

Covariance and Correlation

Definition of covariance: Covariance of X and Y is

$$Cov(X, Y) = E[(X - EX)(Y - EY)].$$

We can also denote $Cov(X, Y) = \sigma_{X,Y}$.

Two special cases: $Cov(X, X) = Var(X)$ and $Cov(X, c) = 0$.

Definition of correlation: Correlation of X and Y is

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

By the definition we see $\rho(X, X) = 1$, and $\rho(X, -X) = -1$.

We can show $|\rho| \leq 1$.

A list of properties of Covariance

$$(1). \text{Cov}(X, Y) = E(XY) - EX \cdot EY$$

$$(2). \text{Cov}(X, Y) = \text{Cov}(Y, X)$$

$$(3). \text{Cov}(aX, bY) = ab\text{Cov}(X, Y)$$

$$(4). \text{Cov}(X + Y, Z) = \text{Cov}(X, Z) + \text{Cov}(Y, Z)$$

Remarks:

(a) We often use property (1) to compute $\text{Cov}(X, Y)$.

(b) Property (2) says the covariance operation is symmetric about X and Y .

(c) By (3) we know $\text{Cov}(X, -Y) = -\text{Cov}(X, Y)$.

(d) By (4) and (2) we know

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

Ex1

If X and Y are independent, then

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

and

$$\rho_{X,Y} = 0.$$

Proof: $\text{Cov}(X, Y) = E(XY) - EX \cdot EY$. By independence, we know $E(XY) = EX \cdot EY$, so $\text{Cov}(X, Y) = 0$.

By definition of correlation,

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = 0.$$

Therefore,

if $\text{Cov}(X, Y) \neq 0$, then X and Y are not independent.

Ex2

Suppose X and Z are independent. $Var(X) = 1$ and $Var(Z) = 0.01$. $Y = X + Z$. Compute the correlation between X and Y .

Solution: Use the definition.

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

$$\begin{aligned} Cov(X, Y) &= Cov(X, X + Z) \\ &= Cov(X, X) + Cov(X, Z) = 1 + 0 = 1. \end{aligned}$$

$$\begin{aligned} Var(Y) &= Var(X + Z) \\ &= Var(X) + Var(Z) \\ &\quad \text{by independence assumption} \\ &= 1.01. \end{aligned}$$

So

$$\rho_{X,Y} = \frac{1}{\sqrt{1.01}} = 0.995.$$

A useful variance formula

$$\begin{aligned} & \text{Var}(aX + bY) \\ &= a^2\text{Var}(X) + 2ab\text{Cov}(X, Y) + b^2\text{Var}(Y). \end{aligned}$$

Proof:

$$\begin{aligned} & \text{Var}(aX + bY) \\ &= \text{Cov}(aX + bY, aX + bY) \\ &= \text{Cov}(aX, aX + bY) + \text{Cov}(bY, aX + bY) \\ &= \text{Cov}(aX, aX) + \text{Cov}(aX, bY) \\ & \quad + \text{Cov}(bY, aX) + \text{Cov}(bY, bY) \\ &= a^2\text{Cov}(X, X) + 2ab\text{Cov}(X, Y) + b^2\text{Cov}(Y, Y) \\ &= a^2\text{Var}(X) + 2ab\text{Cov}(X, Y) + b^2\text{Var}(Y). \end{aligned}$$

A more general formula If X_1, X_2, \dots, X_n be n random variables, a_1, a_2, \dots, a_n are constants.

Then

$$\begin{aligned} & \text{Var}(a_1X_1 + \dots + a_nX_n) \\ &= \sum_{i=1}^n a_i^2\text{Var}(X_i) + 2 \sum_{i < j}^n a_i a_j \text{Cov}(X_i, X_j). \end{aligned}$$

The proof is left as an optional Hw problem.

Ex3 If $Var(X) = 1$, $Var(Y) = 2$ and $Cov(X, Y) = -1$. If $U = 3X - 2Y$, $V = X + 2Y$. Find $Var(U)$, $Var(V)$ and $Cov(U, V)$.

$$\begin{aligned}Var(U) &= Var(3X - 2Y) \\&= 3^2Var(X) + 2 \cdot 3 \cdot (-2)Cov(X, Y) \\&\quad + (-2)^2Var(Y) \\&= 9 \cdot 1 + 2 \cdot 3 \cdot (-2) \cdot (-1) + 4 \cdot 2 = 29.\end{aligned}$$

$$\begin{aligned}Var(V) &= Var(X + 2Y) \\&= 1^2Var(X) + 2 \cdot 1 \cdot 2Cov(X, Y) \\&\quad + (2)^2Var(Y) \\&= 1 - 4 + 8 = 5.\end{aligned}$$

$$\begin{aligned}Cov(U, V) &= Cov(3X - 2Y, X + 2Y) \\&= Cov(3X - 2Y, X) + Cov(3X - 2Y, 2Y) \\&= Cov(3X, X) + Cov(-2Y, X) \\&\quad + Cov(3X, 2Y) + Cov(-2Y, 2Y) \\&= 3Cov(X, X) + (-2)Cov(Y, X) \\&\quad + 3 \cdot 2Cov(X, Y) + (-2) \cdot 2Cov(Y, Y) \\&= 3Var(X) + 4Cov(X, Y) - 4Var(Y) \\&= 3 - 4 - 4(2) = -9.\end{aligned}$$

Proof of $|\rho| \leq 1$

We want to show for any X, Y , $|\rho(X, Y)| \leq 1$.

Let $Z_t = X - tY$ where t is a real number. Then we have

$$\text{Var}(Z_t) = \text{Var}(X) - 2t\text{Cov}(X, Y) + t^2\text{Var}(Y)$$

Let $g(t) = \text{Var}(Z_t)$ as a function of t . Consider $t = t_0 = \frac{\text{Cov}(X, Y)}{\text{Var}(Y)}$. We find

$$g(t_0) = \text{Var}(X) - \frac{[\text{Cov}(X, Y)]^2}{\text{Var}(Y)}$$

Since $g(t) = \text{Var}(Z_t) \geq 0$ for all t , we must have

$$\text{Var}(X) - \frac{[\text{Cov}(X, Y)]^2}{\text{Var}(Y)} \geq 0$$

which means

$$1 \geq \frac{[\text{Cov}(X, Y)]^2}{\text{Var}(X)\text{Var}(Y)}$$

Thus by the definition of $\rho(X, Y)$ we see

$$1 \geq \rho^2(X, Y).$$

Markov Inequality

Let X be a positive random variable and $E[X] < \infty$. Then for every positive real number a , we have

$$\Pr(X > a) \leq \frac{E[X]}{a}.$$

Proof: We note that

$$Y = X - aI(X > a) \geq 0$$

Why? because if $X \leq a$ then $Y = X - 0 = X > 0$; and if $X \geq a$, then $Y = X - a \geq 0$. Since Y is a non-negative random variable, by the definition of expectation, its mean is greater or equal to zero, so $E[Y] \geq 0$.

$$E[Y] = E[X - aI(X > a)] = E[X] - aE[I(X > a)]$$

Thus we end up with

$$E[X] \geq aE[I(X > a)] = a\Pr(X > a).$$

We used the fact $E[I(X > a)] = \Pr(X > a)$.

Chebyshev Inequality

Let X be a random variable with mean μ and variance σ^2 . Then for any $a > 0$ we have

$$\Pr(|X - \mu| > a) \leq \frac{\text{Var}(X)}{a^2}.$$

Proof: We use Markov inequality. Observe the following fact

$$\Pr(|X - \mu| > a) = \Pr((X - \mu)^2 > a^2)$$

By Markov inequality, we know

$$\Pr((X - \mu)^2 > a^2) \leq \frac{E[(X - \mu)^2]}{a^2}$$

where we consider $(X - \mu)^2$ is the X in Markov inequality. Note that

$$E[(X - \mu)^2] = \text{Var}(X)$$

Hence we end up with

$$\Pr(|X - \mu| > a) \leq \frac{\text{Var}(X)}{a^2}.$$

Let $a = k\sigma$ in Chebyshev inequality, we then have

$$\Pr(|X - \mu| > k\sigma) \leq \frac{\text{Var}(X)}{k^2\sigma^2} = \frac{1}{k^2}$$

suppose $k = 3$, then

$$\Pr(|X - \mu| > 3\sigma) \leq \frac{1}{9} = 0.11.$$

Or we can conclude that

$$\Pr(\mu - 3\sigma < X < \mu + 3\sigma) \geq 1 - \frac{1}{9} = 0.89.$$

With 89% chance the value of X will fall into the interval $(\mu - 3\sigma, \mu + 3\sigma)$.

An important application of Chebyshev inequality

Let X_1, \dots, X_n be iid random variables. We assume they have a common mean μ and variance σ^2 . Let

$$\bar{X} = \frac{\sum_{i=1}^n X_i}{n}.$$

Then for $a > 0$,

$$\Pr(|\bar{X} - \mu| > a) \leq \frac{\sigma^2}{na^2}.$$

Why? Use Chebyshev inequality on \bar{X} . By the iid assumption,

$$\text{Var}(\bar{X}) = \frac{1}{n} \text{Var}(X_1) = \frac{1}{n} \sigma^2$$

Chebyshev inequality says

$$\Pr(|\bar{X} - \mu| > a) \leq \frac{\text{Var}(\bar{X})}{a^2} = \frac{\sigma^2}{na^2}.$$

The Law of Large Numbers

Because for any $a > 0$ (no matter how small it is),

$$\Pr(|\bar{X} - \mu| > a) \leq \frac{\sigma^2}{na^2},$$

we can conclude

$$\lim_{n \rightarrow \infty} \Pr(|\bar{X} - \mu| > a) = 0.$$

The above equation tells us the sample mean converges to the true mean in probability. This is called the weak law of large numbers.

There is also the strong law of large numbers.

The mathematical expression is

$$\Pr(\lim_{n \rightarrow \infty} \bar{X} = \mu) = 1.$$