

2.6 Variance

How far are values of X away from $E[X]$?

Definition 43 X RV, $\mu := E[X]$

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

is the variance of X .

Remarks $\text{Var}(X)$ has better mathematical properties than $E[|X - \mu|]$

Note:
$$\begin{aligned}\text{Var}(X) &= E[(X - \mu)^2] \\ &= E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + E[\mu^2] \\ &= E[X^2] - 2\mu^2 + \mu^2 \\ &= E[X^2] - E[X]^2\end{aligned}$$

Example 44 X = number shown when rolling a die. We know $E[X] = \frac{7}{2}$.

$$E[X^2] = \frac{91}{6} \quad (\text{Example 37})$$

$$\begin{aligned}\Rightarrow \text{Var}(X) &= E[X^2] - E[X]^2 \\ &= \frac{91}{6} - \left(\frac{7}{2}\right)^2 = \frac{91}{6} - \frac{49}{4} = \frac{182 - 147}{12} = \frac{35}{12}\end{aligned}$$

Properties of $\text{Var}(\cdot)$. Let $E[X] = \mu$

$$\begin{aligned}\text{Var}(aX+b) &= E[(aX+b - E[aX+b])^2] \\ &= E[(aX+b - a\mu - b)^2] \\ &= E[(aX - a\mu)^2] \\ &= E[a^2(X-\mu)^2] = a^2 E[(X-\mu)^2] \\ &= a^2 \text{Var}(X)\end{aligned}$$

We call $\sigma := \sqrt{\text{Var}(X)}$ the standard deviation of X .

Note that then

$$\text{Var}(X) = \sigma^2$$

2.7 Covariance

We note

$$\text{Var}(X + X) = \text{Var}(2X) = 4 \text{Var}(X)$$

$$\neq \text{Var}(X) + \text{Var}(X)$$

What about $\text{Var}(X + Y)$ if X, Y are indep.?

Definition 45 X, Y RVs, $\mu_X = E[X], \mu_Y = E[Y]$

Then

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

Note: This assumes a joint distribution of X and Y .

Property of Cov

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

Proposition 46 $\text{Cov}(X_1 + X_2, Y) = \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)$

$$\begin{aligned}\text{Cov}(X_1 + X_2, Y) &= E[(X_1 + X_2) \cdot Y] - E[X_1 + X_2]E[Y] \\ &= E[X_1 Y] + E[X_2 Y] - E[X_1]E[Y] - E[X_2]E[Y] \\ &= E[X_1 Y] - E[X_1]E[Y] + E[X_2 Y] - E[X_2]E[Y] \\ &= \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)\end{aligned}$$

Theorem 47

$$\text{Cov}\left(\sum_i X_i, \sum_j Y_j\right) = \sum_i \sum_j \text{Cov}(X_i, Y_j)$$

Consequence:

$$\text{Var}\left(\sum_i X_i\right) = \text{Cov}\left(\sum_i X_i, \sum_i X_i\right)$$

$$= \sum_i \sum_j \text{Cov}(X_i, X_j)$$

$$= \sum_i \left(\sum_{j \neq i} \text{Cov}(X_i, X_j) + \text{Cov}(X_i, X_i) \right)$$

$$= \sum_i \sum_{j \neq i} \text{Cov}(X_i, X_j) + \sum_i \text{Cov}(X_i, X_i)$$

$$= \sum_i \text{Var}(X_i, X_i) + \sum_i \sum_{j \neq i} \text{Cov}(X_i, X_j)$$

For $n=2$:

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

Theorem 48

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

Proof: Show $E[XY] = E[X]E[Y]$. For continuous case let f, g be the densities of X, Y ; resp.

$$\begin{aligned} E[XY] &= \int_{\mathbb{R}} \int_{\mathbb{R}} x \cdot y f(x) g(y) dx dy \\ &= \int_{\mathbb{R}} y g(y) \left(\int_{\mathbb{R}} x f(x) dx \right) dy \\ &= \int_{\mathbb{R}} y g(y) E[X] dy \\ &= E[X] E[Y] \end{aligned}$$

For discr. case by distributive law.

Example 49 Variance of sum of 10 independent rolls of a die.

let X_i be i -th roll.

$$\begin{aligned} \text{Var} \left(\sum_{i=1}^n X_i \right) &= \sum_{i=1}^n \text{Var}(X_i) = \\ &\quad \underbrace{\hspace{10em}}_{\text{independence}} \\ &= \sum_{i=1}^n \frac{35}{12} = 10 \cdot \frac{35}{12} = \frac{175}{6} \end{aligned}$$

Meaning of covariance $\text{Cov}(X, Y)$

> 0 : X, Y grow together

< 0 : X, Y grow in opposite direction

Normalize: correlation!

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

This value is always in $[-1, 1]$