

Statistics HW01 Solution

Chapter 2

Problem 67

(a)

The density function can be obtained by direct differentiation :

$$f(x) = \frac{d}{dx}F(x) = \frac{\beta}{\alpha} \left(\frac{x}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{x}{\alpha}\right)^\beta\right) = \frac{\beta}{\alpha^\beta} x^{\beta-1} \exp\left(-\left(\frac{x}{\alpha}\right)^\beta\right), \quad x \geq 0, \alpha > 0, \beta > 0$$

(b)

Let $X = \left(\frac{W}{\alpha}\right)^\beta$, then the support of X is $\{x \in \mathcal{R} \mid 0 \leq x < \infty\}$, $W = \alpha X^{\frac{1}{\beta}}$, and $\frac{dw}{dx} = \frac{\alpha}{\beta} x^{\frac{1}{\beta}-1}$. Thus, we have

$$f_X(x) = f_W(\alpha x^{\frac{1}{\beta}}) \left| \frac{dw}{dx} \right| = \frac{\beta}{\alpha} \left(\frac{1}{\alpha} \times \alpha x^{\frac{1}{\beta}}\right)^{\beta-1} \exp\left\{-\left(\frac{1}{\alpha} \times \alpha x^{\frac{1}{\beta}}\right)^\beta\right\} \left(\frac{\alpha}{\beta} x^{\frac{1}{\beta}-1}\right) = e^{-x}, \quad 0 \leq x < \infty$$

This shows $X \sim \text{Exp}(1)$. Note that the pdf specifies a distribution.

(c)

We may use the inverse cdf method (TB p.63 Proposition D) to do so.

Theorem : Let $U \sim U[0, 1]$, and let $X = F^{-1}(U)$. Then the cdf of X is F .

*Proof : $\Pr(X \leq x) = \Pr(F^{-1}(U) \leq x) = \Pr(U \leq F(x)) = F(x)$

*FYI : $\left(\begin{array}{l} \text{This proof required that } F \text{ is strictly increasing.} \\ \text{If } F \text{ is not strictly increasing, we may redefine } F^{-1}(u) := \inf\{x : F(x) \geq u\}. \end{array} \right)$

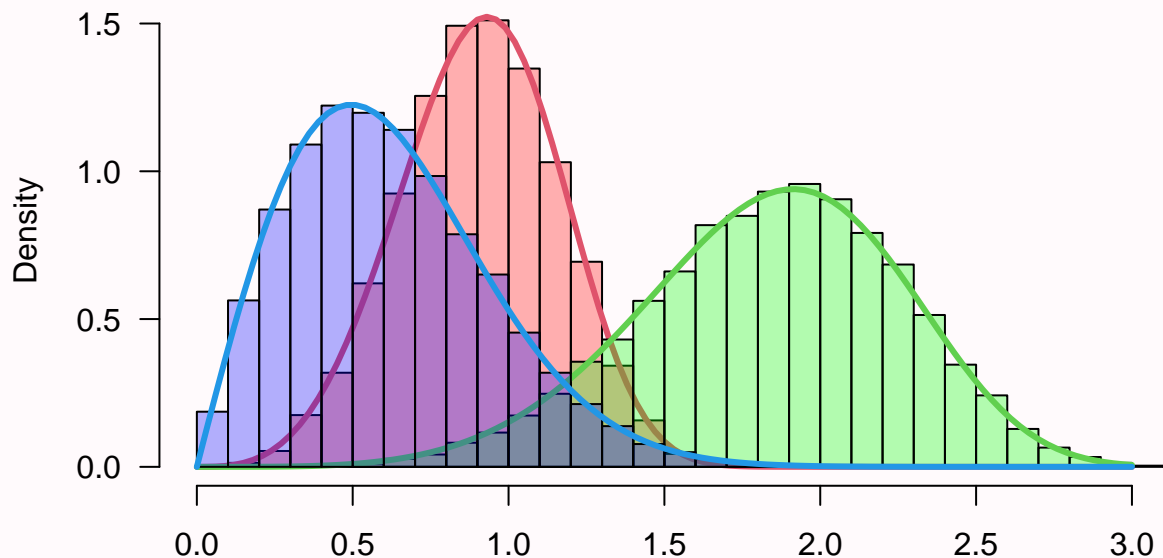
$$\text{Set } F_X(s) = t = 1 - e^{-\left(\frac{s}{\alpha}\right)^\beta} \implies s = \alpha \left(-\log(1-t)\right)^{\frac{1}{\beta}} \implies F_X^{-1}(t) = \alpha \left(-\log(1-t)\right)^{\frac{1}{\beta}}$$

So we can use the random number generator to generate $U_1, \dots, U_n \stackrel{i.i.d.}{\sim} U(0,1)$,
 then $F_X^{-1}(U_1), \dots, F_X^{-1}(U_n)$ are I.I.D. from the distribution with cdf F_X (**Weibull**(α, β) – distribution).

We can use R to verify this method :

```
set.seed(77) # choose what you like
U <- runif(20102) # so big
S <- 1*(-log(1-U))^(1/4) # alpha = 1, beta = 4
hist(S,breaks = 15,probability = T,xlab="",
     main = "Histograms of samples of size 20102 (with theoretical densities)",las=1,
     col = rgb(1, 0, 0, 0.3),ylim = c(0,1.6),xlim=c(0,3))
curve(dweibull(x,shape = 4,scale = 1),col=2,lwd=3,add=T)
UU <- runif(20102)
SS <- 2*(-log(1-UU))^(1/5) # alpha = 2, beta = 5
hist(SS,breaks = 30,probability = T,main="",add=T, col = rgb(0, 1, 0, 0.3))
curve(dweibull(x,shape = 5,scale = 2),col=3,lwd=3,add=T)
UUU <- runif(20102)
SSS <- (0.7)*(-log(1-UUU))^(1/2) # alpha = 0.7, beta = 2
hist(SSS,breaks = 30,probability = T,main="",add=T, col = rgb(0, 0, 1, 0.3))
curve(dweibull(x,shape = 2,scale = 0.7),col=4,lwd=3,add=T)
```

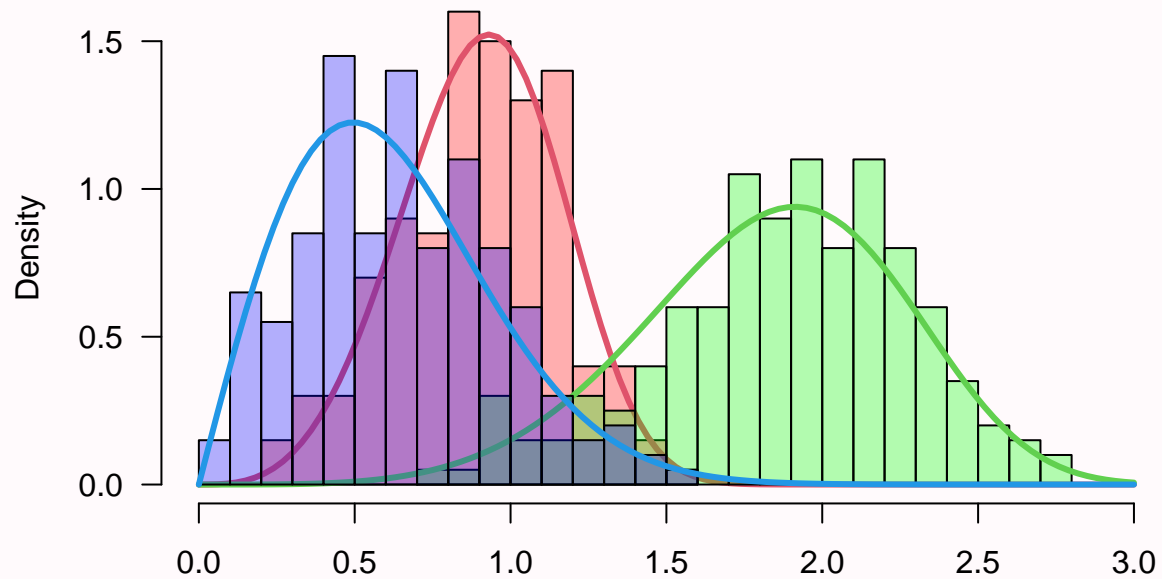
Histograms of samples of size 20102 (with theoretical densities)



What happens if we choose a small sample size?

(The code is omitted.)

Histograms of samples of size 200 (with theoretical densities)



What difference do you see? Is this method good?

FYI: There is another method called rejection sampling.

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Chapter 3

Problem 7

We can find the desired densities by direct differentiation :

$$\left\{ \begin{array}{ll} f_{X,Y}(x,y) = \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x,y) & = \alpha \beta e^{-\alpha x - \beta y} \quad , \ x \geq 0, \ y \geq 0, \ \alpha > 0, \ \beta > 0 \\ f_X(x) = \int_0^\infty f_{X,Y}(x,y) dy & = \alpha e^{-\alpha x} \left(\int_0^\infty \beta e^{-\beta y} dy \right) = \alpha e^{-\alpha x} \quad , \ x \geq 0, \ \alpha > 0 \\ f_Y(y) = \int_0^\infty f_{X,Y}(x,y) dx & = \beta e^{-\beta y} \left(\int_0^\infty \alpha e^{-\alpha x} dx \right) = \beta e^{-\beta y} \quad , \ y \geq 0, \ \beta > 0 \end{array} \right.$$

Alternative method :

$$\begin{aligned} & \left\{ \begin{array}{l} F_X(x) = \lim_{y \rightarrow \infty} F_{X,Y}(x,y) = 1 - e^{-\alpha x} \\ F_Y(y) = \lim_{x \rightarrow \infty} F_{X,Y}(x,y) = 1 - e^{-\beta y} \end{array} \right. \\ \Rightarrow & \left\{ \begin{array}{l} f_X(x) = \frac{d}{dx} F_X(x) = \alpha e^{-\alpha x} \quad , \ x \geq 0 \\ f_Y(y) = \frac{d}{dy} F_Y(y) = \beta e^{-\beta y} \quad , \ y \geq 0 \end{array} \right. \end{aligned}$$

\Rightarrow This yields the same results!

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Problem 10

(a)

First find the marginal densities :

$$\begin{aligned}
 f_X(x) &= \int_0^\infty x e^{-x(y+1)} dy \\
 &= \left(-e^{-x(y+1)} \right) \Big|_0^\infty \\
 &= e^{-x}, \quad x \in [0, \infty) \\
 f_Y(y) &= \int_0^\infty x e^{-x(y+1)} dx \\
 &\stackrel{(*)}{=} \left(\left(\left(\frac{-x}{y+1} \right) e^{-x(y+1)} \right) \Big|_0^\infty \right) + \left(\frac{1}{y+1} \int_0^\infty e^{-x(y+1)} dx \right) \\
 &= \left(\frac{1}{y} \right) \left(\frac{-1}{y+1} e^{-x(y+1)} \right) \Big|_0^\infty \\
 &= \frac{1}{(y+1)^2}, \quad y \in [0, \infty)
 \end{aligned}$$

(*) :
 Do integration by parts with $\begin{pmatrix} u = x & du = dx \\ v = \frac{-1}{y+1} e^{-x(y+1)} & dv = e^{-x(y+1)} dx \end{pmatrix}$ over $\{x \in \mathcal{R} \mid 0 \leq x < \infty\}$
 and recall that $\int_0^\infty u dv = uv \Big|_0^\infty - \int_0^\infty v du$

Since $f_{X,Y}(x,y) \neq f_X(x)f_Y(y)$, we conclude that X and Y are not independent.

(b)

With the help of both of the joint density and the marginal densities, we can find :

$$\begin{cases} f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = (y+1)^2 x e^{-x(y+1)} & , \quad x \in [0, \infty) \text{ and } y \in [0, \infty) \\ f_{Y|X}(y|x) = \frac{f(x,y)}{f_X(x)} = x e^{-xy} & , \quad x \in [0, \infty) \text{ and } y \in [0, \infty) \end{cases}$$

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Problem 21

Define $\mathbf{I} := \begin{cases} 1 & , \text{ if } X \text{ is detected.} \\ 0 & , \text{ otherwise.} \end{cases} \implies \Pr(\mathbf{I} = 1 | X = x) = R(x)$

(\star) : By the multiplicative law, the joint distribution of (X, \mathbf{I}) when $\mathbf{I} = 1$ is :

$$f_{X, \mathbf{I}}(x, 1) = f_X(x) \times \Pr(\mathbf{I} = 1 | X = x) = f(x)R(x)$$

$$\implies G_Y(y) = \Pr(Y \leq y) = \Pr(X \leq y | \mathbf{I} = 1) = \frac{\Pr(X \leq y, \mathbf{I} = 1)}{\Pr(\mathbf{I} = 1)} = \frac{\int_0^y f_{X, \mathbf{I}}(x, 1) dx}{\int_{-\infty}^{\infty} f_{X, \mathbf{I}}(x, 1) dx} \stackrel{(\star)}{=} \frac{\int_0^y R(x) f(x) dx}{\int_0^{\infty} R(x) f(x) dx}$$

$$\implies g_Y(y) = \frac{d}{dy} G_Y(y) = \frac{R(y) f(y)}{\int_0^{\infty} R(x) f(x) dx}$$

Holds by the fundamental theorem of calculus.

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Problem 64

Since X and Y are independent, we have :

$$f_{X,Y}(x, y) = f_X(x) f_Y(y) = \lambda^2 e^{-\lambda(x+y)}, \quad x > 0, y > 0$$

Now, consider the transformation :

$$\text{Define } \begin{cases} V = X + Y \\ W = X/Y \end{cases} \implies \begin{cases} X = VW/(W+1) \\ Y = V/(W+1) \end{cases}$$

This transformation corresponds to a Jacobian \mathbf{J} , which satisfies :

$$\det(\mathbf{J}) = \begin{vmatrix} \frac{\partial x}{\partial v} & \frac{\partial x}{\partial w} \\ \frac{\partial y}{\partial v} & \frac{\partial y}{\partial w} \end{vmatrix} = \frac{-v}{(w+1)^2}$$

So the joint pdf of V and W is :

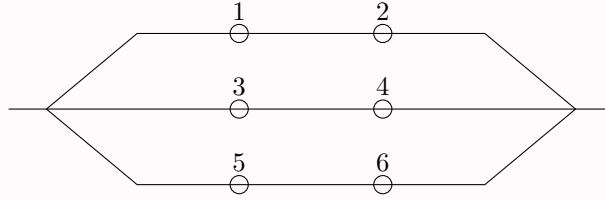
$$f_{V,W}(v, w) = f_{X,Y}\left(\frac{vw}{w+1}, \frac{v}{w+1}\right) \times |\mathbf{J}| = \underbrace{\left(ve^{-\lambda v} \mathbf{I}_{(0, \infty)}(v)\right)}_{:= g_1(v)} \times \underbrace{\left(\frac{\lambda^2}{(w+1)^2} \mathbf{I}_{(0, \infty)}(w)\right)}_{:= g_2(w)}$$

Since the joint pdf of (V, W) can be written as a product of the marginal pdf of V and the marginal pdf of W and their supports are not related, $(X+Y)$ and (X/Y) are independent.

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Problem 66

First label the points as the following graph :



Let $\{T_1, T_2\}$, $\{T_3, T_4\}$ and $\{T_5, T_6\}$ be the lifetimes of the top 2, middle 2, and the bottom 2 components, respectively.

Let T^* be the lifetime of the system.

Follow the hint, we know that :

$$T^* = \max\{W_1, W_2, W_3\}, \text{ where } W_1 = \min\{T_1, T_2\}, W_2 = \min\{T_3, T_4\}, W_3 = \min\{T_5, T_6\}.$$

Since T_1, \dots, T_6 are IID, W_1, W_2, W_3 are also IID, hence it suffices to find the distribution of W_1 :

$$\begin{aligned} Pr(W_1 \leq w_1) &= Pr(\min\{T_1, T_2\} \leq w) \\ &= 1 - Pr(\min\{T_1, T_2\} > w) \\ &= 1 - Pr(T_1 > w_1, T_2 > w_1) \\ &= 1 - Pr(T_1 > w_1)Pr(T_2 > w_1) \quad \text{By the independence between } T_1 \text{ and } T_2 \\ &= 1 - e^{-2\lambda w_1}, w_1 > 0 \end{aligned}$$

Thus, we have :

$$(\square) \begin{cases} Pr(W_1 \leq w_1) = 1 - e^{-2\lambda w_1} & , w_1 > 0. \\ Pr(W_2 \leq w_2) = 1 - e^{-2\lambda w_2} & , w_2 > 0. \\ Pr(W_3 \leq w_3) = 1 - e^{-2\lambda w_3} & , w_3 > 0. \end{cases}$$

The cdf of the system's lifetime is :

$$\begin{aligned} F_{T^*}(t) &= Pr(T^* \leq t) \\ &= Pr(\max\{W_1, W_2, W_3\} \leq t) \\ &= Pr(W_1 \leq t, W_2 \leq t, W_3 \leq t) \\ &\stackrel{(\triangle)}{=} Pr(W_1 \leq t)Pr(W_2 \leq t)Pr(W_3 \leq t) \quad (\triangle) : \text{By the independence of } W_1, W_2 \text{ and } W_3 \\ &\stackrel{(\square)}{=} (1 - e^{-2\lambda t})^3, t \geq 0 \end{aligned}$$

The density of the system's lifetime is :

$$f_{T^*}(t) = \frac{d}{dt} F_{T^*}(t) = 6\lambda e^{-2\lambda t} (1 - e^{-2\lambda t})^2, \quad t \geq 0$$

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Problem 70

$$\begin{aligned}
 F(x, y) &= Pr(X_{(1)} \leq x, X_{(n)} \leq y) \\
 &= Pr(X_{(n)} \leq y) - Pr(X_{(1)} > x, X_{(n)} \leq y) \\
 &= Pr(X_1 \leq y, \dots, X_n \leq y) - Pr(X_1 \in (x, y], \dots, X_n \in (x, y]) \\
 &= \prod_{i=1}^n F_{X_i}(y) - \prod_{i=1}^n (F_{X_i}(y) - F_{X_i}(x)) && \text{By the independence between each pair of } X_1, \dots, X_n \\
 &= (F(y))^n - (F(y) - F(x))^n, \quad x \leq y && \text{By the identically distributed property of } X_1, \dots, X_n
 \end{aligned}$$

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Chapter 4

Problem 54

Since X, Y, Z are uncorrelated, we have $Cov(X, Y) = Cov(Y, Z) = Cov(Z, X) = 0$, so

$$\begin{aligned}
 & Cov(U, V) \\
 &= Cov(Z + X, Z + Y) \\
 &= Cov(Z, Z) + \cancel{Cov(Z, Y)} + \cancel{Cov(X, Z)} + \cancel{Cov(X, Y)} \\
 &= Cov(Z, Z) = Var(Z) = \sigma_Z^2 \\
 \\
 & \begin{cases} Var(U) = Var(Z + X) &= Var(Z) + Var(X) + 2\cancel{Cov(Z, X)} &= \sigma_Z^2 + \sigma_X^2 \\ Var(V) = Var(Z + Y) &= Var(Z) + Var(Y) + 2\cancel{Cov(Z, Y)} &= \sigma_Z^2 + \sigma_Y^2 \end{cases} \\
 & \Rightarrow \rho_{UV} = \frac{Cov(U, V)}{\sqrt{Var(U)Var(V)}} = \frac{\sigma_Z^2}{\sqrt{(\sigma_Z^2 + \sigma_X^2)(\sigma_Z^2 + \sigma_Y^2)}}
 \end{aligned}$$

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Problem 60

First note that $E(S) = 1 \times Pr(S = 1) + (-1) \times Pr(S = -1) = 1 \times \frac{1}{2} - 1 \times \frac{1}{2} = 0$, so

$$\begin{aligned}
 Cov(X, Y) &= E(XY) - E(X)E(Y) \\
 &= E(SY^2) - E(SY)E(Y) \\
 &= E(S)E(Y^2) - E(S)E(Y)E(Y) \\
 &= 0 \quad \text{Since } S \text{ and } Y \text{ are independent.}
 \end{aligned}$$

$$\begin{aligned}
 F_X(x) &= Pr(X \leq x) \\
 &= Pr(X \leq x, S = 1) + Pr(X \leq x, S = -1) \\
 &= Pr(X \leq x | S = 1)Pr(S = 1) + Pr(X \leq x | S = -1)Pr(S = -1) \\
 &= Pr(Y \leq x) \times \frac{1}{2} + Pr(-Y \leq x) \times \frac{1}{2} \\
 &= Pr(Y \leq x) \times \frac{1}{2} + Pr(Y \leq x) \times \frac{1}{2} \\
 &= Pr(Y \leq x) \\
 &= F_Y(x)
 \end{aligned}$$

$$\Rightarrow f_X(x) = f_Y(x), \text{ i.e. } X \text{ and } Y \text{ have the same pdf.}$$

To show $Pr(-Y \leq x) = Pr(Y \leq x)$:

$$\begin{aligned}
 Pr(-Y \leq x) &= Pr(Y \geq -x) \\
 &= \int_{-x}^{\infty} f_Y(y) dy \\
 &= - \int_x^{-\infty} f_Y(-w) dw \quad \left(\text{Let } w = -y \right) \\
 &= \int_{-\infty}^x f_Y(w) dw \quad \left(\begin{array}{l} \text{Since } f_Y \text{ is symmetric about 0,} \\ \text{we have } f_Y(w) = f_Y(-w) \forall w \in \mathcal{R}. \end{array} \right) \\
 &= Pr(Y \leq x)
 \end{aligned}$$

$$\begin{aligned}
 F_{X,Y}(x,x) &= Pr(X \leq x, Y \leq x) \\
 &= Pr(X \leq x, Y \leq x, S = 1)Pr(S = 1) + Pr(X \leq x, Y \leq x, S = -1)Pr(S = -1) \\
 &= \frac{1}{2}Pr(Y \leq x, X \leq x) + \frac{1}{2}Pr(-Y \leq x, X \leq x) \\
 &= \frac{1}{2}Pr(Y \leq x) + \frac{1}{2}Pr(-x \leq Y \leq x) \\
 &= \frac{1}{2}Pr(Y \leq x) + \frac{1}{2}\left(Pr(Y \leq x) - Pr(Y \leq -x)\right) \\
 &= Pr(Y \leq x) - \frac{1}{2}Pr(Y \leq -x) \\
 &\neq F_X(x)F_Y(y), \text{ in general} \quad \Rightarrow \quad X \text{ and } Y \text{ are not independent!}
 \end{aligned}$$

*Another simpler method :

The conditional distribution of $(X \mid Y)$ is

$$f_{X|Y}(x|y) = \begin{cases} Pr(S = 1) = \frac{1}{2} & , \text{ if } x = y \\ Pr(S = -1) = \frac{1}{2} & , \text{ if } x = -y \\ 0 & , \text{ otherwise} \end{cases}$$

Because the conditional distribution of $(X \mid Y)$ is not the marginal distribution of X (i.e., $f_{X|Y}(x|y) \neq f_X(x)$), X and Y are not independent!

Another even simpler method :

Note that $Pr(X \in [-\delta, \delta] \mid Y = \delta) = 1 \neq Pr(X \in [-\delta, \delta])$
 , for some suitably chosen $\delta > 0$.

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Problem 61

(a)

Let $U_1, U_2 \stackrel{i.i.d.}{\sim} U[0, 1]$ and let $X = \min(U_1, U_2)$, $Y = \max(U_1, U_2)$, then $f_{X,Y}(x, y) = 2$, $0 \leq x \leq y \leq 1$

$$\begin{aligned} \Rightarrow & \begin{cases} f_X(x) = \int_x^1 2dy = 2(1-x) & , 0 \leq x \leq 1 \\ f_Y(y) = \int_0^y 2dx = 2y & , 0 \leq y \leq 1 \end{cases} \\ \Rightarrow & \begin{cases} E(X) = \int_0^1 xf_X(x)dx = \int_0^1 (2x - 2x^2)dx = \left(x^2 - \frac{2}{3}x^3\right)\Big|_0^1 = \frac{1}{3} \\ E(Y) = \int_0^1 yf_Y(y)dy = \int_0^1 2y^2dy = \left(\frac{2}{3}y^3\right)\Big|_0^1 = \frac{2}{3} \\ E(X^2) = \int_0^1 x^2f_X(x)dx = \int_0^1 (2x^2 - 2x^3)dx = \left(\frac{2}{3}x^3 - \frac{1}{2}x^4\right)\Big|_0^1 = \frac{1}{6} \\ E(Y^2) = \int_0^1 y^2f_Y(y)dy = \int_0^1 2y^3dy = \left(\frac{1}{2}y^4\right)\Big|_0^1 = \frac{1}{2} \\ E(XY) = \int_0^1 \int_0^y 2xydx dy = \int_0^1 y^3dy = \left(\frac{1}{4}y^4\right)\Big|_0^1 = \frac{1}{4} \end{cases} \\ \Rightarrow & \begin{cases} Var(X) = E(X^2) - (E(X))^2 = \frac{1}{6} - \left(\frac{1}{3}\right)^2 = \frac{1}{18} \\ Var(Y) = E(Y^2) - (E(Y))^2 = \frac{1}{2} - \left(\frac{2}{3}\right)^2 = \frac{1}{18} \end{cases} \\ \Rightarrow & \begin{cases} Cov(X, Y) = E(XY) - E(X)E(Y) = \frac{1}{4} - \frac{1}{3} \times \frac{2}{3} = \frac{1}{36} \\ Cor(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}} = \frac{\frac{1}{36}}{\sqrt{\frac{1}{18} \frac{1}{18}}} = \frac{1}{2} \end{cases} \end{aligned}$$

The sign of the correlation makes sense intuitively, because $Y > X$. So :

$$\begin{cases} \text{if } X \text{ is large} & , \text{ then so is } Y. \\ \text{if } Y \text{ is small} & , \text{ then so is } X. \end{cases}$$

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(b)

$$\begin{aligned} & \begin{cases} f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{1}{y} & , 0 \leq x \leq y \leq 1 \\ f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{1}{1-x} & , 0 \leq x \leq y \leq 1 \end{cases} \\ \Rightarrow & \begin{cases} E(X|Y=y) = \int_0^y \frac{x}{y} dx = \left(\frac{x^2}{2y}\right)\Big|_0^y = \frac{y}{2} & , 0 \leq y \leq 1 \\ E(Y|X=x) = \int_x^1 \frac{y}{1-x} dy = \left(\frac{y^2}{2(1-x)}\right)\Big|_x^1 = \frac{1+x}{2} & , 0 \leq x \leq 1 \end{cases} \\ \Rightarrow & \boxed{\text{These results make sense, because we have } \begin{cases} (X | Y=y) \sim U[0,y] \\ (Y | X=x) \sim U[x,1] \end{cases}} \end{aligned}$$

Does this match your intuition?

(c)

First note that $E(X|Y)$ is a function of Y , $E(Y|X)$ is a function of X !

$$\begin{aligned} \text{Define } & \begin{cases} Z := E(X|Y) = \boxed{\frac{Y}{2}} & \boxed{\text{By part (b)}} \\ W := E(Y|X) = \boxed{\frac{1+X}{2}} & \boxed{\text{By part (b)}} \end{cases} \\ \Rightarrow & \begin{cases} F_Z(z) = Pr(Z \leq z) = Pr(Y \leq 2z) = \begin{cases} \int_0^{2z} 2y dy = 4z^2 & , 0 \leq z < \frac{1}{2} \\ 1 & , \frac{1}{2} \leq z \end{cases} \\ F_W(w) = Pr(W \leq w) = Pr(X \leq 2w-1) = \begin{cases} \int_0^{2w-1} 2(1-x) dx = -4w^2 + 8w - 3 & , \frac{1}{2} \leq w < 1 \\ 1 & , 1 \leq w \end{cases} \end{cases} \\ \Rightarrow & \begin{cases} f_Z(z) = \frac{dF_Z(z)}{dz} = (8z) \times (\mathbf{I}_{(0, \frac{1}{2})}(z)) \\ f_W(w) = \frac{dF_W(w)}{dw} = (8(1-w)) \times (\mathbf{I}_{(\frac{1}{2}, 1)}(w)) \end{cases} \end{aligned}$$

(d)

To find $\underset{(a,b)}{\operatorname{argmin}} E\left(\left(Y-(a+bX)\right)^2\right) = \underset{(a,b)}{\operatorname{argmin}} \mathcal{G}(a,b)$, where

$$\mathcal{G}(a,b) := E\left(\left(Y-\hat{Y}\right)^2\right) = E\left(\left(Y-(a+bX)\right)^2\right) = E\left(Y^2 - 2aY - 2bXY + a^2 + b^2X^2 + 2abX\right)$$

$$\text{Set } \begin{cases} \frac{\partial}{\partial a} \mathcal{G}(a,b) = 0 \\ \frac{\partial}{\partial b} \mathcal{G}(a,b) = 0 \end{cases} \implies \begin{cases} a = E(Y) - bE(X) = \frac{1}{2} \\ b = -2E(XY) + 2bE(X^2) + 2E(Y)E(X) - 2b\left(E(X)\right)^2 = 0 \end{cases}$$

$$\implies b\left(E(X^2) - \left(E(X)\right)^2\right) = E(XY) - E(X)E(Y) \implies b = \frac{\operatorname{Cov}(X,Y)}{\operatorname{Var}(X)} = \frac{1}{2}$$

So $\hat{Y} = \frac{1+X}{2}$ is the linear predictor of Y in terms of X that has minimal MSE, and its corresponding mean square prediction error is

$$\begin{aligned} E\left(\left(Y - \frac{1+X}{2}\right)^2\right) &= \operatorname{Var}\left(Y - \frac{1+X}{2}\right) + \left(E\left(Y - \frac{1+X}{2}\right)\right)^2 \\ &= \operatorname{Var}(Y) + \operatorname{Var}\left(\frac{1+X}{2}\right) - 2\operatorname{Cov}\left(Y, \frac{1+X}{2}\right) + \left(\frac{2}{3} - \frac{1+\frac{1}{3}}{2}\right)^2 \\ &= \operatorname{Var}(Y) + \operatorname{Var}\left(\frac{X}{2}\right) - 2\operatorname{Cov}\left(Y, \frac{X}{2}\right) \\ &= \operatorname{Var}(Y) + \left(\frac{1}{2}\right)^2 \operatorname{Var}(X) - 2\operatorname{Cov}\left(Y, X\right) \times \frac{1}{2} \\ &= \frac{1}{18} + \frac{1}{4} \times \frac{1}{18} - 2 \times \frac{1}{36} \times \frac{1}{2} \\ &= \frac{1}{24} \end{aligned}$$

(d*)

We can also use Example 3.4 at LN p.2 – 54 to solve this problem.

BEST linear prediction of Y using X :

$$E_{X,Y} \left[Y - (a + bX) \right]^2 \geq E_{X,Y} \left\{ Y - \left[\mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (X - \mu_X) \right] \right\}^2 = \sigma_Y^2 (1 - \rho^2)$$

The equality holds if and only if $a = \mu_Y - b\mu_X$ and $b = \rho \frac{\sigma_Y}{\sigma_X}$.

Plug $\mu_X = \frac{1}{3}, \mu_Y = \frac{2}{3}, \sigma_X = \sqrt{\frac{1}{18}}, \sigma_Y = \sqrt{\frac{1}{18}}, \rho = \frac{1}{2}$ into the above equality.

Then we also get $\hat{Y} = \frac{1+X}{2}$ and the PMSE = $\frac{1}{24}$ can be calculated in the same way.

(e)

To find $\operatorname{argmin}_{h(X)} E\left(\left(Y - h(X)\right)^2\right)$, consider the following decomposition :

$$\begin{aligned}
 & E\left\{\left(Y - h(X)\right)^2\right\} \\
 &= E\left\{E\left(\left(Y - h(X)\right)^2 \middle| X\right)\right\} \\
 &= E\left\{E\left(\left(Y - E(Y|X) + E(Y|X) - h(X)\right)^2 \middle| X\right)\right\} \\
 &= E\left\{E\left(\left(Y - E(Y|X)\right)^2 + \left(E(Y|X) - h(X)\right)^2 + 2\left(Y - E(Y|X)\right)\left(E(Y|X) - h(X)\right) \middle| X\right)\right\} \\
 &= E\left\{E\left(\left(Y - E(Y|X)\right)^2 \middle| X\right)\right\} + E\left\{E\left(\left(E(Y|X) - h(X)\right)^2 \middle| X\right)\right\} \\
 &\quad + 2E\left\{\left(E(Y|X) - h(X)\right) \times \left(E\left(\left(Y - E(Y|X)\right) \middle| X\right)\right)\right\} = 0 \\
 &= E\left\{Var\left(Y \middle| X\right)\right\} + E\left\{E\left(\left(E(Y|X) - h(X)\right)^2 \middle| X\right)\right\} \geq 0, \text{ equality holds } \Leftrightarrow h(X) = E(Y|X). \\
 \Rightarrow h(X) = E(Y|X) = \frac{1+X}{2} = \operatorname{argmin}_{h(X)} E\left(\left(Y - h(X)\right)^2\right), \text{ PMSE of } \frac{1+X}{2} \text{ is } \frac{1}{24}.
 \end{aligned}$$

(e*)

We can also use [Example 3.3 at LN p.2 – 54](#) to solve this problem.

BEST prediction of Y using X :

$$E_{X,Y}\left[Y - h(X)\right]^2 \geq E_{X,Y}\left[Y - E_{X,Y}(Y|X)\right]^2 = E_X\left[Var_{Y|X}(Y|X)\right]$$

The equality holds if and only if $h(x) = E_{Y|X}(Y|x)$.

By the result of part (b), the equality holds if and only if $h(x) = \frac{1+x}{2}$.

So the desired predictor is $\hat{Y} = \frac{1+X}{2}$, and the PMSE is also $\frac{1}{24}$.

■

(supplementary information)

FYI:

The \hat{Y} in problem 61 should be pronounced as "Y hat".

In statistics, we usually put a hat on a parameter to represent a statistic, which is used to estimate that (unknown but fixed) parameter.

\hat{Y} in this problem is used to estimate μ_Y .

Problem 67

We may use the $\overbrace{\text{law of total expectation}}^{(*)}$ and $\overbrace{\text{the following equation}}^{(**)}$ to find the desired quantities.

To show $\overbrace{E(XY) = E(XE(Y|X)) = E(E(XY|X))}^{(**)}$:

$$\begin{aligned}
 E(XY) &= \int \int xyf(x,y)dxdy \\
 &= \int \int xyf_X(x)f_{Y|X}(y|x)dxdy \\
 &= \int x \left(\int yf_{Y|X}(y|x)dy \right) f_X(x)dx && E(XE(Y|X)) \\
 &= \int \left(\int xyf_{Y|X}(y|x)dy \right) f_X(x)dx && E(E(XY|X))
 \end{aligned}$$

$$\text{Also note that } \left\{ \begin{array}{ll} X \sim U(0,1) \implies E(X) &= \int_0^1 xdx = \left(\frac{x^2}{2}\right)\Big|_0^1 = \frac{1}{2} \\ (Y|X) \sim U(0,X) \implies E(Y|X=x) &= \int_0^x \frac{y}{x}dy = \left(\frac{y^2}{2x}\right)\Big|_0^x = \frac{x}{2} \end{array} \right.$$

The expected circumference is

$$E(2X + 2Y) = 2E(X) + 2E(Y) \stackrel{(*)}{=} 1 + 2E(E(Y|X)) = 1 + 2E\left(\frac{X}{2}\right) = 1 + E(X) = \frac{3}{2}$$

The expected area is

$$E(XY) \stackrel{(**)}{=} E(E(XY|X)) \stackrel{(**)}{=} E(XE(Y|X)) = E\left(\frac{X^2}{2}\right) = \int_0^1 \frac{x^2}{2}dx = \left(\frac{x^3}{6}\right)\Big|_0^1 = \frac{1}{6}$$

■

Problem 75

Suppose $T \sim \text{Exp}(\lambda)$ and $E(T) = \frac{1}{\lambda}$.

We may use the $\overbrace{\text{law of total expectation}}^{(*)}$ and the $\overbrace{\text{law of total variance}}^{(**)}$ to find $E(U)$ and $\text{Var}(U)$, to this end, we need to find $E(U|T)$ and $\text{Var}(U|T)$:

$$(U|T) \sim \text{Uniform}(0, T) \Rightarrow \left\{ \begin{array}{l} E(U|T=t) = \int_0^t \frac{u}{t} du = \left(\frac{u^2}{2t} \right) \Big|_0^t = \frac{t}{2} \\ E(U^2|T=t) = \int_0^t \frac{u^2}{t} du = \left(\frac{u^3}{3t} \right) \Big|_0^t = \frac{t^2}{3} \end{array} \right\}$$

$$\Rightarrow \text{Var}(U|T) = E(U^2|T=t) - \left(E(U|T=t) \right)^2 = \frac{T^2}{3} - \frac{T^2}{4} = \frac{T^2}{12}$$

So we have :

$$\left\{ \begin{array}{l} E(U) \stackrel{(*)}{=} E\left(E(U|T)\right) = E\left(\frac{T}{2}\right) = \frac{1}{2\lambda} \\ \text{Var}(U) \stackrel{(**)}{=} E\left(\text{Var}(U|T)\right) + \text{Var}\left(E(U|T)\right) = E\left(\frac{T^2}{12}\right) + \text{Var}\left(\frac{T}{2}\right) = \frac{5}{12\lambda^2} \end{array} \right.$$

■