

## Transformations and Expectations

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- 2.1 a.  $f_x(x) = 42x^5(1-x)$ ,  $0 < x < 1$ ;  $y = x^3 = g(x)$ , monotone, and  $\mathcal{Y} = (0, 1)$ . Use Theorem 2.1.5.

$$\begin{aligned} f_Y(y) &= f_x(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| = f_x(y^{1/3}) \frac{d}{dy} (y^{1/3}) = 42y^{5/3}(1-y^{1/3}) \left( \frac{1}{3} y^{-2/3} \right) \\ &= 14y(1-y^{1/3}) = 14y - 14y^{4/3}, \quad 0 < y < 1. \end{aligned}$$

To check the integral,

$$\int_0^1 (14y - 14y^{4/3}) dy = 7y^2 - 14 \frac{y^{7/3}}{7/3} \Big|_0^1 = 7y^2 - 6y^{7/3} \Big|_0^1 = 1 - 0 = 1.$$

- b.  $f_x(x) = 7e^{-7x}$ ,  $0 < x < \infty$ ,  $y = 4x + 3$ , monotone, and  $\mathcal{Y} = (3, \infty)$ . Use Theorem 2.1.5.

$$f_Y(y) = f_x\left(\frac{y-3}{4}\right) \left| \frac{d}{dy} \left(\frac{y-3}{4}\right) \right| = 7e^{-(7/4)(y-3)} \left| \frac{1}{4} \right| = \frac{7}{4} e^{-(7/4)(y-3)}, \quad 3 < y < \infty.$$

To check the integral,

$$\int_3^\infty \frac{7}{4} e^{-(7/4)(y-3)} dy = -e^{-(7/4)(y-3)} \Big|_3^\infty = 0 - (-1) = 1.$$

- c.  $F_Y(y) = P(0 \leq X \leq \sqrt{y}) = F_X(\sqrt{y})$ . Then  $f_Y(y) = \frac{1}{2\sqrt{y}} f_X(\sqrt{y})$ . Therefore

$$f_Y(y) = \frac{1}{2\sqrt{y}} 30(\sqrt{y})^2(1-\sqrt{y})^2 = 15y^{1/2}(1-\sqrt{y})^2, \quad 0 < y < 1.$$

To check the integral,

$$\int_0^1 15y^{1/2}(1-\sqrt{y})^2 dy = \int_0^1 (15y^{1/2} - 30y + 15y^{3/2}) dy = 15\left(\frac{2}{3}\right) - 30\left(\frac{1}{2}\right) + 15\left(\frac{2}{5}\right) = 1.$$

- 2.2 In all three cases, Theorem 2.1.5 is applicable and yields the following answers.

- a.  $f_Y(y) = \frac{1}{2}y^{-1/2}$ ,  $0 < y < 1$ .
- b.  $f_Y(y) = \frac{(n+m+1)!}{n!m!} e^{-y(n+1)}(1-e^{-y})^m$ ,  $0 < y < \infty$ .
- c.  $f_Y(y) = \frac{1}{\sigma^2} \frac{\log y}{y} e^{-(1/2)((\log y)/\sigma)^2}$ ,  $0 < y < \infty$ .

- 2.3  $P(Y = y) = P\left(\frac{X}{X+1} = y\right) = P\left(X = \frac{y}{1-y}\right) = \frac{1}{3}\left(\frac{2}{3}\right)^{y/(1-y)}$ , where  $y = 0, \frac{1}{2}, \frac{2}{3}, \frac{3}{4}, \dots, \frac{x}{x+1}, \dots$ .

- 2.4 a.  $f(x)$  is a pdf since it is positive and

$$\int_{-\infty}^{\infty} f(x) dx = \int_{-\infty}^0 \frac{1}{2} \lambda e^{\lambda x} dx + \int_0^{\infty} \frac{1}{2} \lambda e^{-\lambda x} dx = \frac{1}{2} + \frac{1}{2} = 1.$$

b. Let  $X$  be a random variable with density  $f(x)$ .

$$P(X < t) = \begin{cases} \int_{-\infty}^t \frac{1}{2} \lambda e^{\lambda x} dx & \text{if } t < 0 \\ \int_{-\infty}^0 \frac{1}{2} \lambda e^{\lambda x} dx + \int_0^t \frac{1}{2} \lambda e^{-\lambda x} dx & \text{if } t \geq 0 \end{cases}$$

where,  $\int_{-\infty}^t \frac{1}{2} \lambda e^{\lambda x} dx = \frac{1}{2} e^{\lambda x} \Big|_{-\infty}^t = \frac{1}{2} e^{\lambda t}$  and  $\int_0^t \frac{1}{2} \lambda e^{-\lambda x} dx = -\frac{1}{2} e^{-\lambda x} \Big|_0^t = -\frac{1}{2} e^{-\lambda t} + \frac{1}{2}$ .  
Therefore,

$$P(X < t) = \begin{cases} \frac{1}{2} e^{\lambda t} & \text{if } t < 0 \\ 1 - \frac{1}{2} e^{-\lambda t} & \text{if } t \geq 0 \end{cases}$$

c.  $P(|X| < t) = 0$  for  $t < 0$ , and for  $t \geq 0$ ,

$$\begin{aligned} P(|X| < t) &= P(-t < X < t) = \int_{-t}^0 \frac{1}{2} \lambda e^{\lambda x} dx + \int_0^t \frac{1}{2} \lambda e^{-\lambda x} dx \\ &= \frac{1}{2} [1 - e^{-\lambda t}] + \frac{1}{2} [-e^{-\lambda t} + 1] = 1 - e^{-\lambda t}. \end{aligned}$$

2.5 To apply Theorem 2.1.8. Let  $A_0 = \{0\}$ ,  $A_1 = (0, \frac{\pi}{2})$ ,  $A_3 = (\pi, \frac{3\pi}{2})$  and  $A_4 = (\frac{3\pi}{2}, 2\pi)$ . Then  $g_i(x) = \sin^2(x)$  on  $A_i$  for  $i = 1, 2, 3, 4$ . Therefore  $g_1^{-1}(y) = \sin^{-1}(\sqrt{y})$ ,  $g_2^{-1}(y) = \pi - \sin^{-1}(\sqrt{y})$ ,  $g_3^{-1}(y) = \sin^{-1}(\sqrt{y}) + \pi$  and  $g_4^{-1}(y) = 2\pi - \sin^{-1}(\sqrt{y})$ . Thus

$$\begin{aligned} f_Y(y) &= \frac{1}{2\pi} \left| \frac{1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}} \right| + \frac{1}{2\pi} \left| -\frac{1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}} \right| + \frac{1}{2\pi} \left| \frac{1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}} \right| + \frac{1}{2\pi} \left| -\frac{1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}} \right| \\ &= \frac{1}{\pi \sqrt{y(1-y)}}, \quad 0 \leq y \leq 1 \end{aligned}$$

To use the cdf given in (2.1.6) we have that  $x_1 = \sin^{-1}(\sqrt{y})$  and  $x_2 = \pi - \sin^{-1}(\sqrt{y})$ . Then by differentiating (2.1.6) we obtain that

$$\begin{aligned} f_Y(y) &= 2f_X(\sin^{-1}(\sqrt{y})) \frac{d}{dy}(\sin^{-1}(\sqrt{y})) - 2f_X(\pi - \sin^{-1}(\sqrt{y})) \frac{d}{dy}(\pi - \sin^{-1}(\sqrt{y})) \\ &= 2\left(\frac{1}{2\pi} \frac{1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}}\right) - 2\left(\frac{1}{2\pi} \frac{-1}{\sqrt{1-y}} \frac{1}{2\sqrt{y}}\right) \\ &= \frac{1}{\pi \sqrt{y(1-y)}} \end{aligned}$$

2.6 Theorem 2.1.8 can be used for all three parts.

a. Let  $A_0 = \{0\}$ ,  $A_1 = (-\infty, 0)$  and  $A_2 = (0, \infty)$ . Then  $g_1(x) = |x|^3 = -x^3$  on  $A_1$  and  $g_2(x) = |x|^3 = x^3$  on  $A_2$ . Use Theorem 2.1.8 to obtain

$$f_Y(y) = \frac{1}{3} e^{-y^{1/3}} y^{-2/3}, \quad 0 < y < \infty$$

b. Let  $A_0 = \{0\}$ ,  $A_1 = (-1, 0)$  and  $A_2 = (0, 1)$ . Then  $g_1(x) = 1 - x^2$  on  $A_1$  and  $g_2(x) = 1 - x^2$  on  $A_2$ . Use Theorem 2.1.8 to obtain

$$f_Y(y) = \frac{3}{8} (1-y)^{-1/2} + \frac{3}{8} (1-y)^{1/2}, \quad 0 < y < 1$$

- c. Let  $A_0 = \{0\}$ ,  $A_1 = (-1, 0)$  and  $A_2 = (0, 1)$ . Then  $g_1(x) = 1 - x^2$  on  $A_1$  and  $g_2(x) = 1 - x$  on  $A_2$ . Use Theorem 2.1.8 to obtain

$$f_Y(y) = \frac{3}{16}(1 - \sqrt{1-y})^2 \frac{1}{\sqrt{1-y}} + \frac{3}{8}(2-y)^2, \quad 0 < y < 1$$

2.7 Theorem 2.1.8 does not directly apply.

- a. Theorem 2.1.8 does not directly apply. Instead write

$$\begin{aligned} P(Y \leq y) &= P(X^2 \leq y) \\ &= \begin{cases} P(-\sqrt{y} \leq X \leq \sqrt{y}) & \text{if } |x| \leq 1 \\ P(1 \leq X \leq \sqrt{y}) & \text{if } x \geq 1 \end{cases} \\ &= \begin{cases} \int_{-\sqrt{y}}^{\sqrt{y}} f_X(x) dx & \text{if } |x| \leq 1 \\ \int_1^{\sqrt{y}} f_X(x) dx & \text{if } x \geq 1 \end{cases}. \end{aligned}$$

Differentiation gives

$$f_Y(y) = \begin{cases} \frac{2}{9} \frac{1}{\sqrt{y}} & \text{if } y \leq 1 \\ \frac{1}{9} + \frac{1}{9} \frac{1}{\sqrt{y}} & \text{if } y \geq 1 \end{cases}.$$

- b. If the sets  $B_1, B_2, \dots, B_K$  are a partition of the range of  $Y$ , we can write

$$f_Y(y) = \sum_k f_Y(y) I(y \in B_k)$$

and do the transformation on each of the  $B_k$ . So this says that we can apply Theorem 2.1.8 on each of the  $B_k$  and add up the pieces. For  $A_1 = (-1, 1)$  and  $A_2 = (1, 2)$  the calculations are identical to those in part (a). (Note that on  $A_1$  we are essentially using Example 2.1.7).

2.8 For each function we check the conditions of Theorem 1.5.3.

- a. (i)  $\lim_{x \rightarrow 0} F(x) = 1 - e^{-0} = 0$ ,  $\lim_{x \rightarrow -\infty} F(x) = 1 - e^{-\infty} = 1$ .  
 (ii)  $1 - e^{-x}$  is increasing in  $x$ .  
 (iii)  $1 - e^{-x}$  is continuous.  
 (iv)  $F_x^{-1}(y) = -\log(1 - y)$ .  
 b. (i)  $\lim_{x \rightarrow -\infty} F(x) = e^{-\infty}/2 = 0$ ,  $\lim_{x \rightarrow \infty} F(x) = 1 - (e^{1-\infty}/2) = 1$ .  
 (ii)  $e^{-x/2}$  is increasing,  $1/2$  is nondecreasing,  $1 - (e^{1-x}/2)$  is increasing.  
 (iii) For continuity we only need check  $x = 0$  and  $x = 1$ , and  $\lim_{x \rightarrow 0} F(x) = 1/2$ ,  $\lim_{x \rightarrow 1} F(x) = 1/2$ , so  $F$  is continuous.  
 (iv)

$$F_X^{-1}(y) = \begin{cases} \log(2y) & 0 \leq y < \frac{1}{2} \\ 1 - \log(2(1 - y)) & \frac{1}{2} \leq y < 1 \end{cases}$$

- c. (i)  $\lim_{x \rightarrow -\infty} F(x) = e^{-\infty}/4 = 0$ ,  $\lim_{x \rightarrow \infty} F(x) = 1 - e^{-\infty}/4 = 1$ .  
 (ii)  $e^{-x}/4$  and  $1 - e^{-x}/4$  are both increasing in  $x$ .  
 (iii)  $\lim_{x \downarrow 0} F(x) = 1 - e^{-0}/4 = \frac{3}{4} = F(0)$ , so  $F$  is right-continuous.  
 (iv)  $F_X^{-1}(y) = \begin{cases} \log(4y) & 0 \leq y < \frac{1}{4} \\ -\log(4(1 - y)) & \frac{1}{4} \leq y < 1 \end{cases}$

- 2.9 From the probability integral transformation, Theorem 2.1.10, we know that if  $u(x) = F_x(x)$ , then  $F_x(X) \sim \text{uniform}(0, 1)$ . Therefore, for the given pdf, calculate

$$u(x) = F_x(x) = \begin{cases} 0 & \text{if } x \leq 1 \\ (x-1)^2/4 & \text{if } 1 < x < 3 \\ 1 & \text{if } 3 \leq x \end{cases}$$

- 2.10 a. We prove part b), which is equivalent to part a).

- b. Let  $A_y = \{x : F_x(x) \leq y\}$ . Since  $F_x$  is nondecreasing,  $A_y$  is a half infinite interval, either open, say  $(-\infty, x_y)$ , or closed, say  $(-\infty, x_y]$ . If  $A_y$  is closed, then

$$F_Y(y) = P(Y \leq y) = P(F_x(X) \leq y) = P(X \in A_y) = F_x(x_y) \leq y.$$

The last inequality is true because  $x_y \in A_y$ , and  $F_x(x) \leq y$  for every  $x \in A_y$ . If  $A_y$  is open, then

$$F_Y(y) = P(Y \leq y) = P(F_x(X) \leq y) = P(X \in A_y),$$

as before. But now we have

$$P(X \in A_y) = P(X \in (-\infty, x_y)) = \lim_{x \uparrow y} P(X \in (-\infty, x]),$$

Use the Axiom of Continuity, Exercise 1.12, and this equals  $\lim_{x \uparrow y} F_X(x) \leq y$ . The last inequality is true since  $F_x(x) \leq y$  for every  $x \in A_y$ , that is, for every  $x < x_y$ . Thus,  $F_Y(y) \leq y$  for every  $y$ . To get strict inequality for some  $y$ , let  $y$  be a value that is “jumped over” by  $F_x$ . That is, let  $y$  be such that, for some  $x_y$ ,

$$\lim_{x \uparrow y} F_X(x) < y < F_X(x_y).$$

For such a  $y$ ,  $A_y = (-\infty, x_y)$ , and  $F_Y(y) = \lim_{x \uparrow y} F_X(x) < y$ .

- 2.11 a. Using integration by parts with  $u = x$  and  $dv = xe^{-\frac{x^2}{2}} dx$  then

$$EX^2 = \int_{-\infty}^{\infty} x^2 \frac{1}{2\pi} e^{-\frac{x^2}{2}} dx = \frac{1}{2\pi} \left[ -xe^{-\frac{x^2}{2}} \Big|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx \right] = \frac{1}{2\pi} (2\pi) = 1.$$

Using example 2.1.7 let  $Y = X^2$ . Then

$$f_Y(y) = \frac{1}{2\sqrt{y}} \left[ \frac{1}{\sqrt{2\pi}} e^{-\frac{y}{2}} + \frac{1}{\sqrt{2\pi}} e^{-\frac{y}{2}} \right] = \frac{1}{\sqrt{2\pi y}} e^{-\frac{y}{2}}.$$

Therefore,

$$EY = \int_0^{\infty} \frac{y}{\sqrt{2\pi y}} e^{-\frac{y}{2}} dy = \frac{1}{\sqrt{2\pi}} \left[ -2y^{\frac{1}{2}} e^{-\frac{y}{2}} \Big|_0^{\infty} + \int_0^{\infty} y^{-\frac{1}{2}} e^{-\frac{y}{2}} dy \right] = \frac{1}{\sqrt{2\pi}} (\sqrt{2\pi}) = 1.$$

This was obtained using integration by parts with  $u = 2y^{\frac{1}{2}}$  and  $dv = \frac{1}{2} e^{-\frac{y}{2}}$  and the fact the  $f_Y(y)$  integrates to 1.

- b.  $Y = |X|$  where  $-\infty < x < \infty$ . Therefore  $0 < y < \infty$ . Then

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(|X| \leq y) = P(-y \leq X \leq y) \\ &= P(x \leq y) - P(X \leq -y) = F_X(y) - F_X(-y). \end{aligned}$$

Therefore,

$$F_Y(y) = \frac{d}{dy} F_Y(y) = f_X(y) + f_X(-y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y}{2}} + \frac{1}{\sqrt{2\pi}} e^{\frac{-y}{2}} = \sqrt{\frac{2}{\pi}} e^{-\frac{y}{2}}.$$

Thus,

$$EY = \int_0^\infty y \sqrt{\frac{2}{\pi}} e^{-\frac{y}{2}} dy = \sqrt{\frac{2}{\pi}} \int_0^\infty e^{-u} du = \sqrt{\frac{2}{\pi}} [-e^{-u}]_0^\infty = \sqrt{\frac{2}{\pi}},$$

where  $u = \frac{y}{2}$ .

$$EY^2 = \int_0^\infty y^2 \sqrt{\frac{2}{\pi}} e^{-\frac{y}{2}} dy = \sqrt{\frac{2}{\pi}} \left[ -ye^{-\frac{y}{2}} \Big|_0^\infty + \int_0^\infty e^{-\frac{y}{2}} dy \right] = \sqrt{\frac{2}{\pi}} \sqrt{\frac{\pi}{2}} = 1.$$

This was done using integration by part with  $u = y$  and  $dv = ye^{-\frac{y}{2}} dy$ . Then  $\text{Var}(Y) = 1 - \frac{2}{\pi}$ .

2.12 We have  $\tan x = y/d$ , therefore  $\tan^{-1}(y/d) = x$  and  $\frac{d}{dy} \tan^{-1}(y/d) = \frac{1}{1+(y/d)^2} \frac{1}{d} dy = dx$ . Thus,

$$f_Y(y) = \frac{2}{\pi d} \frac{1}{1+(y/d)^2}, \quad 0 < y < \infty.$$

This is the Cauchy distribution restricted to  $(0, \infty)$ , and the mean is infinite.

2.13  $P(X = k) = (1-p)^k p + p^k(1-p)$ ,  $k = 1, 2, \dots$  Therefore,

$$\begin{aligned} EX &= \sum_{k=1}^\infty k[(1-p)^k p + p^k(1-p)] = (1-p)p \left[ \sum_{k=1}^\infty k(1-p)^{k-1} + \sum_{k=1}^\infty kp^{k-1} \right] \\ &= (1-p)p \left[ \frac{1}{p^2} + \frac{1}{(1-p)^2} \right] = \frac{1-2p+2p^2}{p(1-p)}. \end{aligned}$$

2.14

$$\begin{aligned} \int_0^\infty (1 - F_X(x)) dx &= \int_0^\infty P(X > x) dx \\ &= \int_0^\infty \int_x^\infty f_X(y) dy dx \\ &= \int_0^\infty \int_0^y dx f_X(y) dy \\ &= \int_0^\infty y f_X(y) dy = EX, \end{aligned}$$

where the last equality follows from changing the order of integration.

2.15 Assume without loss of generality that  $X \leq Y$ . Then  $X \vee Y = Y$  and  $X \wedge Y = X$ . Thus  $X + Y = (X \wedge Y) + (X \vee Y)$ . Taking expectations

$$E[X + Y] = E[(X \wedge Y) + (X \vee Y)] = E(X \wedge Y) + E(X \vee Y).$$

Therefore  $E(X \vee Y) = EX + EY - E(X \wedge Y)$ .

2.16 From Exercise 2.14,

$$ET = \int_0^\infty [ae^{-\lambda t} + (1-a)e^{-\mu t}] dt = \frac{-ae^{-\lambda t}}{\lambda} - \frac{(1-a)e^{-\mu t}}{\mu} \Big|_0^\infty = \frac{a}{\lambda} + \frac{1-a}{\mu}.$$

2.17 a.  $\int_0^m 3x^2 dx = m^3 \stackrel{\text{set}}{=} \frac{1}{2} \Rightarrow m = (\frac{1}{2})^{1/3} = .794.$

b. The function is symmetric about zero, therefore  $m = 0$  as long as the integral is finite.

$$\frac{1}{\pi} \int_{-\infty}^{\infty} \frac{1}{1+x^2} dx = \frac{1}{\pi} \tan^{-1}(x) \Big|_{-\infty}^{\infty} = \frac{1}{\pi} \left( \frac{\pi}{2} + \frac{\pi}{2} \right) = 1.$$

This is the Cauchy pdf.

2.18  $E|X - a| = \int_{-\infty}^{\infty} |x - a| f(x) dx = \int_{-\infty}^a -(x - a) f(x) dx + \int_a^{\infty} (x - a) f(x) dx.$  Then,

$$\frac{d}{da} E|X - a| = \int_{-\infty}^a f(x) dx - \int_a^{\infty} f(x) dx \stackrel{\text{set}}{=} 0.$$

The solution to this equation is  $a = \text{median}$ . This is a minimum since  $d^2/da^2 E|X - a| = 2f(a) > 0$ .

2.19

$$\begin{aligned} \frac{d}{da} E(X - a)^2 &= \frac{d}{da} \int_{-\infty}^{\infty} (x - a)^2 f_X(x) dx = \int_{-\infty}^{\infty} \frac{d}{da} (x - a)^2 f_X(x) dx \\ &= \int_{-\infty}^{\infty} -2(x - a) f_X(x) dx = -2 \left[ \int_{-\infty}^{\infty} x f_X(x) dx - a \int_{-\infty}^{\infty} f_X(x) dx \right] \\ &= -2[EX - a]. \end{aligned}$$

Therefore if  $\frac{d}{da} E(X - a)^2 = 0$  then  $-2[EX - a] = 0$  which implies that  $EX = a$ . If  $EX = a$  then  $\frac{d}{da} E(X - a)^2 = -2[EX - a] = -2[a - a] = 0$ .  $EX = a$  is a minimum since  $d^2/da^2 E(X - a)^2 = 2 > 0$ . The assumptions that are needed are the ones listed in Theorem 2.4.3.

2.20 From Example 1.5.4, if  $X = \text{number of children until the first daughter}$ , then

$$P(X = k) = (1 - p)^{k-1} p,$$

where  $p = \text{probability of a daughter}$ . Thus  $X$  is a geometric random variable, and

$$\begin{aligned} EX &= \sum_{k=1}^{\infty} k(1 - p)^{k-1} p = p - \sum_{k=1}^{\infty} \frac{d}{dp} (1 - p)^k = -p \frac{d}{dp} \left[ \sum_{k=0}^{\infty} (1 - p)^k - 1 \right] \\ &= -p \frac{d}{dp} \left[ \frac{1}{p} - 1 \right] = \frac{1}{p}. \end{aligned}$$

Therefore, if  $p = \frac{1}{2}$ , the expected number of children is two.

2.21 Since  $g(x)$  is monotone

$$Eg(X) = \int_{-\infty}^{\infty} g(x) f_X(x) dx = \int_{-\infty}^{\infty} y f_X(g^{-1}(y)) \frac{d}{dy} g^{-1}(y) dy = \int_{-\infty}^{\infty} y f_Y(y) dy = EY,$$

where the second equality follows from the change of variable  $y = g(x)$ ,  $x = g^{-1}(y)$  and  $dx = \frac{d}{dy} g^{-1}(y) dy$ .

2.22 a. Using integration by parts with  $u = x$  and  $dv = xe^{-x^2/\beta^2}$  we obtain that

$$\int_0^{\infty} x^2 e^{-x^2/\beta^2} dx = \frac{\beta^2}{2} \int_0^{\infty} e^{-x^2/\beta^2} dx.$$

The integral can be evaluated using the argument on pages 104-105 (see 3.3.14) or by transforming to a gamma kernel (use  $y = -x^2/\beta^2$ ). Therefore,  $\int_0^{\infty} e^{-x^2/\beta^2} dx = \sqrt{\pi}\beta/2$  and hence the function integrates to 1.

$$\text{b. } EX = 2\beta/\sqrt{\pi} \quad EX^2 = 3\beta^2/2 \quad \text{Var}X = \beta^2 \left[ \frac{3}{2} - \frac{4}{\pi} \right].$$

- 2.23 a. Use Theorem 2.1.8 with  $A_0 = \{0\}$ ,  $A_1 = (-1, 0)$  and  $A_2 = (0, 1)$ . Then  $g_1(x) = x^2$  on  $A_1$  and  $g_2(x) = x^2$  on  $A_2$ . Then

$$f_Y(y) = \frac{1}{2}y^{-1/2}, \quad 0 < y < 1.$$

$$\text{b. } EY = \int_0^1 y f_Y(y) dy = \frac{1}{3} \quad EY^2 = \int_0^1 y^2 f_Y(y) dy = \frac{1}{5} \quad \text{Var}Y = \frac{1}{5} - \left(\frac{1}{3}\right)^2 = \frac{4}{45}.$$

$$2.24 \text{ a. } EX = \int_0^1 x a x^{a-1} dx = \int_0^1 a x^a dx = \left. \frac{a x^{a+1}}{a+1} \right|_0^1 = \frac{a}{a+1}.$$

$$EX^2 = \int_0^1 x^2 a x^{a-1} dx = \int_0^1 a x^{a+1} dx = \left. \frac{a x^{a+2}}{a+2} \right|_0^1 = \frac{a}{a+2}.$$

$$\text{Var}X = \frac{a}{a+2} - \left( \frac{a}{a+1} \right)^2 = \frac{a}{(a+2)(a+1)^2}.$$

$$\text{b. } EX = \sum_{x=1}^n \frac{x}{n} = \frac{1}{n} \sum_{x=1}^n x = \frac{1}{n} \frac{n(n+1)}{2} = \frac{n+1}{2}.$$

$$EX^2 = \sum_{i=1}^n \frac{x^2}{n} = \frac{1}{n} \sum_{i=1}^n x^2 = \frac{1}{n} \frac{n(n+1)(2n+1)}{6} = \frac{(n+1)(2n+1)}{6}.$$

$$\text{Var}X = \frac{(n+1)(2n+1)}{6} - \left( \frac{n+1}{2} \right)^2 = \frac{2n^2+3n+1}{6} - \frac{n^2+2n+1}{4} = \frac{n^2+1}{12}.$$

$$\text{c. } EX = \int_0^2 x \frac{3}{2} (x-1)^2 dx = \frac{3}{2} \int_0^2 (x^3 - 2x^2 + x) dx = 1.$$

$$EX^2 = \int_0^2 x^2 \frac{3}{2} (x-1)^2 dx = \frac{3}{2} \int_0^2 (x^4 - 2x^3 + x^2) dx = \frac{8}{5}.$$

$$\text{Var}X = \frac{8}{5} - 1^2 = \frac{3}{5}.$$

- 2.25 a.  $Y = -X$  and  $g^{-1}(y) = -y$ . Thus  $f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| = f_X(-y) | -1 | = f_X(y)$  for every  $y$ .

- b. To show that  $M_X(t)$  is symmetric about 0 we must show that  $M_X(0 + \epsilon) = M_X(0 - \epsilon)$  for all  $\epsilon > 0$ .

$$\begin{aligned} M_X(0 + \epsilon) &= \int_{-\infty}^{\infty} e^{(0+\epsilon)x} f_X(x) dx = \int_{-\infty}^0 e^{\epsilon x} f_X(x) dx + \int_0^{\infty} e^{\epsilon x} f_X(x) dx \\ &= \int_0^{\infty} e^{\epsilon(-x)} f_X(-x) dx + \int_{-\infty}^0 e^{\epsilon(-x)} f_X(-x) dx = \int_{-\infty}^{\infty} e^{-\epsilon x} f_X(x) dx \\ &= \int_{-\infty}^{\infty} e^{(0-\epsilon)x} f_X(x) dx = M_X(0 - \epsilon). \end{aligned}$$

- 2.26 a. There are many examples; here are three. The standard normal pdf (Example 2.1.9) is symmetric about  $a = 0$  because  $(0 - \epsilon)^2 = (0 + \epsilon)^2$ . The Cauchy pdf (Example 2.2.4) is symmetric about  $a = 0$  because  $(0 - \epsilon)^2 = (0 + \epsilon)^2$ . The uniform(0, 1) pdf (Example 2.1.4) is symmetric about  $a = 1/2$  because

$$f((1/2) + \epsilon) = f((1/2) - \epsilon) = \begin{cases} 1 & \text{if } 0 < \epsilon < \frac{1}{2} \\ 0 & \text{if } \frac{1}{2} \leq \epsilon < \infty \end{cases}.$$

- b.

$$\begin{aligned} \int_a^{\infty} f(x) dx &= \int_0^{\infty} f(a + \epsilon) d\epsilon && \text{(change variable, } \epsilon = x - a) \\ &= \int_0^{\infty} f(a - \epsilon) d\epsilon && (f(a + \epsilon) = f(a - \epsilon) \text{ for all } \epsilon > 0) \\ &= \int_{-\infty}^a f(x) dx. && \text{(change variable, } x = a - \epsilon) \end{aligned}$$

Since

$$\int_{-\infty}^a f(x)dx + \int_a^{\infty} f(x)dx = \int_{-\infty}^{\infty} f(x)dx = 1,$$

it must be that

$$\int_{-\infty}^a f(x)dx = \int_a^{\infty} f(x)dx = 1/2.$$

Therefore,  $a$  is a median.

c.

$$\begin{aligned} EX - a &= E(X - a) = \int_{-\infty}^{\infty} (x - a)f(x)dx \\ &= \int_{-\infty}^a (x - a)f(x)dx + \int_a^{\infty} (x - a)f(x)dx \\ &= \int_0^{\infty} (-\epsilon)f(a - \epsilon)d\epsilon + \int_0^{\infty} \epsilon f(a + \epsilon)d\epsilon \end{aligned}$$

With a change of variable,  $\epsilon = a - x$  in the first integral, and  $\epsilon = x - a$  in the second integral we obtain that

$$\begin{aligned} EX - a &= E(X - a) \\ &= - \int_0^{\infty} \epsilon f(a - \epsilon)d\epsilon + \int_0^{\infty} \epsilon f(a + \epsilon)d\epsilon \quad (f(a + \epsilon) = f(a - \epsilon) \text{ for all } \epsilon > 0) \\ &= 0. \quad (\text{two integrals are same}) \end{aligned}$$

Therefore,  $EX = a$ .

d. If  $a > \epsilon > 0$ ,

$$f(a - \epsilon) = e^{-(a-\epsilon)} > e^{-(a+\epsilon)} = f(a + \epsilon).$$

Therefore,  $f(x)$  is not symmetric about  $a > 0$ . If  $-\epsilon < a \leq 0$ ,

$$f(a - \epsilon) = 0 < e^{-(a+\epsilon)} = f(a + \epsilon).$$

Therefore,  $f(x)$  is not symmetric about  $a \leq 0$ , either.

e. The median of  $X = \log 2 < 1 = EX$ .

2.27 a. The standard normal pdf.

b. The uniform on the interval  $(0, 1)$ .

c. For the case when the mode is unique. Let  $a$  be the point of symmetry and  $b$  be the mode. Let assume that  $a$  is not the mode and without loss of generality that  $a = b + \epsilon > b$  for  $\epsilon > 0$ . Since  $b$  is the mode then  $f(b) > f(b + \epsilon) \geq f(b + 2\epsilon)$  which implies that  $f(a - \epsilon) > f(a) \geq f(a + \epsilon)$  which contradict the fact the  $f(x)$  is symmetric. Thus  $a$  is the mode.

For the case when the mode is not unique, there must exist an interval  $(x_1, x_2)$  such that  $f(x)$  has the same value in the whole interval, i.e.,  $f(x)$  is flat in this interval and for all  $b \in (x_1, x_2)$ ,  $b$  is a mode. Let assume that  $a \notin (x_1, x_2)$ , thus  $a$  is not a mode. Let also assume without loss of generality that  $a = (b + \epsilon) > b$ . Since  $b$  is a mode and  $a = (b + \epsilon) \notin (x_1, x_2)$  then  $f(b) > f(b + \epsilon) \geq f(b + 2\epsilon)$  which contradict the fact the  $f(x)$  is symmetric. Thus  $a \in (x_1, x_2)$  and is a mode.

d.  $f(x)$  is decreasing for  $x \geq 0$ , with  $f(0) > f(x) > f(y)$  for all  $0 < x < y$ . Thus  $f(x)$  is unimodal and 0 is the mode.



2.28 a.

$$\begin{aligned}
\mu_3 &= \int_{-\infty}^{\infty} (x-a)^3 f(x) dx = \int_{-\infty}^a (x-a)^3 f(x) dx + \int_a^{\infty} (x-a)^3 f(x) dx \\
&= \int_{-\infty}^0 y^3 f(y+a) dy + \int_0^{\infty} y^3 f(y+a) dy \quad (\text{change variable } y = x - a) \\
&= \int_0^{\infty} -y^3 f(-y+a) dy + \int_0^{\infty} y^3 f(y+a) dy \\
&= 0. \quad (f(-y+a) = f(y+a))
\end{aligned}$$

b. For  $f(x) = e^{-x}$ ,  $\mu_1 = \mu_2 = 1$ , therefore  $\alpha_3 = \mu_3$ .

$$\begin{aligned}
\mu_3 &= \int_0^{\infty} (x-1)^3 e^{-x} dx = \int_0^{\infty} (x^3 - 3x^2 + 3x - 1) e^{-x} dx \\
&= \Gamma(4) - 3\Gamma(3) + 3\Gamma(2) - \Gamma(1) = 3! - 3 \times 2! + 3 \times 1 - 1 = 3.
\end{aligned}$$

c. Each distribution has  $\mu_1 = 0$ , therefore we must calculate  $\mu_2 = EX^2$  and  $\mu_4 = EX^4$ .

- (i)  $f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$ ,  $\mu_2 = 1$ ,  $\mu_4 = 3$ ,  $\alpha_4 = 3$ .  
(ii)  $f(x) = \frac{1}{2}$ ,  $-1 < x < 1$ ,  $\mu_2 = \frac{1}{3}$ ,  $\mu_4 = \frac{1}{5}$ ,  $\alpha_4 = \frac{9}{5}$ .  
(iii)  $f(x) = \frac{1}{2} e^{-|x|}$ ,  $-\infty < x < \infty$ ,  $\mu_2 = 2$ ,  $\mu_4 = 24$ ,  $\alpha_4 = 6$ .

As a graph will show, (iii) is most peaked, (i) is next, and (ii) is least peaked.

2.29 a. For the binomial

$$\begin{aligned}
EX(X-1) &= \sum_{x=2}^n x(x-1) \binom{n}{x} p^x (1-p)^{n-x} \\
&= n(n-1)p^2 \sum_{x=2}^n \binom{n-2}{x-2} p^{x-2} (1-p)^{n-x} \\
&= n(n-1)p^2 \sum_{y=0}^{n-2} \binom{n-2}{y} p^y (1-p)^{n-2-y} = n(n-1)p^2,
\end{aligned}$$

where we use the identity  $x(x-1)\binom{n}{x} = n(n-1)\binom{n-2}{x-2}$ , substitute  $y = x - 2$  and recognize that the new sum is equal to 1. Similarly, for the Poisson

$$EX(X-1) = \sum_{x=2}^{\infty} x(x-1) \frac{e^{-\lambda} \lambda^x}{x!} = \lambda^2 \sum_{y=0}^{\infty} \frac{e^{-\lambda} \lambda^y}{y!} = \lambda^2,$$

where we substitute  $y = x - 2$ .b.  $\text{Var}(X) = E[X(X-1)] + EX - (EX)^2$ . For the binomial

$$\text{Var}(X) = n(n-1)p^2 + np - (np)^2 = np(1-p).$$

For the Poisson

$$\text{Var}(X) = \lambda^2 + \lambda - \lambda^2 = \lambda.$$

c.

$$EY = \sum_{y=0}^n y \frac{a}{y+a} \binom{n}{y} \frac{\binom{a+b-1}{a}}{\binom{n+a+b-1}{y+a}} = \sum_{y=1}^n n \frac{a}{(y-1)+(a+1)} \binom{n-1}{y-1} \frac{\binom{a+b-1}{a}}{\binom{(n-1)+(a+1)+b-1}{(y-1)+(a+1)}}$$

$$\begin{aligned}
&= \sum_{y=1}^n n \frac{a}{(y-1) + (a+1)} \binom{n-1}{y-1} \frac{\binom{a+b-1}{a}}{\binom{(n-1)+(a+1)+b-1}{(y-1)+(a+1)}} \\
&= \frac{\frac{na}{a+1} \binom{a+b-1}{a}}{\binom{a+1+b-1}{a+1}} \sum_{y=1}^n \frac{a+1}{(y-1) + (a+1)} \binom{n-1}{y-1} \frac{\binom{a+1+b-1}{a+1}}{\binom{(n-1)+(a+1)+b-1}{(y-1)+(a+1)}} \\
&= \frac{na}{a+b} \sum_{j=0}^{n-1} \frac{a+1}{j + (a+1)} \binom{n-1}{j} \frac{\binom{a+1+b-1}{a+1}}{\binom{(n-1)+(a+1)+b-1}{j+(a+1)}} = \frac{na}{a+b},
\end{aligned}$$

since the last summation is 1, being the sum over all possible values of a beta-binomial( $n-1, a+1, b$ ).  $E[Y(Y-1)] = \frac{n(n-1)a(a+1)}{(a+b)(a+b+1)}$  is calculated similar to  $EY$ , but using the identity  $y(y-1)\binom{n}{y} = n(n-1)\binom{n-2}{y-2}$  and adding 2 instead of 1 to the parameter  $a$ . The sum over all possible values of  $a$  beta-binomial( $n-2, a+2, b$ ) will appear in the calculation. Therefore

$$\text{Var}(Y) = E[Y(Y-1)] + EY - (EY)^2 = \frac{nab(n+a+b)}{(a+b)^2(a+b+1)}.$$

2.30 a.  $E(e^{tX}) = \int_0^c e^{tx} \frac{1}{c} dx = \frac{1}{ct} e^{tx} \Big|_0^c = \frac{1}{ct} e^{tc} - \frac{1}{ct} 1 = \frac{1}{ct} (e^{tc} - 1).$

b.  $E(e^{tX}) = \int_0^c \frac{2x}{c^2} e^{tx} dx = \frac{2}{c^2 t^2} (cte^{tc} - e^{tc} + 1).$  (integration-by-parts)

c.

$$\begin{aligned}
E(e^{tx}) &= \int_{-\infty}^{\alpha} \frac{1}{2\beta} e^{(x-\alpha)/\beta} e^{tx} dx + \int_{\alpha}^{\infty} \frac{1}{2\beta} e^{-(x-\alpha)/\beta} e^{tx} dx \\
&= \frac{e^{-\alpha/\beta}}{2\beta} \frac{1}{(\frac{1}{\beta} + t)} e^{x(\frac{1}{\beta} + t)} \Big|_{-\infty}^{\alpha} + -\frac{e^{\alpha/\beta}}{2\beta} \frac{1}{(\frac{1}{\beta} - t)} e^{-x(\frac{1}{\beta} - t)} \Big|_{\alpha}^{\infty} \\
&= \frac{4e^{\alpha t}}{4 - \beta^2 t^2}, \quad -2/\beta < t < 2/\beta.
\end{aligned}$$

d.  $E(e^{tX}) = \sum_{x=0}^{\infty} e^{tx} \binom{r+x-1}{x} p^r (1-p)^x = p^r \sum_{x=0}^{\infty} \binom{r+x-1}{x} ((1-p)e^t)^x$ . Now use the fact that  $\sum_{x=0}^{\infty} \binom{r+x-1}{x} ((1-p)e^t)^x (1 - (1-p)e^t)^r = 1$  for  $(1-p)e^t < 1$ , since this is just the sum of this pmf, to get  $E(e^{tX}) = \left(\frac{p}{1-(1-p)e^t}\right)^r$ ,  $t < -\log(1-p)$ .

2.31 Since the mgf is defined as  $M_X(t) = Ee^{tX}$ , we necessarily have  $M_X(0) = Ee^0 = 1$ . But  $t/(1-t)$  is 0 at  $t=0$ , therefore it cannot be an mgf.

2.32

$$\left. \frac{d}{dt} S(t) \right|_{t=0} = \left. \frac{d}{dt} (\log(M_x(t))) \right|_{t=0} = \left. \frac{\frac{d}{dt} M_x(t)}{M_x(t)} \right|_{t=0} = \frac{EX}{1} = EX \quad (\text{since } M_X(0) = Ee^0 = 1)$$

$$\begin{aligned}
\left. \frac{d^2}{dt^2} S(t) \right|_{t=0} &= \left. \frac{d}{dt} \left( \frac{M'_x(t)}{M_x(t)} \right) \right|_{t=0} = \left. \frac{M_x(t)M''_x(t) - [M'_x(t)]^2}{[M_x(t)]^2} \right|_{t=0} \\
&= \frac{1 \cdot EX^2 - (EX)^2}{1} = \text{Var}X.
\end{aligned}$$

2.33 a.  $M_X(t) = \sum_{x=0}^{\infty} e^{tx} \frac{e^{-\lambda} \lambda^x}{x!} = e^{-\lambda} \sum_{x=1}^{\infty} \frac{(e^t \lambda)^x}{x!} = e^{-\lambda} e^{\lambda e^t} = e^{\lambda(e^t - 1)}.$

$$EX = \left. \frac{d}{dt} M_x(t) \right|_{t=0} = e^{\lambda(e^t - 1)} \lambda e^t \Big|_{t=0} = \lambda.$$

$$EX^2 = \frac{d^2}{dt^2} M_x(t) \Big|_{t=0} = \lambda e^t e^{\lambda(e^t-1)} \lambda e^t + \lambda e^t e^{\lambda(e^t-1)} \Big|_{t=0} = \lambda^2 + \lambda.$$

$$\text{Var}X = EX^2 - (EX)^2 = \lambda^2 + \lambda - \lambda^2 = \lambda.$$

b.

$$\begin{aligned} M_x(t) &= \sum_{x=0}^{\infty} e^{tx} p(1-p)^x = p \sum_{x=0}^{\infty} ((1-p)e^t)^x \\ &= p \frac{1}{1-(1-p)e^t} = \frac{p}{1-(1-p)e^t}, \quad t < -\log(1-p). \\ EX &= \frac{d}{dt} M_x(t) \Big|_{t=0} = \frac{-p}{(1-(1-p)e^t)^2} \left( -(1-p)e^t \right) \Big|_{t=0} \\ &= \frac{p(1-p)}{p^2} = \frac{1-p}{p}. \\ EX^2 &= \frac{d^2}{dt^2} M_x(t) \Big|_{t=0} \\ &= \frac{\left( 1-(1-p)e^t \right)^2 \left( p(1-p)e^t \right) + p(1-p)e^t 2 \left( 1-(1-p)e^t \right) (1-p)e^t}{(1-(1-p)e^t)^4} \Big|_{t=0} \\ &= \frac{p^3(1-p) + 2p^2(1-p)^2}{p^4} = \frac{p(1-p) + 2(1-p)^2}{p^2}. \\ \text{Var}X &= \frac{p(1-p) + 2(1-p)^2}{p^2} - \frac{(1-p)^2}{p^2} = \frac{1-p}{p^2}. \end{aligned}$$

c.  $M_x(t) = \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} dx = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-(x^2-2\mu x-2\sigma^2 tx+\mu^2)/2\sigma^2} dx$ . Now complete the square in the numerator by writing

$$\begin{aligned} x^2 - 2\mu x - 2\sigma^2 tx + \mu^2 &= x^2 - 2(\mu + \sigma^2 t)x \pm (\mu + \sigma^2 t)^2 + \mu^2 \\ &= (x - (\mu + \sigma^2 t))^2 - (\mu + \sigma^2 t)^2 + \mu^2 \\ &= (x - (\mu + \sigma^2 t))^2 - [2\mu\sigma^2 t + (\sigma^2 t)^2]. \end{aligned}$$

Then we have  $M_x(t) = e^{[2\mu\sigma^2 t + (\sigma^2 t)^2]/2\sigma^2} \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2\sigma^2}(x-(\mu+\sigma^2 t))^2} dx = e^{\mu t + \frac{\sigma^2 t^2}{2}}$ .

$$EX = \frac{d}{dt} M_x(t) \Big|_{t=0} = (\mu + \sigma^2 t) e^{\mu t + \sigma^2 t^2/2} \Big|_{t=0} = \mu.$$

$$EX^2 = \frac{d^2}{dt^2} M_x(t) \Big|_{t=0} = (\mu + \sigma^2 t)^2 e^{\mu t + \sigma^2 t^2/2} + \sigma^2 e^{\mu t + \sigma^2 t^2/2} \Big|_{t=0} = \mu^2 + \sigma^2.$$

$$\text{Var}X = \mu^2 + \sigma^2 - \mu^2 = \sigma^2.$$

2.35 a.

$$\begin{aligned} EX_1^r &= \int_0^{\infty} x^r \frac{1}{\sqrt{2\pi}x} e^{-(\log x)^2/2} dx \quad (f_1 \text{ is lognormal with } \mu = 0, \sigma_2 = 1) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{y(r-1)} e^{-y^2/2} e^y dy \quad (\text{substitute } y = \log x, dy = (1/x)dx) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2 + ry} dy = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(y^2 - 2ry + r^2)/2} e^{r^2/2} dy \\ &= e^{r^2/2}. \end{aligned}$$

b.

$$\begin{aligned}
\int_0^\infty x^r f_1(x) \sin(2\pi \log x) dx &= \int_0^\infty x^r \frac{1}{\sqrt{2\pi x}} e^{-(\log x)^2/2} \sin(2\pi \log x) dx \\
&= \int_{-\infty}^\infty e^{(y+r)^2/2} \frac{1}{\sqrt{2\pi}} e^{-(y+r)^2/2} \sin(2\pi y + 2\pi r) dy \\
&\quad \text{(substitute } y = \log x, dy = (1/x)dx) \\
&= \int_{-\infty}^\infty \frac{1}{\sqrt{2\pi}} e^{(r^2-y^2)/2} \sin(2\pi y) dy \\
&\quad \text{(sin}(a + 2\pi r) = \sin(a) \text{ if } r = 0, 1, 2, \dots) \\
&= 0,
\end{aligned}$$

because  $e^{(r^2-y^2)/2} \sin(2\pi y) = -e^{(r^2-(-y)^2)/2} \sin(2\pi(-y))$ ; the integrand is an odd function so the negative integral cancels the positive one.

2.36 First, it can be shown that

$$\lim_{x \rightarrow \infty} e^{tx - (\log x)^2} = \infty$$

by using l'Hôpital's rule to show

$$\lim_{x \rightarrow \infty} \frac{tx - (\log x)^2}{tx} = 1,$$

and, hence,

$$\lim_{x \rightarrow \infty} tx - (\log x)^2 = \lim_{x \rightarrow \infty} tx = \infty.$$

Then for any  $k > 0$ , there is a constant  $c$  such that

$$\int_k^\infty \frac{1}{x} e^{tx} e^{(\log x)^2/2} dx \geq c \int_k^\infty \frac{1}{x} dx = c \log x|_k^\infty = \infty.$$

Hence  $M_x(t)$  does not exist.2.37 a. The graph looks very similar to Figure 2.3.2 except that  $f_1$  is symmetric around 0 (since it is standard normal).b. The functions look like  $t^2/2$  – it is impossible to see any difference.c. The mgf of  $f_1$  is  $e^{K_1(t)}$ . The mgf of  $f_2$  is  $e^{K_2(t)}$ .d. Make the transformation  $y = e^x$  to get the densities in Example 2.3.10.2.39 a.  $\frac{d}{dx} \int_0^x e^{-\lambda t} dt = e^{-\lambda x}$ . Verify

$$\frac{d}{dx} \left[ \int_0^x e^{-\lambda t} dt \right] = \frac{d}{dx} \left[ -\frac{1}{\lambda} e^{-\lambda t} \Big|_0^x \right] = \frac{d}{dx} \left( -\frac{1}{\lambda} e^{-\lambda x} + \frac{1}{\lambda} \right) = e^{-\lambda x}.$$

b.  $\frac{d}{d\lambda} \int_0^\infty e^{-\lambda t} dt = \int_0^\infty \frac{d}{d\lambda} e^{-\lambda t} dt = \int_0^\infty -te^{-\lambda t} dt = -\frac{\Gamma(2)}{\lambda^2} = -\frac{1}{\lambda^2}$ . Verify

$$\frac{d}{d\lambda} \int_0^\infty e^{-\lambda t} dt = \frac{d}{d\lambda} \frac{1}{\lambda} = -\frac{1}{\lambda^2}.$$

c.  $\frac{d}{dt} \int_t^1 \frac{1}{x^2} dx = -\frac{1}{t^2}$ . Verify

$$\frac{d}{dt} \left[ \int_t^1 \frac{1}{x^2} dx \right] = \frac{d}{dt} \left( -\frac{1}{x} \Big|_t^1 \right) = \frac{d}{dt} \left( -1 + \frac{1}{t} \right) = -\frac{1}{t^2}.$$

d.  $\frac{d}{dt} \int_1^\infty \frac{1}{(x-t)^2} dx = \int_1^\infty \frac{d}{dt} \left( \frac{1}{(x-t)^2} \right) dx = \int_1^\infty 2(x-t)^{-3} dx = -(x-t)^{-2} \Big|_1^\infty = \frac{1}{(1-t)^2}$ . Verify

$$\frac{d}{dt} \int_1^\infty (x-t)^{-2} dx = \frac{d}{dt} \left[ -(x-t)^{-1} \Big|_1^\infty \right] = \frac{d}{dt} \frac{1}{1-t} = \frac{1}{(1-t)^2}.$$