ECE 361 Probability for Engineers (Fall, 2016) Lecture 7b

§4.1 Derived distributions

Let the RV Y be a function Y = g(X) of a continuous RV X. We aim to calculate the PDF of Y, which we call the *derived* distribution. The two steps to doing this are:

Calculation of the PDF of Y = g(X) of a continuous RV X.

1. Calculate the CDF F_Y using:

$$F_Y(y) = \mathbb{P}(g(X) \le y) = \int_{x:g(x) \le y} f_X(x) dx. \tag{1}$$

2. Differentiate to obtain the PDF f_Y via:

$$f_Y(y) = \frac{\mathrm{d}}{\mathrm{d}y} F_Y(y). \tag{2}$$

Example. Let X be uniform over [0,1] and $Y=\sqrt{X}$:

$$F_Y(y) = \mathbb{P}(Y \le y) = \mathbb{P}(\sqrt{X} \le y) = \mathbb{P}(X \le y^2) = y^2. \tag{3}$$

Thus:

$$f_Y(y) = \frac{\mathrm{d}}{\mathrm{d}y} F_Y(y) = 2y, \ 0 \le y \le 1.$$
 (4)

See Fig. 1.

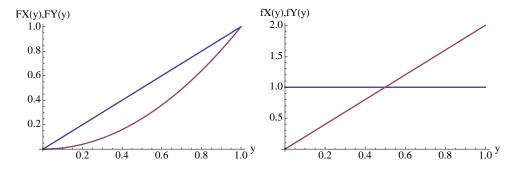


Figure 1: The CDF (left) and the PDF (right) for X (blue) and $Y = \sqrt{X}$.

Example. John Slow drives 180 miles from Boston to New York City at a constant speed, where the speed is uniformly chosen at random between 30 and 60 mph. What is the PDF of the trip duration?

Let $X \sim \text{Uni}(30,60)$ be the speed and Y = 180/X the duration. The CDF for Y is:

$$\mathbb{P}(Y \le y) = \mathbb{P}\left(\frac{180}{X} \le y\right) = \mathbb{P}\left(X \ge \frac{180}{y}\right) = 1 - F_X(180/y), \ 3 \le y \le 6.$$
 (5)

Now:

$$F_X(x) = \frac{x - 30}{30}, \ 30 \le x \le 60,$$
 (6)

so that

$$F_Y(y) = 1 - F_X(180/y) = 1 - \frac{180/y - 30}{30} = 2 - 6/y, \ 3 \le y \le 6.$$
 (7)

Now differentiate to obtain:

$$f_Y(y) = \frac{6}{y^2}, \ 3 \le y \le 6.$$
 (8)

See Fig. 2.

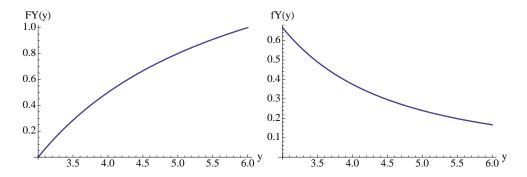


Figure 2: The CDF (left) and the PDF (right) for the trip duration in the example.

Example. Let $Y = X^2$ where X is an RV with known PDF. Then:

$$F_Y(y) = \mathbb{P}(Y \le y) = \mathbb{P}(X^2 \le y) = \mathbb{P}(-\sqrt{y} \le X \le \sqrt{y}) = F_X(\sqrt{y}) - F_X(-\sqrt{y}), \ y \ge 0.$$
 (9)

Differentiation gives:

$$f_Y(y) = \frac{1}{2\sqrt{y}} \left(f_X(\sqrt{y}) + f_X(-\sqrt{y}) \right).$$
 (10)

The linear case

Let Y = aX + b. Suppose a > 0. Then:

$$F_Y(y) = \mathbb{P}(Y \le y) = \mathbb{P}(aX + b \le y) = \mathbb{P}\left(X \le \frac{y - b}{a}\right) = F_X\left(\frac{y - b}{a}\right)$$
(11)

and

$$f_Y(y) = \frac{1}{a} f_X\left(\frac{y-b}{a}\right). \tag{12}$$

The case for a < 0 is similar. We find:

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right). \tag{13}$$

Example. Let $X \sim \text{Exp}(\lambda)$ and Y = aX + b. Then:

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right) = \begin{cases} \frac{\lambda}{|a|} e^{-\lambda \frac{y-b}{a}}, & \frac{y-b}{a} \ge 0\\ 0, & \text{else} \end{cases}$$
 (14)

Example. Let $X \sim N(\mu, \sigma)$ and Y = aX + b. Then:

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right) = \frac{1}{|a|} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\left(\frac{y-b}{a}-\mu\right)^2}{2\sigma^2}} = \frac{1}{\sqrt{2\pi}(|a|\sigma)} e^{-\frac{\left(y-(a\mu+b)\right)^2}{2(|a|\sigma)^2}}.$$
 (15)

Thus $Y \sim N(a\mu + b, |a|\sigma)$. We can obtain the same result a different way. Recall that for $X \sim N(\mu, \sigma)$ we have $\mathbb{E}[X] = \mu$ and $\text{var}(X) = \sigma^2$. Further, recall that for Y = aX + b we have $\mathbb{E}[Y] = a\mathbb{E}[X] + b$ and $\text{var}(Y) = a^2\sigma^2$ (for any X, not just normal). Further recall that linear functions of normal RVs are normal RVs, so we know Y = aX + b is normal. Combining, we must conclude that $Y \sim N(a\mu + b, |a|\sigma)$.

The monotonic case

A strictly monotonic function g is of one of two types: i) increasing $(x < y \Rightarrow g(x) < g(y))$, or ii) decreasing $(x < y \Rightarrow g(x) > g(y))$. We will restrict our attention in this subsection to continuous strictly monotonic functions, which have an inverse function: y = g(x) iff x = h(y). Examples:

$$g(x) = \frac{c}{x}, h(y) = \frac{c}{y}, \quad g(x) = ax + b, h(y) = \frac{y - b}{a}, \quad g(x) = e^{ax}, h(y) = \frac{1}{a} \log y.$$
 (16)

The main result is that we can directly compute the PDF of Y = g(X) for strictly monotonic g.

PDF for a strictly monotonic function of a continuous RV. Let g be strictly monotonic with inverse h, i.e., y = g(x) iff x = h(y). Then

$$f_Y(y) = f_X(h(y)) \left| \frac{\mathrm{d}}{\mathrm{d}y} h(y) \right|. \tag{17}$$

The proof is straightforward. For increasing g

$$F_Y(y) = \mathbb{P}(g(X) \le y) = \mathbb{P}(X \le h(y)) = F_X(h(y)) \Rightarrow f_Y(y) = f_X(h(y)) \frac{\mathrm{d}}{\mathrm{d}y} h(y). \tag{18}$$

The proof for decreasing g is similar. See Fig. 4.3.

Example. Let $Y = X^2$ for $X \sim \text{Uni}[0,1]$. Thus g is strictly increasing with inverse $h(y) = \sqrt{y}$ and:

$$f_Y(y) = f_X(h(y)) \left| \frac{\mathrm{d}}{\mathrm{d}y} h(y) \right| = 1 \left| \frac{1}{2\sqrt{y}} \right| = \frac{1}{2\sqrt{y}}, \ y \in [0, 1].$$
 (19)

References

[1] Introduction to Probability, 2nd Edition by Dimitri P. Bertsekas and John N. Tsitsiklis, Athina Scientific Press, 2008.