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Q1: Let X, X_1, X_2, \dots be a sequence of random variables defined on the same probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Further, let $g : \mathbb{R} \rightarrow \mathbb{R}$. Let D_g be the set of the discontinuity points of g . Assume that $\mathbb{P}(X \in D_g) = 0$. Prove the following continuous mapping theorem for convergence in distribution: If $X_n \xrightarrow{D} X$, then $g(X_n) \xrightarrow{D} g(X)$.

$$\because X_n \xrightarrow{D} X$$

$$\therefore \exists Y_n, Y \text{ has the same distribution with } X_n, X \text{ s.t. } Y_n \xrightarrow{a.s.} Y$$

For any bounded, continuous $f : \mathbb{R} \rightarrow \mathbb{R}$, $D_{f \circ g} \subset D_g$

$$0 \leq \mathbb{P}(Y \in D_{f \circ g}) = \mathbb{P}(X \in D_{f \circ g}) \leq \mathbb{P}(X \in D_g) = 0$$

$$\Rightarrow \mathbb{P}(Y \in D_{f \circ g}) = 0$$

$$\Rightarrow f(g(Y_n)) \xrightarrow{a.s.} f(g(Y))$$

Also, $\because f$ is bounded. by the bounded convergence thm, we have

$$E[f(g(Y_n))] \rightarrow E[f(g(Y))] \quad \forall f \text{ bounded}$$

$$\Rightarrow g(Y_n) \xrightarrow{D} g(Y)$$

$$\Rightarrow g(X_n) \xrightarrow{D} g(X)$$

Q2: Suppose $g, h : \mathbb{R} \rightarrow \mathbb{R}$ are continuous with $g(x) > 0$, and $|h(x)|/g(x) \rightarrow 0$ as $|x| \rightarrow \infty$. Let F, F_1, F_2, \dots be a sequence of distribution functions. Suppose $F_n \rightarrow F$ weakly and $\int g(x) dF_n(x) \leq C < \infty$ uniformly in n . Prove

$$\int h(x) dF_n(x) \rightarrow \int h(x) dF(x).$$

$$\therefore F_n \rightarrow F$$

$$\therefore \exists \bar{F}_n, \bar{F} \text{ s.t. } \bar{F}_n \stackrel{D}{=} F_n, \bar{F} = F \text{ s.t. } \bar{F}_n \xrightarrow{a.s.} \bar{F}$$

We can assume $h(0)=0$, since $\int h(x) + c dF_n(x) = \int h(x) dF_n(x) + c$

we can always subtract a constant $h(0)$ from h and the conclusion will not be affected.

Select a large enough M s.t. $P(|\bar{F}| = M) = 0$

$$\text{Let } \bar{F} = \bar{F} \mathbb{1}_{(|\bar{F}| \leq M)}, \quad \bar{F}_n = \bar{F}_n \mathbb{1}_{(|\bar{F}_n| \leq M)}$$

Then, $\bar{F}_n \xrightarrow{a.s.} \bar{F}$ and $h(\bar{F}_n)$ is bounded

By bounded convergence thm, we have $E h(\bar{F}_n) \rightarrow E h(\bar{F})$

$$\therefore h(0)=0. \text{ Let } \varepsilon_n = \sup \left\{ \frac{|h(x)|}{g(x)} : |x| \geq M \right\}$$

$$\begin{aligned} |E h(\bar{F}_n) - E h(\bar{F}_n)| &\leq E |h(\bar{F}_n) - h(\bar{F}_n)| \\ &\leq E [h(\bar{F}_n) \mathbb{1}_{(|\bar{F}_n| > M)}] \\ &\leq \varepsilon_n E g(\bar{F}_n) \\ &\leq C \varepsilon_n \end{aligned}$$

By Fatou's Lemma,

$$E g(x) = \liminf_{n \rightarrow \infty} E g(x_n) \leq \limsup_{n \rightarrow \infty} E g(x_n) \leq C$$

Similarly,

$$\begin{aligned} |E h(\bar{F}) - E h(\bar{F})| &\leq E |h(\bar{F}) - h(\bar{F})| \\ &\leq E |h(\bar{F}) \mathbb{1}_{(|\bar{F}| > M)}| \\ &\leq \varepsilon_n E g(x) \\ &\leq C \varepsilon_n \end{aligned}$$

As a result,

$$\begin{aligned} |E h(\bar{F}_n) - E h(\bar{F})| &\leq |E h(\bar{F}_n) - E h(\bar{F}_n)| + |E h(\bar{F}_n) - E h(\bar{F})| + |E h(\bar{F}) - E h(\bar{F})| \\ &\leq 3C \varepsilon_n \rightarrow 0 \end{aligned}$$

Q3: Let X_1, X_2, \dots be i.i.d. and have the standard normal distribution. It is known that

$$\mathbb{P}(X_i > x) \sim \frac{1}{\sqrt{2\pi}x} \exp\left(-\frac{x^2}{2}\right) \quad \text{as } x \rightarrow \infty.$$

where $a(x) \sim b(x)$ means $a(x)/b(x) \rightarrow 1$ if $x \rightarrow \infty$.

(i): Prove that for any real number θ ,

$$\mathbb{P}(X_i > x + \frac{\theta}{x}) / \mathbb{P}(X_i > x) \rightarrow \exp(-\theta), \quad \text{as } x \rightarrow \infty$$

(ii) Show that if we define b_n by $\mathbb{P}(X_i > b_n) = 1/n$,

$$\mathbb{P}(b_n(\max_{1 \leq i \leq n} X_i - b_n) \leq x) \rightarrow \exp(-e^{-x}).$$

(iii) Show that $b_n \sim (2 \log n)^{\frac{1}{2}}$ and conclude $\max_{1 \leq i \leq n} X_i / (2 \log n)^{\frac{1}{2}} \rightarrow 1$ in probability.

$$\begin{aligned} \text{(i)} \quad \lim_{x \rightarrow \infty} \frac{\mathbb{P}(X_i > x + \frac{\theta}{x})}{\mathbb{P}(X_i > x)} &= \lim_{x \rightarrow \infty} \frac{x}{x + \frac{\theta}{x}} e^{-\frac{(x + \frac{\theta}{x})^2}{2} + \frac{x^2}{2}} \\ &= \lim_{x \rightarrow \infty} \frac{x}{x + \frac{\theta}{x}} e^{-\theta - \frac{\theta^2}{2x^2}} \\ &= e^{-\theta} \end{aligned}$$

$$\begin{aligned} \text{(ii)} \quad \mathbb{P}(b_n(\max X_i - b_n) \leq x) &= \mathbb{P}(b_n(X_i - b_n) \leq x)^n \\ &= (1 - \mathbb{P}(b_n(X_i - b_n) > x))^n \\ &= (1 - \mathbb{P}(X_i > b_n + \frac{x}{b_n}))^n \end{aligned}$$

$$\text{From (i), } \frac{\mathbb{P}(X_i > b_n + \frac{x}{b_n})}{\mathbb{P}(X_i > b_n)} = n \mathbb{P}(X_i > b_n + \frac{x}{b_n}) \rightarrow e^{-x} \text{ as } b_n \rightarrow \infty$$

$$\text{Then } \mathbb{P}(b_n(\max X_i - b_n) \leq x) \rightarrow \lim_{n \rightarrow \infty} (1 - \frac{e^{-x}}{n})^n = e^{-e^{-x}}$$

$$\begin{aligned} \text{(iii)} \quad \mathbb{P}(X_i > (2 \log n)^{\frac{1}{2}}) &\sim \frac{1}{\sqrt{2\pi} (2 \log n)^{\frac{1}{2}}} e^{-\frac{2 \log n}{2}} \\ &= \frac{1}{2\sqrt{\pi} (\log n)^{\frac{1}{2}}} \cdot \frac{1}{n} \\ &= \frac{1}{2\sqrt{\pi} (\log n)^{\frac{1}{2}}} \mathbb{P}(X_i > b_n) \end{aligned}$$

$b_n \leq (2 \log n)^{\frac{1}{2}}$ when n is sufficiently large

Moreover,

$$\mathbb{P}(X_i > (2 \log n - 2 \log \log n)^{\frac{1}{2}}) \sim \frac{1}{\sqrt{2\pi} (2 \log n - 2 \log \log n)^{\frac{1}{2}}} e^{-\frac{2 \log n - 2 \log \log n}{2}}$$

$$\sim \frac{1}{\sqrt{2\pi} (\log n)^{\frac{1}{2}}} \frac{(\log n)}{n}$$

$$= \frac{(\log n)^{\frac{1}{2}}}{2\sqrt{\pi}} \mathbb{P}(\bar{Z}_i > b_n)$$

For sufficiently large n . $(2 \log n - 2 \log \log n)^{\frac{1}{2}} \leq b_n$

$$\therefore b_n \sim (2 \log n)^{\frac{1}{2}}$$

From (ii), we have

$$\mathbb{P}(b_n(\max \bar{Z}_i - b_n) \leq x) \rightarrow e^{-e^{-x}} \quad (1)$$

$$\therefore \mathbb{P}(b_n(\max \bar{Z}_i - b_n) \geq x) \rightarrow 1 - e^{-e^{-x}} \quad (2)$$

Let $x = \bar{z}_n$ in (1)

$$\mathbb{P}(\max \bar{Z}_i - b_n \leq \frac{\bar{z}_n}{b_n}) \rightarrow e^{-e^{-\bar{z}_n}}$$

Let $\bar{z}_n = o(b_n) \rightarrow \infty$, we have

$$\mathbb{P}(\max \bar{Z}_i - b_n \leq 0) \rightarrow 1$$

Moreover, let $x = Y_n$ in (2), we have

$$\mathbb{P}(\max \bar{Z}_i - b_n \geq \frac{Y_n}{b_n}) \rightarrow 1 - e^{-e^{-Y_n}}$$

Let $Y_n = o(b_n) \rightarrow -\infty$, we have

$$\mathbb{P}(\max \bar{Z}_i - b_n \geq 0) \rightarrow 1$$

$$\therefore \mathbb{P}\left(\frac{\max \bar{Z}_i}{b_n} = 1\right) \rightarrow 1$$

$$\therefore \mathbb{P}\left(\frac{\max \bar{Z}_i}{(2 \log n)^{\frac{1}{2}}} = 1\right) \rightarrow 1$$

Q4: Let X_1, X_2, \dots be independent taking values 0 and 1 with probability $1/2$ each. Let $X = 2 \sum_{j \geq 1} X_j / 3^j$. Compute the characteristic function of X .

$$P(X_j = 0) = \frac{1}{2}, \quad P(X_j = 1) = \frac{1}{2}$$

$$\varphi_j(t) = E e^{it X_j} = \frac{1}{2} + \frac{1}{2} e^{it}$$

$$\text{Then } E e^{it \frac{2 X_j}{3^j}} = \varphi_j\left(\frac{2}{3^j} t\right) = \frac{1}{2} + \frac{1}{2} e^{\frac{2it}{3^j}}$$

$$\text{Denote } S_n = \sum_{j=1}^n \frac{2 X_j}{3^j}$$

$$\text{Then } E e^{it S_n} = E e^{it \sum_{j=1}^n \frac{2 X_j}{3^j}} = \prod_{j=1}^n E e^{\frac{2it X_j}{3^j}}$$

$$\therefore S_n \xrightarrow{\text{a.s.}} 8$$

$$\therefore S_n \xrightarrow{D} 8$$

$$\text{Then } E e^{it S_n} \longrightarrow E e^{it 8}$$

$$\therefore E e^{it 8} = \prod_{j=1}^{\infty} E e^{\frac{2it X_j}{3^j}} = \prod_{j=1}^{\infty} \frac{1 + e^{\frac{2it}{3^j}}}{2}$$

Q5: Let $S_n = X_1 + \dots + X_n$ in the following problems.

(a): Suppose that X_i 's are independent and $\mathbb{P}(X_i = i) = \mathbb{P}(X_i = -i) = \frac{i^{-\alpha}}{4}$ and $\mathbb{P}(X_i = 0) = 1 - \frac{i^{-\alpha}}{2}$ for some nonnegative parameter α . Find $a_n(\alpha), b_n(\alpha)$ such that $(S_n - a_n(\alpha))/b_n(\alpha) \Rightarrow N(0, 1)$ when $\alpha \in (0, 1)$ and prove this CLT.

(b): Suppose that X_i 's are independent and $\mathbb{P}(X_i = 1) = \frac{1}{i} = 1 - \mathbb{P}(X_i = 0)$. Find a_n and b_n such that $(S_n - a_n)/b_n \Rightarrow N(0, 1)$ and prove this CLT.

$$(a) \quad \mathbb{E}(X_i) = 0 \quad \text{Var}(X_i) = \mathbb{E}(X_i^2) = \frac{i^{2-\alpha}}{2}$$

$$\text{Then } \mathbb{E}(S_n) = \mathbb{E}(\sum X_i) = 0$$

$$\text{Var}(S_n) = \text{Var}(\sum X_i) = \sum \frac{i^{2-\alpha}}{2} \sim \frac{1}{2(3-\alpha)} n^{3-\alpha}$$

$$\text{Let } Z_{n,m} = \frac{(2(3-\alpha))^{\frac{1}{2}} X_m}{n^{\frac{3-\alpha}{2}}}$$

$$\text{Then } \mathbb{E} Z_{n,m} = 0.$$

$$\sum \mathbb{E} X_{n,m}^2 \rightarrow 1$$

Since $0 < \alpha < 1$.

$$\forall \varepsilon > 0. \exists n_\varepsilon \text{ s.t. when } n \geq n_\varepsilon. |Z_{n,m}| = \left| \frac{\sqrt{2(3-\alpha)} X_m}{n^{\frac{3-\alpha}{2}}} \right| \leq \frac{\sqrt{2(3-\alpha)} \eta}{n^{\frac{3-\alpha}{2}}} < \varepsilon$$

$$\therefore \sum \mathbb{E}[Z_{n,m}^2 \mathbb{1}(|Z_{n,m}| > \varepsilon)] = 0 \text{ when } n \geq n_\varepsilon$$

$$\text{Then } \frac{S_n}{\sqrt{\text{Var}(S_n)}} = \frac{\sqrt{2(3-\alpha)} S_n}{n^{\frac{3-\alpha}{2}}} \sim N(0, 1)$$

$$\text{Thus } a_n(\alpha) = 0$$

$$b_n(\alpha) = \frac{1}{\sqrt{2(3-\alpha)}} n^{\frac{3-\alpha}{2}}$$

$$(b) \quad \mathbb{E}(X_i) = \frac{1}{i}$$

$$\text{Var}(X_i) = \mathbb{E}(X_i^2) - (\mathbb{E} X_i)^2 = \frac{1}{i^2} - \frac{1}{i^2}$$

$$\mathbb{E}(S_n) = \mathbb{E}(\sum X_i) = \sum \frac{1}{i} \sim \log n$$

$$\text{Var}(S_n) = \text{Var}(\sum X_i) = \sum \frac{1}{i^2} - \frac{1}{i^2} \sim \log n$$

$$\text{Let } Z_{n,m} = \frac{X_m - \frac{1}{m}}{(\log n)^{\frac{1}{2}}}$$

$$\text{Then } \mathbb{E} Z_{n,m} = 0, \sum \mathbb{E} X_{n,m}^2 \rightarrow 1$$

$$\forall \varepsilon > 0. \exists n_\varepsilon \text{ s.t. when } n \geq n_\varepsilon.$$

$$|Z_{n,m}| \leq \frac{1}{(\log n)^{\frac{1}{2}}} < \varepsilon$$

$$\sum_{m=1}^n E [x_{n,m}^2 \mathbb{1}(|x_{n,m}| > \varepsilon)] = 0$$

Then

$$\frac{S_n - \sum \frac{1}{i}}{(\log n)^{\frac{1}{2}}} \sim N(0,1) \quad \text{or} \quad \frac{S_n - \log n}{(\log n)^{\frac{1}{2}}} \sim N(0,1)$$

$$\therefore a_n = \log n, \quad b_n = (\log n)^{\frac{1}{2}}$$

Q6: Suppose that X_n and Y_n are independent, and $X_n \rightarrow X_\infty$ in distribution and $Y_n \rightarrow Y_\infty$ in distribution. Show that $X_n^2 + Y_n^2$ converges in distribution.

$$\therefore X_n \xrightarrow{D} X_\infty, \quad Y_n \xrightarrow{D} Y_\infty$$

Also, $g(x) = x^2$ is continuous

By Continuous Mapping Thm. $X_n^2 \xrightarrow{D} X_\infty^2$
 $Y_n^2 \xrightarrow{D} Y_\infty^2$

$$\text{and } X_n^2 \perp Y_n^2, \quad X_\infty^2 \perp Y_\infty^2$$

By Lévy's continuity Thm. $\forall t$

$$\varphi_{X_n^2}(t) \rightarrow \varphi_{X_\infty^2}(t)$$

$$\varphi_{Y_n^2}(t) \rightarrow \varphi_{Y_\infty^2}(t)$$

$$\therefore X_n^2 \perp Y_n^2, \quad X_\infty^2 \perp Y_\infty^2$$

$$\therefore \varphi_{X_n^2 + Y_n^2}(t) = \varphi_{X_n^2}(t) \varphi_{Y_n^2}(t) \rightarrow \varphi_{X_\infty^2}(t) \varphi_{Y_\infty^2}(t)$$

and $\varphi_{X_\infty^2}(t), \varphi_{Y_\infty^2}(t)$ are continuous at 0

Then, $\varphi_{X_\infty^2}(t) \varphi_{Y_\infty^2}(t)$ is the characteristic function of $X_\infty^2 + Y_\infty^2$

$$\therefore X_n^2 + Y_n^2 \xrightarrow{D} X_\infty^2 + Y_\infty^2$$

Q7: Let X_1, X_2, \dots be i.i.d. with a density that is symmetric about 0, and continuous and positive 0. Find the limiting distribution of

$$\frac{1}{n} \left(\frac{1}{X_1} + \dots + \frac{1}{X_n} \right).$$

$$\begin{aligned} \therefore P\left(\frac{1}{\bar{X}_i} > \pi\right) &= P\left(0 < \bar{X}_i < \frac{1}{\pi}\right) \\ &= \int_0^{\frac{1}{\pi}} f(y) dy \sim \frac{f(0)}{\pi} \quad \text{as } \pi \rightarrow \infty \end{aligned}$$

$$\begin{aligned} P\left(\frac{1}{\bar{X}_i} < -\pi\right) &= P\left(-\frac{1}{\pi} < \bar{X}_i < 0\right) \\ &= \int_{-\frac{1}{\pi}}^0 f(y) dy \sim \frac{f(0)}{\pi} \quad \text{as } \pi \rightarrow \infty \end{aligned}$$

$$\therefore \lim_{\pi \rightarrow \infty} \frac{P(\bar{X}_i > \pi)}{P(|\bar{X}_i| > \pi)} = \frac{1}{2}$$

$$P(|\bar{X}_i| > \pi) \sim 2f(0) \cdot \pi^{-1}$$

$$\text{Let } a_n = \inf \left\{ \pi : P(|\bar{X}_i| > \pi) \leq \frac{1}{n} \right\}.$$

$$\text{Then } a_n \sim 2f(0)n$$

\therefore Density of \bar{X}_i is symmetric about 0

$$\therefore b_n = n E(\bar{X}_i \mathbb{1}_{(|\bar{X}_i| \leq a_n)}) = 0$$

$$\text{Then, } \frac{S_n - b_n}{a_n} \sim \frac{S_n}{2f(0)n} \Rightarrow Y$$

where the characteristic function of Y is $e^{itc - b|t|^{-1}}$.

Q8: Do some self-study and explain why the *Stable distributions* and *Infinitely divisible distributions* bear such names.

Stable distribution :

A distribution is said to be stable if summing independent random variables from it results in a random variable in the same distribution.

It is called stable because its shape remains unchanged (thus stable) when being summed.

Infinitely divisible distribution:

A sufficient condition for Z to be a limit of sums of the form

$$S_n = Z_{n,1} + \dots + Z_{n,n}$$

is that Z has an infinitely divisible distribution, i.e. for each n

\exists i.i.d. sequence $Y_{n,1} \dots Y_{n,n}$ s.t.

$$Z \stackrel{d}{=} Y_{n,1} + \dots + Y_{n,n}$$