

# Independent RVs

①

For 2 RVs,  $X, Y$  are independent if  $f_{XY}(x, y) = f_X(x) \cdot f_Y(y)$ .

For 2 events  $A, B$  are independent if  $P[A \cap B] = P[A] \cdot P[B]$ .

For  $n$  RVs  $X_1, X_2, \dots, X_n$  are independent if

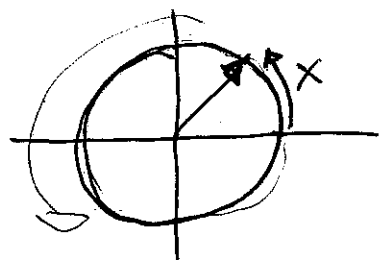
• discrete PMF  $P_{X_1, X_2, \dots, X_n}(x_1, x_2, \dots, x_n) = P_{X_1}(x_1) P_{X_2}(x_2) \dots P_{X_n}(x_n)$

• continuous PDF  $f_{X_1, X_2, \dots, X_n}(x_1, x_2, \dots, x_n) = f_{X_1}(x_1) f_{X_2}(x_2) \dots f_{X_n}(x_n)$ .

In the example from last class,  $X_1, X_2, X_3$  were independent.

EX: Consider an experiment that consists of spinning a pointer on a wheel of circumference  $1$  m,  $n$  times ( $n$  independent spins) and we observe  $Y_n$  metres, the maximal position of the pointer in the  $n$  spins. Assume pointer is equally likely to land anywhere on the circle and that spins are independent. Find the CDF and PDF of  $Y_n$ .

Sol:

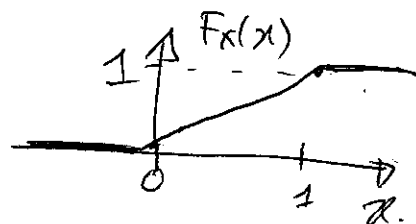
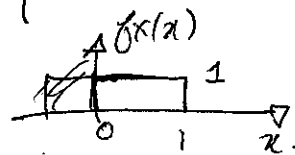


PDF/CDF of one spin, RV  $X$ .

$$S_X = [0, 1], f_X(x) = \begin{cases} 1 & 0 \leq x \leq 1 \\ 0 & \text{else.} \end{cases}$$

$X$  Uniform RV on  $[0, 1]$  !!

CDF of  $X$  is  $F_X(x) = \int_{-\infty}^x f_X(u) du = \int_0^x 1 \cdot du = x$  for  $0 \leq x \leq 1$



Let  $X_i =$  pointer location of spin  $i$  for  $1 \leq i \leq n$ .

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These are  $n$  RVs  $X_1, X_2, \dots, X_n$ .

For  $n$  independent spins  $Y_n = \max(X_1, X_2, \dots, X_n)$ .

Want the PDF and CDF of  $Y_n$ .

First find CDF of  $Y_n$ , then take derivative to find PDF of  $Y_n$ .

$$F_{Y_n}(y) \stackrel{\text{def}}{=} P[Y_n \leq y] = P[\max(X_1, X_2, \dots, X_n) \leq y].$$

dummy variable.

$$\begin{aligned} & \stackrel{\text{(Thm 5.7)}}{\downarrow} = P[X_1 \leq y, X_2 \leq y, \dots, X_n \leq y] \\ & = P[X_1 \leq y] P[X_2 \leq y] \dots P[X_n \leq y]. \end{aligned}$$

$$= (P[X \leq y])^n.$$

$$= (F_X(y))^n.$$

since all  $X_i$ 's are distributed in the same way. all  $X_i$ 's are uniform on  $[0, 1]$ .

CDF ✓

$$= \begin{cases} 0 & y < 0 \\ 1 & y > 1 \\ y^n & 0 \leq y \leq 1. \end{cases}$$

PDF

$$f_{Y_n}(y) = \frac{d}{dy} [F_{Y_n}(y)] = \begin{cases} n y^{n-1} & 0 \leq y \leq 1 \\ 0 & \text{else.} \end{cases}$$

This example showed how to find the PDF and CDF of functions of  $n$  RVs, i.e. first get CDF then ~~the~~ take derivative to get PDF.

Expected values:  $(n \times 1)$

Let  $\bar{X} \triangleq \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix}$  (my convention is to let  $\bar{X}$  be a column vector).

$\bar{X}^T \triangleq [X_1 \dots X_n]$ .  $(1 \times n)$  ( $T$  is "transpose").

~~$E[g(\bar{X})]$~~   $E[\bar{X}] = \begin{bmatrix} E[X_1] \\ E[X_2] \\ \vdots \\ E[X_n] \end{bmatrix}$  is an  $(n \times 1)$  vector.

$$E[g(\bar{X})] = \sum_{x_1 \in S_{X_1}} \sum_{x_2 \in S_{X_2}} \dots \sum_{x_n \in S_{X_n}} g(\bar{x}) P_{\bar{X}}(\bar{x}) \quad (\text{discrete})$$
$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} g(\bar{x}) f_{\bar{X}}(\bar{x}) d\bar{x} \quad (\text{continuous}).$$

Theorem 5.11: If  $\bar{X}$  is a continuous Random Vector and  $A$  is an invertible matrix, then  $\bar{Y} = A\bar{X} + b$  has pdf.

$$f_{\bar{Y}}(\bar{y}) = \frac{1}{|\det(A)|} f_{\bar{X}}(A^{-1}(\bar{y} - b))$$

(Result of the change of variables in integration, formula).

$\det(A) = \text{determinant of } A = ad - bc$

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

$$A^{-1} = \text{inverse of } A = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

# Expected value + correlation matrix

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- $E[\bar{X}]$  is a vector of ~~length~~ dimension  $(n \times 1) = \mu_{\bar{X}}$
- Correlation of a random vector  $\bar{X}$  is an  $n \times n$  matrix,  $R_{\bar{X}}$  where  $(i, j)$  the element  $R_{\bar{X}}(i, j) \triangleq E[X_i X_j]$ .

In vector notation.

$$R_{\bar{X}} = E[\bar{X} \bar{X}^T] = \begin{matrix} \text{(for } 3 \times 3, \bar{X} = [X_1, X_2, X_3]^T) \\ \begin{bmatrix} E[X_1^2] & E[X_1 X_2] & E[X_1 X_3] \\ E[X_2 X_1] & E[X_2^2] & E[X_2 X_3] \\ E[X_3 X_1] & E[X_3 X_2] & E[X_3^2] \end{bmatrix} \end{matrix}$$

( $n \times n$  matrix)

example.

↓  
symmetric matrix meaning

$$R_{\bar{X}}^T = R_{\bar{X}}$$