### Empirical Processes with Applications in Statistics 1.Introduction

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Conférence Universitaire de Suisse Occidentale Programme Doctoral en Statistique et Probabilités Appliquées Les Diablerets, February 4–5, 2020

# A classical example

- ►  $X_1, X_2, \dots$  i.i.d. random variables on  $\mathbb{R}$
- Cumulative distribution functions: for  $x \in \mathbb{R}$ ,

$$F(x) = P(X_i \le x)$$
$$\mathbb{F}_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1} \{X_i \le x\}$$

• Law of large numbers: for every  $x \in \mathbb{R}$ ,

$$\mathbb{F}_n(x) \to F(x)$$
 a.s.,  $n \to \infty$ 

▶ Multivariate central limit theorem: for every  $(x_1, \ldots, x_\ell) \in \mathbb{R}^\ell$ ,

$$\left(\sqrt{n}\left\{\mathbb{F}_n(x_j)-F(x_j)\right\}\right)_{j=1}^\ell \stackrel{d}{\longrightarrow} \mathcal{N}_\ell(0,\Sigma), \qquad n \to \infty$$

with covariances  $\sigma_{jk} = F(x_j \wedge x_k) - F(x_j)F(x_k)$ 



### Goodness-of-fit testing

Test of a simple hypothesis on the distribution: for a given  $F_0$ ,

$$H_0: F = F_0$$
 vs  $H_1: F \neq F_0$ 

Test statistic:

$$T_n = \sup_{x \in \mathbb{R}} \sqrt{n} \left| \mathbb{F}_n(x) - F_0(x) \right|$$

Distribution under  $H_0$ ? Limit distribution as  $n \to \infty$ ?

For a vector  $(x_1, \ldots, x_\ell) \in \mathbb{R}$ , we could consider

$$T_n(x_1,\ldots,x_\ell) := \max_{\substack{j=1,\ldots,\ell}} \sqrt{n} \left| \mathbb{F}_n(x_j) - \mathcal{F}_0(x_j) \right|$$
$$\stackrel{d}{\longrightarrow} \max_{\substack{j=1,\ldots,\ell}} |B(x_j)|$$

where  $(B(x_1), \ldots, B(x_\ell)) \sim \mathcal{N}(0, \Sigma)$  as on the previous slide. How to go from "max<sub>x1,...,x\ell</sub>" to "sup<sub>x \in R</sub>?



**Kolmogorov (1933), Doob (1949), Donsker (1952)** If *F* is continuous, the law of  $T_n$  under  $H_0$  does not depend on  $F_0$ , and

$$T_n \stackrel{d}{\longrightarrow} \sup_{t \in [0,1]} |B(t)|, \qquad n \to \infty$$

where  $(B(t))_{t \in [0,1]}$  is a Brownian bridge

Brownian bridge:

- zero-mean Gaussian process
  (= collection of jointly normal random variables)
- (almost surely) continuous trajectories  $t \mapsto B(t)$
- covariance function

 $\forall s, t \in [0, 1], \qquad \mathsf{E}[B(s)B(t)] = s \wedge t - st$ 

### Pointwise convergence: not sufficient for suprema

- Kolmogorov's result does not follow from the multivariate CLT: pointwise convergence does not imply convergence of suprema
- Sufficient (but not necessary) is uniform convergence

Example: construct functions  $f_n : [0, 1] \rightarrow [0, 1]$  such that, at the same time

$$\lim_{n \to \infty} f_n(t) = 0 \qquad \forall t \in [0, 1]$$
  
$$\sup_{t \in [0, 1]} f_n(t) = 1 \qquad \forall n$$

even though, for all  $(t_1, \ldots, t_\ell) \in [0, 1]^\ell$ , we must have

$$\max_{j=1,\dots,\ell} f_n(t_j) \to 0, \qquad n \to \infty$$



Uniform convergence of stochastic processes?

For simplicity, assume *F* is uniform on [0, 1]

Kolmogorov's result would follow from a "uniform" version of

$$\left(\sqrt{n}\left\{\mathbb{F}_n(t) - F(t)\right\}\right)_{t \in [0,1]} \stackrel{d}{\to} (B(t))_{t \in [0,1]}, \qquad n \to \infty$$

Meaning? Certainly not<sup>1</sup>

$$\sup_{t\in[0,1]} \left| \sqrt{n} \left\{ \mathbb{F}_n(t) - F(t) \right\} - B(t) \right| \xrightarrow{??} 0, \qquad n \to \infty$$

<sup>&</sup>lt;sup>1</sup>Although such statements can be given a formal meaning via Skorohod constructions

# Random elements in a function space

View  $t \mapsto \sqrt{n} \{\mathbb{F}_n(t) - F(t)\}$  as a random function: map from probability space  $\Omega$  carrying the  $X_i$  into some function space

- Space should contain almost all trajectories of  $\sqrt{n}(\mathbb{F}_n F)$
- Function space to be equipped with a *metric* or norm, so we can consider the corresponding Borel *σ*-field
- Metric should be strong enough so that convergence of functions has useful consequences

• E.g.:  $z_n \rightarrow z$  should imply  $\sup_t |z_n(t)| \rightarrow \sup_t |z(t)|$ 

In that function space, show weak convergence  $\sqrt{n}(\mathbb{F}_n - F) \stackrel{d}{\rightarrow} B$ 

# Which function space?

C([0, 1]) Continuous functions, supremum norm

$$\|z\|_{\infty} = \sup_{0 \le t \le 1} |z(t)|$$

- ▶  $t \mapsto \mathbb{F}_n(t)$  is not continuous, but we could make it so
- Enforcing continuity could get awkward on other domains

 $\mathcal{D}([0, 1])$  càdlàg functions with (some) Skorohod topology. Drawbacks:

- Addition of functions is not continuous in Skorohod metric
- Difficult to generalize to other domains than intervals
  Billingsley (1968)
- $L_p([0, 1])$  Convergence in *p*-th mean does not even imply pointwise convergence, let alone convergence of suprema

Space of bounded functions

 $\ell^{\infty}([0, 1])$  Space of all bounded functions  $z : [0, 1] \to \mathbb{R}$  equipped with the supremum norm

$$||z||_{\infty} := \sup_{0 \leq t \leq 1} |z(t)|$$

- Strong notion of convergence, easy to apply
- No worries about regularity of trajectories
- Easy to extend from [0, 1] to general domains But...

### [Error on slide 12: non-measurable mapping]

Non-measurability of the empirical process The map

$$\Psi: [0,1] \to \ell^{\infty}([0,1]): x \mapsto \mathbb{1}_{[0,x]}$$

is not Borel measurable.

Proof. Let  $A \subset [0, 1]$  be *not* Borel measurable. The set

$$G = \bigcup_{y \in A} \left\{ z \in \ell^{\infty}([0,1]) \mid ||z - \mathbb{1}_{[0,y]}||_{\infty} \leq 1/2 \right\}$$

is a union of open balls in  $\ell^\infty([0,1]),$  therefore open, therefore Borel measurable. But

$$\mathbb{1}_{[0,x]} \in G \iff x \in A$$

so  $\Psi^{-1}(G) = A$ , which is not Borel measurable.



# Possible fix #1: the ball $\sigma$ -field

Lack of measurability is not to be taken lightly (ask S. Banach and A. Tarski)

Possible solution: on  $\ell^{\infty}([0, 1])$ , consider a smaller  $\sigma$ -field, the one generated by open balls (Dudley, 1966; Pollard, 1984)

The set G on slide 13 is not in the ball σ-field The union there is uncountable

Drawback: Natural link with topology on  $\ell^{\infty}([0, 1])$  is lost

- ► Continuous mappings on ℓ<sup>∞</sup>([0, 1]) are not automatically ball-measurable
- Continuous mapping theorem and functional delta method become potentially more difficult to apply

# Possible fix #2: allow for non-measurable mappings

Hoffmann-Jørgensen (1984, 1991):

- Use inner/outer expectation and inner/outer probability for non-measurable mappings and sets
- Insist on measurability only in the limit

Theory works especially well when limit Borel probability measure *L* on  $\ell^{\infty}([0, 1])$  is *tight*:

- For all ε > 0, there exists compact K ⊂ ℓ<sup>∞</sup>([0, 1]) such that L(K) ≥ 1 − ε
- Then L concentrates on stochastic processes with sample paths that are uniformly continuous with respect to some nice semimetric on [0, 1]

Extends to  $\ell^{\infty}(T)$ , where T is any set:

 $\implies$  T is a family of functions: empirical processes indexed by *functions* 

# Empirical process indexed by functions

- X<sub>1</sub>, X<sub>2</sub>,... i.i.d. random variables on some probability space Ω and into some measurable space (X, A) with common distribution P
- ► Family  $\mathcal{F} \subset L_2(P)$  of *P*-square integrable functions  $f : X \to \mathbb{R}$

**Definition: Empirical process indexed by**  $\mathcal{F}$ **.** For  $f \in \mathcal{F}$ ,

$$\mathbb{G}_n f = \sqrt{n} \left( \frac{1}{n} \sum_{i=1}^n f(X_i) - \mathbb{E}[f(X_1)] \right)$$

Examples:

▶ ...

- ▶ The empirical process  $\sqrt{n}(\mathbb{F}_n F)$  above: all  $f = \mathbb{1}_{[0,x]}$  for  $x \in \mathbb{R}$
- Multivariate weighted empirical distribution functions
- Functions  $f_{\theta}$  indexed by a parameter  $\theta$ , e.g., parametric models

## Convergence of finite-dimensional distributions

Multivariate central limit theorem. For every  $(f_1, \ldots, f_\ell) \in \mathcal{F}^\ell$ ,

$$(\mathbb{G}_n f_1, \ldots, \mathbb{G}_n f_\ell) \xrightarrow{d} (\mathbb{G} f_1, \ldots, \mathbb{G} f_\ell), \qquad n \to \infty$$

The limit vector is centered multivariate normal with covariances

$$\mathsf{E}[\mathbb{G}f_j \,\mathbb{G}f_k] = \mathsf{cov}\left(f_j(X_1), f_k(X_1)\right)$$

Cannot conclude that

$$\sup_{f \in \mathcal{F}} |\mathbb{G}_n f| \stackrel{d}{\longrightarrow} \sup_{f \in \mathcal{F}} |\mathbb{G}f|, \qquad n \to \infty$$

• CLT *uniform* in  $f \in \mathcal{F}$ ?

# Empirical process as a random bounded function

Suppose  $\mathcal{F}$  is such that almost every trajectory  $f \mapsto \mathbb{G}_n f$  is bounded:

- ▶  $\sup_{f \in \mathcal{F}} |f(x)| < \infty$  for *P*-almost every  $x \in X$
- $\sup_{f\in\mathcal{F}} |\mathsf{E}[f(X_1)]| < \infty$

View  $\mathbb{G}_n$  as a possibly nonmeasurable map into  $\ell^{\infty}(\mathcal{F})$ :

$$\mathbb{G}_n: \Omega \to \ell^\infty(\mathcal{F})$$

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

$$\mathbb{G}_n \xrightarrow{?} \mathbb{G}, \qquad n \to \infty$$

Limit process G should be a P-Brownian bridge

- centered Gaussian process indexed by F
- covariances as on slide 18
- "nice" trajectories  $f \mapsto \mathbb{G}f$

### Approach will work for some, but not all, families ${\mathcal F}$

For weak convergence of  $\mathbb{G}_n$  in  $\ell^{\infty}(\mathcal{F})$ , the choice of  $\mathcal{F}$  is crucial:

For  $X = \mathbb{R}$  and any *P*, weak convergence always holds for

$$\mathcal{F} = \left\{ \mathbb{1}_{(-\infty,x]} \mid x \in \mathbb{R} \right\}$$

• Counterexample: for X = [0, 1] with P the uniform distribution and

$$\mathcal{F} = \{ all \text{ polynomial } f : [0, 1] \rightarrow [0, 1] \}$$

we have, by the Stone-Weierstrass theorem,

$$\sup_{f\in\mathcal{F}}|\mathbb{G}_n f|=\sup_{f\in\mathcal{F}}\sqrt{n}\left|\frac{1}{n}\sum_{i=1}^n f(X_i)-\int_0^1 f(x)\,dx\right|=\sqrt{n}$$

 $\implies \mathcal{F}$ -based Kolmogorov–Smirnov test breaks down



# Course outline

- 1. Introduction
- 2. Stochastic Convergence in Metric Spaces
- 3. Glivenko-Cantelli and Donsker Theorems
- 4. Tools to Work with Empirical Processes

Main sources for these lectures:

- van der Vaart and Wellner (1996)
- van der Vaart (1998)
- Kosorok (2008)

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