

556: MATHEMATICAL STATISTICS I

WORKED EXAMPLES: CALCULATIONS FOR MULTIVARIATE DISTRIBUTIONS

EXAMPLE 1 Let X_1 and X_2 be discrete rvs each with range $\{1, 2, 3, \dots\}$ and joint mass function

$$f_{X_1, X_2}(x_1, x_2) = \frac{c}{(x_1 + x_2 - 1)(x_1 + x_2)(x_1 + x_2 + 1)} \quad x_1, x_2 = 1, 2, 3, \dots$$

and zero otherwise. The marginal mass function for X is given by

$$\begin{aligned} f_{X_1}(x_1) &= \sum_{x_2=-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) = \sum_{x_2=1}^{\infty} \frac{c}{(x_1 + x_2 - 1)(x_1 + x_2)(x_1 + x_2 + 1)} \\ &= \sum_{x_2=1}^{\infty} \frac{c}{2} \left[\frac{1}{(x_1 + x_2 - 1)(x_1 + x_2)} - \frac{1}{(x_1 + x_2)(x_1 + x_2 + 1)} \right] \\ &= \frac{c}{2} \frac{1}{x_1(x_1 + 1)} \end{aligned}$$

as all other terms cancel, and to calculate c , note that

$$\sum_{x_1=-\infty}^{\infty} f_{X_1}(x_1) = \sum_{x_1=1}^{\infty} \frac{c}{2} \frac{1}{x_1(x_1 + 1)} = \frac{c}{2} \sum_{x_1=1}^{\infty} \left[\frac{1}{x_1} - \frac{1}{x_1 + 1} \right] = \frac{c}{2}$$

as all terms in the sum except the first cancel. Hence $c = 2$. Also, as the joint function is symmetric in form for X_1 and X_2 , f_{X_1} and f_{X_2} are identical.

EXAMPLE 2 Let X_1 and X_2 be continuous rvs with ranges $\mathbb{X}_1 = \mathbb{X}_2 = (0, 1)$ and joint pdf defined by

$$f_{X_1, X_2}(x_1, x_2) = 4x_1x_2 \quad 0 < x_1 < 1, 0 < x_2 < 1$$

and zero otherwise. For $0 < x_1, x_2 < 1$,

$$\begin{aligned} F_{X_1, X_2}(x_1, x_2) &= \int_{-\infty}^{x_2} \int_{-\infty}^{x_1} f_{X_1, X_2}(t_1, t_2) dt_1 dt_2 = \int_0^{x_2} \int_0^{x_1} 4t_1t_2 dt_1 dt_2 \\ &= \left\{ \int_0^{x_1} 2t_1 dt_1 \right\} \left\{ \int_0^{x_2} 2t_2 dt_2 \right\} = (x_1x_2)^2 \end{aligned}$$

and a full specification for F_{X_1, X_2} is

$$F_{X_1, X_2}(x_1, x_2) = \begin{cases} 0 & x_1, x_2 \leq 0 \\ (x_1x_2)^2 & 0 < x_1, x_2 < 1 \\ x_1^2 & 0 < x_1 < 1, x_2 \geq 1 \\ x_2^2 & 0 < x_2 < 1, x_1 \geq 1 \\ 1 & x_1, x_2 \geq 1 \end{cases}$$

To calculate, for $c \in \mathbb{R}$,

$$P_{X_1, X_2} \left[\frac{X_1 + X_2}{2} < c \right]$$

we need to integrate f_{X_1, X_2} over the set $A_c = \{(x_1, x_2) : 0 < x_1, x_2 < 1, (x_1 + x_2)/2 < c\}$, that is, if $c = 1/2$,

$$P_{X_1, X_2}[(X_1 + X_2) < 1] = \int_0^1 \int_0^{1-x_1} 4x_1x_2 dx_2 dx_1 = \int_0^1 2x_1(1-x_1)^2 dx_1 = \frac{1}{6}$$

EXAMPLE 3 Let X_1, X_2 be continuous random variables with ranges $\mathbb{X}_1 \equiv \mathbb{X}_2 \equiv [0, 1]$, and joint pdf defined by

$$f_{X_1, X_2}(x_1, x_2) = 1 \quad 0 \leq x_1, x_2 \leq 1$$

and zero otherwise. Let $Y = X_1 + X_2$. The has range $\mathbb{Y} \equiv [0, 2]$,

$$F_Y(y) = P_Y[Y \leq y] = P_{X_1, X_2}[X_1 + X_2 \leq y]$$

To calculate $P[X_1 + X_2 \leq y]$, need to integrate f_{X_1, X_2} over the set

$$A_y = \{(x_1, x_2) : 0 < x_1, x_2 < 1, x_1 + x_2 \leq y\}$$

This region is a portion of the unit square (that is, $\mathbb{X}_1 \times \mathbb{X}_2$) ; the line $x_1 + x_2 = y$ is a line with negative slope that cuts the x_1 (horizontal) axis at $x_1 = y$, and the x_2 axis (vertical) at $x_2 = y$. Now for $0 \leq y \leq 1$, A_y is the dark shaded lower triangle in the left panel of the figure below; hence, for fixed y ,

$$P_{X_1, X_2}[X_1 + X_2 < y] = \int_0^y \int_0^{y-x_2} 1 \, dx_1 dx_2 = \int_0^y (y - x_2) dx_2 = \frac{y^2}{2}.$$

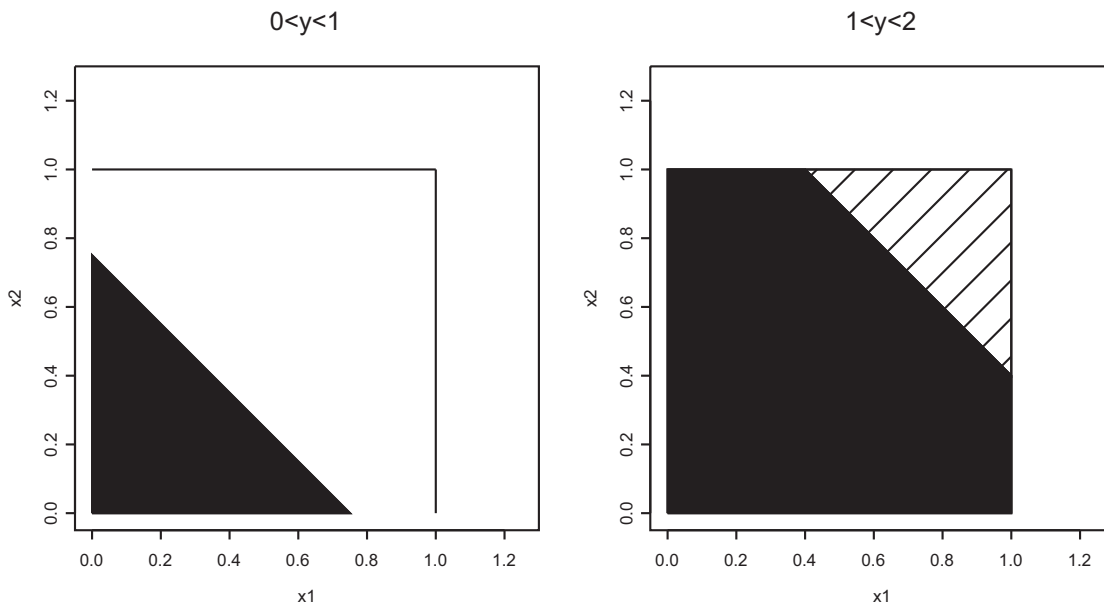
For $1 \leq y \leq 2$, A_y is more complicated see the figure below (right panel). It is easier mathematically to describe the complement of A_y within $\mathbb{X}_1 \times \mathbb{X}_2$ (striped in the right panel of the figure below), so we instead compute the complement probability as follows:

$$\begin{aligned} P[X_1 + X_2 \leq y] &= 1 - P[X_1 + X_2 > y] \\ &= 1 - \int_{y-1}^1 \int_{y-x_2}^1 1 \, dx_1 dx_2 = 1 - \int_{y-1}^1 (1 - y + x_2) dx_2 = -\frac{y^2}{2} + 2y - 1 \end{aligned}$$

These two expressions give the cdf F_Y , and hence by differentiation we have

$$f_Y(y) = \begin{cases} y & 0 \leq y \leq 1 \\ 2 - y & 1 \leq y \leq 2 \end{cases}$$

and zero otherwise.



EXAMPLE 4 Let X_1 and X_2 be continuous rvs with ranges $\mathbb{X}_1 = (0, 1)$, $\mathbb{X}_2 = (0, 2)$ and joint pdf

$$f_{X_1, X_2}(x_1, x_2) = c \left(x_1^2 + \frac{x_1 x_2}{2} \right) \quad 0 < x_1 < 1, 0 < x_2 < 2$$

and zero otherwise.

(i) To calculate c , we have

$$\begin{aligned} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 &= \int_0^2 \left\{ \int_0^1 c \left(x_1^2 + \frac{x_1 x_2}{2} \right) dx_1 \right\} dx_2 \\ &= \int_0^2 c \left[\frac{x_1^3}{3} + \frac{x_1^2 x_2}{4} \right]_0^1 dx_2 \\ &= \int_0^2 c \left(\frac{1}{3} + \frac{x_2}{4} \right) dx_2 \\ &= c \left[\frac{x_2}{3} + \frac{x_2^2}{8} \right]_0^2 = c \frac{7}{6} \end{aligned}$$

so $c = 6/7$. The marginal pdf of X_1 is given, for $0 < x_1 < 1$, by

$$f_{X_1}(x_1) = \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) dx_2 = \int_0^2 \frac{6}{7} \left(x_1^2 + \frac{x_1 x_2}{2} \right) dx_2 = \frac{6}{7} \left[x_1^2 x_2 + \frac{x_1 x_2^2}{4} \right]_0^2 = \frac{6x_1(2x_1 + 1)}{7}$$

and is zero otherwise.

(ii) To compute $P_{X_1, X_2}[X_1 > X_2]$, let

$$A = \{ (x_1, x_2) : 0 < x_1 < 1, 0 < x_2 < 2, x_2 < x_1 \}$$

so that

$$\begin{aligned} P_{X_1, X_2}[X_1 > X_2] &= \iint_A f_{X_1, X_2}(x_1, x_2) dx_2 dx_1 \\ &= \int_0^1 \left\{ \int_0^{x_1} \frac{6}{7} \left(x_1^2 + \frac{x_1 x_2}{2} \right) dx_2 \right\} dx_1 \\ &= \int_0^1 \left[x_1^2 x_2 + \frac{x_1 x_2^2}{4} \right]_0^{x_1} dx_1 \\ &= \int_0^1 \left(x_1^3 + \frac{x_1^3}{4} \right) dx_1 \\ &= \frac{6}{7} \left[\frac{5x_1^4}{16} \right]_0^1 \\ &= \frac{15}{56} \end{aligned}$$

EXAMPLE 5 Let X_1, X_2 and X_3 be continuous rvs with joint pdf defined by

$$f_{X_1, X_2, X_3}(x_1, x_2, x_3) = c \quad 0 < x_1 < x_2 < x_3 < 1$$

and zero otherwise. The support of this pdf is $\mathbb{X}^{(3)} = \{(x_1, x_2, x_3) : 0 < x_1 < x_2 < x_3 < 1\}$.

(i) **Normalization:** To calculate c , integrate carefully over $\mathbb{X}^{(3)}$, that is

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X_1, X_2, X_3}(x_1, x_2, x_3) dx_1 dx_2 dx_3 = 1$$

gives that

$$\int_0^1 \left\{ \int_0^{x_3} \left\{ \int_0^{x_2} c dx_1 \right\} dx_2 \right\} dx_3 = 1$$

Now

$$\int_0^1 \left\{ \int_0^{x_3} \left\{ \int_0^{x_2} c dx_1 \right\} dx_2 \right\} dx_3 = \int_0^1 \left\{ \int_0^{x_3} cx_2 dx_2 \right\} dx_3 = \int_0^1 \frac{cx_3^2}{2} dx_3 = \frac{c}{6}$$

and hence $c = 6$.

(ii) **Marginalization:** for $0 < x_3 < 1$, f_{X_3} is given by

$$f_{X_3}(x_3) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X_1, X_2, X_3}(x_1, x_2, x_3) dx_1 dx_2 = \int_0^{x_3} \left\{ \int_0^{x_2} 6 dx_1 \right\} dx_2 = \int_0^{x_3} 6x_2 dx_2 = 3x_3^2$$

and is zero otherwise. Similar calculations for X_1 and X_2 give

$$\begin{aligned} f_{X_1}(x_1) &= 3(1-x_1)^2 & 0 < x_1 < 1 \\ f_{X_2}(x_2) &= 6x_2(1-x_2) & 0 < x_2 < 1 \end{aligned}$$

with both densities equal to zero outside of these ranges. Furthermore, for the **joint marginal** of X_1 and X_2 , we have

$$f_{X_1, X_2}(x_1, x_2) = \int_{-\infty}^{\infty} f_{X_1, X_2, X_3}(x_1, x_2, x_3) dx_3 = \int_{x_2}^1 6 dx_3 = 6(1-x_2) \quad 0 < x_1 < x_2 < 1$$

and zero otherwise. Combining these results, we have, for example, for the conditional of X_1 given $X_2 = x_2$,

$$f_{X_1|X_2}(x_1|x_2) = \frac{f_{X_1, X_2}(x_1, x_2)}{f_{X_2}(x_2)} = \frac{1}{x_2} \quad 0 < x_1 < x_2$$

and zero otherwise for **fixed** x_2 .

(iii) **Expectations:** we can calculate the expectation of X_1 either directly or using the *Law of Iterated Expectation*: we have

$$\mathbb{E}_{X_1}[X_1] = \int_{-\infty}^{\infty} x_1 f_{X_1}(x_1) dx_1 = \int_0^1 x_1 3(1-x_1)^2 dx_1 = \frac{1}{4}$$

or, alternatively,

$$\mathbb{E}_{X_1|X_2}[X_1|X_2 = x_2] = \int_{-\infty}^{\infty} x_1 f_{X_1|X_2}(x_1|x_2) dx_1 = \int_0^{x_2} x_1 \frac{1}{x_2} dx_1 = \frac{x_2}{2}$$

and hence by the law of iterated expectation

$$\begin{aligned} \mathbb{E}_{X_1}[X_1] &= \mathbb{E}_{X_2}[\mathbb{E}_{X_1|X_2}[X_1|X_2]] = \int_{-\infty}^{\infty} \{\mathbb{E}_{X_1|X_2}[X_1|X_2]\} f_{X_2}(x_2) dx_2 \\ &= \int_0^1 \frac{x_2}{2} 6x_2(1-x_2) dx_2 = \frac{1}{4} \end{aligned}$$

EXAMPLE 6 Let X_1, X_2 be continuous random variables with joint density f_{X_1, X_2} and let rv Y be defined by $Y = g(X_1, X_2)$. To calculate the pdf of Y we could use the multivariate transformation theorem after defining another (dummy) variable Z as some function of X_1 and X_2 , and consider the joint transformation $(X_1, X_2) \rightarrow (Y, Z)$. Defining $Z = X_1$, we have

$$f_Y(y) = \int_{-\infty}^{\infty} f_{Y,Z}(y, z) dz = \int_{-\infty}^{\infty} f_{Y|Z}(y|z) f_Z(z) dz = \int_{-\infty}^{\infty} f_{Y|X_1}(y|x_1) f_{X_1}(x_1) dx_1$$

as $f_{Y,Z}(y, z) = f_{Y|Z}(y|z) f_Z(z)$ by the chain rule for densities; $f_{Y|X_1}(y|x_1)$ is a univariate (conditional) pdf for Y given $X_1 = x_1$.

Now, **given** that $X_1 = x_1$, we have that $Y = g(x_1, X_2)$, that is, Y is a transformation of X_2 only. Hence the conditional pdf $f_{Y|X_1}(y|x_1)$ can be derived using single variable (rather than multivariate) transformation techniques. Specifically, if $Y = g(x_1, X_2)$ is a 1-1 transformation from X_2 to Y , then the inverse transformation $X_2 = g^{-1}(x_1, Y)$ is well defined, and by the transformation theorem

$$f_{Y|X_1}(y|x_1) = f_{X_2|X_1}(g^{-1}(x_1, y)) |J(y; x_1)| = f_{X_2|X_1}(g^{-1}(x_1, y)|x_1) \left| \frac{\partial}{\partial t} \{g^{-1}(x_1, t)\}_{t=y} \right|$$

and hence

$$f_Y(y) = \int_{-\infty}^{\infty} \left\{ f_{X_2|X_1}(g^{-1}(x_1, y)|x_1) \left| \frac{\partial}{\partial t} \{g^{-1}(x_1, t)\}_{t=y} \right| \right\} f_{X_1}(x_1) dx_1$$

For example, if $Y = X_1 X_2$, then $X_2 = Y/X_1$, and hence

$$\left| \frac{\partial}{\partial t} \{g^{-1}(x_1, t)\}_{t=y} \right| = \left| \frac{\partial}{\partial t} \left\{ \frac{t}{x_1} \right\}_{t=y} \right| = |x_1|^{-1}$$

so

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X_2|X_1}(y/x_1|x_1) |x_1|^{-1} f_{X_1}(x_1) dx_1.$$

The conditional density $f_{X_2|X_1}$ and/or the marginal density f_{X_1} may be zero on parts of the range of the integral. Alternatively, the **cdf** of Y is given by

$$F_Y(y) = P[Y \leq y] = P[g(X_1, X_2) \leq y] = \iint_{A_y} f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

where $A_y = \{ (x_1, x_2) : g(x_1, x_2) \leq y \}$ so the cdf can be calculated by carefully identifying and integrating over the set A_y .

EXAMPLE 7 Let X_1, X_2 be rvs with joint density f_{X_1, X_2} and let $g(X_1)$. Then

$$\begin{aligned} \mathbb{E}_{X_1, X_2} [g(X_1)] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x_1) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\ &= \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} g(x_1) f_{X_1|X_2}(x_1|x_2) f_{X_2}(x_2) dx_1 \right\} dx_2 \\ &= \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} g(x_1) f_{X_1|X_2}(x_1|x_2) dx_1 \right\} f_{X_2}(x_2) dx_2 \\ &= \mathbb{E}_{X_2} [\mathbb{E}_{X_1|X_2} [g(X_1)|X_2]] = \mathbb{E}_{X_1} [g(X_1)] \end{aligned}$$

by the law of iterated expectation. Thus, we can compute the expectation with respect to the marginal f_{X_1} rather than the joint pdf.

EXAMPLE 8 Let X_1, X_2 be continuous random variables with joint pdf given by

$$f_{X_1, X_2}(x_1, x_2) = x_1 \exp\{-(x_1 + x_2)\} \quad x_1, x_2 > 0$$

and zero otherwise. Let $Y = X_1 + X_2$. Then by the Convolution Theorem,

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, y - x_1) dx_1 = \int_0^y x_1 \exp\{-(x_1 + (y - x_1))\} dx_1 = \frac{y^2}{2} e^{-y} \quad y > 0$$

and zero otherwise. Note that the integral range is 0 to y as the joint density f_{X_1, X_2} is only non-zero when both its arguments are positive, that is, when $x_1 > 0$ and $y - x_1 > 0$ for fixed y , or when $0 < x_1 < y$. It is straightforward to check that this density is a valid pdf, the *Gamma*(3, 1).

EXAMPLE 9 Let X_1, X_2 be continuous random variables with joint pdf given by

$$f_{X_1, X_2}(x_1, x_2) = 2(x_1 + x_2) \quad 0 \leq x_1 \leq x_2 \leq 1$$

and zero otherwise. Let $Y = X_1 + X_2$. Then by the Convolution Theorem,

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, y - x_1) dx_1 = \begin{cases} \int_0^{y/2} 2y dx_1 & 0 \leq y \leq 1 \\ \int_{y-1}^{y/2} 2y dx_1 & 1 \leq y \leq 2 \end{cases}$$

and zero otherwise, as $f_{X_1, X_2}(x_1, y - x_1) = 2y$; this holds when both x_1 and $y - x_1$ lie in the interval $[0, 1]$ with $x_1 \leq y - x_1$ for fixed y , and zero otherwise. Clearly Y takes values on $\mathbb{Y} \equiv [0, 2]$; for $0 \leq y \leq 1$, the constraints $0 \leq x_1 \leq y - x_1 \leq 1$ imply that $0 \leq 2x_1 \leq y$, or $0 \leq x_1 \leq y/2$ (for fixed y); if $1 \leq y \leq 2$ the constraints imply $y - 1 \leq x_1 \leq y/2$. Hence

$$f_Y(y) = \begin{cases} y^2 & 0 \leq y \leq 1 \\ y(2 - y) & 1 \leq y \leq 2 \end{cases}$$

It is straightforward to check that this density is a valid pdf. The region of (X_1, Y) space on which the joint density $f_{X_1, X_2}(x_1, y - x_1)$ is **positive**; this region is the triangle with corners $(0, 0)$, $(1, 2)$, $(0, 1)$.

COVARIANCE If X_1 and X_2 are continuous rvs with joint mass function/pdf f_{X_1, X_2} , then the covariance of X_1 and X_2 is defined by

$$\begin{aligned} \text{Cov}_{X_1, X_2}[X_1, X_2] &= \mathbb{E}_{X_1, X_2}[(X_1 - \mu_1)(X_2 - \mu_2)] = \iint (x_1 - \mu_1)(x_2 - \mu_2) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\ &= \mathbb{E}_{X_1, X_2}[X_1 X_2] - \mu_2 \mathbb{E}_{X_1}[X_1] - \mu_1 \mathbb{E}_{X_2}[X_2] + \mu_1 \mu_2 \\ &= \mathbb{E}_{X_1, X_2}[X_1 X_2] - \mu_1 \mu_2 \end{aligned}$$

where $\mu_i = \mathbb{E}_{X_i}[X_i]$ is the marginal expectation of X_i , for $i = 1, 2$

It follows that if $Y = X_1 + X_2$, then

$$\begin{aligned} \mathbb{E}_Y[Y] &= \mathbb{E}_{X_1, X_2}[X_1 + X_2] = \iint (x_1 + x_2) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\ &= \iint x_1 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 + \iint x_2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\ &= \mathbb{E}_{X_1}[X_1] + \mathbb{E}_{X_2}[X_2] \end{aligned}$$

and

$$\begin{aligned}
\text{Var}_Y[Y] &= \text{Var}_{X_1, X_2}[X_1 + X_2] = \mathbb{E}_{X_1, X_2} [(X_1 + X_2 - (\mu_1 + \mu_2))^2] \\
&= \iint (x_1 + x_2 - \mu_1 - \mu_2)^2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\
&= \iint [(x_1 - \mu_1)^2 + (x_2 - \mu_2)^2 + 2(x_1 - \mu_1)(x_2 - \mu_2)] f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\
&= \iint (x_1 - \mu_1)^2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 + \iint (x_2 - \mu_2)^2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\
&\quad + 2 \iint (x_1 - \mu_1)(x_2 - \mu_2) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 \\
&= \text{Var}_{X_1}[X_1] + \text{Var}_{X_2}[X_2] + 2 \text{Cov}_{X_1, X_2}[X_1, X_2]
\end{aligned}$$

and the result for the sum of n variables follows similarly, or by induction.

EXAMPLE 10 Let X_1, X_2 be continuous random variables with joint pdf given by

$$f_{X_1, X_2}(x_1, x_2) = c \quad 0 < x_1 < 1, x_1 < x_2 < x_1 + 1$$

and zero otherwise. To calculate c , we have

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) dx_2 dx_1 = \int_0^1 \int_{x_1}^{x_1+1} c dx_2 dx_1 = \int_0^1 c [x_2]_{x_1}^{x_1+1} dx_1 = \int_0^1 c dx_1 = c$$

so $c = 1$. The marginal pdf of X_1 is given by

$$f_{X_1}(x_1) = \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) dx_2 = \int_{x_1}^{x_1+1} 1 dx_2 = 1 \quad 0 < x_1 < 1$$

and zero otherwise, and the marginal pdf for X_2 is given by

$$f_{X_2}(x_2) = \int_{-\infty}^{\infty} f_{X_1, X_2}(x_1, x_2) dx_1 = \begin{cases} \int_0^{x_2} 1 dx_1 & = x_2 & 0 < x_2 < 1 \\ \int_{x_2-1}^1 1 dx_1 & = 2 - x_2 & 1 \leq x_2 < 2 \end{cases}$$

and zero otherwise. Hence

$$\begin{aligned}
\mathbb{E}_{X_1}[X_1] &= \int_{-\infty}^{\infty} x_1 f_{X_1}(x_1) dx_1 = \int_0^1 x_1 dx_1 = \frac{1}{2} \\
\text{Var}_{X_1}[X_1] &= \int_{-\infty}^{\infty} x_1^2 f_{X_1}(x_1) dx_1 - \{\mathbb{E}_{X_1}[X_1]\}^2 = \int_0^1 x_1^2 dx_1 - \frac{1}{4} = \frac{1}{12}
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}_{X_2}[X_2] &= \int_{-\infty}^{\infty} x_2 f_{X_2}(x_2) dx_2 = \int_0^1 x_2^2 dx_2 + \int_1^2 x_2(2-x_2) dx_2 \\
&= \frac{1}{3} - \left(1 - \frac{1}{3}\right) + \left(4 - \frac{8}{3}\right) = 1
\end{aligned}$$

$$\begin{aligned}
\text{Var}_{X_2}[X_2] &= \int_{-\infty}^{\infty} x_2^2 f_{X_2}(x_2) dx_2 - \{\mathbb{E}_{X_2}[X_2]\}^2 \\
&= \int_0^1 x_2^2 x_2 dx_2 + \int_1^2 x_2^2(2-x_2) dx_2 - 1 \\
&= \frac{1}{4} - \left(\frac{2}{3} - \frac{1}{4}\right) + \left(\frac{16}{3} - 4\right) - 1 = \frac{1}{6}
\end{aligned}$$

The covariance and correlation of X_1 and X_2 are then given by

$$\begin{aligned}
\text{Cov}_{X_1, X_2}[X_1, X_2] &= \left\{ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 f_{X_1, X_2}(x_1, x_2) dx_2 \right\} dx_1 - \mathbb{E}_{X_1}[X_1] \mathbb{E}_{X_2}[X_2] \\
&= \int_0^1 \left\{ \int_{x_1}^{x_1+1} x_1 x_2 dx_2 \right\} dx_1 - \frac{1}{2} \cdot 1 \\
&= \int_0^1 x_1 \left[\frac{x_2^2}{2} \right]_{x_1}^{x_1+1} dx_1 - \frac{1}{2} \\
&= \int_0^1 \left(x_1^2 + \frac{x_1}{2} \right) dx_1 - \frac{1}{2} \\
&= \left[\frac{x_1^3}{3} + \frac{x_1^2}{4} \right]_0^1 - \frac{1}{2} = \frac{7}{12} - \frac{1}{2} = \frac{1}{12}
\end{aligned}$$

and hence

$$\text{Corr}_{X_1, X_2}[X_1, X_2] = \frac{\text{Cov}_{X_1, X_2}[X_1, X_2]}{\sqrt{\text{Var}_{X_1}[X_1] \text{Var}_{X_2}[X_2]}} = \frac{1/12}{\sqrt{1/12} \sqrt{1/6}} = \frac{1}{\sqrt{2}}$$