

Last lecture:

LLNs: Weak: X_n , uncorr, $E[X_n] = \mu$, $\text{Var}(X_n) = \sigma^2$
then $\bar{X}_n \xrightarrow{P} \mu$.

Strong: X_n iid etc
then $\bar{X}_n \xrightarrow{\text{a.s.}} \mu$.

Sums of R.V.s

① $\frac{1}{N} \sum_{n=1}^N X_n \rightarrow \mu$ (under some conditions)
LLNs

② $\sum_{n=1}^N X_n \rightarrow \infty$ blow up / not converge

→ ③ $\frac{1}{\sqrt{N}} \sum_{n=1}^N X_n \xrightarrow{d}$ non-degenerate dist.
proper scaling

Theorem: Central Limit Theorem

If I have X_n that are iid w/ $E[X_n] = \mu$
and $\text{Var}(X_n) = \sigma^2 < \infty$ then

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

Notice: $\sqrt{N} \bar{X} = \sqrt{N} \frac{1}{N} \sum_{n=1}^N X_n = \frac{1}{\sqrt{N}} \sum_{n=1}^N X_n.$

Intuition:

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

Can't we rewrite CLT like

$$\bar{X}_N \xrightarrow{d} N(\mu, \sigma^2/N)?$$

\nwarrow N in my limit!
Not allowed!

Proper way:

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

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

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

Other notation:

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

\uparrow purely notational

\swarrow asymptotically normal

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

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

recall that $\mu = E[X_n] = p$

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

CLT says:

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

In intro stats: $\bar{X} = \hat{p}$ as estimate for "yes" responses to a poll.

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

maybe we form a ^{95%} CI for \hat{p} as

$$\hat{p} \pm 2 \sqrt{\frac{\hat{p}(1-\hat{p})}{N}}.$$

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

$$E[X_n] = \lambda = \text{Var}(X_n).$$

CLT:

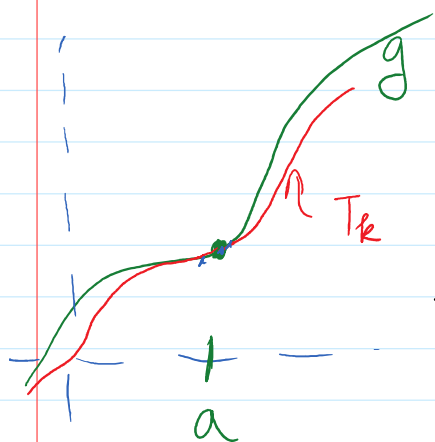
$$\sqrt{n} \left(\frac{\bar{X} - \mu}{\sqrt{s}} \right) \xrightarrow{d} N(0, 1)$$

Recall: $\lim_{n \rightarrow \infty} \left(1 + \frac{c}{n} \right) = e^c$.

Theorem: Taylor's Theorem

I have a function $g: \mathbb{R} \rightarrow \mathbb{R}$ that is k -times differentiable. The k^{th} -Order Taylor polynomial about $a \in \mathbb{R}$ is

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



$$\begin{aligned} &= \frac{g^{(0)}(a)}{0!} (x-a)^0 + \frac{g^{(1)}(a)}{1!} (x-a)^1 + \frac{g^{(2)}(a)}{2!} (x-a)^2 + \dots \\ &= g(a) + g^{(1)}(a)(x-a) + \frac{g^{(2)}(a)}{2} (x-a)^2 + \dots \end{aligned}$$

Let $R = g(x) - T_k(x)$

then $R \rightarrow 0$ as $x \rightarrow a$

↑ fast

Punchline: for $x \approx a$ we have $g(x) \approx T_a(x)$.

CLT: Statement: X_n iid, $E[X_n] = \mu$, $\text{Var}(X_n) = \sigma^2 < \infty$,
$$\sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right) \xrightarrow{d} N(0, 1).$$

Let $Y_n = \frac{X_n - \mu}{\sigma}$ then $E[Y_n] = \frac{1}{\sigma} (E[X_n] - \mu) = 0$
 $\text{Var}(Y_n) = \frac{1}{\sigma^2} \text{Var}(X_n) = \frac{\sigma^2}{\sigma^2} = 1$

$$Y = \sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right)$$
$$= \sqrt{N} \left(\frac{\frac{1}{N} \sum_{n=1}^N X_n - \mu}{\sigma} \right)$$

$$= \frac{\sqrt{N}}{N} \left(\sum_{n=1}^N X_n - N\mu \right)$$

$$\sum (X_n - \mu) = \sum X_n - N\mu$$

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

$$\left(\frac{1}{\sqrt{N}} \sum_{n=1}^N Y_n \right)$$

recall that my Y 's are independent

Consider

$$M(t) = \text{mgf of } Y_n$$

$$M_Y(t) = M_{\frac{1}{\sqrt{N}} \sum_{n=1}^N Y_n}(t) = M\left(\frac{t}{\sqrt{N}}\right)^N$$

two rules:

$$\begin{cases} M_{\sum X_i}(t) = M(t)^N \\ M_{aX}(t) = M_X(at) \end{cases}$$

Consider a second order Taylor Approx of $M(t)$ at $t=0$.

$$M(t) = M(0) + M'(0)(t-0) + \frac{M''(0)}{2}(t-0)^2 + R$$

$$M(0) = \mathbb{E}[e^{0 Y_n}] = \mathbb{E}[1] = 1$$

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

hence

$$M_Y(t) = M\left(\frac{t}{\sqrt{N}}\right)^N$$

$$= \left(1 + \frac{t^2}{2N} + R\left(\frac{t}{\sqrt{N}}\right)\right)^N$$

as $N \rightarrow \infty$ then $t/\sqrt{N} \rightarrow 0$ so
 $R \rightarrow 0$ (very fast)

$$\text{So } M_Y(t) \sim \left(1 + \frac{t^2}{2N}\right)^N \sim \left(1 + \frac{c}{N}\right)^N$$

$$\text{i.e. } \lim_{n \rightarrow \infty} M_Y(t) = e^{t^2/2}$$

MGF of $N(0,1)$

Have shown:

$Y = \sqrt{N} \left(\frac{\bar{X} - \mu}{\sigma} \right)$ has an MGF $\xrightarrow{p} \text{MGF of a } N(0,1)$.

So since the MGF converges to the MGF of a $N(0,1)$ so w/ the CDF (*)

then by defn:

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

Ex. If X_n that are iid w/ $\mu = 2$ and $\sigma^2 = 9$ then CLT says

$$\sqrt{N} \left(\frac{\bar{X} - 2}{3} \right) \xrightarrow{d} N(0, 1)$$

Q: what about $\log \bar{X}$?

First Order Delta Method

Theorem: Let Y_n be a seq of RVs where

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

↑ some constant

Ex, $Y_n = \bar{X}$ and $\theta = \mu$, $\tau^2 = \sigma^2$ the CLT

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

then if g is differentiable and $g'(\theta) \neq 0$
we have

$$\sqrt{N}(g(Y_n) - g(\theta)) \xrightarrow{d} N(0, (g'(\theta))^2 \tau^2)$$

Ex, CLT says that

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

let $g(x) = \log(x)$.

$$g'(x) = 1/x \Rightarrow (g'(\mu))^2 = 1/\mu^2$$

1.1 x ... 1.1 1.1

then Δ -method

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

1.2.

$$\sqrt{n}(\log(\bar{x}) - \log(\mu)) \xrightarrow{d} N(0, \sigma^2/\mu^2)$$

1.2.

$$\bar{x} \sim AN(\mu, \sigma^2/n) \text{ and } \log(\bar{x}) \sim AN(\log(\mu), \frac{\sigma^2}{n\mu^2})$$

Proof.

Taylor approx of g around θ

$$g(x) \approx g(\theta) + g'(\theta)(x - \theta)$$

So

$$g(x) - g(\theta) \approx g'(\theta)(x - \theta)$$

$$\text{So if } \sqrt{n}(Y_n - \theta) \xrightarrow{d} N(0, \tau^2)$$

then

$$\begin{aligned} \sqrt{n}(g(Y_n) - g(\theta)) &\approx \sqrt{n}g'(\theta)(Y_n - \theta) \\ &= g'(\theta)\sqrt{n}(Y_n - \theta) \end{aligned}$$

So...

$$\xrightarrow{d} N(0, \tau^2)$$
$$\rightarrow N(0, (g'(\theta))^2 \tau^2)$$

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

then CLT says that

$$\sqrt{N}(\bar{X} - \lambda) \xrightarrow{d} N(0, \lambda).$$

Consider $g(x) = 1/x$

$$\text{then } g'(x) = -1/x^2$$

and so

$$\sqrt{N}\left(\frac{1}{\bar{X}} - \frac{1}{\lambda}\right) \xrightarrow{d} N\left(0, \left(-\frac{1}{\lambda}\right)^2 \lambda\right)$$
$$= N\left(0, \frac{1}{\lambda}\right)$$

i.e. $\bar{X} \sim AN(\lambda, \lambda/N)$

$$\frac{1}{\bar{X}} \sim AN\left(\frac{1}{\lambda}, \frac{1}{N\lambda}\right).$$

