

# SDS 387 Linear Models

Fall 2025

Lecture 4 - Tue, Sept 11, 2025

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- Last time, the event

$$A_i = \{ |\hat{F}_n(x_i) - F_X(x_i)| < \epsilon \}$$

should be

$$A_i = \{ |\hat{F}_n(x_i) - F_X(x_i)| < \epsilon \text{ eventually} \}$$

- Then by SLN  $\mathbb{P}(A_i) = 1$  all  $i$  or  $n \rightarrow \infty$

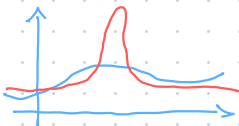
$$\Rightarrow \mathbb{P}\left(\bigcap A_i\right) = \mathbb{P}\left(\left\{\max_i |\hat{F}_n(x_i) - F_X(x_i)| < \epsilon \text{ eventually}\right\}\right) = 1$$

- Glivenko Contelli:  $\hat{F}_n \rightarrow F_X$  <sup>empirical cdf</sup>  $\xrightarrow{\text{true cdf}}$   $\| \hat{F}_n - F_X \|_\infty \xrightarrow{\text{w.p. 1}} 0$

Aside:  $f: \mathbb{R}^d \rightarrow \mathbb{R}$

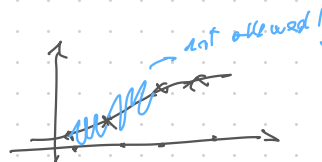
The sup-norm of  $f$  is

$$\sup_{x \in \mathbb{R}^d} |f(x)|$$



$$\sup_{x \in \mathbb{R}} |\hat{F}_n(x) - F_X(x)|$$

PA/



Let  $F = F_X$ .

Let  $\varepsilon > 0$  arbitrarily small. Then  $\exists K = K(\varepsilon) \in \mathbb{N}_+$  and a set of points

$$-\infty = x_0 < x_1 < \dots < x_{K-1} < x_K = +\infty$$

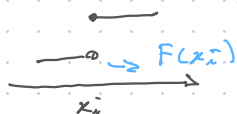
s.t.

$$0 \leq F(x_i^-) - F(x_{i-1}) < \varepsilon \quad \text{all } i. \quad (*)$$

$$\lim_{y \uparrow x_i} F(y)$$

$[F(x_i^-) < F(x_i) \text{ if there is positive mass at } x_i:]$

$$P(X = x_i) > 0]$$



• Remark: points  $x$  at which  $F(x) - F(x^-) > \varepsilon$  are among the  $x_i$ 's.

• Take any  $x \in \mathbb{R}$ . Then  $\exists n$  s.t.  $x_{i-1} \leq x < x_i$

Then

$$\hat{F}_n(x) - F(x) \leq \hat{F}_n(x_i^-) - F(x_{i-1})$$

$$\leq \hat{F}_n(x_i^-) - F(x_i^-) + \varepsilon$$

using (\*)

Similarly

$$\hat{F}_n(x) - F(x) \geq \hat{F}_n(x_{i-1}) - F(x_{i-1}) - \varepsilon$$

using (2) and the fact that

$$F(x) \leq F(x_i^-) \leq F(x_{i-1}) + \varepsilon$$

Therefore, for any  $x$ :

$$\begin{aligned} |\hat{F}_n(x) - F(x)| &\leq \max_i \left\{ |\hat{F}_n(x_i^-) - F(x_i^-)|, |\hat{F}_n(x_{i-1}) - F(x_{i-1})| \right\} + \varepsilon \\ &= A + \varepsilon \end{aligned} \quad (2)$$

as  $n \rightarrow \infty$   $A \xrightarrow{\text{a.s.}} 0$  by the arguments discussed last time

↓

$$\limsup_n |\hat{F}_n(x) - F(x)| \leq \varepsilon \quad \text{up 1}$$

Because  $\varepsilon > 0$  is arbitrary this  $\limsup$  is 0.  $\square$

Remark: this is a great result but not a quantitative one.

Q: how fast is this convergence?

• As alluded last time, a more informative result is

DKW inequality

↓  
see Massart's (1991)  
paper

$$P(\|\hat{F}_n - F\|_\infty \geq \varepsilon) \leq 2 \exp\{-2n\varepsilon^2\}$$

• DKW inequality implies Glivenko Cantelli. This follows from Borel - Cantelli's First Lemma.

If  $\{A_n\}$  is a sequence of events s.t.  $\sum_n P(A_n) < \infty$   
then  $P(\limsup_n A_n) = 0$

↳  $A_n$  happens i.o.

• Back to DKW let  $A_n = \{\|\hat{F}_n - F\|_\infty \geq \varepsilon\}$ . Then  
 $P(A_n) \leq 2 \exp\{-n\varepsilon^2\}$  so  $\sum_n P(A_n) < \infty$ .

↳  $P(\limsup A_n) = 0$

PA/ Borel-Cantelli's First Lemma.

$$\limsup_n A_n = \bigcap_{n=1}^{\infty} \bigcup_{m=n}^{\infty} A_m := \bigcap_{n=1}^{\infty} B_n. \quad \text{Next}$$

$B_n$  is a decreasing sequence (i.e.  $B_n \supseteq B_{n+1}$ )

By continuity of the probability:

$$P\left(\bigcap_n B_n\right) = \lim_n P(B_n)$$

$$\text{But } P(B_n) \leq \sum_{m=n}^{\infty} P(A_m) \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

↓  
union bound

because  
 $\sum_n P(A_n) < \infty$ .

$$P\left(\limsup_n A_n\right) = P\left(\bigcap_n B_n\right) = 0 \quad \square$$

Final comment about convergence in probability.  $\lim_{n \rightarrow \infty} P(d(X_n, X) \geq \varepsilon) = 0 \quad \forall \varepsilon > 0$

It is important to realize that there needs to be some knowledge about the joint distribution of  $X_n$  and  $X$ , for all  $n$ .

Example

Consider the sequence  $\{X_n\}$  s.t.

$$P(X_n = 1) = 1 - P(X_n = 0) = \frac{1}{2} \frac{n+1}{n}$$

Let  $X \sim \text{Bernoulli}(1/2)$

Q:  $X_n \xrightarrow{P} X$  ?

In fact, we cannot answer without further info about the joint distribution of  $(X_n, X)$ .

Suppose  $X_n \not\perp\!\!\!\perp X$ , Then  $X_n \not\stackrel{P}{\rightarrow} X$ .

↓  
independent

Because:

$$P(|X_n - X| > \varepsilon) = P(|X_n - X| = 1)$$

↓

$$\varepsilon \in (0, 1) \quad = \underbrace{\frac{1}{2} \frac{1}{2} \frac{n+1}{n}}_{P(X_n=1)} + \underbrace{\frac{1}{2} \frac{1}{2} \frac{n-1}{n}}_{P(X_n=0)} = \frac{1}{2}$$

• On the other hand, assume:

$$P(X_n = 1 \mid X = 1) = 1 \quad \text{and} \quad P(X_n = 1 \mid X = 0) = \frac{1}{n}$$

[Aside: these conditionals are compatible with the marginals]  
check!

$$\begin{aligned} \downarrow \quad P(|X_n - X| > \varepsilon) &= P(X_n = 1 \mid X = 0) P(X = 0) + \\ &\quad \downarrow \\ &\quad \varepsilon \in (0, 1) \quad P(X_n = 0 \mid X = 1) P(X = 1) \\ &= \frac{1}{2n} \rightarrow 0 \quad \text{as } n \rightarrow \infty \end{aligned}$$

• Convergence in prob. may not be as natural as we think!

$$X_n = Z \sim N(0, 1) \quad \text{all } n \quad X = -Z \sim N(0, 1)$$

Then  $X_n \not\stackrel{P}{\rightarrow} X$  even though

$$X_n \stackrel{d}{=} X$$

↓  
equality in distribution

# $L_p$ CONVERGENCE

For a <sup>univariate</sup> random variable  $X$  and  $p \geq 1$  let

$L_p$  norm of  $X$   $\leftarrow \|X\|_p = \left( \mathbb{E}[|X|^p] \right)^{1/p}$

$\hookrightarrow$  this is a "norm":

Remark if  $p < 1$  this is not a norm as it fails triangle ineq.

$$\|X\|_p = 0 \text{ if } X = 0 \text{ w.p. 1}$$

$$\|X\|_p \geq 0 \quad \text{a.s.}$$

$$\|aX\|_p = |a| \|X\|_p$$

$$\|X+Y\|_p \leq \|X\|_p + \|Y\|_p$$

$\hookrightarrow$  triangle ineq

$L_p$  convergence  $X_n \xrightarrow{L_p} X$  when

$$\|X_n - X\|_p \rightarrow 0 \text{ as } n \rightarrow \infty$$

The case of  $p=2$  is by far the most common.

For example, in stats, if  $\theta$  is a parameter of interest and  $\hat{\theta}_n$  an estimator of  $\theta$ , the mean

squared error is

$$\|\hat{\theta}_n - \theta\|_2^2 = \mathbb{E}[(\hat{\theta}_n - \theta)^2] = \underbrace{(\mathbb{E}[\hat{\theta}_n] - \theta)^2}_{\text{squared bias of } \hat{\theta}_n} + \underbrace{\mathbb{E}[(\hat{\theta}_n - \mathbb{E}[\hat{\theta}_n])^2]}_{\text{variance of } \hat{\theta}_n}$$

We can also take  $p = \infty$ !

$$\|X\|_\infty = \inf \{a: P(X > a) = 0\}$$

$\nwarrow$   
essential supremum of  $X$

$\|X\|_p \uparrow \|X\|_\infty \text{ as } p \rightarrow \infty$

## Properties of $L_p$ norms:

$$i) \quad X, Y \in L_p \quad X+Y \in L_p$$

use the following fact (C<sub>r</sub> inequality):

$$|x+y|^p \leq \begin{cases} |x| + |y| & 0 < p < 1 \\ 2^{p-1} (|x|^p + |y|^p) & p \geq 1 \end{cases}$$