

Continuity  
Theorem

convergence of MGF implies convergence of CDF

Let  $X_1, X_2, \dots, X_n$  be a sequence of R.V.s with CDFs

$F_1(\cdot), F_2(\cdot), \dots$  and  $M_{X_1}(\cdot), M_{X_2}(\cdot), \dots$ . Suppose that:

$$M_{X_n}(t) \rightarrow M_X(t) \text{ as } n \rightarrow \infty \text{ for all } t \in \mathbb{R}$$

where  $X$  is another R.V. with CDF  $F(\cdot)$  and MGF  $M_X(\cdot)$

Then  $F_n(x) \rightarrow F(x)$  as  $n \rightarrow \infty$  for all  $x$  at which  $F$  is

continuous

Example Poisson( $\lambda$ ) converges to a normal dist as  $\lambda \rightarrow \infty$ . as  $n \rightarrow \infty$ .

• Let  $\lambda_1 < \lambda_2 < \lambda_3 < \dots < \lambda_n < \dots$  be an increasing sequence  $\lambda_n \rightarrow \infty$

• Let  $X_n \sim \text{Pois}(\lambda_n)$   $E(X_n) = \lambda_n$   $\text{Var}(X_n) = \lambda_n$

• MGF of Pois( $\lambda_n$ )  $M_{X_n}(t) = e^{\lambda_n(e^t - 1)}$   $t \in \mathbb{R}$

• Standardize  $X_n$  as:

otherwise  $Z_n = \frac{X_n - \lambda_n}{\sqrt{\lambda_n}}$   $\rightarrow$  Now, we want to show  $Z_n$  converges to  $N(0, 1)$  as  $\lambda_n \rightarrow \infty$  ( $n \rightarrow \infty$ )

$X_n$  is Pois.  $Z_n$  is a function of  $X_n$ , then

$$Z_n = -\frac{1}{\sqrt{\lambda_n}} + \left(\frac{1}{\sqrt{\lambda_n}}\right) \cdot X_n$$

$$M_{Z_n}(t) = e^{(-\frac{1}{\sqrt{\lambda_n}})t + M_{X_n}(\frac{1}{\sqrt{\lambda_n}}t)} \quad [\text{by MGF property (1)}]$$

$$= e^{(-\frac{1}{\sqrt{\lambda_n}})t} \cdot e^{\lambda_n(e^{\frac{1}{\sqrt{\lambda_n}}t} - 1)} \quad \text{(1)}$$

What to show  $M_{Z_n}(t)$  is the MGF of  $N(0, 1)$ , which is  $e^{\frac{1}{2}t^2}$  (2)

$$\text{try to p.f. (1) } = (2) \Rightarrow (-\frac{1}{\sqrt{\lambda_n}}t + \lambda_n(e^{\frac{1}{\sqrt{\lambda_n}}t} - 1)) = \frac{1}{2}t^2 \text{ as } n \rightarrow \infty$$

using Taylor expansion  $e^x = e^0 + xe^0 + \frac{x^2}{2}e^0 + \dots$  [ $(e^x)' = e^x$ ]

$$-\sqrt{\lambda_n}t + \lambda_n(1 + \frac{t}{\sqrt{\lambda_n}} + \frac{t^2}{2\sqrt{\lambda_n}} + \frac{1}{3!}(\frac{t}{\sqrt{\lambda_n}})^3 - 1) = -\sqrt{\lambda_n}t + \sqrt{\lambda_n}t + \frac{t^2}{2} + \frac{1}{3!}\frac{t^3}{\sqrt{\lambda_n}}$$

taylor expansion

$$[a_n = o(b_n) \Rightarrow \lim_{n \rightarrow \infty} \frac{a_n}{b_n} = 0]$$

$\therefore \lambda_n \rightarrow \infty$ ,  $\frac{t^2}{2} + \underset{n \rightarrow \infty}{o}(\frac{1}{3!}\frac{1}{\sqrt{\lambda_n}}t^3 + o(\frac{1}{\sqrt{\lambda_n}}))$  goes to 0 faster than  $b_n$

$$= \frac{t^2}{2} + o(\frac{1}{\sqrt{\lambda_n}}) \cdot \frac{t^3}{\sqrt{\lambda_n}} = o(\frac{1}{\sqrt{\lambda_n}})$$

$\therefore$  we've shown  $\log M_{Z_n}(t) \xrightarrow{n \rightarrow \infty} \log M_Z(t) \Rightarrow M_{Z_n}(t) \xrightarrow{n \rightarrow \infty} M_Z(t)$  continuity Thm  $\Rightarrow Z_n \xrightarrow{d} Z(0, 1)$ .

$\therefore$  standardized Poiss( $\lambda$ ) R.V. conv. in dist to  $N(0, 1)$  as  $\lambda \rightarrow \infty$   $\blacksquare$

Central Limit Theorem Let  $x_1, x_2, \dots, x_n$  be iid R.V.s with mean  $\mu$  and var.  $\sigma^2 < \infty$ , and MGF( $\cdot$ ) defined in the neighborhood of 0.

$$\text{Let } S_n = \sum_{i=1}^n x_i ; \bar{x}_n = \frac{1}{n} S_n \star$$

↳ Standardize  $S_n$ :

$$\begin{aligned} E(S_n) &= n\mu & \frac{S_n - E(S_n)}{\sqrt{\text{Var}(S_n)}} &= \frac{S_n - n\mu}{\sqrt{n\sigma^2}} = \frac{S_n - n\mu}{\sqrt{n}\sigma} \quad \textcircled{1} \\ \text{Var}(S_n) &= n\sigma^2 & E(\bar{x}_n) &= E\left(\frac{S_n}{n}\right) = \mu \\ E(\bar{x}_n) &= E\left(\frac{S_n}{n}\right) = \mu & \text{Var}(\bar{x}_n) &= \text{Var}\left(\frac{S_n}{n}\right) = \frac{\sigma^2}{n} \end{aligned}$$

- do the experiment  $n$  times → take the average  $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$  ( $x_1, x_2, \dots, x_n$ ) →  $\bar{x}_n$  becomes stable  $\text{Var}(\bar{x}_n) = \frac{\sigma^2}{n}$
- $E(\bar{x}_n)$   $\text{Var}(\bar{x}_n)$  always use capital  $\bar{x}_n$  to represent R.V.s

↳ Standardize  $\bar{x}_n$ :

$$\frac{\bar{x}_n - E(\bar{x}_n)}{\sqrt{\text{Var}(\bar{x}_n)}} = \frac{\bar{x}_n - \mu}{\sigma/\sqrt{n}} = \frac{S_n/n - \mu}{\sigma/\sqrt{n}} = \frac{S_n - n\mu}{\sqrt{n}\sigma} \quad \textcircled{2}$$

Standardize Sum  $\textcircled{1}$  = Standardize average  $\textcircled{2}$

CLT statement

$$\frac{S_n - n\mu}{\sqrt{n}\sigma} = \frac{\bar{x}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{d} N(0,1) \text{ as } n \rightarrow \infty$$

↳ # of samples in one realization  $\star \sigma^2 < \infty$

$\star$  No matter what dist you have, with variance  $< \infty$  (finite var.)  
the <sup>standardized</sup> average will follow Normal  $N(0,1)$   $\star$

realization  $\textcircled{1} \rightarrow$  collect  $n: x_1, \dots, x_n \rightarrow$  calculate  $\bar{x}_n$

imagination  $\textcircled{2} \rightarrow$  collect  $n: \star$  another  $x_1, \dots, x_n \rightarrow$  calculate  $\bar{x}_n \quad \left. \right\} \Rightarrow$  end up with dist of  $\bar{x}_n$ .

(K) repeat to get the  $K^{\text{th}}$   $\bar{x}_n$

$\star$  in practice, we usually only have one realization of the experiments, say  $\textcircled{1}$ , so we only have one  $\bar{x}_n$ , what we do is to use imagination to see potential behavior of collective data (which not being collected) had they collected. [See beyond observed] interests: How K  $\bar{x}_n$  collectively looks like?

what we have: 1  $\bar{x}_n / (K-1) \rightarrow$  imagination.  
from n samples.

Proof  
CLT

Let  $Z_n = \frac{S_n - n\mu}{\sqrt{n}\sigma}$ , what to find  $M_{Z_n}(t)$ , known  $E(X)$ ,  $\text{Var}(X)$

$$Z_n = -\frac{\mu\sqrt{n}}{\sqrt{n}\sigma} + \frac{1}{\sqrt{n}\sigma} \cdot S_n \quad \begin{array}{l} \bullet S_n \text{ relates to } X_i \\ \bullet \text{want to apply MGF property (i)} \end{array}$$

$$M_{Z_n}(t) = e^{\frac{\mu\sqrt{n}t}{\sqrt{n}\sigma} + \frac{1}{2} \text{Var}(S_n)} \rightarrow S_n = \sum_{i=1}^n X_i$$

$$= e^{\mu\sqrt{n}t} \cdot \left[ M_X\left(\frac{1}{\sqrt{n}\sigma} \cdot t\right) \right]^n \quad [ \text{MGF}^{\text{Normal example}} ]$$

want to show  $M_{Z_n}(t) \rightarrow M_Z(t) = e^{\frac{1}{2}t^2}$ ; equivalently  
 $\log M_{Z_n}(t) = \log M_Z(t) \Rightarrow (-\sqrt{n}\mu/\sigma)t + n \log M_X\left(\frac{t}{\sqrt{n}\sigma}\right) = \frac{1}{2}t^2$

Taylor expansion

$$\begin{aligned} M_X\left(\frac{t}{\sqrt{n}\sigma}\right) &= M_X(0) + \frac{t}{\sqrt{n}\sigma} \cdot M_X'(0) + \frac{1}{2!} \left(\frac{t}{\sqrt{n}\sigma}\right)^2 M_X''(0) + \frac{1}{3!} \left(\frac{t}{\sqrt{n}\sigma}\right)^3 M_X'''(0) + \dots \\ M_X(t) &\approx 1 + \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2!} \left(\frac{t}{\sqrt{n}\sigma}\right)^2 E(X^2) + \dots \quad \text{Goal} \star \\ &\text{around 0.} \end{aligned}$$

(Taylor expansion)  $\log M_X\left(\frac{t}{\sqrt{n}\sigma}\right) = \log \left[ 1 + \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2!} \left(\frac{t}{\sqrt{n}\sigma}\right)^2 (1^2 + \sigma^2) + \frac{1}{3!} \left(\frac{t}{\sqrt{n}\sigma}\right)^3 E(X^3) + \dots \right]$

$$\begin{aligned} \log(1+x) &= \log(1+0) + x \cdot \frac{d \log(1+x)}{dx} \Big|_{x=0} + \frac{1}{2!} x^2 \cdot \frac{d^2 \log(1+x)}{dx^2} \Big|_{x=0} + \dots \\ &= 0 + x \cdot \left(\frac{1}{1+x}\Big|_{x=0}\right) + \frac{1}{2!} x^2 \left(-\frac{1}{(1+x)^2}\Big|_{x=0}\right) \\ &= 0 + x - \frac{1}{2} x^2 + \dots \end{aligned}$$

$\therefore \log(1+x) \approx x$

$$\begin{aligned} \log M_X\left(\frac{t}{\sqrt{n}\sigma}\right) &= \log \{1+x\} \approx x = \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2!} \left(\frac{t}{\sqrt{n}\sigma}\right)^2 (1^2 + \sigma^2) + \frac{1}{3!} \left(\frac{t}{\sqrt{n}\sigma}\right)^3 E(X^3) + \dots \\ &= \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2} \frac{t^2}{n\sigma^2} (1^2 + \sigma^2) + O\left(\frac{1}{n}\right) \quad \frac{1}{n\sigma} = o\left(\frac{1}{n}\right) \end{aligned}$$

$$\begin{aligned} \log M_X\left(\frac{t}{\sqrt{n}\sigma}\right) &= \log \{1+x\} = 0 + x + -\frac{1}{2} x^2 + \frac{1}{3!} x^3 \\ &= \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2} \frac{t^2}{n\sigma^2} (1^2 + \sigma^2) + O\left(\frac{1}{n}\right) \quad \xrightarrow{x^2 \rightarrow \text{open each term, see it each term converge to 0 faster than } \frac{1}{n}} \end{aligned}$$

$$-\frac{1}{2} \left(\frac{t^2}{n\sigma^2}\right) \mu^2 + O\left(\frac{1}{n}\right)$$

$$= \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2} \frac{t^2}{n\sigma^2} \cdot \sigma^2 + O\left(\frac{1}{n}\right)$$

$$= \frac{t}{\sqrt{n}\sigma} \cdot \mu + \frac{1}{2} \frac{t^2}{n} + O\left(\frac{1}{n}\right)$$

$$\text{back to our goal: } (-\sqrt{n}\mu/\sigma)t + n \log M_X\left(\frac{t}{\sqrt{n}\sigma}\right) = -\sqrt{n}\mu/\sigma + \frac{\sqrt{n}t}{\sigma} \cdot \mu + \frac{t^2}{2} + O(1) = \frac{t^2}{2} \xrightarrow{\rightarrow 0}$$

$$\therefore \log M_{Z_n}(t) \xrightarrow{n \rightarrow \infty} \frac{1}{2}t^2 \Rightarrow M_{Z_n}(t) \rightarrow M_Z(t) = e^{-\frac{1}{2}t^2}$$

$\Rightarrow$  By continuity thm,  $Z_n \xrightarrow{d} Z_t \Rightarrow Z_n \xrightarrow{d} N(0, 1)$