

Lecture - 17

11/11/2020

Consider rv's X_1, X_2, \dots, X_n iid but PMF/PDF is unknown but we know it has expectation μ and variance σ^2 ;

$$\text{Let } T_n = X_1 + X_2 + \dots + X_n$$

$$\text{Let } \bar{X}_n = \frac{T_n}{n} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

From 241, we know $E[\bar{X}_n] = \mu$, $\text{Var}[\bar{X}_n] = \sigma^2/n$

$$\text{Let } Z_n := \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \underbrace{\frac{\sqrt{n}}{\sigma}}_a \bar{X}_n + \underbrace{\frac{-\sqrt{n}}{\sigma} \mu}_b \quad \left\{ \begin{array}{l} E[Z_n] = 0 \\ \text{Var}[Z_n] = 1 \\ = \text{SD}[Z_n] \end{array} \right.$$

" \bar{X} standardized"

$$\phi_{T_n}(t) \stackrel{(P3)}{=} \phi_{X_1}(t) \phi_{X_2}(t) \dots \phi_{X_n}(t) \stackrel{(P1)}{=} \phi_X(t)^n \quad a = e^{\ln a}$$

$$\phi_{\bar{X}_n}(t) \stackrel{(P2)}{=} \phi_{T_n}(t/n) = \phi_X(t/n)^n$$

$$\phi_{Z_n}(t) = e^{itb} \phi_{\bar{X}_n}(at) = e^{-\frac{it\mu\sqrt{n}}{\sigma}} \underbrace{\frac{\sqrt{n}}{\sigma}}_{\text{red}} \phi_X\left(\frac{\sqrt{n}}{\sigma} \cdot \frac{t}{\sqrt{n}}\right)^n$$

$$= e^{-\frac{it\mu\sqrt{n}}{\sigma}} e^{\ln(\phi_X(t/\sigma\sqrt{n})^n)}$$

$$= e^{-\frac{it\mu\sqrt{n}}{\sigma} + n \ln(\phi_X(t/\sigma\sqrt{n}))} \frac{1/n}{1/n}$$

$$= e^{\frac{-it\mu}{\sigma\sqrt{n}} + \frac{\ln(\phi_X(t/\sigma\sqrt{n}))}{1/n} \cdot \frac{t^2/\sigma^2}{t^2/\sigma^2}}$$

$$= e^{t^2/\sigma^2 \left(\frac{\ln(\phi_X(t/\sigma\sqrt{n})) - \frac{-it\mu}{\sigma\sqrt{n}}}{t^2/\sigma^2 n} \right)} = \phi_{2n}(t)$$

We want to investigate now $\lim_{n \rightarrow \infty} \phi_{2n}(t) = ?$

$$= e^{t^2/\sigma^2 \lim_{n \rightarrow \infty} \frac{\ln(\phi_X(t/\sigma\sqrt{n})) - \frac{-it\mu}{\sigma\sqrt{n}}}{t^2/\sigma^2 n}}$$

$$= e^{t^2/\sigma^2 \lim_{u \rightarrow 0} \frac{\ln(\phi_X(u)) - i\mu u}{u^2}}$$

$$\begin{cases} \text{let } u = t/\sigma\sqrt{n} \Rightarrow n \rightarrow \infty \\ \Rightarrow u \rightarrow 0 \end{cases}$$

$$= e^{t^2/2\sigma^2 \frac{\phi_X'(0) \phi_X''(0) - \phi_X'(0)^2}{\phi_X'(0)^3}}$$

$$\textcircled{P0} = e^{t^2/2\sigma^2 (\phi_X''(0) - \phi_X'(0)^2)}$$

$$\textcircled{P4} = e^{t^2/2\sigma^2 (i E[X^2] - (i E[X])^2)}$$

$$= e^{-t^2/2\sigma^2 (E[X^2] - E[X]^2)} = e^{-t^2/2} = \phi_2(t)$$

$$\textcircled{P8} \Rightarrow Z_n \xrightarrow{d} Z \text{ where } Z \text{ has chf } \phi_Z(t) = e^{-t^2/2},$$

$$Z \sim \int_2(2) = ?$$

Use $\textcircled{P6}$ to find PDF of Z . Check $\phi_Z(t) \in L^1 \Rightarrow \int_{\mathbb{R}} e^{-t^2/2} dt = \sqrt{2\pi} < \infty$.
Gaussian Integral 4E

$$f_Z(z) = \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-itZ} \phi_Z(t) dt$$

$$= \frac{1}{2\lambda} \int_{\mathbb{R}} e^{-it^2} \underbrace{e^{-t^2/2}}_{e^{-\frac{(it^2 + t^2/2)}}} dt = \frac{1}{2\lambda} \int_{\mathbb{R}} e^{-(it^2 + t^2/2)} dt$$

$$\frac{t^2}{2} + it^2 = \left(\frac{t}{\sqrt{2}} + \frac{\sqrt{2}it}{2} \right)^2 - \left(\frac{\sqrt{2}it}{2} \right)^2 = \frac{t^2}{2} + \frac{\sqrt{2}it}{\sqrt{2}} + \frac{i^2 2}{2} - \frac{i^2 2}{2}$$

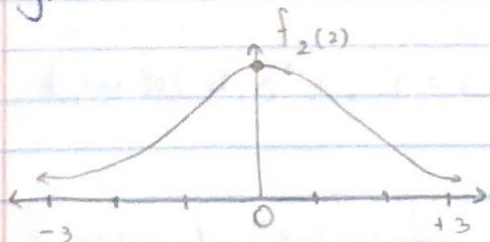
$$\stackrel{\text{↙}}{=} \frac{1}{2\lambda} \int_{\mathbb{R}} e^{-\left(\frac{t}{\sqrt{2}} + \frac{\sqrt{2}it}{2}\right)^2} e^{-2^2/2} dt.$$

$$= \frac{1}{2\lambda} e^{-2^2/2} \int_{\mathbb{R}} e^{-\left(\frac{t}{\sqrt{2}} + \frac{\sqrt{2}it}{2}\right)^2} dt.$$

let $y = t/\sqrt{2} + \sqrt{2}it/2 \Rightarrow dy/dt = 1/\sqrt{2}, t \rightarrow \infty \Rightarrow y \rightarrow \infty, t \rightarrow -\infty \Rightarrow y \rightarrow -\infty$

$$= \frac{1}{2\lambda} e^{-2^2/2} \int_{\mathbb{R}} e^{-y^2} \underbrace{\sqrt{2}}_{\text{Gaussian Integral}} dy \stackrel{\text{↙}}{=} \frac{1}{2\lambda} e^{-2^2/2} \underbrace{\sqrt{2}\sqrt{\lambda}}_{\text{standard Normal rv}} = \frac{1}{\sqrt{2\lambda}} e^{-2^2/2} = N(0,1)$$

This completes the proof of the "central limit theorem" (CLT), the crown jewel of a basic probability class, one of the most useful results that probability has given to the world at large.



AKA Laplace's Second Error Distribution. It is the most famous and widely-used error distribution on Earth.

CLT: X_1, \dots, X_n iid mean μ , Variance σ^2 , $\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \xrightarrow{d} N(0,1)$

Let $\sigma > 0$

$Z \sim N(0,1), X = \mu + \sigma Z \sim f_X(x) = ?$

$$\phi_X(t) \stackrel{(\text{P2})}{=} e^{it\mu} \phi_Z(\sigma t) = e^{it\mu - \sigma^2 t^2/2}.$$

$$f_X(x) = \frac{1}{\sigma} \int_2 \left(\frac{x-\mu}{\sigma} \right) = \frac{1}{\sigma} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2}$$

$$= \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2}\sigma^2 (x-\mu)^2} = N(\mu, \sigma^2)$$

$$E[Z] = \frac{\phi'_2(0)}{1} = 0, \text{Var}[Z] = E[Z^2] - \cancel{E[Z]^2} = \frac{\phi''_2(0)}{\frac{1^2}{-1}} = 1 \checkmark$$

$$\phi'_2(t) = \frac{d}{dt} [e^{-t^2/2}] = -t e^{-t^2/2}, \phi''_2(t) = \frac{d}{dt} [-t e^{-t^2/2}] = -(-t^2 e^{-t^2/2} + e^{-t^2/2})$$

$$= t^2 e^{-t^2/2} - e^{-t^2/2}$$

$$E[X] = E[\mu + \sigma Z] = \mu, \text{Var}[X] = \text{Var}[\mu + \sigma Z] = \sigma^2, \text{SD}[X] = \sigma$$

$$X_1 \sim N(\mu_1, \sigma_1^2) \text{ indep. of } X_2 \sim N(\mu_2, \sigma_2^2), T = X_1 + X_2 \sim f_T(t) = ?$$

$$\phi_T(t) \stackrel{(P3)}{=} \phi_{X_1}(t) \phi_{X_2}(t) = e^{it\mu_1 - \sigma_1^2 t^2/2} e^{it\mu_2 - \sigma_2^2 t^2/2}$$

$$= e^{it(\mu_1 + \mu_2) - (\sigma_1^2 + \sigma_2^2) t^2/2} \stackrel{(P1)}{=} T \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

$$X \sim N(\mu, \sigma^2), Y = e^X \sim f_Y(y) = ? \quad g^{-1}(y) = \ln(y) \left| \frac{d}{dy} [g^{-1}(y)] \right| = \frac{1}{y}$$

$$f_Y(y) = f_X(\ln(y)) \frac{1}{|y|} = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2\sigma^2} (\ln(y) - \mu)^2} \frac{1}{|y|}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2 y^2}} e^{-\frac{1}{2\sigma^2} (\ln(y) - \mu)^2} = \text{Log } N(\mu, \sigma^2)$$

Log-Normal distribution.