

Math 3236 Statistical Theory

1/17/2023

Law of Large Numbers.

X_i are i.i.d r.v

random Sample

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

$$\bar{X}_n \xrightarrow[n \rightarrow \infty]{P} E(X_i)$$

$$\forall \epsilon \quad P(|\bar{X}_n - E(X_i)| > \epsilon) \xrightarrow[n \rightarrow \infty]{} 0$$

Chebyshev.

X is a r.v. and $\mu = E(X)$

$$P(|X - \mu| > \delta) \leq \frac{V(X)}{\delta^2}$$

if X_i are i.i.d. and $\sigma^2 = V(X_i)$

$$\text{Var}(\bar{X}) = \frac{1}{N} \sigma^2.$$

Suppose that $X_n \xrightarrow{P} Y$

$$\forall \varepsilon \quad P(|X_n - Y| > \varepsilon) \xrightarrow[n \rightarrow \infty]{} 0$$

and f is a continuous function

$$f(X_n) \xrightarrow{P} f(Y)$$

Markov Inequality

if X is positive ($P(X \geq 0) = 1$)

$$P(X > \delta) \leq \frac{E(X)}{\delta}$$

C.L.T.:

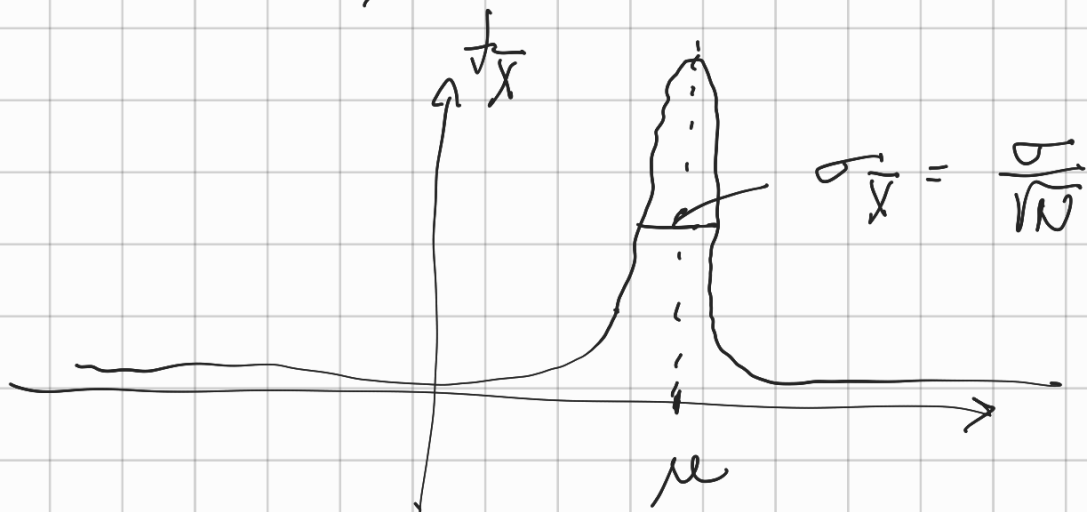
X_i is a random Sample

$$E(X_i) = \mu$$

$$V(X_i) = \sigma^2$$

$$\bar{X} = \frac{1}{N} \sum_i X_i$$

$$E(\bar{X}) = \mu \quad V(\bar{X}) = \frac{\sigma^2}{N}$$



$$Z_N = \frac{1}{\sqrt{N}} \sum_i \frac{X_i - \mu}{\sigma}$$

$$E(Z_N) = 0 \quad V(Z_N) = 1 \quad \forall N$$

Theorem:

$$Z_N \xrightarrow{N \rightarrow \infty} Z$$

Z is $N(0, 1)$

$$P(Z_N \leq z) \xrightarrow{N \rightarrow \infty} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-\frac{x^2}{2}} dx$$

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-\frac{x^2}{2}} dx$$

Berry-Esseen Inequalities.

$$|P(Z_n \leq z) - \Phi(z)| \approx \frac{C(z)}{\sqrt{n}}$$

X_i are random sample

$$E(X_i) = \mu$$

$$V(X_i) = \sigma^2$$

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{X_i - \mu}{\sigma} \rightarrow z \quad \text{where } z \text{ is } N(0,1)$$

$$\bar{X} = \frac{1}{n} \sum_i X_i$$

$$\frac{1}{\sqrt{n}} \left(\frac{1}{\bar{X}} - \frac{1}{\mu} \right) \Rightarrow$$

Delta method.

Y_n is a sequence of r.v.

a_n is a sequence of real numbers

$$\lim_{n \rightarrow \infty} a_n = \infty$$

θ is a real number

$$a_n (Y_n - \theta) \xrightarrow{d} F^*$$

(previous case

$$Y_n = \frac{1}{n} \sum_{i=1}^n X_i \quad X_i \text{ i.i.d.}$$

$$\theta = \mu$$

$$a_n = \frac{\sqrt{n}}{\sigma}$$

$$\begin{aligned} a_n (Y_n - \theta) &= \frac{\sqrt{n}}{\sigma} \left(\frac{1}{n} \sum_{i=1}^n X_i - \mu \right) = \\ &= \frac{1}{\sqrt{n}} \left(\sum_{i=1}^n \frac{X_i - \mu}{\sigma} \right) \end{aligned}$$

$\alpha(x)$ is a differentiable function

$$\alpha_n \left(\alpha(Y_n) - \alpha(\theta) \right)$$

$\alpha_n(Y_n - \theta) \rightarrow$ converge to a dist.

$\alpha_n(Y_n - \theta)$ is almost always finite

$\alpha_n \rightarrow \infty \Rightarrow Y_n - \theta$ must be small.

$$\alpha(Y_n) \approx \alpha(\theta) + \alpha'(\theta)(Y_n - \theta) + \dots$$

$$\alpha_n \left(\alpha(Y_n) - \alpha(\theta) \right) \approx \alpha_n \alpha'(\theta) (Y_n - \theta)$$

$$\frac{\alpha_n}{\alpha'(\theta)} \left(\alpha(Y_n) - \alpha(\theta) \right) \approx \alpha_n (Y_n - \theta)$$

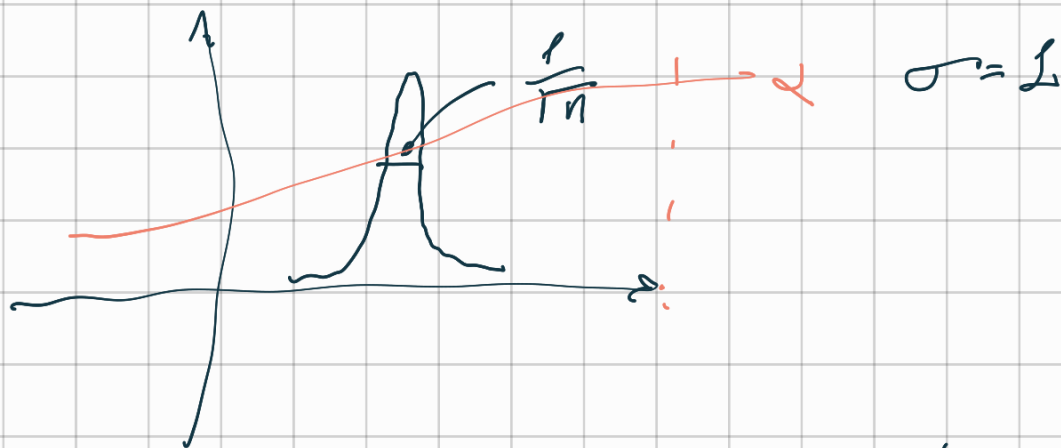
$$\lim_{n \rightarrow \infty} \frac{a_n}{\sigma} \left(\alpha(Y_n) - \alpha(\theta) \right) = \mathbb{N}^*$$

$$\alpha(x) = \frac{1}{x}$$

$$\alpha'(\mu) = -\frac{1}{\mu^2}$$

$$\rightarrow \frac{n^{1/2} \mu^2}{\sigma} \left(\frac{1}{\bar{X}_n} - \frac{1}{\mu} \right) \rightarrow \mathcal{N}(0, 1)$$

$$\frac{1}{\bar{X}_n} - \frac{1}{\mu} \approx \mathcal{N}\left(0, \frac{\sigma^2}{n\mu^4}\right)$$



$$\frac{1}{n} \sum_i X_i = \bar{X}$$

$$Z_n = \frac{1}{\sqrt{n}} \sum_i (X_i - \mu)$$

$$\sqrt{n}(\bar{X} - \mu) = Z_n$$