36-752: Advance Probability Spring 2018

Lecture 15: March 27

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Example 17: Consider the measure space  $(\Omega, \mathcal{F}, P)$ , where  $\Omega = (0, 1)$  and P is the Lebesgue measure. Define the following series of functions:

$$
f_1 = 1
$$
,  $f_2 = 1\!\!1_{(0,1/2]}$ ,  $f_3 = 1\!\!1_{[1/2,1)}$ ,  $f_4 = 1\!\!1_{[2/3,1)}$ , ...

Then

$$
f_n \xrightarrow{L^p} 0 \,\forall p,
$$

but  $f_n$  does not convergence to 0 since  $\limsup f_n \neq \liminf f_n$ . Example 18: Consider

$$
f_n = \begin{cases} 0 \text{ if } 0 < \omega < \frac{1}{n} \\ \frac{1}{\omega} \text{ if } \omega \ge \frac{1}{n} \end{cases}
$$

Then

$$
\lim_{n \to \infty} f_n(\omega) = \frac{1}{\omega} \quad \forall \omega \in (0, 1)
$$

but  $f_n$  does not converge in  $L^p$  even if  $f_n \in L^p \forall n$ . Example 19: Consider

$$
f_n(\omega) \begin{cases} n \text{ if } 0 < \omega < \frac{1}{n} \\ 0 \text{ if } \omega \ge \frac{1}{n} \end{cases}
$$

Then  $f_n \stackrel{as}{\longrightarrow} 0$  and  $Y_n \stackrel{p}{\longrightarrow} 0$  where  $Y_n = f_n(X)$  with X being a uniformly distributed random variable on [0, 1]. However,  $\int_0^1 |f_n| dx = n \forall n, p \ge 1$ ; hence  $f_n$  does not convergence in  $L^p$  to 0.

Claim 15.1  $L^p$  convergence implies convergence in probability. Almost sure convergence implies convergence in probability.

Proof: First part: prove it using Markov's inequality. Second part: fix  $\epsilon > 0$ ,  $A_{n,\epsilon} = \{ |X_n - X| > \epsilon \}.$  Then  $A_{n,\epsilon}$  is a decreasing sequence so that

$$
\lim_{n \to \infty} \mathbb{P}(A_{n,\epsilon}) = \lim_{n} \sup \mathbb{P}(A_{n,\epsilon}) \le \mathbb{P}(\lim_{n} \sup A_{n,\epsilon}) = 0
$$

by Fatou's lemma.

**Lemma 15.2** Let  $\{f_n\}$  and f be non negative functions in  $L^1(\Omega, \mathcal{F}, P)$ . If  $f_n \stackrel{as}{\longrightarrow} f$ , then  $\int |f_n - f| dP \to 0$ if and only if  $\int f_n dP \to \int f dP$  ( $L^1$  convergence).

Proof: First part:

$$
\left|\int f_n - \int f\right|dP \le \int |f_n - f|dP \to 0.
$$

Second part: let  $g_n = \min\{f_n, f\}$ ; then  $g_n \leq f$  a.e. and  $\int g_n \to \int f$  by dominated convergence theorem. Then

$$
\int |f_n - f|dP = \int f_n dP + \int f dP - 2 \int g_n dP \to \int f dP + \int f dP - 2 \int f dP = 0.
$$

**Corollary 15.3** Let  $\mu_n$  and  $\mu$  be measures on  $(\Omega, \mathcal{F}, \nu)$  with  $\mu_n(A) = \int_A f_n d\nu_n$  and  $\mu(A) = \int_A f \nu \ \forall A \in \mathcal{F}$ . If  $\mu(\Omega) = \mu_n(\Omega) < \infty$  and  $f_n \stackrel{as}{\longrightarrow} f$ , then

$$
\sup_{A \in \mathcal{F}} |\mu_n(A) - \mu(A)| \le \int |f_n - f| d\nu \to 0.
$$

## 15.1 Strong law of large numbers

**Definition 15.4** (Tail  $\sigma$ -field) Let  $\tau_n = \sigma(\lbrace X_i, i \geq n \rbrace)$ . The tail  $\sigma$ -field is defined as  $\tau = \cap_n \tau_n$ 

Events in  $\tau$  are not affected by changes in a finite number of terms in the sequence. Some examples of tail events:

- $\{\lim_{n} X_n = x\};$
- $\{\sum_{n} X_n$  converges };
- $\sup_n X_n$  is measurable with respect to  $\tau$ .

**Theorem 15.5** (Kolmogorov 0-1 law) Let  $\{X_n\}$  be a sequence of independent random variables. If  $A \in \tau$ , then  $\mathbb{P}(A)$  is either 1 or 0.

**Proof:** Let  $U_n = \sigma(\{X_i : i \leq n\})$  and  $U = \cup_n U_n$ . Then U is not a  $\sigma$ -field. Let  $B \in U, A \in \tau$ , then  $B \in U \Rightarrow \exists n_0 \text{ s.t. } B \in U_{n_0}$ . But since  $A \in \tau$ , then  $A \in \tau_{n_0+1}$ . Then

$$
\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B),
$$

ie U and  $\tau$  are independent, hence  $\sigma(U)$  is independent of  $\tau$ . On the other hand,  $\tau \subset \sigma(U)$ ; hence  $\tau$  is independent of itself. Therefore

$$
\mathbb{P}(A \cap A) = \mathbb{P}(A)\mathbb{P}(A) \,\forall A \in \tau.
$$

This equality is satisfied if and only if  $\mathbb{P}(A)$  is either 0 or 1.

**Theorem 15.6** (First Borel Cantelli Lemma) Let  $\{A_n\}$  be a sequence of events in F such that  $\sum_{n\geq 1} \mathbb{P}(A_n)$ ∞. Then

$$
\mathbb{P}(\limsup A_n) = 0
$$

**Proof:** Let  $B_i = \bigcup_{n=i}^{\infty} A_n$ . Then  $B_i$  is a decreasing sequence, and

$$
\lim_{n} \mathbb{P}(B_i) = \mathbb{P}(\lim B_i) = \mathbb{P}(\cap_i B_i) = \mathbb{P}(\lim \sup A_n).
$$

Then

$$
\mathbb{P}(B_i) \le \sum_{n=i}^{\infty} \mathbb{P}(A_n) \to 0 \text{ as } i \to \infty.
$$

 $\sum_{n\geq 1} \mathbb{P}(A_n) = \infty$ . Then  $\mathbb{P}(\limsup A_n) = 1$ . **Theorem 15.7** (Second Borel Cantelli Lemma) Let  $\{A_n\}$  be a sequence of independent events in F and

Corollary 15.8 If  $X_n \stackrel{p}{\rightarrow} X$ , then  $\exists \{n_k\}$  st.  $X_{n_k} \stackrel{as}{\longrightarrow} X$ .

**Proof:** Wlog consider  $n_k > n_{k-1}$  and  $\mathbb{P}(d(X_n, X) > \frac{1}{2^k}) < \frac{1}{2^k}$ . Then  $\sum_{k=1}^{\infty} \mathbb{P}(d(X_{n_k}, X) > \frac{1}{2^k}) < \infty$ . By the first Borel Cantelli lemma  $\mathbb{P}(d(X_{n_k}, X) > \frac{1}{2^k} i.o.) = 0$ . Hence  $X_{n_k} \stackrel{as}{\longrightarrow} X \,\forall \omega \in A^c$ ,  $\mathbb{P}(A^c) = 1$ .

## 15.1.1 Completeness of  $L^p$  spaces

**Definition 15.9** Let  $(X, d)$  be a metric space. A sequence  $\{X_n\} \subset \chi$  is Cauchy if  $\forall \epsilon > 0 \ \exists n \ s.t. \ \forall n, m > 0$ N,  $d(X_n, X_m) < \epsilon$ .

**Example:** Let  $X = \mathbb{Q}$ ,  $d(x, y) = |x - y|$ . Then  $x_n = \left(1 + \frac{1}{n}\right)^n$  but  $x_n \to e \notin \mathbb{Q}$ . Therefore  $\mathbb{Q}$  is not complete.

Claim 15.10 If  $x_n$  is Cauchy and a subsequence converges to x, then the whole sequence converges to x.

**Lemma 15.11**  $L^p$  spaces are complete.

## 15.2 Strong Law of Large Numbers

**Theorem 15.12** (Kolmogorov's maximal inequality) Let  $X_1, \ldots, X_n$  be independent random variables with mean 0 and finite variance. Let  $S_k = \sum_{i=1}^k X_i$ ,  $k = 1, \ldots, n$ ; then

$$
\mathbb{P}(\max_{k=1,\dots,n}|S_k > \epsilon) \le \frac{Var(S_n)}{\epsilon^2}
$$

**Theorem 15.13** Let  $X_1, \ldots, X_n$  be independent random variables with mean 0 and bounded variance. If  $\sum_{i=1}^{n} Var(X_i) = \sum_{i=1}^{n} \sigma_i^2 < \infty$   $\forall n$ , then  $\exists S_{\infty}$  s.t.  $S_n \to S_{\infty}$  almost surely and in  $L^2$  with  $\mathbb{E}[S_{\infty}^2] = \sum_{i=1}^{\infty} \sigma_i^2$ .

**Proof:**  $L^2$  convergence follows from completeness of the space  $L^2$ . For almost surely convergence:  $S_n$  is almost surely Cauchy if  $\sup_{p,q>n}|S_p-S_q| \stackrel{as}{\longrightarrow} 0 \forall n$ . This occurs if  $\mathbb{P}(\sup_{p,q>n}|S_p-S_q|>\epsilon) \to 0 \forall \epsilon$  by the homework. П