

Lecture 14

Midterm on Nov. 10th

QP/SP 5-8

Lectures 8-13

Continue example from last time:

Q: $\hat{\sigma}^2 = \frac{1}{N} \sum_{n=1}^N (X_n - \bar{X})^2$, is this consistent for σ^2 ?

Notice: $\hat{\sigma}^2 = \frac{N-1}{N} S^2 = C_n S^2$ where $C_n = \frac{N-1}{N}$

so by my algebraic properties

Since $C_n \rightarrow 1$ as $N \rightarrow \infty$

and $S^2 \xrightarrow{P} \sigma^2$

thus $\hat{\sigma}^2 = C_n S^2 \xrightarrow{P} 1 \cdot \sigma^2 = \sigma^2$

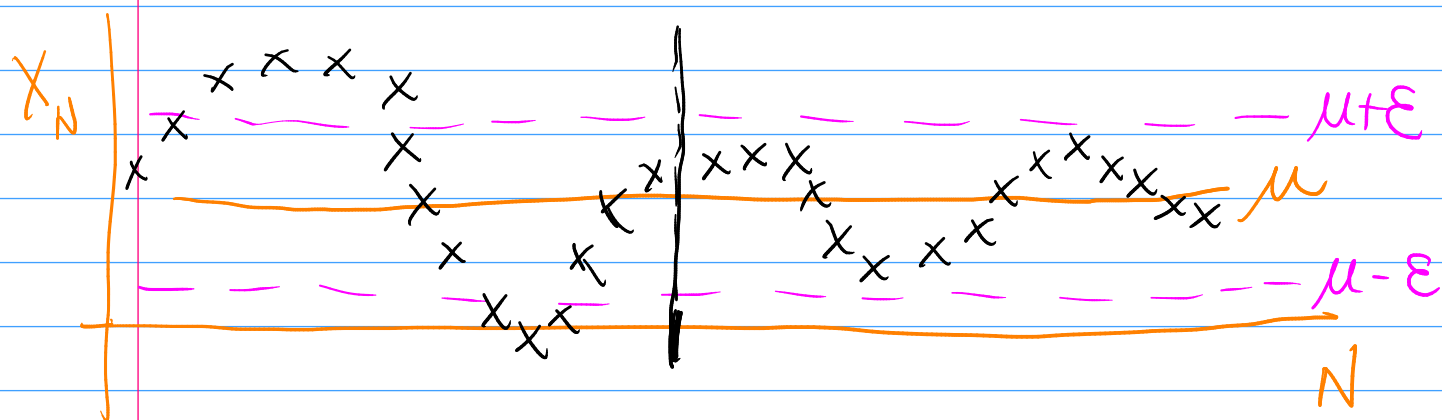
i.e. $\hat{\sigma}^2$ is consistent for σ^2 .

Theorem: Strong Law of Large Numbers (SLLN)

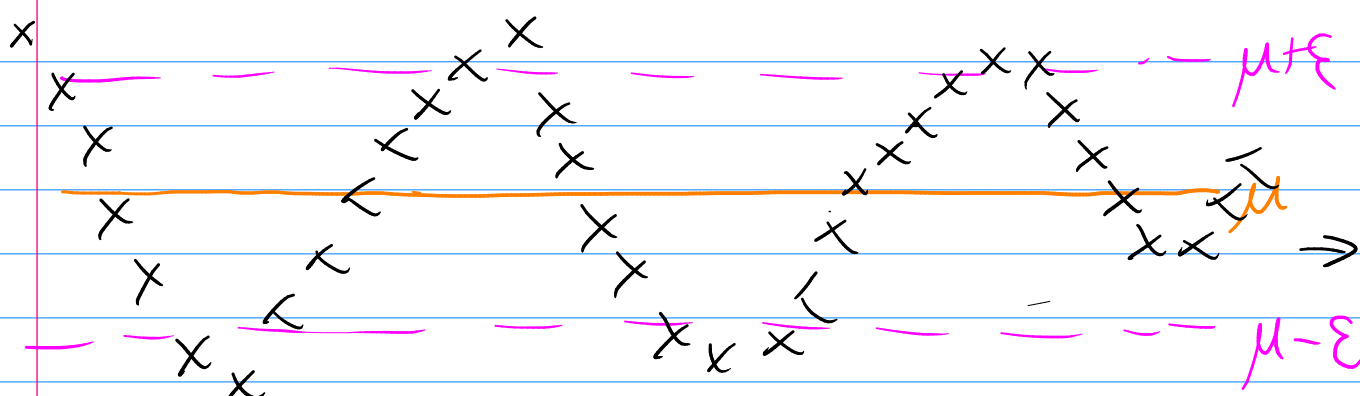
If $X_n \stackrel{iid}{\sim} \mu$ w/ $EX_n = \mu$, $\text{Var}(X_n) = \sigma^2 < \infty$

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

Convergence of a seq of numbers $x_n \rightarrow \mu$

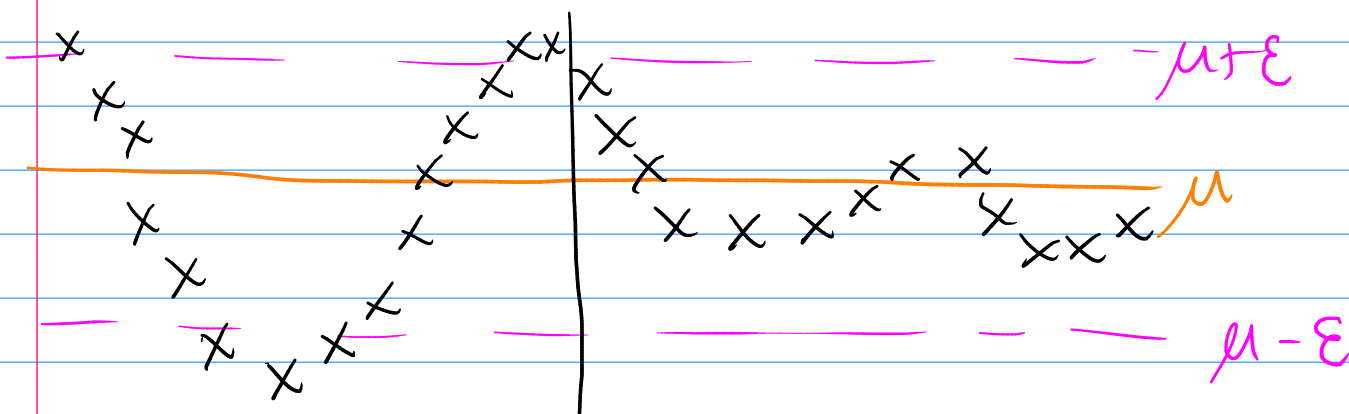


WLLN: $\bar{X} \xrightarrow{P} \mu$



So as $N \rightarrow \infty$ Prob \bar{X}_N is more than ϵ away from μ goes to zero.

SLLN: $\bar{X} \xrightarrow{a.s.} \mu$



Sums of RVs

① $\sum_n X_n \rightarrow \infty$

② $\frac{1}{N} \sum_n X_n \rightarrow \mu$ (under same condition
w/ μ , s/ σ)

↑ constant

③ $\frac{1}{\sqrt{N}} \sum_n X_n \rightarrow$ non degenerate dist

↑ proper scaling

Theorem: Central Limit Theorem (CLT)

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

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

If $\mu = 0$ and $\sigma = 1$ then

$$\sqrt{N} \bar{X} = \sqrt{N} \frac{1}{N} \sum_n X_n = \frac{1}{\sqrt{N}} \sum_n X_n \rightarrow N(0, 1)$$

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

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

↑ no N in limit

Proper way to write CLT

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

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

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

notation that means above (1)-(3)

z-score $E\bar{X} = \mu$
 $\text{Var}\bar{X} = \sigma^2/N \rightarrow \text{Sd}\bar{X} = \sigma/\sqrt{N}$

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

asymptotically normal

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

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

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

CLT says \swarrow 90% of 1s

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

Intro stats: $\hat{p} = \bar{X}$ = sample proportion

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

$$\hat{p} = \bar{x} \sim \text{AN}\left(p, \frac{p(1-p)}{N}\right)$$

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

$$\mu = \mathbb{E}X_n = \lambda = \text{Var} X_n = \sigma^2$$

$$\text{so } \sigma = \sqrt{\lambda}$$

CLT: $\bar{X} \sim \text{AN}(\lambda, \lambda/N)$

Theorem: MGFs and Convergence in Dist.

If I have a seq of RVs X_n w/ MGFs

M_n and a limit X w/ MGF M

then if $M_n \rightarrow M$ (pointwise)

then $X_n \xrightarrow{d} X$.

Theorem: Taylor's Theorem

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

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

then $T_k(x) \rightarrow g(x)$ as $x \rightarrow a$

i.e. $T_k \approx g$ when $x \approx a$

$$\text{e.g. } g(x) \approx g(a) + \frac{g'(a)}{1}(x-a) + \frac{g''(a)}{2}(x-a)^2 + \frac{g'''(a)}{3!}(x-a)^3 + \dots$$

when $x \approx a$

Pf. of CLT

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

$$Z_n = \frac{X_n - \mu}{\sigma} = \text{standardized } X_n$$

notice! $E Z_n = 0$ $\text{Var } Z_n = 1$

$$\begin{aligned} Y_N &= \sqrt{N} \left(\frac{\bar{X}_N - \mu}{\sigma} \right) \\ &= \sqrt{N} \left(\frac{\frac{1}{N} \sum_n X_n - \frac{1}{N} \sum_n \mu}{\sigma} \right) \end{aligned}$$

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

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

$$= \frac{1}{\sqrt{N}} \sum_n Z_n$$

$$Y_N = \frac{1}{\sqrt{N}} \sum_n z_n \quad \leftarrow \text{indep w/ mean 0, Var 1}$$

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

$$\begin{aligned} M_{Y_N}(t) &= \prod_n M_{z_n}(t/\sqrt{N}) \\ &= \left(M(t/\sqrt{N}) \right)^N \end{aligned} \quad \leftarrow \text{MGF of any } \underline{z_n}$$

2nd order Taylor approx. of $M(t)$ about 0

$$M(t) \approx \underbrace{M(0)}_1 + \underbrace{\frac{M'(0)}{1}}_0 (t-0) + \underbrace{\frac{M''(0)}{2}}_{\frac{\text{Var}(z_n)}{2}} \underbrace{(t-0)^2}_{\frac{1}{2}t^2}$$

\downarrow $\mathbb{E} e^{0x} = 1$ $\mathbb{E} z_n = 0$

$$\rightarrow = 1 + \frac{t^2}{2}$$

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

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

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

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