

INTRODUCTION TO ESTIMATION THEORY

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CONVERGENCE IN DISTRIBUTION

DEFINITION (CONVERGENCE IN DISTRIBUTION)

Let random variables X_n and X have distributions $F_n(\cdot)$ and $F(\cdot)$ respectively. Then X_n is said to converge in distribution to X , if

$$F_n \Rightarrow F$$

or equivalently,

$$\lim_{n \rightarrow \infty} Pr[X_n \leq x] = Pr[X \leq x]$$

for every x such that $Pr[X = x] = 0$.

Remark: We only require $F_n(\cdot)$ to converge at every continuous point!

CONVERGENCE IN DISTRIBUTION

EXAMPLE

Take $p_{n,k} = \frac{\lambda}{n}$

$$\mu\{k\} = \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}, \text{ for } 0 \leq k \leq n$$

Then

$$\mu_n \Rightarrow \text{Poisson}(\lambda).$$

$$X_n \xrightarrow{\mathcal{P}} X \text{ IMPLIES } X_n \Rightarrow X$$

THEOREM

$$X_n \xrightarrow{\mathcal{P}} X \text{ implies } X_n \Rightarrow X$$

PROOF.

Observe that $Pr[A \leq a] - Pr[|A - B| > \epsilon] \leq Pr[B \leq a + \epsilon]$.

Then

$$Pr[X \leq x - \epsilon] - Pr[|X_n - X| > \epsilon] \leq Pr[X_n \leq (x - \epsilon) + \epsilon] = Pr[X_n \leq x],$$

and

$$Pr[X_n \leq x] - Pr[|X_n - X| > \epsilon] \leq Pr[X \leq x + \epsilon].$$

Hence we get

$$\begin{aligned} Pr[X \leq x - \epsilon] - Pr[|X_n - X| > \epsilon] &\leq Pr[X_n \leq x] \\ &\leq Pr[X \leq x + \epsilon] + Pr[|X_n - X| > \epsilon] \end{aligned}$$

$$X_n \xrightarrow{\mathcal{P}} X \text{ IMPLIES } X_n \Rightarrow X$$

CON'D.

which implies that

$$\begin{aligned} Pr[X \leq x - \epsilon] &\leq \liminf Pr[X_n \leq x] \\ &\leq \limsup Pr[X_n \leq x] \\ &\leq Pr[X \leq x + \epsilon] \end{aligned}$$

Therefore, for each continuous point, we have

$$\lim_{n \rightarrow \infty} Pr[X_n \leq x] = Pr[X \leq x]$$



Remark: $X_n \Rightarrow X$ does not imply $X_n \xrightarrow{\mathcal{P}} X$

COUNTEREXAMPLE FOR $X_n \Rightarrow X$ IMPLYING $X_n \xrightarrow{\mathcal{P}} X$

EXAMPLE

$X \perp\!\!\!\perp Y$ and $X \sim \text{Ber}(p)$, $Y \sim \text{Ber}(p)$. Let $X_n = X$, for all n . Then we have

$$X_n \Rightarrow Y, \text{ but } X_n \not\xrightarrow{\mathcal{P}} Y$$

Remark: Convergence in distribution gives NO information between the correlation of each random variables!

FUNDAMENTAL THEOREM

THEOREM (SKOROGOD'S THEOREM)

Suppose μ_n and μ are probability measures on $(\mathbb{R}, \mathcal{B})$, and $\mu_n \Rightarrow \mu$. Then there exist random variables Y_n and Y such that:

1. they are both defined on common probability space $(\Omega, \mathcal{F}, \mathcal{P})$
2. $Pr[Y_n \leq y] = \mu_n(-\infty, y]$, for all y
3. $Pr[Y \leq y] = \mu(-\infty, y]$, for all y
4. $\lim_{n \rightarrow \infty} Y_n(\omega) = Y(\omega)$, for every ω in Ω

Remark: This implies that cdfs are sufficient; we do not need to rely on the inherited probability space.

Historical Aspects

- CLT concerns the situation that the limit distribution of the normalized sum is normal
- As an example, for i.i.d. zero-mean sequence X_1, X_2, \dots

$$\frac{X_1 + \dots + X_n}{n\mathbb{E}[X_i^2]} \Rightarrow N$$

where N has standard normal distribution

- **Question:** What is the rate of convergence of normalized sum distribution to standard normal distribution?

BERRY-ESSEEN THEOREM

- The first convergence rate estimates in the CLT were obtained by A.M. Lyapounov in 1900-1901
- In the beginning of 1940s, the classic Berry-Esseen estimate came to the light

BERRY-ESSEEN THEOREM

THEOREM (BERRY-ESSEEN THEOREM (I.I.D. CASE))

$$\sup_{x \in \mathbf{R}} |F_n(x) - \Phi(x)| \leq C \frac{\beta_3}{\sigma^3 \sqrt{n}}$$

where

- F_n is the cdf of $\frac{X_1 + \dots + X_n}{n\mathbb{E}[X_i^2]}$
- Φ is the standard normal cdf
- $\beta_3 = \mathbb{E}[|X - \mathbb{E}X|^3]$
- $\sigma^2 = \mathbb{E}[|X - \mathbb{E}X|^2]$
- C is a universal constant, independent of n , F_n

BERRY-ESSEEN THEOREM

THEOREM (BERRY-ESSEEN THEOREM (INDEPENDENT CASE))

$$\sup_{x \in \mathbf{R}} \left| Pr \left[\frac{X_1 + \dots + X_n}{s_n} \leq a \right] - \Phi(x) \right| \leq C \frac{r_n}{s_n^3}$$

where

- Φ is the standard normal cdf
- $r_n = \mathbb{E}[|(X_1 + \dots + X_n) - \mathbb{E}(X_1 + \dots + X_n)|^3]$
- $s_n^2 = \mathbb{E}[|(X_1 + \dots + X_n) - \mathbb{E}(X_1 + \dots + X_n)|^2]$
- C is a universal constant, independent of n , F_n

Remark:

- Lower bound of C : $C \geq \frac{\sqrt{10} + 3}{6\sqrt{2\pi}} \approx 0.40973$ (Esseen (1956))
- Upper bound of C : $C \leq 0.4785$ (Tyurin (2010))