

# May 14 Lec—Linear Trans. of Random Variables, Uniform Cont., Normal, Gamma

Quiz 2 is tonight/tomorrow morning, on Chapter 3.

Continuing the discussion of uniform distributions:

## Proposition (linear transformations of random variables)

If  $Y = \alpha X + \beta$ ,  $\alpha \neq 0$ , the pdf of  $X$  and  $Y$  are linked through the equation

$$f_Y(y) = \frac{1}{|\alpha|} f_X\left(\frac{y - \beta}{\alpha}\right)$$

### Proof

Case 1:  $\alpha < 0$ . The case  $\alpha > 0$  is left as an exercise.

We have

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(\alpha X + \beta \leq y) \\ &= P\left(X \geq \frac{y - \beta}{\alpha}\right) \end{aligned}$$

(notice that we switched the sign of the inequality because  $\alpha < 0$ )

$$\begin{aligned} &= 1 - P\left(X \leq \frac{y - \beta}{\alpha}\right) \\ &= 1 - F_X\left(\frac{y - \beta}{\alpha}\right) \end{aligned}$$

So the pdf of  $Y$  is

$$f_Y(y) = F'_Y(y) = \frac{d}{dy} \left[ 1 - F_X\left(\frac{y - \beta}{\alpha}\right) \right]$$

Applying the Chain Rule (and making the ghastly assumption that

$\frac{d}{dx}F_X = f_X$  exists at  $y$ ), we have

$$\begin{aligned}f_Y(y) &= -\frac{1}{\alpha}F'_X\left(\frac{y-\beta}{\alpha}\right) \\&= -\frac{1}{\alpha}f_X\left(\frac{y-\beta}{\alpha}\right)\end{aligned}$$

By the definition of absolute value,

$$\frac{1}{|\alpha|}f_X\left(\frac{y-\beta}{\alpha}\right)$$

Back to the uniform distribution:

### Remark

If  $X \sim U(a, b)$  then  $Y = \frac{1}{b-a}(X - a) \sim U(0, 1)$  (i.e.  $X = (b - a)Y + a$ )

### Proof

Apply the previous proposition with

$$f_X(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{otherwise} \end{cases}$$

and  $\alpha = |\frac{1}{b-a}| = \frac{1}{b-a}$  (since we assume  $b > a$ ),  $\beta = \frac{-a}{b-a}$ .

So by the previous proposition,

$$f_Y(y) = \frac{1}{|\alpha|}f_X\left(\frac{y-\beta}{\alpha}\right)$$

We have  $\frac{1}{|\alpha|} = \frac{1}{\alpha} = b - a$ , and

$$\frac{y-\beta}{\alpha} = \frac{1}{\alpha}\left(y + \frac{a}{b-a}\right) = (b-a)\left(y + \frac{a}{b-a}\right) = (b-a)y + a$$

So

$$f_Y(y) = (b-a)f_X((b-a)y + a)$$

### Proposition

If  $X \sim U(a, b)$  then

1.  $\mathbb{E}(X) = \frac{b+a}{2}$
2.  $V(X) = \frac{(b-a)^2}{12}$

### Proof

We have the relationship

$$X = (b - a)Y + a$$

thus

$$\mathbb{E}(X) = (b - a)\mathbb{E}(Y) + a$$

, where  $Y \sim U(0, 1)$

and

$$V(X) = (b - a)^2 V(Y)$$

We have

$$\mathbb{E}(Y) = \int_0^1 y \cdot 1 \, dy = \frac{1}{2}$$

and

$$\mathbb{E}(Y^2) = \int_0^1 y^2 \cdot 1 \, dy = \frac{1}{3}$$

and

$$\begin{aligned} V(Y) &= \mathbb{E}(Y^2) - (\mathbb{E}(Y))^2 \\ &= \frac{1}{3} - \frac{1}{4} = \frac{1}{12} \end{aligned}$$

So

$$\mathbb{E}(X) = (b - a) \cdot \frac{1}{2} + a = \frac{b + a}{2}$$

and

$$V(X) = (b - a)^2 \cdot \frac{1}{12}$$

### Example

Assume  $X \sim U(0, 5)$ .

1. Find  $P(-2 \leq x \leq 3)$ .
2. Find  $\mathbb{E}(X^4)$ .

$$P(-2 \leq X \leq 3) = P(0 \leq X \leq 3) = \frac{1}{5} \cdot (3 - 0) = 0.6$$

The professor ended up showing  $\mathbb{E}(X^5) = \int_0^5 x^5 \cdot \frac{1}{5} dx$ . You can also compute this in another way: since  $X = 5Y$ , we have

$$\mathbb{E}(X^5) = 5^5 \mathbb{E}(Y^5) = 5^5 \mathbb{E}(Y^5) = 5^5 \cdot \int_0^1 y^5 dy = \frac{5^6}{6}.$$

## Normal distribution

### Definition: Normal distribution

We say that a continuous random variable  $X$  has a **normal distribution** with mean  $\mu$  and variance  $\sigma^2$  ( $X \sim N(\mu, \sigma^2)$ ) if the pdf of  $X$  is

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

for all  $x \in \mathbb{R}$ .

The reason for this weird formula is

$$\int_{-\infty}^{\infty} e^{-t^2/2} dt = \sqrt{2\pi}$$

(this can be shown with Calc 3 knowledge). So

$$\Phi_Z(t) := \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dx = 1$$

which is the cdf of the *standard normal distribution* ( $Z \sim N(0,1)$ ).

Accordingly, its pdf is  $f(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}$ .

Because there is no closed form to the integral  $\int_{-\infty}^x e^{-t^2/2} dt$ , the values of  $\Phi_Z(t)$  can only be computed numerically (usually with a table of pre-computed values). But we do know trivially that  $\Phi_Z(0) = \frac{1}{2}$  and  $\Phi_Z(x) + \Phi_Z(-x) = 1$ , by symmetry.

### Proposition

If  $X \sim N(\mu, \sigma^2)$  then  $Z := \frac{X - \mu}{\sigma} \sim N(0,1)$

### Proof

We have

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \quad x \in \mathbb{R}$$

$$\text{and } Z = \underbrace{\frac{1}{\sigma}}_{\alpha} x - \underbrace{\frac{\mu}{\sigma}}_{\beta}.$$

By the proposition we had earlier, we have

$$\begin{aligned} f_Z(z) &= \frac{1}{|\alpha|} f_X\left(\frac{z - \beta}{\alpha}\right) \\ &= \sigma \cdot f_X\left(\left(z + \frac{\mu}{\sigma}\right) \cdot \sigma\right) \\ &= \sigma \cdot f_X(\sigma z + \mu) \\ &= \sigma \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}\left(\frac{\sigma z + \mu - \mu}{\sigma}\right)^2} \\ &= \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{1}{2}z^2} \end{aligned}$$

which is the pdf of a standard normal distribution. So  $Z \sim N(0,1)$ .

### Proposition

If  $X \sim N(\mu, \sigma^2)$  then

1.  $\mathbb{E}(X) = \mu$
2.  $V(X) = \sigma^2$

### Proof

Since  $X = \sigma Z + \mu$  where  $Z \sim N(0,1)$ , proving the above is equivalent to proving that  $\mathbb{E}(Z) = 0$  and  $V(Z) = 1$ .

We observe that

$$\mathbb{E}(Z) = \int_{-\infty}^{\infty} \frac{t}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} dx$$

This integral converges, and since the integrand is an odd function we have that the integral is 0.

On the other hand,

$$\mathbb{E}(Z)^2 = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 e^{-\frac{1}{2}t^2} dx$$

The integral converges, and the integrand is an even function. So

$$\mathbb{E}(Z^2) = 2 \cdot \frac{1}{\sqrt{2\pi}} \int_0^{\infty} t^2 e^{-\frac{1}{2}t^2} dt$$

Using integration by parts,

$$\begin{aligned} &= \frac{2}{\sqrt{2\pi}} \left[ \int_0^{\infty} t \cdot t e^{-t^2/2} dt \right] \\ &= \frac{2}{\sqrt{2\pi}} \cdot \left[ \cancel{-te^{-t^2/2}} \Big|_0^{\infty} + \int_0^{\infty} e^{-t^2/2} dt \right] \end{aligned}$$

Because  $e^{-t^2/2}$  is an even function and  $\int_{-\infty}^{\infty} e^{-t^2/2} dt = \sqrt{2\pi}$ , we have

$$\mathbb{E}(Z^2) = \frac{2}{\sqrt{2\pi}} \cdot \frac{1}{2} \cdot \sqrt{2\pi} = 1$$

So  $V(Z) = \mathbb{E}(Z^2) - (\mathbb{E}(Z))^2 = 1$ .

For  $Z \sim N(0,1)$ , what is  $\mathbb{E}(Z^{2n+1})$ ? (0)

Find  $\mathbb{E}(Z^{2n})$  by iteration, i.e. find a recursive formula dependent on  $n$ .  
(will be solved in class tomorrow)

### Example

Refer to 4.71.

For  $X \sim N(\mu = 0.13, \sigma^2 = (0.005)^2)$ , compute  $P(0.12 < X < 0.14)$ .

$$\begin{aligned} P(0.12 < X < 0.14) &= P(0.12 < 0.005Z + 0.13 < 0.14) \\ &= P\left(-\frac{0.01}{0.005} < Z < \frac{0.01}{0.005}\right) \\ &= P(-2 < Z < 2) \\ &= 1 - 2\Phi_Z(-2) \end{aligned}$$

which (after consulting the table) we found to be 0.944.

Let the above be the probability that a wire manufactured by a certain factory passes the specifications. Suppose you buy 4 of those wires. What is the probability that all 4 pass specifications?

Let  $X$  be the number of wires that pass specifications among the 4.

We see that  $X \sim B(4, 0.944)$ . So  $p_X(4) = C_4^4(0.944)^4(1 - 0.944)^0 = 0.944^4$ .

---

## A quick review of the gamma function

### Definition: Gamma function

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

We have

$$\Gamma(\alpha) = \underbrace{\int_0^1 t^{\alpha-1} e^{-t} dt}_{\text{comparable to } \int_0^1 t^{\alpha-1} dt \text{ which converges for } \alpha > 0} + \underbrace{\int_1^\infty t^{\alpha-1} e^{-t} dt}_{\text{always converges}}$$

So  $\Gamma(\alpha)$  is defined for  $\alpha > 0$ .

### Properties of the gamma function

For all  $\alpha > 0$ , we have  $\Gamma(\alpha + 1) = \alpha\Gamma(\alpha)$ .

#### Proof

$$\Gamma(\alpha + 1) = \int_0^\infty t^\alpha e^{-t} dt$$

Applying integration by parts,

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

We compute that  $\Gamma(1) = \int_0^\infty e^{-t} dt = -e^{-t}|_0^\infty = 1$ . By induction (here the scribe skips a thousand steps which are left as exercise to the reader), for  $n \in \mathbb{N}$ , we have  $\Gamma(n) = (n-1)!$ .

Given that  $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$ , we have  $\Gamma\left(\frac{3}{2}\right) = \frac{1}{2} \cdot \Gamma\left(\frac{1}{2}\right) = \frac{1}{2}\sqrt{\pi}$ ,  $\Gamma\left(\frac{5}{2}\right) = \frac{3}{2} \cdot \frac{1}{2}\sqrt{\pi}$ , ... We observe that

$$\begin{aligned} \Gamma\left(\frac{2n+1}{2}\right) &= \underbrace{\frac{2n-1}{2} \cdot \frac{2n-3}{2} \cdots \frac{1}{2}}_{n \text{ terms}} \cdot \sqrt{\pi} \\ &= \frac{1}{2^n} (2n-1)(2n-3) \cdots (3)(1) \sqrt{\pi} \\ &= \frac{\sqrt{\pi}}{2^n} \left[ \frac{(2n)!}{\underbrace{(2n)(2n-2) \cdots (4)(2)}}_{n \text{ terms}} \right] \end{aligned}$$



$$\begin{aligned}
 &= \frac{\sqrt{\pi}}{2^n} \left[ \frac{(2n)!}{2^n(n)(n-1)\dots(2)(1)} \right] \\
 &= \frac{\sqrt{\pi}}{2^n} \left[ \frac{(2n)!}{2^n \cdot n!} \right] \\
 &= \frac{(2n)!}{2^{2n} \cdot n!} \sqrt{\pi}
 \end{aligned}$$

### Key formula

$$\int_0^\infty t^a e^{-bt} dt = \frac{1}{b^{a+1}} \Gamma(a+1)$$

for  $b > 0$ ,  $a + 1 > 0$ .

### Proof

Make the change of variables  $s = bt$ . We have

$$\begin{aligned}
 \int_0^\infty t^a e^{-bt} dt &= \frac{1}{b} \int_0^\infty \left(\frac{s}{b}\right)^a e^{-s} ds \\
 &= \frac{1}{b^{a+1}} \int_0^\infty s^a e^{-s} ds \\
 &= \frac{1}{b^{a+1}} \Gamma(a+1)
 \end{aligned}$$

### Remark

For  $\alpha > 0, \beta > 0$ , we have

$$\int_0^\infty x^{\alpha-1} e^{-x/\beta} dx = \frac{\Gamma(\alpha)}{\left(\frac{1}{\beta}\right)^\alpha} = \beta^\alpha \Gamma(\alpha)$$

hence  $\frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^{\alpha-1} e^{-x/\beta} dx = 1$ .

### Definition: Gamma distribution

The function

$$f_X(x) = \begin{cases} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} & x \in (0, \infty) \\ 0 & \text{otherwise} \end{cases}$$

is a pdf.  $X$  is said to have a Gamma distribution with parameter  $\alpha, \beta$ , written as  $X \sim \text{Gamma}(\alpha, \beta)$ .

### Exercise

If  $X \sim G(\alpha, \beta)$ , then  $Y := \frac{X}{\beta} \sim G(\alpha, 1)$ .

### Proposition

If  $X \sim G(\alpha, \beta)$ , then

1.  $\mathbb{E}(X) = \beta\alpha$
2.  $V(X) = \beta^2\alpha$

### Proof

$$\begin{aligned} \mathbb{E}(X) &= \int_0^\infty x f_X(x) dx \\ &= \int_0^\infty \frac{1}{\Gamma(\alpha)\beta^\alpha} x^\alpha e^{-x/\beta} dx \\ &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \int_0^\infty x^\alpha e^{-x/\beta} dx \\ &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \cdot (\beta)^{\alpha+1} \cdot \Gamma(\alpha+1) \\ &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \cdot \beta^{\alpha+1} \cdot \alpha\Gamma(\alpha) \\ &= \beta\alpha \end{aligned}$$

and

$$\mathbb{E}(X^2) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^{\alpha+1} e^{-x/\beta} dx$$

$$\begin{aligned}
 &= \frac{1}{\beta^\alpha \Gamma(\alpha)} \cdot \beta^{\alpha+2} \Gamma(\alpha+2) \\
 &= \frac{1}{\beta^\alpha \Gamma(\alpha)} \cdot \beta^{\alpha+2} (\alpha+1)(\alpha) \Gamma(\alpha) \\
 &= \beta^2 (\alpha+1)(\alpha)
 \end{aligned}$$

So  $V(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2 = \beta^2 \alpha$

### Exercise

For  $X \sim G(\alpha, \beta)$  we have

$$\mathbb{E}(X^n) = \beta^n (\alpha)(\alpha+1)(\alpha+2) \dots (\alpha+n-1)$$

For tomorrow:

Many distributions come from the gamma distribution, such as the exponential distribution ( $\alpha = 1$ ) and chi-square distribution ( $\beta = 2, \alpha = \frac{p}{2}$ ).