

## Section 2.4 and 2.5

# Weak Convergence and Empirical Processes

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# Today's program

We will discuss chapter's 2.4 and 2.5, in order. These chapters are respectively concerned with:

- What condition on  $\mathcal{F}$  guarantees that it is  $P$ -Glivenko-Cantelli?
- What condition on  $\mathcal{F}$  guarantees that it is  $P$ -Donsker?

# Glivenko-Cantelli Classes

A function class  $\mathcal{F}$  is called *P-Glivenko-Cantelli* if

$$\|\mathbb{P}_n - P\|_{\mathcal{F}} \rightarrow 0 \text{ in outer probability}$$

where  $\|\cdot\|_{\mathcal{F}}$  denotes the uniform norm.

# Conditions on $\mathcal{F}$

Showing  $\|\mathbb{P}_n - P\|_{\mathcal{F}} \rightarrow 0$  is generally not straightforward.

- sup over  $\mathcal{F}$  of infinite cardinality are generally nasty.
- Measurability issues.

A way to deal with these issues is through entropy conditions on  $\mathcal{F}$ :  
“sup smells like entropy”

Two flavours of entropy conditions:

- Bracketing entropy
- Metric entropy

# Bracketing entropy based Glivenko-Cantelli

## Theorem

*Let  $\mathcal{F}$  be a class of measurable functions such that  $N_{[]}(\varepsilon, \mathcal{F}, L_1(P)) < \infty$  for every  $\varepsilon > 0$ . Then,  $\mathcal{F}$  is Glivenko-Cantelli.*

**Proof:** Fix  $\varepsilon > 0$ , choose a finite amount of brackets  $[l_i, u_i]$  such that  $P(u_i - l_i) < \varepsilon$ .

Every  $f \in \mathcal{F}$  lives in one of these brackets so

$$(\mathbb{P}_n - P)f \leq (\mathbb{P}_n - P)u_i + P(u_i - f) \leq (\mathbb{P}_n - P)u_i + \varepsilon.$$

This means

$$\sup_{f \in \mathcal{F}} (\mathbb{P}_n - P)f \leq \max_i (\mathbb{P}_n - P)u_i + \varepsilon$$

which is measurable. A similar argument can be made for the inf. We conclude that  $\limsup \|\mathbb{P}_n - P\|_{\mathcal{F}}^* \leq \varepsilon$ .

# (Random semi) metric entropy based Glivenko-Cantelli

## Theorem

*Let  $\mathcal{F}$  be a  $P$ -measurable class with envelope  $F$  such that  $P^*F < \infty$ .  
Let  $\mathcal{F}_M$  be the class of functions  $f1\{F \leq M\}$  when  $f \in \mathcal{F}$ .*

*Then,  $\|\mathbb{P}_n - P\|_{\mathcal{F}}^* \rightarrow 0$  almost surely if and only if  
 $n^{-1} \log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n)) \rightarrow 0$  in outer probability.*

*In the above case, the convergence is also in outer mean.*



Proof:  $\Leftarrow$ 

Assume  $n^{-1} \log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n)) \rightarrow 0$  in outer probability.

Recall the Symmetrization Lemma (2.3.1): For every nondecreasing, convex  $\Phi : \mathbb{R} \rightarrow \mathbb{R}$  and measurable  $\mathcal{F}$ ,

$$E^* \Phi(\|\mathbb{P}_n - P\|_{\mathcal{F}}) \leq E^* \Phi \left( 2 \left\| n^{-1} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\mathcal{F}} \right).$$

Proof:  $\Leftarrow$ 

This yields

$$E^* \|\mathbb{P}_n - P\|_{\mathcal{F}} \leq 2E_X E_\varepsilon \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\mathcal{F}}.$$

which we can bound further using our envelope:

$$2E_X E_\varepsilon \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\mathcal{F}_M} + 2P^* F\{F > M\}.$$

The first term can be dealt with using a maximal inequality.

## Maximal inequality (Lemma 2.2.2)

Let  $\psi : \mathbb{R} \rightarrow \mathbb{R}$  convex, nondecreasing and nonzero except for in the point 0. Recall that *the Orlicz-norm* for  $\psi$  is defined as

$$\|X\|_{\psi} := \inf \left\{ C > 0 : E \left( \frac{|X|}{C} \right) \leq 1 \right\}.$$

Suppose  $\limsup_{x,y \rightarrow \infty} \psi(x)\psi(y)/\psi(cxy) < \infty$  for some  $c \in \mathbb{R}$ . Then,

$$\left\| \max_{1 \leq i \leq m} X_i \right\|_{\psi} \leq K \psi^{-1}(m) \max_{1 \leq i \leq m} \|X_i\|_{\psi}$$

for  $K > 0$  depending only on  $\psi$ .

Proof:  $\Leftarrow$ 

To apply this, note that we can choose a net  $\mathcal{G}$  of cardinality  $\log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n))$  such that

$$2E_X E_\varepsilon \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\mathcal{F}_M} \leq \sqrt{1 + \log |\mathcal{G}|} \sup_{f \in \mathcal{G}} \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\psi_2}$$

where we note that the  $L_1$ -norm on the right is bounded by the  $\psi_2(x) := e^{x^2} - 1$  Orlicz-norm.

Proof:  $\Leftarrow$ 

We have the Hoeffding increment bound for this choice of Orlicz norm from Chapter 2.2:

$$\|X_s - X_t\|_{\psi_2} \leq \sqrt{6}d(s, t).$$

We can apply this for the  $L_2(\mathbb{P}_n)$  distance. By the envelope condition,  $\mathbb{P}_n f^2 \leq M^2$  for all  $f \in \mathcal{F}$ . This gives us

$$\begin{aligned} E^* \|\mathbb{P}_n - P\|_{\mathcal{F}} &\leq 2E_X E_\varepsilon \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right\|_{\mathcal{F}_M} + \varepsilon \\ &\leq E_X \sqrt{1 + \log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n))} \frac{1}{n} \sqrt{6}M + \varepsilon. \end{aligned}$$

Since  $\varepsilon$  can be chosen arbitrarily small and  $n^{-1} \log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n)) \rightarrow 0$  in outer probability.

Proof:  $\implies$ 

For the other direction, assume  $\|\mathbb{P}_n - P\|_{\mathcal{F}}^* \rightarrow 0$  almost surely.

Desymmetrization (Lemma 2.3.6) then implies

$$\frac{1}{2} E^* \left\| \frac{1}{n} \sum_{i=1}^n \varepsilon_i (f(X_i) - Pf) \right\|_{\mathcal{F}} \leq E^* \|\mathbb{P}_n - P\|_{\mathcal{F}}^* \rightarrow 0.$$

We can take  $\varepsilon_i = Z_i \sim \mathcal{N}(0, 1)$ .

The link with entropy is provided by Sudakov's inequality.

# Sudakov's inequality

For a centered, separable Gaussian process  $X$  indexed by  $T$ ,

$$\sup_{\varepsilon > 0} \varepsilon \sqrt{\log N(\varepsilon, T, \rho)} \leq \sqrt{2\pi \log 2} E \sup_{t \in T} X_t$$

where  $\rho(s, t) = \sigma(X_s - X_t)$ .

The symmetrized process  $\{n^{-1} \sum_{i=1}^n Z_i f(X_i) : f \in \mathcal{F}\}$  is centered and Gaussian and  $\rho$  here is the  $L_2(\mathbb{P}_n)$  norm!

Proof:  $\implies$ 

We obtain that  $n^{-1/2} \sqrt{\log N(\varepsilon, \mathcal{F}, L_2(\mathbb{P}_n))} \rightarrow 0$  in outer expectation.

Note also that  $N(\varepsilon, \mathcal{F}_M, L_2(\mathbb{P}_n)) \leq N(\varepsilon, \mathcal{F}_M, L_\infty(\mathbb{P}_n)) \leq (\frac{2M}{\varepsilon})^n$ .

We finalize our proof:

$$\frac{1}{n} \log N(\varepsilon, \mathcal{F}_M, L_2(\mathbb{P}_n)) \leq \frac{1}{n} \sqrt{\log[(\frac{2M}{\varepsilon})^n]} \sqrt{\log N(\varepsilon, \mathcal{F}, L_2(\mathbb{P}_n))} \rightarrow 0$$

in outer expectation.



# Addendum to the theorem

Recall the last claim of the theorem:

## Theorem

*Let  $\mathcal{F}$  be a  $P$ -measurable class with envelope  $F$  such that  $P^*F < \infty$ . Let  $\mathcal{F}_M$  be the class of functions  $f1\{F \leq M\}$  when  $f \in \mathcal{F}$ .*

*Then,  $\|\mathbb{P}_n - P\|_{\mathcal{F}}^* \rightarrow 0$  almost surely if and only if  $n^{-1} \log N(\varepsilon, \mathcal{F}_M, L_1(\mathbb{P}_n)) \rightarrow 0$  in outer probability.*

***In the above case, the convergence is also in outer mean.***

This shown via a martingale argument.

# Hoffmann-Jorgensen inequality for moments (colloquial version)

Let  $X_1, \dots, X_n$  independent stochastic processes indexed by  $T$ . Then there exist  $C > 0$  and  $0 < \nu < 1$  such that

$$\mathbb{E}^* \max_{k \leq n} \left\| \sum_{i=1}^k X_k \right\|_T \leq C \left( \mathbb{E}^* \max_{k \leq n} \|X_k\|_T + F^{-1}(\nu) \right)$$

where  $F^{-1}$  denotes the quantile function of  $\max_{k \leq n} \left\| \sum_{i=1}^k X_k \right\|_T$ .

# Multiplier inequality (Lemma 2.9.1, colloquial version)

Let  $Z_1, \dots, Z_n$  iid standard normals and let  $X_1, \dots, X_n$  iid stochastic processes indexed by  $T$ , jointly independent.

$$\mathbb{E}^* \max_{k \leq n} \left\| \sum_{i=1}^k X_k \right\|_T \leq C \left( \mathbb{E}^* \max_{k \leq n} \|X_k\|_T + F^{-1}(v) \right)$$

where  $F^{-1}$  denotes the quantile function of  $\max_{k \leq n} \left\| \sum_{i=1}^k X_k \right\|_T$ .

## Desymmetrization Lemma (2.3.1)

# Bracketing numbers of $\mathcal{F}$

A function class  $\mathcal{F}$  is called *P-Donsker* if

$$\mathbb{G}_n := n^{-1/2}(\mathbb{P}_n - P) \rightsquigarrow \ell^\infty(\mathcal{F}).$$

# Weak convergence in $\ell^\infty(\mathcal{F})$

Recall:  $X_\alpha$  converges weakly to a tight limit taking values in  $\ell^\infty(\mathcal{F})$  if and only if  $X_\alpha$  is asymptotically tight and its marginals converge weakly.

By the CLT, we already have marginal convergence, so asymptotic tightness of  $\mathbb{G}_n$  is what we are after.

# Asymptotic tightness

Recall that a net  $X_\alpha$  is asymptotically tight if for every  $\varepsilon > 0$  there exists a compact set  $K$  such that

$$\liminf P_*(X_\alpha \in K^\delta) \geq 1 - \varepsilon \quad \text{for every } \delta > 0.$$

This is hard to show directly for  $\mathbb{G}_n$ , but we can use a characterization: *asymptotic equicontinuity*.

# Asymptotic equicontinuity

A net  $X_\alpha : \Omega \rightarrow \ell^\infty(T)$  is *asymptotically uniformly  $\rho$ -equicontinuous in probability* if for every  $\varepsilon, \eta > 0$  there exists a  $\delta > 0$  such that

$$\limsup_{\alpha} P^* \left( \sup_{\rho(s,t) < \delta} |X_\alpha(s) - X_\alpha(t)| > \varepsilon \right) < \eta.$$

**Theorem 1.5.7:**  $X_\alpha$  is asymptotically tight if and only if  $X_\alpha(t)$  is asymptotically tight in  $\mathbb{R}$  for every  $t$  and there exists a semimetric  $\rho$  on  $T$  such that  $(T, \rho)$  is totally bounded and  $X_\alpha$  is asymptotically uniformly  $\rho$ -equicontinuous in probability.



The Donsker theorems come in two flavours (two types of conditions on  $\mathcal{F}$ ):

- Based on the uniform entropy condition

$$\int_0^\infty \sup_Q \sqrt{\log N(\varepsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q))} d\varepsilon < \infty.$$

- Based on bracketing entropy

$$\int_0^\infty \sqrt{\log N_{[]}(\varepsilon, \mathcal{F}, L_2(P))} d\varepsilon < \infty.$$

These conditions are generally not comparable. Examples of function classes satisfying either or both are given in Chapter 2.7.

# Donsker Theorem's based on bracketing

## Theorem

*Any class  $\mathcal{F}$  of measurable functions satisfying*

$$\int_0^\infty \sqrt{\log N_{[]}(\varepsilon, \mathcal{F}, L_2(P))} d\varepsilon < \infty$$

*is  $P$ -Donsker.*

This result is a consequence of the following more general theorem.

# First, let's define a norm

Define the  $L_{2,\infty}$ -“norm” on  $\mathcal{F}$  as

$$\|f\|_{P,2,\infty} = \sup_{x>0} \left( x^2 P(|f| > x) \right)^{1/2}.$$

This norm is weaker than the the  $L_2(P)$  norm.

# Donsker Theorem's based on bracketing

## Theorem

*Any class  $\mathcal{F}$  of measurable functions satisfying*

$$\int_0^\infty \sqrt{\log N_{[]}(\varepsilon, \mathcal{F}, L_{2,\infty}(P))} d\varepsilon + \int_0^\infty \sqrt{\log N(\varepsilon, \mathcal{F}, L_2(P))} d\varepsilon < \infty$$

*is  $P$ -Donsker.*

This is more general than the previous result (why?).

# Sketch of the proof

The proof relies on applying the following result (Theorem 1.5.6) for proving asymptotic tightness:

A net  $X_\alpha$  taking values in  $\ell^\infty(T)$  is asymptotically tight if and only if  $X_\alpha(t)$  is asymptotically tight in  $\mathbb{R}$  for every  $t \in T$  and if there exist a finite partition  $T = \dot{\cup} T_i$  such that asymptotic equicontinuity holds uniformly over these partitions in the following sense:

$$\limsup P^* \left( \sup_i \sup_{s,t \in T_i} |X_\alpha(s) - X_\alpha(t)| > \varepsilon \right) < \eta.$$

The statement “ $X_\alpha(t)$  is asymptotically tight in  $\mathbb{R}$  for every  $t \in T$ ” holds already in our situation..

# Sketch of the proof

The "joint entropy" condition

$$\int_0^\infty \sqrt{\log N_{[]}(\varepsilon, \mathcal{F}, L_{2,\infty}(P))} d\varepsilon + \int_0^\infty \sqrt{\log N(\varepsilon, \mathcal{F}, L_2(P))} d\varepsilon < \infty$$

is used to construct the partition for which the second condition of 1.5.6 is satisfied. That is, a partition  $\bigcup \mathcal{F}_i = \mathcal{F}$  for which we can show  $E^* \max_i \|\mathbb{G}_n\|_{\mathcal{F}_i} \rightarrow 0$ , which yields asymptotic equicontinuity through

$$P^*(\max_i \|\mathbb{G}_n\|_{\mathcal{F}_i} > x) \leq \frac{1}{x} E^* \max_i \|\mathbb{G}_n\|_{\mathcal{F}_i}.$$

# Sketch of the proof

In order to show  $E^* \max_i \|\mathbb{G}_n\|_{\mathcal{F}_i} \rightarrow 0$ , we will aim to use the maximal inequality of Lemma 2.2.10:

Let  $X_1, \dots, X_n$  satisfy the tailbound

$$P(|X_i| > x) \leq 2e^{-\frac{1}{2} \frac{x^2}{b+ax}}$$

for all  $x, i$  and fixed  $a, b > 0$ . Then,

$$\|\max_i X_i\|_{\psi_1} \leq K \left( a \log(1+m) + \sqrt{b} \sqrt{\log(1+m)} \right).$$

# Sketch of the proof

As a consequence of Bernstein's inequality, the condition of Lemma 2.2.10 is satisfied:

$$P(|\mathbb{G}_n f| > x) \leq 2e^{-\frac{1}{2} \frac{x^2}{Pf^2 + 2/3 \|f\|_\infty x / \sqrt{n}}},$$

which holds for square integrable, uniformly bounded  $f \in \mathcal{F}$ .



# Sketch of the proof

So, if we partition  $\mathcal{F} = \cup \mathcal{F}_i$  such that we can consider  $\|\mathbb{G}_n\|_{\mathcal{F}_i}$  as (bounded by something) that runs over a finite amount of functions (say  $m$  functions) we obtain

$$E^* \|\mathbb{G}_n\|_{\mathcal{F}_i} \lesssim \max_{f_1, \dots, f_m} \frac{\|f\|_{\infty}}{\sqrt{n}} \log(1+m) + \max_{f_1, \dots, f_m} \|f\|_{P,2} \sqrt{\log(1+m)}.$$

# Sketch of the proof

The partitions follow from the “joint” entropy condition and

$$\sqrt{\log N_{[]}(\varepsilon, \mathcal{F}, L_{2,\infty}(P))} \leq \sqrt{\log N(\varepsilon, \mathcal{F}, L_2(P))}$$

(note that the latter norm is stronger).

For a natural number  $q \in \mathbb{N}$  we obtain  $N_q^1$ - $L_2(P)$  balls of radius  $2^{-q}$  and similarly  $N_q^2$ - $L_{\infty,2}(P)$  balls of radius  $2^{-q}$  such that

$$\sum_{q \in \mathbb{N}} 2^{-q} \sqrt{\log N_q} < \infty$$

for  $N_q = N_q^1 N_q^2$ .

The intersection and disjointification of our balls form the partitions  $\mathcal{F} = \cup \mathcal{F}_i^q$ .

A (lengthy) chaining argument based on these partitions one can show that for all big enough  $q_0$ ,

$$E^* \max_i \|\mathbb{G}_n\|_{\mathcal{F}_i^q} \lesssim \sum_{\infty}^{q_0} [2^{-q} \sqrt{\log N_q}]$$

which is finite by construction and hence goes to 0 as  $q_0 \rightarrow \infty$ , finishing the proof.

Thanks for listening!