

Lecture 11

Last time

- ▷ Branching Process continued.
- ▷ Convergence in L^p .

Uniform integrability

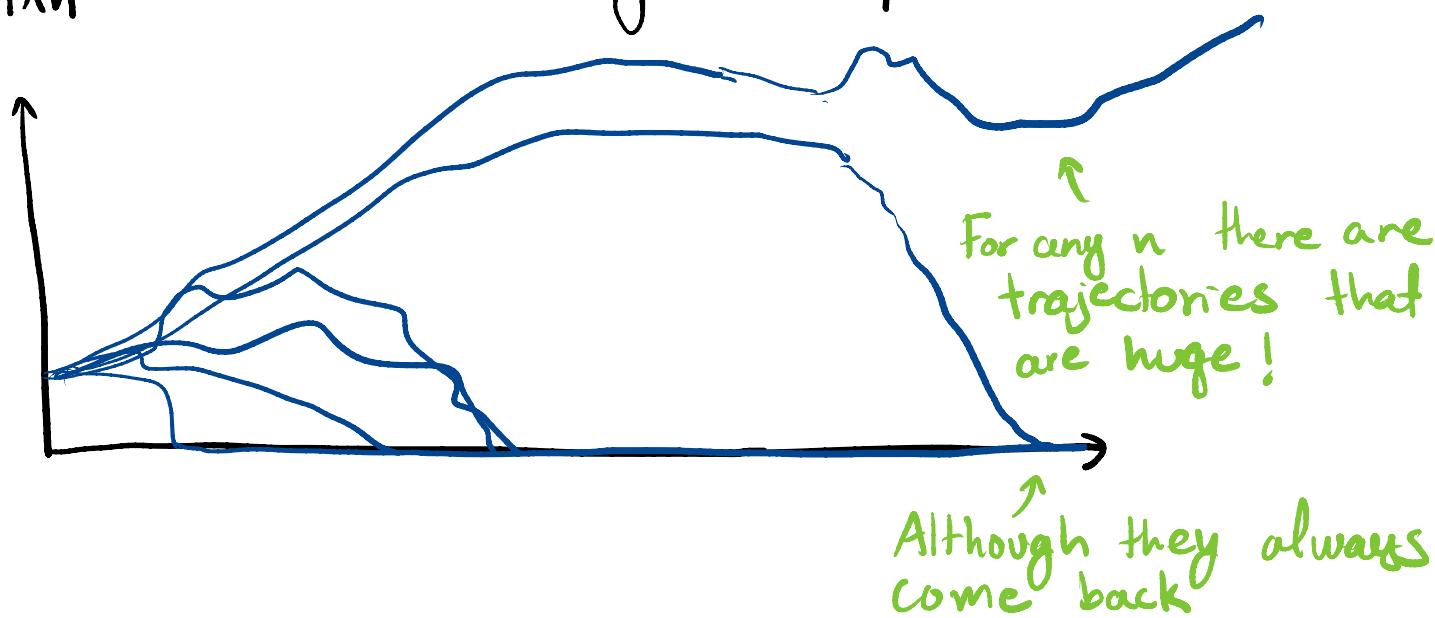
Why is it that we can fail to converge in L^1 ?

Recall our example

$$S_0 = 1, \quad S_n = \sum_{k=1}^n \xi_k \quad \text{and} \quad T = \inf \{k \mid S_k = 0\}.$$

Then $S_{T \wedge n} \xrightarrow{\text{a.s.}} S_T$ (Convergence theorem).

BUT $\mathbb{E} S_{T \wedge n} = \mathbb{E} S_0 = 1 \neq 0 = \mathbb{E} S_T$. Thus $S_{T \wedge n}$ does not converge to S_T in L^1 .



Monday Feb 26 / 24

Today

- ▷ Uniform integrability
- ▷ Convergence in L^1 .

The issue here is heavy tails!

Def: A collection of random variables is uniformly integrable if

$$\lim_{M \rightarrow \infty} \sup_{\alpha \in \Delta} \mathbb{E}[|X_\alpha| \mathbb{1}_{\{|X_\alpha| \geq M\}}] = 0.$$

Remarks: Δ does not have to be countable.

- ▷ This definition is general (no martingales).
- ▷ Intuitively we are asking the tail averages to decrease at similar rates.
- ▷ There are large collections of r.v. that are UI, e.g., let Y be integrable and let $\{X_\alpha\}_{\alpha \in \Delta}$ be the collection of r.v. dominated by Y ($|X_\alpha| < Y$), then $\{X_\alpha\}_{\alpha \in \Delta}$ is UI.

We care about UI because it characterizes L^1 convergence.

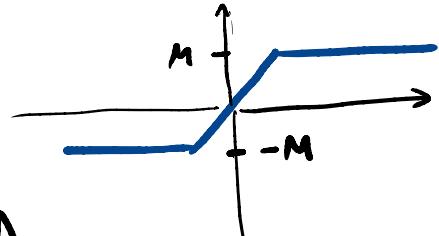
Theorem (No martingales!) Suppose $\mathbb{E}|X_n| < \infty \quad \forall n$ and

- $X_n \rightarrow X$ in probability (i.e., $\lim P(|X_n - X| \geq \epsilon) = 0$). Then, the following are equivalent:
- $\{X_n : n \geq 0\}$ is UI.

- b) $X_n \rightarrow X$ in L^1 .
c) $\mathbb{E}|X_n| \rightarrow \mathbb{E}|X| < \infty$.

Proof: a) \Rightarrow b) For any M , define the function

$$\Psi_M(x) = \begin{cases} M & \text{if } x \geq M, \\ x & \text{if } |x| \leq M, \\ -M & \text{if } x \leq -M. \end{cases}$$



We now apply triangle inequality

$$|X_n - X| \leq |X_n - \Psi_M(X_n)| + |\Psi_M(X_n) - \Psi_M(X)| + |\Psi_M(X) - \Psi(X)|.$$

Notice that $|\Psi_M(Y)| = (|Y| - M)^+ \leq |Y| \mathbf{1}_{\{|Y| \geq M\}}$.

Thus,

$$\mathbb{E}|X_n - X| \leq \underbrace{\mathbb{E}|X_n| \mathbf{1}_{\{|X_n| \geq M\}}}_{T_1} + \underbrace{\mathbb{E}|\Psi_M(X_n) - \Psi_M(X)|}_{T_2} + \underbrace{\mathbb{E}|X| \mathbf{1}_{\{|X| \geq M\}}}_{T_3}.$$

Let's show that we can make each term small

T₁) By UI we can pick M large enough to ensure that $T_1 \leq \epsilon$.

T₂) By the Continuous Mapping Thm $\Psi_M(X_n) \rightarrow \Psi_M(X)$ in probability. Since $Y_n = |\Psi_M(X_n) - \Psi_M(X)|$ converges in prob to 0 \Rightarrow By BCT for convergence in prob (Exercise 2.3.5 Durrett) $\mathbb{E} Y_n \rightarrow 0$.

T₃) By Fatou's lemma for convergence in

probability (Exercise 2.3.4 Durret)

$$\begin{aligned}\mathbb{E}|X| &= \mathbb{E}|\liminf X| \\ &\leq \liminf \mathbb{E}|X_n| \\ &\leq \sup \mathbb{E}|X_n| < \infty,\end{aligned}$$

Thus $\lim_{M \rightarrow \infty} \mathbb{E}|X| \mathbf{1}_{\{|X| \geq M\}} = 0$, and for large M , $T_3 \leq \epsilon$.

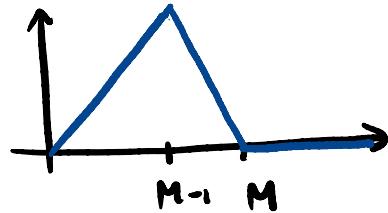
Thus we derive $\lim_{n \rightarrow \infty} \mathbb{E}|X_n - X| \leq 2\epsilon$ $\forall \epsilon$, which shows the implication after $\epsilon \downarrow 0$.

b) \Rightarrow c) By Jensen's

$$|\mathbb{E}|X_n| - \mathbb{E}|X|| \leq \mathbb{E}|X_n| - |\mathbb{E}X| \leq \mathbb{E}|X_n - X| \rightarrow 0.$$

c) \Rightarrow a) Define the function

$$\Psi_M(x) = \begin{cases} x & \text{if } x \in [0, M-1] \\ \text{linear} & \text{if } x \in [M-1, M] \\ 0 & \text{otherwise} \end{cases}$$



We can bound

$$\begin{aligned}\mathbb{E}(|X_n| \mathbf{1}_{\{|X_n| > M\}}) &\leq \mathbb{E}|X_n| - \mathbb{E}\Psi_M(|X_n|) \\ &\leq \underbrace{\mathbb{E}|X| - \mathbb{E}\Psi_M(|X|)}_{T_1} + \underbrace{(\mathbb{E}|X_n| - \mathbb{E}\Psi_M(|X_n|))}_{T_2} \\ &\quad - (\mathbb{E}|X| - \mathbb{E}\Psi_M(|X|))\end{aligned}$$

T1 By DCT, for large M we have $T_1 \leq \epsilon$.

T₂) By the same reasoning as in a) \Rightarrow b)

$$\mathbb{E} Y_n(X_n) \rightarrow \mathbb{E} Y(X), \text{ so } T_2 \leq \varepsilon \text{ for large } n \geq n_0.$$

Then for all $n \geq n_0$ we have

$\mathbb{E}(|X_n| \mathbf{1}_{\{|X_n| > M\}}) \leq \varepsilon$. For $1 \leq n \leq n_0$ we can take M larger to ensure that the same inequality holds $\Rightarrow X_n$ is UI.

□

L^1 convergence

Theorem Let X_n be a supermartingale. Then the following are equivalent:

- X_n is UI.
- X_n converges a.s. and in L^1 .
- X_n converges in L^1 .

Proof:

$$\begin{aligned} a) \Rightarrow b) \text{ Pick } M \text{ so that } \sup \mathbb{E} |X_n| \mathbf{1}_{\{|X_n| \geq M\}} \leq 1. \text{ Then} \\ \sup \mathbb{E} |X_n| = \sup \mathbb{E} |X_n| \mathbf{1}_{\{|X_n| \leq M\}} + \mathbb{E} |X_n| \mathbf{1}_{\{|X_n| \geq M\}} \\ \leq M + \sup |X_n| \mathbf{1}_{\{|X_n| \geq M\}} \\ \leq M + 1 < \infty. \end{aligned}$$

Then by Doob's Convergence Thm, $X_n \rightarrow X$

a.s. Recall that a.s. convergence implies convergence in prob. Then by Theorem (V) $X_n \rightarrow X$ in L^1 .

b) \Rightarrow c) Trivial.

c) \Rightarrow a) Recall that L^1 convergence implies convergence in probability. Then by Theorem (V) X_n is UI. \square

Q: How can we check uniform integrability?

Theorem: Let φ be any nonnegative function with $x/\varphi(x) \rightarrow 0$ as $x \rightarrow \infty$. Suppose $E\varphi(|X_\alpha|) \leq C$ for all $\alpha \in \Delta$. Then, $\{X_\alpha\}_{\alpha \in \Delta}$ is UI.

Proof: Let $\varepsilon_M := \sup\{x/\varphi(x) \mid x \geq M\}$. For $\alpha \in \Delta$ we have

$$\begin{aligned} E(|X_\alpha| \mathbb{1}_{\{|X_\alpha| \geq M\}}) &\leq \varepsilon_M E(\varphi(|X_\alpha|) \mathbb{1}_{\{|X_\alpha| \geq M\}}) \\ &\leq \varepsilon_M C. \end{aligned}$$

By assumption $\varepsilon_M \rightarrow 0$ as $M \rightarrow \infty$ so the result follows. \square

Useful functions are $\varphi(x) = x^\rho$ (which

yields the same condition as in the L^p convergence Thm from last class) and $\Psi(x) = x \log^+ x$ (which will appear in the homework).