

Solution of Problem Set 3

Problem 1:

1. We will demand that the double integral of $f_{XY}(x, y)$ throughout R^2 result in 1:

$$1 = \iint_{R^2} f_{XY}(x, y) dx dy = A \left[\int_{-1}^0 \int_{-1}^0 xy dx dy + \int_0^1 \int_0^1 xy dx dy \right] = 2A \left(\int_0^1 x dx \right) \left(\int_0^1 y dy \right) = \frac{A}{2}$$

$$\Rightarrow A = 2$$

- 2.

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy = \begin{cases} \int_0^0 2xy dy & -1 < x < 0 \\ \int_{-1}^1 2xy dy & 0 < x < 1 \\ 0 & \text{o.w} \end{cases}$$

$$= \begin{cases} -x & -1 < x < 0 \\ x & 0 < x < 1 \\ 0 & \text{o.w} \end{cases}$$

$$= \begin{cases} |x| & |x| < 1 \\ 0 & \text{o.w} \end{cases}$$

Problem 2:

1. $f_{XY}(x, y) = \frac{\partial^2}{\partial x \partial y} F_{XY}(x, y) = e^{-x} e^{-y} u(x) u(y)$

The CDF is continuous throughout all R^2 and, thus, the PDF does not include delta functions.

2. It can be seen that the PDF may be separated: $f_{XY}(x, y) = f_X(x) f_Y(y)$

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy = \int_{-\infty}^{\infty} f_X(x) f_Y(y) dy = f_X(x) \underbrace{\int_{-\infty}^{\infty} f_Y(y) dy}_{=1} = f_X(x) = e^{-x} u(x)$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx = e^{-y} u(y)$$

3. Since $f_{XY}(x, y) = f_X(x) f_Y(y)$, X and Y are independent.
 4. The inverse transformation is:

$$X = \frac{1}{2}(W + Z)$$

$$Y = \frac{1}{2}(W - Z)$$

And the Jacobian is:

$$|J| = \left| \frac{\partial(W, Z)}{\partial(X, Y)} \right| = \left| \det \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \right| = 2$$

Therefore:

$$\begin{aligned} f_{WZ}(w, z) &= \frac{f_{XY}\left(\frac{1}{2}(w+z), \frac{1}{2}(w-z)\right)}{|J|} = \frac{1}{2} e^{-w} u(w+z) u(w-z) \\ &= \begin{cases} \frac{1}{2} e^{-w} & w > 0, \quad -w < z < w \\ 0 & \text{o.w} \end{cases} \end{aligned}$$

Notice that:

$$u(w+z) = u\left(\frac{1}{2}(w+z)\right), u(w-z) = u\left(\frac{1}{2}(w-z)\right)$$

5. We will start by finding the marginal PDFs and then we will check whether they are independent:

$$\begin{aligned} f_W(w) &= \int_{-\infty}^{\infty} f_{WZ}(w, z) dz = \int_{-w}^w \frac{1}{2} e^{-w} dz = w e^{-w} u(w) \\ f_Z(z) &= \int_{-\infty}^{\infty} f_{WZ}(w, z) dw = \frac{1}{2} \int_{|z|}^{\infty} e^{-w} dw = \frac{1}{2} e^{-|z|} \\ \Rightarrow f_W(w) f_Z(z) &= \frac{1}{2} w e^{-w} e^{-|z|} u(w) \neq f_{WZ}(w, z) \end{aligned}$$

From here, W and Z are not independent.

Problem 3:

We will start by finding the expectation of the distance given A, and then we will reach the expectation on A using the smoothing theorem:

$$\begin{aligned} E(B-A | A) &= E(B | A) - A = \frac{A+1}{2} - A = \frac{1-A}{2} \\ \text{Var}(B-A | A) &= \text{Var}(B | A) - 0 = \frac{(1-A)^2}{12} \\ E((B-A)^2 | A) &= \text{Var}(B-A | A) + (E(B-A | A))^2 = \frac{(1-A)^2}{3} \end{aligned}$$

To get rid of the conditioning, let us use the smoothing theorem:

$$\begin{aligned} E(B-A) &= E(E(B-A | A)) = E\left(\frac{1-A}{2}\right) = \frac{1-E(A)}{2} = \frac{1-\frac{1}{2}}{2} = \frac{1}{4} \\ E((B-A)^2) &= E(E((B-A)^2 | A)) = E\left(\frac{(1-A)^2}{3}\right) = \frac{E(A^2) - 2E(A) + 1}{3} = \frac{\frac{1}{3} - 1 + 1}{3} = \frac{1}{9} \\ \Rightarrow \text{Var}(B-A) &= \frac{1}{9} - \left(\frac{1}{4}\right)^2 = \frac{7}{144} \end{aligned}$$

Consider this – what's not right with the following solution?

$$\text{Var}(B - A) = E[\text{Var}(B - A|A)] = E\left[\frac{(1-A)^2}{12}\right] = \frac{1}{4} E\left(\frac{(1-A)^2}{3}\right) = \frac{1}{4} \frac{1}{9} = \frac{1}{36}$$

Problem 4:

1. First, let us find the distribution function – and from it, we will derivate the density function:

$$\begin{aligned} F_Z(z) &= \Pr(Z \leq z) = \Pr\left(\max_i X_i \leq z\right) = \Pr(X_1 \leq z, X_2 \leq z, \dots, X_N \leq z) \\ &= \Pr(X_1 \leq z) \cdot \Pr(X_2 \leq z) \cdots \Pr(X_N \leq z) = (F_X(z))^N \end{aligned}$$

$$f_Z(z) = \frac{dF_Z(z)}{dz} = N \cdot (F_X(z))^{N-1} f_X(z)$$

$$\begin{aligned} F_W(w) &= \Pr(W \leq w) = \Pr\left(\min_i X_i \leq w\right) = 1 - \Pr\left(\min_i X_i > w\right) \\ &= 1 - \Pr(X_1 > w, X_2 > w, \dots, X_N > w) \\ &= 1 - \Pr(X_1 > w) \cdots \Pr(X_N > w) = 1 - (1 - F_X(w))^N \end{aligned}$$

$$f_Z(z) = \frac{dF_W(w)}{dw} = N \cdot (1 - F_X(w))^{N-1} f_X(w)$$

Problem 5:

1. We will start by calculating given M:

$$\begin{aligned} E(Y | X_1 = x_1, M = m) &= E(x_1 + X_2 + \cdots + X_m | X_1 = x_1, M = m) = \\ &= x_1 + E(X_2 + \cdots + X_m | X_1 = x_1, M = m) \stackrel{(a)}{=} x_1 + E(X_2) + \cdots + E(X_m) = x_1 \\ \Rightarrow E(Y | X_1) &= E(E(Y | X_1, M) | X_1) = E(X_1 | X_1) = X_1 \end{aligned}$$

where in the equality (a) we based on the fact that the variables X_2, \dots, X_m are i.i.d.

2. Again, let us first calculate given M:

$$\begin{aligned} \text{Var}(Y | X_1 = x_1, M = m) &= \text{Var}(x_1 + X_2 + \cdots + X_m | X_1 = x_1, M = m) \\ &\stackrel{(a)}{=} \text{Var}(X_2 + \cdots + X_m | X_1 = x_1, M = m) \stackrel{(b)}{=} \text{Var}(X_2) + \cdots + \text{Var}(X_m) = m - 1 \end{aligned}$$

where (a) results from the fact that adding a constant has no effect on the variance, and (b) since the variables X_2, \dots, X_m are i.i.d.

Now, let us use:

$$\text{Var}(Y | X_1, M) = E(Y^2 | X_1, M) - E^2(Y | X_1, M)$$

and the result from the last section so as to obtain:

$$\begin{aligned} E(Y^2 | X_1, M) &= M - 1 + X_1^2 \\ \Rightarrow E(Y^2 | X_1) &= E(M - 1 + X_1^2 | X_1) = \frac{n+1}{2} - 1 + X_1^2 = \frac{n-1}{2} + X_1^2 \\ \Rightarrow \text{Var}(Y | X_1) &= E(Y^2 | X_1) - E^2(Y | X_1) = \frac{n-1}{2} + X_1^2 - X_1^2 = \frac{n-1}{2} \end{aligned}$$

3. We will start by using the smoothing theorem to calculate the first two moments of Y:

$$\begin{aligned} E(Y | X_1) &= X_1 \\ \Rightarrow E(Y) &= E(X_1) = 0 \\ E(Y^2 | X_1) &= \frac{n-1}{2} + X_1^2 \\ \Rightarrow E(Y^2) &= E\left(\frac{n-1}{2} + X_1^2\right) = \frac{n-1}{2} + 1 = \frac{n+1}{2} \\ \Rightarrow \text{Var}(Y) &= \frac{n+1}{2} - 0^2 = \frac{n+1}{2} \end{aligned}$$

Problem 6:

1. Let us find according to the definition:

$$E\{W\} = E\{Y^2 + Z^2\} = E\{\cos^2(X) + \sin^2(X)\} \underset{(a)}{=} E\{1\} \underset{(b)}{=} 1$$

where (a) results from a basic trigonometric identity, and (b) is true since the expectation of a deterministic number is the number itself.

2. The integral of $\cos^2(X)$ throughout a whole period is equal to the integral of $\cos^2(Y)$:

$$\int_{-\pi}^{\pi} \cos^2(x) dx \stackrel{y=x+\pi/2}{=} \int_{-\pi+\pi/2}^{\pi+\pi/2} \cos^2(y-\pi/2) dy = \int_{-\pi+\pi/2}^{\pi+\pi/2} \sin^2(y) dy = \int_{-\pi}^{\pi} \sin^2(y) dy$$

And, thus:

$$\begin{aligned} E\{Y^2\} &= E\{\cos^2(X)\} = \int_{-\infty}^{+\infty} \cos^2(x) f_X(x) dx = \frac{1}{2\pi} \int_{-\pi}^{+\pi} \cos^2(x) dx \\ &= \frac{1}{2\pi} \int_{-\pi}^{+\pi} \sin^2(x) dx = E\{\sin^2(X)\} = E\{Z^2\} \end{aligned}$$

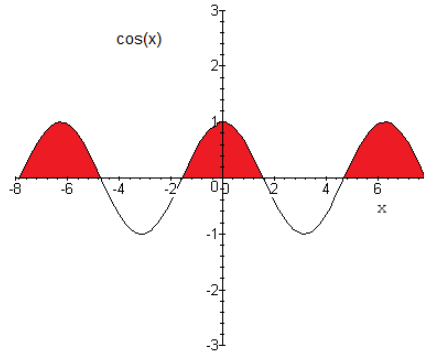
From here we get:

$$E\{Y^2\} = \frac{E\{Y^2\} + E\{Z^2\}}{2} = \frac{E\{Y^2 + Z^2\}}{2} = \frac{E\{1\}}{2} = \frac{1}{2}$$

3. Let us find:

$$E\{Y^2 | Y \geq 0\} = E\{\cos^2(X) | \cos(X) \geq 0\}$$

We will make use of the symmetry and periodicity of the cosine function:



$$E\{\cos^2(X) | \cos(X) \geq 0\} = E\{\cos^2(X + \pi) | \cos(X + \pi) \leq 0\} = E\{\cos^2(X') | \cos(X') \leq 0\}$$

X'

Since both X and X' distribute uniformly throughout a whole period, $\cos(X')$ distributes like $\cos(X)$:

$$E\{\cos^2(X) | \cos(X) \geq 0\} = E\{\cos^2(X) | \cos(X) \leq 0\}$$

Now we will use the law of total probability:

$$\begin{aligned} E\{\cos^2(X)\} &= P(\cos(X) \geq 0) \cdot E\{\cos^2(X) | \cos(X) \geq 0\} + P(\cos(X) \leq 0) \cdot E\{\cos^2(X) | \cos(X) \leq 0\} = \\ &= P(\cos(X) \geq 0)E\{\cos^2(X) | \cos(X) \geq 0\} + P(\cos(X) \leq 0)E\{\cos^2(X) | \cos(X) \leq 0\} \\ &= E\{\cos^2(X) | \cos(X) \geq 0\} \end{aligned}$$

Thus, all in all:

$$E\{Y^2 | Y \geq 0\} = E\{Y^2\} = \frac{1}{2}$$

Problem 7:

1. We will use the proposition of transformation of random vectors for a linear transformation. Clearly, the Jacobian of this transformation is simply the determinant of the matrix $J(g^{-1}(\underline{y})) = T^{-1}$.

This can easily be seen, since for a specific x_i :

$$x_i = T_{i1}^{-1}y_1 + T_{i2}^{-1}y_2 + T_{i3}^{-1}y_3 + T_{i4}^{-1}y_4 + \dots$$

Thus, the derivative of x_i by y_j will yield the element T_{ij}^{-1} in the matrix. Thus, if we proposition this in the above formula, when $\det(T^{-1}) = 1/\det(T)$, we get the following result:

$$f_{\bar{Y}}(\bar{y}) = \frac{1}{|\det T|} f_{\bar{X}}(T^{-1}\bar{y})$$

2. Let us use the proposition on the given transformation. It is obvious that the inverse matrix of A is:

$$A = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \rightarrow A^{-1} = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$

when the inverse may be found by simple inversion or by inverting the transformation itself:

$$\begin{cases} X_1 = Y_1 \\ X_2 = Y_2 - Y_1 \end{cases}$$

Therefore, we get the joint distribution $f_{Y_1, Y_2}(y_1, y_2) = \frac{1}{|1|} f_{X_1, X_2}(y_1, y_2 - y_1)$.

Let us observe the distribution of Y_2 , which is of course $X_1 + X_2$. Assume that X_1 and X_2 distribute independently; we get the following marginal distribution:

$$\begin{aligned} f_{X_1 + X_2}(y_2) &= f_{Y_2}(y_2) = \int_{-\infty}^{\infty} f_{Y_1, Y_2}(y_1, y_2) dy_1 \\ &= \int_{-\infty}^{\infty} f_{X_1, X_2}(y_1, y_2 - y_1) dy_1 = \int_{-\infty}^{\infty} f_{X_1}(y_1) f_{X_2}(y_2 - y_1) dy_1 \end{aligned}$$

We can see that we got a distribution equal to $f_{X_1} * f_{X_2}$, as required.