

Convergence

Convergence in distn $X_n: \Omega \rightarrow \mathbb{R}$ random variables
 $X: \Omega \rightarrow \mathbb{R}$ r.v.

let $F_n(a) = P(X_n \leq a) \in \text{CDF of } X_n$

$F(a) = P(X \leq a) \in \text{CDF of } X$

$$\lim_{n \rightarrow \infty} F_n(a) = F(a)$$

We say that $X_n \xrightarrow{D} X$ ("in distn")

If for all real a , F is cts at a , we have $\lim_{n \rightarrow \infty} F_n(a) = F(a)$

Levy's Continuity theorem

① If $X_n \xrightarrow{D} X$ then: for all $t \in \mathbb{R}$ we have: $\lim_{n \rightarrow \infty} \varphi_{X_n}(t) = \varphi_X(t)$

② Let X_n be a sequence of random variable, and suppose there is a ftn: $\varphi: \mathbb{R} \rightarrow \mathbb{C}$
s.t. $\lim_{n \rightarrow \infty} \varphi_{X_n}(t) = \varphi(t)$ for all $t \in \mathbb{R}$.

For all $t \in \mathbb{R}$ and φ is cts at $t=0$, then φ is the characteristic ftn of some random variable X and $X_n \xrightarrow{D} X$.

Central Limit Theorems

Generally, they deal with situations $X_n \xrightarrow{D} X$ where X is Gaussian.

Main ex:



let X_1, X_2, \dots, X_n be i.i.d \rightarrow (have the same CDF)
r.v. $E(X_n) = 0$, $\text{Var}(X_n) = 1$.

let $Y_n = \frac{1}{\sqrt{n}} \sum_{k=1}^n X_k$, $n=1, 2, \dots$

$$\sqrt{n}(\bar{Y} - \mu) \Rightarrow N(0, \sigma^2)$$

then $Y_n \xrightarrow{D} Y$ where Y is standard normal.

Note $E(Y_n) = 0, \text{Var}(Y_n) = 1$ *sanity check*

Proof:

$$\text{let } \psi(t) \equiv \psi_{X_n}(t) = E e^{itX_n}$$

$$\psi_{Y_n}(t) = E e^{itY_n} = E e^{it \frac{1}{\sqrt{n}} \sum_{k=1}^n X_k}$$

$$= E \left[e^{i \frac{t}{\sqrt{n}} X_1} e^{i \frac{t}{\sqrt{n}} X_2} \dots e^{i \frac{t}{\sqrt{n}} X_n} \right]$$

$$\stackrel{\text{indep}}{=} E \left[e^{i \frac{t}{\sqrt{n}} X_1} \right] \times \dots \times E \left[e^{i \frac{t}{\sqrt{n}} X_n} \right]$$

$$= \psi \left(\frac{t}{\sqrt{n}} \right)$$

We can see $a_t = O(t)$. Since $\left| \frac{a_t}{t} \right|$ is bounded as $t \rightarrow 0$, we know $a_t \rightarrow 0$ as t in some neighborhood of 0.

$\frac{O(t)}{t} \rightarrow 0$ as $t \rightarrow 0$ *M.C.S.T.*

$$\frac{\psi'''(0)}{3!} t^3$$

Taylor Expansion: $\psi(t) = \psi(0) + \psi'(0)t + \frac{\psi''(0)}{2!}t^2 + \underbrace{O(t)^2}_{O(t) \cdot t^2}$ where $O(t) \rightarrow 0$ as $t \rightarrow 0$. \triangle

$$\psi(0) = 1, \quad \psi'(0) = i E(X_n) = 0, \quad \psi''(0) = -E(X_n^2) = -\text{Var}(X_n) = -1$$

$$\text{Hence } \psi_{X_n}(t) = \left(1 - \frac{t^2}{2n} + \underbrace{O(t)}_{\rightarrow 0 \text{ as } t \rightarrow 0} \frac{t^2}{2n} \right)^n$$

$$\psi(t) = \psi(0) + \psi'(0)t + \frac{\psi''(0)}{2!}t^2 + O(t) \cdot t^2$$

$O(t) \rightarrow 0$ as $t \rightarrow 0$

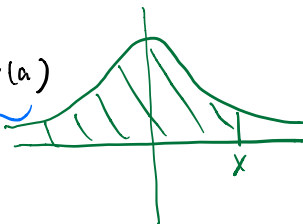
$\rightarrow e^{-t^2/2}$, which is the characteristic fn of standard normal

\Downarrow Levy's continuity theorem

$Y_n \xrightarrow{D} Y$
standard normal

let $\phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt$, which is the CDF of the standard normal.

$Y_n \xrightarrow{D} Y \Leftrightarrow$ for all $a < b$, $P(a \leq Y_n \leq b) \rightarrow \phi(b) - \phi(a)$
standard Gaussian



$\phi(x)$ is tabulated for $x \geq 0$. by symmetry, $\phi(x) + \phi(-x) = 1$

Q: How fast is the convergence?

A: Tricky. Buzzwords: Stein Method, Berry-Esseen Theorem.

CLT under special situations (not always true)

Sometimes, if X_1, \dots, X_n are indep r.v. no need for i.i.d

$$Y_n = \frac{\sum_{k=1}^n X_k - \left(\sum_{k=1}^n E(X_k)\right)}{\sqrt{\sum_{k=1}^n \text{Var}(X_k)}} \quad , \text{ so that } E(Y_n) = 0, \text{Var}(Y_n) = 1.$$

$Y_n \xrightarrow{D} \underline{Y}$
standard Gaussian

If that happens, we have central limit theorem.

One More Example (Lyapunov Theorem) x need

If $E(X_n) = 0, \text{Var}(X_n) = b_n^2, E|X_n|^3 = \delta_n$

And $S_n^2 = \sum_{k=1}^n b_k^2 = \text{Var}(Y_n),$

and $\lim_{n \rightarrow \infty} \frac{1}{S_n^3} \sum_{k=1}^n \delta_k = 0$

then $Y_n \xrightarrow{D} \underline{Y}$
standard normal

ex. (Typical)

We roll a fair die n times.

Let Y_n be the total sum.

$Y_n = X_1 + \dots + X_n$

X_k : # shown on the k -th roll

$$E(Y_n) = \sum_{i=1}^n E(X_i) = \frac{7}{2}n$$

$$D(Y_n) = \sum_{i=1}^n \text{Var}(X_i) = \frac{35n}{12}$$

$$\text{CLT: } \frac{Y_n - \frac{7}{2}n}{\sqrt{\frac{35n}{12}}} \xrightarrow{D} N(0,1)$$

$$E(Y_n) = E(X_1) + \dots + E(X_n) = \frac{7}{2}n$$

$$\text{Var}(Y_n) = \underset{\substack{\uparrow \\ \text{indep}}}{\text{Var}(X_1) + \dots + \text{Var}(X_n)} = \frac{35}{12}n$$

$$P(a \leq \frac{Y_n - \frac{7}{2}n}{\sqrt{\frac{35n}{12}}} \leq b) \rightarrow \phi(b) - \phi(a) \quad \text{as } n \rightarrow \infty$$

$$P(\sqrt{\frac{35n}{12}}a + \frac{7}{2}n \leq Y_n \leq \sqrt{\frac{35n}{12}}b + \frac{7}{2}n) \rightarrow \phi(b) - \phi(a)$$

Central Limit says:

$$\frac{Y_n - \frac{7}{2}n}{\sqrt{\frac{35n}{12}}} \xrightarrow{D} \text{standard normal}$$

for any $a < b$,

$$P(a \leq \frac{Y_n - \frac{7}{2}n}{\sqrt{\frac{35n}{12}}} \leq b) \rightarrow \phi(b) - \phi(a) \quad \text{when } n \rightarrow \infty.$$

$$P(\frac{7}{2}n + a\sqrt{\frac{35n}{12}} \leq Y_n \leq \frac{7}{2}n + b\sqrt{\frac{35n}{12}}) \xrightarrow[n \rightarrow \infty]{} \phi(b) - \phi(a)$$

Choose, for ex.

$$a = -5\sqrt{\frac{12}{35}}, \quad b = 5\sqrt{\frac{12}{35}} \\ \approx -2.93 \quad \approx 2.93$$

$$\text{then: } P(\frac{7}{2}n - 5\sqrt{n} \leq Y_n \leq \frac{7}{2}n + 5\sqrt{n}) \xrightarrow{n \rightarrow \infty} \phi(5\sqrt{\frac{12}{35}}) - \phi(-5\sqrt{\frac{12}{35}}) = 2\phi(5\sqrt{\frac{12}{35}}) \approx 0.997$$

$$\text{Hence, } \lim_{n \rightarrow \infty} P(|Y_n - \frac{7}{2}n| > 5\sqrt{n}) \approx 0.003$$

rely on n (hard to figure out)

Compare with Cheby Shev,

$$P(|Y_n - \frac{7}{2}n| > 5\sqrt{n}) \leq \frac{\text{Var}(Y_n)}{25n} = \frac{\frac{35}{12}n}{25n} = \frac{35}{12 \times 25} = \frac{7}{60} \approx 0.12$$

Compare with Bernstein,

$$P(|Y_n - \frac{7}{2}n| > 5\sqrt{n}) = P(|\frac{2}{5}Y_n - \frac{7}{5}n| > 2\sqrt{n}) \leq 2e^{-2} \approx 0.27$$

true for any n

$$\begin{aligned}
 p(|x| > a) &\leq 2e^{-a^2/n} \\
 &\leq 2e^{-an/n}
 \end{aligned}$$