

$$g(\mu_x, \mu_y) + (x - \mu_x) \cdot \frac{\partial g}{\partial x}(\mu_x, \mu_y) + (y - \mu_y) \cdot \frac{\partial g}{\partial y}(\mu_x, \mu_y) + \frac{1}{2} \left[ (x - \mu_x)^2 \cdot \frac{\partial^2 g}{\partial x^2}(\mu_x, \mu_y) + 2(x - \mu_x)(y - \mu_y) \frac{\partial^2 g}{\partial x \partial y}(\mu_x, \mu_y) + (y - \mu_y)^2 \cdot \frac{\partial^2 g}{\partial y^2}(\mu_x, \mu_y) \right]$$

Now:  $Z = g(X, Y)$ ,  $E[X] = \mu_x$ ,  $E[Y] = \mu_y$ ,  $\text{var}[X] = \sigma_x^2$ ,  $\text{var}[Y] = \sigma_y^2$ ,  $\text{cov}(X, Y) = \sigma_{xy}$

Bivariate Delta method:

$$E[Z] \approx$$

$$\text{cov}(X-a, Y-b)$$

$$= \text{cov}(X, Y)$$

$$E[X - \mu_x]$$

$$= E[X] - \mu_x = \mu_x - \mu_x = 0$$

$$E[aX] = a E[X]$$

$$E[X|Y]$$

$$E[XY] = E[E[X|Y]Y]$$

$$\text{var}[Z] \approx$$

$$Z = g(X, Y) \approx g(\mu_x, \mu_y) + (X - \mu_x) \cdot \frac{\partial g}{\partial x}(\mu_x, \mu_y) + (Y - \mu_y) \cdot \frac{\partial g}{\partial y}(\mu_x, \mu_y) + \frac{1}{2} \left[ (X - \mu_x)^2 \cdot \frac{\partial^2 g}{\partial x^2}(\mu_x, \mu_y) + 2(X - \mu_x)(Y - \mu_y) \frac{\partial^2 g}{\partial x \partial y}(\mu_x, \mu_y) + (Y - \mu_y)^2 \cdot \frac{\partial^2 g}{\partial y^2}(\mu_x, \mu_y) \right]$$

$$E[Z] \approx g(\mu_x, \mu_y) + E[X - \mu_x] \cdot \frac{\partial g}{\partial x}(\mu_x, \mu_y) + 0 + \frac{1}{2} \left[ E[(X - \mu_x)^2] \cdot \frac{\partial^2 g}{\partial x^2}(\mu_x, \mu_y) + 2E[(X - \mu_x)(Y - \mu_y)] \cdot \frac{\partial^2 g}{\partial x \partial y}(\mu_x, \mu_y) + E[(Y - \mu_y)^2] \cdot \frac{\partial^2 g}{\partial y^2}(\mu_x, \mu_y) \right]$$

$$= g(\mu_x, \mu_y) + \frac{1}{2} \left[ \underbrace{E[(X - \mu_x)^2]}_{=\sigma_x^2} \cdot \frac{\partial^2 g}{\partial x^2}(\mu_x, \mu_y) + 2 \underbrace{E[(X - \mu_x)(Y - \mu_y)]}_{=\sigma_{xy}} \cdot \frac{\partial^2 g}{\partial x \partial y}(\mu_x, \mu_y) + \underbrace{E[(Y - \mu_y)^2]}_{=\sigma_y^2} \cdot \frac{\partial^2 g}{\partial y^2}(\mu_x, \mu_y) \right]$$

$$\text{var}[Z] \approx \text{var} \left[ g(\mu_x, \mu_y) + (X - \mu_x) \cdot \frac{\partial g}{\partial x}(\mu_x, \mu_y) + (Y - \mu_y) \cdot \frac{\partial g}{\partial y}(\mu_x, \mu_y) \right]$$

$$= \left( \frac{\partial g}{\partial x}(\mu_x, \mu_y) \right)^2 \cdot \text{var}(X) + 2 \left( \frac{\partial g}{\partial x}(\mu_x, \mu_y) \right) \cdot \left( \frac{\partial g}{\partial y}(\mu_x, \mu_y) \right) \cdot \text{cov}(X, Y) + \left( \frac{\partial g}{\partial y}(\mu_x, \mu_y) \right)^2 \cdot \text{var}(Y)$$

$$\text{var}[aX + bY] = a \text{var}[X] + b \text{var}[Y]$$

$$\text{var}[aX] = a^2 \text{var}[X]$$

$$= a^2 \text{var}[X] + b^2 \text{var}[Y]$$

$$E[(aX - aE[X])^2]$$

$$a^2 \text{var}(X) + 2ab \text{cov}(X, Y) + b^2 \text{var}(Y)$$

$$= a^2 E[(X - E[X])^2]$$

$$= a^2 \text{var}[X]$$

$$\text{var}(X+Y) = E[(X+Y - \mu_x - \mu_y)^2] = E[(X - \mu_x + Y - \mu_y)^2] \text{var}[X+Y] = \text{var}[X] + 2\text{cov}(X, Y) + \text{var}[Y]$$

$$= E[(X - \mu_x)^2 + 2(X - \mu_x)(Y - \mu_y) + (Y - \mu_y)^2]$$

$$= E[(X - \mu_x)^2] + 2E[(X - \mu_x)(Y - \mu_y)] + E[(Y - \mu_y)^2]$$



Continuity Theorem (conv of MGF  $\rightarrow$  conv of CDF)

Let  $X_1, X_2, \dots$  be a sequence of R.V.s with CDFs  $F_1(\cdot), F_2(\cdot), \dots$  and MGFs  $M_{X_1}(\cdot), M_{X_2}(\cdot), \dots$ . Suppose that

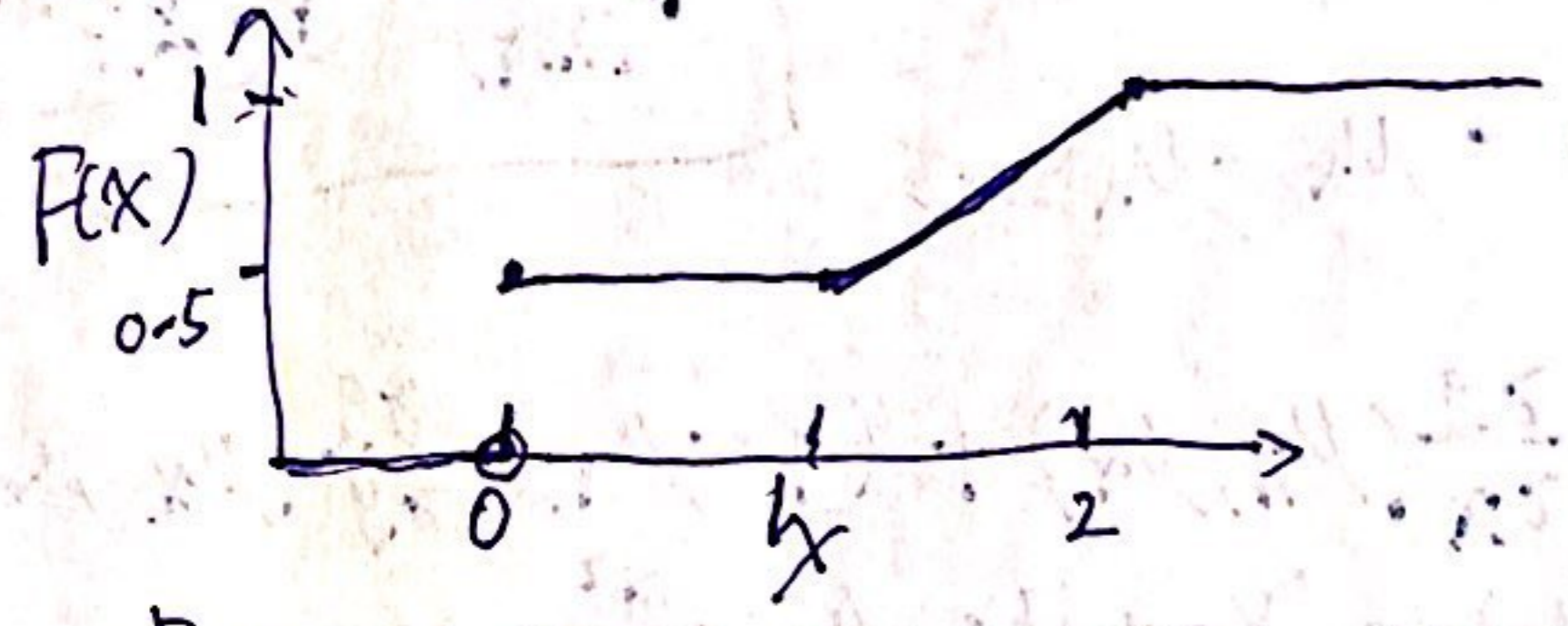
$$M_{X_n}(t) \rightarrow M_X(t) \text{ as } n \rightarrow \infty \text{ for all } t \in \mathbb{R}$$

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

e.g.  $X = 0$  with probability 0.5, &  $X \sim \text{Unif}[1, 2]$  with probability 0.5

Recall  $F(x) = P(X \leq x) =$



$$\begin{cases}
 0 & \text{if } x < 0 \\
 0.5 & x = 0 \\
 0.5 & 0 < x \leq 1 \\
 0.5 + 0.5(x-1) & 1 < x \leq 2 \\
 1 & x > 2
 \end{cases}$$

$P(X \leq 0.5) = P(X=0)$   
 $P(X \leq x) = P(X=0) + P(1 < X \leq x)$   
 $= 0.5 + 0.5 \cdot (x-1)$

$F$  is cont. everywhere except at 0.

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

Pf: Let  $0 < \lambda_1 < \lambda_2 < \dots < \lambda_n < \dots$  be an increasing sequence  $\lambda_n \rightarrow \infty$  as  $n \rightarrow \infty$

Let  $X_n \sim \text{Poisson}(\lambda_n)$ .  $E[X_n] = \lambda_n$ ,  $\text{var}[X_n] = \lambda_n$

Recall  $X_n$  has MGF  $M_{X_n}(t) = e^{\lambda_n(e^t - 1)}$   $t \in \mathbb{R}$

Standardize  $X_n$  as

$$Z_n = \frac{X_n - \lambda_n}{\sqrt{\lambda_n}}$$

Try to show that  $Z_n$  converges to a  $N(0, 1)$  R.V. as  $\lambda_n \rightarrow \infty$  ( $n \rightarrow \infty$ )

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

So  $M_{Z_n}(t) = e^{-\sqrt{\lambda_n}t} \cdot M_{X_n}\left(\frac{1}{\sqrt{\lambda_n}}t\right) = e^{-\sqrt{\lambda_n}t} \cdot e^{\lambda_n(e^{\frac{1}{\sqrt{\lambda_n}}t} - 1)}$

Hint:

$$\begin{aligned}
 e^x &= e^0 + x e^0 \\
 &+ \frac{x^2}{2} e^0 \\
 &+ \dots \\
 &= 1 + x + \frac{x^2}{2} + \dots
 \end{aligned}$$

Say  $Z \sim N(0, 1)$ , then  $Z$  has MGF  $M_Z(t) = e^{\frac{1}{2}t^2}$

So we want to show  $- \sqrt{\lambda_n}t + \lambda_n(e^{\frac{1}{\sqrt{\lambda_n}}t} - 1) \xrightarrow{n \rightarrow \infty} \frac{1}{2}t^2$