Moments, Covariance and Correlation Coefficient

Let $\underline{X} = (X_1, X_2, \ldots, X_n)$ be a $n-$dimensional ($n \geq 2$) random vector and $\psi : \mathbb{R}^n \longrightarrow \mathbb{R}$ be a function such that $\psi^{-1}(A) \in \mathbb{B}_{\mathbb{R}^n}$, for all $A \in \mathbb{B}_{\mathbb{R}}$. Suppose $E(\psi(\underline{X}))$ is finite.

(1) If $\underline{X}$ is of discrete type with joint p.m.f. $f_{\underline{X}}$ and support $E_{\underline{X}}$, then

$$E(\psi(\underline{X})) = \sum_{(x_1,x_2,\ldots,x_n)\in E_{\underline{X}}} \psi(x_1, x_2, \ldots, x_n)) f_{\underline{X}}(x_1, x_2, \ldots, x_n).$$

(2) If $\underline{X}$ is of continuous type with joint p.d.f. $f_{\underline{X}}$, then

$$E(\psi(\underline{X})) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \psi(x_1, x_2, \ldots, x_n) f_{\underline{X}}(x_1, x_2, \ldots, x_n)\, dx_1\, dx_2 \cdots dx_n.$$

(3) For nonnegative integers $k_1, k_2, \ldots, k_n$, let $\psi(x_1, x_2, \ldots, x_n) = x_1^{k_1} x_2^{k_2} \cdots x_n^{k_n}$. Then

$$\mu'_{k_1,k_2,\ldots,k_n} = E(\psi(\underline{X})) = E(X_1^{k_1} X_2^{k_2} \cdots X_n^{k_n}),$$

provided it is finite, is called the joint moment of order $k_1 + k_2 + \cdots + k_n$ of $\underline{X} = (X_1, X_2, \ldots, X_n)$.

(4) For $n = 2$, let $\psi(x_1, x_2) = (x_1 - E(X_1))(x_2 - E(X_2))$. Then

$$Cov(X_1, X_2) = E\Big((X_1 - E(X_1))(X_2 - E(X_2))\Big),$$

provided it is finite, is called the covariance between X_1 and X_2.

Note: By the definition of covariance, it is easy to see

$$Cov(X_1, X_1) = Var(X_1);$$
$$Cov(X_1, X_2) = Cov(X_2, X_1);$$
$$Cov(X_1, X_2) = E(X_1X_2) - E(X_1)E(X_2).$$

Theorem 1. *Let $\underline{X} = (X_1, X_2)$ and $\underline{Y} = (Y_1, Y_2)$ be two random vectors and a_1, a_2, b_1, b_2 be real constants. Then, provided the involved expectations are finite,*

(1) $E(a_1X_1 + a_2X_2) = a_1E(X_1) + a_2E(X_2)$*;*

(2) $Cov(a_1X_1+a_2X_2, b_1Y_1+b_2Y_2) = a_1b_1\, Cov(X_1, Y_1)+a_1b_2\, Cov(X_1, Y_2)+a_2b_1\, Cov(X_2, Y_1)+ a_2b_2\, Cov(X_2, Y_2) = \sum_{i=1}^{2}\sum_{j=1}^{2} a_ib_jCov(X_i, Y_j).$

In particular,
$Var(a_1X_1 + a_2X_2) = Cov(a_1X_1 + a_2X_2, a_1X_1 + a_2X_2) = a_1^2Var(X_1) + a_2^2Var(X_2) + 2a_1a_2Cov(X_1, X_2).$

Proof. (1) Suppose $\underline{X}$ is continuous type with joint p.d.f. $f_{\underline{X}}$. Let $\psi(x_1, x_2) = a_1x_1 + a_2x_2$. Then

$$\begin{aligned}
E(a_1X_1 + a_2X_2) &= E(\psi(\underline{X})) \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (a_1x_1 + a_2x_2) f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2 \\
&= a_1 \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_1 f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2 + a_2 \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_2 f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2
\end{aligned}$$

By taking $\psi_1(x_1, x_2) = x_1$ and $\psi_2(x_1, x_2) = x_2$, we have

$$E(X_1) = E(\psi_1(\underline{X})) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_1 f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2$$

and

$$E(X_2) = E(\psi_2(\underline{X})) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_2 f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2.$$

Thus,

$$E(a_1X_1 + a_2X_2) = a_1E(X_1) + a_2E(X_2).$$

Similarly, we can prove for discrete type random vector.

(2)

$$\begin{aligned}
&Cov(a_1X_1 + a_2X_2, b_1Y_1 + b_2Y_2)\\
&= Cov(\sum_{i=1}^{2} a_iX_i, \sum_{j=1}^{2} b_jY_j)\\
&= E\Big((\sum_{i=1}^{2} a_iX_i - E(\sum_{i=1}^{2} a_iX_i))(\sum_{j=1}^{2} b_jY_j - E(\sum_{j=1}^{2} b_jY_j))\Big)\\
&= E\Big((\sum_{i=1}^{2} a_i(X_i - E(X_i)))(\sum_{j=1}^{2} b_j(Y_j - E(Y_j)))\Big) \text{ (by (1))}\\
&= E\Big(\sum_{i=1}^{2}\sum_{j=1}^{2} a_ib_j\big(X_i - E(X_i)\big)\big(Y_j - E(Y_j)\big)\Big)\\
&= \sum_{i=1}^{2}\sum_{j=1}^{2} a_ib_jE\Big(\big(X_i - E(X_i)\big)\big(Y_j - E(Y_j)\big)\Big)\\
&= \sum_{i=1}^{2}\sum_{j=1}^{2} a_ib_jCov(X_i, Y_j).
\end{aligned}$$

□

Remark 2. *In general, we have*

(1) $E(a_1X_1 + a_2X_2 + \cdots + a_nX_n) = a_1E(X_1) + a_2E(X_2) + \cdots + a_nE(X_n)$;

(2) $Cov(\sum_{i=1}^{n_1} a_iX_i, \sum_{j=1}^{n_2} b_jY_j) = \sum_{i=1}^{n_1}\sum_{j=1}^{n_2} a_ib_jCov(X_i, Y_j)$.

In particular,

$Var(\sum_{i=1}^{n_1} a_iX_i) = \sum_{i=1}^{n_1} a_iVar(X_i) + 2\sum\sum_{1\le i<j\le n_1} Cov(X_i, X_j)$

Theorem 3. *Let $X_1, X_2, \ldots, X_n$ be the independent random variables. Let $\psi_i : \mathbb{R} \longrightarrow \mathbb{R}$ be a function such that $\psi_i^{-1}(A) \in \mathbb{B}_{\mathbb{R}}$, for all $A \in \mathbb{B}_{\mathbb{R}}$, for $i = 1, 2, \cdots, n$. Then*

$$E\Big(\prod_{i=1}^{n} \psi_i(X_i)\Big) = \prod_{i=1}^{n} E\Big(\psi_i(X_i)\Big),$$

provided the involved expectations are finite.

Proof. We will prove the theorem for $n = 2$ and continuous random vector. Suppose $\underline{X} = (X_1, X_2)$ is a continuous type random vector with joint p.d.f. $f_{\underline{X}}$. Consider the function

$\psi(x_1, x_2) = \psi_1(x_1)\psi_2(x_2)$. Then

$$\begin{aligned}
E(\psi_1(X_1)\psi_2(X_2)) &= E(\psi(\underline{X})) \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \psi_1(x_1)\psi_2(x_2) f_{\underline{X}}(x_1, x_2)\, dx_1\, dx_2 \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \psi_1(x_1)\psi_2(x_2) f_{X_1}(x_1) f_{X_2}(x_2)\, dx_1\, dx_2 \text{ (since } X_1 \text{ and } X_2 \text{ are independent)} \\
&= \Big(\int_{-\infty}^{\infty} \psi_1(x_1) f_{X_1}(x_1)\, dx_1\Big)\Big(\int_{-\infty}^{\infty} \psi_2(x_2) f_{X_2}(x_2)\, dx_2\Big) \\
&= E(\psi_1(X_1))E(\psi_2(X_2))
\end{aligned}$$

□

Corollary 4. *Let $X_1, X_2, \ldots, X_n$ be the independent random variables. Then*

$$Cov(X_i, X_j) = 0, \ \forall\ i \neq j$$

and for real constants $a_1, a_2, \ldots, a_n$,

$$Var(\sum_{i=1}^{n} a_i X_i) = \sum_{i=1}^{n} a_i Var(X_i),$$

provided the involved expectations are finite.

Proof. Fix $i, j \in \{1, 2, \ldots, n\}, i \neq j$. Then by Theorem 3, we have

$$\begin{aligned}
&E(X_i X_j) = E(X_i)E(X_j) \\
\Rightarrow &Cov(X_i, X_j) = E(X_i X_j) - E(X_i)E(X_j) = 0
\end{aligned}$$

Since $Cov(X_i, X_j) = 0, \ \forall\ i \neq j$, by Remark 2,

$$Var(\sum_{i=1}^{n} a_i X_i) = \sum_{i=1}^{n} a_i Var(X_i).$$

□

Definition 5.
1. *The correlation coefficient between random variables X and Y is defined by*

$$\rho(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}},$$

provided $0 < Var(X), Var(Y) < \infty$.

2. *The random variables X and Y are said to be uncorrelated if $Cov(X, Y) = 0$.*

Note: By definition, it is clear that if X and Y are independent random variables, then they are uncorrelated but converse need not be true.

Theorem 6. *Let X and Y be two random variables. Then, provided the involved expectations are finite,*

1. $(E(XY))^2 \leq E(X^2)E(Y^2)$. *Moreover, $(E(XY))^2 = E(X^2)E(Y^2)$ if and only if $P(Y = cX) = 1$ or $P(X = cY) = 1$, for some $c \in \mathbb{R}$.*
   This inequality is know as Cauchy-Schwarz inequality for random variables.
2. $|\rho(X, Y)| \leq 1$. *To prove it, apply (1) on random variables $X' = X - E(X)$ and $Y' = Y - E(Y)$.*

Example 7. *Let $\underline{Z} = (X, Y)$ be a random vector of discrete type with joint p.m.f.*

$$f(x,y) = \begin{cases} p_1, & \text{if } (x,y) = (-1,1) \\ p_2, & \text{if } (x,y) = (0,0) \\ p_1, & \text{if } (x,y) = (1,1) \\ 0, & \text{otherwise} \end{cases}$$

where $p_1, p_2 \in (0,1)$ and $2p_1 + p_2 = 1$.

Then the support of $\underline{Z}, X$ and Y are

$$E_{\underline{Z}} = \{(-1,1), (0,0), (1,1)\}$$
$$E_X = \{-1, 0, 1\}$$

and

$$E_Y = \{0, 1\},$$

respectively. Clearly $E_{\underline{Z}} \neq E_X \times E_Y$. So, X and Y are not independent.

Now,

$$E(XY) = \sum_{(x,y)\in E_{\underline{Z}}} xyf(x,y) = 0;$$
$$E(X) = \sum_{(x,y)\in E_{\underline{Z}}} xf(x,y) = 0;$$
$$E(Y) = \sum_{(x,y)\in E_{\underline{Z}}} yf(x,y) = 2p_1;$$
$$\Rightarrow Cov(X,Y) = E(XY) - E(X)E(Y) = 0 \Rightarrow \rho(X,Y) = 0$$

This shows that X and Y are uncorrelated but not independent.

We can also show that X and Y are not independent by another way.

The marginal p.m.f. of X is

$$f_X(x) = \begin{cases} \sum\limits_{y \in R_x} f(x,y), & \text{if } x \in \{-1,0,1\} \\ 0, & \text{otherwise} \end{cases}$$
$$= \begin{cases} p_1, & \text{if } x = -1 \\ p_2, & \text{if } x = 0 \\ p_1, & \text{if } x = 1 \\ 0, & \text{otherwise} \end{cases}$$

Similarly, the marginal p.m.f. of Y is

$$f_Y(y) = \begin{cases} \sum\limits_{x \in R_y} f(x,y), & \text{if } y \in \{0,1\} \\ 0, & \text{otherwise} \end{cases}$$
$$= \begin{cases} p_2, & \text{if } x = 0 \\ 2p_1, & \text{if } x = 1 \\ 0, & \text{otherwise} \end{cases}$$

Since $f(-1,1) \neq f_X(-1)f_Y(1)$, X and Y are not independent.

Example 8. *Let $\underline{Z} = (X, Y)$ be a random vector of continuous type with joint p.d.f.*

$$f(x,y) = \begin{cases} 1, & \text{if } 0 < |y| \leq x < 1 \\ 0, & \text{otherwise} \end{cases}$$

Now,

$$\begin{aligned}
E(XY) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} xyf(x,y)\,dx\,dy = \int_{0}^{1}\int_{-x}^{x} xy\,dy\,dx = 0;\\
E(X) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} xf(x,y)\,dx\,dy = \int_{0}^{1}\int_{-x}^{x} x\,dy\,dx = \frac{2}{3};\\
E(Y) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} yf(x,y)\,dx\,dy = \int_{0}^{1}\int_{-x}^{x} y\,dy\,dx = 0;\\
&\Rightarrow Cov(X,Y) = E(XY) - E(X)E(Y) = 0 \Rightarrow \rho(X,Y) = 0
\end{aligned}$$

Thus X and Y are uncorrelated.

The marginal p.d.f. of X is

$$\begin{aligned}
f_X(x) &= \int_{-\infty}^{\infty} f(x,y)\,dy\\
&= \begin{cases} \int_{-x}^{x} dy, & \textit{if } 0 < x < 1\\ 0, & \textit{otherwise}\end{cases}\\
&= \begin{cases} 2x, & \textit{if } 0 < x < 1\\ 0, & \textit{otherwise}\end{cases}
\end{aligned}$$

Similarly, the marginal p.d.f. of Y is

$$\begin{aligned}
f_Y(y) &= \int_{-\infty}^{\infty} f(x,y)\,dx\\
&= \begin{cases} \int_{|y|}^{1} dx, & \textit{if } -1 < y < 1\\ 0, & \textit{otherwise}\end{cases}\\
&= \begin{cases} 1-|y|, & \textit{if } -1 < y < 1\\ 0, & \textit{otherwise}\end{cases}
\end{aligned}$$

Since $f(x,y) \neq f_X(x)f_Y(y)$, X and Y are not independent.

We can also show that X and Y are not independent by another way. Then the support of $\underline{Z}, X$ and Y are

$$E_{\underline{Z}} = \{(x,y) \in \mathbb{R}^2 \mid 0 < |y| \leq x < 1\}$$
$$E_X = (0,1)$$

and

$$E_Y = (-1,1),$$

respectively. Clearly $E_{\underline{Z}} \neq E_X \times E_Y$. So, X and Y are not independent.

This example also shows that X and Y are uncorrelated but not independent.