

*The Foundations for Probability Limiting Theory* by ZHENGYAN LIN & CHUANRONG LU & ZHONGGEN SU

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## ***Lecture Notes for Probability Limiting Theory Seminar***

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# Lecture 1

## Preliminary

### 1.1 Basis for Martingale

Let  $(\Omega, \mathcal{A}, P)$  is a probability space and  $X$  is an integrable random variable,  $\mathcal{G}$  is a subalgebra of  $\mathcal{A}$ .

**Definition 1.1.1.** For an integrable random variable  $X$ , if there exist a random variable  $Y$  such that

- $Y$  is  $\mathcal{G}$ -measurable;
- for any  $A \in \mathcal{G}$  we have

$$\int_A Y dP = \int_A X dP,$$

then we say  $Y$  is the conditional expectation of  $X$  given  $\sigma$ -algebra  $\mathcal{G}$ . We can write it as  $E[X|\mathcal{G}]$ .

**Remark 1.1.2.** The conditional expectation is unique in the sense of a.s., see Jacod and Protter [2012].

**Remark 1.1.3.** • For any real number  $c_1$  and  $c_2$ , we have

$$E(c_1 X_1 + c_2 X_2 | \mathcal{G}) = c_1 E(X_1 | \mathcal{G}) + c_2 E(X_2 | \mathcal{G}) \quad a.s.$$

- Let  $Y$  is  $\mathcal{G}$ -measurable,  $E|XY| < \infty$ ,  $E|X| < \infty$ , then we have

$$E(XY | \mathcal{G}) = YE(X | \mathcal{G}) \quad a.s.$$

If  $Y = 1_B(u)$ ,  $\forall B$  is  $\mathcal{G}$ -measurable.  
 $\forall A$  is  $\mathcal{G}$ -measurable, we have  
 $\int_A E(X 1_B | \mathcal{G}) dP = \int_A X 1_B dP$   
 $= \int_{A \cap B} X dP$   
 $= \int_{A \cap B} E(X | \mathcal{G}) dP$   
 $= \int_A 1_B \cdot E(X | \mathcal{G}) dP$

$\forall A$  is  $\mathcal{G}_1$ -measurable

- Let  $\mathcal{G}_1 \subset \mathcal{G}_2 \subset \mathcal{A}$ , then we have

$$\int_A E[E(X | \mathcal{G}_2) | \mathcal{G}_1] dP = \int_A E(X | \mathcal{G}_2) dP$$

$$= \int_A X dP = \int_A E(X | \mathcal{G}_1) dP$$

$$E[E(X | \mathcal{G}_2) | \mathcal{G}_1] = E(X | \mathcal{G}_1) = E[E(X | \mathcal{G}_1) | \mathcal{G}_2] \quad a.s.$$

Note that when  $\mathcal{G}_1 = \emptyset$  the first equality will turn to the normal Adam's law.

Let  $\{X_n\}$  is a sequence of independent random variables with zero mean and  $S_n = \sum_{j=1}^n X_j$ . Then we have

$$E(S_{n+1} | X_1, \dots, X_n) = E(S_n + X_{n+1} | X_1, \dots, X_n)$$

$$= S_n + EX_{n+1} = S_n \quad a.s.,$$

which indicates that the conditional expectation of  $S_{n+1}$  only relates to the **previous  $n$  random variables**.

*discrete-time*

**Definition 1.1.4.** Let  $\{\mathcal{A}_n\}$  is an **increasing sequence of sub  $\sigma$ -algebra of  $\mathcal{A}$** . We say a sequence of random variables  $\{S_n\}$  is a **martingale** if

- (i)  $S_n$  is  $\mathcal{A}_n$ -measurable;
- (ii)  $E[S_n] < \infty$ ;
- (iii) for  $m < n$ ,  $E(S_n | \mathcal{A}_m) = S_m$  a.s.,

if the equality in (iii) turns out to be  $\leq$  ( $\geq$ ) then we say  $\{S_n\}$  is a supermartingale (submartingale).

**Example 1.1.1.** See pp.24.

**Example 1.1.2.** See pp.24.

**Lemma 1.1.5.** (i)  $\{S_n\}$  is a submartingale (supermartingale),  $\Phi$  is a **non-decreasing convex (concave) real function**. if  $E|\Phi(S_n)| < \infty$ , then  $\{\Phi(S_n)\}$  is also a submartingale (supermartingale).

- (ii)  $\{S_n\}$  is a martingale,  $\Phi$  is a **real convex function**. if  $E|\Phi(S_n)| < \infty$ , then  $\{\Phi(S_n)\}$  is a **submartingale**.

*Proof.* We only prove the submartingale case in (i). **Why convex function is measurable:  $\forall a \in \mathbb{R}$ , we consider  $A = \{x: \Phi(x) \leq a\}$ . Let  $x_1 = \sup\{x: \Phi(x) \leq a\}$ ,  $x_2 = \inf\{x: \Phi(x) > a\}$ .  $\forall \varepsilon > 0$ , we have  $\Phi(\theta(x_1 - \varepsilon) + (1-\theta)(x_2 + \varepsilon)) \leq \theta\Phi(x_1 - \varepsilon) + (1-\theta)\Phi(x_2 + \varepsilon) \leq a$ . Thus,  $\forall \varepsilon > 0$ ,  $[x_1 - \varepsilon, x_2 + \varepsilon] \subset A$ .  $\downarrow$   $(x_2, x_1) \subset A$ . By the definition of  $x_1$  and  $x_2$ , we have the other side naturally.**

- (Measurability.) Since  $\Phi$  is a convex function on real line, we can see that  $\{x: \Phi(x) \leq a\}$  will be either an empty set or an interval for any  $a \in \mathbb{R}$ . And the mixture of measurable function will be measurable function. Thus  $\{\Phi(S_n)\}$  is  $\mathcal{A}_n$ -measurable.
- (Inequality.) By Jensen's inequality, we have

$$E[\Phi(S_n) | \mathcal{A}_{n-1}] \geq \Phi[E(S_n | \mathcal{A}_{n-1})] \geq \Phi(S_{n-1}) \quad \text{a.s.}$$

□

**Example 1.1.3.**  $\Phi(x) = x^+$  and  $\Phi(x) = |x|^p$ .

Let  $\{\mathcal{A}_n\}$  is an increasing sequence of sub  $\sigma$ -algebra of  $\mathcal{A}$  and  $N_\infty = \{1, 2, \dots, \infty\}$ .

**Definition 1.1.6.** Let  $\alpha$  is a random variable:

$$\alpha: \Omega \rightarrow N_\infty.$$

If  $\alpha$  satisfies

$$\{\alpha = n\} \in \mathcal{A}_n, \quad n \geq 1$$

or equivalently

$$\{\alpha \leq n\} \in \mathcal{A}_n, \quad n \geq 1 \quad (1.1.1)$$

then we say  $\alpha$  is a **stopping time**.

**Remark 1.1.7.** It means that the "decision" of whether to stop at time  $n$  must be based only on the information present at time  $n$ , not on any future info.

**Definition 1.1.8.** Let  $\alpha$  is a stopping time and  $\mathcal{A}_\infty = \sigma(\{\mathcal{A}_n, n \geq 1\})$ . We define

$$\mathcal{A}_\alpha = \{E : E \in \mathcal{A}_\infty, E \cap \{\alpha = n\} \in \mathcal{A}_n, n \geq 1\}$$

as the stopping time  $\sigma$ -algebra  $\mathcal{A}_\alpha$ .

By checking  $\mathcal{A}_\alpha$  is closed under complement of sets and union of countable sets we can see that this definition is reasonable.   
*Note:  $E \cap \{\alpha = n\} = \{\alpha = n\} \setminus (E \cap \{\alpha \neq n\})$ .*

**Lemma 1.1.9 (Doob's).** Let  $\{S_n\}$  is a martingale (submartingale) and  $\alpha, \beta$  are two bounded stopping time. If  $\alpha \leq \beta$ , then we have

$$E(S_\beta | \mathcal{A}_\alpha) = S_\alpha (\geq S_\alpha) \quad a.s.$$

*Proof.* We only prove the case of submartingale. To complete our proof, we need to verify

- integrability of  $S_\beta$ ;
- $S_\alpha$  is  $\mathcal{A}_\alpha$ -measurable; *→ 等式是有意义的.*
- Inequality.

Assume  $\alpha$  and  $\beta$  can be bounded by  $m$ . We have  $S_\beta = \sum_{n=1}^m S_n \mathbb{1}_{\{\beta = n\}}$  and  $\{S_n\}$  is a martingale. It follows that  $S_\beta$  is integrable. Let  $B$  is a Borel set on real line. Since

$$\begin{aligned} \{S_\alpha \in B\} &= \bigcup_{k=1}^m \underbrace{(\{S_k \in B\} \cap \{\alpha = k\})}_{\in \mathcal{A}_k} \in \mathcal{A}_\infty \\ \{S_\alpha \in B\} \cap \{\alpha = n\} &= \underbrace{\{S_n \in B\}}_{\in \mathcal{A}_n} \cap \underbrace{\{\alpha = n\}}_{\in \mathcal{A}_n} \in \mathcal{A}_n. \end{aligned}$$

Thus,  $S_\alpha$  is  $\mathcal{A}_\alpha$ -measurable. To prove the inequality we only need to prove that for any  $\Lambda \in \mathcal{A}_\alpha$

$$\int_\Lambda S_\alpha dP \leq \int_\Lambda E(S_\beta | \mathcal{A}_\alpha) dP = \int_\Lambda S_\beta dP. \quad (1.1.2)$$

What we want to do is to fix the index in (1.1.2) and change problem into fixed  $\alpha$  and fixed  $\beta$ . Thus we define  $\Lambda_n = \Lambda \cap \{\alpha = n\}$  to fix  $\alpha$  and  $\Lambda_n \cap \{\beta > k\}$  to fixed  $\beta$ , here  $k \geq j$ . The details of proof can be found in pp.25.  $\square$

**Definition 1.1.10.** (Continuous case.) See pp.26.





## Lecture 2

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# Infinite Divisible Distribution Function

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### 2.1 Definition of Infinite Divisible Distribution Function

**Definition 2.1.1.** (From the perspective of c.f.) We say a characteristic function  $f(t)$  is **infinite divisible** (i.d.) iff.  $\forall n \in \mathbb{Z}^*$ , there exist some characteristic function  $f_n(t)$  such that

$$f(t) = [f_n(t)]^n.$$

And the corresponding distribution function  $F$  is called infinite divisible distribution function.

**Definition 2.1.2.** (From the perspective of r.v.) Let  $X$  is a random variable, we say **the distribution of  $X$  is infinite divisible** iff.  $\forall n \in \mathbb{Z}$ , there exist an **i.i.d** random variable sequence  $\{X_k^{(n)}\}_{n \geq k \geq 1}$  such that

$$X = X_1^{(n)} + X_2^{(n)} + \dots X_n^{(n)}.$$

**Definition 2.1.3.** (From the perspective of d.f.) We say a distribution function  $F$  is a **infinite divisible distribution function** iff.  $\forall n \in \mathbb{Z}$ , there exist another distribution function  $F_n$  such that

$$F = F_n^{*n}.$$

*Definition*

**Remark 2.1.4.** From (2.1.1) we have

$$[f(t)]^{\frac{1}{n}} = f_n(t).$$

Thus, for i.d.c.f.  $f(t)$ ,  $[f(t)]^{\frac{1}{n}}$  will always be a c.f. (对i.d.c.f., 其开n次方后还是c.f.)

**Example 2.1.1.** See pp.30.

### 2.2 Properties of i.d.c.f.

**Theorem 2.2.1.** (i) I.d.c.f. are closed under finite multiplications; (ii) if  $f$  is a i.d.c.f., so does  $|f|$ .

**Theorem 2.2.2.** If  $f(t)$  is a i.d.c.f., then  $f(t) \neq 0$ .

*Proof.* It's hard to consider the zeros of a complex function, thus we consider  $g = |f|^2$ . We assume  $f(t) = [f_n(t)]^n$ , then  $g = |f|^2 = |f_n|^{2n} \triangleq g_n^n$ , where  $g_n = |f_n|^2$  is also a c.f. Here we transform a problem of complex function into a problem of real function. We define

$$|f_n(t)|^2 = f_n(t) \cdot \overline{f_n(t)}$$

$$h(t) \triangleq \lim_{n \rightarrow \infty} g_n = \begin{cases} 1, & \text{if } g(t) > 0, \\ 0, & \text{if } g(t) = 0. \end{cases}$$

we only need to show  $h \equiv 1$ . Note that  $g(0) = 1$  which indicates that  $h(0) = 1$ . Since  $g_n$ s are continuous, thus  $h(t)$  will also be continuous. Thus,  $h$  is nowhere 0.

$\Rightarrow$  c.f. is uniform conti.  $\square$

**Theorem 2.2.3.** Let  $\{f^{(m)}(t)\}$  is a sequence of i.d.c.f. If there exist a c.f.  $f(t)$  such that

$$f^{(m)}(t) \rightarrow f(t),$$

then  $f(t)$  is a i.d.c.f.

$$(f^{(m)}(t))^{\frac{1}{n}} = \exp\left\{\frac{1}{n} \log f^{(m)}(t)\right\}$$

Condition. ①  $f_n^{(m)}(t) = (f_n^{(m)}(t))^n$ , where

$$f_n^{(m)}(t) = (f^{(m)}(t))^{\frac{1}{n}}$$

And  $f_n^{(m)}(t) \rightarrow (f(t))^{\frac{1}{n}}$  ( $m \rightarrow +\infty$ ).

②  $f(t)$  is conti at 0 &  $f_n^{(m)}(t)$  are c.f.  $\Rightarrow (f(t))^{\frac{1}{n}}$  is c.f.

*Proof.* We only need to note that  $f_n^{(m)}(t)$  is a c.f. and Levy's Continuity theorem.

**Remark 2.2.4.** Note that this theorem does not tell us that i.d.c.f. are closed in the sense of limitation because we need the limiting function is a c.f.

**Definition 2.2.5.** If c.f.  $f(t)$  satisfies

$$f(t) = \exp\{i\alpha t + \lambda(e^{i\beta t} - 1)\},$$

where  $\lambda \geq 0$  and  $\alpha, \beta$  are real number, then we say  $f(t)$  is a **poisson type c.f.**

**Theorem 2.2.6.**  $f(t)$  is an i.d.c.f. iff. it can be written as the limitation of the product of finite poisson type c.f.

*Proof.* For the sufficient part we need to prove  $f(t)$  is a c.f. and it is i.d. We assume

$$f(t) = \lim_{n \rightarrow \infty} \left[ \prod_{k=1}^n \exp\left\{i \frac{\alpha_k}{n} t + \frac{\lambda_k}{n} (e^{i\beta_k t} - 1)\right\} \right]^n = \lim_{n \rightarrow \infty} \prod_{k=1}^n \exp\{i\alpha_k t + \lambda_k (e^{i\beta_k t} - 1)\}.$$

Note that the finite multiplication of c.f. is also a c.f. and  $f(t)$  is continuous at 0, we conclude that  $f(t)$  is a c.f. And it's easy to see  $f(t)$  is i.d. The proof of necessary condition can be found at pp.31.  $\square$

**Remark 2.2.7.** This theorem implies that the limitation of a sequence of i.d.c.f. must be a c.f. Keep this result in mind, and combine it with Theorem 2.2.3 indicate that the i.d.c.f. class is closed under limitation.

**Example 2.2.1.** See pp.32.

## 2.3 Levy-Khinchine Representation

Let  $\gamma$  is a real constant and  $G(x)$  is a non-decreasing bounded and left continuous function. We define

$$\psi(t) = i\gamma t + \int_{-\infty}^{\infty} g(t, x) dG(x),$$

where

$$g(t, x) = \begin{cases} (e^{itx} - 1 - \frac{itx}{1+x^2}) \frac{1+x^2}{x^2}, & \text{if } x \neq 0, \rightarrow -\frac{t^2}{2} \quad (x \rightarrow 0). \\ -\frac{t^2}{2}, & \text{if } x = 0. \end{cases}$$

Thus it's easy to see  $g(t, x)$  is continuous on  $\mathbb{R}^2$ . (Check the limit of  $g(t, x)$  at  $x = 0$ .)

**Theorem 2.3.1.**  $e^{\psi(t)}$  is a i.d.c.f. ( $e$  的积分, 用 L-S 积分和定义证).

*Proof.* Note that  $g(t, x)$  has different form at 0 and other points, we separate the integral into three different parts. For any  $1 > \epsilon > 0$ , let

$$\epsilon = x_0 < x_1 < \cdots < x_n = 1/\epsilon, \quad x_k \leq \xi_k < x_{k+1} \quad (k = 0, 1, \dots, n-1).$$

We consider

$$\begin{aligned} & \int_{\epsilon}^{1/\epsilon} g(t, x) dG(x) \quad (g(t, x) \text{ 在 } x=0 \text{ 和 } x \neq 0 \text{ 的表达式不同, 故分两部分}). \\ &= \int_{\epsilon}^{1/\epsilon} \left( e^{itx} - 1 - \frac{itx}{1+x^2} \right) \frac{1+x^2}{x^2} dG(x) \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} \left( e^{it\xi_k} - 1 - \frac{it\xi_k}{1+\xi_k^2} \right) \frac{1+\xi_k^2}{\xi_k^2} [G(x_{k+1}) - G(x_k)] \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} \left( i \frac{\xi_k(1+\xi_k^2)[G(x_{k+1}) - G(x_k)]}{(1+\xi_k^2)\xi_k^2} t + \frac{1+\xi_k^2}{\xi_k^2} [G(x_{k+1}) - G(x_k)] (e^{i\xi_k t} - 1) \right). \end{aligned}$$

Thus, by Theorem 2.2.6 we see that

$$f_1^{(\epsilon)}(t) = \exp \left\{ \int_{\epsilon}^{1/\epsilon} g(t, x) dG(x) \right\}$$

is an i.d.c.f. By Lebesgue's dominated convergence theorem (LDCT) we got

$$f_1^{(\epsilon)}(t) \rightarrow I_1(t) = \exp \left\{ \int_{x>0} g(t, x) dG(x) \right\}, \quad (\epsilon \rightarrow +\infty).$$

again, by Theorem 2.2.3 or 2.2.6 we can see that  $I_1(t)$  is also a i.d.c.f. Similarly, if we consider the integral of  $g(t, x)$  on  $(-\epsilon, -\frac{1}{\epsilon})$  we can prove that

$$I_2(t) = \exp \left\{ \int_{x<0} g(t, x) dG(x) \right\}$$

is also an i.d.c.f. Now we write

$$e^{\psi(t)} = I_1 \times I_2 \times e^{i\gamma t} \times \left( -\frac{t^2}{2} \right) [G(+0) - G(-0)].$$

Then we can see that  $e^{\psi(t)}$  is a i.d.c.f. □

Our goal is to prove the sufficiency of Theorem 2.3.1. Before that we define

$$\Lambda(x) = \int_{-\infty}^x A(y) dG(y),$$

where

$$A(y) = \begin{cases} \left(1 - \frac{\sin y}{y}\right) \frac{1+y^2}{y^2}, & \text{if } y \neq 0; \\ \frac{1}{3!}, & \text{if } y = 0. \end{cases}$$

and

$$\lambda(t) = \psi(t) - \int_0^1 \frac{\psi(t+h) - \psi(t-h)}{2} dh.$$

Then we have following observation:

- $A(y)$  is continuous and bounded. (Because it is bounded at  $[\epsilon, \infty]$  and  $[0, \epsilon]$ .)
- $\Lambda(x)/\Lambda(+\infty)$  is a d.f.

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## *Bibliography*

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Jean Jacod and Philip Protter. *Probability essentials*. Springer Science & Business Media, 2012.