

Lecture 14

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Recap: $1_A : \Omega \rightarrow \mathbb{R}, A \in \mathcal{F}$

$$1_A(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}$$

Claim: $\mathbb{E}(1_A) = \mathbb{P}(A)$

$$1_A(\omega) = \begin{cases} 1 & \text{w.p. } \mathbb{P}(A) \\ 0 & \text{w.p. } 1 - \mathbb{P}(A) \end{cases}$$

$$1_A \sim \text{Bernoulli}(\mathbb{P}(A)) \implies \mathbb{E}(1_A) = \mathbb{P}(A)$$

Aside:

$$1_{A \cap B} = 1_A \cdot 1_B \quad 1_{A \cup B} = 1_A + 1_B - 1_{A \cap B}$$

$$\mathbb{E}(1_{A \cap B}) = \mathbb{E}(1_A) + \mathbb{E}(1_B) - \mathbb{E}(1_{A \cup B})$$

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cup B)$$

If X and Y are independent, then $\text{Cov}(X, Y) = 0$. But if $\text{Cov}(X, Y) = 0$, then we cannot that X and Y are independent.

E.g.: $X \sim U(-1, 1), Y = X^2$

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

$$= \mathbb{E}(X^3) = \int_{-1}^1 x^3 \frac{dx}{2}$$

$$= \left. \frac{x^4}{4} \right|_{-1}^1 = 0$$

Detailed proof that X and Y are not independent,

$$\begin{aligned} F_{X,Y}(x, y) &= \mathbb{P}(X \leq x, Y \leq y) \\ &= \mathbb{P}(X \leq x, X^2 \leq y) \\ &= \mathbb{P}(-1 \leq X \leq x, -\sqrt{y} \leq X \leq \sqrt{y}) \\ &= \mathbb{P}(-\sqrt{y} \leq X \leq \min(x, \sqrt{y})) \\ &= \mathbb{P}(-\sqrt{y} < X \leq \min(x, \sqrt{y})) \\ &= F_X(\min(x, \sqrt{y})) - F_X(-\sqrt{y}) \\ &= \frac{\min(x, \sqrt{y}) + \sqrt{y}}{2} \end{aligned}$$

which cannot be factor into $F_X(x)F_Y(y)$.

$$F_{X,Y}(x, y) = \begin{cases} \mathbb{P}(-\sqrt{y} < X \leq x) & -\sqrt{y} < x \\ 0 & -\sqrt{y} \geq x \end{cases}$$

Properties of the covariance

Proof: 1. $\text{Cov}(X, X) = \text{Var } X$

$$\begin{aligned} \text{Cov}(X, X) &= \mathbb{E}[(X - \mathbb{E}X)(X - \mathbb{E}X)] \\ &= \mathbb{E}[(X - \mathbb{E}X)^2] \\ &= \text{Var } X \end{aligned}$$

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

$$\begin{aligned} \text{Cov}(X, Y) &= \mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)] \\ &= \mathbb{E}[(Y - \mathbb{E}Y)(X - \mathbb{E}X)] \\ &= \text{Cov}(Y, X) \end{aligned}$$

Proof: 3. $\text{Cov}(cX, Y) = c \text{Cov}(X, Y)$, $c \in \mathbb{R}$

$$\begin{aligned}\text{Cov}(cX, Y) &= \mathbb{E}(cX \cdot Y) - \mathbb{E}(cX)\mathbb{E}Y \\ &= c\mathbb{E}(XY) - c\mathbb{E}X\mathbb{E}Y \\ &= c\{\mathbb{E}(XY) - \mathbb{E}X\mathbb{E}Y\} \\ &= c \text{Cov}(X, Y)\end{aligned}$$

Similarly,

$$\begin{aligned}\text{Cov}(X, cY) &= \text{Cov}(cY, X) \\ &= c \text{Cov}(Y, X) \\ &= c \text{Cov}(X, Y)\end{aligned}$$

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

$$\begin{aligned}\text{Cov}(X, Y + Z) &= \mathbb{E}(X(Y + Z)) - \mathbb{E}X \cdot \mathbb{E}(Y + Z) \\ &= \mathbb{E}(XY) + \mathbb{E}(XZ) - \mathbb{E}X\{\mathbb{E}Y + \mathbb{E}Z\} \\ &= \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) + \mathbb{E}(XZ) - \mathbb{E}X \cdot \mathbb{E}Z \\ &= \text{Cov}(X, Y) + \text{Cov}(X, Z)\end{aligned}$$

Similarly,

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

Proof: By mathematical induction, properties 2-4 imply

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

\therefore We say that covariance is a symmetric, bi-linear operator.

$$\begin{bmatrix} x_1^2 & x_1 x_2 & \cdots & x_1 x_n \\ x_2 x_1 & x_2^2 & \cdots & x_2 x_n \\ \vdots & \vdots & \ddots & \vdots \\ x_n x_1 & x_n x_2 & \cdots & x_n^2 \end{bmatrix}$$

$$\begin{aligned}\text{Var}\left(\sum_{i=1}^n X_i\right) &= \text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^n X_j\right) \\ &= \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, X_j) \\ &= \sum_{i=1}^n \text{Cov}(X_i, X_i) + \sum_{i \neq j}^n \text{Cov}(X_i, X_j) \\ &= \sum_{i=1}^n \text{Var } X_i + 2 \sum_{i \leq j \leq n} \text{Cov}(X_i, X_j)\end{aligned}$$

Specialize $n = 2$:

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

Specialize X_i s are independent:

$$\text{Var}(\text{sum}) = \text{sum}(\text{Var})$$