

1 Covariance

Let X and Y be two random variables, with mean μ_X and μ_Y respectively. The *covariance* $\text{Cov}(X, Y)$ of X and Y is defined as:

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

Observations

- $\text{Cov}(X, X) = E[(X - \mu_X)(X - \mu_X)] = \text{Var}(X)$.
- $\text{Cov}(X, Y) := E[(X - \mu_X)(Y - \mu_Y)] = E[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y] = E[XY] - \mu_X \mu_Y$.
- X, Y independent $\implies \text{Cov}(X, Y) = 0$.

PROOF X, Y independent $\implies f_{X,Y}(x, y) = f_X(x)f_Y(y) \implies E[XY] = \int xy \cdot f_{X,Y}(x, y) dx dy$

$$= \int xy \cdot f_X(x)f_Y(y) dx dy = \left(\int x \cdot f_X(x) dx \right) \left(\int y \cdot f_Y(y) dy \right) = E[X] \cdot E[Y] = \mu_X \mu_Y. \quad \square$$

Fact Let X_1, X_2, \dots, X_n be random variables, and $\alpha_1, \dots, \alpha_n \in \mathbb{R}$. Then,

$$\text{Var}(\alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_n X_n) = \sum_{i=1}^n \alpha_i^2 \text{Var}(X_i) + \sum_{1 \leq i < j \leq n} \alpha_i \alpha_j \text{Cov}(X_i, X_j)$$

2 Correlation

Let X and Y be two random variables with nonzero variance (equivalently, X, Y are non-constant). Let μ_X and μ_Y be the means of X and Y respectively. Let σ_X^2 and σ_Y^2 be the variances of X and Y respectively. The *correlation* $\rho(X, Y)$ of X and Y is defined as:

$$\rho(X, Y) := E\left[\left(\frac{X - \mu_X}{\sigma_X}\right) \cdot \left(\frac{Y - \mu_Y}{\sigma_Y}\right)\right]$$

Observations

$$\rho(X, Y) = \text{Cov}\left[\frac{X - \mu_X}{\sigma_X}, \frac{Y - \mu_Y}{\sigma_Y}\right] = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Theorem 2.1 For any two random variables X and Y ,

- $|\rho(X, Y)| \leq 1$, and
- $|\rho(X, Y)| = 1$ if and only if X and Y are affinely dependent, i.e. there exist $\alpha, \beta, \gamma \in \mathbb{R}$, not all zero, such that $\alpha X + \beta Y + \gamma = 0$ almost surely.