

# Convergence in Probability

**Definition:**  $X_n \rightarrow_p X$  iff  $\forall \varepsilon > 0$ ,  
 $P(|X_n - X| > \varepsilon) \rightarrow 0$ .

**Remark:**

① Indeed, convergence in probability could be metrization, define:

$$\underline{d(X, Y)} := \mathbb{E} \frac{|X - Y|}{|X - Y| + 1},$$

then  $X_n \rightarrow_p X \Leftrightarrow d(X_n, X) \rightarrow 0$ ,  
which implies that the convergence is similar  
to other convergence in metric space.

We mark that  $X_n \rightarrow_p 0$ :

$$\text{and } X_n = o_p(1),$$

$$X_n = o_p(Y_n) \text{ iff } \frac{X_n}{Y_n} = o_p(1).$$

**Definition:**  $X_n = O_p(1)$  iff  $\forall \delta > 0, \exists M > 0$  s.t.

$$\sup_n P(|X_n| > M) < \delta,$$

which is said to be bounded in probability.

**Remark:**

① We assume that  $X = O_p(1)$ .

**Pro**

If  $X_n \rightarrow_p X$ , then  $X_n = O_p(1)$

Pf:  $X_n = X_n - X + X$ , we just need to prove

$$X - X_n = O_p(1)$$

Since  $X - X_n = O_p(1)$ , then  $\exists k$ , for  $M_0$ .  $\forall \varepsilon$ ,  $P(|X - X_n| > M_0) < \varepsilon$ ,  $n \geq k$

For  $i < k$ ,  $\exists M_i$  s.t.

$$P(|X - X_i| > M_i) < \varepsilon$$

Let  $M = \max\{M_0, \dots, M_{k-1}\}$ , then  $\sup_n P(|X - X_n| > M) < \varepsilon$



**Continuous Mapping Theorem:** If  $g$  is a continuous function, and  $X_n \rightarrow_p X$ , then  $g(X_n) \rightarrow_p g(X)$

Pf:  $\forall \varepsilon > 0$ ,

$$\begin{aligned} & P(|g(X_n) - g(X)| > \varepsilon) \\ & \leq P(|g(X_n) - g(X)| > \varepsilon \text{ and } |X_n|, |X| \leq K) \\ & \quad + P(|X| > K) + P(|X_n| > K). \end{aligned}$$

Since  $X, X_n \in O_p(1)$ , we can choose a suitable  $K$  s.t.  $\forall \delta > 0$ ,

$$\begin{aligned} P(|X| > K) &< \delta/3, \\ \sup_n P(|X_n| > K) &< \delta/3. \end{aligned}$$

Note that  $g$  is uniformly continuous on  $\bar{B}(0; K)$ , which means that  $\exists M_\varepsilon$  s.t.

$$\begin{aligned} & P(|g(X) - g(X_n)| > \varepsilon \mid |X_n|, |X| \leq K) \\ \Rightarrow & \leq P(|X - X_n| > M_\varepsilon \mid |X_n|, |X| \leq K) \\ & P(|g(X_n) - g(X)| > \varepsilon) \end{aligned}$$

$$\leq P(|X - X_n| > M_\varepsilon) + \frac{2\delta}{3}, \text{ and } \exists k \text{ s.t. } \forall n \geq k,$$

$$P(|X - X_n| > M_\varepsilon) < \delta/3.$$

□

Pro

$$\frac{1}{\sqrt{n}} O_p(1) + O_p(1) = O_p(1)$$

$$O_p(1) + O_p(1) = O_p(1)$$

Lemma

①  $X_n = o_p(1)$ ,  $R(h) = o(|h|^P)$ , as  $h \rightarrow 0$ , then

$$R(X_n) = o_p(|X_n|^P)$$

②  $X_n = O_p(1)$ ,  $R(h) = O(|h|^P)$ , then

$$R(X_n) = O_p(|X_n|^P)$$

Pf: ① Let  $g(h) = \begin{cases} R(h)/|h|^P, & h \neq 0 \\ 0, & h = 0 \end{cases}$

$$g(h) = o(1), h \rightarrow 0^+.$$

②  $g(h) = O(1), h \rightarrow 0^+$ , then  $\forall \epsilon > 0$ ,

$\exists M$  s.t.  $|g(h)| \leq M$  if  $|h| < \delta$ ,  $h \neq 0$ .

Then for  $\forall \epsilon > 0$ ,  $\exists \delta > 0$  s.t.

$$1 - \epsilon \leq P(|X_n| < \delta) \leq P(|g(X_n)| \leq M)$$

□

## Weak convergence

Let  $F_x(x) = \mathbb{P}(X \leq x)$ .

**Definition:**  $X_n \rightarrow_w X$  iff

$F_{X_n}(x) \rightarrow F_X(x)$ , where  $x$  is a continuous points of  $F_X$ .

**Remark:**  $X_n, X$  don't need to be defined in a same probability space, while they should value the same space. (Define on law!)

Pro ①  $X_n \rightarrow_w X$  if  $X_n \rightarrow_p X$ ;  
②  $X_n \rightarrow_w C$  if  $X_n \rightarrow_p C$ .

Pf: ①  $\forall$  continuous point of  $F_X$ ,

$$\mathbb{P}(X_n \leq x)$$

$$= \mathbb{P}(X_n \leq x, X > x) + \mathbb{P}(X_n \leq x, X \leq x)$$
$$= \mathbb{P}(X_n \leq x, X > x) - \mathbb{P}(X_n > x, X \leq x)$$
$$+ \mathbb{P}(X \leq x)$$

Note  $\mathbb{P}(x < X \leq x + \delta) = o(1)$ , as  $\delta \rightarrow 0^+$ ,  
then

$$\begin{aligned} \mathbb{P}(X_n \leq x, X > x) &= \mathbb{P}(X_n \leq x, X > x + \delta) \\ &\quad + o(1) \\ &\leq \mathbb{P}(|X_n - X| > \delta) + o(1) \\ &= o(1). \end{aligned}$$

Do the similar step for  
 $\mathbb{P}(X_n > x, X \leq x)$ ,  
then  $\mathbb{P}(X_n \leq x) \rightarrow \mathbb{P}(X \leq x)$ .

②  $\forall \varepsilon > 0$ ,

$$\begin{aligned} & \mathbb{P}(|X_n - c| > \varepsilon) \\ &= F_{X_n}(c - \varepsilon) + 1 - F_{X_n}(c + \varepsilon) \\ &\rightarrow F_X(c - \varepsilon) + 1 - F_X(c + \varepsilon) \\ &= \mathbb{P}(|X - c| > \varepsilon) = 0. \end{aligned}$$

□

### Skorokhod's Representation Theorem

If  $X_n \xrightarrow{w} X$ , then  $\exists \tilde{X}_n, \tilde{X}$ , which is defined in the same probability space s.t.

$$F_{\tilde{X}_n} = F_{X_n},$$

$$F_{\tilde{X}} = F_X,$$

and  $\tilde{X}_n \xrightarrow{\text{a.s.}} \tilde{X} \quad (X_n, X \in \mathbb{R}^P)$

Pf: Let  $\tilde{X}_n = F_n^{-1}(U)$ ,  $\tilde{X} = F^{-1}(U)$ ,  
 $U \sim \text{Unif}[0, 1]$ . Claim that:

$$\tilde{X}_n \xrightarrow{\text{a.s.}} \tilde{X}$$

Let  $p=1$ , note that  $\tilde{X}_n, \tilde{X}$  is defined in  $([0, 1], \mathcal{B}([0, 1]))$ .

Assume that  $C_x = \{y \in \mathbb{R};$   
 $y \text{ is continuous point of } F\}$ .

$\forall x \in (0,1), \varepsilon > 0, \exists y \in C_x \text{ s.t.}$

$$F^{-1}(x) - \varepsilon < y < F^{-1}(x)$$

$\Rightarrow F(y) < x, \text{ then } \exists k \text{ s.t.}$

$$F_n(y) < x, n \geq k$$

$$\Rightarrow y < F_n^{-1}(x)$$

$$\Rightarrow F_n^{-1}(x) - \varepsilon < F_n^{-1}(x) \quad ①$$

Similarly, pick  $x' \in (0,1), y \in C_x, \text{ s.t. } x < x',$   
 $F^{-1}(x') < y < F^{-1}(x') + \varepsilon$

$\Rightarrow x' < F_n(y), \text{ if } n \text{ is large enough}$

$$\Rightarrow F_n^{-1}(x') < y$$

$$\Rightarrow F_n^{-1}(x) < F_n^{-1}(x') < F^{-1}(x') + \varepsilon \quad ②$$

①+②:

$$F^{-1}(x) \leq \liminf_n F_n^{-1}(x) \leq \limsup_n F_n^{-1}(x)$$

$$(\text{continuous}) \leq F^{-1}(x'),$$

Let  $x' \downarrow x, \text{ claim holds.}$

□

Remark: If  $X_n \rightarrow_w X, g$  is continuous,  
 $\exists \tilde{X}_n \xrightarrow{\tilde{X}} a.s. \Rightarrow g(\tilde{X}_n) \rightarrow_w g(\tilde{X})$   
 $\Rightarrow g(X_n) \rightarrow_w g(X).$

## Portmanteau Lemma

The following statements are equivalent.

(1)  $\mathbb{P}(X_n \leq x) \rightarrow \mathbb{P}(X \leq x)$  for all continuous points  $x \mapsto \mathbb{P}(X \leq x)$ .

(2)  $\mathbb{E} f(X_n) \rightarrow \mathbb{E} f(X)$  for all bound, Lipschitz function  $f$ .

(3)  $\lim_n \mathbb{P}(X_n \in G) \geq \mathbb{P}(X \in G)$  for  $G$  open  $G$ .

(4)  $\lim_n \mathbb{P}(X_n \in F) \leq \mathbb{P}(X \in F)$  for  $F$  closed  $F$ .

(5)  $\mathbb{P}(X_n \in B) \rightarrow \mathbb{P}(X \in B)$  for  $\forall B$  s.t.  $\mathbb{P}(X \in \partial B) = 0$ .

Pf: (1)  $\Rightarrow$  (2):

$$\begin{aligned} X_n &\xrightarrow{w} X \Rightarrow g(X_n) \xrightarrow{w} g(X) \\ \Rightarrow \mathbb{E} g(X_n) &\rightarrow \mathbb{E} g(X) \end{aligned}$$

(2)  $\Rightarrow$  (3)

Let  $f_m(x) = (\min d(x, A^c)) \wedge 1$

$$\Rightarrow f_m(x) \uparrow 1_{G(x)}, \forall \varepsilon > 0$$

$$\underline{\lim}_n P(X_n \in G)$$

$$= \underline{\lim}_n \lim_m \mathbb{E} f_m(X_n)$$

$$\geq \underline{\lim}_n \mathbb{E} f_m(X_n) = \mathbb{E} f_m(X)$$

$$\Rightarrow \underline{\lim}_n P(X_n \in G) \geq P(X \in G)$$

(3)  $\Leftrightarrow$  (4): Easy

(3) + (4)  $\Rightarrow$  (5):

$$\underline{\lim}_n P(X_n \in \overset{\circ}{B}) \geq P(X \in \overset{\circ}{B})$$

$$\overline{\lim}_n P(X_n \in \bar{B}) \leq P(X \in \bar{B})$$

Since  $P(X \in \overset{\circ}{B}) = P(X \in \bar{B})$   
and

$$\begin{aligned} \underline{\lim}_n P(X_n \in \overset{\circ}{B}) &\leq \underline{\lim}_n P(X_n \in B) \\ &\leq \overline{\lim}_n P(X_n \in B) \leq \overline{\lim}_n P(X_n \in \bar{B}) \end{aligned}$$

(5)  $\Rightarrow$  (1): Easy. □

- Prohorov's Theorem**
- (1)  $X_n \rightarrow_w X$ , then  $X_n = O_p(1)$ . ✓
  - (2) If  $X_n = O_p(1)$ , then  $\exists X_{n_k}, X$  s.t.  $X_{n_k} \rightarrow_w X, X = O_p(1)$ .

Pf: (1) Given  $M > 0$ ,  
 $\overline{\lim_n} P(|X_n| \geq M) \leq P(|X| \geq M)$ ,  
let  $M$  be large enough.

(2) (Helly Selection) Let  $Q = \{q_i\}$  be the set of rational. Note that

$\{F_{X_n}(q_1)\}$  is bounded

$\Rightarrow \exists \{n_{k_1}\}$  s.t.  $F_{X_{n_{k_1}}}(q_1) \rightarrow \tilde{F}(q_1)$

$\Rightarrow \{F_{X_n}(q_2)\}$  is bounded

$\Rightarrow \exists \{n_{k_2}\} \subset \{n_{k_1}\}$  s.t.

$F_{X_{n_{k_2}}} \rightarrow \tilde{F}(q_2)$

$\Rightarrow \dots \Rightarrow \exists \{n_{k_j}\} \subset \{n_{k_{j-1}}\}$  s.t.

$F_{X_{n_j}}(q_j) \rightarrow \tilde{F}(q_j)$

$\Rightarrow \exists \{n_R\}$  s.t.

$F_{X_{n_R}}(q) \rightarrow \tilde{F}(q), \forall q \in Q$

and  $\tilde{F} \uparrow$ . Let

$$F(x) = \inf_{q > x} \tilde{F}(q).$$

choose  $q, q' \in Q$  for a continuous point of

$$\begin{aligned}
 & F \text{ s.t. } q < x < q' \\
 \Rightarrow & F(q) \leq F(x) \leq F(q') \\
 \Rightarrow & F_{n_k}(q) \leq F_{n_k}(x) \leq F_{n_k}(q') \\
 \Rightarrow & F(q) \leq \liminf_n F_{n_k}(x) \leq \limsup_n F_{n_k}(x) \leq F(q') \\
 \text{Let } & q, q' \rightarrow x: \\
 \Rightarrow & F_{n_k}(x) \rightarrow F(x) \\
 \text{Since } & X_{n_k} = O_p(1), \forall \varepsilon > 0, \exists M \\
 & P(|X_{n_k}| > M) < \varepsilon, \text{ then } \exists M \\
 \text{s.t. } & P(|X| > M) < \varepsilon \\
 \Rightarrow & X = O_p(1) \quad \square
 \end{aligned}$$

Remark:

① If  $X_n = O_p(1)$ , if we want to show  $X_n \xrightarrow{w} X$ , just need to show  $\forall \varepsilon, \exists N, \forall n > N, P(|X_n - X| > \varepsilon) < \varepsilon$ .

$$\begin{aligned}
 & O_p(1) O_p(1)^{-1} = O_p(1) \\
 & (1 + O_p(1))^{-1} = O_p(1) \\
 & O_p(O_p(1)) = O_p(1)
 \end{aligned}$$

**Pro**

① If  $X_n \rightarrow_w X$ ,  $X_n - Y_n = o_p(1)$ ,  
then  $Y_n \rightarrow_w X$ .

② If  $X_n \rightarrow_w X$ ,  $Y_n \rightarrow_p C$ , then  
 $(X_n, Y_n) \rightarrow_w (X, C)$

Pf: ① A bound Lipschitz function  $f$ , if  $|f(x) - f(y)| \leq L|x-y|$   
 $\mathbb{E} f(Y_n) = \mathbb{E} f(X_n + Y_n - X_n)$   
 $= \mathbb{P}(|Y_n - X_n| > \varepsilon)M +$   
 $\mathbb{E} \underline{\mathbf{1}}(|Y_n - X_n| \leq \varepsilon) f(X_n) + L\varepsilon$   
 $= \mathbb{E} f(X_n) + 2\mathbb{P}(|Y_n - X_n| > \varepsilon)M + L\varepsilon$   
 $\Rightarrow \mathbb{E} f(Y_n) \rightarrow \mathbb{E} f(X_n).$

②  $(X_n, Y_n) - (X_n, C) = o_p(1)$   
 and A bound Lipschitz function  $f$ ,  $\mathbb{E} f(X_n, C) \rightarrow \mathbb{E} f(X, C)$   
 $\Rightarrow (X_n, C) \rightarrow_w (X, C)$  □

Remark: (Slutsky)

①  $X_n + Y_n \xrightarrow{w} X + C$

②  $X_n Y_n \xrightarrow{w} C X$

③  $X_n / Y_n \xrightarrow{w} X / C, C \neq 0$

if  $X_n \xrightarrow{w} X, Y_n \xrightarrow{w} C$ .

## Polya's Theorem

If  $X_n \xrightarrow{w} X$ , and  $F_X$  is continuous,

then  $\|F_{X_n} - F_X\|_\infty = \sup_x |F_{X_n}(x) - F_X(x)| \rightarrow 0$ .

Pf: Let  $F^{-1}(c) = x_i$ , then  $\exists i$  s.t.  
 $F_X(x_{i-1}) \leq F_X(x) \leq F_X(x_i)$

then

$$\begin{aligned} F_X(x) - F_{X_n}(x) &\leq F_X(x_i) - F_{X_n}(x_{i-1}) \\ &= F_X(x_{i-1}) - F_{X_n}(x_{i-1}) + \frac{1}{k} \end{aligned}$$

$$\begin{aligned} F_X(x) - F_{X_n}(x) &\geq F_X(x_{i+1}) - F_{X_n}(x_i) \\ &= F_X(x_i) - F_{X_n}(x_i) - \frac{1}{k} \end{aligned}$$

$$\Rightarrow \sup_x |F_X(x) - F_{X_n}(x)| \leq \sup_i |F_X(x_i) - F_{X_n}(x_i)| + \frac{1}{k}$$

□

# Characteristic Functions.

## Definition

$$\psi_{X(t)} = \mathbb{E} e^{itX}$$

$$= \mathbb{E} (\cos(tX) + i\mathbb{E} \sin(tX))$$

Remark:  $\psi_X \Leftrightarrow F_X$

## Pro

①  $\psi(0) = 1$  and  $|\psi(t)| \leq 1$

②  $\psi$  is continuous at  $t=0$ .

Pf:  $|\psi(t) - 1| \leq \mathbb{E} |e^{itX} - 1| \rightarrow 0$  □

③  $\psi(t)$  is uniformly continuous.

Pf:  $|\psi(t) - \psi(g)| = |\mathbb{E} e^{itX} - \mathbb{E} e^{igX}|$   
 $= |\mathbb{E} e^{itX} (e^{i(g-t)X} - 1)|$   
 $\leq \mathbb{E} |e^{i(g-t)X} - 1| \rightarrow 0$  □

④  $X \perp Y \Leftrightarrow \psi_{X,Y}(t, g) = \psi_X(t) \psi_Y(g)$

Pf: " $\Rightarrow$ "  $\psi_{X,Y}(t, g) = \mathbb{E} e^{i(tX + g^T Y)}$   
 $= \mathbb{E} e^{itX} \cdot \mathbb{E} e^{ig^T Y}$

" $\Leftarrow$ ": Define  $P = F_X \cdot F_Y$ , then  
 $\psi_P(t, g) = \psi_{X,Y}(t, g), \forall t, g$

$$\Rightarrow F_{X,Y} = F_X \cdot F_Y. \quad \square$$

### Theorem

If  $\mathbb{E}|X|^k < \infty$ , then  $\psi_x^{(k)}(t)$  exists and is a uniformly continuous function s.t.

$$\psi_x^{(k)}(0) = i^k \mathbb{E} X^k$$

Pf:  $\forall t, k \in \mathbb{R}$

$$\begin{aligned} \psi_x(t) - \psi_x(g) / (t-g) \\ = \frac{\mathbb{E}(e^{i(t-g)X} - 1)}{t-g} \cdot e^{igX} \end{aligned}$$

$$= \mathbb{E}(iX e^{igX} + \text{op}(1)), \quad g \rightarrow t$$

$$\rightarrow i \mathbb{E} X e^{itX}$$

$$\Rightarrow \psi'_x(t) = i \mathbb{E} X e^{itX}$$

$$\Rightarrow \psi_x^{(k)}(t) = i^k \mathbb{E} X^k e^{itX}$$

And

$$|\psi_x^{(k)}(g) - \psi_x^{(k)}(t)|$$

$$= |\mathbb{E} X^k e^{i(t-g)X} - 1| \rightarrow 0, \quad t \rightarrow k \quad \square$$

Lemma

$$\mathbb{P}(|X| > \frac{2}{\alpha}) \leq \frac{1}{\alpha} \int_{-a}^a (1 - \Phi_X(t)) dt$$

Pf:

$$\frac{1}{\alpha} \int_{-a}^a (1 - \Phi_X(t)) dt$$

$$= \frac{1}{\alpha} \int_{-a}^a (1 - \mathbb{E} e^{itX}) dt$$

$$= \frac{1}{\alpha} \mathbb{E} \int_{-a}^a (1 - e^{itX}) dt$$

$$= \mathbb{E} 2 - \frac{1}{\alpha} \int_{-a}^a \cos(tx) dt$$

$$= \mathbb{E} \left( 2 - \frac{2 \sin(ax)}{ax} \right)$$

$$\geq \mathbb{E} \left( 2 - \frac{2 \sin(ax)}{ax} \right) \mathbf{1}_{\{|ax| \geq 2\}}$$

$$\geq \mathbb{P}(|ax| \geq 2)$$



# Levy continuous theorem

- ①  $X_n \rightarrow_w X \Rightarrow \psi_{X_n}(t) \rightarrow \psi_X(t), \forall t$
- ② If  $\psi_{X_n}(t) \rightarrow \psi(t)$ ,  $\psi$  is continuous at 0, then  $\exists X$  s.t.

$$X_n \rightarrow_w X, \psi_X = \psi$$

Pf: ①  $\psi_{X_n}(t) = \mathbb{E} e^{itX_n} \rightarrow \mathbb{E} e^{itX}$ .

② Claim that  $X_n = O_p(1)$ ,  
since

$$\begin{aligned} \mathbb{P}(|X_n| > M) &\leq 2M \int_{-\frac{M}{2}}^{\frac{M}{2}} (1 - \psi_{X_n}(t)) \\ &= 2M \int_{-\frac{M}{2}}^{\frac{M}{2}} (1 - \psi(t)) + o(1) \end{aligned}$$

then  $X_n = O_p(1)$

$\Rightarrow \forall \{X_{n_k}\}, \exists \{X_{n_{kj}}\}, X$  s.t.

$X_{n_{kj}} \rightarrow_w X$   
 $\Rightarrow \psi_{X_{n_{kj}}}(t) \rightarrow \psi_X(t) = \psi(t)$

$\Rightarrow X_n \rightarrow_w X$



Remark: (Cramer-Wold device)  
 $X_n \rightarrow_w X$  iff  $c^T X_n \rightarrow_w c^T X, \forall c$

### Weak Law of Large Number

If  $X_1, \dots, X_n$  is iid, and  $\mu = \mathbb{E}X$ , exists, then

$$\bar{X}_n := \frac{X_1 + \dots + X_n}{n} = \mu + o_p(1).$$

$$\begin{aligned} \text{Pf: } \Phi_{\bar{X}_n}(t) &= \mathbb{E} e^{it \frac{X_1 + \dots + X_n}{n}} \\ &= (\mathbb{E} e^{it \frac{X_1}{n}})^n \\ &= (1 + \frac{i\mu t}{n} + o(\frac{t}{n}))^n \\ &= e^{nc i \mu t (1 + o(\frac{1}{n}))} \\ &\xrightarrow{\quad \rightarrow e^{i \mu t} \quad} \\ \Rightarrow \bar{X}_n &\rightarrow_w \mu \end{aligned}$$



Remark:  $X_1 + \dots + X_n = O_p(n)$ .

# Central Limit Theorem

If  $X_1, \dots, X_n$  iid and  $\mathbb{E} X_i^2 < \infty$ ,  
then

$$\frac{\bar{X}_n - \mu}{\sigma} \xrightarrow{w} N(0, 1),$$

where  $\mu = \mathbb{E} X$ ,  $\sigma = \sqrt{\text{Var } X}$ .

Pf: Let  $\mu = 0$ ,  $\sigma = 1$ ,

$$\begin{aligned}\Psi_{\sqrt{n}\bar{X}_n}(t) &= (\mathbb{E} e^{it\frac{\bar{X}_n}{\sqrt{n}}})^n \\ &= (1 - \frac{1}{2}\frac{t^2}{n} + o(\frac{1}{n}))^n \\ &\rightarrow e^{-\frac{1}{2}t^2}\end{aligned}$$

$$\Rightarrow \sqrt{n} \bar{X}_n \xrightarrow{w} N(0, 1)$$

□

Remark: ①  $X_1 + \dots + X_n = O_p(\sqrt{n})$ .

$$\begin{aligned}② \quad X &\sim N(0, 1), \\ \sup_t |\mathbb{P}(\sqrt{n}\frac{\bar{X}_n - \mu}{\sigma} \geq t) - \mathbb{P}(X \geq t)| &\rightarrow 0.\end{aligned}$$

# Lindeberg - Feller CLT

If  $X_{n,1}, \dots, X_{n,k_n}$  are independent, and

- ①  $\sum_{i=1}^{k_n} \mathbb{E} X_{n,i} = 0$ ,
- ②  $\sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 = 1$ ,  $k_n \rightarrow \infty$ .

and  $\sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 \frac{\mathbb{P}(X_{n,i} > \varepsilon)}{\varepsilon} \rightarrow 0$ ,  $\forall \varepsilon > 0$

then

$$\sum_{i=1}^{k_n} X_{n,i} \xrightarrow{w} N(0, 1)$$

$$Pf: \left| \sum_{i=1}^{k_n} \log(\Phi_{X_{n,i}}(t)) - (\Phi_{X_{n,i}}(t) - 1) \right|$$

$$\leq \sum_{i=1}^{k_n} |\phi_i(t)|^2, \quad \phi_i(t) := \Phi_{X_{n,i}}(t) - 1$$

( $\ln(1+x) - x \leq x^2$ , if  $x$  is small enough)

$$\leq \max_i |\phi_{i,n}(t)| \sum_{i=1}^{k_n} |\phi_{i,n}(t)|,$$

Note

$$|\phi_{i,n}(t)| = |\mathbb{E} e^{i t \sqrt{\mathbb{E} X_{n,i}^2} \frac{X_{n,i}}{\sqrt{\mathbb{E} X_{n,i}^2}}} - 1|$$

$$= \left| 1 - \frac{t^2}{2} \mathbb{E} X_{n,i}^2 + o(t^2 \mathbb{E} X_{n,i}^2) \right|$$

$\leq \frac{t^2}{2} \mathbb{E} X_{n,i}^2$ , if  $\mathbb{E} X_{n,i}^2$  is small enough.

$$\Rightarrow |\phi_{i,n}(t)| = o(1)$$

$$\sum_{i=1}^{k_n} |\phi_{i,n}(t)| \leq \frac{t^2}{2}$$

$$\Rightarrow \sum_{i=1}^{k_n} \log \psi_{X_{n,i}}(t) = \sum_{i=1}^{k_n} (\psi_{X_{n,i}}(t) - 1) + o(1)$$

Note that  $\psi_{X_{n,i}}(t) - 1 = -\psi_{X_{n,i}}^{(2)}(C_{i,t}) \frac{t^2}{2}$  (where  $0 \leq C_{i,t} \leq t$ )

$$= -\frac{t^2}{2} \mathbb{E} X_{n,i}^2 + \underbrace{(\psi_{X_{n,i}}^{(2)}(0) - \psi_{X_{n,i}}^{(2)}(C_{i,t}))}_{\downarrow} \frac{t^2}{2}$$

$$\mathbb{E} X_{n,i}^2 < 1 - e^{-iC_{i,t} X_{n,i}}$$

Among

$$\left| \sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 (1 - e^{i(c_i + t X_{n,i})}) \right|$$

$$\leq 2 \sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 \mathbb{1}(|X_{n,i}| > \varepsilon)$$

$$+ \sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 |1 - e^{i(c_i + t X_{n,i})}| \mathbb{1}(|X_{n,i}| \leq \varepsilon)$$

$$\leq \sum_{i=1}^{k_n} + \mathbb{E} X_{n,i}^3 \mathbb{1}(|X_{n,i}| \leq \varepsilon)$$

$$\leq t \varepsilon \sum_{i=1}^{k_n} \mathbb{E} X_{n,i}^2 \leq t \varepsilon$$

$$\Rightarrow \log \Phi \sum_{i=1}^{k_n} X_{n,i} (t) = -\frac{t^2}{2} + o(1)$$

□

Remark:

- ①  $X_1, \dots, X_n$  is independent, and
- △  $\mathbb{E} X_i = \mu_i$
- △  $\sum_{i=1}^n \text{Var } X_i := \sigma_n^2 < \infty$
- $\mathbb{E} X_i^2 \mathbf{1}(|X_i| \geq \sigma_n \varepsilon) / \sigma_n^2 < \infty,$

$\forall \varepsilon > 0$ . Then:

$$\frac{\sum_{i=1}^n X_i - \mu_i}{\sigma_n} \xrightarrow{w} N(0, 1)$$

- ② (Lyapunov) If  $\exists \delta > 0$ ,

s.t.

$$\frac{\sum_{i=1}^n \mathbb{E} |X_i|^{2+\delta}}{\sigma_n^{2+\delta}} \rightarrow 0,$$

then

$$\frac{\sum_{i=1}^n X_i - \mu_i}{\sigma_n} \xrightarrow{w} N(0, 1),$$

where  $X_1, \dots, X_n$  is independent.

## Stein's Method

Let  $Z \sim N(0, 1)$ , define Stein's equation:

$$f'(w) - wf(w) = \mathbb{1}_{\{w \leq x\}} - \Phi(x),$$

where  $\Phi(x) = P(Z \leq x)$ .

Indeed,  $\forall x$ ,  $\exists!$  bounded  $f$  to achieve Stein's equation.

If  $X \sim N(0, 1)$ , then

$$\mathbb{E} f'(X) - xf(X) = 0 \text{ for}$$

some bound, differentiable functions.

Actually, if  $f$  is bounded, absolutely continuous,  $\int |f'| < \infty$ , then

$$\mathbb{E} f'(x) = \mathbb{E} X f(x),$$

which is called the Stein's identity.

Now, let  $X_1, \dots, X_n$  iid s.t.  
 $\mathbb{E} X_i = 0$ ,  $\sum_{i=1}^n \mathbb{E} X_i^2 = 1$ , and  $\gamma = \mathbb{E}|X_1|^3 < \infty$ ,  
 $S_n = \sum_{i=1}^n X_i$ , then

## Berry - Esseen

$$\sup_t |\mathbb{P}(S_n \leq t) - \Phi(t)| \leq n\gamma$$

$$\text{Pf: } \mathbb{P}(S_n \leq t) - \Phi(t)$$

$$= \mathbb{E} (\mathbb{1}(S_n \leq t) - \Phi(t)), \exists f_t$$

$$= \mathbb{E} f'_t(S_n) - S_n f_t(S_n) \quad (1)$$

Among,

$$\mathbb{E} S_n f(S_n) = n \mathbb{E} X_n f(S_n)$$

$$= n \mathbb{E} X_n (f(S_n) - f(S_{n-1}))$$

$$= n \mathbb{E} X_n \int_0^{X_n} f'(t + S_{n-1}) dt$$

$$= n \mathbb{E}_{S_{n-1}} \underbrace{\mathbb{E}_{X_n} X_n \int_0^{X_n} f'(t + S_{n-1}) dt}$$

$$\begin{aligned}
 &= \mathbb{E}_{X_n} \int (\underbrace{\mathbf{1}_{(0 \leq t \leq X_n)} + \mathbf{1}_{(X_n \leq t \leq 0)}}_{\text{red line}}) \\
 &\quad \cdot X_n f'(t + S_{n-1}) dt \\
 &= \int_0^\infty \mathbb{E}_{X_n} X_n f'(t + S_{n-1}) \underline{dt} ,
 \end{aligned}$$

then

$$\mathbb{E} S_n f(S_n) = \mathbb{E} \int_{-\infty}^\infty f'(t + S_{n-1}) K(t) dt,$$

where

$$K(t) = n \mathbb{E} X_n (\mathbf{1}_{(0 \leq t \leq X_n)} + \mathbf{1}_{(X_n \leq t \leq 0)}),$$

and

$$\begin{aligned}
 \int_{-\infty}^\infty K(t) dt &= n \int_{-\infty}^0 \mathbb{E} X_n \mathbf{1}_{(X_n \leq t)} dt \\
 &\quad + n \int_0^{+\infty} \mathbb{E} X_n \mathbf{1}_{(X_n \geq t)} dt \\
 &= n \int_0^{+\infty} \mathbb{E} |X_n| \mathbf{1}_{(|X_n| \geq t)} dt
 \end{aligned}$$

$$= n \mathbb{E} X_n^2 = 1$$

Let  $T \sim K(t)$ ,  $T \perp X_1, \dots, X_n$

$$\Rightarrow \mathbb{E}_{S_n} f(S_n) = \mathbb{E} f'(S_{n-1} + T)$$

(Stein identity)

$$\begin{aligned} \text{Then } c(1) &= \mathbb{E} f'_x(S_n) - f'_x(S_{n-1} + T) \\ &= \mathbb{E} S_n f'_x(S_n) - (S_{n-1} + T) f'_x(S_{n-1} + T) \\ &\quad + \mathbb{E} (\mathbf{1}_{\{S_n \leq x\}} - \mathbf{1}_{\{S_{n-1} + T \leq x\}}) \end{aligned}$$

$$\leq \mathbb{E} |X_n| + \mathbb{E} |T| +$$

$$\mathbb{P}\{x - \max\{X_n, T\} \leq S_{n-1} \leq x - \min\{X_n, T\}\}$$

where

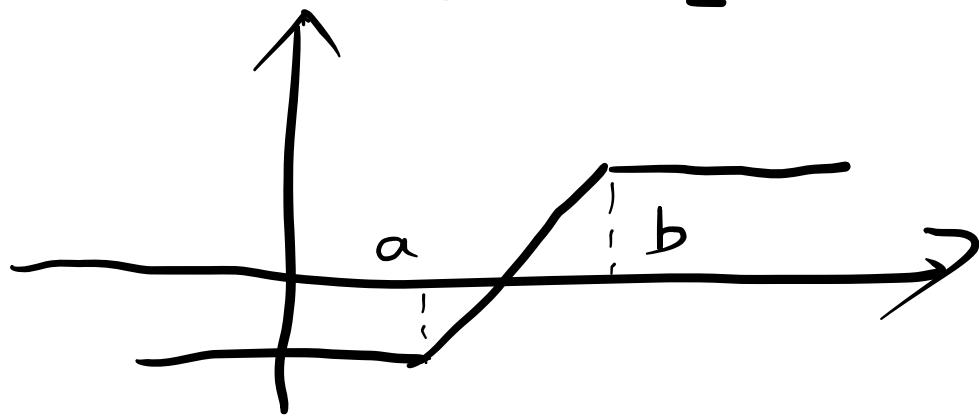
$$\begin{aligned} \mathbb{E} |T| &= n \int_0^{+\infty} \mathbb{E} |X_n| |t| \mathbf{1}_{\{|X_n| \geq t\}} dt \\ &= n \mathbb{E} \frac{|X_n|^3}{2} = \frac{n \sigma^3}{2} \end{aligned}$$

$$\begin{aligned}
 \text{Since } \mathbb{E}|X_n|^3 &\geq \mathbb{E}|X_n| \mathbb{E}|X_n|^2 \\
 &= \mathbb{E}|X_n| / n \\
 \Rightarrow \mathbb{E}|X_n| + \mathbb{E}|T| &\leq \mathbb{E}|T| \\
 &= nr
 \end{aligned}$$

Note that A reasonable  $f$ ,

$$\mathbb{E} S_n f(S_n) = \mathbb{E} f'(S_{n-1} + T)$$

let  $f'(w) = \mathbb{1}_{(a \leq w \leq b)}$

$$|f(w)| \leq \frac{b-a}{2}$$


$$\begin{aligned}
 & \text{Then } |\mathbb{E} S_n f(S_n)| \\
 & \leq \frac{b-a}{2} \mathbb{E}|S_n| \\
 & \leq \frac{b-a}{2} (\mathbb{E} S_n^2)^{\frac{1}{2}} \\
 & \leq \frac{b-a}{2}
 \end{aligned}$$

$$\begin{aligned}
 & \text{and } \mathbb{E} S_n f(cS_n) \\
 & = P(a \leq S_{n-1} + T \leq b) \\
 & \geq P(a - \delta \leq S_{n-1} \leq b + \delta, |T| \leq \delta) \\
 & \geq P(a - \delta \leq S_{n-1} \leq b + \delta) \left(1 - \frac{\mathbb{E}|T|}{\delta}\right)
 \end{aligned}$$

then (Stein's concentration)  $\frac{b-a}{1 - \frac{\mathbb{E}|T|}{\delta}}$

$$P(a - \delta \leq S_{n-1} \leq b + \delta) \leq \frac{b-a}{1 - \frac{\mathbb{E}|T|}{\delta}}$$

$$\Rightarrow (\delta = 2|\mathbb{E}T|)$$

$$\begin{aligned} & \mathbb{P}(x - \max\{X_n, T\} \leq S_{n-1} \leq x - \min\{X_n, T\} | X_n, T) \\ & \leq x - \min\{X_n, T\} - 2\mathbb{E}(T) \end{aligned}$$

$$\begin{aligned} & - (x - \max\{X_n, T\}) + 2\mathbb{E}(T) \\ & = |X_n - T| + 4\mathbb{E}|T| \end{aligned}$$

$$\begin{aligned} & \Rightarrow \mathbb{P}(x - \max\{X_n, T\} \leq S_{n-1} \leq x - \min\{X_n, T\}) \\ & \leq \mathbb{E}|T| \end{aligned}$$

$\Rightarrow$

$$\sup_t |\mathbb{P}(S_n \leq t) - \Phi(t)| \leq \mathbb{E}|T| = n\sigma$$

Remark:

$$① \text{ Since } \mathbb{E}|X_n| \leq \frac{1}{\sqrt{n}}$$

$$\Rightarrow |X_n| = O_p(\frac{1}{\sqrt{n}}) \Rightarrow |X_n|^3 = O_p\left(\frac{1}{\sqrt{n}}\right)^3$$

$$\Rightarrow \mathbb{E}|X_n|^3 = O\left(\frac{1}{\sqrt{n}}\right)^3$$

$$\Rightarrow n\gamma = O\left(\frac{1}{\sqrt{n}}\right)$$

② If we just know  $\sigma^2 = \mathbb{E}X_i^2$  and  $\gamma = \mathbb{E}|X_i|^3 < \infty$ , let

$$Y_i = \frac{X_i}{\sqrt{n}\sigma}$$

$$\Rightarrow \sup_t |\mathbb{P}\left(\sum_{i=1}^n Y_i \leq t\right) - \Phi(t)|$$

$$\leq n \mathbb{E}|Y_n|^3$$

$$= n \mathbb{E}|X_n|^3 / (n\sqrt{n}\sigma^3)$$

$$= \frac{\gamma}{\sqrt{n}\sigma^3} .$$