. LLN \Rightarrow Unif. CLT

Motivation

(1) M-estimation / ERM (emp. risk minimization).

$$\theta_0 := \underset{\theta \in \Theta}{\operatorname{argmin}} \mathbb{E} m(X; \theta) \equiv \mathbb{P} m(X; \theta).$$

\uparrow
 $\theta \in \mathbb{R}$

$X_1, \dots, X_n \stackrel{\text{i.i.d.}}{\sim} \mathbb{P}_{\theta_0}$, θ_0 unknown

$$\hat{\theta}_n = \underset{\theta \in \Theta}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^n m(X_i; \theta) \equiv \mathbb{P}_n m(X; \theta)$$

(1) $\hat{\theta}_n \xrightarrow{\mathbb{P}} \theta_0$ (Strong Law: ULLN). $\sup_{\theta \in \Theta} |\hat{\theta}_n - \theta_0| \xrightarrow{\mathbb{P}} 0$?

(2) $|\hat{\theta}_n - \theta_0| = n^{-\alpha}$ (rate-of-convergence)

(3) $\sqrt{n} (\hat{\theta}_n - \theta_0) \stackrel{?}{\Rightarrow} N(0, \sigma^2)$.

m convex $\frac{1}{n} \sum_{i=1}^n m'(X_i; \theta) = 0$.

$$\mathcal{F}: \{m'(\cdot; \theta), \theta \in \Theta\}.$$

m : -log-likelihood.

L_2 -risk. $(\gamma - f_{\theta}(X_i))^2$

L_1 -risk. "minimal deviation"

(2). Semi-parametric.

MLE. $\eta = (\theta, f)$.

$\theta \in \mathbb{R}$. $f \in \mathcal{F}$ infinite-dimensional Sub-linear space.

$\hat{\theta}_{MLE}(\hat{f})$ plug-in.

$$\sup_{f \in \mathcal{F}} \sqrt{n} (\hat{\theta}_{MLE}(\hat{f}) - \theta_0) \stackrel{?}{\Rightarrow} N(0, \sigma^2).$$

$$(X, R) \quad R=1, X = X^{\text{true}}$$

$$R=0, X = \text{"NA"}$$

$$\mathbb{E}X = \theta. \quad R \text{ missing me.}$$

\hat{f} : sample split.

$$\theta_0 \text{ solves } \mathbb{E} \psi(X; \theta) \equiv 0 \quad \psi = m'$$

$$\hat{\theta}_n \text{ solves } \frac{1}{n} \sum_{i=1}^n \psi(X_i; \theta) \equiv 0.$$

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \psi(X_i; \hat{\theta}_n) - \sqrt{n} \mathbb{E} \psi(X; \theta) \equiv 0.$$

$$= \frac{1}{\sqrt{n}} \sum_{i=1}^n (\psi(X_i; \hat{\theta}_n) - \mathbb{E} \psi(X; \hat{\theta}_n)) - \frac{1}{\sqrt{n}} \sum_{i=1}^n (\psi(X_i; \theta_0) - \mathbb{E} \psi(X; \theta_0))$$

$$+ \sqrt{n} (\mathbb{E} \psi(X; \hat{\theta}_n) - \mathbb{E} \psi(X; \theta_0)) \quad \sqrt{n} C (\hat{\theta}_n - \theta_0)$$

$$+ \frac{1}{\sqrt{n}} \sum_{i=1}^n (\psi(X_i; \theta_0) - \mathbb{E} \psi(X; \theta_0)) \sim N(0, \sigma^2).$$

$$= \sqrt{n} (P_n - P) (\psi(X; \hat{\theta}_n) - \psi(X; \theta_0)) = o_p(1) \quad \checkmark.$$

$$+ \text{---} + \text{---}.$$

$$\sqrt{n} (P_n - P) (\cdot) = \mathcal{G}_n(\cdot).$$

$$\mathcal{G}_n (\psi(X; \hat{\theta}_n) - \psi(X; \theta_0))$$

$$\mathcal{G}_n (f(\hat{\theta}_n) - f(\theta_0))$$

$$\underbrace{\hspace{10em}}_{\text{"f"}}$$

$$\sup_{\theta_n \in \mathcal{F}} |\mathbb{G}_n f(\theta_n) - f(\theta_n)| =: p(1).$$

$$\theta_n \in \{\theta : \|\theta_n - \theta\| \leq \delta\}. \quad \mathbb{G}_n f(\theta_0)$$

In general: \mathcal{F} is Donsker if $\{\mathbb{G}_n f : f \in \mathcal{F}\} \Rightarrow \mathbb{G}P$ in $\ell^\infty(\mathcal{F})$.

Thm: (Dudley)

$$\text{Define } J(\delta, \mathcal{F}, L_2) = \int_0^\delta \sup_{\mathcal{F}} \sqrt{\log N(\epsilon \|\cdot\|_{L_2, \mathcal{Q}}, \mathcal{F}, L_2(\mathcal{Q}))} d\epsilon.$$

\mathcal{F} : envelope of \mathcal{F} . $\|\mathcal{F}\|_{L_2(P)}^2 < \infty$. unif. entropy integral $\int \mathcal{F}^2$

If $J(\delta, \mathcal{F}, L_2) \rightarrow 0$ as $\delta \rightarrow 0$, then \mathcal{F} is Donsker

IF: Lemma. $\{\mathbb{G}_n f : f \in \mathcal{F}\} \Rightarrow \{\mathbb{G}P f : f \in \mathcal{F}\} \leftarrow \text{tight}$
 in $\ell^\infty(\mathcal{F})$ Gaussian process (a) $n \rightarrow \infty$.

iff. (i) $\{\mathbb{G}_n f_1, \dots, \mathbb{G}_n f_k\} \Rightarrow \{\mathbb{G}P f_1, \dots, \mathbb{G}P f_k\} \quad \forall k \in \mathbb{N}$.
 $f_1, \dots, f_k \in \mathcal{F}$.

(ii) asymp. equicontinuity.

$$\forall \epsilon > 0, \lim_{\delta \rightarrow 0} \lim_{n \rightarrow \infty} \mathbb{P} \left(\sup_{f, g \in \mathcal{F}, \|f-g\| \leq \delta} |\mathbb{G}_n f - \mathbb{G}_n g| > \epsilon \right) \rightarrow 0.$$

(Bodhisattva Sen. for proof)

Back to Dudley:

Define $G_\delta := \{f-g; f \in \mathcal{F}, g \in \mathcal{F}, \|f-g\| \leq \delta\}$.

G_δ : envelope $2\mathcal{F}$.

need to show: $\forall \epsilon > 0$.

$$\lim_{\delta \rightarrow 0} \lim_{n \rightarrow \infty} P\left(\sup_{h \in G_\delta} |\mathcal{G}_n h| \geq \epsilon\right)$$

Markov.

$$\leq \frac{1}{\epsilon} \lim_{\delta \rightarrow 0} \lim_{n \rightarrow \infty} \mathbb{E}\left(\sup_{h \in G_\delta} |\mathcal{G}_n h|\right) \rightarrow 0 \quad \checkmark.$$

$$\mathbb{E}\left(\sup_{h \in G_\delta} |\mathcal{G}_n h|\right) \quad \frac{1}{\sqrt{n}}.$$

"symm"

$$\leq \mathbb{E}_X \mathbb{E}_\varepsilon \sup_{h \in G_\delta} \frac{1}{\sqrt{n}} \left| \sum_{i=1}^n h(X_i) \varepsilon_i \right|$$

$$\mathbb{E}_\varepsilon \sup_{h \in G_\delta} \frac{1}{\sqrt{n}} \left| \sum_{i=1}^n h(X_i) \varepsilon_i \right| \quad X_n.$$

?

$$\leq \mathbb{E}_\varepsilon \sup_{h \in G_\delta} \frac{1}{\sqrt{n}} \sum_{i=1}^n \left| (h(X_i) - \Pi h(X_i)) \varepsilon_i \right| + \frac{1}{\sqrt{n}} \sum_{i=1}^n \left| \Pi h(X_i) \varepsilon_i \right|$$

Chaining.

Assume: G_δ finite. Fix $h_0 \in G_\delta$.

$$\begin{matrix} T_i & \varepsilon_i - \text{net.} & \mathbb{E} \sup_{h \in G_\delta} |X_n| \\ \Pi_i & & \end{matrix}$$

$$\leq \mathbb{E} \sup_{h \in G_\delta} |X_n - X_{\Pi(h)}| + |X_{\Pi(h)}|$$

$$\bar{T}_2 \epsilon_2\text{-net} \leq \mathbb{E} \sup_{h \in \mathcal{G}_S} |X_{\pi_1(h)}| + \sup_{h \in \mathcal{G}_S} |X_{\pi_1(h)} - X_{\pi_2(h)}|$$

$$+ \mathbb{E} \sup_{h \in \mathcal{G}_S} |X_{\pi_2(h)} - X_h|$$

⋮

$$\bar{T}_N \epsilon_k\text{-net} \leq \sum_{k=1}^N \mathbb{E} \sup_{h \in \mathcal{G}_S} |X_{\pi_k(h)} - X_{\pi_{k-1}(h)}| \quad \pi_N(h) = h.$$

$$h \quad \pi_1(h) \quad \pi_2(h)$$

$$\leq \sum_{k=1}^N \sqrt{\log \frac{|\pi_{k-1}|}{|\pi_k|}} \cdot \left\{ \underbrace{|X_{\pi_k(h)} - X_h|}_{\leq \epsilon_k} + \underbrace{|X_{\pi_{k-1}(h)} - X_h|}_{\leq \epsilon_{k-1}} \right\}$$

$$\frac{\pi_N(h)}{=h} \leq \sum_{k=1}^N \epsilon_{k-1} \sqrt{\log N(\epsilon_k, \mathcal{G}_S, L_2) N(\epsilon_{k-1}, \mathcal{G}_S, L_2)}.$$

ϵ_{k-1}

$$\leq \sum_{k=1}^N \frac{\epsilon_{k-1}}{\epsilon_k} \epsilon_k \sqrt{\log N(\epsilon_k, \mathcal{G}_S, L_2)} \leq p \sum_{k=1}^N \epsilon_k \sqrt{\log N(\epsilon_k, \mathcal{G}_S, L_2)}$$

$$\frac{\epsilon_{k-1}}{\epsilon_k} = p \leq \sum_{k=1}^N \int_{\epsilon_{k+1}}^{\epsilon_k} \sqrt{\log N(\epsilon, \mathcal{G}_S, L_2)} d\epsilon.$$

$p=0.5$

$$= \int_{\epsilon_N}^{\epsilon_1} \sqrt{\log N(\epsilon, \mathcal{G}_S, L_2)} d\epsilon$$

$$\epsilon_0 : \text{Diam}(\mathcal{G}_S). \quad \epsilon_1 = \frac{\text{Diam}(\mathcal{G}_S)}{2} \quad \epsilon_{N+1}$$

$$\leq \int_{\frac{\text{Diam}(\mathcal{G}_S)}{2}}^{\frac{\text{Diam}(\mathcal{G}_S)}{2}} \sqrt{\log N(\epsilon, \mathcal{G}_S, L_2)} d\epsilon$$

\leq

$$\leq \int_0^{\frac{M(z)}{z}} \sup_{\Theta} \sqrt{\log N(\epsilon, \delta_{\epsilon}, L_2(\Theta))} d\epsilon.$$