# $\begin{array}{c} {\rm CASELLA\text{-}BERGER} \\ {\rm STATISTICAL} \ {\rm INFERENCE} \ {\rm SOLUTION:} \\ {\rm CHAPTER} \ 4 \end{array}$

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# August 9, 2022

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(a) We want to know the probability for (X,Y) to land inside the circle

$$X^2 + Y^2 = 1.$$

This circle has area  $\pi$ , so the probability is  $\frac{\pi}{4}$ .

(b) We want to know the probability for (X,Y) to land below the line

$$2X - Y = 0.$$

This line divides the square into two uniform trapeziums. One of them has vertices  $\left(\pm\frac{1}{2},\pm1\right)$ , and has area 2. Therefore, the probability is  $\frac{1}{2}$ . (c) The region |X+Y|<2 contains the square, so the probability is 1.

(a)

$$1 = \int_0^1 \int_0^2 C(x + 2y) \, dx \, dy$$
  
= 4C

$$f_X(x) = \int_0^1 \frac{x + 2y}{4} dy$$
$$= \frac{x+1}{4}$$

$$F_{XY}(x,y) = P(X \le x, Y \le y)$$

$$= \begin{cases} 0 & \text{if } x \le 0 \text{ or } y \le 0\\ 1 & \text{if } x \ge 2, y \ge 1 \end{cases}$$

$$= \begin{cases} \int_0^y \int_0^x f(u,v) \ du \ dv & \text{if else} \end{cases}$$

The if else case requires some work.

$$\int_{0}^{y} \int_{0}^{x} f(u, v) \ du \ dv = \begin{cases} \int_{0}^{y} \int_{0}^{x} f(u, v) \ du \ dv & \text{if } 0 < x < 2, \ 0 < y < 1 \\ \int_{0}^{1} \int_{0}^{x} f(u, v) \ du \ dv & \text{if } 0 < x < 2, \ y \ge 1 \\ \int_{0}^{y} \int_{0}^{2} f(u, v) \ du \ dv & \text{if } 0 < x < 2, \ y \ge 1 \end{cases}$$

$$= \begin{cases} \frac{xy(x+2y)}{8} & \text{if } 0 < x < 2, \ 0 < y < 1 \\ \frac{x(x+2)}{8} & \text{if } 0 < x < 2, \ y \ge 1 \end{cases}$$

(d) Let 
$$z = g(x) = \frac{9}{(x+1)^2}$$
, then  $g^{-1}(z) = \frac{3}{\sqrt{z}} - 1$ , and  $\frac{d}{dz}g^{-1}(z) = \frac{3}{-2z^{\frac{3}{2}}}$ . Therefore,

$$f_Z(z) = f_X(g^{-1}(z)) \cdot \left| \frac{d}{dz} g^{-1}(z) \right|$$
$$= \frac{9}{8z^2}$$

$$P(X > \sqrt{Y}) = \int_0^1 \int_{\sqrt{y}}^1 x + y \, dx \, dy$$
$$= \frac{7}{20}$$

$$P(X^{2} < Y < X) = \int_{0}^{1} \int_{x^{2}}^{x} 2x \, dy \, dx$$
$$= \frac{1}{6}$$

Let X (resp. Y) be the arrival time of A (resp. B), so that  $X \sim \text{Uniform}([0,1]) \sim Y$ . Let T be the waiting time. Then

$$T = \max\left\{Y - X, 0\right\}.$$

Therefore,

$$P(T < t) = P(Y - X < t, Y \ge X) + P(Y < X).$$

The first summand represents the area inside the square  $[0,1] \times [0,1]$ , bounded between the lines y=x+t and y=x. The second summand represents the area of half of the square. Thus,

$$P(T < t) = P(Y - X < t, Y \ge X) + P(Y < X)$$

$$= \int_0^{1-t} t \ dx + \int_{1-t}^1 1 - x \ dx + \frac{1}{2}$$

$$= -\frac{t^2}{2} + t + \frac{1}{2}$$

We represent the period from 8 AM to 9 AM by the closed interval [0,1]. Then  $X \sim \text{Uniform}\left(\left[0,\frac{1}{2}\right]\right)$ , and  $Y \sim \text{Uniform}\left(\left[\frac{2}{3},\frac{5}{6}\right]\right)$ . The arrival time is given by X+Y, with  $f_{X+Y}(x,y)=12$ .

Therefore

$$P(X + Y < 1) = \int_{R} f_{X+Y}(x, y) dA$$
$$= 12 (\text{area of } R).$$

The region R is bounded by the functions:

$$\begin{cases} x+y &= 1\\ y &= \frac{1}{2}\\ y &= \frac{5}{6}\\ x &= 0 \end{cases}$$

It is a trapezium with vertices  $\left(0,\frac{5}{6}\right), \left(\frac{1}{6},\frac{5}{6}\right), \left(0,\frac{2}{3}\right), \left(\frac{1}{3},\frac{2}{3}\right)$ , and has area  $\frac{1}{24}$ . Therefore,

$$P(X + Y < 1) = 12 \cdot \frac{1}{24} = \frac{1}{2}.$$

$$P(a \le X \le b, c \le Y \le d) = P(X \le b, c \le Y \le d) - P(X \le a, c \le Y \le d)$$

$$= [P(X \le b, Y \le d) - P(X \le b, Y \le c)] - [P(X \le a, Y \le d) - P(X \le a, Y \le c)]$$

$$= F_{X,Y}(b, d) - F_{X,Y}(b, c) - F_{X,Y}(a, d) + F_{X,Y}(a, c)$$

$$= [F_X(b) - F_X(a)] F_Y(d) - [F_X(b) - F_X(a)] F_Y(c)$$

$$= [F_X(b) - F_X(a)] [F_Y(d) - F_Y(c)]$$

$$= P(a \le X \le b) P(c \le Y \le d)$$

(a) The marginal pdfs are given by

$$f_X(1) = \frac{1}{4}$$
  $f_Y(2) = \frac{1}{3}$   $f_X(2) = \frac{1}{2}$   $f_Y(3) = \frac{1}{3}$   $f_Y(4) = \frac{1}{3}$ 

We see that

$$P(X = 2, Y = 3) = 0$$
  
 $\neq \frac{1}{2} \cdot \frac{1}{3}$   
 $= f_X(2) f_Y(3)$ 

Therefore, they are dependent.

(b) Let U = X, V = Y, and the pair (U, V) has distribution

$$f_{U,V}(u,v) = f_U(u) f_V(v)$$
.

# 8. Exercise 4.11

Both V and V follow negative binomial distribution:

$$U \sim \text{NegBinomial}(1, p)$$
,

$$V \sim \text{NegBinomial}(2, p)$$
.

In particular,

$$P(V = k) = p \cdot P(U = k - 1).$$

This shows they are dependent.

Without loss of generality, say the stick is given by the interval (0,1). Let X, Y be points chosen from (0,1). Then  $X \sim \text{Uniform}((0,1)) \sim Y$ , and

$$f_{X,Y}(x,y) = 1$$

on 
$$(0,1) \times (0,1)$$
.

By symmetry, we may assume y > x first. The points x, y divide (0,1) into three pieces of length x, y - x, 1 - y respectively. A triangle can be formed if and only if they satisfy the triangle inequality:

$$\begin{cases} x + (y - x) & \geq 1 - y \\ x + (1 - y) & \geq y - x \\ (y - x) + (1 - y) & \geq x \end{cases}$$

or equivalently,

$$\begin{cases} y & \geq \frac{1}{2} \\ y - x & \leq \frac{1}{2} \\ x & \leq \frac{1}{2} \end{cases}$$

This is the triangle given by

$$\begin{cases} 0 \le x \le \frac{1}{2}, \\ \frac{1}{2} \le y \le x + \frac{1}{2} \end{cases}$$

Combining with the case x > y, the required probability is

$$2\int_{0}^{\frac{1}{2}} \int_{\frac{1}{2}}^{x+\frac{1}{2}} f_{X,Y}(x,y) \, dy \, dx = 2 \cdot \text{(area of the triangle)}$$
$$= \frac{1}{4}.$$

Since X and Y are independent, the joint distribution is given by

$$f_{X,Y}(x,y) = \frac{1}{2\pi} e^{-\frac{(x^2+y^2)}{2}}$$
(a)
$$P(X^2 + Y^2 < 1) = \int_{x^2+y^2 < 1} f_{X,Y}(x,y) \, dA$$

$$= \frac{1}{2\pi} \cdot \int_0^{2\pi} \int_0^1 r e^{-\frac{r^2}{2}} \, dr \, d\theta$$

$$= 1 - e^{-\frac{1}{2}}$$

(b) Let  $Y = X^2$ , then

$$f_Y(y) = f_X(\sqrt{y}) + f_X(-\sqrt{y})$$
$$= \frac{1}{\sqrt{2\pi y}} e^{-\frac{y}{2}}$$

which is the pdf for  $\chi_1^2$ . Therefore,

$$P(X^2 < 1) = \int_0^1 f_Y(y) \ dy$$
$$\approx 0.682689$$

Let U = X + Y, and V = X. Then  $U \sim \text{Poisson}(\theta + \lambda)$ ; and U, V are independent by [BC01, Theorem 4.3.2 on page 158].

We repeat the same computation as in [BC01, Example 4.3.1 on page 157] to find the joint pdf

$$f(v, u) = \frac{\lambda^{u-v} \theta^v e^{-(\theta+\lambda)}}{(u-v)! v!}$$

for (U, V). Therefore, the conditional distribution is given by

$$f(v|u) = \frac{f(v,u)}{f(u)}$$

$$= \frac{\lambda^{u-v}\theta^v e^{-(\theta+\lambda)}}{(u-v)! v!} \cdot \frac{u!}{(\theta+\lambda)^u e^{-(\theta+\lambda)}}$$

$$= \binom{u}{v} \left(\frac{\theta}{\theta+\lambda}\right)^v \left(\frac{\lambda}{\theta+\lambda}\right)^{u-v}$$

$$\sim \text{Binomial } \left(u, \frac{\theta}{\theta+\lambda}\right).$$

Likewise,  $Y|X+Y \sim \text{Binomial}\left(u, \frac{\lambda}{\theta + \lambda}\right)$ .

Write  $X \sim \text{Geometric}(p) \sim Y$ .

(a) The joint distribution is given by

$$\begin{split} f(u,v) &= P(U=u,\ V=v) \\ &= P(\min(X,Y)=u,\ X-Y=v) \\ &= \left\{ \begin{array}{l} P(Y=u,\ X=v+u) & \text{if } v \geq 0 \\ P(X=u,\ Y=u-v) & \text{if } v < 0 \end{array} \right. \\ &= \left\{ \begin{array}{l} (1-p)^{2u+v-2}p^2 & \text{if } v \geq 0 \\ (1-p)^{2u-v-2}p^2 & \text{if } v < 0 \end{array} \right. \\ &= (1-p)^{2u+|v|-2}p^2 \\ &= \underbrace{\left[ (1-p)^{2u-1}p \right]}_{g(u)} \underbrace{\left[ (1-p)^{|v|-1}p \right]}_{h(v)}. \end{split}$$

[BC01, Lemma 4.2.7 on page 153] then says U, V are independent.

(b) We begin by noting Z takes values in  $\mathbb{Q}$ . Therefore, we represent all possible values of Z by fractions  $\frac{r}{s}$  with  $\gcd(r,s)=1$ . We then compute

$$P(Z = \frac{r}{s}) = P(\frac{X}{X+Y} = \frac{r}{s})$$

$$= \sum_{n=1}^{\infty} P(X = nr, X+Y = ns)$$

$$= \sum_{n=1}^{\infty} P(X = nr, Y = n(s-r))$$

$$= \sum_{n=1}^{\infty} (1-p)^{ns-2} p^2$$

$$= \frac{(1-p)^{s-2} p^2}{1-(1-p)^{s-2}}$$

$$P(X = u, X + Y = v) = P(X = u, Y = v - u)$$
$$= (1 - p)^{v-2}p^{2}$$

(a)

$$P(Y = y) = P(y \le X < y + 1)$$

$$= \int_{y}^{y+1} e^{-x} dx$$

$$= (1 - e^{-1}) (e^{-1})^{y}$$

$$\sim \text{Geometric } (e^{-1})$$

(b) Let Z = X - 4. We compute the cdf first.

$$P(Z \le z | Y \ge 5) = \frac{P(Z \le z, Y \ge 5)}{P(Y \ge 5)}$$

$$= \frac{P(Z \le z, X \ge 4)}{P(X \ge 4)}$$

$$= \frac{P(4 \le X \le z + 4)}{P(X \ge 4)}$$

$$= \frac{e^{-4} - e^{-4-z}}{e^{-4}}$$

$$= 1 - e^{-z}$$

Therefore, the pdf is given by

$$P(Z = z | Y \ge 5) = \frac{d}{dz} 1 - e^{-z}$$
  
=  $e^{-z}$ 

on  $\mathcal{Z} = [0, \infty)$ .

# 14. Exercise 4.18

Polar coordinates.

(a) By [BC01, Theorem 4.2.14 on page 156], if  $X \sim \text{Normal}(\mu_X, \sigma_X^2)$  and  $Y \sim \text{Normal}(\mu_Y, \sigma_Y^2)$ , then  $X - Y \sim \text{Normal}(\mu_X - \mu_Y, \sigma_X^2 + \sigma_Y^2)$ . In particular, when X and Y are both standard normal, the difference

$$\frac{X-Y}{\sqrt{2}} \sim \text{Normal}(0,1)$$

is standard normal as well. It follows from Exercise 4.14 that

$$\frac{(X-Y)^2}{2} = \left(\frac{X-Y}{\sqrt{2}}\right)^2$$

$$\sim (\text{Normal } (0,1))^2$$

$$\sim \chi_1^2$$

(b) Refer to [BC01, page 158]. Define

$$\begin{cases} y_1 = \frac{x_1}{x_1 + x_2}, \\ y_2 = x_1 + x_2, \end{cases}$$

so that

$$\begin{cases} x_1 = y_1 y_2, \\ x_2 = y_2 (1 - y_1). \end{cases}$$

Next, the Jacobi determinant is given by

$$|J| = \begin{vmatrix} \frac{\partial x_1}{\partial y_1} & \frac{\partial x_1}{\partial y_2} \\ \frac{\partial x_2}{\partial y_1} & \frac{\partial x_2}{\partial y_2} \end{vmatrix}$$
$$= \begin{vmatrix} y_2 & y_1 \\ -y_2 & 1 - y_1 \end{vmatrix}$$
$$= |y_2|.$$

Therefore, the joint distribution for  $Y_1 = \frac{X_1}{X_1 + X_2}$  and  $Y_2 = X_1 + X_2$  is given by

$$f_{Y_{1},Y_{2}}(y_{1},y_{2}) = f_{X_{1},X_{2}}(y_{1}y_{2},y_{2}(1-y_{1})) \cdot |y_{2}|$$

$$= f_{X_{1}}(y_{1}y_{2}) \cdot f_{X_{2}}(y_{2}(1-y_{1})) \cdot |y_{2}| \qquad \text{(since } X_{1} \text{ and } X_{2} \text{ are independent.)}$$

$$= \frac{(y_{1}y_{2})^{\alpha_{1}-1}e^{-y_{1}y_{2}}}{\Gamma(\alpha_{1})} \cdot \frac{(y_{2}(1-y_{1}))^{\alpha_{2}-1}e^{-y_{2}(1-y_{1})}}{\Gamma(\alpha_{2})} \cdot |y_{2}|$$

$$= \left[\frac{y_{1}^{\alpha_{1}-1}(1-y_{1})^{\alpha_{2}-1}}{\Gamma(\alpha_{1})\Gamma(\alpha_{2})}\right] \cdot \left[y_{2}^{\alpha_{1}+\alpha_{2}-1}e^{-y_{2}}\right]$$

$$= \underbrace{\left[\frac{\Gamma(\alpha_{1}+\alpha_{2})}{\Gamma(\alpha_{1})\Gamma(\alpha_{2})}y_{1}^{\alpha_{1}-1}(1-y_{1})^{\alpha_{2}-1}\right]}_{f_{Y_{2}}(y_{1})} \cdot \underbrace{\left[\frac{y_{2}^{\alpha_{1}+\alpha_{2}-1}e^{-y_{2}}}{\Gamma(\alpha_{1}+\alpha_{2})}\right]}_{f_{Y_{2}}(y_{2})}.$$

In particular, this shows  $Y_1 \sim \text{Beta}(\alpha_1, \alpha_2)$ . Finding the pdf of  $\frac{X_2}{X_1 + X_2} = 1 - Y_1$  is similar.

We can think of the variables as Cartesian coordinates versus polar coordinates on  $\mathbb{R}^2$ . The variables are related as:

$$x_1 = \sqrt{y_1}y_2,$$
  
$$x_2 = \pm \sqrt{y_1 - y_1y_2^2},$$

and we have two Jacobi matrices:

$$J_{\pm} = \begin{bmatrix} \frac{y_2}{2\sqrt{y_1}} & \sqrt{y_1} \\ \pm \sqrt{y_1 - y_1 y_2^2} & \mp \frac{y_1 y_2}{\sqrt{y_1 - y_1 y_2^2}} \end{bmatrix},$$

with  $|J_{\pm}| = \frac{1}{2\sqrt{1-y_0^2}}$ . As a result, the joint distribution is given by

$$f_{Y_1,Y_2}(y_1,y_2) = \left[ f_{X_1,X_2} \left( \sqrt{y_1} y_2, \sqrt{y_1 - y_1 y_2^2} \right) + f_{X_1,X_2} \left( \sqrt{y_1} y_2, -\sqrt{y_1 - y_1 y_2^2} \right) \right] \cdot \frac{1}{2\sqrt{1 - y_2^2}}$$

$$= \left[ \frac{1}{2\pi\sigma^2} e^{-\frac{y_1}{2\sigma^2}} \right] \cdot \left[ \frac{1}{\sqrt{1 - y_2^2}} \right],$$

proving  $Y_1$ ,  $Y_2$  are independent as well.

Write  $\mathcal{R} = \mathbb{R}^2$ . Then

$$f_{X,Y}(x,y) = f_{\mathcal{R},\theta} \left( \mathcal{R} = x^2 + y^2, \theta = \arctan\left(\frac{y}{x}\right) \right) \cdot \begin{vmatrix} \frac{\partial \mathcal{R}}{\partial x} & \frac{\partial \mathcal{R}}{\partial dy} \\ \frac{\partial \theta}{\partial x} & \frac{\partial \theta}{\partial dy} \end{vmatrix}$$
$$= \left[ \frac{1}{2} e^{-\frac{x^2 + y^2}{2}} \right] \cdot \frac{1}{2\pi} \cdot \begin{vmatrix} \frac{2x}{x^2 + y^2} & -\frac{2y}{x^2 + y^2} \\ -\frac{y}{x^2 + y^2} & -\frac{x}{x^2 + y^2} \end{vmatrix}$$
$$= \left[ \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \right] \cdot \left[ \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \right]$$

We have

$$\begin{cases} x = \frac{u-b}{a}, \\ y = \frac{v-d}{c}. \end{cases}$$

The Jacobi determinant is then given by

$$|J| = \begin{vmatrix} \frac{1}{a} & 0 \\ 0 & \frac{1}{c} \end{vmatrix}$$
$$= \frac{1}{ac}.$$

Therefore, the result follows immediately from [BC01, page 158].

Let

$$\begin{cases} u = x + y, \\ v = x - y \end{cases}$$

Then

$$\begin{split} f_{U,V}(u,v) &= f_{X,Y}(x(u,v),y(u,v)) \cdot |J| \\ &= f_X(x(u,v)) \cdot f_Y(y(u,v)) \cdot |J| \\ &\text{(since $X$ and $Y$ are independent)} \\ &= f_X(x(u,v)) \cdot f_Y(y(u,v)) \cdot \left| \frac{1}{2} - \frac{1}{2} - \frac{1}{2} \right| \\ &= \frac{1}{2} \cdot f_X\left(\frac{u+v}{2}\right) \cdot f_Y\left(\frac{u-v}{2}\right) \\ &= \frac{1}{4\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2} \left[ \left(\frac{u+v}{2} - \mu\right)^2 + \left(\frac{u-v}{2} - \gamma\right)^2 \right] \right) \\ &= \frac{1}{4\pi\sigma^2} \exp\left(-\frac{1}{8\sigma^2} \left[ [(u+v) - 2\mu]^2 + [(u-v) - 2\gamma]^2 \right] \right) \\ &= \frac{1}{4\pi\sigma^2} \exp\left(-\frac{1}{8\sigma^2} \left[ 2 \left[ u - (\gamma + \mu) \right]^2 - 2(\gamma + \mu)^2 + 2v^2 + 4(\gamma - \mu)v + 4\mu^2 + 4\gamma^2 \right] \right) \\ &= \frac{1}{4\pi\sigma^2} \exp\left(-\frac{1}{8\sigma^2} \left[ 2 \left[ u - (\gamma + \mu) \right]^2 + 2 \left[ v - (\mu - \gamma) \right]^2 \right] \right) \\ &= \underbrace{\frac{1}{\sqrt{2\pi}} \cdot \sqrt{2}\sigma} \exp\left(-\frac{1}{2} \cdot \frac{\left[ u - (\gamma + \mu) \right]^2}{2\sigma^2} \right) \cdot \underbrace{\frac{1}{\sqrt{2\pi}} \cdot \sqrt{2}\sigma} \exp\left(-\frac{1}{2} \cdot \frac{\left[ v - (\gamma - \mu) \right]^2}{2\sigma^2} \right)}_{f_V(v)} \\ &\sim \operatorname{Normal}\left(\gamma + \mu, 2\sigma^2\right) \cdot \operatorname{Normal}\left(\gamma - \mu, 2\sigma^2\right) \end{split}$$

(a) Firstly,

$$EY = E(E(Y|X))$$

$$([BC01, Theorem 4.4.3 on page 164])$$

$$= E(E(Normal(x, x^2)))$$

$$= E(X)$$

$$= \frac{1}{2}.$$

Secondly,

$$Var(Y) = E(Var(Y|X)) + Var(E(Y|X))$$

$$= E(Var(Normal(x, x^2))) + Var(E(Normal(x, x^2)))$$

$$= E(X^2) + Var(X)$$

$$= 2 Var(X) + E(X)^2$$

$$= \frac{5}{12}$$

Finally, to compute Cov(X, Y), we notice we have to deal with the random variable XY. Let U = XY, V = X. [BC01, page 158] gives the joint distribution

$$f_{U,V}(u,v) = \frac{1}{v} f_{X,Y}\left(v, \frac{u}{v}\right),$$
 (20.0.1)

and (hence) the conditional distribution is given by

$$f_{U|V}(u|v) = \frac{f_{U,V}(u,v)}{f_V(v)}$$

$$= \frac{\frac{1}{v}f_{X,Y}(v,\frac{u}{v})}{f_X(v)}$$

$$= \frac{1}{v}f_{Y|X}\left(\frac{u}{v}\middle|v\right). \tag{20.0.2}$$

This allows us to prove the following formula for expectation:

$$E(E(XY|X)) = E(E(U|V))$$

$$(U = XY, V = X)$$

$$= E\left(\int u f_{U|V}(u|v) du\right)$$

$$= E\left(\int \frac{u}{v} f_{Y|X}\left(\frac{u}{v}|v\right) du\right)$$

$$= E\left(\int xy f_{Y|X}(y|x) dy\right)$$

$$\left(y = \frac{u}{v}, x = v, dy = \frac{1}{v}du\right)$$

$$= E(XE(Y|X)). \tag{20.0.3}$$

As a result,

$$Cov (X, Y) = E(XY) - (EX) (EY)$$

$$= E(XY) - \frac{1}{4}$$

$$= E(XY|X) - \frac{1}{4}$$

$$= E(XE(Y|X)) - \frac{1}{4}$$

$$= E(X \cdot E(Normal (x, x^2))) - \frac{1}{4}$$

$$= E(X^2) - \frac{1}{4}$$

$$= Var (X) + (EX)^2 - \frac{1}{4}$$

$$= \frac{1}{12}.$$

(b) Let  $U = \frac{Y}{X}$ , V = X. The Jacobi matrix is given by

$$\left[\begin{array}{cc} 0 & 1 \\ v & u \end{array}\right],$$

and the joint distribution is given by

$$f_{U,V}(u,v) = f_{X,Y}(v,uv) \cdot |J|$$

$$([BC01, page 158])$$

$$= v \cdot f_X(v) \cdot f_{Y|X}(uv|v)$$

$$= v \cdot 1 \cdot \frac{1}{\sqrt{2\pi}v} e^{-\frac{1}{2}\left(\frac{uv-v}{v}\right)^2}$$

$$= \underbrace{\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(u-1)^2} \cdot \underbrace{1}_{f_V(v)}}_{f_U(u)} \cdot \text{Normal } (1,1) \cdot \text{Uniform } (0,1).$$

# REFERENCES

 $[BC01]\;$  Roger Berger and George Casella. Statistical Inference. 2nd edition. Florence, AL: Duxbury Press, June 2001.