

Chapter 2. Transformations & Expectations

2.1 Distributions of functions of a rand. variable

Given $X \sim F_X(\cdot)$ and $g: \mathcal{X} \mapsto \mathcal{Y}$, $Y = g(X) \sim ?$

$$\begin{aligned} P_Y(A) &= P(Y \in A) = P(\{s \mid Y(s) \in A\}) = P(\{s \mid g(X(s)) \in A\}) \\ &= P(\{s \mid X(s) \in g^{-1}(A)\}) \end{aligned}$$

(e.g.) $X \sim B(n, p)$

$$f_X(x) = P(X=x) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x=0, 1, 2, \dots, n$$

$$g(x) = n-x$$

$Y = g(X) = n-X$ ($=$ # of failures) $\sim ?$

s.t. $\mathcal{X} = \{0, 1, 2, \dots, n\} \xrightarrow{g} \mathcal{Y} = \{0, 1, 2, \dots, n\}$

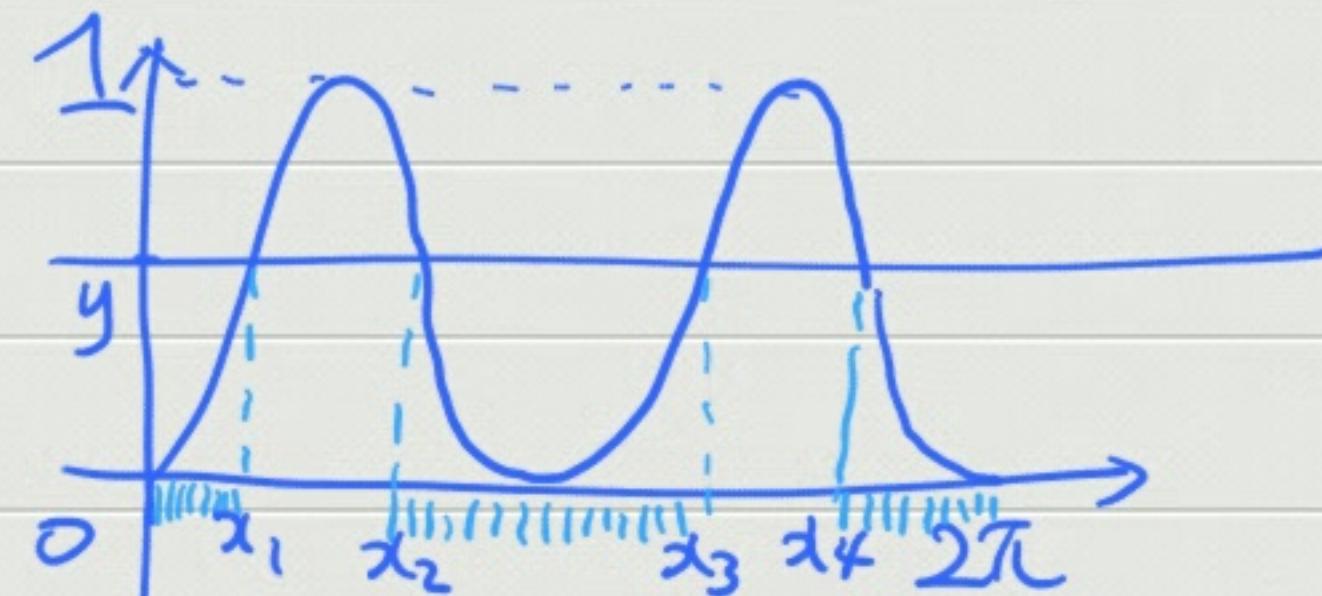
$$f_Y(y) = P(Y=y) = P(n-X=y) = P(X=n-y) = \binom{n}{n-y} p^{n-y} (1-p)^y : B(n, p')$$

(e.g.) $X \sim \text{Uniform}(0, 2\pi)$
 $Y = \sin^2 X \sim ?$

sol. $X = [0, 2\pi]$, $y = [0, 1]$

$$P(Y \leq y) = P(X \leq x_1) + P(x_2 \leq X \leq x_3) + P(X \geq x_4)$$

where x_1, x_2, x_3 and x_4 are the solutions to $\sin^2 x = y$. //



Thm: $X \sim F_X(\cdot)$, $Y = g(X)$ with $g: \mathcal{X} \mapsto \mathcal{Y}$

a. If g is \uparrow on \mathcal{X} , then $F_Y(y) = F_X(g^{-1}(y))$, $y \in \mathcal{Y}$

b. If g is \downarrow on \mathcal{X} , then $F_Y(y) = 1 - F_X(g^{-1}(y))$, $y \in \mathcal{Y}$

(e.g.) $X \sim \text{Uniform}(0,1)$. Then $F_X(x) = \begin{cases} 0, & x < 0 \\ x, & 0 \leq x \leq 1 \\ 1, & x > 1 \end{cases}$

$Y = g(X) = -\log X \sim ?$

s.t. $\mathcal{X} = [0,1]$, $\mathcal{Y} = (0, \infty)$.

$$F_X(x) = x, \quad 0 \leq x \leq 1$$

$$\forall y \in \mathcal{Y}, \quad F_Y(y) = (-F_X(g^{-1}(y))) = 1 - F_X(e^{-y}) = 1 - e^{-y}. \quad //$$

($\because g: \downarrow f^+$)

Exponential

Th: $X \sim f_X(\cdot)$, $Y = g(X)$ with g : monotone, $X \mapsto Y$.

then $f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$, $y \in \mathcal{Y}$.

By the chain rule... //

(e.g.) $X \sim \text{Gamma}(\alpha, \beta)$, $Y = g(X) = 1/X \sim ?$

s.o.l. $g'(y) = -1/y$. $\frac{d}{dy} g^{-1}(y) = -1/y^2$.

$$f_Y(y) = f_X(1/y) \left| -\frac{1}{y^2} \right|$$

$$= \frac{1}{\Gamma(\alpha)\beta^\alpha} \left(\frac{1}{y}\right)^{\alpha-1} e^{-\frac{1}{\beta}y} \cdot \frac{1}{y^2} = \frac{1}{\Gamma(\alpha)\beta^\alpha} \left(\frac{1}{y}\right)^{\alpha+1} e^{-\frac{1}{\beta}y}, \quad y > 0.$$

(e.g.) $X \sim N(0, 1)$, $Y = X^2 \sim ?$

Sol. $g(x) = x^2$ is not monotone on \mathbb{R} , but monotone on $(-\infty, 0)$ and $(0, \infty)$.



$$f_Y(y) = \frac{1}{\sqrt{2\pi}} e^{-(-\sqrt{y})^2/2} \left| -\frac{1}{2\sqrt{y}} \right| + \frac{1}{\sqrt{2\pi}} e^{(\sqrt{y})^2/2} \left| \frac{1}{2\sqrt{y}} \right|$$
$$= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sqrt{y}} e^{-y/2}, \quad y > 0. //$$

χ_1^2

Ih^m: $X \sim F_X(\cdot)$, conti.

$\mapsto Y = F_X(X) \sim \text{Uniform}(0, 1).$

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

(e.g.) $X \sim \text{Exp}(1)$. $f_X(x) = e^{-x}, x > 0.$

$$F_X(x) = 1 - e^{-x}$$

$$Y = 1 - F_X(x) = (-e^{-x}) \sim \text{Uniform}(0, 1).$$

2.2 Expected values

If $E g(x) = \begin{cases} \sum_{x \in X} g(x) f(x) \\ \int_X g(x) f(x) dx \end{cases}$ (the expectation or the mean)

(e.g.) $X \sim \text{Exponential } (\lambda)$

$$f_X(x) = \frac{1}{\lambda} e^{-x/\lambda}, x > 0$$

$$E(X) = \int_0^\infty x \cdot \frac{1}{\lambda} e^{-x/\lambda} dx = \lambda. //$$

(e.g.) $X \sim B(n, p)$

$$\begin{aligned} E(X) &= \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k} = \sum_{k=1}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k} = \sum_{k=1}^n k \times \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k} \\ &= \sum_{k=1}^n \frac{(n-1)!}{(k-1)!(n-1-(k-1))!} p^{k-1} (1-p)^{n-1-(k-1)} \times np = \sum_{k=0}^{n-1} B(n-1, p) \times np = np, \end{aligned}$$

(e.g.) $X \sim \text{Cauchy}(0, 1)$

$$f_X(x) = \frac{1}{\pi(1+x^2)}, \quad x \in \mathbb{R}.$$

$$E(X) = \int_{-\infty}^{\infty} x \cdot \frac{1}{\pi(1+x^2)} dx = \infty. //$$

Thm: (see Thm 2.2.5 in page 57).

Pf. (HW)

(e.g.) $\downarrow_a E(x-a)^2$

sol. $E(x-a)^2 = E x^2 - 2a E(x) + a^2$

$$\frac{d}{da} E(x-a)^2 = -2E(x) + 2a = 0 \quad \therefore a^* = \arg \min_a E(x-a)^2 = E(x). //$$

2.3 Moments and moment generating functions

Defn. $\mu_n' = E X^n$ (n -th moment of a r.v. X)

$\mu_n = E(X - \mu)^n$ (n -th central moment of a r.v. X)

where $\mu = \mu_1' = E(X)$.

Defn $\text{Var}(X) = E(X - Ex)^2$. (variance of a r.v. X)

Th^m: $\text{Var}(aX+b) = a \text{Var}(X)$.

If (Hw).

Def: $M_X(t) = E e^{tX}$ (the moment generating function of a nr. X).
 provided that the expectation exists for t in some nbhd. of 0 .
 "neighborhood"

Thm: $E X^n = M_X^{(n)}(0)$?

pf: $M'_X(t) = \frac{d}{dt} \int_{\mathbb{R}} e^{tx} f_X(x) dx = \int_{\mathbb{R}} \frac{d}{dt} e^{tx} f_X(x) dx = \int_{\mathbb{R}} e^{tx} x f_X(x) dx$

$M'_X(0) = \int_{\mathbb{R}} e^{0x} x f_X(x) dx = \int_{\mathbb{R}} x f_X(x) dx = \mu'_1$.

$M_X^{(n)}(t) = \frac{d^n}{dt^n} \int_{\mathbb{R}} e^{tx} f_X(x) dx = \int_{\mathbb{R}} \frac{d^n}{dt^n} e^{tx} f_X(x) dx = \int_{\mathbb{R}} e^{tx} x^n f_X(x) dx //$

$M_X^{(n)}(0) = \int_{\mathbb{R}} e^{0x} x^n f_X(x) dx = \int_{\mathbb{R}} x^n f_X(x) dx = \mu'_n //$

$$(e.g.) \quad X \sim f_X(x) = \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta}, \quad x > 0$$

$$\begin{aligned} M_X(t) &= E e^{tX} = \int_0^\infty e^{tx} \cdot \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta} dx \\ &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \int_0^\infty x^{\alpha-1} e^{-\underbrace{(1/\beta-t)x}_{>0}} dx \quad i.e. \quad t < 1/\beta \\ &= \frac{\Gamma(\alpha)(1/\beta-t)^{-\alpha}}{\Gamma(\alpha)\beta^\alpha} \int_0^\infty \text{Gamma}(\alpha, (1/\beta-t)^{-1}) dx \\ &= (1 - \beta t)^{-\alpha}, \quad t < 1/\beta. \end{aligned}$$

$$E(X) = M'_X(t) \Big|_{t=0} = -\alpha(1 - \beta t)^{-\alpha-1} \cdot (-\beta) \Big|_{t=0} = \alpha\beta,$$

$$\begin{aligned}
 (\text{e.g.}) \quad B(n, p) : M_X(t) &= \sum_{x=0}^n e^{tx} \binom{n}{x} p^x (1-p)^{n-x} = \sum_{x=0}^n \binom{n}{x} (pe^t)^x (1-p)^{n-x} \\
 &= (pe^t + (1-p))^n
 \end{aligned}$$

nonuniqueness of moments : (see Example 2.3.10 in page 64)

(i) Bounded support \rightarrow the moments uniquely determines the distribution.

(ii) mgf exists in a nbhd. of 0 \rightarrow the moments uniquely determines the dist
no matter what its support.

Thm: x_1, x_2, \dots , a seq. of r.v.'s, each with mgf $M_1(t), M_2(t), \dots$

$\lim_{i \rightarrow \infty} M_i(t) = M(t)$ for all $t \in \text{nbhd of } 0$ and $M(t)$ is an mgf

$\Rightarrow \exists 1 \text{ cdf } F_X \text{ corresponding to } M(\cdot) \text{ s.t. } F_{x_i}(x) \xrightarrow{i \uparrow \infty} F_X(x)$.

Thm: $M_{ax+b}(t) = e^{bt} M_x(at)$

(pf. I trivial.)

(e.g.) $X \sim B(n, p)$, n is very large and p is small ...
 np is still small, but $np \approx \lambda$.

$$M_X(t) = (pe^t + 1-p)^n \underset{(p=\lambda/n)}{\approx} \left(\frac{\lambda(e^t - 1)}{n} + 1\right)^n \approx e^{\lambda(e^t - 1)} : \text{Poisson}(\lambda)$$

(Poisson approx.)

c.f. (Cumulative generating function)

$$\log M_X(t)$$

c.f. (characteristic function)

$$E e^{itX}$$