

## Applied Stochastic Models (SS 08)

### Problem Set 3

#### Problem 1

Let  $T_1$  and  $T_2$  be independent and uniformly distributed on  $[-1, 1]$ . Show that, conditional on the event that  $R := \sqrt{T_1^2 + T_2^2} \leq 1$ ,

$$X := \frac{T_1}{R} \sqrt{-2 \ln R^2}, \quad Y := \frac{T_2}{R} \sqrt{-2 \ln R^2}$$

are independent standard normal random variables.

#### Solution:

First, we investigate the conditional distributions of  $\Theta := \arccos(\frac{T_1}{R}) = \arcsin(\frac{T_2}{R})$  and  $R^2$ , given that  $R \leq 1$ . We have  $\Theta \in (0, 2\pi)$ ,  $R^2 \in (0, 1)$ , and thus for  $\theta \in (0, 2\pi)$  and  $r \in (0, 1)$

$$\mathbb{P}(R^2 \leq r | R \leq 1) = \frac{\mathbb{P}(R^2 \leq r, R \leq 1)}{\mathbb{P}(R \leq 1)} = \frac{\mathbb{P}(R \leq \sqrt{r})}{\mathbb{P}(R \leq 1)} = \frac{\frac{\pi r}{4}}{\frac{\pi}{4}} = r,$$

$$\mathbb{P}(\Theta \leq \theta | R \leq 1) = \frac{\mathbb{P}(\Theta \leq \theta, R \leq 1)}{\mathbb{P}(R \leq 1)} = \frac{\frac{\pi \theta}{4}}{\frac{\pi}{4}} = \frac{\theta}{2\pi}.$$

Hence  $R^2 | R \leq 1 =: U \sim U(0, 1)$  and  $\Theta | R \leq 1 =: 2\pi \tilde{U}$  where  $U, \tilde{U} \sim U(0, 1)$ . Using  $U, \tilde{U}$ , we have

$$X = \cos(2\pi \tilde{U}) \sqrt{-2 \ln U}, \quad Y = \sin(2\pi \tilde{U}) \sqrt{-2 \ln U},$$

and using the transformation

$$T : \begin{cases} (0, 1)^2 & \rightarrow \mathbb{R}^2 \\ (u, \tilde{u}) & \mapsto (\cos(2\pi \tilde{u}) \sqrt{-2 \ln u}, \sin(2\pi \tilde{u}) \sqrt{-2 \ln u}) \end{cases},$$

we can write  $(X, Y) = T(U, \tilde{U})$ . The determinant of the Jacobian of  $T$  is easily calculated as

$$\det(T')(u, \tilde{u}) = -\frac{2\pi}{u}.$$

Since this depends only on  $u$  and the joint density of  $U, \tilde{U}$  is the constant 1, it will be enough to express  $u$  in terms of  $(x, y) = T(u, \tilde{u})$ . This can be done by observing that  $x^2 + y^2 = -2 \ln(u)$ , and hence  $u = e^{-\frac{x^2 + y^2}{2}}$ . Thus the transformation formula for densities yields

$$f^{(X,Y)}(x, y) = \frac{f^{(U,V)}(T^{-1}(x, y))}{\Delta(T^{-1}(x, y))} = \frac{1}{2\pi} e^{-\frac{x^2 + y^2}{2}} = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}.$$

**Problem 2**

Let  $X_1, X_2, \dots, X_n$  be independent and exponentially distributed with parameter  $\lambda$ . Show that

$$Y_1 = nX_{(1)}, Y_r = (n + 1 - r)(X_{(r)} - X_{(r-1)}), 1 < r \leq n$$

are also independent and have the same joint distribution as the  $X_i$ .

**Solution:** The joint density of the  $X_i$  is by independence given by

$$f^{(X_1, \dots, X_n)}(x_1, \dots, x_n) = \lambda^n e^{-\lambda x_1} \dots e^{-\lambda x_n},$$

while their order statistics  $X_{(i)}$  have joint density

$$f^{(X_{(1)}, \dots, X_{(n)})}(x_1, \dots, x_n) = n! \lambda^n e^{-\lambda x_1} \dots e^{-\lambda x_n} \mathbf{1}_D(x_1, \dots, x_n),$$

where  $D = \{(x_1, \dots, x_n) \in \mathbb{R}^n : x_1 < x_2 < \dots < x_n\}$ . Using the transformation

$$T_n := x \mapsto A_n x,$$

where

$$A_n := \begin{pmatrix} n & 0 & 0 & \dots & 0 \\ -(n-1) & (n-1) & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & \dots & -2 & 2 & 0 \\ 0 & \dots & 0 & -1 & 1 \end{pmatrix},$$

we have  $(Y_1, \dots, Y_n) = T_n(X_{(1)}, \dots, X_{(n)})$ . One calculates recursively

$$\begin{aligned} X_{(1)} &= \frac{1}{n} Y_1 \\ X_{(2)} &= \frac{1}{n-1} Y_2 + \frac{1}{n} Y_1 \\ X_{(3)} &= \frac{1}{n-2} Y_3 + \frac{1}{n-1} Y_2 + \frac{1}{n} Y_1 \\ &\vdots \\ X_{(n)} &= Y_n + \frac{1}{2} Y_{n-1} + \dots + \frac{1}{n} Y_1 \end{aligned}$$

which yields

$$A_n^{-1} = \begin{pmatrix} \frac{1}{n} & 0 & 0 & \dots & 0 \\ \frac{1}{n} & \frac{1}{n-1} & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \frac{1}{n} & \frac{1}{n-1} & \dots & \frac{1}{2} & 0 \\ \frac{1}{n} & \frac{1}{n-1} & \dots & \frac{1}{2} & 1 \end{pmatrix}.$$

The Jacobian of  $T_n$  is just  $A_n$ , whose determinant is obviously  $n!$ , hence

$$\Delta \equiv n!.$$

The transformation theorem for densities thus yields for  $y_1, \dots, y_n \geq 0$

$$f^{(Y_1, \dots, Y_n)}(y_1, \dots, y_n) = \frac{n! \lambda^n e^{-\lambda(\frac{1}{n}y_1)} e^{-\lambda(\frac{1}{n}y_1 + \frac{1}{n-1}y_2)} \dots e^{-\lambda(\frac{1}{n}y_1 + \dots + \frac{1}{2}y_{n-1} + y_n)}}{n!} = \lambda^n e^{-\lambda y_1} \dots e^{-\lambda y_n},$$

and hence shows that the  $Y_i$  have the same joint distribution as the initial  $X_i$ !

### Problem 3

Let  $X_1, X_2, \dots, X_n$  be independent and uniformly distributed in  $[0, 1]$ , with order statistics  $X_{(1)}, X_{(2)}, \dots, X_{(n)}$ . Show that  $-\ln(X_{(k)})$  has the same distribution as  $\sum_{i=k}^n Y_i/i$ , where the  $Y_i$  are independent exponential random variables with parameter 1.

**Solution:** The joint density of the  $X_{(i)}$  is given by

$$f^{(X_{(1)}, \dots, X_{(n)})}(x_1, \dots, x_n) = n! \mathbb{1}_{[0,1]^n}(x_1, \dots, x_n) \mathbb{1}_D(x_1, \dots, x_n),$$

where  $D = \{(x_1, \dots, x_n) \in \mathbb{R}^n : x_1 < x_2 < \dots < x_n\}$ . Define

$$\begin{aligned} U_n &:= -n \ln X_{(n)}, \\ U_k &:= -k \ln \frac{X_{(k)}}{X_{(k+1)}}, \quad 1 \leq k < n. \end{aligned}$$

Then

$$\begin{aligned} X_{(n)} &= e^{-\frac{U_n}{n}}, \\ X_{(k)} &= X_{(k+1)} e^{-\frac{U_k}{k}} = e^{-\sum_{i=k}^n \frac{U_i}{i}}, \quad 1 \leq k < n. \end{aligned}$$

Let  $T$  denote the above transformation, i.e.  $(U_1, \dots, U_n) = T(X_{(1)}, \dots, X_{(n)})$ . Then

$$\Delta(x_1, \dots, x_n) = (\det T')(x_1, \dots, x_n) = \begin{vmatrix} -\frac{1}{x_1} & \frac{1}{x_2} & 0 & \dots & 0 \\ 0 & -\frac{2}{x_2} & \frac{2}{x_3} & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \dots & -\frac{n-1}{x_{n-1}} & \frac{n-1}{x_n} \\ 0 & 0 & \dots & 0 & -\frac{n}{x_n} \end{vmatrix} = \frac{(-1)^n n!}{x_1 \dots x_n}.$$

Hence, the joint density of the  $U_i$  is given by

$$f^{(U_1, \dots, U_n)}(u_1, \dots, u_n) = \frac{f^{(X_{(1)}, \dots, X_{(n)})}(T^{-1}(u_1, \dots, u_n))}{|\Delta(T^{-1}(u_1, \dots, u_n))|} = \frac{n!}{n!} e^{-(u_1 + \dots + u_n)}.$$

This means that the  $U_i$  are iid  $Exp(1)$ . As shown above, we have  $-\ln(X_{(k)}) = \sum_{i=k}^n \frac{U_i}{i}$ .

### Problem 4

Let  $X_1, X_2, X_3, \dots, X_n$  be independent and exponentially distributed with parameter 1. Show that

$$\lim_{n \rightarrow \infty} \mathbb{P}(X_{(n)} - \ln n \leq x) = \exp(-e^{-x}).$$

Using this, show that  $\int_0^\infty [1 - \exp(-e^{-x})] dx = \gamma$ , where  $\gamma$  denotes Eulers constant ( $\gamma = \lim_{n \rightarrow \infty} [\sum_{k=1}^n \frac{1}{k} - \ln(n)]$ ).

**Solution:**

For the first assertion, note that

$$\begin{aligned}\mathbb{P}(X_{(n)} - \ln n \leq x) &= \mathbb{P}(\max\{X_1, \dots, X_n\} \leq x + \ln n) = \mathbb{P}(X_i \leq x + \ln n, i \in \{1, \dots, n\}) \\ &= (1 - e^{-(x+\ln n)})^n = (1 - \frac{e^{-x}}{n})^n \rightarrow e^{-e^{-x}}.\end{aligned}$$

The integral can now be expressed as follows:

$$\int_0^\infty [1 - \exp(-e^{-x})]dx = \int_0^\infty \lim_{n \rightarrow \infty} \mathbb{P}(X_{(n)} - \ln n > x)dx.$$

Here,

$$\mathbb{P}(X_{(n)} - \ln n > x) = 1 - (1 - \frac{e^{-x}}{n})^n,$$

is monotonically decreasing in  $n$ , hence

$$\mathbb{P}(X_{(n)} - \ln n > x) \leq 1 - (1 - \frac{e^{-x}}{1})^1 = e^{-x},$$

which has a finite integral. Hence, we may apply the dominated convergence theorem to interchange limit and integration:

$$\int_0^\infty [1 - \exp(-e^{-x})]dx = \lim_{n \rightarrow \infty} \int_0^\infty \mathbb{P}(X_{(n)} - \ln n > x)dx.$$

From here, we proceed as follows:

$$\begin{aligned}\int_0^\infty [1 - \exp(-e^{-x})]dx &= \lim_{n \rightarrow \infty} \int_0^\infty \mathbb{P}(X_{(n)} - \ln n > x)dx \\ &= \lim_{n \rightarrow \infty} \mathbb{E}[X_{(n)} - \ln n].\end{aligned}$$

For the expectation, we have

$$\begin{aligned}\mathbb{E}[X_{(n)}] &= \int_0^\infty \mathbb{P}(X_{(n)} > x)dx = \int_0^\infty 1 - \mathbb{P}(X_{(n)} \leq x)dx \\ &= \int_0^\infty 1 - \mathbb{P}(X_1, \dots, X_n \leq x)dx = \int_0^\infty 1 - (1 - e^{-x})^n dx \\ &= \int_0^\infty 1 - \sum_{i=0}^n \binom{n}{i} (-e^{-x})^i dx \\ &= - \sum_{i=1}^n \binom{n}{i} (-1)^i \int_0^\infty e^{-ix} dx \\ &= \sum_{i=1}^n \binom{n}{i} (-1)^{i-1} \frac{1}{i}.\end{aligned}$$

We need to show that this equals  $\sum_{i=1}^n \frac{1}{i}$ . Using the generating function

$$f(z) := \sum_{i=1}^n \binom{n}{i} (-1)^{i-1} \frac{z^i}{i}$$

of the above series, we find for its derivative that

$$\begin{aligned} f'(z) &= \frac{1}{z} \sum_{i=1}^n \binom{n}{i} (-1)^{i-1} z^i = \frac{-1}{z} \sum_{i=1}^n \binom{n}{i} (-z)^i = \frac{1 - (1-z)^n}{1 - (1-z)} \\ &= 1 + (1-z) + (1-z)^2 + \dots + (1-z)^{n-1}. \end{aligned}$$

Integrating this from 0 to  $z$  yields

$$f(z) - f(0) = z - \frac{(1-z)^2}{2} - \frac{(1-z)^3}{3} - \dots - \frac{(1-z)^n}{n} + 0 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n},$$

and hence

$$f(1) = 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n}.$$

Finally, this means that

$$\int_0^\infty [1 - \exp(-e^{-x})] dx = \lim_{n \rightarrow \infty} \left[ \sum_{i=1}^n \frac{1}{i} - \ln n \right] = \gamma.$$