

# Reading Group: Probability With Martingales Ch13

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Summer 2020

**Uniform integrability**

# Motivation

- Convergence in probability is easy to establish, e.g.
  - WLLN for independent RVs
  - Ergodic theorem for dependent RVs (discussed last semester in recursive TAVC)
  - Dominated convergence theorem
- Convergence in  $\mathcal{L}^p$ -norm is harder to establish on the other hand
- Uniform integrability is a necessary and sufficient condition to link them

# An “absolute continuity” property

- Lemma 13.1.1

- Suppose that  $X \in \mathcal{L}^1 = \mathcal{L}^1(\Omega, \mathcal{F}, \mathbb{P})$
- Then, given  $\epsilon > 0$ ,  $\exists \delta > 0$  s.t. for  $F \in \mathcal{F}$ ,  $P(F) < \delta \implies E(|X|; F) < \epsilon$

- Proof

- If the conclusion is false, then, for some  $\epsilon_0 > 0$ , we can find  $\{F_n\}$  consists of elements of  $\mathcal{F}$  s.t.

$$P(F_n) < 2^{-n}, E(|X|; F_n) \geq \epsilon_0$$

- Construction of “contracting” events
- Let  $H := \limsup F_n$ . Then BC1 shows that  $P(H) = 0$
- Yet reverse Fatou lemma shows that  $E(|X|; H) \geq \limsup_{n \rightarrow \infty} E(|X|; F_n) = \epsilon_0$
- Contradiction arises since  $P(H) = 0 \implies E(|X|; H) = 0$

# An “absolute continuity” property

- Corollary 13.1.2
  - Suppose that  $X \in \mathcal{L}^1$  and that  $\epsilon > 0$
  - Then  $\exists K \in [0, \infty)$  such that  $E(|X|; |X| > K) < \epsilon$
- Proof
  - Let  $\delta$  be as in lemma 13.1.1
  - Since  $KP(|X| > K) \leq E(|X|)$ , we can choose  $K$  such that  $P(|X| > K) \leq \delta$
  - Application of lemma 13.1.1 yields the result

# UI family

- A class  $\mathcal{C}$  of RVs is called uniformly integrable (UI) if given  $\epsilon > 0$ ,

$$\exists K \in [0, \infty) \text{ s.t. } E(|X|; |X| > K) < \epsilon, \forall X \in \mathcal{C}$$

- For such a class  $\mathcal{C}$ , we have (with  $K_1$  relating to  $\epsilon = 1$ ) for every  $X \in \mathcal{C}$ ,

$$\begin{aligned} E(|X|) &= E(|X|; |X| > K_1) + E(|X|; |X| \leq K_1) \\ &\leq 1 + K_1 \end{aligned}$$

- The first term comes from choice of  $K_1$  and corollary 13.1.2
- The second term comes from idea of Markov's inequality
- This means that a UI family is bounded in  $\mathcal{L}^1$  but the converse is not true
  - Counterexample: Take  $(\Omega, \mathcal{F}, \mathbb{P}) = ([0, 1], \mathcal{B}[0, 1], \text{Leb})$
  - Let  $E_n = (0, \frac{1}{n})$  and  $X_n = nI_{E_n}$
  - Then  $E(|X_n|) = 1, \forall n$  so that  $\{X_n\}$  is bounded in  $\mathcal{L}^1$
  - However, for any  $K > 0$ , we have for  $n > K$ ,  $E(|X_n|; |X_n| > K) = nP(E_n) = 1$
  - This means  $\{X_n\}$  is not UI. Here,  $X_n \rightarrow 0$  but  $E(X_n) \not\rightarrow 0$

# Two sufficient conditions for the UI property

- First condition: boundedness in  $\mathcal{L}^p$  where  $p > 1$ 
  - Suppose that  $\mathcal{C}$  is a class of RVs bounded in  $\mathcal{L}^p$  for some  $p > 1$
  - Thus, for some  $A \in [0, \infty)$ ,  $E(|X|^p) < A, \forall X \in \mathcal{C}$
  - Then  $\mathcal{C}$  is UI

- Proof

- If  $v \geq K > 0$ , then  $v^{1-p} \leq K^{1-p} \implies v \leq K^{1-p} v^p$
- Hence, for  $K > 0$  and  $X \in \mathcal{C}$ , we have

$$E(|X|; |X| > K) \leq K^{1-p} E(|X|^p; |X| > K) \leq K^{1-p} A$$

- The result follows from the fact that we can choose  $K$  based on the value of  $\epsilon := K^{1-p} A$

- Idea

- Boundedness in  $\mathcal{L}^p$  for some  $p > 1$  implies boundedness in  $\mathcal{L}^1$ 
  - Which is a property of UI family
  - While  $\mathcal{L}^p$  provides a “faster” convergence

# Two sufficient conditions for the UI property

- Second condition: dominated by an integrable non-negative variable
  - Suppose that  $\mathcal{C}$  is a class of RVs which is dominated by an integrable non-negative variable  $Y$ :

$$|X(\omega)| \leq Y(\omega), \forall X \in \mathcal{C} \text{ and } E(Y) < \infty$$

- Then  $\mathcal{C}$  is UI
- Proof
  - For  $K > 0$  and  $X \in \mathcal{C}$ , we have

$$E(|X|; |X| > K) \leq E(Y; Y > K) < \epsilon$$

- where the last inequality comes from corollary 13.1.2
- Remark
  - It is precisely this which makes dominated convergence theorem works for our  $(\Omega, \mathcal{F}, \mathbb{P})$
  - An extension of dominated convergence theorem to the whole class  $\mathcal{C}$



# UI property of conditional expectation

- Theorem 13.4.1
  - Let  $X \in \mathcal{L}^1$ . Then the class  $\{E(X|\mathcal{G}) : \mathcal{G} \text{ a sub-}\sigma\text{-algebra of } \mathcal{F}\}$  is uniformly integrable
  - Formally, the definition of the class  $\mathcal{C}$  is  $Y \in \mathcal{C}$  if and only if  $Y$  is a version of  $E(X|\mathcal{G})$  for some sub- $\sigma$ -algebra  $\mathcal{G}$  of  $\mathcal{F}$
- Proof
  - Let  $\epsilon > 0$  be given
  - By lemma 13.1.1, we can choose  $\delta > 0$  such that, for  $F \in \mathcal{F}$ ,  $P(F) < \delta \implies E(|X|; F) < \epsilon$
  - Choose  $K$  so that  $K^{-1}E(|X|) < \delta$
  - Now let  $\mathcal{G}$  be a sub- $\sigma$ -algebra of  $\mathcal{F}$  and let  $Y$  be any version of  $E(X|\mathcal{G})$
  - By Jensen's inequality,  $|Y| \leq E(|X||\mathcal{G})$  a.s. (absolute function is convex)
  - Hence  $E(|Y|) \leq E(|X|)$  by tower property and  $KP(|Y| > K) \leq E(|Y|) \leq E(|X|)$
  - By the choice of  $K$ , we now have  $P(|Y| > K) < \delta$  from last inequality
  - But  $\{|Y| > K\} \in \mathcal{G}$ , so that  $E(|Y|; |Y| \geq K) \leq E(|X|; |Y| \geq K) < \epsilon$  completes the proof
    - By  $|Y| \leq E(|X||\mathcal{G})$ , property of conditional expectation and lemma 13.1.1

# Convergence of random variables

# Convergence in probability

- Definition

- Let  $\{X_n\}$  be a sequence of RVs and  $X$  be a RV

- We say that  $X_n \xrightarrow{p} X$  if for every  $\epsilon > 0$

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) \rightarrow 0$$

- Lemma 13.5.1: almost sure convergence implies convergence in probability

- $X_n \xrightarrow{a.s.} X \implies X_n \xrightarrow{p} X$

- Proof

- Suppose that  $X_n \xrightarrow{a.s.} X$  and that  $\epsilon > 0$

- Then by reverse Fatou lemma for sets,

$$\begin{aligned} 0 &= P(|X_n - X| > \epsilon, \text{ i.o.}) = P(\limsup\{|X_n - X| > \epsilon\}) \\ &\geq \limsup P(|X_n - X| > \epsilon) \end{aligned}$$

- The result is proved by non-negativity of probability and sandwich theorem

# Bounded convergence theorem

- Let  $\{X_n\}$  be a sequence of RVs and  $X$  be a RV
- Suppose that  $X_n \xrightarrow{p} X$  and that for some  $K \in [0, \infty)$ , we have  $|X_n(\omega)| \leq K, \forall n, \forall \omega$
- Then  $E(|X_n - X|) \rightarrow 0$

• Proof

- Let's check that  $P(|X| \leq K) = 1$ . By assumption, for  $k \in \mathbb{N}$ ,

$$P(|X| > K + k^{-1}) \leq P(|X - X_n| > k^{-1}), \forall n$$

- $X_n \xrightarrow{p} X$  implies  $P(|X| > K + k^{-1}) = 0$
- Hence  $P(|X| > K) = P(\cup_k \{|X| > K + k^{-1}\}) = 0$
- Now let  $\epsilon > 0$  be given
- Choose  $n_0$  such that  $P(|X_n - X| > \frac{1}{3}\epsilon) < \frac{\epsilon}{3K}$  when  $n \geq n_0$
- Then, for  $n \geq n_0$ ,

$$\begin{aligned} E(|X_n - X|) &= E\left(|X_n - X|; |X_n - X| > \frac{1}{3}\epsilon\right) + E\left(|X_n - X|; |X_n - X| \leq \frac{1}{3}\epsilon\right) \\ &\leq 2KP\left(|X_n - X| > \frac{1}{3}\epsilon\right) + \frac{1}{3}\epsilon \leq \epsilon \end{aligned}$$

• Remark

- This proof shows that convergence in probability is a natural concept (how?)

# A necessary and sufficient condition for $\mathcal{L}^1$ convergence

- Theorem 13.7.1
  - Let  $\{X_n\}$  be a sequence in  $\mathcal{L}^1$  and let  $X \in \mathcal{L}^1$
  - Then  $X_n \xrightarrow{\mathcal{L}^1} X$ , equivalently  $E(|X_n - X|) \rightarrow 0$ , if and only if  $X_n \xrightarrow{p} X$  and  $\{X_n\}$  is UI
- Remarks
  - The “if” part is more useful since it improves dominated convergence theorem
    - This can be seen from 13.3 the second sufficient condition of UI
  - The “only if” part is less surprising
    - Convergence in  $\mathcal{L}^p, p \geq 1$  implies convergence in probability

• Proof of “if” part

– Suppose that  $X_n \xrightarrow{p} X$  and  $\{X_n\}$  is UI. For  $K \in [0, \infty)$ , define  $\varphi_K : \mathbb{R} \rightarrow [-K, K]$  by

$$\varphi_K(x) := \begin{cases} K & , x > K \\ x & , |x| \leq K \\ -K & , x < -K \end{cases}$$

- Let  $\epsilon > 0$  be given. By the UI property of  $\{X_n\}$  and corollary 13.1.2, choose  $K$  so that

$$E[|\varphi_K(X_n) - X_n|] < \frac{\epsilon}{3}, \forall n; E[|\varphi_K(X) - X|] < \frac{\epsilon}{3}$$

– Note that  $|\varphi_K(x) - \varphi_K(y)| \leq |x - y| \implies \varphi_K(x) \xrightarrow{p} \varphi_K(y)$  by taking probability

- Applying bounded convergence theorem, we can choose  $n_0$  such that, for  $n \geq n_0$ ,

$$E[|\varphi_K(X_n) - \varphi_K(X)|] < \frac{\epsilon}{3}$$

- Minkowski inequality shows that, for  $n \geq n_0$ ,

$$E(|X_n - X|) = E[|X_n - \varphi_K(X_n) + \varphi_K(X) - X + \varphi_K(X_n) - \varphi_K(X)|] < \epsilon$$

- Proof of “only if” part

- Suppose that  $X_n \rightarrow X$  in  $\mathcal{L}^1$ . Let  $\epsilon > 0$  be given
- Choose  $N$  such that  $n \geq N \implies E(|X_n - X|) < \frac{\epsilon}{2}$
- By lemma 13.1.1, we can choose  $\delta > 0$  such that whenever  $P(F) < \delta$ , we have

$$E(|X_n|; F) < \epsilon, 1 \leq n \leq N; \quad E(|X|; F) < \frac{\epsilon}{2}$$

- The second inequality probably comes from choice of  $N$  instead of lemma 13.1.1
- Since  $\{X_n\}$  is bounded in  $\mathcal{L}^1$ , we can choose  $K$  such that  $K^{-1} \sup_r E(|X_r|) < \delta$
- Then for  $n \geq N$ , we have  $P(|X_n| > K) < \delta$  (by idea in Markov inequality) and

$$E(|X_n|; |X_n| > K) \leq E(|X|; |X_n| > K) + E(|X - X_n|) < \epsilon$$

- By lemma 13.1.1 and choice of  $N$
- For  $n \leq N$ , we have  $P(|X_n| > K) < \delta$  and  $E(|X_n|; |X_n| > K) < \epsilon$  by choice of  $\delta$
- Hence  $\{X_n\}$  is a UI family
- Since  $\epsilon P(|X_n - X| > \epsilon) \leq E(|X_n - X|) \rightarrow 0$ , we have  $X_n \xrightarrow{p} X$



**Concluding remarks**

# Comments

- UI allows us to establish stronger  $\mathcal{L}^1$  convergence from weaker convergence in probability
  - This is appealing as there are more standard devices for convergence in probability
- UI appears naturally in conditional expectation, which is central to martingale property
  - Thus UI martingale is studied in next chapter