

Probability and Statistics. IDEA. Answers to List 5.

1. (a)

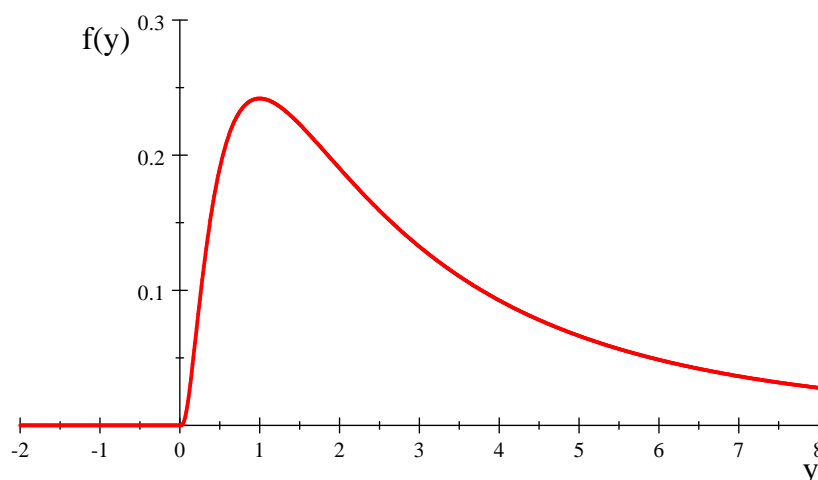
$$\tilde{x} \sim f_{\tilde{x}}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \quad \text{for } -\infty < x < \infty$$

$$\tilde{x} = g^{-1}(\tilde{y}) = \ln \tilde{y}; \quad \tilde{y} = g(\tilde{x}) = e^{\tilde{x}} \implies \tilde{y} > 0$$

$$\left| \frac{dx}{dy} \right| = \left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{y} \quad \text{for } y > 0$$

$$\tilde{y} \sim f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{x}}(\ln y) \cdot \left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{\sqrt{2\pi}\sigma y} e^{-\frac{1}{2}\left(\frac{\ln y - \mu}{\sigma}\right)^2}, & \text{for } y > 0 \\ 0, & \text{otherwise} \end{cases}$$

The log-normal density:



Note that  $\lim_{y \rightarrow 0^+} \underbrace{\frac{1}{\sqrt{2\pi}\sigma y} e^{-\frac{1}{2}\left(\frac{\ln y - \mu}{\sigma}\right)^2}}_{f_{\tilde{y}}(y)} = 0$  (Check it!). Hence, the log-normal

density is continuous.

(b)

$$m = E(\tilde{y}) = E(e^{\tilde{x}}) = M_{\tilde{x}}(1) = e^{\mu + \frac{1}{2}\sigma^2} > 0.$$

$$\begin{aligned}
s^2 &= \text{Var}(\tilde{y}) = \text{Var}(e^{\tilde{x}}) = \mathbb{E}[(e^{\tilde{x}})^2] - [\mathbb{E}(e^{\tilde{x}})]^2 = \mathbb{E}[e^{2\tilde{x}}] - [e^{\mu + \frac{1}{2}\sigma^2}]^2 \\
&= M_{\tilde{x}}(2) - e^{2\mu + \sigma^2} = e^{2\mu + \frac{1}{2} \cdot 4 \cdot \sigma^2} - e^{2\mu + \sigma^2} = e^{2\mu + \sigma^2} \cdot (e^{\sigma^2} - 1).
\end{aligned}$$

$$\text{CV}_{\tilde{y}} = \frac{[\text{Var}(\tilde{y})]^{1/2}}{|\mathbb{E}(\tilde{y})|} = \frac{e^{\mu + \frac{1}{2}\sigma^2} (e^{\sigma^2} - 1)^{1/2}}{e^{\mu + \frac{1}{2}\sigma^2}} = (e^{\sigma^2} - 1)^{1/2}.$$

(c) Note that  $m = \mathbb{E}(\tilde{y}) > 0$  as  $\tilde{y} > 0$ .

$$\text{CV}_{\tilde{y}} = \frac{s}{m} = (e^{\sigma^2} - 1)^{1/2} \implies \sigma^2 = \ln(1 + (\text{CV}_{\tilde{y}})^2) = \ln\left(\frac{m^2 + s^2}{m^2}\right).$$

$$m = e^{\mu + \frac{1}{2}\sigma^2} > 0 \implies \ln m = \mu + \frac{1}{2}\sigma^2 \implies$$

$$\mu = \ln m - \frac{1}{2}\sigma^2 = \ln m - \frac{1}{2} \ln\left(\frac{m^2 + s^2}{m^2}\right)$$

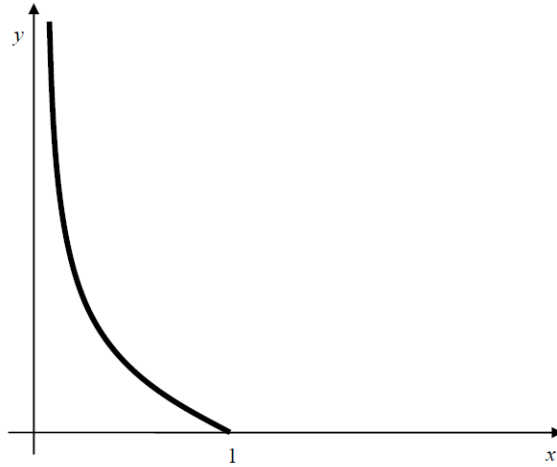
$$\begin{aligned}
&= \ln m - \frac{1}{2} \ln(m^2 + s^2) + \frac{1}{2} \ln m^2 = \ln m - \frac{1}{2} \ln(m^2 + s^2) + \ln(m^2)^{1/2} \\
&= 2 \ln m - \frac{1}{2} \ln(m^2 + s^2) = \ln\left(\frac{m^2}{[m^2 + s^2]^{1/2}}\right).
\end{aligned}$$

2.

$$\tilde{x} \sim f_{\tilde{x}}(x) = \begin{cases} 1 & \text{for } 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\tilde{y} = g(\tilde{x}) = -2 \ln \tilde{x} > 0, \text{ for } \tilde{x} \in (0, 1)$$

$$\tilde{x} = g^{-1}(\tilde{y}) = e^{-\tilde{y}/2}$$



$$x = 0 \rightarrow y = \infty$$

$$x = 1 \rightarrow y = 0$$

$$\frac{dx}{dy} = \frac{dg^{-1}(y)}{dy} = \frac{e^{-y/2}}{(-2)} \rightarrow \left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{2}e^{-y/2}$$

Therefore

$$f_{\tilde{y}}(y) = \begin{cases} 1 \cdot \frac{1}{2}e^{-y/2} = \frac{1}{2}e^{-y/2} & \text{for } 0 < y < \infty \\ 0 & \text{elsewhere} \end{cases}$$

This is the density of an exponential distribution (or of the gamma distribution with  $\alpha = 1$  and  $\beta = 2$ ).

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**3.**

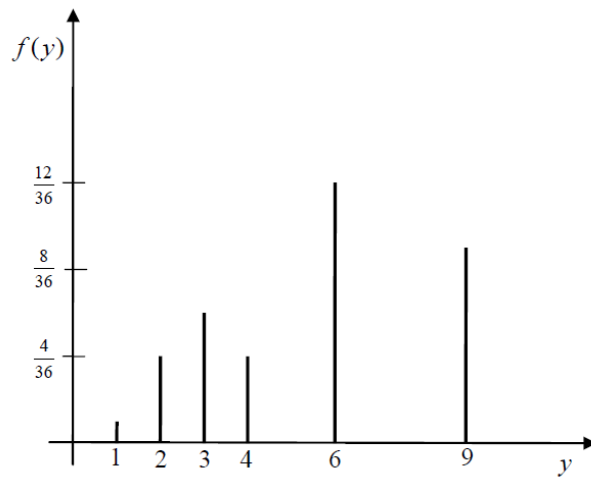
$x_1 \setminus x_2$	1	2	3
1	$\frac{1}{36}$	$\frac{2}{36}$	$\frac{3}{36}$
2	$\frac{2}{36}$	$\frac{4}{36}$	$\frac{6}{36}$
3	$\frac{3}{36}$	$\frac{6}{36}$	$\frac{9}{36}$

(a)  $\tilde{y} = \tilde{x}_1 \cdot \tilde{x}_2 \sim f_{\tilde{y}}(y)$ .

$$\begin{array}{lll}
 \tilde{y} = 1 & (1, 1) & \frac{1}{36} \\
 \tilde{y} = 2 & (1, 2) (2, 1) & \frac{2}{36} + \frac{2}{36} = \frac{4}{36} \\
 \tilde{y} = 3 & (1, 3) (3, 1) & \frac{3}{36} + \frac{3}{36} = \frac{6}{36} \\
 \tilde{y} = 4 & (2, 2) & \frac{4}{36} \\
 \tilde{y} = 6 & (2, 3) (3, 2) & \frac{6}{36} + \frac{6}{36} = \frac{12}{36} \\
 \tilde{y} = 9 & (3, 3) & \frac{9}{36}
 \end{array}$$

$\implies$

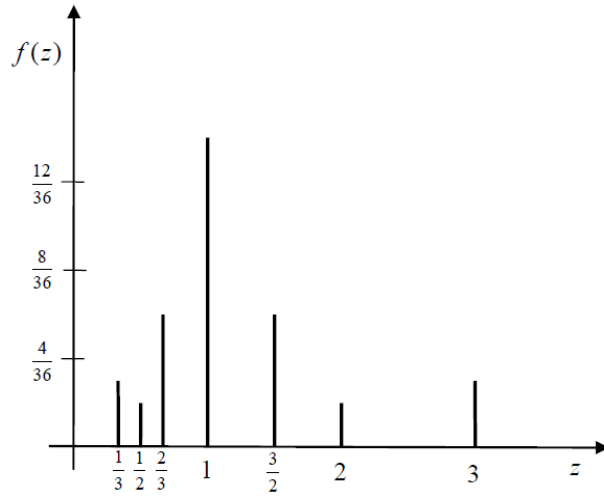
$y$	$f_{\tilde{y}}(y)$
1	$\frac{1}{36}$
2	$\frac{4}{36}$
3	$\frac{6}{36}$
4	$\frac{4}{36}$
6	$\frac{12}{36}$
9	$\frac{9}{36}$



(b)  $\tilde{z} = \frac{\tilde{x}_1}{\tilde{x}_2} \sim f_{\tilde{z}}(z)$

$\tilde{z} = 1$	(1, 1) (2, 2) (3, 3)	$\frac{1}{36} + \frac{4}{36} + \frac{9}{36}$	
$\tilde{z} = \frac{1}{2}$	(1, 2)	$\frac{2}{36}$	
$\tilde{z} = \frac{1}{3}$	(1, 3)	$\frac{3}{36}$	
$\tilde{z} = \frac{2}{3}$	(2, 3)	$\frac{6}{36}$	$\implies$
$\tilde{z} = 2$	(2, 1)	$\frac{2}{36}$	
$\tilde{z} = 3$	(3, 1)	$\frac{3}{36}$	
$\tilde{z} = \frac{3}{2}$	(3, 2)	$\frac{6}{36}$	

$z$	$f_z(z)$
$\frac{1}{3}$	$\frac{3}{36}$
$\frac{1}{2}$	$\frac{2}{36}$
$\frac{2}{3}$	$\frac{6}{36}$
1	$\frac{14}{36}$
$\frac{3}{2}$	$\frac{6}{36}$
2	$\frac{2}{36}$
3	$\frac{3}{36}$



4.

$$\tilde{x}_i \sim \Gamma(\alpha, \beta), \quad i = 1, \dots, n$$

$$M_{\tilde{x}_i}(t) = (1 - \beta t)^{-\alpha}, \quad i = 1, \dots, n, \quad \text{for } t < 1/\beta$$

$$\tilde{y} = \sum_{i=1}^n \tilde{x}_i$$

Since the  $\tilde{x}_i$ 's are independent,

$$\begin{aligned} M_{\tilde{y}}(t) &= \mathbb{E}(e^{t\tilde{y}}) = \mathbb{E}\left(\exp\left(t\sum_{i=1}^n \tilde{x}_i\right)\right) = \mathbb{E}\left(\exp\left(\sum_{i=1}^n t\tilde{x}_i\right)\right) \\ &= \mathbb{E}\left(\prod_{i=1}^n e^{t\tilde{x}_i}\right) = \prod_{i=1}^n \mathbb{E}(e^{t\tilde{x}_i}) = \prod_{i=1}^n M_{\tilde{x}_i}(t) = [(1 - \beta t)^{-\alpha}]^n = (1 - \beta t)^{-(n\alpha)}, \end{aligned}$$

for  $t < 1/\beta$ . This has the same form as the MGF of a  $\Gamma$  variable. Since the exponent of  $M_{\tilde{y}}(t)$  is  $-n\alpha$ , the parameter corresponding to  $\alpha$  in the  $\Gamma$  is now  $n\alpha$ ,

$$f_{\tilde{y}}(y; n\alpha, \beta) = \frac{1}{\beta^{n\alpha} \Gamma(n\alpha)} y^{n\alpha-1} e^{-y/\beta}; \quad \text{for } y > 0,$$

and  $f_{\tilde{y}}(y; n\alpha, \beta) = 0$ , otherwise. Thus,  $\tilde{y} \sim \Gamma(n\alpha, \beta)$ .

Since the exponential distribution is the gamma distribution with  $\alpha = 1$  and  $\beta = \theta$ , the sum of  $n$  independent exponential random variables has the gamma distribution with parameters  $n$  and  $\theta$ ,  $\Gamma(n, \theta)$ .

Note that the gamma distribution when  $\alpha$  is equal to a natural number  $n$  is used to model waiting time in a queue when the individual under consideration is in the  $n$ th position in that queue. In this case, we know that the expected waiting time will be  $\alpha\beta = n\theta$ .

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**5.** If  $\tilde{\theta}$  is the angle that a "random spinner" makes with the positive side of the  $x$  axis, what is the density function of  $\tan \tilde{\theta}$ ? Note that the distribution of the angle  $\tilde{\theta}$  is obviously absolutely continuous and uniform on  $(-\pi/2, \pi/2)$ .

Thus, this exercise can be formulated as follows:

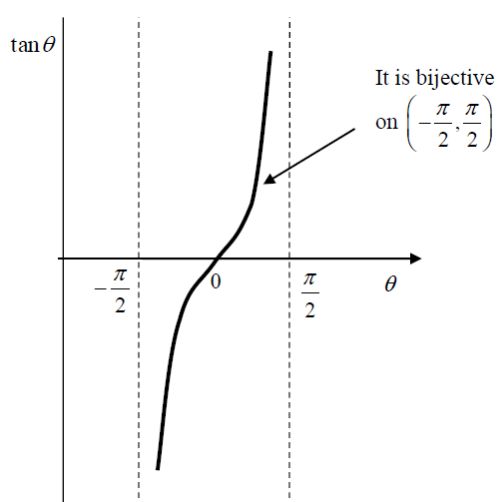
$$f_{\tilde{\theta}}(\theta) = \frac{1}{\pi}, \text{ for } -\frac{\pi}{2} < \theta < \frac{\pi}{2}$$

and  $f_{\tilde{\theta}}(\theta) = 0$ , otherwise.

$$g : t = g(\theta) = \tan \theta \in (-\infty, \infty) ,$$

$$g^{-1} : \theta = g^{-1}(t) = \arctan t \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right) .$$

$$f_{\tilde{t}}(t) = ?$$



$$J_{g^{-1}}(t) = \frac{d\theta}{dt} = \frac{1}{1+t^2} > 0$$

Hence,

$$f_{\tilde{t}}(t) = \frac{1}{\pi} \cdot |J_{g^{-1}}(t)| = \frac{1}{\pi} \cdot \frac{1}{1+t^2} \text{ for } -\infty < t < \infty \quad (\text{Density of the Cauchy distribution})$$

Check (for free!):

$$\begin{aligned}\int_{-\infty}^{\infty} \frac{1}{\pi} \cdot \frac{1}{1+t^2} dt &= \frac{1}{\pi} [\arctan t]_{-\infty}^{\infty} = \frac{1}{\pi} \left[ \lim_{t \rightarrow \infty} \arctan(t) - \lim_{t \rightarrow -\infty} \arctan(t) \right] \\ &= \frac{1}{\pi} \left[ \frac{\pi}{2} - \left( -\frac{\pi}{2} \right) \right] = 1\end{aligned}$$

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**6.**

$$f(x_1, x_2) = 1, \quad \text{for } 0 < x_1 < 1, \quad 0 < x_2 < 1$$

$$g : \begin{cases} u_1 = (-2 \ln x_1)^{\frac{1}{2}} \sin(2\pi x_2), & -\infty < u_1 < \infty \\ u_2 = (-2 \ln x_1)^{\frac{1}{2}} \cos(2\pi x_2), & -\infty < u_2 < \infty \end{cases}$$

$$f_{\tilde{u}_1, \tilde{u}_2}(u_1, u_2) = ?$$

$$u_1^2 = -2 \ln x_1 \sin^2(2\pi x_2)$$

$$u_2^2 = -2 \ln x_1 \cos^2(2\pi x_2)$$

Since

$$u_1^2 + u_2^2 = -2 \ln x_1 [\sin^2(2\pi x_2) + \cos^2(2\pi x_2)] = -2 \ln x_1,$$

then

$$x_1 = e^{-\frac{1}{2}(u_1^2 + u_2^2)} \in (0, 1).$$

Since

$$\begin{aligned}\frac{u_1}{u_2} &= \tan(2\pi x_2), \\ 2\pi x_2 &= \arctan\left(\frac{u_1}{u_2}\right),\end{aligned}$$

then

$$x_2 = \frac{1}{2\pi} \arctan\left(\frac{u_1}{u_2}\right) \in (0, 1)$$

$$\begin{aligned}|J_{g^{-1}}(u_1, u_2)| &= \left| \det \begin{bmatrix} \frac{dx_1}{du_1} & \frac{dx_1}{du_2} \\ \frac{dx_2}{du_1} & \frac{dx_2}{du_2} \end{bmatrix} \right| = \left| \det \begin{bmatrix} e^{-\frac{1}{2}(u_1^2+u_2^2)}(-u_1) & e^{-\frac{1}{2}(u_1^2+u_2^2)}(-u_2) \\ \frac{1}{2\pi} \frac{1}{1+\left(\frac{u_1}{u_2}\right)^2} \frac{1}{u_2} & \frac{1}{2\pi} \frac{1}{1+\left(\frac{u_1}{u_2}\right)^2} \left(-\frac{u_1}{u_2}\right) \end{bmatrix} \right| \\ &= \frac{1}{2\pi} \frac{1}{1+\frac{u_1^2}{u_2^2}} e^{-\frac{1}{2}(u_1^2+u_2^2)} \left| \det \begin{bmatrix} -u_1 & -u_2 \\ \frac{1}{u_2} & -\frac{u_1}{u_2} \end{bmatrix} \right| = \frac{1}{2\pi} \frac{1}{1+\frac{u_1^2}{u_2^2}} e^{-\frac{1}{2}(u_1^2+u_2^2)} \left[ 1 + \frac{u_1^2}{u_2^2} \right] \\ &= \frac{1}{2\pi} e^{-\frac{1}{2}(u_1^2+u_2^2)}\end{aligned}$$

$$f_{\tilde{u}_1, \tilde{u}_2}(u_1, u_2) = 1 \cdot |J_{g^{-1}}(u_1, u_2)| = \frac{1}{2\pi} e^{-\frac{1}{2}(u_1^2+u_2^2)}, \text{ for } -\infty < u_1 < \infty, -\infty < u_2 < \infty.$$

Thus,  $(\tilde{u}_1, \tilde{u}_2) \sim \text{MN}(\underline{0}, \text{I})$ , where I is the identity matrix. That is,  $\tilde{u}_1$  and  $\tilde{u}_2$  are independently distributed standard normal variables.

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7.

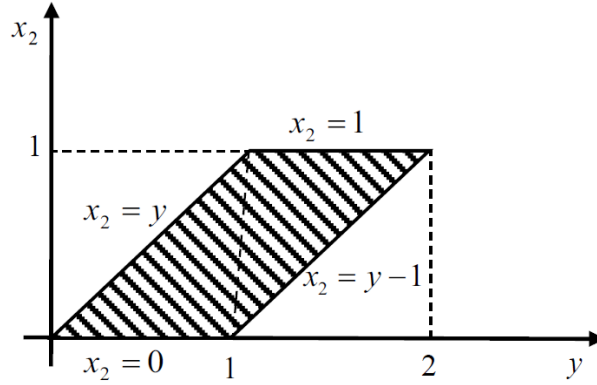
$$g : \begin{cases} y = x_1 + x_2 \in (x_2, x_2 + 1) \\ x_2 = x_2 \in (0, 1) \end{cases} \implies g^{-1} : \begin{cases} x_1 = y - x_2 \in (0, 1) \\ x_2 = x_2 \in (0, 1) \end{cases}$$

$$|J_{g^{-1}}(y, x_2)| = \left| \det \begin{bmatrix} \frac{dx_1}{dy} & \frac{dx_1}{dx_2} \\ \frac{dx_2}{dy} & \frac{dx_2}{dx_2} \end{bmatrix} \right| = \left| \det \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \right| = 1.$$

Then,

$$f_{\tilde{y}, \tilde{x}_2}(y, x_2) = 1 \cdot 1 = 1 \text{ for } 0 < x_2 < 1 \text{ and } x_2 < y < x_2 + 1$$

$$f_{\tilde{y}, \tilde{x}_2}(y, x_2) = \begin{cases} 1 & \text{for } 0 < x_2 < 1 \text{ and } x_2 < y < x_2 + 1 \\ 0 & \text{elsewhere} \end{cases}$$



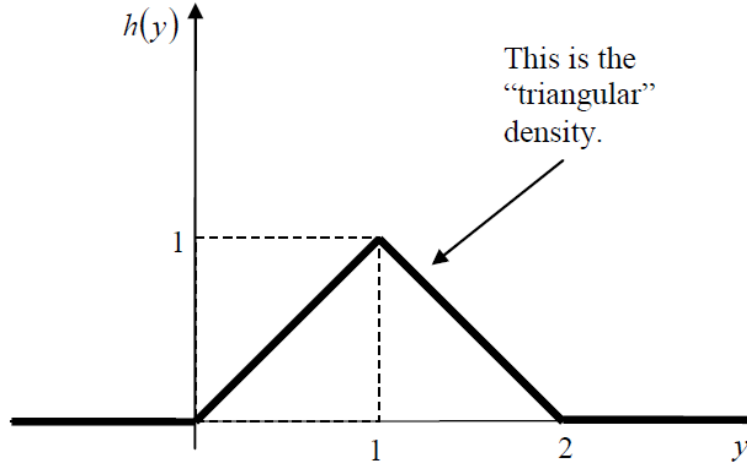
The density of  $y$  for  $y \in (0, 2)$  is

$$h(y) = \int_{-\infty}^{\infty} f_{\tilde{y}, \tilde{x}_2}(y, x_2) dx_2 = \int_{\mathbb{R}} \mathbb{I}_C(y, x_2) \cdot 1 dx_2 = \int_{C(y)} 1 dx_2,$$

where the set  $C$  is the interior of the parallelogram in the previous figure.

Then,

$$h(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y 1 dx_2 = y & \text{for } 0 < y \leq 1 \\ \int_{y-1}^1 1 dx_2 = 2 - y & \text{for } 1 < y < 2 \\ 0 & \text{for } y \geq 2 \end{cases}$$



8. (a) The joint distribution of the random vector  $(\tilde{x}, \tilde{y})$  is

$$f(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2\sigma^2}(x^2+y^2)}, \quad \text{for } x \in (-\infty, +\infty) \text{ and } y \in (-\infty, +\infty).$$

Let  $(r, \theta) = g(x, y)$  with  $r = (x^2 + y^2)^{1/2}$  and  $\theta = \arctan(\frac{y}{x})$ . Thus,  $(x, y) = g^{-1}(r, \theta)$  is given by  $x = r \cos \theta$  and  $y = r \sin \theta$ . Therefore,  $|J_{g^{-1}}(r, \theta)| = r > 0$ .

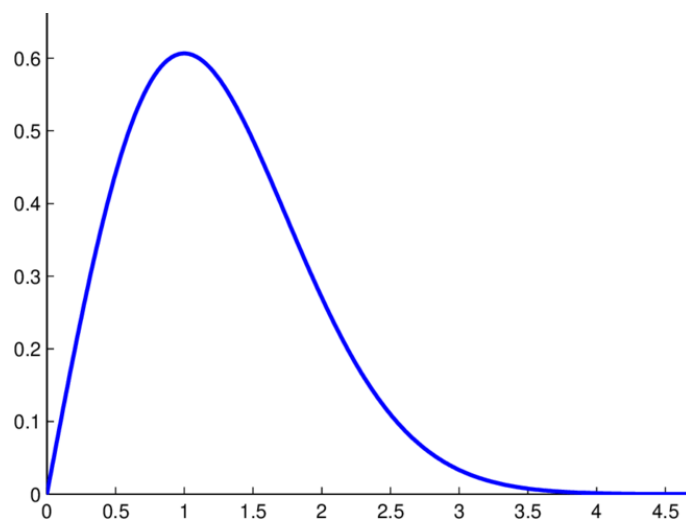
Then,

$$f_{\tilde{r}, \tilde{\theta}}(r, \theta) = \begin{cases} \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} & \text{for } r \in (0, \infty) \text{ and } \theta \in [0, 2\pi) \\ 0 & \text{otherwise.} \end{cases}$$

Therefore, computing the marginal density of  $\tilde{r}$ ,

$$f_{\tilde{r}}(r) = \begin{cases} \int_0^{2\pi} f_{\tilde{r}, \tilde{\theta}}(r, \theta) d\theta = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} r [\theta]_0^{2\pi} = \frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}} & \text{for } r \in (0, \infty) \\ 0 & \text{otherwise.} \end{cases}$$

Thus, the distribution of the modulus  $\tilde{r}$  of the vector  $(\tilde{x}, \tilde{y})$  with random coordinates that are independent and normally distributed with zero mean and standard deviation  $\sigma$  is the Rayleigh distribution with parameter  $\sigma$ . Its density looks like this:



Moreover, computing the marginal density of  $\tilde{\theta}$ ,

$$f_{\tilde{\theta}}(\theta) = \begin{cases} \int_0^{\infty} f_{\tilde{r}, \tilde{\theta}}(r, \theta) dr = \frac{1}{2\pi} \left[ -e^{-\frac{r^2}{2\sigma^2}} \right]_0^{\infty} = \frac{1}{2\pi} & \text{for } \theta \in [0, 2\pi) \\ & \text{or for } \theta \in (0, 2\pi) \\ 0 & \text{otherwise.} \end{cases}$$

(b) The random variables  $\tilde{r}$  and  $\tilde{\theta}$  are independent since we see that

$$f_{\tilde{r}, \tilde{\theta}}(r, \theta) = f_{\tilde{z}}(z) f_{\tilde{r}}(r) \quad \text{for all } r \text{ and } \theta.$$

(c) To find the density of the square of the modulus  $\tilde{w} = \tilde{r}^2 = \tilde{x}^2 + \tilde{y}^2$  with

$r \in (0, \infty)$ , we note that  $\tilde{r} = \tilde{w}^{1/2} > 0$  so that

$$\left| \frac{dr}{dw} \right| = \frac{1}{2w^{1/2}} > 0.$$

Then,

$$f_{\tilde{w}}(w) = f_{\tilde{r}}(w^{1/2}) \left| \frac{dr}{dw} \right| = \frac{w^{1/2}}{\sigma^2} e^{-\frac{w}{2\sigma^2}} \frac{1}{2w^{1/2}} = \frac{1}{2\sigma^2} e^{-\frac{w}{2\sigma^2}}, \text{ for } w \in (0, \infty),$$

and  $f_{\tilde{w}}(w) = 0$ , otherwise. This is the density of an exponential distribution with parameter  $2\sigma^2$ .

The previous result also tells us that, if  $\tilde{w}$  is exponential with parameter  $\lambda$ ,

$$f_{\tilde{w}}(w) = \begin{cases} \frac{1}{\lambda} e^{-w/\lambda} & \text{for } w > 0 \\ 0 & \text{otherwise,} \end{cases}$$

then the random variable  $\tilde{r} = \tilde{w}^{1/2} = \sqrt{\tilde{w}} > 0$  is Rayleigh with the scale parameter  $\sigma = \sqrt{\lambda/2} > 0$ .

Since the density of a  $\chi_\nu^2$  distribution is

$$f(w; \nu) = \begin{cases} \frac{1}{2^{\nu/2} \Gamma(\frac{\nu}{2})} w^{\frac{\nu-2}{2}} e^{-w/2} & \text{for } w > 0 \\ 0 & \text{otherwise,} \end{cases}$$

it is immediate to see that

$$f_{\tilde{w}}(w) = f(w; 2) = \begin{cases} \frac{1}{2}e^{-w/2} & \text{for } w > 0 \\ 0 & \text{otherwise,} \end{cases}$$

when  $\sigma = 1$  so that  $\tilde{w} \sim \chi_2^2$ .

(d) We integrate by parts.

$$\begin{aligned} \mathbb{E}(\tilde{r}) &= \int_0^\infty r f_{\tilde{r}}(r) dr = \int_0^\infty \underbrace{r}_{F(r)} \underbrace{\frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}}}_{G'(r)} dr = \\ &= \left[ -r e^{-\frac{r^2}{2\sigma^2}} \right]_0^\infty - \int_0^\infty \underbrace{1}_{F'(r)} \underbrace{\left( -e^{-\frac{r^2}{2\sigma^2}} \right)}_{G(r)} dr = 0 + \int_0^\infty e^{-\frac{r^2}{2\sigma^2}} dr = \dots \end{aligned}$$

Make the change of variable  $z = r/\sigma$  so that  $\left| \frac{dr}{dz} \right| = \sigma > 0$ .

$$\begin{aligned} \dots &= \int_0^\infty e^{-\frac{z^2}{2}} \sigma dz = \sigma \int_0^\infty e^{-\frac{z^2}{2}} dz = \sigma \sqrt{\frac{\pi}{2}}. \\ \mathbb{E}(\tilde{r}^2) &= \int_0^\infty r^2 f_{\tilde{r}}(r) dr = \int_0^\infty \underbrace{r^2}_{F(r)} \underbrace{\frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}}}_{G'(r)} dr = \\ &= \left[ -r^2 e^{-\frac{r^2}{2\sigma^2}} \right]_0^\infty - \int_0^\infty \underbrace{2r}_{F'(r)} \underbrace{\left( -e^{-\frac{r^2}{2\sigma^2}} \right)}_{G(r)} dr = 0 + 2 \int_0^\infty r e^{-\frac{r^2}{2\sigma^2}} dr = \dots \\ &= 2 \left[ -\sigma^2 e^{-\frac{r^2}{2\sigma^2}} \right]_0^\infty = 2\sigma^2. \end{aligned}$$

Thus,

$$\text{Var}(\tilde{r}) = \mathbb{E}(\tilde{r}^2) - [\mathbb{E}(\tilde{r})]^2 = 2\sigma^2 - \left(\frac{\pi}{2}\right) \sigma^2 = \left(2 - \frac{\pi}{2}\right) \sigma^2.$$

(e) As  $\tilde{\theta}$  is uniform on  $[0, 2\pi)$  or, without loss of generality, on  $(0, 2\pi)$ ,

$$E(\tilde{\theta}) = \pi \quad \text{and} \quad \text{Var}(\tilde{\theta}) = \frac{(2\pi)^2}{12} = \frac{\pi^2}{3}.$$

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9. (a)

$$F(x, y) = \begin{cases} 0 & \text{if } x < 0 \text{ or } y < 0 \\ \int_0^y \int_0^x \frac{r+2t}{12} dr dt = \frac{xy(x+2y)}{24} & \text{if } 0 \leq x < 2, 0 \leq y < 2 \\ \int_0^2 \int_0^x \frac{r+2t}{12} dr dt = \frac{x(x+4)}{12} & \text{if } 0 \leq x < 2, y \geq 2 \\ \int_0^y \int_0^2 \frac{r+2t}{12} dr dt = \frac{y(y+1)}{6} & \text{if } x \geq 2, 0 \leq y < 2, \\ 1 & \text{if } x \geq 2, y \geq 2. \end{cases}$$

(b)

$$f_{\tilde{x}}(x) = \begin{cases} \int_0^2 \frac{x+2y}{12} dy = \frac{x+2}{6} & \text{if } x \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

$$f_{\tilde{y}}(y) = \begin{cases} \int_0^2 \frac{x+2y}{12} dx = \frac{1+2y}{6} & \text{if } y \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

(c)

$$f_{\tilde{y}|\tilde{x}}(y|x) = \begin{cases} \frac{f(x,y)}{f_{\tilde{x}}(x)} = \frac{\frac{1}{12}(x+2y)}{\frac{x+2}{6}} = \frac{x+2y}{2x+4} & \text{if } y \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

for  $x \in (0, 2)$ .

$$f_{\tilde{y}|\tilde{x}}\left(y \middle| \frac{1}{2}\right) = \begin{cases} \frac{f\left(\frac{1}{2}, y\right)}{f_{\tilde{x}}\left(\frac{1}{2}\right)} = \frac{1+4y}{10} & \text{if } y \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

(d)

$$\mathbb{E}(\tilde{y}) = \int_{-\infty}^{\infty} y f_{\tilde{y}}(y) dy = \int_0^2 y \frac{1+2y}{6} dy = \frac{11}{9},$$

or, equivalently,

$$\mathbb{E}(\tilde{y}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x, y) dx dy = \int_0^2 \int_0^2 y \frac{x+2y}{12} dx dy = \frac{11}{9}.$$

$$\mathbb{E}(\tilde{y} | \tilde{x} = 1/2) = \int_{-\infty}^{\infty} y f_{\tilde{y}|\tilde{x}}\left(y \middle| \frac{1}{2}\right) dy = \int_0^2 y \frac{1+4y}{10} dy = \frac{19}{15}.$$

(e)

$$P(\{0 < \tilde{x} < 1\} \cap \{1 < \tilde{y} < 3/2\}) = \int_0^1 \int_1^{3/2} \frac{x+2y}{12} dy dx = \frac{1}{8}.$$

(f) Note that  $f_{\tilde{y}|\tilde{x}}(y|x) = f_{\tilde{y}}(y)$  for all  $y \in (-\infty, \infty)$  if and only if

$$\frac{x+2y}{2(x+2)} = \frac{1+2y}{6}.$$

for all  $y \in (0, 2)$ . Hence,  $x = 1$ .

The random variables  $\tilde{x}$  and  $\tilde{y}$  are not independent since

$$f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y) = \frac{x+2}{6} \cdot \frac{1+2y}{6} = \frac{(x+2) \cdot (1+2y)}{36} \neq f(x, y) = \frac{1}{12}(x+2y),$$

for all  $(x, y) \in (0, 2) \times (0, 2)$ , except when  $(x, y) = (1, 1)$ . Note that, for  $(x, y) \in (0, 2) \times (0, 2)$ ,

$$\begin{aligned} f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y) - f(x, y) &= \frac{(x+2) \cdot (1+2y)}{36} - \frac{1}{12}(x+2y) \\ &= \frac{1}{18}(x-1)(y-1) = 0 \text{ if and only if } (x, y) = (1, 1). \end{aligned}$$

(g) Let  $y \in (0, 2)$ . Then,  $w = g(y) = 2 - y^{1/3} \iff y = g^{-1}(w) = (2 - w)^3$  for  $g^{-1}\{(0, 2)\} = (2 - 2^{1/3}, 2) = (0.74, 2)$ .

Moreover,

$$\frac{dy}{dw} = \frac{dg^{-1}(w)}{dw} = -3(2-w)^2 < 0$$

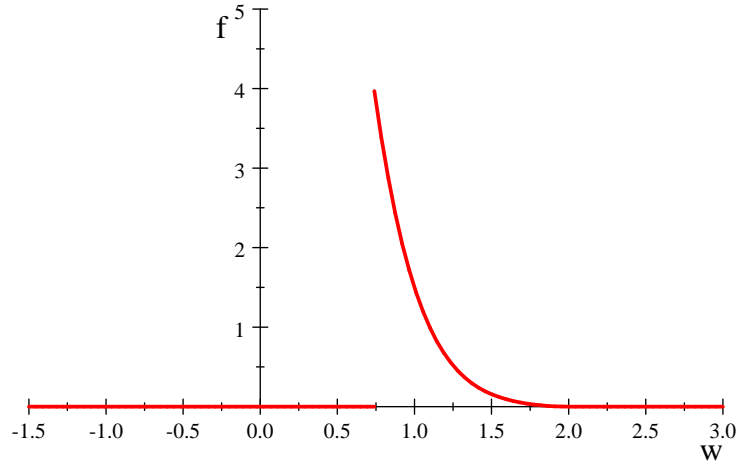
for  $w \in (2 - 2^{1/3}, 2) \iff y \in (0, 2)$ .

Since  $f_{\tilde{y}}(y) = \frac{1+2y}{6}$  for  $y \in (0, 2)$ , then

$$\begin{aligned} f_{\tilde{w}}(w) &= f_{\tilde{y}}(g^{-1}(w)) \left| \frac{dg^{-1}(w)}{dw} \right| = \frac{1+2(2-w)^3}{6} 3(2-w)^2 \\ &= \left( \frac{1}{2} + (2-w)^3 \right) (2-w)^2, \text{ for } w \in (2 - 2^{1/3}, 2). \end{aligned}$$

Thus,

$$f_{\tilde{w}}(w) = \begin{cases} \left(\frac{1}{2} + (2-w)^3\right) (2-w)^2 & \text{for } 2 - 2^{1/3} < w < 2 \\ 0 & \text{otherwise.} \end{cases}$$



$$\begin{aligned} \mathbb{E}(\tilde{w}) &= \int_{-\infty}^{\infty} g(y) f_{\tilde{y}}(y) dy = \int_0^2 (2 - y^{1/3}) \frac{1 + 2y}{6} dy \\ &= \frac{1}{6} \int_0^2 (2 + 4y - y^{1/3} - 2y^{4/3}) dy = \frac{1}{6} \left[ 2y + 2y^2 - \frac{3}{4}y^{4/3} - \frac{6}{7}y^{7/3} \right]_0^2 \\ &= \frac{1}{6} \left[ 12 - \left( \frac{69}{14} \cdot 2^{1/3} \right) \right] = 2 - \left( \frac{23}{28} \cdot 2^{1/3} \right) = 0.965. \end{aligned}$$

Alternatively (and much more difficult and inefficient), we can compute

$$\mathbb{E}(\tilde{w}) = \int_{2-2^{1/3}}^2 \underbrace{w \left( \frac{1}{2} + (2-w)^3 \right) (2-w)^2}_{f_{\tilde{w}}(w)} dw = 2 - \left( \frac{23}{28} \cdot 2^{1/3} \right) = 0.965.$$

(h) *Density function method:* Let  $(z, t) = g(x, y)$  be given by  $z = xy$  and

$t = y$ . Therefore,  $(x, y) = g^{-1}(z, t)$  is given by  $x = z/t$  and  $y = t$ . Therefore,

$$|J_{g^{-1}}(z, t)| = \left| \det \begin{pmatrix} 1/t & -z/t^2 \\ 0 & 1 \end{pmatrix} \right| = 1/t$$

and

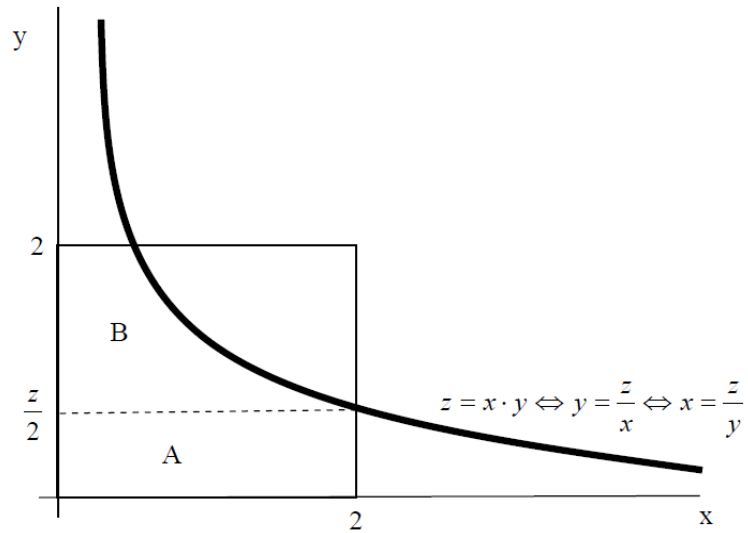
$$f_{\tilde{z}, \tilde{t}}(z, t) = \begin{cases} f_{\tilde{x}, \tilde{y}}\left(\frac{z}{t}, t\right) |J_{g^{-1}}(z, t)| = \frac{1}{12} \left(\frac{z}{t} + 2t\right) \frac{1}{t} = \frac{1}{12} \left(\frac{z}{t^2} + 2\right) & \text{if } \frac{z}{t} \in (0, 2) \text{ and } t \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

The set of positive density,  $C = \{z/t \in (0, 2) \text{ and } t \in (0, 2)\}$ , can also be written as  $\{z \in (0, 2t) \text{ and } t \in (0, 2)\}$  or as  $\{z \in (0, 4) \text{ and } t \in (z/2, 2)\}$ . Make a draw in the plain  $(z, t)$  to see this!

Then, computing the marginal density of  $\tilde{z}$ ,

$$f_{\tilde{z}}(z) = \begin{cases} \int_{\mathbb{R}} \mathbb{I}_C(z, t) f_{\tilde{z}, \tilde{t}}(z, t) dt = \int_{z/2}^2 \frac{1}{12} \left(\frac{z}{t^2} + 2\right) dt = \frac{4-z}{8} & \text{if } z \in (0, 4) \\ 0 & \text{otherwise.} \end{cases}$$

*Distribution function method:*



$$F_z(z) = \begin{cases} 0 & \text{if } z < 0 \\ \int_A \frac{1}{12} (x + 2y) d(x, y) + \int_B \frac{1}{12} (x + 2y) d(x, y) = \frac{1}{2}z - \frac{1}{16}z^2 & \text{if } z \in [0, 4] \\ 1 & \text{if } z > 4 \end{cases}$$

Note that

$$\int_A \frac{1}{12} (x + 2y) d(x, y) + \int_B \frac{1}{12} (x + 2y) d(x, y) = \int_0^{\frac{z}{2}} \int_0^2 \frac{1}{12} (x + 2y) dx dy + \int_{\frac{z}{2}}^2 \int_0^{\frac{z}{x}} \frac{1}{12} (x + 2y) dx dy = \frac{z}{2} - \frac{z^2}{16}.$$

Therefore, by just differentiating,

$$f_{\tilde{z}}(z) = \begin{cases} F'(z) = \frac{4-z}{8} & \text{if } z \in (0, 4) \\ 0 & \text{otherwise.} \end{cases}$$

-----

10. If  $x < 0$ , then

$$F_{\tilde{x}}(x) = \int_{-\infty}^x \frac{1}{2} e^t dt = \frac{1}{2} e^x.$$

If  $x \geq 0$ , then

$$\int_{-\infty}^x \frac{1}{2} e^{-|t|} dt = \underbrace{\int_{-\infty}^0 \frac{1}{2} e^t dt}_{1/2} + \int_0^x \frac{1}{2} e^{-t} dt = \frac{1}{2} + \frac{1}{2} - \frac{1}{2} e^{-x} = 1 - \frac{1}{2} e^{-x}.$$

Therefore,

$$F_{\tilde{x}}(x) = \begin{cases} \frac{1}{2} e^x & \text{for } x < 0 \\ 1 - \frac{1}{2} e^{-x} & \text{for } x \geq 0. \end{cases}$$

Note that  $y = g(x) = x^3$  is a one-to-one correspondence (or bijection) and  $x = g^{-1}(y) = y^{1/3}$  so that

$$f_{\tilde{y}}(y) = \frac{1}{6} e^{-|y^{1/3}|} |y|^{-2/3} \text{ for } x \in (-\infty, \infty)$$

Note that  $z = g(x) = \ln(|x| + 1) \geq 0$  is not a bijection. Then, we use the

distribution function method. Note that for  $z \geq 0$  we have

$$F_{\tilde{z}}(z) = P\{\tilde{z} \leq z\} = P\{\ln(|\tilde{x}| + 1) \leq z\} = P\{1 - e^z \leq \tilde{x} \leq e^z - 1\} =$$

$$F_{\tilde{x}}(\underbrace{e^z - 1}_{\geq 0}) - F_{\tilde{x}}(\underbrace{1 - e^z}_{\leq 0}) = 1 - \frac{1}{2}e^{-(e^z - 1)} - \frac{1}{2}e^{(1 - e^z)} = 1 - e^{(1 - e^z)}.$$

Therefore,

$$F_{\tilde{z}}(z) = \begin{cases} 0 & \text{for } z < 0 \\ 1 - e^{(1 - e^z)} & \text{for } z \geq 0. \end{cases}$$

Differentiating  $F_{\tilde{z}}$  one gets the density function,

$$f_{\tilde{z}}(z) = \begin{cases} e^{1 - e^z} e^z = e^{1 + z - e^z} & \text{for } z > 0. \\ 0 & \text{for } z \leq 0. \end{cases}$$

-----

**11.**  $y = g(x) = 9 - x^2$  is a one-to-one correspondence (or bijective function) on  $(0, 3)$ . When  $x \in (0, 3)$  then  $y \in (0, 9)$ . Therefore,  $x = g^{-1}(y) = (9 - y)^{1/2}$  with  $y \in (0, 9)$ . Moreover,

$$\left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{2} (9 - y)^{-1/2}.$$

$$f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{x}}(g^{-1}(y)) \left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{6} (9 - y)^{-1/2} & \text{for } y \in (0, 9) \\ 0 & \text{otherwise.} \end{cases}$$

Integrating the density  $f_{\tilde{y}}$  we get the distribution function:

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y \frac{1}{6}(9-t)^{-1/2} dt = 1 - \frac{(9-y)^{1/2}}{3} & \text{for } y \in (0, 9) \\ 1 & \text{for } y \geq 9. \end{cases}$$

We could have used instead the distribution function method:

$F_{\tilde{y}}(y) = 0$  for  $y \leq 0$ ,  $F_{\tilde{y}}(y) = 1$  for  $y \geq 9$ , and, for  $y \in (0, 9)$ , we have,

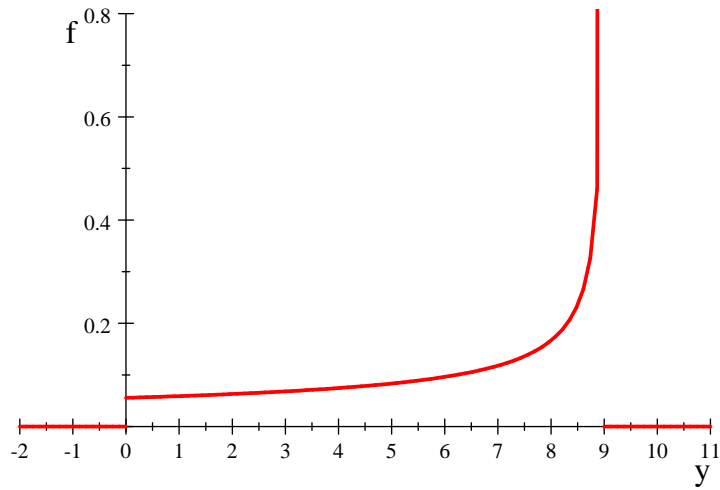
$$\begin{aligned} F_{\tilde{y}}(y) &= P\{\tilde{y} \leq y\} = P\{9 - \tilde{x}^2 \leq y\} = P\{9 - y \leq \tilde{x}^2\} \\ &= P(\{(9-y)^{1/2} \leq \tilde{x}\} \cup \{\tilde{x} \leq -(9-y)^{1/2}\}) \\ &= P\{(9-y)^{1/2} \leq \tilde{x}\} + P\{\tilde{x} \leq -(9-y)^{1/2}\} = P\{(9-y)^{1/2} \leq \tilde{x}\} + 0. \end{aligned}$$

Note that  $P\left\{\tilde{x} \leq \underbrace{-(9-y)^{1/2}}_{\text{negative}}\right\} = 0$  for  $y \in (0, 9)$  since the density of  $\tilde{x}$  is positive only on  $(0, 3)$ .

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ P\{(9-y)^{1/2} \leq \tilde{x}\} = \int_{(9-y)^{1/2}}^3 \frac{1}{3} dx = 1 - \frac{(9-y)^{1/2}}{3} & \text{for } y \in (0, 9) \\ 1 & \text{for } y \geq 9, \end{cases}$$

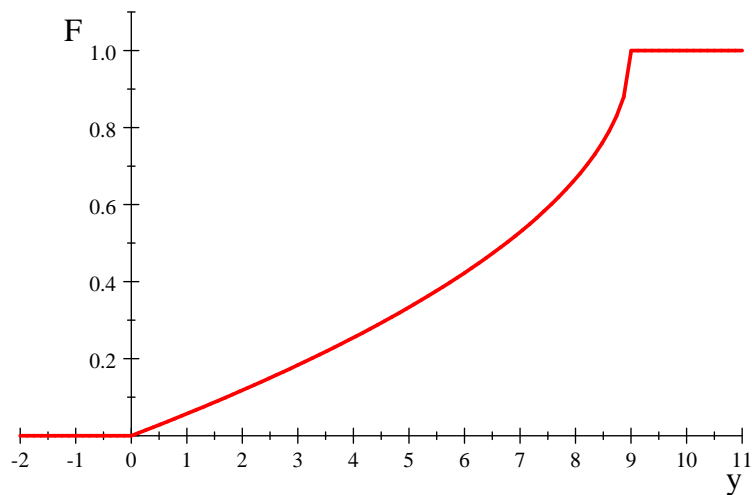
which is the same as before. Differentiating  $F_{\tilde{y}}(y)$  we obtain  $f_{\tilde{y}}(y)$  a.s.

Density function  $f_{\tilde{y}}$  :



Note that  $\lim_{y \rightarrow 0^+} f_{\tilde{y}}(y) = 1/18$  and  $\lim_{y \rightarrow 9^-} f_{\tilde{y}}(y) = \infty$ .

Distribution function  $F_{\tilde{y}}$  :



Note that  $F_{\tilde{y}}$  is continuous and differentiable except at  $y = 0$  and  $y = 9$  since  $\lim_{y \rightarrow 0^-} F_{\tilde{y}}(y) = \lim_{y \rightarrow 0^+} F_{\tilde{y}}(y) = 0$ ,  $\lim_{y \rightarrow 9^-} F_{\tilde{y}}(y) = \lim_{y \rightarrow 9^+} F_{\tilde{y}}(y) = 1$ ,  $\lim_{y \rightarrow 0^-} F'_{\tilde{y}}(y) = 0 \neq \lim_{y \rightarrow 0^+} F'_{\tilde{y}}(y) = 1/18$  and  $\lim_{y \rightarrow 9^-} F'_{\tilde{y}}(y) = \infty \neq \lim_{y \rightarrow 9^+} F'_{\tilde{y}}(y) = 0$ .

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12. (a)

$$F_{\tilde{y}}(y) = P\{\tilde{y} \leq y\} = P\{|\tilde{x}| \leq y\} = P\{-y \leq \tilde{x} \leq y\} = F_{\tilde{x}}(y) - \lim_{z \rightarrow -y^-} F_{\tilde{x}}(z) \quad \text{for } y \geq 0$$

and  $F_{\tilde{y}}(y) = 0$  for  $y < 0$ .

(b)

$$F_{\tilde{y}}(y) = F_{\tilde{x}}(y) - F_{\tilde{x}}(-y) \quad \text{for } y \geq 0$$

and  $F_{\tilde{y}}(y) = 0$  for  $y < 0$ .

(c)

$$f_{\tilde{y}}(y) = f_{\tilde{x}}(y) + f_{\tilde{x}}(-y) \quad \text{for } y > 0$$

and  $f_{\tilde{y}}(y) = 0$  for  $y \leq 0$ .

(d)

$$f_{\tilde{y}}(y) = 2f_{\tilde{x}}(y) \quad \text{for } y > 0$$

and  $f_{\tilde{y}}(y) = 0$  for  $y \leq 0$ .

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13. (a)  $y = g(x) = x^2 - 8$  is bijective on  $(0, 4)$ . When  $x \in (0, 4)$  then  $y \in (-8, 8)$ . Therefore,  $x = g^{-1}(y) = (y + 8)^{1/2}$  with  $y \in (-8, 8)$ . Moreover,

$$\left| \frac{dg^{-1}(y)}{dy} \right| = \frac{1}{2}(y + 8)^{-1/2}.$$

Therefore,

$$f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{x}}(g^{-1}(y)) \left| \frac{dg^{-1}(y)}{dy} \right| = \frac{(y+8)^{1/2}}{8} \cdot \frac{1}{2} (y+8)^{-1/2} = \frac{1}{16} & \text{for } y \in (-8, 8) \\ 0 & \text{otherwise.} \end{cases}$$

Integrating the density  $f_{\tilde{y}}$  we get the distribution function:

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq -8 \\ \int_{-8}^y \frac{1}{16} dy = \frac{1}{2} \left( \frac{y}{8} + 1 \right) & \text{for } y \in (-8, 8) \\ 1 & \text{for } y \geq 8. \end{cases}$$

We could have used instead the distribution function method:

$F_{\tilde{y}}(y) = 0$  for  $y \leq -8$ ,  $F_{\tilde{y}}(y) = 1$  for  $y \geq 8$ , and, for  $y \in (-8, 8)$ , we have,

$$\begin{aligned} F_{\tilde{y}}(y) &= P\{\tilde{y} \leq y\} = P\{\tilde{x}^2 - 8 \leq y\} = P\{\tilde{x}^2 \leq y + 8\} \\ &= P\{-(y+8)^{1/2} \leq \tilde{x} \leq (y+8)^{1/2}\} = P\{\tilde{x} \leq (y+8)^{1/2}\} \end{aligned}$$

since  $-(y+8)^{1/2}$  is negative for  $y \in (-8, 8)$  and the density of  $\tilde{x}$  is positive only on  $(0, 4)$ .

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq -8 \\ P\{\tilde{x} \leq (y+8)^{1/2}\} = \int_0^{(y+8)^{1/2}} \frac{x}{8} dx = \frac{1}{2} \left( \frac{y}{8} + 1 \right) & \text{for } y \in (-8, 8) \\ 1 & \text{for } y \geq 8, \end{cases}$$

which is the same as before. Computing the derivative of  $F_{\tilde{y}}(y)$  we obtain the density  $f_{\tilde{y}}(y)$ .

$$(b) P\{1 < \tilde{y} < 3\} = F_{\tilde{y}}(3) - F_{\tilde{y}}(1) = \frac{1}{2} \left( \frac{3}{8} + 1 \right) - \frac{1}{2} \left( \frac{1}{8} + 1 \right) = \frac{1}{8} = 0.125.$$

$$P\{\tilde{y} \geq -2\} = 1 - F_{\tilde{y}}(-2) = 1 - \frac{1}{2} \left( \frac{-2}{8} + 1 \right) = \frac{5}{8} = 0.625.$$

-----

14. (a)

$$E(\tilde{y}) = \int_0^1 x^3 6x(1-x) dx = \frac{1}{5},$$

$$E(\tilde{y}^2) = \int_0^1 x^6 6x(1-x) dx = \frac{1}{12},$$

and, thus,

$$\text{Var}(\tilde{y}) = \frac{1}{12} - \left( \frac{1}{5} \right)^2 = \frac{13}{300}.$$

(b)

$$f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{x}}(g^{-1}(y)) \left| \frac{dg^{-1}(y)}{dy} \right| = 6y^{1/3}(1-y^{1/3}) \frac{1}{3} y^{-2/3} = 2(y^{-1/3} - 1) & \text{for } y \in (0, 1) \\ 0 & \text{otherwise,} \end{cases}$$

and, integrating, we get

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ 3y^{2/3} - 2y & \text{for } y \in (0, 1) \\ 1 & \text{for } y \geq 1. \end{cases}$$

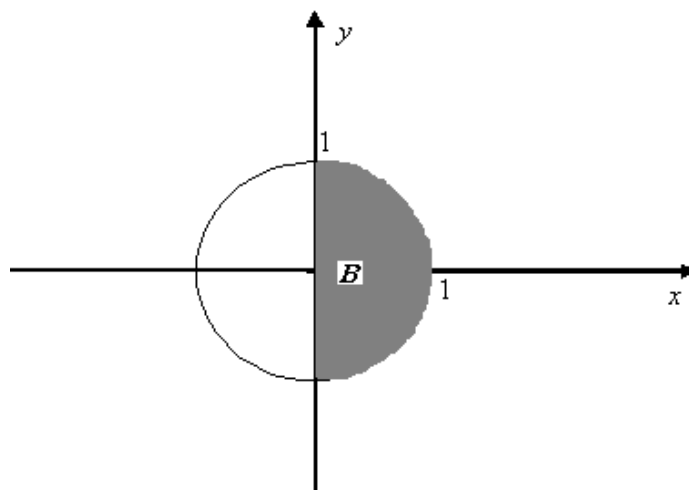
Note that we could also compute the mean of  $\tilde{y}$  by doing

$$\mathbb{E}(\tilde{y}) = \int_0^1 y f_{\tilde{y}}(y) dy = \int_0^1 y \cdot 2(y^{-1/3} - 1) dy = \frac{1}{5},$$

and similarly for the variance.

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15. (a)



$$B = \{(x, y) \in \mathbb{R}^2 \mid x > 0, x^2 + y^2 < 1\},$$

$$\int_B k(x+y) d(x,y) = ?$$

Change of variable to polar coordinates:

$$g^{-1} : \begin{cases} x = r \cos \theta \\ y = r \sin \theta \end{cases} \Rightarrow J_{g^{-1}}(r, \theta) = \begin{pmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{pmatrix}$$

and

$$|J_{g^{-1}}(r, \theta)| = |r \cos^2 \theta + r \sin^2 \theta| = r > 0.$$

Thus,

$$\begin{aligned} \int_B k(x+y) d(x,y) &= \int_0^1 \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} k(r \cos \theta + r \sin \theta) r d\theta dr \\ &= k \left[ \int_0^1 r^2 dr \right] \left[ \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} (\cos \theta + \sin \theta) d\theta \right] = k \cdot \frac{1}{3} \cdot 2 = \frac{2k}{3} \Rightarrow k = \frac{3}{2} \end{aligned}$$

(b) Note that

$$g : \begin{cases} \tilde{z} \stackrel{d}{=} \tilde{r} = (\tilde{x}^2 + \tilde{y}^2)^{\frac{1}{2}} \\ \tilde{\theta} = \arctan\left(\frac{\tilde{x}}{\tilde{y}}\right) \end{cases}$$

so that

$$f_{\tilde{z}, \tilde{\theta}}(z, \theta) = \begin{cases} \frac{3}{2} (z \cos \theta + z \sin \theta) z, & \text{for } z \in (0, 1), \theta \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right) \\ 0, & \text{otherwise,} \end{cases}$$

which implies that

$$f_{\tilde{z}}(z) = \begin{cases} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \frac{3}{2} z^2 (\cos \theta + \sin \theta) d\theta = 3z^2 & \text{for } z \in (0, 1) \\ 0, & \text{otherwise.} \end{cases}$$

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**16.** (a)

$$f_{\tilde{x}_1}(x_1) = \int_0^\infty 6e^{-3x_1-2x_2} dx_2 = 3e^{-3x_1} \text{ for } x_1 > 0 \text{ and } f_{\tilde{x}_1}(x_1) = 0 \text{ otherwise.}$$

Then

$$f_{\tilde{x}_2|\tilde{x}_1}(x_2|x_1) = \frac{f_{\tilde{x}_1, \tilde{x}_2}(x_1, x_2)}{f_{\tilde{x}_1}(x_1)} = \frac{6e^{-3x_1-2x_2}}{3e^{-3x_1}} = 2e^{-2x_2} \text{ for } x_2 > 0$$

and  $f_{\tilde{x}_2|\tilde{x}_1}(x_2|x_1) = 0$  otherwise, with  $x_1 > 0$ . Therefore,

$$f_{\tilde{x}_2|\tilde{x}_1}(x_2|5) = \frac{f_{\tilde{x}_1, \tilde{x}_2}(5, x_2)}{f_{\tilde{x}_1}(5)} = 2e^{-2x_2} \text{ for } x_2 > 0.$$

$\implies$

$$\mathbb{E}(\tilde{x}_2 | \tilde{x}_1 = 5) = \int_0^\infty x_2 \cdot 2e^{-2x_2} dx_2 = \frac{1}{2}.$$

The random variables  $\tilde{x}_1$  and  $\tilde{x}_2$  are independent since

$$f_{\tilde{x}_2}(x_2) = \int_0^\infty 6e^{-3x_1-2x_2} dx_1 = 2e^{-2x_2} \text{ for } x_2 > 0 \text{ and } f_{\tilde{x}_2}(x_2) = 0 \text{ otherwise.}$$

Therefore,

$$f_{\tilde{x}_1, \tilde{x}_2}(x_1, x_2) = 6e^{-3x_1 - 2x_2} = f_{\tilde{x}_1}(x_1) \cdot f_{\tilde{x}_2}(x_2) = 3e^{-3x_1} \cdot 2e^{-2x_2} \text{ for } x_1 > 0, x_2 > 0,$$

and, obviously,  $f_{\tilde{x}_1, \tilde{x}_2}(x_1, x_2) = 0 = f_{\tilde{x}_1}(x_1) \cdot f_{\tilde{x}_2}(x_2)$ , otherwise.

Note that independence implies that  $E(\tilde{x}_2 | \tilde{x}_1 = x_1) = E(\tilde{x}_2) = 1/2$  for all  $x_1 > 0$ .

Similarly,  $E(\tilde{x}_1 | \tilde{x}_2 = x_2) = E(\tilde{x}_1) = \int_0^\infty x_1 \cdot 3e^{-3x_1} dx_1 = 1/3$  for all  $x_2 > 0$ .

(b) If  $f_{\tilde{x}}(x) = \theta e^{-\theta x}$  for  $x > 0$  and  $f_{\tilde{x}}(x) = 0$  otherwise, with  $\theta > 0$ , then

$$M_{\tilde{x}}(t) = \int_0^\infty \theta e^{-\theta x} e^{tx} dx = \theta \int_0^\infty e^{-(\theta-t)x} dx = -\theta \left[ \frac{e^{-(\theta-t)x}}{(\theta-t)} \right]_0^\infty$$

$$= -\theta \left( 0 - \frac{1}{(\theta-t)} \right) = \frac{\theta}{\theta-t} \text{ for } t < \theta.$$

$$E(\tilde{x}) = M'_{\tilde{x}}(t)|_{t=0} = \frac{\theta}{(\theta-t)^2} \Big|_{t=0} = \frac{\theta}{\theta^2} = \frac{1}{\theta},$$

$$E(\tilde{x}^2) = M''_{\tilde{x}}(t) = \frac{2\theta}{(\theta-t)^3} \Big|_{t=0} = \frac{2\theta}{\theta^3} = \frac{2}{\theta^2},$$

$$\text{Var}(\tilde{x}) = E(\tilde{x}^2) - [E(\tilde{x})]^2 = \frac{2}{\theta^2} - \frac{1}{\theta^2} = \frac{1}{\theta^2},$$

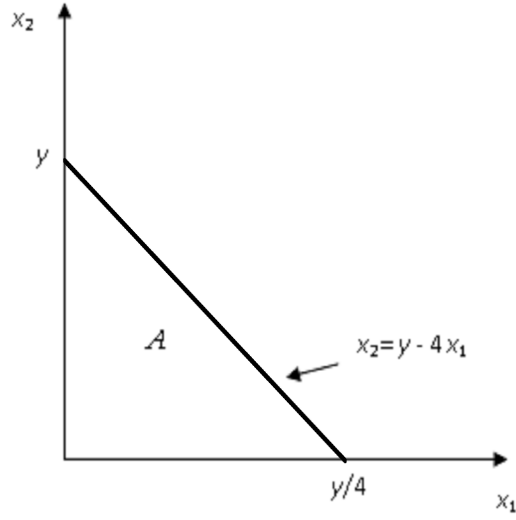
$$\text{CV}_{\tilde{x}} = \frac{\sqrt{\text{Var}(\tilde{x})}}{|E(\tilde{x})|} = \frac{1/\theta}{1/\theta} = 1.$$

Thus,

$$M_{\tilde{x}_1}(t) = \frac{3}{3-t} \text{ for } t < 3, \quad E(\tilde{x}_1) = \frac{1}{3}, \quad \text{Var}(\tilde{x}_1) = \frac{1}{9}, \quad \text{CV}_{\tilde{x}_1} = 1,$$

$$M_{\tilde{x}_2}(t) = \frac{2}{2-t}, \text{ for } t < 2, \quad E(\tilde{x}_2) = \frac{1}{2}, \quad \text{Var}(\tilde{x}_2) = \frac{1}{4}, \quad \text{CV}_{\tilde{x}_2} = 1.$$

(c)



For  $y > 0$ ,

$$\begin{aligned} F_{\tilde{y}}(y) &= P\{\tilde{y} \leq y\} = P\{4\tilde{x}_1 + \tilde{x}_2 \leq y\} = P\{(\tilde{x}_1, \tilde{x}_2) \in A\} \\ &= \int_0^{y/4} \int_0^{y-4x_1} 6e^{-3x_1-2x_2} dx_2 dx_1 = 1 - \frac{8}{5}e^{-\frac{3}{4}y} + \frac{3}{5}e^{-2y}. \end{aligned}$$

Therefore,

$$F_{\tilde{y}}(y) = \begin{cases} 1 - \frac{8}{5}e^{-\frac{3}{4}y} + \frac{3}{5}e^{-2y} & \text{if } y > 0 \\ 0 & \text{if } y \leq 0 \end{cases}$$

(d) Consider the following change of variable for  $x_1 > 0$  and  $x_2 > 0$ :

$$(y, x_2) = g(x_1, x_2) : \begin{cases} y = 4x_1 + x_2 \in (x_2, \infty) \\ x_2 = x_2 \in (0, \infty) \end{cases}$$

so that

$$(x_1, x_2) = g^{-1}(y, x_2) : \begin{cases} x_1 = \frac{1}{4}(y - x_2) \in (0, \infty) \\ x_2 = x_2 \in (0, \infty) \end{cases}$$

$$J_{g^{-1}}(y, x_2) = \begin{pmatrix} 1/4 & -1/4 \\ 0 & 1 \end{pmatrix} \implies |J_{g^{-1}}(y, x_2)| = \frac{1}{4}.$$

Then,

$$f_{\tilde{y}, \tilde{x}_2}(y, x_2) = \begin{cases} 6e^{-3\left[\frac{1}{4}(y - x_2)\right] - 2x_2} \cdot \frac{1}{4} = \frac{3}{2}e^{-\frac{3}{4}y - \frac{5}{4}x_2} & \text{if } y > x_2 \text{ and } x_2 > 0 \\ & \iff x_2 \in (0, y) \\ 0 & \text{otherwise} \end{cases}$$

(e) For  $y > 0$ ,

$$f_{\tilde{y}}(y) = \int_0^y \frac{3}{2}e^{-\frac{3}{4}y - \frac{5}{4}x_2} dx_2 = \frac{6}{5} \left( e^{-\frac{3}{4}y} - e^{-2y} \right).$$

$$f_{\tilde{y}}(y) = \begin{cases} \frac{6}{5} \left( e^{-\frac{3}{4}y} - e^{-2y} \right) & \text{if } y > 0 \\ 0 & \text{otherwise} \end{cases}$$

(f)  $F_{\tilde{y}}(y) = \int_0^y \frac{6}{5} \left( e^{-\frac{3}{4}t} - e^{-2t} \right) dt = 1 - \frac{8}{5}e^{-\frac{3}{4}y} + \frac{3}{5}e^{-2y}$  if  $y > 0$ , and  $F_{\tilde{y}}(y) = 0$  if  $y \leq 0$ .

$f_{\tilde{y}}(y) = F'_{\tilde{y}}(y) = \frac{d \left[ 1 - \frac{8}{5}e^{-\frac{3}{4}y} + \frac{3}{5}e^{-2y} \right]}{dy} = \frac{6}{5} \left( e^{-\frac{3}{4}y} - e^{-2y} \right)$  if  $y > 0$ , and  $f_{\tilde{y}}(y) = 0$  if  $y \leq 0$ .

(g)

$$f_{\tilde{y}|\tilde{x}_2}(y|x_2) = \frac{f_{\tilde{y},\tilde{x}_2}(x_1, x_2)}{f_{\tilde{x}_2}(x_2)} = \frac{\frac{3}{2}e^{-\frac{3}{4}y - \frac{5}{4}x_2}}{2e^{-2x_2}} = \frac{3}{4}e^{-\frac{3}{4}y + \frac{3}{4}x_2}$$

for  $y > x_2$  and  $f_{\tilde{y}|\tilde{x}_2}(y|x_2) = 0$  otherwise, with  $x_2 > 0$ .

Thus,

$$f_{\tilde{y}|\tilde{x}_2}(y|3) = \begin{cases} \frac{3}{4}e^{-\frac{3}{4}y + \frac{9}{4}} & \text{if } y > 3 \\ 0 & \text{otherwise} \end{cases}$$

(h)

$$\begin{aligned} \mathbf{E}(\tilde{y}) &= \mathbf{E}(4\tilde{x}_1 + \tilde{x}_2) = \mathbf{E}(4\tilde{x}_1) + \mathbf{E}(\tilde{x}_2) = 4\mathbf{E}(\tilde{x}_1) + \mathbf{E}(\tilde{x}_2) \\ &= \left(4 \cdot \frac{1}{3}\right) + \frac{1}{2} = \frac{11}{6}. \end{aligned}$$

Alternatively, we can compute

$$\mathbf{E}(\tilde{y}) = \int_0^\infty y \frac{6}{5} \left( e^{-\frac{3}{4}y} - e^{-2y} \right) dy = \frac{11}{6}.$$

$$\begin{aligned} \mathbf{E}(\tilde{y} | \tilde{x}_2 = 3) &= \mathbf{E}(4\tilde{x}_1 + \tilde{x}_2 | \tilde{x}_2 = 3) = \mathbf{E}(4\tilde{x}_1 | \tilde{x}_2 = 3) + \mathbf{E}(\tilde{x}_2 | \tilde{x}_2 = 3) \\ &= \mathbf{E}(4\tilde{x}_1) + 3 = 4\mathbf{E}(\tilde{x}_1) + 3 = \frac{4}{3} + 3 = \frac{13}{3} \end{aligned}$$

since  $\tilde{x}_1$  and  $\tilde{x}_2$  are independent.

Alternatively, we can compute

$$\mathbf{E}(\tilde{y} | \tilde{x}_2 = 3) = \int_3^\infty y \frac{3}{4} e^{-\frac{3}{4}y + \frac{9}{4}} dy = \frac{13}{3}.$$

(i)

$$\begin{aligned}\text{Cov}(\tilde{y}, \tilde{x}_2) &= \text{Cov}(4\tilde{x}_1 + \tilde{x}_2, \tilde{x}_2) = \text{Cov}(4\tilde{x}_1, \tilde{x}_2) + \text{Cov}(\tilde{x}_2, \tilde{x}_2) \\ &= 4\text{Cov}(\tilde{x}_1, \tilde{x}_2) + \text{Var}(\tilde{x}_2) = 0 + \text{Var}(\tilde{x}_2) = \frac{1}{4}.\end{aligned}$$

as  $\text{Cov}(\tilde{x}_1, \tilde{x}_2) = 0$  due to the independence between  $\tilde{x}_1$  and  $\tilde{x}_2$ .

Alternatively, we can compute

$$\text{E}(\tilde{y} \cdot \tilde{x}_2) = \int_0^\infty \int_0^y yx_2 \frac{3}{2} e^{-\frac{3}{4}y - \frac{5}{4}x_2} dx_2 dy = \frac{7}{6}$$

or

$$\text{E}(\tilde{y} \cdot \tilde{x}_2) = \int_0^\infty \int_{x_2}^\infty yx_2 \frac{3}{2} e^{-\frac{3}{4}y - \frac{5}{4}x_2} dy dx_2 = \frac{7}{6}.$$

Then,

$$\text{Cov}(\tilde{y}, \tilde{x}_2) = \text{E}(\tilde{y} \cdot \tilde{x}_2) - \text{E}(\tilde{y}) \text{E}(\tilde{x}_2) = \frac{7}{6} - \left(\frac{11}{6} \cdot \frac{1}{2}\right) = \frac{1}{4}.$$

-----

17. (a)

$$\begin{aligned}F_{\tilde{y}}(y) &= P\{\tilde{y} \leq y\} = P\{\tilde{x}^{1/2} \leq y\} \\ &= P\{\tilde{x} \leq y^2\} = \begin{cases} \int_0^{y^2} e^{-x} dx = 1 - e^{-y^2} & \text{for } y > 0, \\ 0 & \text{otherwise.} \end{cases}\end{aligned}$$

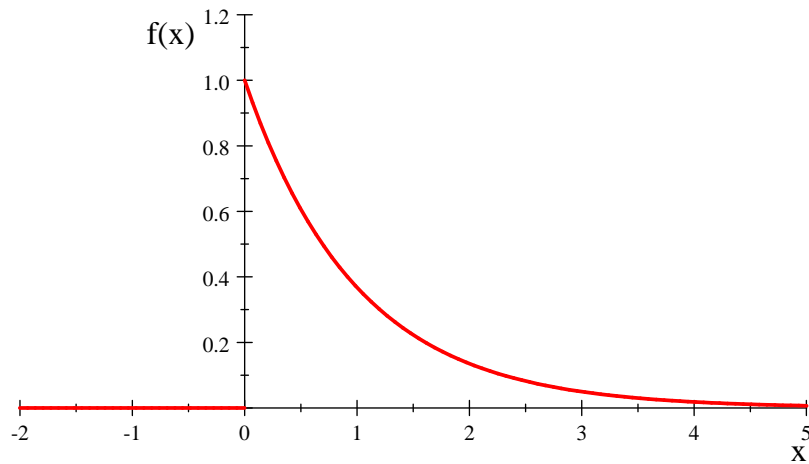
(b)  $y = g(x) = x^{1/2}$  is bijective for  $x > 0$ . Then,  $x = g^{-1}(y) = y^2$  for  $y > 0$

and  $\frac{dg^{-1}(y)}{dy} = 2y > 0$ . Thus,

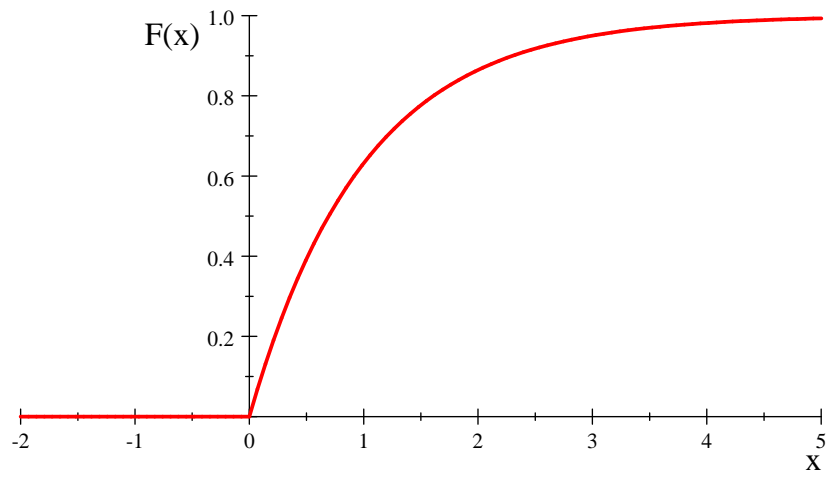
$$f_{\tilde{y}}(y) = \begin{cases} e^{-y^2} \cdot (2y) = 2ye^{-y^2} & \text{for } y > 0, \\ 0 & \text{otherwise.} \end{cases}$$

(c) It is immediate to see that  $F_{\tilde{y}}(y) = \int_{-\infty}^y f_{\tilde{y}}(s)ds$  and  $f_{\tilde{y}}(y) = F'_{\tilde{y}}(y)$  for all  $y \in \mathbb{R}$ .

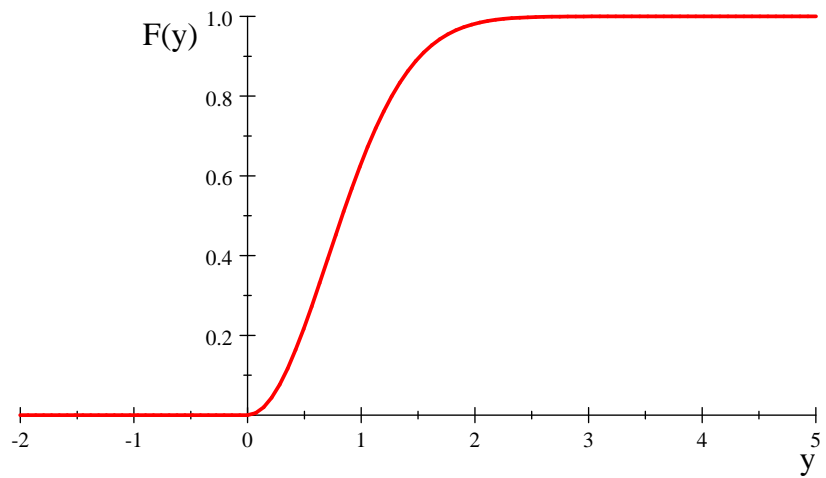
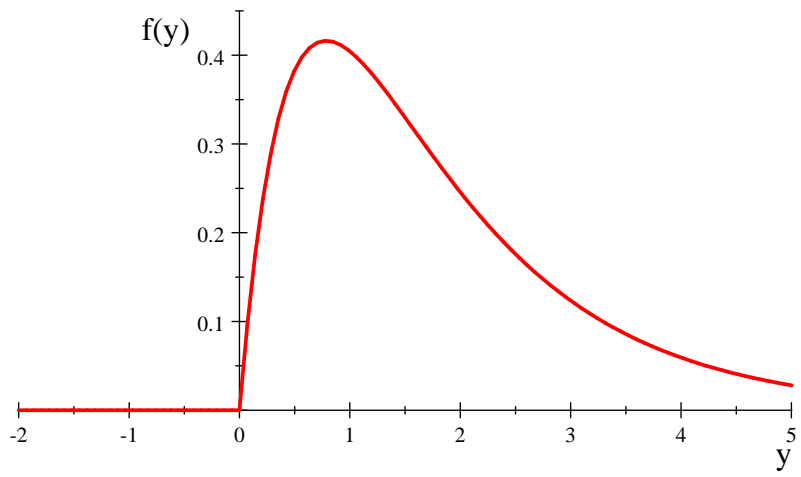
(d)  $F_{\tilde{x}}$  is not differentiable at  $x = 0$  since the density  $f_{\tilde{x}}$  is discontinuous at  $x = 0$ . However,  $f_{\tilde{y}}(0) = 0$  so that the density function  $f_{\tilde{y}}$  is continuous everywhere. Hence, the distribution function  $F_{\tilde{y}}$  is differentiable everywhere. In particular, the derivative of  $F_{\tilde{y}}$  at  $y = 0$  is  $F'_{\tilde{y}}(0) = 0$ .



$$F_{\tilde{x}}(x) = \begin{cases} 1 - e^{-x} & x > 0 \\ 0 & \text{otherwise} \end{cases}$$



Note that  $\arg \max_{y \in \mathbb{R}} f_{\tilde{y}}(y) = \frac{\sqrt{2}}{2}$ .



18. (a)

$$F(x, y) = \begin{cases} \int_0^x \int_0^y e^{-y} e^{-x} dy dx = (1 - e^{-x})(1 - e^{-y}) & \text{if } x > 0, y > 0 \\ 0 & \text{otherwise.} \end{cases}$$

(b)

$$f_{\tilde{x}}(x) = \begin{cases} \int_0^\infty e^{-(x+y)} dy = e^{-x} & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$f_{\tilde{y}}(y) = \begin{cases} \int_0^\infty e^{-(x+y)} dx = e^{-y} & \text{if } y > 0 \\ 0 & \text{otherwise.} \end{cases}$$

$\tilde{x}$  and  $\tilde{y}$  are independent because  $f(x, y) = f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y)$  for all  $(x, y) \in \mathbb{R}^2$ .

(c)

$$f_{\tilde{y}|\tilde{x}}(y|3) = \begin{cases} \frac{f(3, y)}{f_{\tilde{x}}(3)} = \frac{e^{-3-y}}{e^{-3}} = e^{-y} & \text{if } y > 0 \\ 0 & \text{otherwise.} \end{cases}$$

In fact, from independence we have that  $f_{\tilde{y}|\tilde{x}}(y|x) = f_{\tilde{y}}(y)$  for all  $x > 0$ .

(d)

$$\int_0^1 \int_x^1 e^{-(x+y)} dy dx = \frac{1}{2} e^{-2} - e^{-1} + \frac{1}{2} = 0.1998.$$

$$(e) \tilde{z} = \tilde{x} - 3\tilde{y} \iff \tilde{x} = \tilde{z} + 3\tilde{y} \iff \tilde{y} = \frac{1}{3}(\tilde{x} - \tilde{z}).$$

$$F(z) = P\{\tilde{z} \leq z\} = P\{\tilde{x} - 3\tilde{y} \leq z\} = P_{\tilde{x}, \tilde{y}}(C),$$

where  $C = \{(x, y) \in \mathbb{R}^2 \mid x - 3y \leq z\}$ .

Note that  $x = z + 3y > 0$  and  $y > 0$  in the set  $A$  where  $f(x, y) \neq 0$ . Therefore,  $y > \max\{0, -z/3\}$  in the set  $A$ . Hence, if  $z > 0$  then  $y > 0$ , whereas if  $z \leq 0$ , then  $y > -z/3$ .

Therefore, if  $z \leq 0$  then

$$F(z) = P_{\bar{x}, \bar{y}}(C) = \int_{-z/3}^{\infty} \left( \int_0^{z+3y} e^{-(x+y)} dx \right) dy = \frac{3}{4} e^{z/3},$$

whereas, if  $z > 0$ ,

$$F(z) = P_{\bar{x}, \bar{y}}(C) = \int_0^{\infty} \left( \int_0^{z+3y} e^{-(x+y)} dx \right) dy = 1 - \frac{1}{4} e^{-z}.$$

Thus,

$$F(z) = \begin{cases} \frac{3}{4} e^{z/3} & \text{for } z \leq 0 \\ 1 - \frac{1}{4} e^{-z} & \text{for } z > 0. \end{cases}$$

(f) Let us consider the following one-to-correspondence  $g : A \longrightarrow g(A)$ , where  $A$  is the set for which  $f(x, y) \neq 0$  :

$$(z, x) = g(x, y) : \begin{cases} z = x - 3y \in (-\infty, \infty) \\ x = x > \max\{0, z\} \end{cases}$$

$$(x, y) = g^{-1}(z, x) : \begin{cases} x = x > 0 \\ y = \frac{1}{3}(x - z) > 0. \end{cases}$$

Note that  $x > 0$  and  $y = \frac{1}{3}(x - z) > 0$  on the set  $A$  where  $f(x, y) \neq 0$ . Therefore,  $x > \max\{0, z\}$  in the set  $A$ . Hence, if  $z \leq 0$  then  $x > 0$ , whereas if

$z > 0$  then  $x > z$ .

$$J_{g^{-1}}(z, x) = \begin{bmatrix} 0 & 1 \\ -1/3 & 1/3 \end{bmatrix} \implies |J_{g^{-1}}| = \frac{1}{3}.$$

Note that  $-(x + y) = -\left(x + \frac{1}{3}(x - z)\right) = -\frac{1}{3}(4x - z)$ . Therefore,

$$f_{\tilde{z}, \tilde{x}}(z, x) = \begin{cases} f(g^{-1}(z, x)) |J_{g^{-1}}(z, x)| = e^{-\frac{1}{3}(4x-z)} \cdot \frac{1}{3} & \text{for } z \in (-\infty, \infty), x > \max\{0, z\} \\ 0 & \text{otherwise.} \end{cases}$$

Hence, computing the marginal density of  $\tilde{z}$ , we get

$$f_{\tilde{z}}(z) = \int_z^\infty e^{-\frac{1}{3}(4x-z)} \cdot \frac{1}{3} dx = \frac{1}{4} e^{-z} \text{ for } z > 0,$$

and

$$f_{\tilde{z}}(z) = \int_0^\infty e^{-\frac{1}{3}(4x-z)} \cdot \frac{1}{3} dx = \frac{1}{4} e^{z/3} \text{ for } z \leq 0.$$

so that

$$f_{\tilde{z}}(z) = \begin{cases} \frac{1}{4} e^{z/3} & \text{for } z \leq 0 \\ \frac{1}{4} e^{-z} & \text{for } z > 0. \end{cases}$$

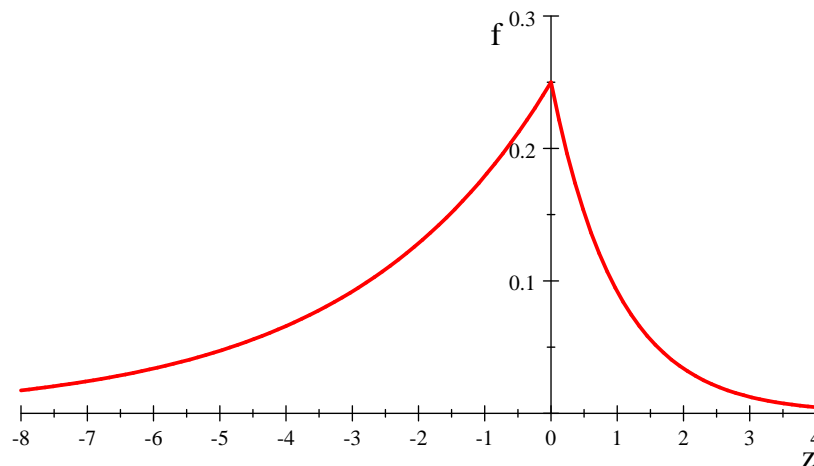
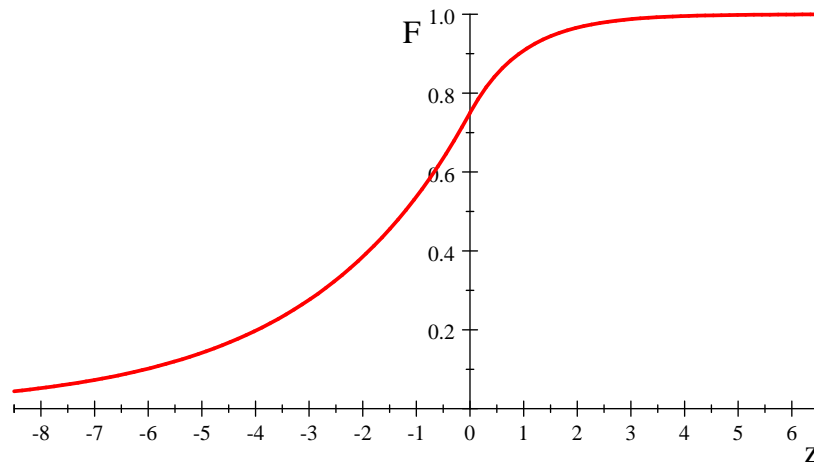
(g) Obviously  $F_{\tilde{z}}(z) = \int_{-\infty}^z f_{\tilde{z}}(z) dz$

$$F_{\tilde{z}}(z) = \begin{cases} \int_{-\infty}^z \frac{1}{4} e^{z/3} dz = \frac{3}{4} e^{z/3} & \text{for } z \leq 0 \\ \int_{-\infty}^0 \frac{1}{4} e^{z/3} dz + \int_0^z \frac{1}{4} e^{-z} dz = \frac{3}{4} + \left(\frac{1}{4} - \frac{1}{4} e^{-z}\right) = 1 - \frac{1}{4} e^{-z} & \text{for } z > 0, \end{cases}$$

while  $f_{\tilde{z}}(z) = F'_{\tilde{z}}(z)$  a.e. since

$$f_{\tilde{z}}(z) = \begin{cases} \frac{d\left(\frac{3}{4}e^{z/3}\right)}{dz} = \frac{1}{4}e^{z/3} & \text{for } z < 0 \\ \frac{d\left(1 - \frac{1}{4}e^{-z}\right)}{dz} = \frac{1}{4}e^{-z} & \text{for } z > 0. \end{cases}$$

(h)



The density function  $f_{\tilde{z}}$  is not differentiable at  $z = 0$ . However, the density  $f_{\tilde{z}}$  is continuous everywhere. This implies that the distribution function  $F_{\tilde{z}}$  is

differentiable everywhere. In particular, note that

$$\lim_{z \rightarrow 0^-} \frac{d\left(\frac{3}{4}e^{z/3}\right)}{dz} = \lim_{z \rightarrow 0^-} \left(\frac{1}{4}e^{z/3}\right) = \lim_{z \rightarrow 0^+} \frac{d\left(1 - \frac{1}{4}e^{-z}\right)}{dz} = \lim_{z \rightarrow 0^+} \left(\frac{1}{4}e^{-z}\right) = \frac{1}{4}.$$

Another implication of the previous facts is that  $F_{\tilde{z}}$  is not twice differentiable at  $z = 0$ .

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**19.** (a)

$$g : \begin{cases} y = x_1 + x_2 \in (x_2, x_2 + 2) \\ x_2 = x_2 \in (0, 1) \end{cases} \implies g^{-1} : \begin{cases} x_1 = y - x_2 \in (0, 2) \\ x_2 = x_2 \in (0, 1) \end{cases}$$

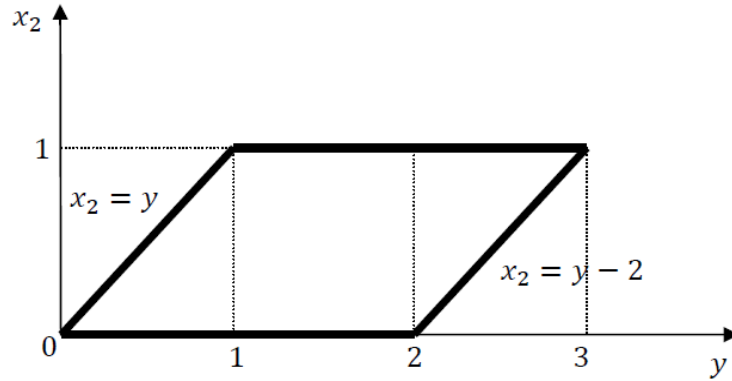
$$|J_{g^{-1}}(y, x_2)| = \left| \det \begin{bmatrix} \frac{dx_1}{dy} & \frac{dx_1}{dx_2} \\ \frac{dx_2}{dy} & \frac{dx_2}{dx_2} \end{bmatrix} \right| = \left| \det \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \right| = 1.$$

Then,

$$f_{\tilde{y}, \tilde{x}_2}(y, x_2) = \frac{1}{2} \cdot 1 = \frac{1}{2} \text{ for } 0 < x_2 < 1 \text{ and } x_2 < y < x_2 + 2,$$

so that

$$f_{\tilde{y}, \tilde{x}_2}(y, x_2) = \begin{cases} \frac{1}{2} & \text{for } 0 < x_2 < 1 \text{ and } x_2 < y < x_2 + 2 \\ 0 & \text{elsewhere.} \end{cases}$$

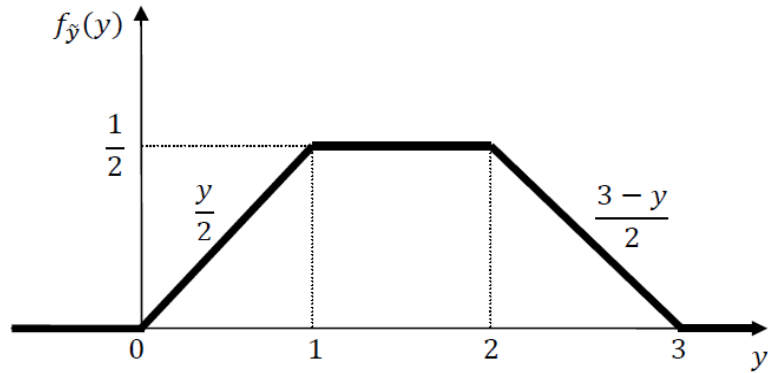


The density of  $y$  for  $y \in (0, 3)$  is

$$f_{\tilde{y}}(y) = \int_{-\infty}^{\infty} f_{\tilde{y}, \tilde{x}_2}(y, x_2) dx_2 = \int_{\mathbb{R}} \mathbb{I}_C(y, x_2) \frac{1}{2} dx_2 = \int_{C(y)} \frac{1}{2} dx_2,$$

where the set  $C$  is the interior of the parallelogram in the previous figure.

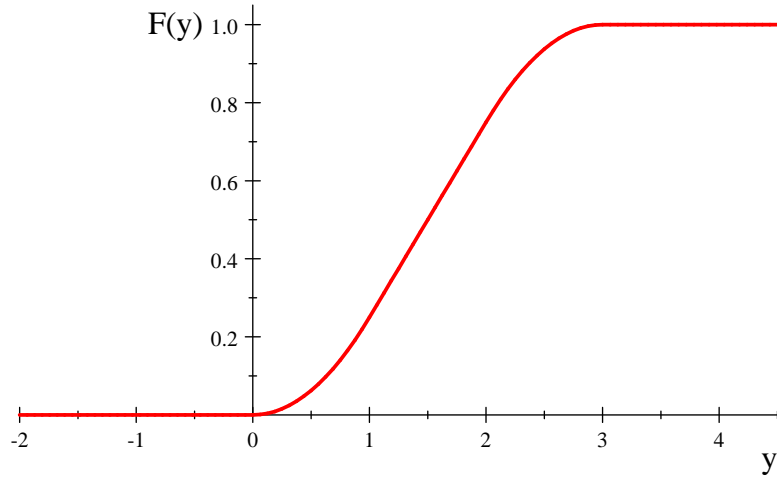
$$f_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y \frac{1}{2} dx_2 = \frac{y}{2} & \text{for } 0 < y \leq 1 \\ \int_0^1 \frac{1}{2} dx_2 = \frac{1}{2} & \text{for } 1 < y \leq 2 \\ \int_{y-2}^1 \frac{1}{2} dx_2 = \frac{3-y}{2} & \text{for } 2 < y < 3 \\ 0 & \text{for } y \geq 3. \end{cases}$$



$$\int_{-\infty}^{\infty} f_{\tilde{y}}(y) dy = 0 + \int_0^1 \frac{y}{2} dy + \int_1^2 \frac{1}{2} dy + \int_2^3 \frac{3-y}{2} dy + 0 = \frac{1}{4} + \frac{1}{2} + \frac{1}{4} = 1.$$

(b)

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y \frac{y}{2} dy = \frac{1}{4}y^2 & \text{for } 0 < y \leq 1 \\ \frac{1}{4} + \int_1^y \frac{1}{2} dy = \frac{2y-1}{4} & \text{for } 1 < y \leq 2 \\ \frac{3}{4} + \int_2^y \frac{3-y}{2} dy = -\frac{y^2}{4} + \frac{3y}{2} - \frac{5}{4} & \text{for } 2 < y < 3 \\ 1 & \text{for } y \geq 3. \end{cases}$$



(c) Note that

$$f_{\tilde{x}_2}(x_2) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 = \int_0^2 \frac{1}{2} dx_1 = 1 \quad \text{for } 0 < x_2 < 1$$

and  $f_{\tilde{x}_2}(x_2) = 0$  otherwise. Therefore

$$f_{\tilde{y}|\tilde{x}_2}(y|x_2) = \frac{f_{\tilde{y},\tilde{x}_2}(y, x_2)}{f_{\tilde{x}_2}(x_2)} = \begin{cases} \frac{1}{2} & \text{for } x_2 < y < x_2 + 2 \\ 0 & \text{elsewhere} \end{cases}$$

with  $0 < x_2 < 1$ . Hence,

$$f_{\tilde{y}|\tilde{x}_2}\left(y \middle| \frac{1}{4}\right) = \begin{cases} \frac{1}{2} & \text{for } \frac{1}{4} < y < \frac{9}{4} \\ 0 & \text{elsewhere.} \end{cases}$$

and, thus,

$$E(\tilde{y}|\tilde{x}_2 = 1/4) = \int_{1/4}^{9/4} y \frac{1}{2} dy = \frac{5}{4}.$$

We have

$$f_{\tilde{x}_2|\tilde{y}}(x_2|y) = \frac{f_{\tilde{y},\tilde{x}_2}(y,x_2)}{f_{\tilde{y}}(y)} = \begin{cases} \frac{1/2}{y/2} = \frac{1}{y} & \text{for } 0 < x_2 < y, 0 < y \leq 1 \\ \frac{1/2}{1/2} = 1 & \text{for } 0 < x_2 < 1, 1 < y \leq 2 \\ \frac{1/2}{(3-y)/2} = \frac{1}{3-y} & \text{for } y-2 < x_2 < 1, 2 < y < 3 \\ 0 & \text{otherwise,} \end{cases}$$

with  $0 < y < 3$ . Therefore

$$f_{\tilde{x}_2|\tilde{y}}\left(x_2 \middle| \frac{5}{2}\right) = \begin{cases} \frac{1}{3-\frac{5}{2}} = 2 & \text{for } \frac{1}{2} < x_2 < 1 \\ 0 & \text{otherwise} \end{cases}$$

so that

$$E(\tilde{x}_2|\tilde{y} = 5/2) = \int_{1/2}^1 x_2 \cdot 2dx_2 = \frac{3}{4}.$$

Moreover,

$$f_{\tilde{x}_2|\tilde{y}}\left(x_2 \middle| \frac{3}{2}\right) = \begin{cases} 1 & \text{for } 0 < x_2 < 1 \\ 0 & \text{otherwise} \end{cases}$$

so that

$$E(\tilde{x}_2|\tilde{y} = 3/2) = \int_0^1 x_2 \cdot 1dx_2 = \frac{1}{2}.$$

-----

20. (a)

$$f_{\tilde{x}}(x) = \begin{cases} \int_0^1 \frac{4}{3}(x + xy)dy = 2x & \text{for } 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_{\tilde{y}}(y) = \begin{cases} \int_0^1 \frac{4}{3}(x + xy)dx = \frac{2}{3}(1 + y) & \text{for } 0 < y < 1 \\ 0 & \text{otherwise} \end{cases}$$

Note that  $f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y) = 2x \cdot \frac{2}{3}(1 + y) = \frac{4}{3}(x + xy)$  so that  $f(x, y) = f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y)$  for  $(x, y) \in (0, 1) \times (0, 1)$  and, obviously,  $f(x, y) = f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y) = 0$  for  $(x, y) \notin (0, 1) \times (0, 1)$ . Therefore,  $\tilde{x}$  and  $\tilde{y}$  are independent.

(b) Since  $\tilde{x}$  and  $\tilde{y}$  are independent,

$$f_{\tilde{y}|\tilde{x}}(y|x) = \frac{f(x, y)}{f_{\tilde{x}}(x)} = \frac{f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y)}{f_{\tilde{x}}(x)} = f_{\tilde{y}}(y), \quad \text{for } 0 < x < 1.$$

Therefore,  $E(\tilde{y}|\tilde{x} = 1/3) = E(\tilde{y})$ ,

$$E(\tilde{y}) = \int_0^1 y \frac{2}{3}(1 + y) dy = \frac{5}{9} = E(\tilde{y}|\tilde{x} = 1/3).$$

(c)

$$E(\ln \tilde{x}) = \int_0^1 (\ln x \cdot 2x) dx \quad (\text{integrating by parts})$$

$$= [\ln x \cdot x^2]_0^1 - \int_0^1 \left(\frac{1}{x} \cdot x^2\right) dx = 0 - \lim_{x \rightarrow 0} (\ln x \cdot x^2) - \int_0^1 x dx = -\frac{1}{2}$$

since

$$\lim_{x \rightarrow 0} (\ln x \cdot x^2) = \lim_{x \rightarrow 0} \left( \frac{\ln x}{x^{-2}} \right) = \frac{-\infty}{\infty},$$

and, thus, we can apply L'Hôpital's rule,

$$\lim_{x \rightarrow 0} \left( \frac{\ln x}{x^{-2}} \right) = \lim_{x \rightarrow 0} \left( \frac{\frac{1}{x}}{-2x^{-3}} \right) = \lim_{x \rightarrow 0} \left( \frac{x^2}{-2} \right) = 0,$$

and

$$\int_0^1 x dx = \left[ \frac{x^2}{2} \right]_0^1 = \frac{1}{2}.$$

(d) If either  $x < 0$  or  $y < 0$ , it follows immediately that  $F(x, y) = 0$ . For  $0 < x < 1$  and  $0 < y < 1$  (Region I of the figure) we get

$$F(x, y) = \int_0^y \int_0^x \frac{4}{3}(x + xy) dx dy = \frac{1}{3} x^2 y (y + 2),$$

for  $x > 1$  and  $0 < y < 1$  (Region II of the figure) we get

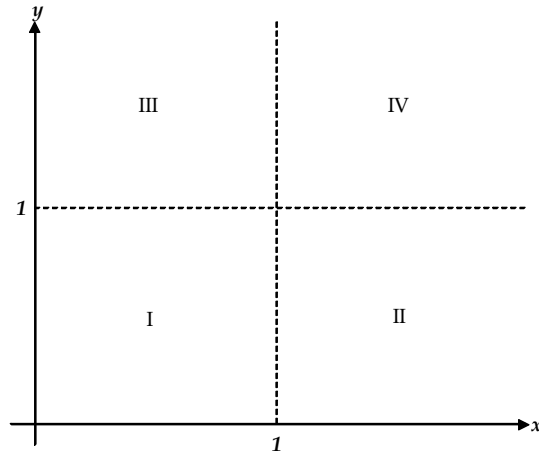
$$F(x, y) = \int_0^y \int_0^1 \frac{4}{3}(x + xy) dx dy = \frac{1}{3} y (y + 2),$$

for  $0 < x < 1$  and  $y > 1$  (Region III of the figure) we get

$$F(x, y) = \int_0^1 \int_0^x \frac{4}{3}(x + xy) dx dy = x^2,$$

and for  $x > 1$  and  $y > 1$  (Region IV of the figure) we get

$$F(x, y) = \int_0^1 \int_0^1 \frac{4}{3}(x + xy) dx dy = 1.$$



Since the joint distribution function is everywhere continuous, the boundaries between any two of these regions can be included in either one, and we can write

$$F(x, y) = \begin{cases} 0 & \text{for } x \leq 0 \text{ or } y \leq 0 \\ \frac{1}{3}x^2y(y+2) & \text{for } 0 < x < 1, 0 < y < 1 \\ \frac{1}{3}y(y+2) & \text{for } x \geq 1, 0 < y < 1 \\ x^2 & \text{for } 0 < x < 1, y \geq 1 \\ 1 & \text{for } x \geq 1, y \geq 1 \end{cases}$$

It is immediate to see that

$$\frac{\partial^2 F(x, y)}{\partial x \partial y} = \frac{4}{3}(x + xy), \text{ for } x \in (0, 1), y \in (0, 1)$$

and

$$\frac{\partial^2 F(x, y)}{\partial x \partial y} = 0, \text{ for } (x, y) \in C,$$

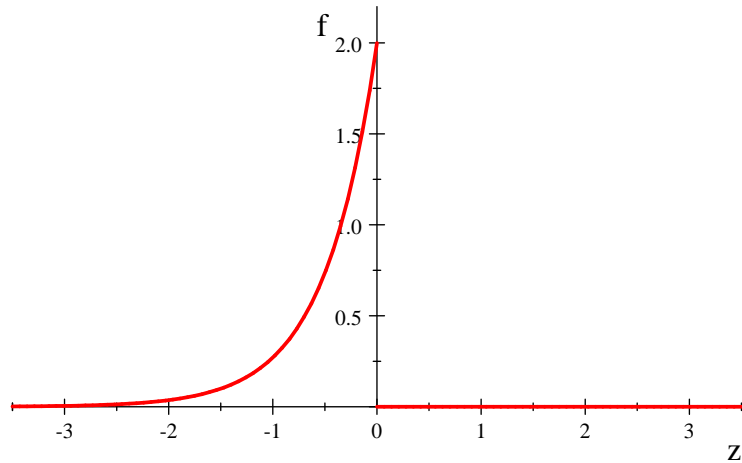
where  $C$  is the interior of the complement of Region I. Note that the boundary of Region I has zero Lebesgue measure. Therefore,  $\frac{\partial^2 F(x, y)}{\partial x \partial y} = f(x, y)$  a.e. with respect to Lebesgue measure in  $\mathbb{R}^2$ . Note also that the discontinuities of the density function  $f(x, y)$  occur only at the boundary of Region I.

(e)

$$z = g(x) = \ln x \in (-\infty, 0), \quad x = g^{-1}(z) = e^z \in (0, 1), \quad \frac{dg^{-1}(z)}{dz} = e^z > 0$$

Then,

$$f_z(z) = \begin{cases} 2e^z e^z = 2e^{2z} & \text{for } z \in (-\infty, 0) \\ 0 & \text{otherwise} \end{cases}$$



(f)

$$\begin{aligned} M_{\tilde{z}}(t) &= \mathbf{E}(e^{t\tilde{z}}) = \int_{-\infty}^0 2e^{2z} e^{tz} dz \\ &= 2 \int_{-\infty}^0 e^{z(2+t)} dz = 2 \left[ \frac{e^{z(2+t)}}{2+t} \right]_{-\infty}^0 = \frac{2}{t+2} = 2(t+2)^{-1} \end{aligned}$$

since  $\lim_{z \rightarrow -\infty} \frac{e^{z(2+t)}}{2+t} = 0$  when  $t$  is around zero. Note that  $M_{\tilde{z}}(t)$  is well defined for  $t > -2$  so that it is well defined in a neighborhood of zero.

$$M'_{\tilde{z}}(t) = -2(t+2)^{-2} \implies \mathbf{E}(\tilde{z}) = M'_{\tilde{z}}(0) = -\frac{1}{2},$$

which agrees with what we have obtained in part (c).

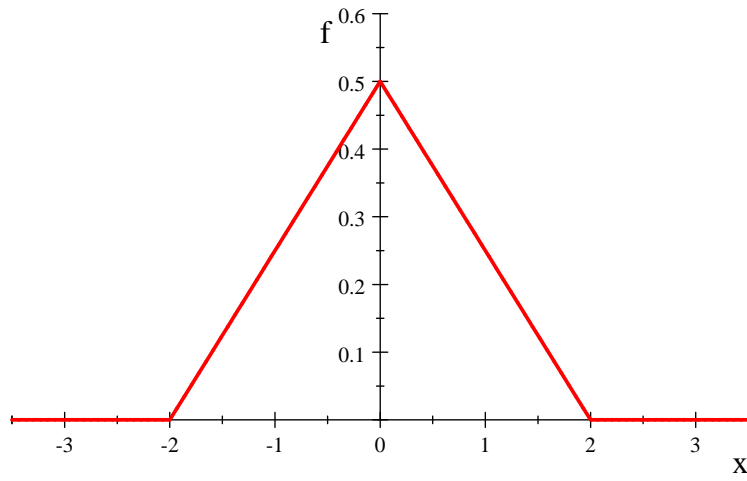
$$M''_{\tilde{z}}(t) = 4(t+2)^{-3} \implies \mathbf{E}(\tilde{z}^2) = M''_{\tilde{z}}(0) = \frac{1}{2}$$

so that

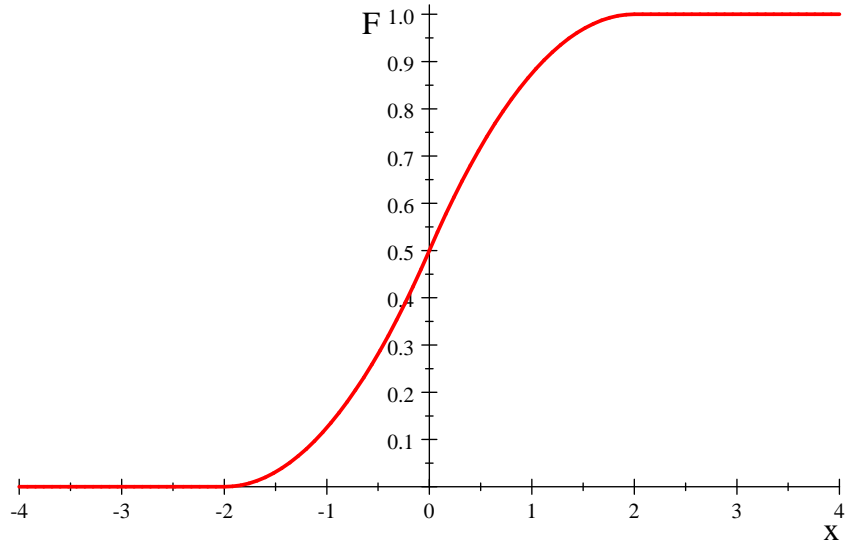
$$\text{Var}(\tilde{z}) = \mathbf{E}(\tilde{z}^2) - [\mathbf{E}(\tilde{z})]^2 = \frac{1}{2} - \left(-\frac{1}{2}\right)^2 = \frac{1}{4}.$$

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**21.** (a)  $f_{\tilde{x}}(x)$



$$F_{\tilde{x}}(x) = \begin{cases} 0 & \text{for } x \leq -2 \\ \int_{-2}^x \frac{x+2}{4} dx = \frac{x^2}{8} + \frac{x}{2} + \frac{1}{2} & \text{for } x \in (-2, 0] \\ \int_{-2}^0 \frac{x+2}{4} dx + \int_0^x \frac{2-x}{4} dx = \frac{1}{2} + \int_0^x \frac{2-x}{4} dx = -\frac{x^2}{8} + \frac{x}{2} + \frac{1}{2} & \text{for } x \in (0, 2) \\ 1 & \text{for } x \geq 2. \end{cases}$$



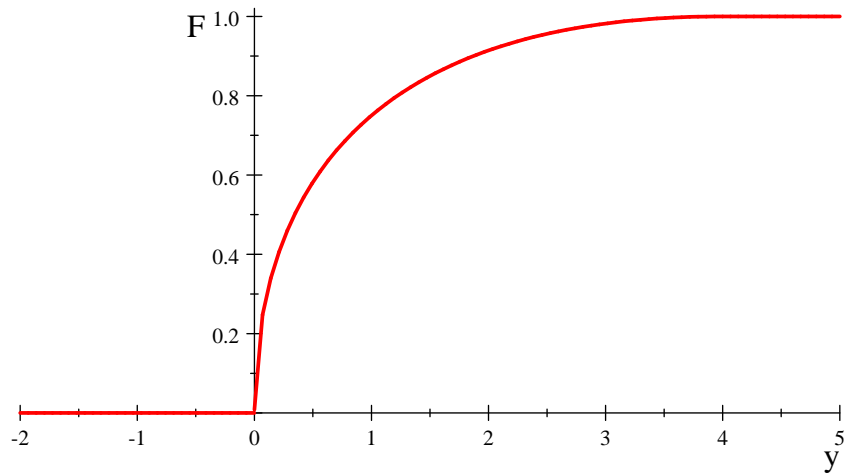
(b) Since

$$F_{\tilde{y}}(y) = P\{\tilde{y} \leq y\} = P\{\tilde{x}^2 \leq y\} = P\{-y^{1/2} \leq \tilde{x} \leq y^{1/2}\}$$

$$= \int_{-y^{1/2}}^0 \frac{x+2}{4} dx + \int_0^{y^{1/2}} \frac{2-x}{4} dx = y^{1/2} - \frac{y}{4} \text{ for } x \in (-2, 2) \iff y \in (0, 4).$$

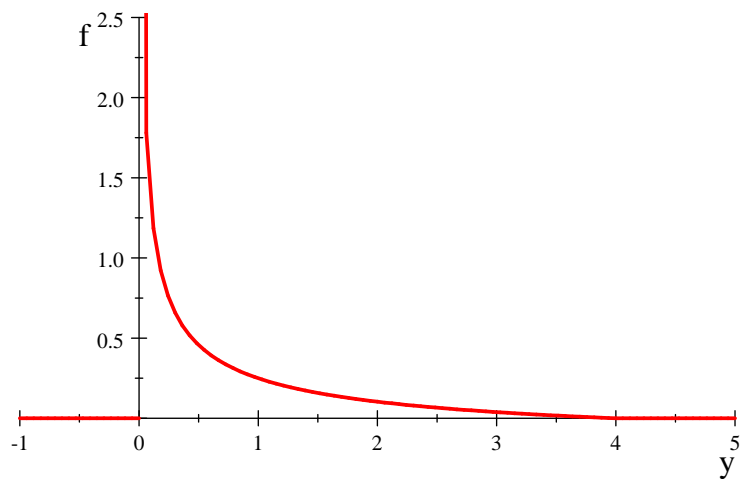
Therefore,

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ y^{1/2} - \frac{y}{4} & \text{for } y \in (0, 4) \\ 1 & \text{for } y \geq 4. \end{cases}$$



We know that  $f_{\tilde{y}}(y) = F'_{\tilde{y}}(y)$  for all  $y$  where the distribution function  $F_{\tilde{y}}$  is differentiable. Thus,

$$f_{\tilde{y}}(y) = \begin{cases} \frac{y^{-1/2}}{2} - \frac{1}{4} & \text{for } y \in (0, 4) \\ 0 & \text{otherwise} \end{cases}$$



Note that the density  $f_{\tilde{y}}$  is continuous at  $y = 4$  and, hence, the distribution function  $F_{\tilde{y}}$  is differentiable at  $y = 4$ . However, the density  $f_{\tilde{y}}$  is discontinuous

at  $y = 0$  and thus the distribution function  $F_{\tilde{y}}$  is non-differentiable at  $y = 0$ .

We see that

$$\lim_{y \rightarrow 0^-} f_{\tilde{y}}(y) = 0 \neq \infty = \lim_{y \rightarrow 0^+} f_{\tilde{y}}(y).$$

*Note:* This exercise could be also solved using the density function technique instead of the distribution function technique. To this end we first need to make the transformation  $\tilde{z} = |\tilde{x}|$  and find the distribution function  $F_{\tilde{z}}$  of  $\tilde{z}$ . Note that

$$\begin{aligned} F_{\tilde{z}}(z) &= P\{\tilde{z} \leq z\} = P\{|\tilde{x}| \leq z\} = P\{-z \leq \tilde{x} \leq z\} \\ &= \int_{-z}^0 \frac{x+2}{4} dx + \int_0^z \frac{2-x}{4} dx = z - \frac{z^2}{4} \text{ for } z \in (-2, 2) \iff z \in (0, 2). \end{aligned}$$

Therefore,

$$F_{\tilde{z}}(z) = \begin{cases} 0 & \text{for } z \leq 0 \\ z - \frac{z^2}{4} & \text{for } z \in (0, 2) \\ 1 & \text{for } z \geq 2. \end{cases}$$

Therefore, the density of  $\tilde{z}$  is

$$f_{\tilde{z}}(z) = \begin{cases} F'_{\tilde{z}}(z) = 1 - \frac{z}{2} & \text{for } z \in (0, 2) \\ 0 & \text{otherwise} \end{cases}$$

Then, define  $\tilde{y} = g(\tilde{z}) = \tilde{z}^2$ . Note that  $g : (0, 2) \rightarrow (0, 4)$  is a one-to-one correspondence. Thus,  $z = g^{-1}(y) = y^{1/2}$  and  $\frac{dz}{dy} = \frac{dg^{-1}(y)}{dy} = \frac{y^{-1/2}}{2} > 0$  for

$y \in (0, 4)$ . Therefore, the density of  $\tilde{y}$  is

$$f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{z}}(g^{-1}(y)) \left| \frac{g^{-1}(y)}{dy} \right| = \left(1 - \frac{y^{1/2}}{2}\right) \frac{y^{-1/2}}{2} = \frac{y^{-1/2}}{2} - \frac{1}{4} & \text{for } y \in (0, 4) \\ 0 & \text{otherwise.} \end{cases}$$

and, thus, the distribution function is

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y \left( \frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = y^{1/2} - \frac{y}{4} & \text{for } y \in (0, 4) \\ 1 & \text{for } y \geq 4. \end{cases}$$

(c) The distribution of the random vector  $(\tilde{x}, \tilde{y})$  does NOT have a density  $f_{\tilde{x}, \tilde{y}}(x, y)$ . To see this, let us define the following subset  $C$  of  $\mathbb{R}^2$ :

$$C = \{(x, y) \in \mathbb{R}^2 \mid y = x^2\}$$

The set  $C$  is the graph of a parabola on the plane. Then, on the one hand,

$$P\{(x, y) \in C\} = 1.$$

but, on the other hand, if the density  $f_{\tilde{x}, \tilde{y}}(x, y)$  exists, we should have

$$\int_C f_{\tilde{x}, \tilde{y}}(x, y) d(x, y) = 1,$$

which is impossible since the set  $C$  has zero Lebesgue measure on  $\mathbb{R}^2$  and, thus, the previous integral should be equal to zero.

(d)

$$\mathbb{E}(\tilde{x}) = \int_{-2}^0 x \cdot \frac{x+2}{4} dx + \int_0^2 x \cdot \frac{2-x}{4} dx = 0,$$

$$\mathbb{E}(\tilde{y}) = \mathbb{E}(\tilde{x}^2) = \int_{-2}^0 x^2 \cdot \frac{x+2}{4} dx + \int_0^2 x^2 \cdot \frac{2-x}{4} dx = \frac{2}{3}$$

or

$$\mathbb{E}(\tilde{y}) = \int_0^4 y \left( \frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = \frac{2}{3},$$

$$\mathbb{E}(\tilde{x} \cdot \tilde{y}) = \mathbb{E}(\tilde{x}^3) = \int_{-2}^0 x^3 \cdot \frac{x+2}{4} dx + \int_0^2 x^3 \cdot \frac{2-x}{4} dx = 0,$$

$$\text{Cov}(\tilde{x}, \tilde{y}) = \mathbb{E}(\tilde{x} \cdot \tilde{y}) - \mathbb{E}(\tilde{x}) \cdot \mathbb{E}(\tilde{y}) = 0 - 0 \cdot \frac{2}{3} = 0.$$

However, even if  $\tilde{x}$  and  $\tilde{y}$  are uncorrelated, they are not independent. It is obvious that the values taken by  $\tilde{y}$  depend on the values taken by  $\tilde{x}$ . According to the definition of independence between two random variables, if  $\tilde{x}$  and  $\tilde{y}$  are independent we should have that

$$P\{\tilde{x} \in B_1, \tilde{y} \in B_2\} = P\{\tilde{x} \in B_1\} \cdot P\{\tilde{y} \in B_2\}$$

for all pairs  $B_1$  and  $B_2$  of Borel sets. Then, we can check that the random variables  $\tilde{x}$  and  $\tilde{y}$  are not independent. For instance,

$$P\{\tilde{x} \in (-1, 0), \tilde{y} \in (2, 4)\} = 0$$

as  $\{\tilde{x} \in (-1, 0)\} \cap \{\tilde{y} \in (2, 4)\} = \emptyset$  because  $\tilde{x} \in (-1, 0) \Rightarrow \tilde{y} \in (0, 1)$ .

Moreover,

$$P\{\tilde{x} \in (-1, 0)\} = \int_{-1}^0 \frac{x+2}{4} dx = \frac{3}{8}$$

$$P\{\tilde{y} \in (2, 4)\} = \int_2^4 \left( \frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = \frac{3}{2} - \sqrt{2},$$

Therefore,

$$P\{\tilde{x} \in (-1, 0), \tilde{y} \in (2, 4)\} \neq P\{\tilde{x} \in (-1, 0)\} \cdot P\{\tilde{y} \in (2, 4)\}.$$

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**22.** Assume that the random variables are absolutely continuous. Define  $\tilde{y} = \tilde{x}_1 + \tilde{x}_2$  so that  $\tilde{z} = \tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3 = \tilde{y} + \tilde{x}_3$ . We know that the density of  $\tilde{y} + \tilde{x}_3$  is

$$f_{\tilde{y}+\tilde{x}_3}(z) = f_{\tilde{x}_1+\tilde{x}_2+\tilde{x}_3}(z) = f_{\tilde{z}}(z) = \int_{\mathbb{R}} f_3(z-y)f_{\tilde{y}}(y)dy.$$

Moreover, the density of  $\tilde{y} = \tilde{x}_1 + \tilde{x}_2$  is

$$f_{\tilde{y}}(y) = f_{\tilde{x}_1+\tilde{x}_2}(y) = \int_{\mathbb{R}} f_2(y-x)f_1(x)dx.$$

Therefore, combining the previous two equations, we get

$$\begin{aligned} f_{\tilde{x}_1+\tilde{x}_2+\tilde{x}_3}(z) &= f_{\tilde{z}}(z) = \int_{\mathbb{R}} f_3(z-y)f_{\tilde{y}}(y)dy \\ &= \int_{\mathbb{R}} f_3(z-y) \left[ \int_{\mathbb{R}} f_2(y-x)f_1(x)dx \right] dy \\ &= \int_{\mathbb{R}} \int_{\mathbb{R}} f_3(z-y)f_2(y-x)f_1(x)dx dy. \end{aligned}$$

We can obtain an alternative formula for the convolution density. To do so, we define  $\tilde{y} = \tilde{x}_2 + \tilde{x}_3$  so that  $\tilde{z} = \tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3 = \tilde{x}_1 + \tilde{y}$ . We know that the density of  $\tilde{x}_1 + \tilde{y}$  is

$$f_{\tilde{x}_1 + \tilde{y}}(z) = f_{\tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3}(z) = f_{\tilde{z}}(z) = \int_{\mathbb{R}} f_{\tilde{y}}(z - x_1) f_1(x_1) dx_1.$$

Moreover, the density of  $\tilde{y} = \tilde{x}_2 + \tilde{x}_3$  is

$$f_{\tilde{y}}(y) = f_{\tilde{x}_2 + \tilde{x}_3}(y) = \int_{\mathbb{R}} f_3(y - x_2) f_2(x_2) dx_2.$$

Therefore, combining the previous two equations, we get

$$\begin{aligned} f_{\tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3}(z) &= f_{\tilde{z}}(z) = \int_{\mathbb{R}} f_{\tilde{y}}(z - x_1) f_1(x_1) dx_1 \\ &= \int_{\mathbb{R}} \left[ \int_{\mathbb{R}} f_3(z - x_1 - x_2) f_2(x_2) dx_2 \right] f_1(x_1) dx_1 \\ &= \int_{\mathbb{R}} \int_{\mathbb{R}} f_3(z - x_1 - x_2) f_2(x_2) f_1(x_1) dx_2 dx_1. \end{aligned}$$

Following the same steps, it is straightforward to prove that, if the random variables are discrete, then the probability function of the convolution is

$$f_{\tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3}(z) = f_{\tilde{z}}(z) = \sum_{y \in \tilde{y}(\Omega)} \sum_{x \in \tilde{x}_1(\Omega)} f_3(z - y) f_2(y - x) f_1(x), \text{ for } z \in \tilde{z}(\Omega),$$

with  $z - y \in \tilde{x}_3(\Omega)$  and  $y - x \in \tilde{x}_2(\Omega)$ .

Alternatively,

$$f_{\tilde{x}_1 + \tilde{x}_2 + \tilde{x}_3}(z) = f_{\tilde{z}}(z) = \sum_{x_2 \in \tilde{x}_2(\Omega)} \sum_{x_1 \in \tilde{x}_1(\Omega)} f_3(z - x_1 - x_2) f_2(x_2) f_1(x_1), \text{ for } z \in \tilde{z}(\Omega),$$

with  $z - x_1 - x_2 \in \tilde{x}_3(\Omega)$ .

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**23.** (a)

$$\begin{aligned} \mathbb{E} [(\tilde{x} - \mu)^k] &= \sum_j p_j \mathbb{E} [(\tilde{x} - \mu)^k | \tilde{x} = \tilde{x}_j] \\ &= \sum_j p_j \mathbb{E} [(\tilde{x}_j - \mu)^k] = \sum_j p_j \mathbb{E} [[(\tilde{x}_j - \mu_j) + (\mu_j - \mu)]^k]. \end{aligned}$$

Making the binomial expansion of  $[(\tilde{x}_j - \mu_j) + (\mu_j - \mu)]^k$ , we get

$$\begin{aligned} &\sum_j p_j \mathbb{E} \left[ \sum_{n=0}^k \binom{k}{n} (\mu_j - \mu)^{k-n} (\tilde{x}_j - \mu_j)^n \right] \\ &= \sum_j p_j \left( \sum_{n=0}^k \binom{k}{n} (\mu_j - \mu)^{k-n} \mathbb{E} [(\tilde{x}_j - \mu_j)^n] \right). \end{aligned}$$

(b) We can evaluate the formula obtained in (a) for  $k = 2$  (please, do it!).

Alternatively, we can also perform a direct computation,

$$\sigma^2 = \mathbb{E} [(\tilde{x} - \mu)^2] = \mathbb{E} (\tilde{x}^2) - \mu^2,$$

where

$$\begin{aligned} \mathbb{E} (\tilde{x}^2) &= \sum_j p_j \mathbb{E} (\tilde{x}^2 | \tilde{x} = \tilde{x}_j) = \sum_j p_j \mathbb{E} (\tilde{x}_j^2) \\ &= \sum_j p_j [\text{Var} (\tilde{x}_j) + [\mathbb{E} (\tilde{x}_j)]^2] = \sum_j p_j (\sigma_j^2 + \mu_j^2). \end{aligned}$$

Therefore,

$$\sigma^2 = \sum_j p_j (\sigma_j^2 + \mu_j^2) - \mu^2 = \sum_j p_j (\sigma_j^2 + \mu_j^2 - \mu^2),$$

where the last equality holds since  $\sum_j p_j = 1$ .

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**24.** (a)  $f_{\tilde{x}}(x) = \int_0^1 \frac{4}{3}(x + xy)dy = 2x$  for  $x \in (0, 1)$  and  $f_{\tilde{x}}(x) = 0$ , otherwise.

$f_{\tilde{y}}(y) = \int_0^1 \frac{4}{3}(x + xy)dx = \frac{2}{3}(1 + y)$  for  $y \in (0, 1)$  and  $f_{\tilde{y}}(y) = 0$ , otherwise.

Clearly  $f_{\tilde{x}, \tilde{y}}(x, y) = f_{\tilde{x}}(x) \cdot f_{\tilde{y}}(y)$  so that  $\tilde{x}$  and  $\tilde{y}$  are independent and, thus,  $\text{Cov}(\tilde{x}, \tilde{y}) = 0$ .

Alternatively, you can compute

$$\mathbf{E}(\tilde{x} \cdot \tilde{y}) = \int_0^1 \int_0^1 xy \frac{4}{3}(x + xy) dx dy = \frac{10}{27},$$

$$\mathbf{E}(\tilde{x}) = \int_0^1 \int_0^1 x \frac{4}{3}(x + xy) dx dy = \int_0^1 x \cdot 2x dx = \frac{2}{3},$$

$$\mathbf{E}(\tilde{y}) = \int_0^1 \int_0^1 y \frac{4}{3}(x + xy) dx dy = \int_0^1 y \cdot \frac{2}{3}(1 + y) dy = \frac{5}{9}.$$

Thus,

$$\text{Cov}(\tilde{x}, \tilde{y}) = \mathbf{E}(\tilde{x} \cdot \tilde{y}) - \mathbf{E}(\tilde{x}) \mathbf{E}(\tilde{y}) = \frac{10}{27} - \left(\frac{2}{3} \cdot \frac{5}{9}\right) = 0.$$

(b)

$$M_{\tilde{x}}(t) = \mathbf{E}(e^{t\tilde{x}}) = \int_0^1 e^{tx} f_{\tilde{x}}(x) dx = \int_0^1 e^{tx} \cdot 2x dx.$$

The previous integral can be solved by parts by making  $F(x) = 2x$  and

$g(x) = G'(x) = e^{tx}$  so that  $f(x) = F'(x) = 2$  and  $G(x) = \frac{e^{tx}}{t}$ . Then,

$$\begin{aligned} M_{\bar{x}}(t) &= \int_0^1 e^{tx} \cdot 2x dx = \left[ 2x \frac{e^{tx}}{t} \right]_0^1 - \int_0^1 2 \frac{e^{tx}}{t} dx = \left[ 2x \frac{e^{tx}}{t} \right]_0^1 - \left[ 2 \frac{e^{tx}}{t^2} \right]_0^1 \\ &= \frac{2e^t}{t} - \frac{2e^t}{t^2} + \frac{2}{t^2} = \frac{2te^t - 2e^t + 2}{t^2}, \text{ for } t \neq 0, \end{aligned}$$

and  $M_{\bar{x}}(0) = 1$ . Note that

$$\lim_{t \rightarrow 0} M_{\bar{x}}(t) = \frac{0}{0}$$

and, from l'Hôpital's rule, we get

$$\lim_{t \rightarrow 0} M_{\bar{x}}(t) = \lim_{t \rightarrow 0} \frac{2te^t}{2t} = \lim_{t \rightarrow 0} e^t = 1.$$

The derivative of  $M_{\bar{x}}(t)$  is

$$M'_{\bar{x}}(t) = \frac{2e^t}{t} - \frac{4e^t}{t^2} + \frac{4e^t}{t^3} - \frac{4}{t^3} = \frac{2t^2e^t - 4te^t + 4e^t - 4}{t^3} \text{ for } t \neq 0.$$

Therefore,

$$\lim_{t \rightarrow 0} M'_{\bar{x}}(t) = \frac{0}{0}.$$

Let us apply l'Hôpital's rule,

$$\lim_{t \rightarrow 0} M'_{\bar{x}}(t) = \lim_{t \rightarrow 0} \frac{2t^2e^t}{3t^2} = \lim_{t \rightarrow 0} \frac{2e^t}{3} = \frac{2}{3}.$$

(c)

$$(w, z) = g(x, y) : \begin{cases} w = \ln x \in (-\infty, 0) \\ z = \ln \left( \frac{x}{y} \right) \in (w, \infty) \end{cases}$$

$$(x, y) = g^{-1}(w, z) : \begin{cases} x = e^w \in (0, 1) \\ y = e^{w-z} \in (0, 1) \end{cases}$$

Note that  $z = \ln x - \ln y = w - \ln y$ . Since  $y \in (0, 1)$ , then  $\ln y \in (-\infty, 0)$  and  $-\ln y \in (0, \infty)$ . Therefore,

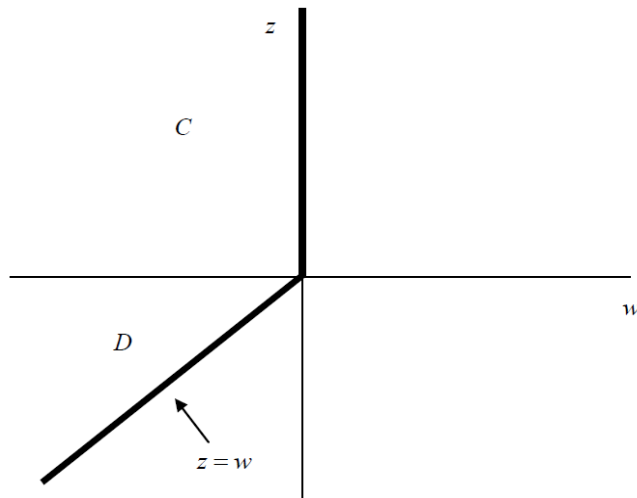
$$z = \ln x - \ln y = w - \ln y \in (w, \infty).$$

$$\begin{aligned} J_{g^{-1}}(w, z) &= \begin{pmatrix} e^w & 0 \\ e^{w-z} & -e^{w-z} \end{pmatrix} \implies \det J_{g^{-1}}(w, z) = -e^{2w-z} < 0 \\ &\implies |\det J_{g^{-1}}| = e^{2w-z} \end{aligned}$$

Then,

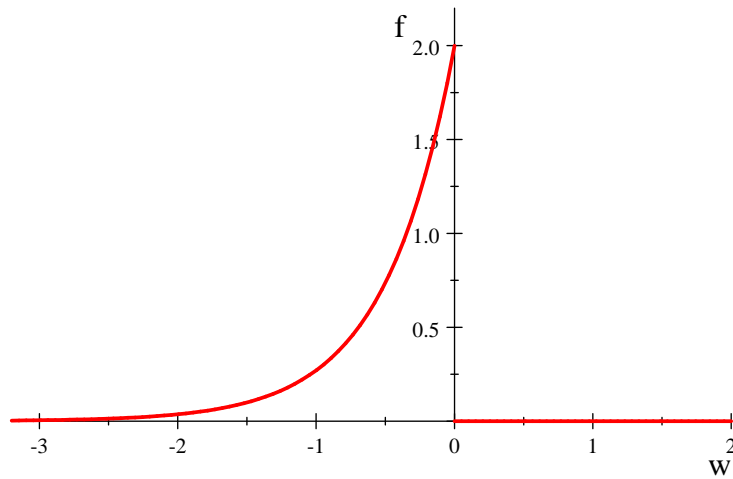
$$f_{\tilde{w}, \tilde{z}}(w, z) = \begin{cases} \frac{4}{3}(e^w + e^w e^{w-z})e^{2w-z} = \frac{4}{3}(e^{3w-z} + e^{4w-2z}), & \text{for } w \in (-\infty, 0), z \in (w, \infty) \\ 0, & \text{otherwise.} \end{cases}$$

(d) The region of positive density for  $f_{\tilde{w}, \tilde{z}}(w, z)$  is  $C \cup D$ :



Marginal density  $f_{\tilde{w}}(w)$  :

$$f_{\tilde{w}}(w) = \begin{cases} \int_w^{\infty} \frac{4}{3} (e^{3w-z} + e^{4w-2z}) dz = 2e^{2w} & \text{for } w \in (-\infty, 0) \\ 0, & \text{otherwise} \end{cases}$$



Marginal density  $f_{\tilde{z}}(z)$  :

If  $z \leq 0$ , then

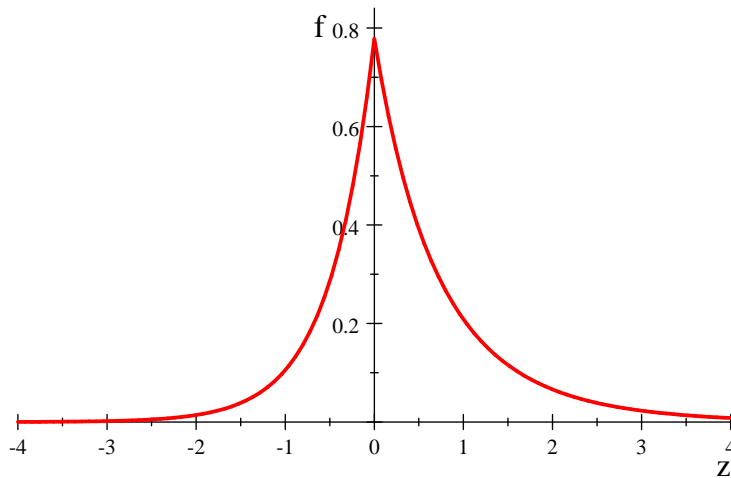
$$\begin{aligned} f_{\bar{z}}(z) &= \int_D f_{\tilde{w}, \bar{z}}(w, z) dw \\ &= \int_{-\infty}^z \frac{4}{3} (e^{3w-z} + e^{4w-2z}) dw = \frac{7}{9} e^{2z}. \end{aligned}$$

If  $z > 0$ , then

$$\begin{aligned} f_{\bar{z}}(z) &= \int_C f_{\tilde{w}, \bar{z}}(w, z) dw \\ &= \int_{-\infty}^0 \frac{4}{3} (e^{3w-z} + e^{4w-2z}) dw = \frac{1}{9} (3e^{-2z} + 4e^{-z}). \end{aligned}$$

Note that  $f_{\bar{z}}(0) = \frac{7}{9}$  and that the density is continuous (but not differentiable) at  $z = 0$ . Thus,

$$f_{\bar{z}}(z) = \begin{cases} \frac{7}{9} e^{2z} & \text{for } z \leq 0 \\ \frac{1}{9} (3e^{-2z} + 4e^{-z}) & \text{for } z > 0. \end{cases}$$



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**25.** (a) Marginal densities:

$$f_{\tilde{x}}(x) = \begin{cases} \int_0^2 \frac{2x+y}{12} dy = \frac{1+2x}{6} & \text{if } x \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

$$f_{\tilde{y}}(y) = \begin{cases} \int_0^2 \frac{2x+y}{12} dx = \frac{y+2}{6} & \text{if } y \in (0, 2) \\ 0 & \text{otherwise.} \end{cases}$$

$$E(\tilde{x}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x, y) dx dy = \int_{-\infty}^{\infty} x f_{\tilde{x}}(x) dx = \int_0^2 x \frac{1+2x}{6} dx = \frac{11}{9}.$$

$$E(\tilde{y}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x, y) dx dy = \int_{-\infty}^{\infty} y f_{\tilde{y}}(y) dy = \int_0^2 y \frac{y+2}{6} dy = \frac{10}{9}.$$

$$E(\tilde{x} \cdot \tilde{y}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dx dy = \int_0^2 \int_0^2 xy \frac{2x+y}{12} dx dy = \frac{4}{3}.$$

$$\text{Cov}(\tilde{x} \cdot \tilde{y}) = E(\tilde{x} \cdot \tilde{y}) - E(\tilde{x})E(\tilde{y}) = \frac{4}{3} - \left( \frac{11}{9} \cdot \frac{10}{9} \right) = -\frac{2}{81}.$$

Thus, since  $\text{Cov}(\tilde{x} \cdot \tilde{y}) \neq 0$ , the random variable  $\tilde{x}$  and  $\tilde{y}$  are not independent.

(b) If  $y \in (0, 2)$ , then

$$f_{\tilde{x}|\tilde{y}}(x|y) = \frac{f(x, y)}{f_{\tilde{y}}(y)} = \frac{\frac{2x+y}{12}}{\frac{y+2}{6}} = \frac{2x+y}{2(y+2)} \text{ for } x \in (0, 2)$$

and  $f_{\tilde{x}|\tilde{y}}(x|y) = 0$  otherwise.

Thus,

$$f_{\tilde{x}|\tilde{y}}(x|1/2) = \frac{2x + \frac{1}{2}}{2\left(\frac{1}{2} + 2\right)} = \frac{4x + 1}{10} \text{ for } x \in (0, 2)$$

and  $f_{\tilde{x}|\tilde{y}}(x|1/2) = 0$  otherwise.

$$\mathbb{E}(\tilde{x}|\tilde{y} = 1/2) = \int_0^2 x \frac{4x + 1}{10} dx = \frac{19}{15}.$$

(c)

$$g : (x, y) \mapsto (z, x) : \begin{cases} z = 3y - \frac{x}{2} \\ x = x \in (0, 2), \end{cases}$$

$$g^{-1} : (z, x) \mapsto (x, y) : \begin{cases} x = x \in (0, 2) \\ y = \frac{1}{3}\left(z + \frac{x}{2}\right) \in (0, 2), \end{cases}$$

$$|J_{g^{-1}}(z, x)| = \det \begin{pmatrix} 0 & 1 \\ 1/3 & 1/6 \end{pmatrix} = \left| -\frac{1}{3} \right| = \frac{1}{3}.$$

Note that

$$\frac{1}{3}\left(z + \frac{x}{2}\right) \in (0, 2) \iff x \in (-2z, 12 - 2z) \iff z \in \left(-\frac{x}{2}, 6 - \frac{x}{2}\right).$$

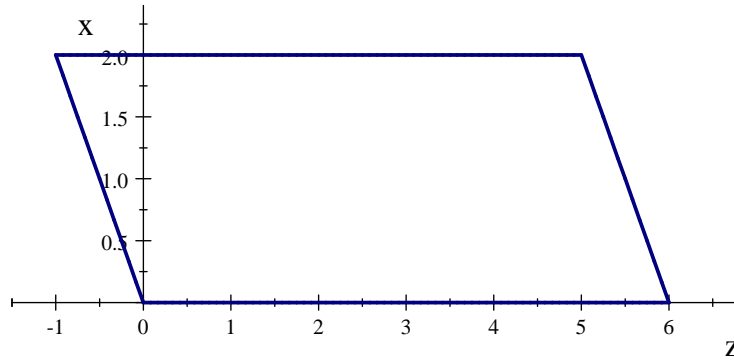
Thus,

$$f_{\tilde{z}, \tilde{x}}(z, x) = \left[ \frac{2x + \frac{1}{3}\left(z + \frac{x}{2}\right)}{12} \right] \cdot \frac{1}{3} \text{ if } x \in (0, 2) \text{ and } x \in (-2z, 12 - 2z),$$

which, after simplifying, becomes

$$f_{\tilde{z}, \tilde{x}}(z, x) = \begin{cases} \frac{1}{108}z + \frac{13}{216}x & \text{if } x \in (0, 2) \text{ and } x \in (-2z, 12 - 2z) \\ 0 & \text{otherwise.} \end{cases}$$

The region where the density of the random vector  $(\tilde{z}, \tilde{x})$  is different from zero is the interior of the following parallelogram, which is  $g((0, 2) \times (0, 2))$  :



To compute the marginal density  $f_{\tilde{z}}(z)$ , we consider the following intervals for  $z$  :

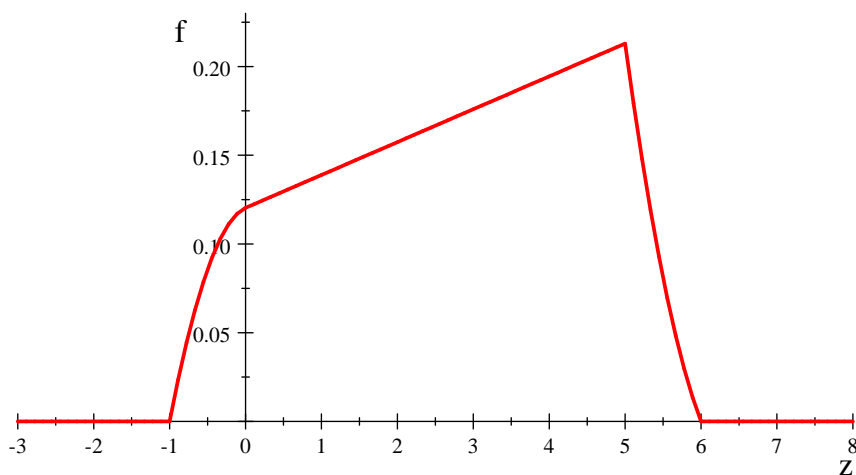
$$\text{for } z \in (-1, 0) \Rightarrow \int_{-2z}^2 \left( \frac{1}{108}z + \frac{13}{216}x \right) dx = -\frac{11}{108}z^2 + \frac{1}{54}z + \frac{13}{108}$$

$$\text{for } z \in (0, 5) \Rightarrow \int_0^2 \left( \frac{1}{108}z + \frac{13}{216}x \right) dx = \frac{1}{54}z + \frac{13}{108}$$

$$\text{for } z \in (5, 6) \Rightarrow \int_0^{12-2z} \left( \frac{1}{108}z + \frac{13}{216}x \right) dx = \frac{11}{108}z^2 - \frac{4}{3}z + \frac{13}{3}$$

Then,

$$f_z(z) = \begin{cases} -\frac{11}{108}z^2 + \frac{1}{54}z + \frac{13}{108} & \text{if } -1 \leq z < 0 \\ \frac{1}{54}z + \frac{13}{108} & \text{if } 0 \leq z < 5 \\ \frac{11}{108}z^2 - \frac{4}{3}z + \frac{13}{3} & \text{if } 5 \leq z < 6 \\ 0 & \text{otherwise.} \end{cases}$$



26.

$$z = cx + b \iff x = \frac{z - b}{c} \text{ so that } \left| \frac{dx}{dz} \right| = \frac{1}{c}.$$

Note that the logistic and the three types of generalized extreme value distributions have a density that can be written as

$$f_{\tilde{x}}(x; m, s, \alpha) = \frac{\alpha}{s} h \left( \left[ \frac{x - m}{s} \right]^k, \left[ \frac{x - m}{s} \right]^{k-1} \right),$$

where  $k = \alpha = 1$  for the logistic and generalized extreme value type I distributions,  $k = -\alpha < 0$  for the generalized extreme value type II distribution, and  $k = \alpha > 0$  for the generalized extreme value type III distribution. Thus, if

$$\tilde{x} \sim f_{\tilde{x}}(x; m, s, \alpha),$$

then the density of  $\tilde{z}$  will be

$$\begin{aligned} f_{\tilde{z}}(z; m, s, \alpha) &= f_{\tilde{x}}\left(\frac{z-b}{c}; m, s, \alpha\right) \frac{1}{c} = \frac{\alpha}{s} h\left(\left[\frac{\frac{z-b}{c} - m}{s}\right]^k, \left[\frac{\frac{z-b}{c} - m}{s}\right]^{k-1}\right) \frac{1}{c} \\ &= \frac{\alpha}{cs} h\left(\left[\frac{z - (cm + b)}{cs}\right]^k, \left[\frac{z - (cm + b)}{cs}\right]^{k-1}\right). \end{aligned}$$

Therefore, the random variable  $\tilde{z}$  has the logistic, generalized extreme value type I, type II or type III distributions with location parameter  $cm + b$  and scale parameter  $cs > 0$  and the shape parameter  $\alpha$  remains the same.

Obviously, if  $c = 1/s$  and  $b = -m/s$ , then the distributions become standard as the density of  $\tilde{z}$  would be

$$\alpha h(z^k, z^{k-1}) = f_{\tilde{z}}(z; 0, 1, \alpha).$$

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27. (a) The density of  $\tilde{w}$  is exponential with parameter equal to one,

$$f_{\tilde{w}}(w) = \begin{cases} e^{-w} & \text{for } w > 0 \\ 0 & \text{otherwise.} \end{cases}$$

Note that  $x = m - s \ln w \in (-\infty, \infty) \iff w = e^{-\left(\frac{x-m}{s}\right)} > 0$ . Then,  $\left|\frac{dw}{dx}\right| = \frac{1}{s}e^{-\left(\frac{x-m}{s}\right)}$ . Thus,

$$f_{\tilde{x}}(x) = f_{\tilde{w}}\left(e^{-\left(\frac{x-m}{s}\right)}\right) \left|\frac{dw}{dx}\right| = e^{-e^{-\left(\frac{x-m}{s}\right)}} \frac{1}{s}e^{-\left(\frac{x-m}{s}\right)} = \frac{1}{s}e^{-\left(\frac{x-m}{s}\right)}e^{-e^{-\left(\frac{x-m}{s}\right)}} \text{ for all } x \in \mathbb{R}.$$

Thus, the random variable  $\tilde{x}$  has the generalized extreme value type I (or Gumbel) distribution distribution with location parameter  $m$  and scale parameter  $s > 0$ ,  $\tilde{x} \sim G(m, s)$ . Conversely, if  $\tilde{x} \sim G(m, s)$  then  $\tilde{w} = e^{-\left(\frac{\tilde{x}-m}{s}\right)}$  is exponential with parameter equal to 1.

(b) Since  $\tilde{w}_1$  and  $\tilde{w}_2$  are independent, their joint density is

$$f_{\tilde{w}_1, \tilde{w}_2}(w_1, w_2) = f_{\tilde{w}_1}(w_1)f_{\tilde{w}_2}(w_2) = \begin{cases} e^{-w_1}e^{-w_2} & \text{for } w_1 > 0 \text{ and } w_2 > 0 \\ 0 & \text{otherwise.} \end{cases}$$

The distribution function of  $\tilde{z} = \tilde{w}_2/\tilde{w}_1$  is

$$F_{\tilde{z}}(z) = P\{\tilde{z} \leq z\} = P\left\{\frac{\tilde{w}_2}{\tilde{w}_1} \leq z\right\} = \int_A e^{-w_1}e^{-w_2}d(w_1, w_2),$$

where  $A = \{(w_1, w_2) \in \mathbb{R}^2 \mid w_2 \leq zw_1\}$ . Hence,

$$\begin{aligned}
F_{\tilde{z}}(z) &= \int_0^\infty \int_0^{zw_1} e^{-w_1} e^{-w_2} dw_2 dw_1 = \int_0^\infty e^{-w_1} \left[ \int_0^{zw_1} e^{-w_2} dw_2 \right] dw_1 \\
&= \int_0^\infty e^{-w_1} [-e^{-w_2}]_0^{zw_1} dw_1 = \int_0^\infty e^{-w_1} (1 - e^{-zw_1}) dw_1 = \int_0^\infty (e^{-w_1} - e^{-(1+z)w_1}) dw_1 \\
&= \left[ -e^{-w_1} + \frac{e^{-(1+z)w_1}}{1+z} \right]_0^\infty = 1 - \frac{1}{1+z} = \frac{z}{1+z} \text{ for } z > 0,
\end{aligned}$$

and  $F_{\tilde{z}}(z) = 0$  for  $z \leq 0$ .

Therefore the density of  $\tilde{z}$  is  $f_{\tilde{z}}(z) = F'_{\tilde{z}}(z) = \frac{1}{(1+z)^2}$  for  $z > 0$ , and  $f_{\tilde{z}}(z) = 0$  otherwise.

(c) Let  $\tilde{y} = \tilde{x}_1 - \tilde{x}_2$  and define the random variable  $\tilde{q}$  as

$$\begin{aligned}
\tilde{q} &= \frac{\tilde{y} - (m_1 - m_2)}{s} = \frac{\tilde{x}_1 - m_1}{s} - \left( \frac{\tilde{x}_2 - m_2}{s} \right) \\
&= \ln \left( e^{\left(\frac{\tilde{x}_1 - m_1}{s}\right) - \left(\frac{\tilde{x}_2 - m_2}{s}\right)} \right) = \ln \left( \frac{e^{-\left(\frac{\tilde{x}_2 - m_2}{s}\right)}}{e^{-\left(\frac{\tilde{x}_1 - m_1}{s}\right)}} \right).
\end{aligned}$$

Let  $\tilde{w}_i = e^{-\left(\frac{\tilde{x}_i - m_i}{s}\right)}$ ,  $i = 1, 2$ . From part (a), since  $\tilde{x}_1$  and  $\tilde{x}_2$  have the Gumbel distribution and are independent,  $\tilde{w}_1$  and  $\tilde{w}_2$  are independent and both have the exponential distribution with parameter equal to 1. Therefore, from part (b), the random variable

$$\tilde{z} = \frac{\tilde{w}_2}{\tilde{w}_1} = \frac{e^{-\left(\frac{\tilde{x}_2 - m_2}{s}\right)}}{e^{-\left(\frac{\tilde{x}_1 - m_1}{s}\right)}}$$

has the density function

$$f_{\tilde{z}}(z) = \begin{cases} \frac{1}{(1+z)^2} & \text{for } z > 0 \\ 0 & \text{otherwise,} \end{cases}$$

Note that

$$q = \ln \left( \frac{e^{-\left(\frac{x_2 - m_2}{s}\right)}}{e^{-\left(\frac{x_1 - m_1}{s}\right)}} \right) = \ln z \in (-\infty, \infty) \iff z = e^q > 0$$

so that  $\left| \frac{dz}{dq} \right| = e^q$ . Thus, the density of  $\tilde{q}$  is

$$f_{\tilde{q}}(q) = f_{\tilde{z}}(e^q) e^q = \frac{e^q}{(1+e^q)^2} = \frac{e^{-q}}{(1+e^{-q})^2} = l(q; 0, 1) \text{ for all } q \in \mathbb{R}.$$

where the third equality follows from multiplying the numerator and the denominator by  $e^{-2q} > 0$ . Thus, we have proved that  $\tilde{q}$  has the standard logistic distribution.

Since

$$q = \frac{y - (m_1 - m_2)}{s} \text{ so that } \left| \frac{dq}{dy} \right| = \frac{1}{s} > 0,$$

the density of  $\tilde{y} = \tilde{x}_1 - \tilde{x}_2 = s\tilde{q} + (m_1 - m_2)$  is

$$f_{\tilde{y}}(y) = f_{\tilde{q}} \left( \frac{\tilde{y} - (m_1 - m_2)}{s} \right) \frac{1}{s} = \frac{e^{-\left(\frac{y - (m_1 - m_2)}{s}\right)}}{s \left[ 1 + e^{-\left(\frac{y - (m_1 - m_2)}{s}\right)} \right]^2} = l(y; m_1 - m_2, s),$$

which is the logistic density with location parameter  $m_1 - m_2$  and scale parameter  $s$ . We could omit this last step by just using the result of Exercise

26.

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