

## VALORE ATTESO e MATRICE DI COVARIANZA

$$(X, Y), \begin{pmatrix} X \\ Y \end{pmatrix}$$

$$\text{VALORE ATTESO: } (\mathbb{E}[X], \mathbb{E}[Y]) \\ \mathbb{E}[(X, Y)]$$

## FUNZIONE DI UN VETTORE ALEATORIO

$$h: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$Z = h(X, Y)$$

### Teorema

$(X, Y)$  vettore aleatorio discreto con densità discreta congiunta con  $P(x, y)$

$$\mathbb{E}[Z] = \mathbb{E}[h(X, Y)] = \sum_{i,j} h(x_i, y_j) P_{(X,Y)}(x_i, y_j)$$

## COROLLARIO

$(X, Y)$  vettore aleatorio discreto (cioè,  $X$  e  $Y$  sono v.a. discrete).

$$X \perp\!\!\!\perp Y \xRightarrow{\text{~~non~~}} \mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y].$$

N.B.

$$X \perp\!\!\!\perp Y : \mathbb{P}(X \in A, Y \in B) = \mathbb{P}(X \in A) \mathbb{P}(Y \in B), \quad A, B \subset \mathbb{R}$$

$$X \perp\!\!\!\perp Y \iff P_{(X,Y)}(x_i, y_j) = P_X(x_i) P_Y(y_j), \quad \forall i, \forall j$$

then:  $h(x, y) = xy$

$X \perp\!\!\!\perp Y$

$$\mathbb{E}[XY] \stackrel{\text{~~non~~}}{=} \sum_{i,j} x_i y_j P_{(X,Y)}(x_i, y_j) \stackrel{\text{~~non~~}}{=} \sum_{i,j} x_i y_j P_X(x_i) P_Y(y_j)$$

$$= \left( \sum_i x_i P_X(x_i) \right) \left( \sum_j y_j P_Y(y_j) \right) = \mathbb{E}[X] \mathbb{E}[Y].$$

DIM

OSS.

$$X \perp\!\!\!\perp Y \iff$$

$$f(X) \perp\!\!\!\perp g(Y)$$

Si può dimostrare che  
 $X \perp\!\!\!\perp Y \iff$

$$\mathbb{E}[f(X)g(Y)] = \mathbb{E}[f(X)]\mathbb{E}[g(Y)]$$

## MATRICE DI COVARIANZA

$$\mathbb{E}[(X, Y)] = (\mathbb{E}[X], \mathbb{E}[Y])$$

$(X, Y) :$

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = \begin{pmatrix} \text{Var}(X) & \text{Cov}(X, Y) \\ \text{Cov}(Y, X) & \text{Var}(Y) \end{pmatrix}$$

$$(X, Y) = (X_1, X_2) \begin{pmatrix} \text{Cov}(X_1, X_1) & \text{Cov}(X_1, X_2) \\ \text{Cov}(X_2, X_1) & \text{Cov}(X_2, X_2) \end{pmatrix}$$

$$a_{ij} = \text{Cov}(X_i, X_j)$$

$$1) \text{Cov}(X_1, X_1) = \text{Var}(X_1) \quad | \quad 2) \text{Cov}(X, Y) = \text{Cov}(Y, X)$$

## Definizione

$X$  e  $Y$  sono v.a. discrete. La **COVARIANZA** di  $X$  e  $Y$  è data da

$$\begin{aligned}\text{Cov}(X, Y) &= \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \\ &= \sum_{i,j} (x_i - \mathbb{E}[X])(y_j - \mathbb{E}[Y]) P_{(X,Y)}(x_i, y_j)\end{aligned}$$

Se  $\text{Cov}(X, Y) = 0$ , le v.a.  $X$  e  $Y$  si dicono

## **SCORRELATE.**

Se  $\text{Var}(X) > 0$  e  $\text{Var}(Y) > 0$ , definiamo il **COEFFICIENTE**

**DI CORRELAZIONE:**

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

OSS.

1)  $x_i - \mathbb{E}[X] =$  scarto dalla media di  $x_i$   
 $\text{Cov}(X, Y) =$  somma del prodotto degli scarti dalla media

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

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

4)  $-1 \leq \rho_{X, Y} \leq 1$

Teorema 3.2 del Cap. "Stat. desc. e Teoremi limite"

Inoltre:  $\rho_{X, Y} = \pm 1 \iff Y = aX + b$

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

5) La covarianza ci dice se c'è approssimativamente  
DIPENDENZA LINEARE.

$\rho_{X,Y} = \pm 1$ , allora c'è veramente dipendenza lineare.

$\rho_{X,Y} = 0$ , allora non è detto che  $X$  e  $Y$  siano  
indipendenti

$X \perp\!\!\!\perp Y \xrightarrow{\text{~~NON~~}} \text{Cov}(X, Y) = 0$  ( $X$  e  $Y$  correlate)

## Teorema

$$X \perp\!\!\!\perp Y \implies \text{Cov}(X, Y) = 0$$

## Lemma

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

## Dim (Lemma)

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

## N.B.

$$\mathbb{E}[aX + b] = a\mathbb{E}[X] + b$$

Dim (Teorema)

$$X \perp\!\!\!\perp Y \implies E[XY] = E[X]E[Y]$$

Quindi

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

$$= 0$$

↑

$X \perp\!\!\!\perp Y$

$$Y = \underbrace{\log_2(1 + \sin X)}_Z$$

### Ex. 2.3

$X$  e  $Y$  v.a. discrete:

$$X \perp\!\!\!\perp Y, \quad X \sim B\left(\frac{1}{2}\right), \quad Y \sim B\left(\frac{1}{2}\right)$$

Siano  $U = X + Y$  e  $V = |X - Y|$

- Determinare congiunta e marginali di  $U$  e  $V$ .
- $\mathbb{P}(V < U) = ?$
- Calcolare  $\text{Var}(U)$ ,  $\text{Var}(V)$ ,  $\text{Cov}(U, V)$ .
- $U$  e  $V$  sono indipendenti?

a)

| $X \backslash Y$ | 0     | 1     | $P_X$ |
|------------------|-------|-------|-------|
| 0                | $1/4$ | $1/4$ | $1/2$ |
| 1                | $1/4$ | $1/4$ | $1/2$ |
| $P_Y$            | $1/2$ | $1/2$ | 1     |

$$S_U = \{0, 1, 2\} \text{ e } S_V = \{0, 1\}$$

| $U \backslash V$ | 0     | 1     | $P_U$ |
|------------------|-------|-------|-------|
| 0                | $1/4$ | 0     | $1/4$ |
| 1                | 0     | $1/2$ | $1/2$ |
| 2                | $1/4$ | 0     | $1/4$ |
| $P_V$            | $1/2$ | $1/2$ | 1     |

| $(X, Y)$ | $(U, V)$ |
|----------|----------|
| (0, 0)   | (0, 0)   |
| (0, 1)   | (1, 1)   |
| (1, 0)   | (1, 1)   |
| (1, 1)   | (2, 0)   |

$$V \sim B\left(\frac{1}{2}\right)$$

$$U \sim \text{Bin}\left(2, \frac{1}{2}\right)$$

$$U = V \pmod{2}$$

$$b) \quad \mathbb{P}(V < U) = \sum_{\substack{i,j: \\ v_j < u_i}} P_{(U,V)}(u_i, v_j)$$

$$= P_{(U,V)}(2,0) + P_{(U,V)}(2,1) = P_U(2) = \frac{1}{4}$$

$$c) \quad \mathbb{E}[U] = 2 \cdot \frac{1}{2} = 1$$

$$\mathbb{E}[V] = \frac{1}{2}$$

$$\text{Var}(U) = 2 \cdot \frac{1}{4} = \frac{1}{2}$$

$$\text{Var}(V) = \frac{1}{4}$$

$$\mathbb{E}[UV] = \sum_{i,j} u_i v_j P_{(U,V)}(u_i, v_j) = 1 \cdot 1 \cdot P_{(U,V)}(1,1) = \frac{1}{2}$$

$$\text{Cov}(U, V) = \mathbb{E}[UV] - \mathbb{E}[U]\mathbb{E}[V] = \frac{1}{2} - \frac{1}{2} = 0$$

d)  $U \perp V$ ?

$$U \perp V \Leftrightarrow P_{(U,V)}(u_i, v_j) = p_U(u_i) p_V(v_j)$$

No, infatti ad esempio

$$P_{(U,V)}(0,0) = \frac{1}{4} \neq \begin{matrix} P_U(0) & P_V(0) \\ \uparrow & \uparrow \\ \frac{1}{4} & \frac{1}{2} \end{matrix}$$