

# NMAI059 Probability and statistics 1

## Class 8

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# Overview

Continuous distributions

Random vectors

Back to the basics

## Which distributions we have seen

- ▶  $U(a, b)$  – uniform on interval  $[a, b]$
  
- ▶  $Exp(\lambda)$  – exponential – how long till something happens
  
- ▶  $N(\mu, \sigma^2)$  – normal – how much does a bread weigh

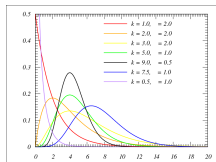
# Gamma distribution

- ▶  $Gamma(w, \lambda)$ , *gamma distribution with parameters*  $w > 0$  and  $\lambda > 0$  has PDF

$$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ \frac{1}{\Gamma(w)} \lambda^w x^{w-1} e^{-\lambda x} & \text{for } x \geq 0 \end{cases}$$

where  $\Gamma(w) = (w - 1)! = \int_0^\infty x^{w-1} e^{-x} dx$ .

- ▶ For  $w = 1$  we get exponential distribution again.
- ▶ If  $X_1, \dots, X_n$  are i.i.d with distribution  $Exp(\lambda)$ , then  $X_1 + \dots + X_n \sim Gamma(n, \lambda)$ .
- ▶ Models lifetime of an electronic component, total of rainfall in a year, web-server latency.



## A many others

- ▶  $Beta(s, t)$  – beta distribution
- ▶  $\chi^2$  distribution with  $k$  degrees of freedom = chi-square ( $\chi_k^2$ ) is an alternative name for  $Gamma(\frac{1}{2}k, \frac{1}{2})$ . It is the distribution  $Z_1^2 + \dots + Z_k^2$ , where  $Z_i \sim N(0, 1)$  are i.i.d.
- ▶ Student  $t$ -distribution
- ▶ etc. etc.

# Uniform distribution

- ▶ R.v.  $X$  has a uniform distribution on  $[a, b]$ , we write  $X \sim U(a, b)$ , if  $f_X(x) = 1/(b - a)$  for  $x \in [a, b]$  and  $f_X(x) = 0$  otherwise.

# Universality of uniform

## Theorem

*Let  $X$  be a r.v. with CDF  $F_X = F$ , let  $F$  be continuous and increasing. Then  $F(X) \sim U(0, 1)$ .*

## Theorem

*Let  $F$  be a function “of CDF-type”: non-decreasing right-continuous function with  $\lim_{x \rightarrow -\infty} F(x) = 0$  and  $\lim_{x \rightarrow +\infty} F(x) = 1$ . Let  $Q$  be the corresponding quantile function.*

*Let  $U \sim U(0, 1)$  and  $X = Q(U)$ . Then  $X$  has CDF  $F$ .*





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# Joint cdf

## Definition

For r.v.  $X, Y$  on probability space  $(\Omega, \mathcal{F}, P)$  we define their joint cdf  $F_{X,Y} : \mathbb{R}^2 \rightarrow [0, 1]$  by

$$F_{X,Y}(x, y) = P(\{\omega \in \Omega : X(\omega) \leq x \ \& \ Y(\omega) \leq y\}).$$

- ▶ Formal condition: we need  $\{X \leq x \ \& \ Y \leq y\} \in \mathcal{F}$ , otherwise  $(X, Y)$  is not a random vector.

- ▶ We can define this also for more than two r.v.:

$$F_{X_1, \dots, X_n}(x_1, \dots, x_n) =$$

- ▶ From here we can derive the probability of a rectangle:  
 $P(X \in (a, b] \ \& \ Y \in (c, d]) =$

## Joint pdf

- ▶ Often we can write a joint cdf as an integral of a nonnegative function  $f_{X,Y}$

$$F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(s, t) dt ds.$$

- ▶ Then we call r.v.  $X, Y$  *jointly continuous*. Function  $f_{X,Y}$  is their *joint pdf*.
- ▶ As in the one-dimension case we can have  $f_{X,Y} > 1$ .
- ▶ As in the one-dimension case we can use joint pdf to find other probabilities for a “reasonable set  $A$ ”.

$$P((X, Y) \in A) = \int_A f_{X,Y}(x, y) dx dy.$$

$$\blacktriangleright f_{X,Y}(x,y) = \frac{\partial^2 F_{X,Y}(x,y)}{\partial x \partial y}$$

$$\blacktriangleright f_{X,Y}(x,y) \doteq \frac{P(x \leq X \leq x + \Delta_x \ \& \ y \leq Y \leq y + \Delta_y)}{\Delta_x \Delta_y}$$

# LOTUS

- ▶ We have a similar formula as for the discrete case:

$$\mathbb{E}(g(X, Y)) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) dx dy.$$

- ▶ And as in the discrete case we conclude:

$$\mathbb{E}(aX + bY + c) = a \cdot \mathbb{E}(X) + b \cdot \mathbb{E}(Y) + c.$$

# Independence of continuous random variables

## Definition

We call random variables  $X, Y$  independent, if the events  $\{X \leq x\}$  and  $\{Y \leq y\}$  are independent for any  $x, y \in \mathbb{R}$ .

Equivalently,

$$P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y),$$

$$F_{X,Y}(x, y) = F_X(x)F_Y(y)$$

## Theorem

Let  $X, Y$  have joint pdf  $f_{X,Y}$  (and pdf's  $f_X, f_Y$ ). The following are equivalent:

- ▶  $X, Y$  are independent
- ▶  $f_{X,Y}(x, y) = f_X(x)f_Y(y)$

# Multidimensional normal distribution

- ▶  $\varphi(t) = \frac{1}{\sqrt{2\pi}} e^{-t^2/2}$
- ▶  $f(t_1, \dots, t_n) = \varphi(t_1)\varphi(t_2) \cdots \varphi(t_n) = \frac{1}{(\sqrt{2\pi})^n} e^{-\frac{t_1^2 + \dots + t_n^2}{2}}$
- ▶  $f(t_1, \dots, t_n) = (2\pi)^{-n/2} e^{-r^2/2}$ , where  $r^2 = t_1^2 + \dots + t_n^2$   
*radially symmetric function*

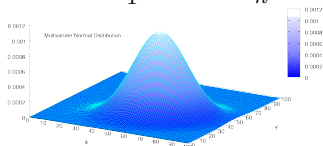


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- ▶ Let  $Z = (Z_1, \dots, Z_n)$  have a pdf  $f$ .
- ▶  $Z_1, \dots, Z_n$  are i.i.d.,  $Z_i \sim N(0, 1)$
- ▶  $Z/\|Z\|$  is a uniformly random point on a unit sphere in  $\mathbb{R}^n$ .
- ▶ Thus the inner product of  $Z$  with any unit vector is  $N(0, 1)$ .
- ▶  $\langle u, Z \rangle = \sum_{i=1}^n u_i Z_i$  follows  $N(0, 1)$

# General multidimensional normal distribution

- ▶ In general we can take a random vector with joint pdf  $c \cdot e^{-Q(t)}$ , where  $c > 0$  is an appropriate constant and  $Q(t)$  is a positive definite quadratic function.
- ▶ Is used in machine learning.
- ▶ Coordinates are not independent!

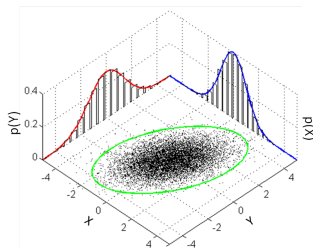


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# Sum of continuous random variables

## Theorem

*Suppose  $X, Y$  are independent continuous variables. Then  $Z = X + Y$  is a continuous random variable and its pdf is obtained by a convolution of  $f_X$  and  $f_Y$ . Explicitly,*

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x)f_Y(z-x)dx.$$

# Conditioning

## Definition

$X$  is a r.v. on  $(\Omega, \mathcal{F}, P)$ ,  $B \in \mathcal{F}$ .

$$F_{X|B}(x) := P(X \leq x \mid B)$$

The corresponding pdf is denoted by  $f_{X|B}$ .

## Theorem

Let  $B_1, B_2, \dots$  be a partition of  $\Omega$ . Then

$$F_X(x) = \sum_i F_{X|B_i} P(B_i) \quad \text{and}$$

$$f_X(x) = \sum_i f_{X|B_i} P(B_i).$$

Proof: Theorem on total probability.

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# Covariance

## Definition

For r.v.'s  $X, Y$  we define their covariance by formula

$$\text{cov}(X, Y) = \mathbb{E}((X - \mathbb{E}X)(Y - \mathbb{E}Y)).$$

## Theorem

$$\text{cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$$

- ▶  $\text{var}(X) = \text{cov}(X, X)$
- ▶  $\text{cov}(X, aY + bZ + c) = a \text{cov}(X, Y) + b \text{cov}(X, Z)$
- ▶  $\text{cov}(X, Y) = 0$  if  $X, Y$  are independent
- ▶ but not only then

# Correlation

## Definition

*Correlation of random variables  $X, Y$  is defined by*

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X) \text{var}(Y)}}.$$

- ▶ “scaled covariance”
- ▶  $-1 \leq \rho(X, Y) \leq 1$  (exercise)
- ▶ Correlation does not imply causation! (In particular, correlation is symmetric.)
- ▶ OTOH, uncorrelation does not imply independence. (Extreme case:  $X$  any r.v.,  $Y = +X$  or  $Y = -X$ , both with the same probability.)

# Variance of a sum

## Theorem

Let  $X = \sum_{i=1}^n X_i$ . Then

$$\text{var}(X) = \sum_{i=1}^n \sum_{j=1}^n \text{cov}(X_i, X_j) = \sum_{i=1}^n \text{var}(X_i) + \sum_{i \neq j} \text{cov}(X_i, X_j).$$

In particular, if  $X_1, \dots, X_n$  are independent, then

$$\text{var}(X) = \sum_{i=1}^n \text{var}(X_i).$$