Lecture 15: Sept 23

Last time

- Transformations of Random Variables

Today

- One-page one-sided letter-size cheat sheet for midterm 1
- Transformations of Random Variables
- Expected Values

Transformations of Random Variables

Example (Linear transformation) Suppose X is a continuous random variable with pdf $f_X(x)$. Let

$$Y = a + bX, \quad \frac{dy}{dx} = b.$$

Then

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

This transformation is often used when X has mean 0 and standard deviation 1. The linear transformation above creates a random variable Y with a distribution that has the same shape as that of X but has mean a and variance b^2.

Conversely, if Y has mean a and standard deviation b, then $X = (Y-a)/b$ has mean 0 and standard deviation 1. This is called sometimes the "Studentized" transformation.

Example (Normal distribution) Let $X \sim N(0, 1)$:

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad -\infty < x < \infty.$$

The transformation

$$Y = \mu + \sigma X, \quad X = \frac{Y-\mu}{\sigma}$$

yields

$$f_Y(y) = f_X(\frac{y-\mu}{\sigma})\frac{1}{\sigma} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}}.$$

More generally, a distribution is a member of the class of *location-scale* distributions if the distribution of a linear transformation of a random variable with that distribution has the same distribution, but with different parameters.

Example (Square root of an exponential RV) Suppose $X \sim exp(\lambda)$, so that

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \geqslant 0 \\ 0 & otherwise \end{cases}$$

and consider the distribution of $Y = \sqrt{X}$. The transformation

$$y = g(x) = \sqrt{x}, \quad x \geqslant 0$$

is one-to-one and has an inverse $x = y^2$ with $dx/dy = 2y$. Thus
This distribution is a particular form of the Rayleigh distribution and is a special case of the Weibull distribution.

Theorem (Probability integral transformation) Let X have continuous cdf $F_X(x)$ and define the random variable Y as $Y = F_X(X)$. Then Y is uniformly distributed on $(0, 1)$, that is, $\Pr(Y \leqslant y) = y, 0 < y < 1$.

Before we prove this theorem, we will digress for a moment and look at F_X^{-1}, the inverse of the cdf F_X, in some detail. If F_X is strictly increasing, then F_X^{-1} is well defined by

$$F_X^{-1}(y) = x \iff F_X(x) = y.$$

However, if F_X is constant on some interval, then F_X^{-1} is not well defined as Figure 14.1 illustrates. Any $x_1 \leqslant x \leqslant x_2$ satisfies $F_X(x) = y$

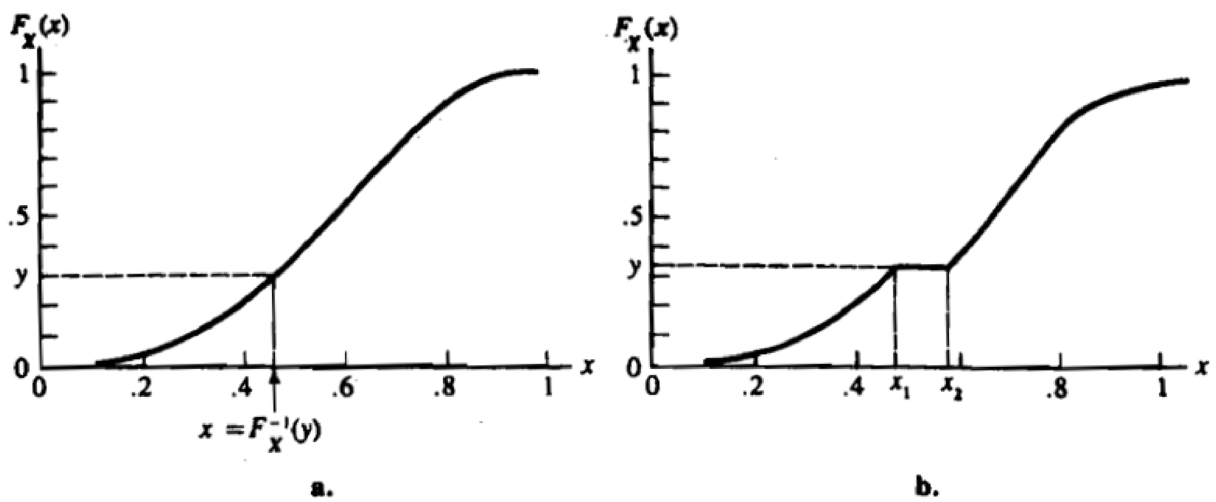

Figure 14.1: Figure 2.1.2. (a) $F_X(x)$ strictly increasing; (b) $F_X(x)$ nondecreasing

This problem is avoided by defining F_X^{-1} for $0 < y < 1$ by

$$F_X^{-1}(y) = \inf\{x : F_X(x) \geqslant y\}.$$

With this definition, for Figure 14.1(b), we have $F_X^{-1}(y) = x_1$.
Proof:

One application of the probability integral transformation is in the generation of random samples from a particular distribution. If it is required to generate an observation X from a population with cdf F_X, we need only generate a uniform random number U, between 0 and 1, and solve for x in the equation $F_X(x) = u$.

Expected Values

Definition The *expected value* or *mean* of a random variable $g(X)$, denoted by $Eg(X)$, is

$$Eg(X) = \begin{cases} \int\limits_{-\infty}^{\infty} g(x)f(x)dx & \text{if } X \text{ is continuous} \\ \sum\limits_{x\in\mathcal{X}} g(x)\Pr(X = x) & \text{if } X \text{ is discrete} \end{cases}$$

Provided the integral or summation exists.

If we let $g(X) = X$, then we get

$$EX = \begin{cases} \int\limits_{-\infty}^{\infty} xf(x)dx & \text{if } X \text{ is continuous} \\ \sum\limits_{x\in\mathcal{X}} x\Pr(X = x) & \text{if } X \text{ is discrete} \end{cases}$$

Example (Exponential mean) Suppose X has an *exponential (λ) distribution*, $X \sim Exp(\lambda)$, that is, it has pdf given by

$$f_X(x) = \frac{1}{\lambda}e^{-x/\lambda}, \quad 0 \leqslant x < \infty, \lambda > 0.$$

Find out EX.
Solution: