

STAT 330: Lecture 12

2024 Spring

June 20, 2024

Last Lecture

- Function of random variables: The CDF method.

1. get the cdf.

2. take the derivative

This Lecture

- Function of random variables: The CDF method and the one-to-one transformation method.

Review

order statistics.

$$X_{(1)} = \min\{X_1, \dots, X_n\}, \quad X_{(n)} = \max\{X_1, \dots, X_n\}$$

CDF of $X_{(n)}$

$$G(y) = \Pr(X_{(n)} \leq y) = \Pr(X_1 \leq y, \dots, X_n \leq y)$$

CDF of $X_{(1)}$

$$\begin{aligned} G(y) &= \Pr(X_{(1)} \leq y) = 1 - \Pr(X_{(1)} > y) \\ &= 1 - \Pr(X_1 > y, \dots, X_n > y) \end{aligned}$$

CDF Method

Examples ① If $Z \sim \text{Norm}(0,1)$, find the pdf of $Y = Z^2$

$$\text{Step 1: } G_Y(y) = \Pr(Y \leq y) = \Pr(Z^2 \leq y), \quad y \geq 0.$$

$$= \Pr(-\sqrt{y} \leq Z \leq \sqrt{y})$$

$$= F_Z(\sqrt{y}) - F_Z(-\sqrt{y})$$

$$\text{Step 2: } g_Y(y) = G'_Y(y) = F'_Z(\sqrt{y}) \frac{1}{2} y^{-\frac{1}{2}} -$$

$$F'_Z(-\sqrt{y}) \cdot (-1) \frac{1}{2} y^{-\frac{1}{2}}$$

$$= f_Z(\sqrt{y}) \frac{1}{2} y^{-\frac{1}{2}} + f'_Z(-\sqrt{y}) \frac{1}{2} y^{-\frac{1}{2}}$$

$$= \frac{1}{\sqrt{\pi}} \exp(-\frac{y}{2}) \cdot y^{-\frac{1}{2}} \sim \text{Gamma}(\frac{1}{2}, z) \quad \text{we call it } \chi_1^2$$

$$\frac{\partial h(g(x))}{\partial x} = h'(g(x))g'(x)$$

$$\text{pdf of } \chi_n^2 : \frac{1}{2^{\frac{n}{2}} \cdot \Gamma(\frac{n}{2})} x^{\frac{n}{2}-1} e^{-\frac{x}{2}} \sim \text{Gamma}(\frac{n}{2}, z)$$

$$\text{②. } f(x) = \frac{\theta}{x^{\theta+1}}, x \geq 1, \theta > 0. \quad \text{Find pdf of } Y = \log X.$$

support of Y , $y \in [0, \infty)$.

$$G_Y(y) = \Pr(Y \leq y) = \Pr(\log X \leq y) = \Pr(X \leq e^y)$$

$$= \int_1^{e^y} \frac{\theta}{x^{\theta+1}} dx = -x^{-\theta} \Big|_1^{e^y} = 1 - e^{-y\theta}, \quad y \geq 0$$

$$g_Y(y) = G'_Y(y) = \theta e^{-y\theta}, \quad y \geq 0.$$

One-to-one Univariate Transformation Method

 X is rv. $Y = h(X)$, $h(\cdot)$ is a one-to-one function.If $h(x)$ is one-to-one, then the pdf of Y is

$$g_Y(y) = f(x) \left| \frac{dx}{dy} \right|, \quad y = h(x), \quad x = h^{-1}(y)$$

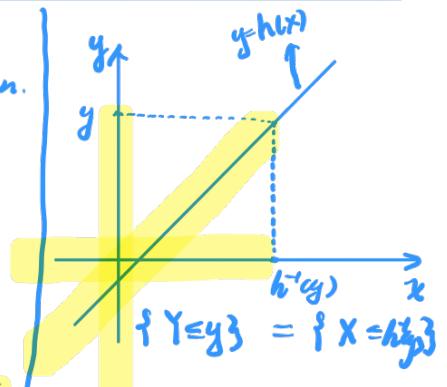
 $f(x)$: $f(h^{-1}(y))$ is a function of y . $| \cdot |$: absolute value.

$$\frac{dx}{dy} : \frac{d(h^{-1}(y))}{dy}$$

proof: $G_Y(y) = \Pr(Y \leq y) = \Pr(h(X) \leq y)$ 1). if $h(\cdot)$ is an increasing function.

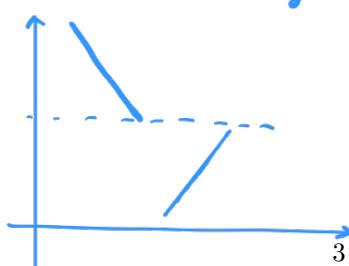
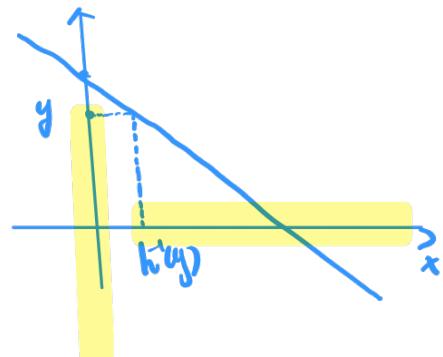
$$\begin{aligned} \Pr(h(X) \leq y) &= \Pr(X \leq h^{-1}(y)) \\ &= F_X(h^{-1}(y)) \end{aligned}$$

$$\begin{aligned} g_Y(y) &= \frac{dF_X(h^{-1}(y))}{dy} = F'_X(h^{-1}(y)) \frac{d(h^{-1}(y))}{dy} \\ &= f(h^{-1}(y)) \cdot \frac{d(h^{-1}(y))}{dy} \\ &= f(x) \frac{dx}{dy} = f(x) \left| \frac{dx}{dy} \right| \end{aligned}$$

2). if $h(\cdot)$ is a decreasing function.

$$\begin{aligned} \Pr(Y \leq y) &= \Pr(h(X) \leq y) \\ &= \Pr(X \geq h^{-1}(y)) \\ &= 1 - \Pr(X < h^{-1}(y)) \\ &= 1 - F_X(h^{-1}(y)) \end{aligned}$$

$$\begin{aligned} g_Y(y) &= 0 - F'_X(h^{-1}(y)) \frac{d(h^{-1}(y))}{dy} \\ &= f(x) \left(-\frac{dx}{dy} \right) = f(x) \left| \frac{dx}{dy} \right| \end{aligned}$$



one-to-one function
= piecewise monotone functions
with no overlap.

Examples

① Suppose X is rv. its pdf is $f(x)$. its cdf is $F(x)$.

find out the distribution of $F(X)$. $F(X)$ is a random variable.

Method 1

$Y = F(X)$. Support of Y , $y \in [0, 1]$, $X = F^{-1}(Y)$

pdf of Y :

$$g_Y(y) = f(x) \cdot \left| \frac{dx}{dy} \right|$$

$$\begin{aligned} \frac{dx}{dy} &= \frac{d(F^{-1}y)}{dy} = \frac{1}{F'(F^{-1}y)} \\ &= \frac{1}{f(x)} \end{aligned}$$

$\Rightarrow g_Y(y) = 1$, Y has uniform $(0, 1)$ regardless of the distribution as long as X is continuous.

For an invertible function h

$$(h^{-1}(a))' = \frac{1}{h'(h^{-1}(a))}$$

Method 2

$$\begin{aligned} \frac{dx}{dy} &= \frac{1}{dy/dx} \\ &= \frac{1}{\frac{d(F(x))}{dx}} = \frac{1}{f(x)} \end{aligned}$$

$$\begin{aligned} y &= h(x), h \text{ is invertible} \\ 1 &= \frac{dy}{dx} = \frac{dh(x)}{dy} = \frac{dh(x)}{dx} \cdot \frac{dx}{dy} \\ &= \frac{dy}{dx} \cdot \frac{dx}{dy} \Rightarrow \frac{dx}{dy} = \frac{1}{dy/dx} \end{aligned}$$

Example. $X \sim \text{Unif}(0, 1)$. Find the pdf of $Y = -\log X$. $x > 0$

Support of Y : $y \in [0, +\infty)$, $y = -\log x$, $x = \exp(-y)$

$$g_Y(y) = f(x) \cdot \left| \frac{dx}{dy} \right| = 1 \times \left| \frac{d(\exp(-y))}{dy} \right| = \exp(-y).$$

Method 2

$$= 1 \times \left| \frac{1}{\frac{d(\log x)}{dx}} \right| = \left| \frac{1}{-\frac{1}{x}} \right| = x = \exp(-y)$$

Method 2

One-to-one Bivariate Transformation Method

X, Y joint pdf $f(x,y)$, $\begin{cases} U = h_1(X, Y) \\ V = h_2(X, Y) \end{cases}$

The goal is to find the joint pdf of (U, V) .

① $h_1(x,y), h_2(x,y)$ are one-to-one.

$(x,y) \rightarrow (u,v)$, $(u,v) \rightarrow (x,y)$ unique.

The two functions h_1, h_2 are one-to-one if there exists another two unique functions st.

$$\begin{cases} x = g_1(u,v) \\ y = g_2(u,v) \end{cases}$$

② Jacobian matrix.

$$J = \frac{\partial(x,y)}{\partial(u,v)} = \begin{bmatrix} \frac{\partial u}{\partial x} & \frac{\partial u}{\partial y} \\ \frac{\partial v}{\partial x} & \frac{\partial v}{\partial y} \end{bmatrix}$$

or Jacobian determinant.

We call its determinant or Jacobian of $\begin{cases} u = h_1(x,y) \\ v = h_2(x,y) \end{cases}$

$$\left| \frac{\partial(x,y)}{\partial(u,v)} \right| \quad \text{determinant notation}$$

$$\det \left(\frac{\partial(x,y)}{\partial(u,v)} \right)$$

$$\frac{\partial(x,y)}{\partial(u,v)} = \begin{bmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{bmatrix} \quad \text{Jacobian matrix for } \begin{cases} x = g_1(u,v) \\ y = g_2(u,v) \end{cases}$$

$$\det \left(\frac{\partial(x,y)}{\partial(u,v)} \right) = \left[\det \left(\frac{\partial(u,v)}{\partial(x,y)} \right) \right]^{-1} \quad \text{in fact } \frac{\partial(x,y)}{\partial(u,v)} = \left[\frac{\partial(u,v)}{\partial(x,y)} \right]^{-1}$$

The joint pdf for $\begin{cases} U = h_1(X,Y) \\ V = h_2(X,Y) \end{cases}$ is

$$g(u,v) = f(x,y) \cdot \left| \det \left(\frac{\partial(x,y)}{\partial(u,v)} \right) \right|$$

absolute value notation
determinant of Jacobian matrix.

The inverse of a Jacobian matrix is the Jacobian of the inverse function.