

Lecture 15

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October 7, 2022

Covariance

Recap:

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

If the X_i 's are independent, then

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

E.g.: In Section 2.6, we will show that if $Y \sim \text{Gamma}(n, \lambda)$, $n \in \mathbb{N}$, then $Y \sim X_1 + X_2 + \cdots + X_n$ in which $X_i \sim \text{Exp}(\lambda)$ and the X_i s are independent.

$$\begin{aligned} \text{Var } Y &= \text{Var}(X_1 + \cdots + X_n) \\ &= \sum_{i=1}^n \text{Var } X_i \\ &= \sum_{i=1}^n \frac{1}{\lambda^2} = \frac{n}{\lambda^2} \end{aligned}$$

E.g.: Suppose $X \sim \text{Bern}(p)$

$$\begin{aligned} X &= \begin{cases} 1 & \text{w.p. } p \\ 0 & \text{w.p. } 1-p \end{cases} \\ \mathbb{E}(X^k) &= 1^k \cdot p + 0^k(1-p) = p, \quad k > 0 \\ \implies \text{Var } X &= \mathbb{E}(X^2) - (\mathbb{E}X)^2 = p - p^2 = p(1-p) \end{aligned}$$

Aside: max when $p = \frac{1}{2}$

Defn: If $Y \sim \text{Bin}(n, p)$, $n \in \mathbb{N}$

The number of successes in n independent trials in which the probability of success is p for any trial.

Let X_i = outcome of the i^{th} trial so that

$$X_i = \begin{cases} 1 & \text{if success, w.p. } p \\ 0 & \text{if failure, w.p. } 1-p \end{cases}$$

$$Y = X_1 + \cdots + X_n,$$

where X_i is independent and identically distributed(IID) $\text{Bern}(p)$.

$$\mathbb{E}Y = \sum_{i=1}^n \mathbb{E}X_i = \sum_{i=1}^n p = np$$

$$\text{Var } Y = n \text{Var } X_1 = np(1-p)$$

Defn: More properties of the covariance:

Last time we showed that Covariance is symmetric and bilinear.

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

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

The same is true for dot product of two vectors \vec{x}, \vec{y} :

$$\begin{aligned} \vec{x} \cdot \vec{y} &= \sum_{i=1}^n x_i y_i \\ \vec{x} \cdot \vec{y} &= \vec{y} \cdot \vec{x} \\ |\vec{x} \cdot \vec{y}|^2 &\leq (\vec{x} \cdot \vec{x})(\vec{y} \cdot \vec{y}) \\ |\vec{x} \cdot \vec{y}| &= \|\vec{x}\| \times \|\vec{y}\| \times \cos \theta \end{aligned}$$

Proof: $|\text{Cov}(X, Y)| \leq \sqrt{\text{Var } X \cdot \text{Var } Y}$

1. $\text{Var } Y = 0$

$$\implies \mathbb{E}[(Y - \mathbb{E}Y)^2] = 0$$

because $(Y - \mathbb{E}Y)^2 \geq 0$,

$$\begin{aligned} \implies Y - \mathbb{E}Y &= 0, & \text{w.p. } 1 \\ \implies \mathbb{P}(Y = a) &= 1 & \exists a \in \mathbb{R} \end{aligned}$$

For example, $X \sim U(0, 1)$

$$\begin{aligned} Y &= \begin{cases} \frac{1}{2} & \text{if } X < \frac{1}{2} \text{ or } X > \frac{1}{2} \\ -\frac{1}{2} & \text{if } X = \frac{1}{2} \end{cases} \\ \therefore Y &= \frac{1}{2} & \text{w.p. } 1 \end{aligned}$$

2. $\text{Var } Y > 0$

Define $Z = X - \frac{\text{Cov}(X, Y)}{\text{Var } Y} \cdot Y$, $\text{Var } Z \geq 0$,

$$\begin{aligned} \text{Var } Z &= \text{Cov}(Z, Z) \\ &= \text{Cov} \left(X - \frac{\text{Cov}(X, Y)}{\text{Var } Y} \cdot Y, X - \frac{\text{Cov}(X, Y)}{\text{Var } Y} \cdot Y \right) \\ &= \text{Cov}(X, X) - 2 \frac{\text{Cov}(X, Y)}{\text{Var } Y} \cdot \text{Cov}(X, Y) + \left(\frac{\text{Cov}(X, Y)}{\text{Var } Y} \right)^2 \cdot \text{Cov}(Y, Y) \end{aligned}$$

$$\begin{aligned} \implies 0 &\leq \text{Var } X - \frac{(\text{Cov}(X, Y))^2}{\text{Var } Y} \\ \implies (\text{Cov}(X, Y))^2 &\leq \text{Var } X \cdot \text{Var } Y \\ \implies \text{Cov}(X, Y) &\leq \sqrt{\text{Var } X \cdot \text{Var } Y} \end{aligned}$$

Cor:

$$\rho_{X, Y} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var } X \cdot \text{Var } Y}} \in [-1, 1]$$