

Math 621 Lec 8 9/26/17

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Midterm 1
Midterm 2
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Transformations of Variables

I Discrete r.v.'s

$$X \sim \text{Bern}(p) = p^x (1-p)^{1-x} \mathbb{1}_{x \in \{0,1\}} = p_X(x)$$

$$Y = 3 + X \sim \begin{cases} 4 \text{ w.p. } p \\ 3 \text{ w.p. } 1-p \end{cases} = p^{Y-3} (1-p)^{1-(Y-3)} \mathbb{1}_{Y \in \{3,4\}} = p_Y(y)$$

$$\text{Supp}(Y) = \{y: y-3 \in \text{Supp}(X)\}$$

the PMF of Y looks like PMF of X except X is replaced with $Y-3$.

$$Y = c + aX$$

We have to keep the probs of the original support values the same, but change the support.

\Rightarrow if Y was realized, then means $X = \frac{Y-c}{a}$, the underlying initial realization

$$\text{Supp}(Y) = \left\{ y: \frac{y-c}{a} \in \text{Supp}(X) \right\} = \left\{ y: \frac{y-c}{a} \in \{0,1\} \right\} = \{c, a+c\}$$

$$Y \sim p^{\frac{Y-c}{a}} (1-p)^{1-\frac{Y-c}{a}} \mathbb{1}_{Y \in \{c, a+c\}}$$

If $Y = c + aX = g(X)$ \Rightarrow transformation of X
 $\Rightarrow g^{-1}(Y) = \frac{Y-c}{a}$

$$\Rightarrow p_Y(y) = p^{g^{-1}(y)} (1-p)^{1-g^{-1}(y)} \mathbb{1}_{g^{-1}(y) \in \text{Supp}(X)} = p_X(g^{-1}(y))$$

(working theory)

$$X \sim \text{Bin}(n, p)$$

$$Y = a + cX \quad p_Y(y) = \binom{n}{g^{-1}(y)} p^{g^{-1}(y)} (1-p)^{n-g^{-1}(y)} \mathbb{1}_{Y \in g(\text{Supp}(X))}$$

g 's Image \longrightarrow Note: $g(A) = \{g(a): a \in A\}$

$$= \binom{n}{\frac{y-c}{a}} p^{\frac{y-c}{a}} (1-p)^{n-\frac{y-c}{a}} \mathbb{1}_{y \in \{c, a+c, 2a+c, \dots, na+c\}}$$

$\frac{y-c}{a} = 0 = 1 = 2$

$$Y \sim \text{Bin}(n, p), Y = X^3$$

$$P_Y(y) = \binom{n}{\sqrt[3]{y}} p^{\sqrt[3]{y}} (1-p)^{n-\sqrt[3]{y}} \mathbb{1}_{y \in \{0, 1, 2^3, 3^3, \dots, n^3\}}$$

$$X \sim \text{Geom}(p)$$

$$Y = \max\{3, X\}$$

What does this look like?

X	Y
0	3
1	3
2	3
3	3
4	4
5	5
⋮	⋮

function

There is no $g^{-1}(y)$ because g is not 1:1.

First note $P_Y(4) = P_X(4)$, $P_Y(5) = P_X(5), \dots$

But $P_Y(3) \neq P_X(3)$

$$P_Y(3) = P_X(0) + P_X(1) + P_X(2) + P_X(3)$$

$\Rightarrow P_Y(y) \neq P_X(g^{-1}(y))$ always ... only for g functions which are 1:1 for support of X .

General formula:

$$P_Y(y) = \sum_{\{x: g(x)=y\}} P_X(x) = \sum_{\{x: x=g^{-1}(y)\}} P_X(x) = P_X(g^{-1}(y))$$

only one value!

$$\text{Here, } P_Y(y) = (p + (1-p)p + (1-p)^2p + (1-p)^3p) \mathbb{1}_{y=3} + \underbrace{p(1-p)^y}_{\text{Geom}(p)} \mathbb{1}_{y \in \{4, 5, \dots\}}$$

$$F_Y(y) = \sum_{\{x: g(x) \leq y\}} P_X(x)$$

$$X_1, X_2 \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda), Y = -X_2 \Rightarrow P_Y(y) = P_X(-y) = \frac{e^{-\lambda} \lambda^{-y}}{(-y)!} \mathbb{1}_{y \in \{0, -1, -2, \dots\}}$$

$$D = X_1 - X_2 = X_1 + Y \quad \text{supp}(D) = \mathbb{Z} \quad (\text{rare!}) \quad \lambda^x \lambda^{-d}$$

$$P_D(d) = \sum_{x \in \text{supp}(D)} P_{X_1}(x) P_Y(d-x) = \sum_{x=0}^{\infty} \frac{e^{-\lambda} \lambda^x}{x!} \frac{e^{-\lambda} \lambda^{-(d-x)}}{\underbrace{(-d+x)!}_{(x-d)!}} \mathbb{1}_{\substack{d-x \in \{0, -1, -2, \dots\} \\ \Downarrow \\ x-d \in \{0, 1, 2, \dots\} \\ \Downarrow \\ x \in \{d, d+1, \dots\}}}$$

If $d > 0$, sum begins at d , if $d \leq 0$, sum begins at $0 \Rightarrow \max\{0, d\}$

$$= e^{-2\lambda} \begin{cases} \sum_{x=d}^{\infty} \frac{\lambda^{2x-d}}{x! (x-d)!} & \text{if } d > 0 \\ \sum_{x=0}^{\infty} \frac{\lambda^{2x-d}}{x! (x-d)!} & \text{if } d \leq 0 \end{cases}$$

$$\rightarrow \text{let } x' = x - d \Rightarrow x = x' + d \Rightarrow \sum_{x'=0}^{\infty} \frac{\lambda^{2(x'+d)-d}}{(x'+d)! x'!} = \sum_{i=0}^{\infty} \frac{\lambda^{2i-d}}{\Gamma(i+1) \Gamma(i-1)}$$

$$\rightarrow \text{let } d' = -d \Rightarrow \sum_{x=0}^{\infty} \frac{\lambda^{2x+d'}}{x! (x+d')!} = \underbrace{\sum_{i=0}^{\infty} \frac{(\frac{2\lambda}{2})^{2i-d'}}{\Gamma(i+d'-1) \Gamma(i-1)}}_{\text{modified Bessel Function of the 1st kind (sol' to Bessel diff eq)}} = I_{d'}(2\lambda)$$

$$\begin{aligned} \text{if } d < 0 &\Rightarrow d' = |d| \\ \text{if } d > 0 &\Rightarrow d' = |d| \end{aligned}$$

$$\Rightarrow P_D(d) = e^{-2\lambda} I_{|d|}(2\lambda) = \text{Skellam}(\lambda, \lambda) \text{ distr. (1946)}$$

Used to model point spreads in basketball, soccer, hockey, ..., difference in photon noise, and more.

Let $X \sim U(0,1)$, $Y = g(X) = g(X)$ s.t. g is 1:1

Can we use the formula

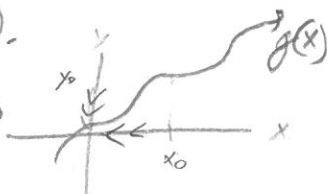
$$P_Y(y) = P_X(g^{-1}(y))?$$

No! there is no $P_X(y)$ (PMF)! This does not guarantee for cont. r.v.'s!!

We need another way!

For $f_Y(y)$ the PDF of $f_X(x)$ is known.

Consider $Y = g(X)$ where g is 1:1. If it's 1:1 it's either strictly increasing or strictly decreasing (from calculus).



(a) If g is increasing...

$$F_Y(y) := P(Y \leq y) = P(g(X) \leq y) = P(X \leq g^{-1}(y)) = F_X(g^{-1}(y))$$

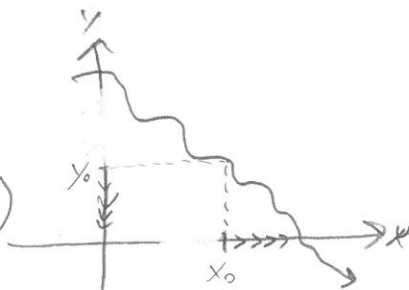
We just found the CDF of Y . Now for the PDF of Y :

$$f_Y(y) = F_Y'(y) = \frac{d}{dy} [F_X(g^{-1}(y))] = F_X'(g^{-1}(y)) \frac{d}{dy} [g^{-1}(y)] = f_X(g^{-1}(y)) \frac{d}{dy} [g^{-1}(y)]$$

by chain rule

(b) If g is decreasing,

$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y) = P(X \geq g^{-1}(y)) = 1 - F_X(g^{-1}(y))$$



We have the CDF of Y . Now we need the PDF of Y :

$$f_Y(y) = F_Y'(y) = \frac{d}{dy} [1 - F_X(g^{-1}(y))] = - f_X(g^{-1}(y)) \frac{d}{dy} [g^{-1}(y)]$$

negative

≥ 0 $\Rightarrow \leq 0$

Let's combine formulas (a) & (b) into one formula for convenience:

Note:

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} [g^{-1}(y)] \right|$$

$$S_{pp}[Y] = g(S_{pp}[X]) = \{g(x) : x \in S_{pp}[X]\}$$

$$= \{y : g^{-1}(y) \in S_{pp}[X]\}$$

if $Y = g(X) = aX + c$ a linear transformation... then this becomes:

$$\Rightarrow Y = aX + c \Rightarrow Y - c = aX \Rightarrow X = \frac{Y - c}{a} = g^{-1}(y) \quad \left| \frac{d}{dy} [g^{-1}(y)] \right| = \frac{1}{|a|}$$

$$\Rightarrow f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-c}{a}\right)$$

Common transformations

If $Y = -X \Rightarrow f_Y(y) = f_X(-y)$

If $Y = X + c \Rightarrow f_Y(y) = f_X(y - c)$

$$X \sim U(0,1) \quad \& \quad Y = aX + c$$

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-c}{a}\right) = \frac{1}{|a|} (1) = \frac{1}{|a|} \quad S_{pp}[Y] = [c, a+c] \Rightarrow Y \sim U(c, a+c)$$

$$X \sim \text{Exp}(\lambda) \quad \& \quad Y = aX \quad (\text{No } c \text{ right now}) \quad S_{pp}(Y) = (0, \infty) \text{ if } a > 0$$

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y}{a}\right) = \frac{1}{|a|} \lambda e^{-\lambda \frac{y}{a}} = \underbrace{\frac{\lambda}{|a|}}_{\lambda'} e^{-\underbrace{\frac{\lambda}{|a|}}_{\lambda'} y} = \text{Exp}\left(\frac{\lambda}{a}\right)$$

Special case:

$$Y = X + c$$

Can a be negative? No...

since $S_{pp} \text{ of } \text{Exp}$ is $(0, \infty)$

$$\Rightarrow f_Y(y) = f_X(y - c) \quad \text{shifted distribution}$$

It will be a r.v. just not an exponential

$$X \sim \text{Exp}(\lambda)$$

$$f_Y(y) = \lambda e^{-\lambda(y-c)} = (e^{\lambda c}) \lambda e^{-\lambda y}$$

scaling term in front

$$S_{pp}(Y) = (c, \infty)$$

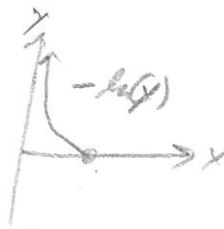
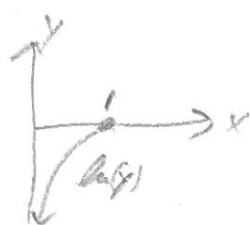
shift

Prove $X \sim U(0,1) \Rightarrow Y = 1 - X \sim U(0,1)$ makes sense!

$$f_Y(y) = \frac{1}{| -1 |} f_X\left(\frac{y-c}{-1}\right) = 1 = U(0,1)$$

$$S_{pp}(Y) = [0, 1]$$

$$X \sim U(0,1), Y = -\ln(X) \\ \Rightarrow \text{supp}(Y) = (0, \infty)$$



$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| \\ = (1) e^{-y} = \text{Exp}(1)$$

$$y = -\ln(x) \Rightarrow x = e^{-y} = g^{-1}(y) \Rightarrow \left| \frac{d}{dy} g^{-1}(y) \right| = e^{-y}$$

$$\Rightarrow Y = -\frac{1}{\lambda} \ln(X) \Rightarrow Y \sim \text{Exp}(\lambda) \text{ based on what we proved before}$$

\Rightarrow if you can generate $U(0,1)$'s, you can generate $\text{Exp}(\lambda)$'s easily!

$$X \sim \text{Exp}(\lambda) \quad Y = -\ln\left(\frac{e^{-\lambda x}}{1 - e^{-\lambda x}}\right)$$

What is $\text{supp}(Y)$?

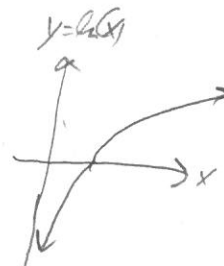
$$= \ln\left(\frac{1 - e^{-\lambda x}}{e^{-\lambda x}}\right) \\ = \ln(e^{\lambda x} - 1)$$

$$X \in (0, \infty)$$

$$e^{\lambda x} \in (1, \infty)$$

$$\Rightarrow e^{\lambda x} - 1 \in (0, \infty)$$

$$\ln(e^{\lambda x} - 1) \in (-\infty, \infty) \Rightarrow \text{supp}(Y) = \mathbb{R}$$

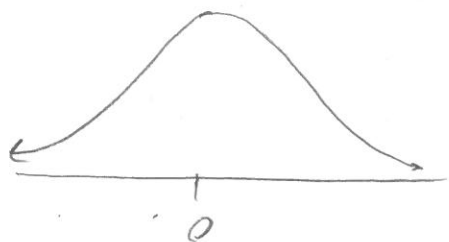


$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$$

$$y = \ln(e^x - 1) \Rightarrow e^y = e^x - 1 \Rightarrow e^x = e^y + 1 \Rightarrow x = \ln(e^y + 1)$$

$$\left| \frac{d}{dy} g^{-1}(y) \right| = \left| \frac{e^y}{e^y + 1} \right| = \frac{e^y}{e^y + 1} \text{ (always positive)}$$

$$f_Y(y) = e^{-\ln(e^y + 1)} \frac{e^y}{e^y + 1} = e^{\ln\left(\frac{1}{e^y + 1}\right)} \frac{e^y}{e^y + 1} = \frac{e^y}{(e^y + 1)^2} = \text{Logistic}(0,1)$$



Looks just like the normal but it has heavier tails

It is important in "deep learning" and "logistic regression".

Due to its heavier tails it is used for many games e.g., US Chess Federation. (ELO system)