

Lecture 13:

$$X_n \stackrel{\text{iid}}{\sim} \text{Pois}(\lambda) ; \mathbb{E}X_n = \text{Var} X_n = \lambda$$

so by WLLN we have $\bar{X} \xrightarrow{P} \lambda$

Consider $Y_N = 1/\bar{X}_N$

then by CMT we have that

$$Y_N = 1/\bar{X}_N \xrightarrow{P} 1/\lambda$$

Consider $Z_n = 1/(1+X_n^2)$

and what does $Z_n \xrightarrow{P}$?

WLLN that $\bar{Z} \xrightarrow{P} \mathbb{E}Z_n$

$$\left(\sum_{x=0}^{\infty} \frac{1}{1+x^2} \lambda^x e^{-\lambda} / x! \right) \approx .07$$

Ex. $X_n \stackrel{\text{iid}}{\sim} \text{Exp}(\lambda)$, $\mathbb{E}X_n = 1/\lambda$

So WLLN : $\bar{X} \xrightarrow{P} 1/\lambda$

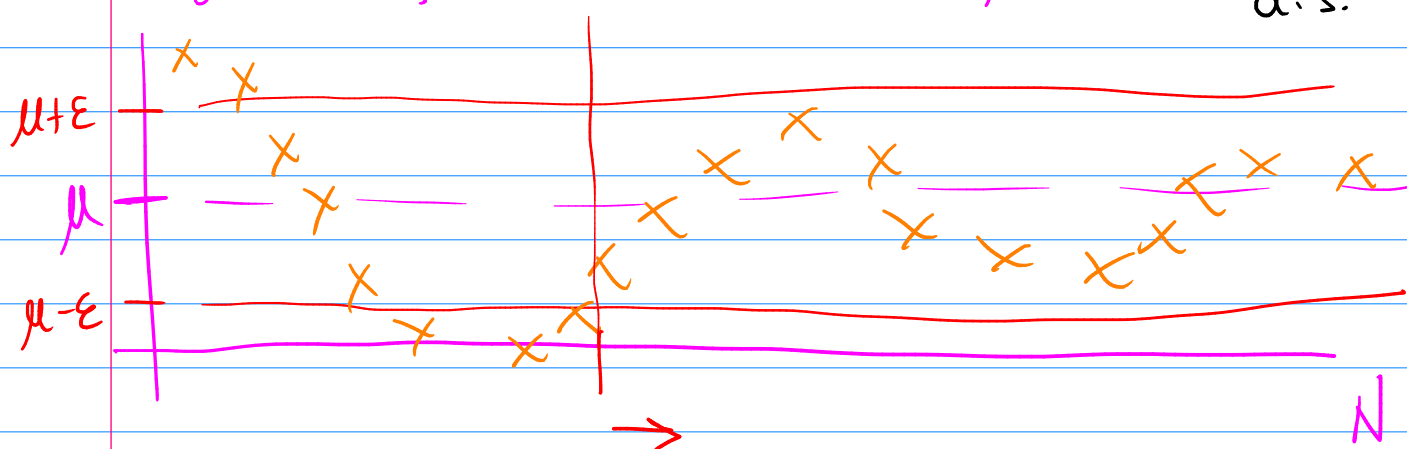
By CMT we have $1/\bar{X} \xrightarrow{P} \lambda$.

Theorem: Strong Law of Large Numbers (SLLN)

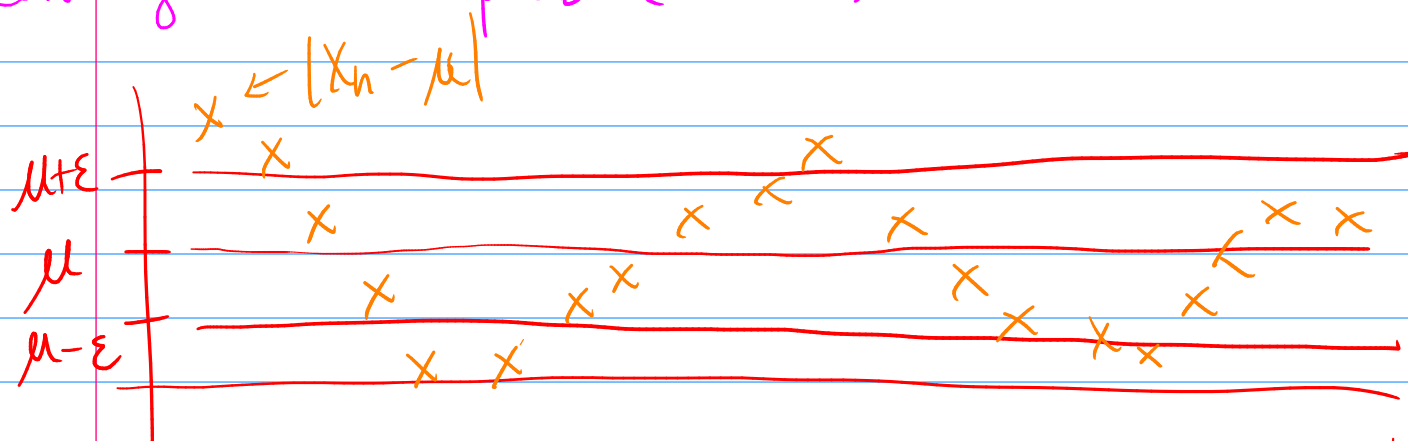
If $X_n \stackrel{iid}{\sim} f$ and $\mathbb{E}X_n = \mu$, $\text{Var} X_n = \sigma^2 < \infty$

then $\bar{X}_N = \frac{1}{N} \sum_{n=1}^N X_n \xrightarrow{\text{a.s.}} \mu.$

Convergence of Numbers: $x_n \rightarrow \mu$ ← more like convergence a.s.



Convergence in prob (WLLN):



as $N \rightarrow \infty$ prob I'm more than ϵ away from μ goes to zero

Sums of RVs

① $\sum_{n=1}^N X_n \rightarrow \pm \infty$ (often)

② $\frac{1}{N} \sum_{n=1}^N X_n = \bar{X} \rightarrow \mu$ (under some conditions)
 \uparrow constant

③ $\frac{1}{\sqrt{N}} \sum_{n=1}^N X_n \rightarrow \text{non-degenerate limit}$
 \uparrow proper scaling

Theorem: Central Limit Theorem

If $X_n \stackrel{\text{iid}}{\sim} f$ w/ $\mathbb{E}X_n = \mu$, $\text{Var}(X_n) = \sigma^2 < \infty$

then
$$\sqrt{N} \left(\frac{\bar{X}_N - \mu}{\sigma} \right) \xrightarrow{d} N(0, 1).$$

Intuition: $\bar{X} \approx N(\mu, \sigma^2/N)$

Might like to say $\bar{X} \xrightarrow{d} N(\mu, \sigma^2/N)$

\uparrow can't have N in my limit

Proper way to write CLT

$$(1) \quad \sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right) \xrightarrow{d} N(0, 1)$$

$$(2) \quad \sqrt{N} (\bar{X} - \mu) \xrightarrow{d} N(0, \sigma^2)$$

$$(3) \quad \frac{\bar{X} - \mu}{\sigma/\sqrt{N}} \xrightarrow{d} N(0, 1)$$

$$(4) \quad \bar{X} \sim AN(\mu, \sigma^2/N)$$

↑ asymptotically normal

Ex. $X_n \stackrel{iid}{\sim} \text{Bern}(p)$

$$\mu = \mathbb{E} X_n = p$$

$$\sigma^2 = \text{Var} X_n = p(1-p)$$

$$\sigma = \sqrt{p(1-p)}$$

CLI says something about $\bar{X} = \hat{p} = \text{pct of 1s}$

CLT: $\sqrt{N} (\hat{p} - p) \xrightarrow{d} N(0, p(1-p))$

So for large N

$$\sqrt{N}(\hat{p} - p) \approx N(0, p(1-p))$$

$$\text{or } \hat{p} \approx N\left(p, \frac{p(1-p)}{N}\right)$$

95% of vals fall w/in $\hat{p} \pm 2\sqrt{\frac{p(1-p)}{N}}$

Intro stat: $\hat{p} \pm 2\sqrt{\underbrace{\frac{\hat{p}(1-\hat{p})}{N}}_{\text{MOE}}}$

Ex. $X_n \stackrel{\text{iid}}{\sim} \text{Pois}(\lambda)$

$$\mu = EX_n = \lambda = \text{Var}(X_n) = \sigma^2$$

so CLT: $\sqrt{N} \left(\frac{\bar{X} - \lambda}{\sqrt{\lambda}} \right) \xrightarrow{d} N(0, 1)$

i.e. $\bar{X} \approx N(\lambda, \lambda/N)$ for large N .

Theorem: MGFs and Convergence in Dist

Let X_n be a seq of RVs w/ MGFs M_n
and X a RV w/ MGF M ,

then if $M_n(t) \rightarrow M(t)$

we have $X_n \xrightarrow{d} X$.

Taylor Series

If g is k -times diff'able function
then the k^{th} order Taylor poly. about a

$$T_k(x) = \sum_{r=0}^k \frac{g^{(r)}(a)}{r!} (x-a)^r$$

e.g. second order about zero is

$$T_2(x) = g(0) + g'(0)x + \frac{g''(0)x^2}{2!}$$

under some conditions

$$g(x) \approx T_k(x) \text{ when } x \approx a.$$

pf. of CLT

$$Y_N = \sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right) \quad \text{want! } Y_N \xrightarrow{d} N(0,1)$$

$$Z_n = \frac{X_n - \mu}{\sigma} \text{ then } E Z_n = 0 \text{ and } \text{Var } Z_n = 1$$

$$Y_N = \sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right)$$

$$= \sqrt{N} \left(\frac{\frac{1}{N} \sum_n X_n - \frac{1}{N} \sum_n \mu}{\sigma} \right)$$

$$= \frac{\sqrt{N}}{N} \left(\frac{\sum_n X_n - \sum_n \mu}{\sigma} \right)$$

$$= \frac{\sqrt{N}}{N} \sum_n \left(\frac{X_n - \mu}{\sigma} \right)$$

$$Y_N = \frac{1}{\sqrt{N}} \sum_n Z_n \quad \text{want } \xrightarrow{d} N(0,1)$$

Get MGF of Y_N ($M_{ax+tb}(t) = e^{tb} M(at)$)

$$M_{Y_N}(t) = \prod_n M_{Z_n}(t/\sqrt{N})$$

all MGFs same

$$= M(t/\sqrt{N})^N$$

$M = \text{MGF of any } Z_n$

Taylor approx of $M(t)$ [Second order around zero]

$$M(t) \approx \underbrace{M(0)}_{1 = Ee^{0 \cdot Z_n}} + \underbrace{M'(0)t}_{E Z_n = 0} + \frac{\overbrace{M''(0)}^{\text{Var } Z_n = 1}}{2} t^2$$

$$\approx 1 + t^2/2$$

$$M_{Y_N}(t) = M(t/\sqrt{N})^N \approx \left(1 + \frac{t^2}{2N}\right)^N$$

$$\text{as } N \rightarrow \infty \rightarrow e^{t^2/2}$$

\uparrow MGF of $N(0,1)$

$$Y_N \xrightarrow{d} N(0,1).$$

$$\left(1 + \frac{c}{n}\right)^n \rightarrow e^c$$

Delta Method

Theorem: First Order Delta Method

If Y_N is a seq of RVs where

$$\sqrt{N}(Y_N - \theta) \xrightarrow{d} N(0, \psi^2(\theta))$$

Think of $Y_N = \bar{X}$, $\theta = \mu$, $\psi^2 = \sigma^2$.

then if g is a diff'able function and $g'(\theta) \neq 0$ then

$$\sqrt{N}(g(Y_N) - g(\theta)) \xrightarrow{d} N(0, [g'(\theta)]^2 \psi^2(\theta)).$$

Intuition! $Y_N \sim AN(\theta, \psi^2/N)$

$$g(Y_N) \sim AN(g(\theta), [g'(\theta)]^2 \psi^2/N)$$

Ex. $X_n \stackrel{iid}{\sim} \text{Pois}(\lambda), \lambda > 0$

$$\underline{\text{CLT}}: \sqrt{n} \left(\frac{\bar{X} - \lambda}{\sqrt{\lambda}} \right) \xrightarrow{d} N(0, 1)$$

$$\underline{\text{or}} \quad \sqrt{n} (\bar{X} - \lambda) \xrightarrow{d} N(0, \lambda)$$

$$\text{let } g(x) = \log(x) \quad ; \quad g'(x) = 1/x$$

$$\sqrt{n} (g(\bar{x}) - g(x)) \xrightarrow{d} N(0, [g'(x)]^2 \lambda)$$

\nearrow FO Δ -method

$$\sqrt{n} (\log(\bar{x}) - \log(x)) \xrightarrow{d} N(0, \underbrace{\frac{1}{x^2} \lambda}_{1/\lambda})$$