

Last topic : Expected value of a RV

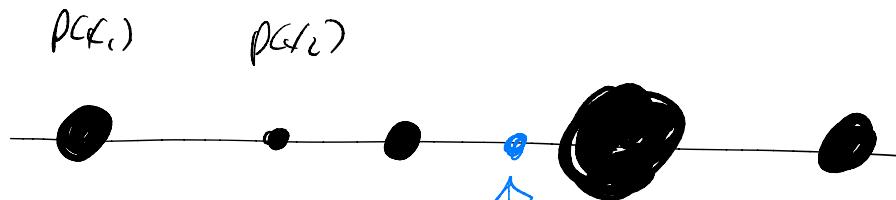
Idea: longterm average

$$X \text{ discr. } \sum_i x_i p(x_i) , \quad x_i \text{ poss. values of } X$$

$$X \text{ cont. } \int_{\mathbb{R}} x \cdot f(x) dx , \quad f \text{ pdf}$$

Another interpretation: center of gravity

X discr.: a number of points x_1, x_2, \dots ,
with weight $p(x_i)$

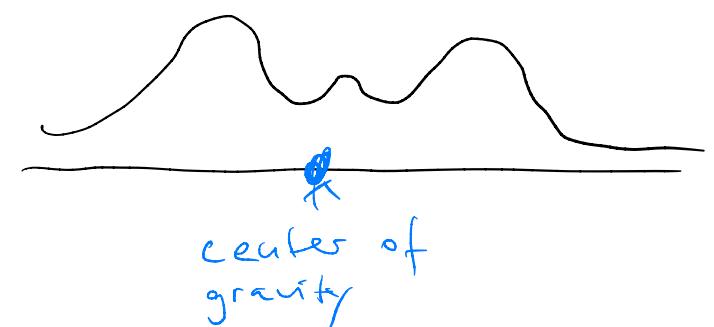


points on a
weightless rod

center of gravity
supports
the construction

X cont

weight proportional to
height of curve



Properties of Exp. V.:

$$E[aX] = a E[X]$$

$$E[b] = b$$

$$E[X + Y] = E[X] + E[Y]$$

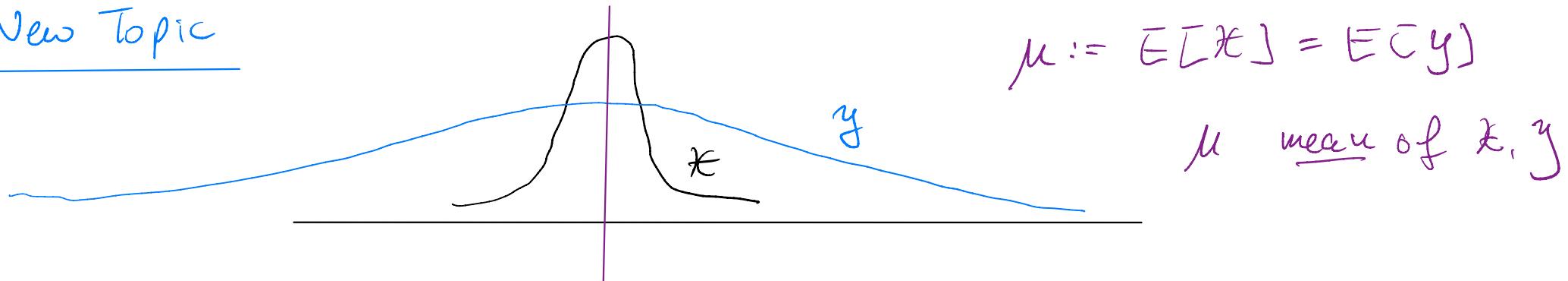
$$E[X_1 + \dots + X_n] = \sum_{i=1}^n E[X_i]$$

! holds also if
 X, Y are not
independent

thus

$$E[g(X)] = \int_{\mathbb{R}} g(x) f(x) dx$$

New Topic



$$\mu := E[X] = E[Y]$$

μ mean of x, y

Values of y are spread much farther around μ than the values of x .

2.6 Variance

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

$$g(x) = (x - \mu)^2$$

is the variance of x .

Why not

$$E[|x - \mu|] ?$$



The definition with the square has better mathematical properties.

How can we calculate $\text{Var}(X)$?

Suppose $X \sim f$.

1) Apply lotus:

$$\text{Var}(X) = \int_{\mathbb{R}} (x - \mu)^2 f(x) dx$$

$$= \int_{\mathbb{R}} (x^2 - 2x\mu + \mu^2) f(x) dx$$

$$= \int_{\mathbb{R}} x^2 f(x) dx - 2\mu \int_{\mathbb{R}} x f(x) dx + \mu^2 \int_{\mathbb{R}} f(x) dx$$

Shortcut

$$= E[X^2] - 2\mu E[X] + \mu^2 \cdot 1$$

$$= E[X^2] - 2\mu^2 + \mu^2$$

$$= E[X^2] - E[X]^2$$

\uparrow square of mean
2nd moment of X

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

$$= E[X^2 - 2\mu X + \mu^2]$$

$$= E[X^2] - 2\mu E[X] + \mu^2$$

$$= E[X^2] - 2\mu^2 + \mu^2 = E[X^2] - \mu^2$$

Example 44 X = number on die

$$E[X] = \frac{7}{2}. \quad \text{Also} \quad E[X^2] = \frac{91}{6} \quad (\text{Ex. 57})$$

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

Units: unit of measurement of H is metre, sec

\Rightarrow unit of measurement of H^2 is metre², sec²

Get back to original unit: take $\sqrt{\cdot}$:

$$\sigma := \sqrt{\text{Var}(X)}$$

is the standard deviation.

One often writes the variance as the square of the standard deviation:

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

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

$$\bullet \text{Var}(X + b) = \text{Var}(X)$$

$$\bullet \text{Var}(aX) = a^2 \text{Var}(X)$$

$$\bullet \text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) \quad \text{only if } X, Y \text{ independent}$$

$$\begin{aligned}\text{Var}(\underbrace{aX + b}_y) &= E[y^2] - E[y]^2 \\ &= E[(aX + b)^2] - E[aX + b]^2 \\ &= (E[a^2 X^2 + 2abX + b^2]) - (aE[X] + b)^2 \\ &= a^2 E[X^2] + 2ab E[X] + E[b^2] \\ &\quad - a^2 \mu^2 - 2ab \mu - b^2\end{aligned}$$

$$= a^2 E[\bar{x}^2] + 2abE[\bar{x}] + E[\bar{y}^2]$$
$$= a^2 \cancel{\mu^2} - 2ab\mu - b^2$$

$$= a^2 E(x^2) + 2ab\cancel{\mu} + \cancel{b^2}$$
$$= a^2 \cancel{\mu^2} - 2ab\cancel{\mu} - \cancel{b^2}$$

$$= a^2 (E(\bar{x}^2) - \mu^2) = a^2 \text{Var}(\bar{x})$$

Note : $\sigma_{a\bar{x}} = a \sigma_{\bar{x}}$

2.7 Covariance

We note

$$\begin{aligned}\text{Var}(\mathcal{X} + \mathcal{X}) &= \text{Var}(2\mathcal{X}) = 4 \text{Var}(\mathcal{X}) \\ &\neq \text{Var}(\mathcal{X}) + \text{Var}(\mathcal{X})\end{aligned}$$

Definition 45: \mathcal{X}, \mathcal{Y} RV, $\mu_{\mathcal{X}} = E[\mathcal{X}]$, $\mu_{\mathcal{Y}} = E[\mathcal{Y}]$

Then

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

This assumes a joint distribution of \mathcal{X} and \mathcal{Y} .

Property of Cov

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

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

Observation: X, Y independent $\Rightarrow E[XY] = E[X] \cdot E[Y]$

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

Proposition 46

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

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

Theorem 47

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

Consequence:

$$\text{Var}(\sum_i \epsilon_i) = \text{Cov}(\sum_i \epsilon_i, \sum_i \epsilon_i)$$

$$= \sum_i \sum_j \text{Cov}(\epsilon_i, \epsilon_j)$$

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

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

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

For $n=2$:

$$\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y) + 2 \text{Cov}(x, y)$$

Observation: X, Y ind. $\Rightarrow E[XY] = E[X] \cdot E[Y]$

Suppose $X \sim f$, $Y \sim g$:

$$E[XY] = \iint_{\mathbb{R}^2} x \cdot y \cdot f(x)g(y) dx dy$$

$$= \int_R y \cdot g(y) \left(\int_{\mathbb{R}} x \cdot f(x) dx \right) dy$$

$$= \int_{\mathbb{R}} x \cdot f(x) dx \cdot \int_{\mathbb{R}} y \cdot g(y) dy$$

$$= E[X] \cdot E[Y]$$

Meaning of covariance

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

> 0 : X, Y grow together in the same direction

< 0 : X, Y grow in sync in opposite directions

≈ 0 : X, Y vary independently

Normalize RVs X, Y by taking $\frac{X}{\delta_X}, \frac{Y}{\delta_Y}$,

$$\text{i.e., } \frac{X}{\sqrt{\text{Var}(X)}} \quad \frac{Y}{\sqrt{\text{Var}(Y)}}$$

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\delta_X \delta_Y}$$

Correlation
between
 X and Y

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

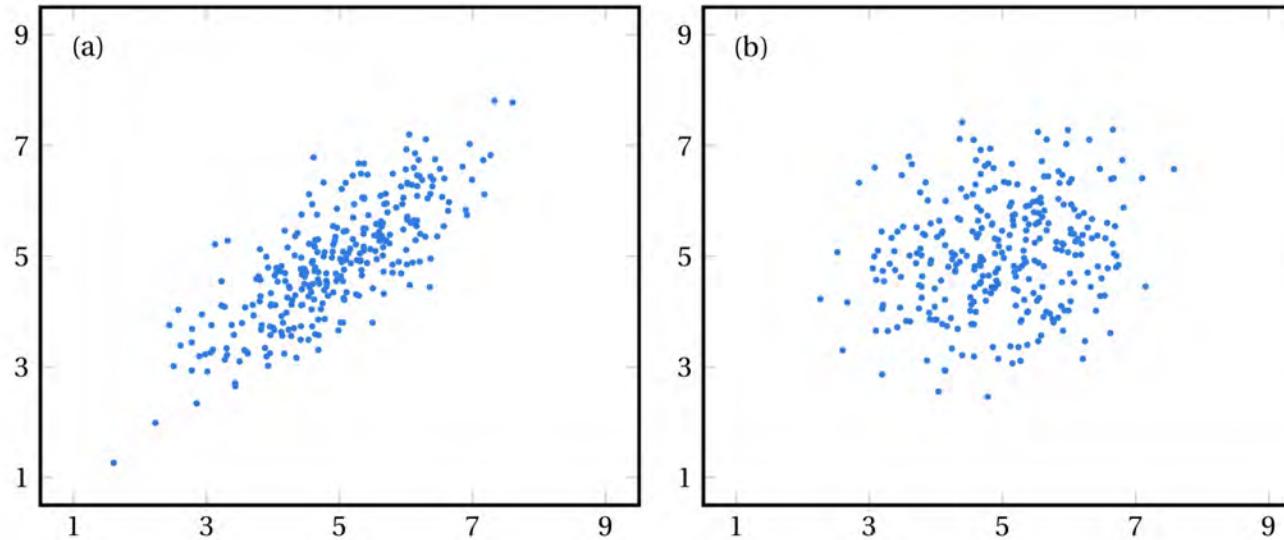
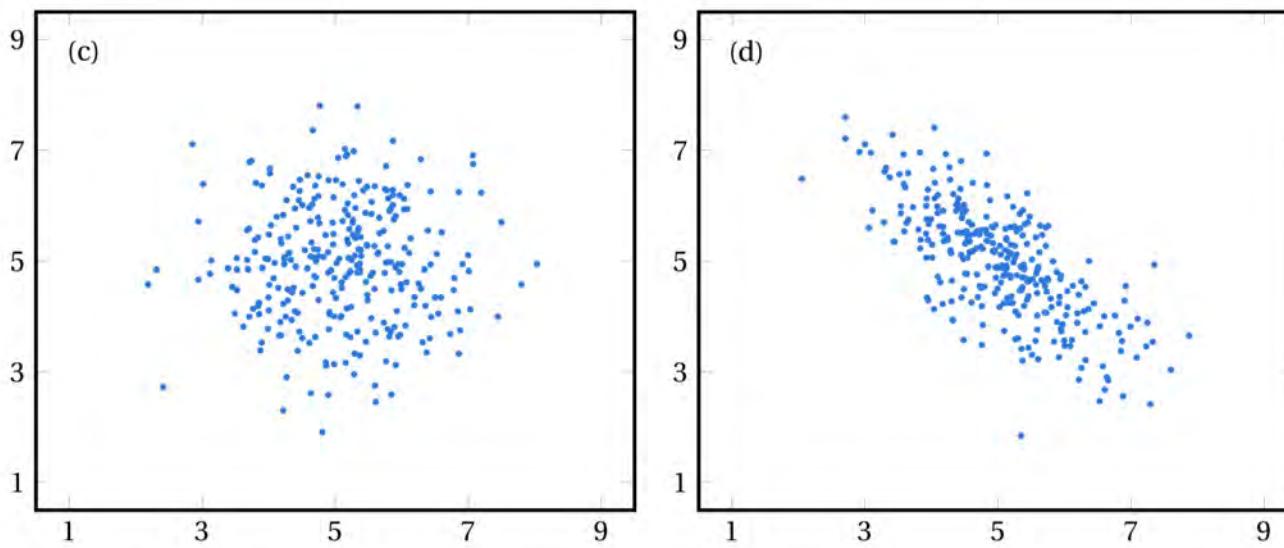


Figure 9: Random variables \mathcal{X} and \mathcal{Y} with correlations (a) 0.75; (b) 0.2; (c) 0; and (d) -0.75.



Example: 10 independent dice rolls: X_i is i-th roll

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \underbrace{\sum_{i=1}^n \text{Var}(X_i)}_{\text{ind}} = \sum_{i=1}^n \frac{35}{12} = 10 \cdot \frac{35}{12}$$

What about the standard deviation?

Var has grown by factor 10,

σ grows by factor $\sqrt{10}$!