

Review

- $E[X_1 + \dots + X_n] = \sum_{i=1}^n E[X_i]$
- (linearity of expectation)
- For two r.v.'s X and Y ,

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

In particular, $\text{Cov}(X, X) = \text{Var}(X)$.

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

Pf. Write $\mu = E[X]$, $\nu = E[Y]$.

$$\begin{aligned}
 \text{Then } \text{Cov}(X, Y) &= E[(X-\mu)(Y-\nu)] \\
 &= E[XY - \mu Y - \nu X + \mu \nu] \\
 &= E[XY] - \mu E[Y] - \nu E[X] + \mu \nu \\
 &= E[XY] - \mu \nu. \quad \blacksquare
 \end{aligned}$$

- If X and Y are independent, then

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

Prop 1. (1) $\text{Cov}(X, Y) = \text{Cov}(Y, X).$

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

(3) $\text{Cov}(\alpha X, Y) = \alpha \text{Cov}(X, Y), \quad \alpha \in \mathbb{R}.$

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

$$= \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j).$$

(1), (3), (4) imply that $\text{Cov}(\cdot, \cdot)$ is bi-linear.

Pf. Let us prove (4) only. Write $\mu_i = E[X_i]$,
 $\nu_j = E[Y_j].$

Then by definition,

$$\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = E\left[\left(\sum_{i=1}^n X_i - \sum_{i=1}^n \mu_i\right) \cdot \left(\sum_{j=1}^m Y_j - \sum_{j=1}^m \nu_j\right)\right]$$

$$= E \left[\sum_{i=1}^n (X_i - \mu_i) \sum_{j=1}^m (Y_j - \nu_j) \right]$$

$$= E \left[\sum_{i=1}^n \sum_{j=1}^m (X_i - \mu_i)(Y_j - \nu_j) \right]$$

By the linearity of E

$$= \sum_{i=1}^n \sum_{j=1}^m E[(X_i - \mu_i)(Y_j - \nu_j)]$$

$$= \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j).$$

□

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

Moreover if X_1, \dots, X_n are pairwise independent,

then

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

Example 1. Let X_1, \dots, X_n be independent and identical distributed, having expected value μ and variance σ^2 .

$$\text{Let } \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \quad (\text{Sample mean})$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (\text{sample variance})$$

Find out ① $\text{Var}(\bar{X})$.

② $E[S^2]$.

$$\text{Solution: } \text{Var}(\bar{X}) = \text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right)$$

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

(notice X_1, \dots, X_n
are independent)

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i)$$

$$= \frac{n \cdot \sigma^2}{n^2} = \sigma^2/n.$$

Recall that $S^2 = \sum_{i=1}^n \frac{(x_i - \bar{x})^2}{n-1}$

So

$$\begin{aligned}
 (n-1)S^2 &= \sum_{i=1}^n (x_i - \bar{x})^2 \\
 &= \sum_{i=1}^n ((x_i - \mu) - (\bar{x} - \mu))^2 \\
 &= \sum_{i=1}^n \left[(x_i - \mu)^2 - 2(x_i - \mu)(\bar{x} - \mu) \right. \\
 &\quad \left. + (\bar{x} - \mu)^2 \right] \\
 &= \sum_{i=1}^n (x_i - \mu)^2 - 2(\bar{x} - \mu) \cdot \sum_{i=1}^n (x_i - \mu) \\
 &\quad + n \cdot (\bar{x} - \mu)^2 \\
 &= \sum_{i=1}^n (x_i - \mu)^2 - 2n(\bar{x} - \mu)^2 + n(\bar{x} - \mu)^2 \\
 &= \sum_{i=1}^n (x_i - \mu)^2 - n(\bar{x} - \mu)^2
 \end{aligned}$$

Hence $E[(n-1)S^2] = \sum_{i=1}^n E[(x_i - \mu)^2]$

$$\begin{aligned}
 &\quad - n E[(\bar{x} - \mu)^2] \\
 &= n \cdot \sigma^2 - n \cdot \frac{\sigma^2}{n}
 \end{aligned}$$

$$= (n-1)\sigma^2.$$

Thus $E[S^2] = \sigma^2$.

□

Example 2. Define \bar{X} as in Example 1.

Show that $\text{Cov}(X_i - \bar{X}, \bar{X}) = 0$

Pf. $\text{Cov}(X_i - \bar{X}, \bar{X})$

$$= \text{Cov}(X_i, \bar{X}) - \text{Cov}(\bar{X}, \bar{X})$$

$$= \text{Cov}\left(X_i, \frac{X_1 + \dots + X_n}{n}\right) - \frac{\sigma^2}{n}$$

$$= \frac{1}{n} \sum_{j=1}^n \text{Cov}(X_i, X_j) - \frac{\sigma^2}{n}$$

$$= \frac{1}{n} \left[\text{Cov}(X_i, X_i) + \sum_{j \neq i} \text{Cov}(X_i, X_j) \right]$$

$$- \frac{\sigma^2}{n}$$

$$= \frac{1}{n} \text{Var}(X_i) - \frac{\sigma^2}{n} = \frac{\sigma^2}{n} - \frac{\sigma^2}{n} = 0,$$