

$\text{Var}(X+X) \neq 2\text{Var}(X)$.

Let \underline{X} and \underline{Y} be two r.v.. The covariance of X and Y will be defined as

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

$$[Y = X; \text{Cov}(X, X) = \text{Var}(X)]$$

Defⁿ: (Standard Deviation)

$$S.D. = \sigma_X = \sqrt{\text{Var}(X)}$$

$$\begin{aligned} \# \text{ Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\ &= E[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y] \\ &= E[XY] - \mu_X \mu_Y - \cancel{\mu_Y \mu_X} + \cancel{\mu_X \mu_Y} \\ &= E[XY] - E[X]E[Y] \end{aligned}$$

$$(i) \operatorname{Cov}(X, Y) = \operatorname{Cov}(Y, X)$$

$$\begin{aligned}(ii) \operatorname{Cov}(aX, Y) &= E[(aX)Y] - E[aX]E[Y] \\ &= aE[XY] - aE[X]E[Y] \\ &= a\operatorname{Cov}(X, Y).\end{aligned}$$

$$(iii) \operatorname{Cov}(X+Y, Z) = \operatorname{Cov}(X, Z) + \operatorname{Cov}(Y, Z)$$

$$(iv) \operatorname{Cov}\left(\sum_{i=1}^n X_i, Y\right) = \sum_{i=1}^n \operatorname{Cov}(X_i, Y)$$

$$(v) \operatorname{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = \sum_{i=1}^n \operatorname{Cov}\left(X_i, \sum_{j=1}^m Y_j\right)$$

$$= \sum_i \operatorname{Cov}\left(\sum_j Y_j, X_i\right)$$

$$= \sum_i \sum_j \operatorname{Cov}(X_i, Y_j)$$

$$\begin{aligned} (vi) \operatorname{Var}(X+Y) &= \operatorname{Cov}(X+Y, X+Y) \\ &= \operatorname{Cov}(X, X) + \operatorname{Cov}(Y, Y) + \operatorname{Cov}(X, Y) + \operatorname{Cov}(Y, X) \end{aligned}$$

$$\Rightarrow \text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2 \text{Cov}(X, Y)$$

$$(viii) \text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_i \text{Var}(X_i)$$

$$+ \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \text{Cov}(X_i, X_j)$$

[Verify]

(viii) If X and Y are independent r.v.s.
then,

$$\text{Cov}(X, Y) = 0$$

Sol:

$$E[XY] = \sum_i \sum_j x_i y_j p_{X,Y}(x_i, y_j)$$

$$= \sum_i \sum_j x_i y_j p_X(x_i) p_Y(y_j)$$

$$= \left(\sum_i x_i p_X(x_i) \right) \left(\sum_j y_j p_Y(y_j) \right)$$

$$\Rightarrow E[XY] = E[X] E[Y]$$

$$\Rightarrow \text{Cov}(X, Y) = 0.$$

Ex: let $X \sim U(-1, 1)$, $f_X(x) = \begin{cases} \frac{1}{2} & \text{if } -1 \leq x \leq 1 \\ 0 & \text{ow} \end{cases}$

Define $Y = X^2$.

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \int_{-1}^1 \frac{x}{2} dx = 0$$

$$E[Y] = E[X^2] = \int_{-\infty}^{\infty} x^2 f_X(x) dx = \int_{-1}^1 \frac{x^2}{2} dx = \frac{1}{3}$$

$$E[XY] = E[X^3] = \int_{-\infty}^{\infty} x^3 f_X(x) dx = \int_{-1}^1 \frac{x^3}{2} dx = 0$$

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &= 0 - 0 \times \frac{1}{3} = 0. \end{aligned}$$

Ex Compute the variance of the sum obtained when 10 independent rolls of a fair dice are made.

X_i : outcome of i th roll of a fair dice

$X_i \in \{1, 2, \dots, 6\}$, $i = 1, 2, \dots, 10$.

$$\text{Var}(X_i) = \frac{35}{12},$$

$$\text{Cov}(X_i, X_j) = 0 \quad \forall i \neq j.$$

$$\text{Var}\left(\sum_{i=1}^{10} X_i\right) = \sum_{i=1}^{10} \text{Var}(X_i) + \sum_{i=1}^{10} \sum_{\substack{j=1 \\ j \neq i}}^{10} \text{Cov}(X_i, X_j)$$

$$= \sum_{i=1}^{10} \frac{35}{12} = 10 \times \frac{35}{12}$$

$$= \frac{175}{6}$$

Ex: Compute the variance of the number of heads resulting from 10 independent tosses of a fair coin.

Sol: let $I_j = \begin{cases} 1 & \text{if } j^{\text{th}} \text{ toss results heads} \\ 0 & \text{tails} \end{cases}$

Total no. of Heads $= \sum_{j=1}^{10} I_j$, $\text{Cov}(I_i, I_j) = 0$
if $i \neq j$.

$$\Rightarrow \text{Var} \left(\sum_{j=1}^{10} I_j \right) = \sum_{j=1}^{10} \text{Var}(I_j)$$

$$= \sum_{j=1}^{10} \frac{1}{2} \left(1 - \frac{1}{2} \right)$$

$$= 10 \times \frac{1}{4} = \frac{5}{2}.$$

$$\text{Var}(I)$$

$$= P(A)[1 - P(A)]$$

$X = \begin{cases} 1 & \text{if event A occurs} \\ 0 & \text{if } \text{~~~~~} \text{does not occur.} \end{cases}$

$Y = \begin{cases} 1 & \text{if event B occurs} \\ 0 & \text{if } \text{~~~~~} \text{does not occur.} \end{cases}$

$XY = \begin{cases} 1 & \text{if } X=1, Y=1 \\ 0 & \text{otherwise.} \end{cases}$

$$E[XY] = P[X=1, Y=1]$$

$$E[X] = P[X=1]$$

$$E[Y] = P[Y=1]$$

$$\text{Cov}(X, Y) = E[XY] - E[X]E[Y]$$

$$= P[X=1, Y=1] - P[X=1]P[Y=1].$$

Now,

$$\text{Cov}(X, Y) > 0$$

(<)

$$\Leftrightarrow P[X=1, Y=1] > P[X=1] P[Y=1]$$

(<)

$$\Leftrightarrow \frac{P[X=1, Y=1]}{P[X=1]} > P[Y=1]$$

(<)

$$\Leftrightarrow P[Y=1 | X=1] > P[Y=1]$$

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In general,

$\text{Cov}(X, Y) > 0$ indicates that Y tends to increase as X does.

$\text{Cov}(X, Y) < 0$ indicates that Y tends to decrease as X increases.

Def! Correlation between X and Y.

$$\begin{aligned}\rho_{X,Y} &= \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y} \\ &= \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}}\end{aligned}$$

Ex! $\rho_{X,Y} \in [-1, 1]$. [Hint: $E[(X-\mu_X) + (Y-\mu_Y)]^2$]

Markov's Inequality

If X is a random variable that takes only non-negative values, then for any value $a > 0$,

$$P[X \geq a] \leq \frac{E[X]}{a}.$$

Proof:

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$$

$$= \int_0^{\infty} x f_X(x) dx$$

$$= \int_0^a x f_X(x) dx + \int_a^{\infty} x f_X(x) dx$$

$$\geq \int_a^{\infty} x f_X(x) dx \geq a \int_a^{\infty} f_X(x) dx \\ = a P[X \geq a]$$

$\forall a > 0,$

$$P[X \geq a] \leq \frac{E[X]}{a}.$$

Chebyshev's inequality

If X is a r.v. with mean μ_X and variance σ_X^2 , then for any $k > 0$,

$$P[|X - \mu_X| \geq k] \leq \frac{\sigma^2}{k^2}$$

Sol: $\{ |X - \mu_X| \geq k \} \Leftrightarrow \{ (X - \mu_X)^2 \geq k^2 \}$

Now, $P[(X - \mu_x)^2 \geq k^2] \leq \frac{E[(X - \mu_x)^2]}{k^2}$

$$= \frac{\sigma_x^2}{k^2}$$

$$\Rightarrow P[|X - \mu_x| \geq k] \leq \frac{\sigma_x^2}{k^2}$$

The weak law of large numbers

Let X_1, X_2, \dots be a sequence of identically distributed independent (i.i.d.) r.v.s each having mean $\mu = E[X]$.

Then, for any $\epsilon > 0$,

$$P \left[\left| \underbrace{\frac{X_1 + X_2 + \dots + X_n}{n}}_{\text{Sample mean}} - \mu \right| > \varepsilon \right] \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

Proof:

$$\sigma_x^2 < \infty.$$

$$E \left[\frac{X_1 + \dots + X_n}{n} \right] = \frac{1}{n} [E[X_1] + \dots + E[X_n]] = \mu$$

$$\text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{1}{n^2} \text{Var}(X_1 + \dots + X_n)$$

$$= \frac{1}{n^2} \sum_i \text{Var}(X_i) = \frac{\cancel{n} \sigma_x^2}{n^2}$$

$$= \frac{\sigma_x^2}{n}$$

Chebyshev's inequality:

$$P[|X - \mu| \geq k] \leq \frac{\sigma_X^2}{k^2}$$

Replacing

$$X = \frac{X_1 + \dots + X_n}{n}, \quad \mu = \mu, \quad \sigma_X^2 \text{ by } \frac{\sigma_X^2}{n}, \quad k = \varepsilon.$$

$$P\left[\left|\frac{X_1 + \dots + X_n}{n} - \mu\right| \geq \varepsilon\right] \leq \frac{\sigma_X^2}{n \varepsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$