

MODULE 5

SOME SPECIAL ABSOLUTELY CONTINUOUS DISTRIBUTIONS

LECTURE 21

Topics

5.1 UNIFORM OR RECTANGULAR DISTRIBUTION

5.1.1 Quantile function and uniform distribution

5.2 GAMMA AND RELATED DISTRIBUTIONS

Lemma 1.1

Let X be a random variable having distribution function $F_X(\cdot)$ and quantile function $Q_X(\cdot)$. Let $x \in \mathbb{R}$, $p \in (0, 1)$ and $0 < p_1 < p_2 < 1$. Then

- (i) $Q_X(F_X(x)) \leq x$, provided $0 < F_X(x) < 1$;
- (ii) $F_X(Q_X(p)) \geq p$;
- (iii) $F_X(Q_X(p)) = p$, provided there exists an $x_0 \in \mathbb{R}$ such that $F_X(x_0) = p$. In particular if $F_X(\cdot)$ is continuous then $F_X(Q_X(p)) = p$;
- (iv) $Q_X(p) \leq x \Leftrightarrow F_X(x) \geq p$;
- (v) $Q_X(p) = F_X^{-1}(p)$, provided $F_X^{-1}(p)$ exists;
- (vi) $Q_X(p_1) \leq Q_X(p_2)$.

Proof. For $p \in (0, 1)$, define

$$S_p = \{s \in \mathbb{R}: F_X(s) \geq p\},$$

so that $Q_X(p) = \inf S_p$, $p \in (0, 1)$.

- (i) Let $x \in \mathbb{R}$ be such that $0 < F_X(x) < 1$. Then $x \in S_{F_X(x)} = \{s \in \mathbb{R}: F_X(s) \geq F_X(x)\}$ and, therefore, $x \geq \inf S_{F_X(x)} = Q(F_X(x))$, i.e., $Q_X(F_X(x)) \leq x$.
- (ii) Let $p \in (0, 1)$. Then $Q_X(p) = \inf S_p$. Thus there exists a sequence $\{t_n: n = 1, 2, \dots\}$ in S_p such that $\lim_{n \rightarrow \infty} t_n = Q_X(p)$. Consequently $t_n \geq Q_X(p)$, $n = 1, 2, \dots$ and $F_X(t_n) \geq p$, $n = 1, 2, \dots$. This implies that $\lim_{n \rightarrow \infty} F_X(t_n) \geq p$. Since $F_X(\cdot)$ is right continuous, $t_n \geq Q_X(p)$, $n = 1, 2, \dots$ and $\lim_{n \rightarrow \infty} t_n = Q_X(p)$, we get

$$F_X(Q_X(p)) = \lim_{n \rightarrow \infty} F_X(t_n) \geq p.$$

- (iii) Let $x_0 \in \mathbb{R}$ be such that $F_X(x_0) = p$. Then

$$x_0 \in S_p = \{s \in \mathbb{R}: F_X(s) \geq p\}$$

$$\Rightarrow x_0 \geq \inf S_p = Q_X(p).$$

Now using (ii) and the fact that $F_X(\cdot)$ is non-decreasing, we get

$$p = F_X(x_0) \geq F_X(Q_X(p)) \geq p$$

$$\Rightarrow F_X(Q_X(p)) = p.$$

Note that $\lim_{x \rightarrow -\infty} F_X(x) = 0$ and $\lim_{x \rightarrow \infty} F_X(x) = 1$. Thus if $F_X(\cdot)$ is continuous then the intermediate value property of continuous functions implies that there exists an $x_0 \in \mathbb{R}$ such that $F_X(x_0) = p \in (0, 1)$ and therefore $F_X(Q_X(p)) = p$.

- (iv) First suppose that $Q_X(p) = \inf S_p \leq x$. Then, since $F_X(\cdot)$ is non-decreasing, we have

$$F_X(Q_X(p)) \leq F_X(x)$$

$$\Rightarrow p \leq F_X(x). \quad (\text{using (ii)})$$

Now suppose that $F_X(x) \geq p$. Then $x \in S_p = \{s \in \mathbb{R}: F_X(s) \geq p\}$ and, therefore,

$$x \geq \inf S_p = Q_X(p).$$

- (v) Since $p_1 < p_2$, we have

$$S_{p_2} = \{s \in \mathbb{R}: F_X(s) \geq p_2\} \subseteq \{s \in \mathbb{R}: F_X(s) \geq p_1\} = S_{p_1}$$

$$\Rightarrow S_{p_2} \subseteq S_{p_1}$$

$$\Rightarrow Q_X(p_1) = \inf S_{p_1} \leq \inf S_{p_2} = Q_X(p_2). \quad \blacksquare$$

Theorem 1.3

Let X be a random variable with distribution function $F_X(\cdot)$ and quantile function $Q_X(\cdot)$.

- (i) (**Probability Integral Transformation**) If the random variable X is of continuous type then $Y \stackrel{\text{def}}{=} F_X(X) \sim U(0, 1)$;
- (ii) Let $U \sim U(0, 1)$. Then $Z \stackrel{\text{def}}{=} Q_X(U) \stackrel{d}{=} X$.

Proof.

- (i) Let $G(\cdot)$ be the d.f. of $Y \stackrel{\text{def}}{=} F_X(X)$, i.e.,

$$G(y) = P(\{F_X(X) \leq y\}), \quad y \in \mathbb{R}.$$

Clearly, for $y < 0$, $G(y) = 0$ and, for $y \geq 1$, $G(y) = 1$. Now suppose that $y \in (0, 1)$. By Lemma 1.1 (iv) we have

$$\{s \in \mathbb{R}: F_X(s) \geq y\} = \{s \in \mathbb{R}: s \geq Q_X(y)\}$$

$$\Rightarrow P(\{F_X(X) \geq y\}) = P(\{X \geq Q_X(y)\})$$

$$\Rightarrow P(\{F_X(X) < y\}) = P(\{X < Q_X(y)\})$$

$$\Rightarrow P(\{F_X(X) < y\}) = P(\{X \leq Q_X(y)\}). \quad (\text{since } F_X(\cdot) \text{ is continuous}) \quad (1.4)$$

Since $F_X(\cdot)$ is continuous $\{x \in \mathbb{R}: F_X(x) = y\} = [x_1, x_2]$, for some real numbers x_1 and x_2 such that $-\infty < x_1 \leq x_2 < \infty$ (see Figures 1.5 (a) & (b)).

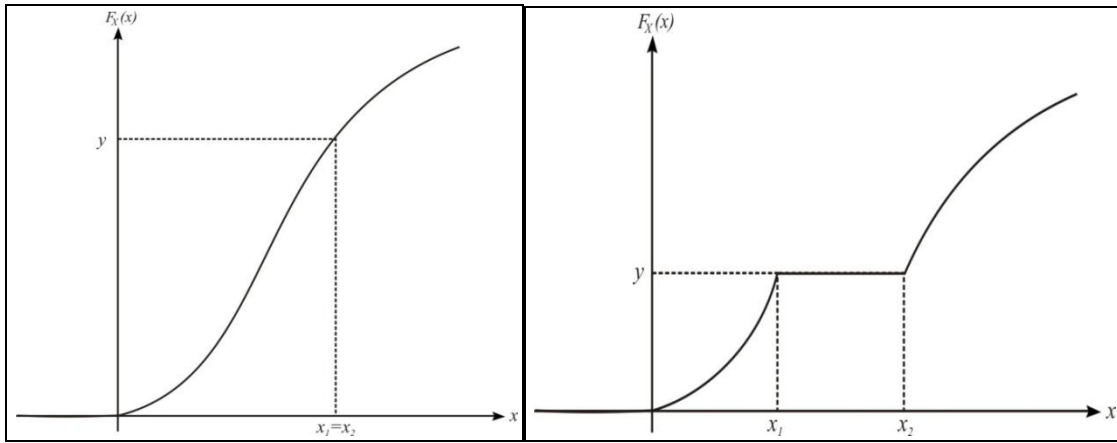


Figure 1.5 (a)

Figure 1.5 (b)

Thus, for $y \in (0, 1)$,

$$\begin{aligned} P(\{F_X(X) = y\}) &= P(\{x_1 \leq X \leq x_2\}) \\ &= F_X(x_2) - F_X(x_1) \\ &= y - y = 0. \end{aligned} \quad (1.5)$$

Using (1.4), (1.5) and Lemma 1.1 (iii) we get, for $y \in (0, 1)$,

$$G(y) = P(\{F_X(X) \leq y\}) = P(\{F_X(X) < y\}) = P(\{X \leq Q_X(y)\}) = y.$$

Also right continuity of d.f. $G(\cdot)$ implies that

$$G(0) = \lim_{x \downarrow 0} G(x) = \lim_{x \downarrow 0} x = 0.$$

Therefore we have

$$G(y) = \begin{cases} 0, & \text{if } y < 0 \\ y, & \text{if } 0 \leq y < 1, \\ 1, & \text{if } y \geq 1 \end{cases}$$

i. e., $Y \stackrel{\text{def}}{=} F_X(X) \sim U(0, 1)$.

- (ii) Let $U \sim U(0, 1)$, so that $P(\{U \leq u\}) = u, \forall u \in [0, 1]$ and $P(\{0 < U < 1\}) = 1$. Then the d.f. of $Z \stackrel{\text{def}}{=} Q_X(U)$ is

$$\begin{aligned}
 H(z) &= P(\{Z \leq z\}) \\
 &= P(\{Q_X(U) \leq z\}) \\
 &= P(\{Q_X(U) \leq z, 0 < U < 1\}) \text{ (since } P(\{0 < U < 1\}) = 1) \\
 &= P(\{F_X(z) \geq U, 0 < U < 1\}) \text{ (using Lemma 1.1 (iv))} \\
 &= P(\{U \leq F_X(z)\}) \\
 &= F_X(z), \quad z \in \mathbb{R} \\
 &\Rightarrow Z \stackrel{d}{=} X. \blacksquare
 \end{aligned}$$

Remark 1.3

The above theorem provides a method to generate observations from any arbitrary distribution using observations from $U(0, 1)$ distribution. Suppose that we require an observation X from a distribution having known d.f. $F(\cdot)$ and quantile function $Q(\cdot)$. To do so, the above theorem suggests that, generate an observation U from the $U(0, 1)$ distribution and take $X = Q(U)$. ■

Example 1.2

Using a random observation $U \sim U(0, 1)$, describe a method to generate a random observation X from the distribution having

- (i) probability density function

$$f(x) = \frac{e^{-|x|}}{2}, -\infty < x < \infty;$$

- (ii) probability mass function

$$g(x) = \begin{cases} \binom{n}{x} \theta^x (1 - \theta)^{n-x}, & \text{if } x \in \{0, 1, \dots, n\}, \\ 0, & \text{otherwise} \end{cases}$$

where $n \in \mathbb{N}$ and $\theta \in (0, 1)$ are real constants.

Solution.

- (i) For $x < 0$, we have

$$\begin{aligned}
 F(x) &= P(\{X \leq x\}) \\
 &= \int_{-\infty}^x f_X(t) dt
 \end{aligned}$$

$$\begin{aligned}
&= \int_{-\infty}^x \frac{e^t}{2} dt \\
&= \frac{e^x}{2},
\end{aligned}$$

and, for $x \geq 0$, we have

$$\begin{aligned}
F(x) &= P(\{X \leq x\}) \\
&= \int_{-\infty}^x f_X(t) dt \\
&= \int_{-\infty}^0 f_X(t) dt + \int_0^x f_X(t) dt \\
&= \int_{-\infty}^0 \frac{e^t}{2} dt + \int_0^x \frac{e^{-t}}{2} dt \\
&= 1 - \frac{e^{-x}}{2}.
\end{aligned}$$

Thus the d.f. of X is given by

$$F(x) = \begin{cases} \frac{e^x}{2}, & \text{if } x < 0 \\ 1 - \frac{e^{-x}}{2}, & \text{if } x \geq 0 \end{cases},$$

and the q.f. of X is given by

$$Q(p) = F^{-1}(p) = \begin{cases} \ln(2p), & \text{if } 0 < p < \frac{1}{2} \\ -\ln(2(1-p)), & \text{if } \frac{1}{2} \leq p < 1 \end{cases}.$$

Using Theorem 1.3 (ii) the desired random observation is given by

$$X = Q(U) = \begin{cases} \ln(2U), & \text{if } 0 < U < \frac{1}{2} \\ -\ln(2(1-U)), & \text{if } \frac{1}{2} \leq U < 1 \end{cases}.$$

(ii) The distribution function of X is given by

$$G(x) = \begin{cases} 0, & \text{if } x < 0 \\ \sum_{j=0}^k \binom{n}{j} \theta^j (1-\theta)^{n-j}, & \text{if } k \leq x < k+1; \quad k = 0, 1, \dots, n-1, \\ 1, & \text{if } x \geq n \end{cases}$$

and the quantile function of X is given by

$$Q(p) = \inf\{s \in \mathbb{R}: G(s) \geq p\}$$

$$= \begin{cases} 1, & \text{if } 0 < p \leq (1 - \theta)^n \\ k, & \text{if } \sum_{j=0}^{k-1} \binom{n}{j} \theta^j (1 - \theta)^{n-j} < p \leq \sum_{j=0}^k \binom{n}{j} \theta^j (1 - \theta)^{n-j} ; \\ & k = 0, 1, \dots, n - 1 \\ n, & \text{if } \sum_{j=0}^{n-1} \binom{n}{j} \theta^j (1 - \theta)^{n-j} < p < 1 \end{cases} .$$

Now, using Theorem 1.3 (ii), the desired random observation is given by

$$X = \begin{cases} 1, & \text{if } 0 < U \leq (1 - \theta)^n \\ k, & \text{if } \sum_{j=0}^{k-1} \binom{n}{j} \theta^j (1 - \theta)^{n-j} < U \leq \sum_{j=0}^k \binom{n}{j} \theta^j (1 - \theta)^{n-j} ; \\ & k = 0, 1, \dots, n - 1 \\ n, & \text{if } \sum_{j=0}^{n-1} \binom{n}{j} \theta^j (1 - \theta)^{n-j} < U < 1 \end{cases} .$$

5.2 GAMMA AND RELATED DISTRIBUTIONS

We begin this section with the definition of gamma function.

Definition 2.1

The function $\Gamma: (0, \infty) \rightarrow (0, \infty)$, defined by,

$$\Gamma(\alpha) = \int_0^{\infty} e^{-t} t^{\alpha-1} dt, \quad \alpha > 0$$

is called the *gamma function*. ■

To examine convergence of the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt, \quad \alpha \in \mathbb{R},$$

consider the following cases.

Case I $\alpha \leq 0$

In this case the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

will converge if, and only if, both the integrals

$$\int_0^1 e^{-t} t^{\alpha-1} dt \text{ and } \int_1^{\infty} e^{-t} t^{\alpha-1} dt$$

converge. Note that, for $\alpha \leq 0$,

$$e^{-t} t^{\alpha-1} \geq \frac{t^{\alpha-1}}{e}, \quad \forall t \in (0,1)$$

and the integral

$$\int_0^1 t^{\alpha-1} dt$$

diverges. This implies that, for $\alpha \leq 0$, the integral

$$\int_0^1 e^{-t} t^{\alpha-1} dt$$

diverges. Consequently the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

diverges for $\alpha \leq 0$.

Case II $0 < \alpha < 1$

In this case again the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

will converge if, and only if, both the integrals

$$\int_0^1 e^{-t} t^{\alpha-1} dt \text{ and } \int_1^{\infty} e^{-t} t^{\alpha-1} dt$$

converge. Note that, for $\alpha > 0$,

$$0 \leq e^{-t} t^{\alpha-1} \leq t^{\alpha-1}, \quad \forall t \in (0,1)$$

and the integral

$$\int_0^1 t^{\alpha-1} dt$$

is convergent. Therefore the integral

$$\int_0^1 e^{-t} t^{\alpha-1} dt$$

is convergent for any $\alpha > 0$.

Now let us examine the convergence of the integral

$$\int_1^{\infty} e^{-t} t^{\alpha-1} dt.$$

Fix $\alpha \in \mathbb{R}$ and choose $k_0 \in \mathbb{N}$ such that $k_0 > \alpha$. Then we know that

$$e^t \geq \frac{t^{k_0}}{k_0!}, \quad \forall t > 0$$

$$\Rightarrow 0 \leq e^{-t} t^{\alpha-1} \leq \frac{k_0!}{t^{k_0-\alpha+1}}, \quad \forall t > 0.$$

Also $k_0 - \alpha + 1 > 1$ and, therefore, the integral

$$\int_1^{\infty} \frac{1}{t^{k_0-\alpha+1}} dt$$

converges. Consequently

$$\int_1^{\infty} e^{-t} t^{\alpha-1} dt$$

converges for any $\alpha \in \mathbb{R}$. From the above discussion it follows that the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

converges for $0 < \alpha < 1$.

Case III $\alpha \geq 1$

In this case the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

will converge if, and only if, the integral

$$\int_1^{\infty} e^{-t} t^{\alpha-1} dt$$

converges. We have seen in the Case II above that the integral

$$\int_1^{\infty} e^{-t} t^{\alpha-1} dt$$

converges for any $\alpha \in \mathbb{R}$.

On combining cases I – III we conclude that the integral

$$\int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

converges if, and only if, $\alpha > 0$.

Using integration by parts, for $\alpha > 0$, we have

$$\begin{aligned} \Gamma(\alpha + 1) &= \int_0^{\infty} e^{-t} t^{\alpha} dt \\ &= [-e^{-t} t^{\alpha}]_0^{\infty} + \alpha \int_0^{\infty} e^{-t} t^{\alpha-1} dt \end{aligned}$$

$$= \alpha \int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

$$\text{i. e., } \boxed{\Gamma(\alpha + 1) = \alpha \Gamma(\alpha), \alpha > 0.} \quad (2.1)$$

Note that

$$\Gamma(1) = \int_0^{\infty} e^{-t} dt = 1. \quad (2.2)$$

For $n \in \mathbb{N}$, using (2.1) and (2.2), we have

$$\Gamma(n + 1) = n \Gamma(n) = n(n - 1) \Gamma(n - 1) = \cdots = n(n - 1) \cdots 3 \cdot 2 \cdot 1 \Gamma(1) = n!. \quad (2.3)$$

On combining (2.1), (2.2) and (2.3) we get

$$\boxed{\Gamma(n) = (n - 1)!, \quad n \in \mathbb{N},} \quad (2.4)$$

with the convention that $0! = 1$.

We have

$$\begin{aligned} \Gamma\left(\frac{1}{2}\right) &= \int_0^{\infty} e^{-t} t^{-1/2} dt \\ &= 2 \int_0^{\infty} e^{-x^2} dx \\ \Rightarrow \left(\Gamma\left(\frac{1}{2}\right)\right)^2 &= 4 \left[\int_0^{\infty} e^{-x^2} dx \right] \left[\int_0^{\infty} e^{-y^2} dy \right] \\ &= 4 \int_0^{\infty} \int_0^{\infty} e^{-(x^2+y^2)} dx dy. \end{aligned}$$

On making the transformation $x = r \cos \theta$ and $y = r \sin \theta$ in the above integral (so that the Jacobian of the transformation is r), we have

$$\left(\Gamma\left(\frac{1}{2}\right)\right)^2 = 4 \int_0^{\infty} \int_0^{\pi/2} r e^{-r^2} d\theta dr$$

$$\begin{aligned}
&= 2\pi \int_0^{\infty} r e^{-r^2} dr \\
&= \pi \int_0^{\infty} e^{-t} dt \\
&= \pi.
\end{aligned}$$

Since

$$\Gamma\left(\frac{1}{2}\right) = \int_0^{\infty} e^{-t} t^{1/2-1} dt \geq 0,$$

we get

$$\boxed{\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}} \quad (2.5)$$

Also, using (2.1),

$$\Gamma\left(\frac{3}{2}\right) = \frac{1}{2} \Gamma\left(\frac{1}{2}\right) = \frac{\sqrt{\pi}}{2},$$

and

$$\Gamma\left(\frac{5}{2}\right) = \frac{3}{2} \cdot \frac{1}{2} \Gamma\left(\frac{1}{2}\right) = \frac{1 \cdot 3}{2^2} \sqrt{\pi},$$

In general

$$\boxed{\Gamma\left(\frac{2n+1}{2}\right) = \frac{1 \cdot 3 \cdot 5 \cdots (2n-1)}{2^n} \sqrt{\pi}, \quad n \in \mathbb{N},} \quad (2.6)$$

i.e., for $n \in \mathbb{N}$,

$$\boxed{\Gamma\left(\frac{2n+1}{2}\right) = \frac{(2n)!}{n! 4^n} \sqrt{\pi}, \quad n \in \mathbb{N}.} \quad (2.7)$$