

SLN 2nd version

$$\text{WLOG } X_i \geq 0 \quad Y_i = X_i I(X_i \leq i)$$

$$S'_n = \sum_{i=1}^n Y_i \quad P(X_i \neq Y_i \text{ i.o.}) = 0$$

Need to show $\frac{1}{n} S'_n \rightarrow m = E(X_1)$

$$E\left(\frac{1}{n} \sum_{i=1}^n Y_i\right) = \frac{1}{n} \sum_{i=1}^n E(X_i I(X_i \leq i)) = \frac{1}{n} \sum_{i=1}^n E(X_1 I(X_1 \leq i))$$

$$E(X_1 I(X_1 \leq i)) \rightarrow E(X_1) = m \text{ as } i \rightarrow \infty$$

$$\text{Show } \frac{1}{n} \sum_{i=1}^n E(X_1 I(X_1 \leq i)) \rightarrow m$$

do this by showing: if $a_i \rightarrow a \in \mathbb{R}$ then

$$\frac{1}{n} \sum_{i=1}^n a_i \rightarrow a$$

 $[y] = \text{greatest integer} \leq y$
Fix $\alpha > 1$

$$\text{Fix } x > 0 \quad u_n = \lfloor \alpha^n \rfloor \nearrow \infty$$

$$\begin{aligned} \rightarrow \sum_{u_n \geq x} \frac{1}{u_n} &\leq \sum_{\alpha^n \geq x} \frac{1}{u_n} = \sum_{k=\log_\alpha(x)}^{\infty} \frac{2}{\alpha^k} \\ &\leq \sum_{k=\log_\alpha(x)}^{\infty} \frac{2}{\alpha^k} = \frac{2}{\alpha^{\log_\alpha(x)}} = \frac{2}{x} \\ &= \frac{2 \cdot \alpha^{-\log_\alpha(x)}}{1 - \frac{1}{\alpha}} \end{aligned}$$

Consider

$$\frac{S'_{u_n} - E(S'_{u_n})}{u_n}$$

(show $\xrightarrow{a.s.} 0$ on this subsequence $u_n \rightarrow \infty$)

$$\sum_{n=1}^{\infty} P\left(\left|\frac{S'_{u_n} - E(S'_{u_n})}{u_n}\right| \geq \epsilon\right)$$

$$\leq \sum_{n=1}^{\infty} \frac{\text{Var}\left(\frac{S'_{u_n}}{u_n}\right)}{\epsilon^2}$$

$$\leq \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 u_n^2} \left(E((S'_{u_n})^2) - (E(S'_{u_n}))^2 \right)$$

$$\leq \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 u_n^2} E((S'_{u_n})^2)$$

$$= \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 u_n^2} \left\{ E(X_1^2 I(X_1 \leq u_n)) + \dots + E(X_{u_n}^2 I(X_{u_n} \leq u_n)) \right\}$$

$$\leq \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 u_n^2} \cdot u_n E(X_1^2 I(X_1 \leq u_n))$$

$$\leq \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 u_n} E(X_1^2 I(X_1 \leq u_n))$$

$$= \frac{1}{\epsilon^2} E\left(X_1^2 \sum_{n=1}^{\infty} \frac{1}{u_n} I(u_n \geq X_1)\right)$$

$$\left(\begin{matrix} 2 & 2 \\ & \geq \end{matrix} \right) \sum_{u \geq x} \frac{1}{u_n}$$

$$\begin{aligned}
 \text{Let } A &= \bigcup_{k=1}^{\infty} A_k^c \\
 P(A^c) &= P\left(\bigcup_{k=1}^{\infty} A_k^c\right) \leq \sum_{k=1}^{\infty} P(A_k^c) \\
 \therefore P(A) &= 1 \\
 \text{if } \omega \in A, \text{ then } \forall k \exists 1 & \\
 \frac{1}{1+\frac{1}{k}} \cdot m &\leq \liminf_{n \rightarrow \infty} \frac{S_n'(\omega)}{n} \leq \limsup_{n \rightarrow \infty} \frac{S_n'(\omega)}{n} \leq m(1+\frac{1}{k}) \\
 \therefore \lim_{m \rightarrow \infty} \lim_{k \rightarrow \infty} \frac{1}{1+\frac{1}{k}} \cdot m &\leq \liminf_{n \rightarrow \infty} \frac{S_n'(\omega)}{n} \leq \limsup_{n \rightarrow \infty} \frac{S_n'(\omega)}{n} \leq \lim_{k \rightarrow \infty} m \cdot (1+\frac{1}{k}) = m \\
 \therefore \lim_{n \rightarrow \infty} \frac{S_n'(\omega)}{n} &= m
 \end{aligned}$$

Chapter 6

Distributions of r.v.'s and Change of Variables Thm.
 X r.v. is $\exists (\Omega, \mathcal{F}, P)$ prob triple such that X is measurable.

Then $\forall B \in \text{Borel sets } \mathcal{B}$, define
 $\mu(B) = P(X \in B) = P \circ X^{-1}(B)$

μ is a measure on $\mathcal{B}$, $\mu(\mathbb{R}) = 1$,
 $\therefore (\mathbb{R}, \mathcal{B}, \mu)$ is also a prob. triple

μ is the "distribution" of X in the sense, we can
 define $X': \mathbb{R} \rightarrow \mathbb{R}$, $X'(y) = y \quad \forall y \in \mathbb{R}$
 X' is a r.v. on $(\mathbb{R}, \mathcal{B}, \mu)$, $\mu(X' \in B) = P(X \in B)$

Change of Variable Theorem

Theorem 6.1.1

Given a prob triple $(\Omega, \mathcal{F}, P)$, let X be r.v.
 with distribution μ . Then for any Borel measurable
 f ,

$$\begin{aligned}
 E_P(f(X)) &= \int_{\Omega} f(X(\omega)) P(d\omega) \\
 &= \int_{\mathbb{R}} f(x) \mu(dx)
 \end{aligned}$$

Proof:

- ① $B \in \mathcal{B}$ $f = \mathbb{I}_B$
 $\int_{\Omega} f(X(\omega)) P(d\omega) = E_P(f(X))$
 $= \int_{\Omega} \mathbb{I}_B(X(\omega)) P(d\omega)$
 $= P(X \in B)$
 $= \mu(B)$
 $= \int_{\mathbb{R}} \mathbb{I}_B(x) \mu(dx)$
- ② B_1, B_2 disjoint $\in \mathcal{B}$
 $f(x) = a_1 \mathbb{I}_{B_1}(x) + a_2 \mathbb{I}_{B_2}(x)$
- ③ verify LHS = RHS for any simple f
- ④ $f \geq 0$. Use $f_n \uparrow f$, apply Monotone convergence theorem
- ⑤ $f = f^+ - f^-$, $f^+ \geq 0$, $f^- \geq 0$

Read Corollary 6.1.3

$Z_{\omega}(X) = Z_{\omega}(Y)$ (even if defined on different
 ob. triples) iff $(f(Y))$ for all f measurable

$$\begin{aligned} \text{Law}(X) &= \text{Law}(Y) \quad (\text{if } \text{prob. triplets}) \\ E(f(X)) &= E(f(Y)) \quad \text{for all } f \text{ measurable} \\ E_{\mu}(f(X)) &= E_{\nu}(f(Y)) \end{aligned}$$

Corollary 6.1.4
If $P(X=Y)=1$ then $E(f(X))=E(f(Y))$

Examples § 6.2

① in some cases μ has a density, say ϕ
 $\mu(B) = \int_B \phi(x) dx$ (Lebesgue integral on $\mathbb{R}$)
 $= \int_B \phi(x) \lambda(dx)$ $\lambda = \text{Lebesgue measure}$

$$\begin{aligned} \text{Then } E(f(X)) &= \int_{\mathbb{R}} f(x) \mu(dx) \\ &= \int_{\mathbb{R}} f(x) \cdot \phi(x) dx \end{aligned}$$

Eg:

$$\text{Law}(X) = \frac{1}{4} \delta_1 + \frac{1}{4} \delta_2 + \frac{1}{2} \mu_N$$

$\delta_1 = \text{prob. measure all mass at } 1$

$\delta_2 = \text{prob. measure all mass at } 2$

$\mu_N = \text{prob. measure of standard Normal}$

$$E(f(X)) = \int_{\mathbb{R}} f(x) \mu(dx) \quad \mu = \text{measure of law of } X = \text{distribution of } X$$

$$a = E(X) = \int_{\mathbb{R}} x \mu(dx)$$

$$= \frac{1}{4} \int_{\mathbb{R}} x \delta_1(dx) + \frac{1}{4} \int_{\mathbb{R}} x \delta_2(dx)$$

$$+ \frac{1}{2} \int_{\mathbb{R}} x \phi(x) dx \quad \phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$E(X^2) = ?$$

$$E((X-a)^2) = ?$$

Exercise 6.3.1

Chapter 7

§ 7.1

Theorem 7.1.1

Let $\mu_1, \mu_2, \dots$ be a sequence of prob measures on $\mathbb{R}$
 then $\exists$ a prob triple $(\Omega, \mathcal{F}, P)$ and $X_1, X_2, \dots$ and $\text{Law}(X_i) = \mu_i$ and

Borel

Let $\mu_1, \mu_2, \dots$ and prob triple
 then $\exists$ r.v.'s $X_1, X_2, \dots$ and prob triple
 $\Rightarrow X_i$ r.v. on $(\Omega, \mathcal{F}, P)$, $\text{Law}(X_i) = \mu_i$ and
 X_i 's are independent.

Lemma 7.1.2

U is Uniform $(0,1)$ r.v. on prob triple $(\Omega, \mathcal{F}, P)$
 $F =$ cdf cumulative distribution function
 i.e. $P(X \leq x) = F(x)$
 F is cdf of Law of X

Set $\phi(u) = \inf\{x \mid F(x) \geq u\}$, $0 < u < 1$

Then $P(\phi(U) \leq x) = F(x)$

Aside: $\phi(U)$ has distribution F