

**VARIANCE**

$X : \Omega \rightarrow \mathbb{R}$  r.v.  $X \in L^2(\Omega)$

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

$$\text{Var}[X] \geq 0$$

NOT RANDOM

$$\begin{aligned} \text{Var}[X] &= E[X^2 + (E[X])^2 - 2X\overbrace{E[X]}^{\text{NOT RANDOM}}] \\ &= E[X^2] + (E[X])^2 - 2E[X] \cdot E[X] \\ &= E[X^2] + (E[X])^2 - 2(E[X])^2 \\ &= \underbrace{E[X^2] - (E[X])^2}_{<+\infty \text{ if } X \in L^2(\Omega)} \end{aligned}$$

- DISCRETE CASE:

$$E[X^2] = \sum_{x \in \mathbb{R}} x^2 p_X(x)$$

$$\text{Var}(X) = \sum_{x \in \mathbb{R}} x^2 p_X(x) - \left( \sum_x x p_X(x) \right)^2$$

**COVARIANCE of two random variables**

$$X, Y \in L^2$$

$$\begin{aligned} \text{Cov}(X, Y) &= E[(X - E[X])(Y - E[Y])] \\ &= E[XY - X\overbrace{E[Y]}^{\cancel{E[X]E[Y]}} - Y\overbrace{E[X]}^{\cancel{E[X]E[Y]}} + E[X]E[Y]] \\ &= E[XY] - E[Y]E[X] - \cancel{E[X]E[Y]} + \cancel{E[X]E[Y]} \\ &= \underbrace{E[XY] - E[X]E[Y]}_{<+\infty} \end{aligned}$$

Lemma if  $X, Y \in L^2(\Omega)$  then  $X \cdot Y \in L^1(\Omega)$

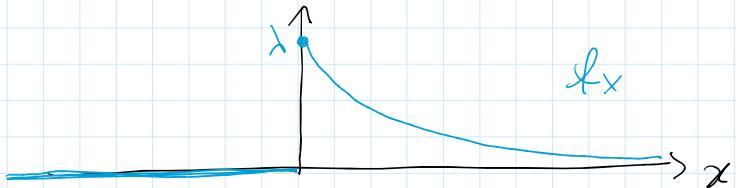
Proof Use inequality  $xy \leq \frac{x^2 + y^2}{2}$   $\forall x, y \in \mathbb{R}$   
 (follows from  $(x-y)^2 \geq 0$ )

$$\begin{aligned}
 & (\text{follows from } (x-y)^2 \geq 0) \\
 E[|XY|] &= E[|X||Y|] \leq E\left[\frac{X^2}{2} + \frac{Y^2}{2}\right] \\
 &\quad \downarrow \text{NONNEGATIVITY} \quad \downarrow \text{LINEARITY} \\
 &\leq \frac{1}{2} E[X^2] + \frac{1}{2} E[Y^2] < +\infty \\
 \Rightarrow XY &\in L^1(\Omega)
 \end{aligned}$$

Example  $X \sim \text{Exp}(\lambda)$   $\lambda > 0$

$X$  absolutely continuous r.v. with density

$$f_X(x) = \begin{cases} 0 & \text{if } x < 0 \\ \lambda e^{-\lambda x} & \text{if } x \geq 0 \end{cases}$$



$$\begin{aligned}
 E[X] &= \int_{-\infty}^{+\infty} x f_X(x) dx \\
 &= \int_{-\infty}^0 x \cdot 0 dx + \int_0^{+\infty} x \lambda e^{-\lambda x} dx
 \end{aligned}$$

INTEGRATION BY PARTS

$$\int_a^b f' g dx = [fg]_a^b - \int_a^b f g' dx$$

$$\frac{d}{dx} x = 1 \quad \int e^{-\lambda x} dx = \frac{1}{-\lambda} e^{-\lambda x} \rightarrow \text{PRIMITIVE}$$

$$= \left[ \lambda x \left( -\frac{1}{\lambda} e^{-\lambda x} \right) \right]_{x=0}^{x \rightarrow +\infty} - \int_0^{+\infty} 1 \cdot \left( -\frac{1}{\lambda} e^{-\lambda x} \right) dx$$

$$= - \lim_{x \rightarrow +\infty} \frac{x}{e^{\lambda x}} + 0 + \int_0^{+\infty} e^{-\lambda x} dx$$

$$= \left[ -\frac{1}{\lambda} e^{-\lambda x} \right]_{x=0}^{x \rightarrow +\infty} = -\frac{1}{\lambda} e^{-\infty} + \frac{1}{\lambda} e^0 = \frac{1}{\lambda}$$

$$E[X] = 1$$

$$\begin{aligned}
 E[X] &= \frac{1}{\lambda} \\
 \bullet E[X^2] &= \int_{-\infty}^{+\infty} x^2 f_X(x) dx = \int_0^{+\infty} x^2 \lambda e^{-\lambda x} dx \\
 &= \text{INTEGRATION BY PARTS} \\
 &= \left[ -x^2 e^{-\lambda x} \right]_{x=0}^{x \rightarrow +\infty} - \int_0^{+\infty} 2x (-e^{-\lambda x}) dx \\
 &= - \underbrace{\lim_{x \rightarrow +\infty} \frac{x^2}{e^{\lambda x}}}_{=0} + 0 + 2 \int_0^{+\infty} x e^{-\lambda x} dx \\
 &\stackrel{\text{BY PARTS}}{=} \left[ -2x e^{-\lambda x} \right]_0^{+\infty} - 2 \int_0^{+\infty} 1 \cdot \left( -\frac{1}{\lambda} e^{-\lambda x} \right) dx \\
 &= \frac{2}{\lambda} \int_0^{+\infty} e^{-\lambda x} dx = \frac{2}{\lambda} \left[ -\frac{1}{\lambda} e^{-\lambda x} \right]_{x=0}^{x \rightarrow +\infty} \\
 &= \frac{2}{\lambda^2} \left( -e^{-\infty} + e^0 \right) = \frac{2}{\lambda^2} \\
 \Rightarrow E[X^2] &= \frac{2}{\lambda^2}
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(X) &= E[X^2] - (E[X])^2 = \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 = \frac{1}{\lambda^2} \\
 \text{Var}(X) &= \frac{1}{\lambda^2}
 \end{aligned}$$

Exercise  $X \sim \text{Exp}(\lambda)$

$$Y = \min(X, 1) \quad (Y(\omega) = \min(X(\omega), 1))$$

note  $X \geq 0, 1 \geq 0 \Rightarrow Y \geq 0$

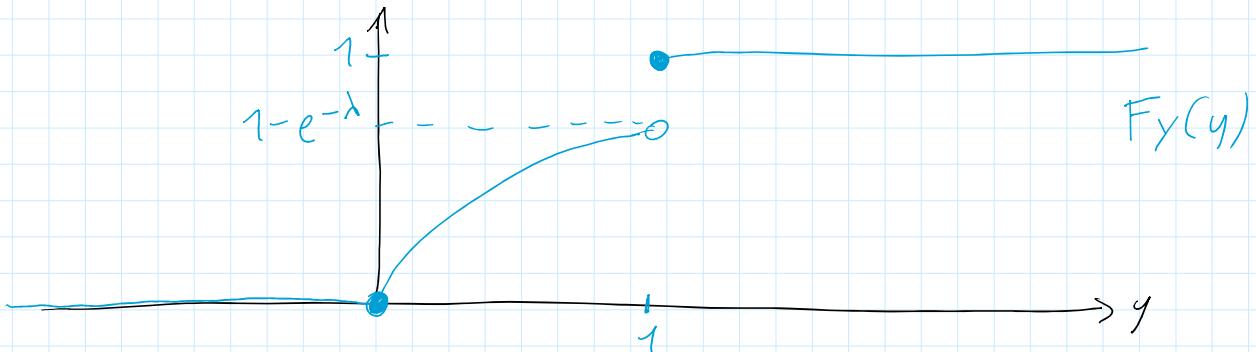
Compute the distribution function of  $Y$

$$F_Y(y) = P(Y \leq y) \quad \forall y \in \mathbb{R}$$

$$\text{Recall } F_X(x) = P(X \leq x) = 1 - e^{-\lambda x}$$

$$F_Y(y) = \begin{cases} 0 & \text{if } y < 0 \\ P(\min(X, 1) \leq y) & \end{cases} = P(X \leq y) = 1 - e^{-\lambda y}$$

$$F_Y(y) = \begin{cases} P(\min(X, 1) \leq y) & = P(X \leq y) = 1 - e^{-\lambda y} \\ \{w : \min(X(w), 1) \leq y\} & \text{if } 0 \leq y < 1 \\ & = \{w : X(w) \leq y\} \\ P(\min(X, 1) \leq y) & = 1 \quad \text{if } y \geq 1 \\ \{w : \min(X(w), 1) \leq y\} & = \{w : 1 \leq y\} = \Omega \end{cases}$$



$F_Y$  has a jump in 1  $\Rightarrow F_Y$  not continuous  
 $\Rightarrow Y$  not absolutely continuous  
 $\Rightarrow$  Need another method to compute expectation

Proposition  $X : \Omega \rightarrow \mathbb{R}$  n.v (general)

i) if  $X \geq 0$  then

$$E[X] = \int_0^{+\infty} (1 - F_X(x)) dx = \int_0^{+\infty} P(X > x) dx$$

$[F_X(x) = P(X \leq x) \quad (X \leq x)^c = (X > x)]$

ii) if  $X \in L^1(\Omega)$  then

$$E[X] = - \int_{-\infty}^0 F_X(x) dx + \int_0^{+\infty} (1 - F_X(x)) dx$$

Proof

of i) in case  $X$  is absolutely continuous

$$X \geq 0 \quad E[X] = \int_0^{+\infty} x f_X(x) dx$$

$$\text{recall } P(a \leq X \leq b) = \int_a^b f_X(x) dx$$

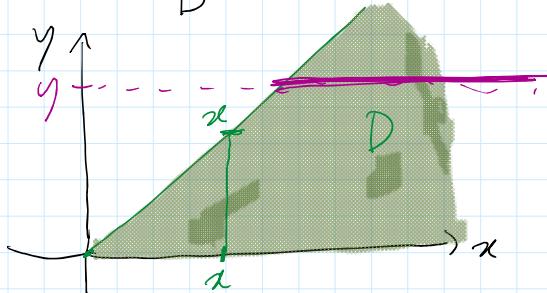
$$\text{write } x = \int_0^x 1 dy$$

$$\therefore E[X] = \int_0^{+\infty} x f_X(x) dx = \int_0^{+\infty} \int_0^x 1 dy f_X(x) dx$$

write  $x = \int_0^x 1 dy$

$$E[X] = \int_0^{+\infty} \left( \int_0^x 1 dy \right) f_X(x) dx$$

$$= \iint_D f_X(x) dx dy \quad \rightarrow \text{iteration formula}$$



projection of  $D$  on  $x$  is  $[0, +\infty)$   
and for  $x$  fixed  
 $0 \leq y \leq x$

$\rightarrow$  projection of  $D$  on  $y$  is  $[0, +\infty)$   
 $\rightarrow$  for  $y$  fixed,  $x$  belongs to  $[y, +\infty)$

from iteration formula of double integral

$$\begin{aligned} \iint_D f_X(x) dx dy &= \int_0^{+\infty} \left( \int_y^{+\infty} f_X(x) dx \right) dy \\ &= \int_0^{+\infty} P(X \in [y, +\infty)) dy \\ &= \int_0^{+\infty} P(X \geq y) dy \end{aligned}$$

Back to the exercise, compute  $(Y \geq 0)$

$$\begin{aligned} E[Y] &= \int_0^{+\infty} (1 - F_Y(y)) dy \\ &= \int_0^1 (1 - (1 - e^{-\lambda y})) dy + \int_1^{+\infty} (1 - 1) dy \\ &= \int_0^1 e^{-\lambda y} dy = \left[ -\frac{1}{\lambda} e^{-\lambda y} \right]_{y=0}^{y=1} \\ &= -\frac{1}{\lambda} (e^{-\lambda} - e^0) = \frac{1}{\lambda} (1 - e^{-\lambda}) \end{aligned}$$

## RANDOM VECTORS

$X : \Omega \rightarrow E$  random variable,  $(E, \mathcal{E})$  measurable space  
 $E = \mathbb{R}^d \rightarrow$  RANDOM VECTOR

Def A **RANDOM VECTOR** is a random variable taking values in  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$

- $\mathcal{B}(\mathbb{R}^d)$  is the BOREL  $\sigma$ -algebra of  $\mathbb{R}^d$ 
  - GENERATED by products of intervals
  - $\mathcal{C} = \{ [a_1, b_1] \times [a_2, b_2] \times \dots \times [a_d, b_d] : a_i, b_i \in [-\infty, +\infty]\}$
  - random vector is such that  $X: \Omega \rightarrow \mathbb{R}^d$
  - $(\Omega, \mathcal{A}, P)$  probability space
  - $X^{-1}([a_1, b_1] \times \dots \times [a_d, b_d]) \in \mathcal{A}$
- $X: \Omega \rightarrow \mathbb{R}^d$   
 $\omega \mapsto (X_1(\omega), X_2(\omega), \dots, X_d(\omega)) = X(\omega)$
- denote  $X = (X_1, \dots, X_d)$
- $X_i: \Omega \rightarrow \mathbb{R}$  are real random variables

**LAW** of a random vector

$$\mu_X(\beta) = P(X^{-1}(\beta)) = P(X \in \beta)$$

for any  $\beta \in \mathcal{B}(\mathbb{R}^d)$

- $\mu_X$  is a probability on  $\mathcal{B}(\mathbb{R}^d)$  and is called the **JOINT DISTRIBUTION** of  $X_1, \dots, X_d$   
 $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d), \mu_X)$  is a probability space

Remark It can be proved that the values of  $\mu_X$  on multiple intervals  $[a_1, b_1] \times \dots \times [a_d, b_d]$  uniquely determines the value of  $\mu_X$  on any  $\beta \in \mathcal{B}(\mathbb{R}^d)$ .

- the joint distribution  $\mu_X = \mu_{X_1, \dots, X_d}$  gives the **MARGINAL DISTRIBUTIONS**  $\mu_{X_i} \quad \forall i = 1, \dots, d$

$$\begin{aligned}
 A \in \mathcal{B}(\mathbb{R}) \quad \mu_{X_1}(A) &= P(X_1 \in A) \\
 \mu_{X_1, \dots, X_d}(A_1 \times A_2 \times \dots \times A_d) &= P(X_1 \\
 &= P((X_1, \dots, X_d) \in A_1 \times \dots \times A_d) \\
 &= P(\{X_1 \in A_1\} \cap \{X_2 \in A_2\} \cap \dots \cap \{X_d \in A_d\}) \\
 &= P(X_1 \in A_1, X_2 \in A_2, \dots, X_d \in A_d)
 \end{aligned}$$

$$\begin{aligned}
 \mu_{X_1}(A) &= P(X_1 \in A) = P(X_1 \in A_1, X_2 \in \mathbb{R}, \dots, X_d \in \mathbb{R}) \\
 &= \mu_{X_1, \dots, X_d}(A_1 \times \mathbb{R} \times \dots \times \mathbb{R})
 \end{aligned}$$

- Having the joint distribution  $\mu_{X_1, \dots, X_d}$

We get the marginal distributions by

$$\mu_{X_i}(A) = \mu_{X_1, \dots, X_d} \left( \underbrace{\mathbb{R} \times \dots \times \mathbb{R}}_{i-1} \times A \times \underbrace{\mathbb{R} \times \dots \times \mathbb{R}}_{d-i} \right)$$

↑ index i