



Continuous Random Variables

Introductory course on Statistics and Probability

Nicholas A. Pearson

Università degli Studi di Trieste

September 11, 2025

Random Variables

A random variable (r.v.) X is a variable whose value is a numerical outcome of a random phenomenon, that is, it is a well defined but unknown number.

There are two main types of random variables: discrete (if it has a finite list of possible outcomes), and continuous (if it can take any value in an interval).

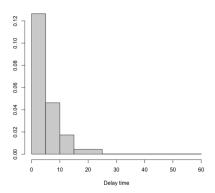
- C the delay time of the airplane
- C the weight of a newborn
- C the duration of a phone call with your mother

For **continuous random variables** we can assign probabilities only to a range of values, using a mathematical function, we express the probability distribution in the continuous space.

Delay time of a flight

About the delay time of a flight, we might observe the following data and plot them using a histogram.

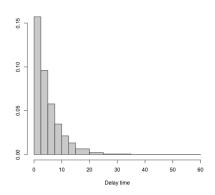
Delay	Р
(0,5]	0.633
(5,10]	0.231
(10, 15]	0.086
(15, 25]	0.043
(25,Inf]	0.006



Delay time of a flight

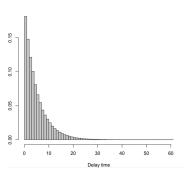
If we increase the number of intervals and make each interval "smaller":

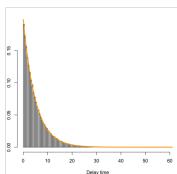
Delay	Р
(0,2.5]	0.393
(2.5,5]	0.240
(5, 7.5]	0.144
(7.5, 10]	0.087
(10,12.5]	0.053
(12.5, 15]	0.033
(15,20]	0.032
(20,25]	0.011
(25, 35]	0.005
(35,Inf]	0.001



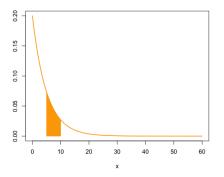
Delay time of a flight

Assuming that we have infinite observations we can increase the number of classes and approximate the histogram with a curve: the probability density function.





The interpretation of the probability density function is analogous to the histogram: the areas represent probabilities rather than frequencies.



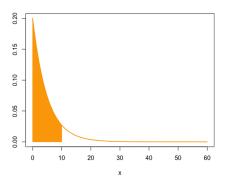
E.g. the probability of observing a value between 5 and 10 is:

$$P(5 \le X \le 10) = 0.234$$

Cumulative distribution function

A relevant quantity is:

$$P(X \leq x)$$

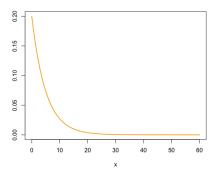


Example: the probability of observing a value smaller than 10 is:

$$P(X \le 10) = 0.865$$



The probability density function is a real-valued function assuming non-negative values.

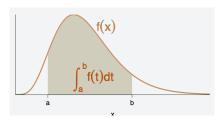


The function in the plot is:

$$f(x) = \frac{1}{5}e^{-x/5}, \qquad x \ge 0$$

The probability density function of a continuous random variable X is a non-negative function f(x). The probability that X lies within a given interval is obtained as the area under the curve of f(x) over that interval.

$$\int_a^b f(t)dt = P(a \le X \le b)$$



The probability density function of a continuous random variable X is a non-negative function f(x). The probability that X lies within a given interval is obtained as the area under the curve of f(x) over that interval.

$$\int_{a}^{b} f(t)dt = P(a \le X \le b)$$

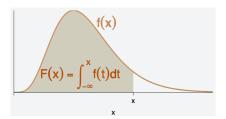
The probability density function satisfies the following properties:

- (i) $f(x) \ge 0$
- (ii) $\int_{-\infty}^{\infty} f(t)dt = 1$

Cumulative distribution function

The **cumulative distribution function** of a random variable X is the function:

$$F(x) = P(X \le x) = \int_{-\infty}^{x} f(t)dt$$



Cumulative distribution function

The **cumulative distribution function** of a random variable X is the function:

$$F(x) = P(X \le x) = \int_{-\infty}^{x} f(t)dt$$

and satisfies the following properties:

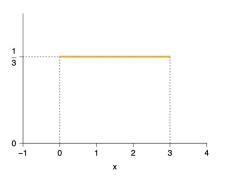
- i. $F(x) \geq 0, \forall x \in \mathbb{R}$;
- ii. F(x) is not decreasing;
- iii. $\lim_{x\to-\infty} F(x) = 0$;
- iv. $\lim_{x\to+\infty} F(x) = 1$.

and note that:

$$P(a \le X \le b) = F(b) - F(a)$$

Example

There are several density functions, any non-negative function that integrates to 1 is a density function.



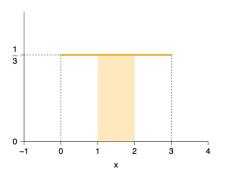
Uniform between 0 and 3

$$f(x) = \begin{cases} 1/3 & \text{for } 0 \le x \le 3\\ 0 & \text{otherwise} \end{cases}$$

Find
$$P(1 \le X \le 2)$$

Example

There are several density functions, any non-negative function that integrates to 1 is a density function.



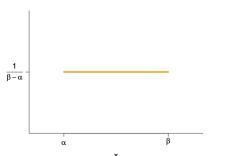
Uniform between 0 and 3

$$f(x) = \begin{cases} 1/3 & \text{if } 0 \le x \le 3\\ 0 & \text{otherwise} \end{cases}$$

$$P(1 \le X \le 2) = (2-1) \times \frac{1}{3} = \frac{1}{3}$$

Probability density functions and parameters

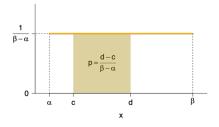
Often it is useful to define a probability density function up to one or more parameters, which is the equivalent of defining a set of density functions.



$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \text{if } \alpha \le x \le \beta \\ 0 & \text{otherwise} \end{cases}$$

f(x) is a probability density function for every α and β , with $\beta > \alpha$.

Uniform distribution on $[\alpha, \beta]$



$$F(x) = \frac{x - \alpha}{\beta - \alpha}$$

$$x$$

$$P(c \le X \le d) = \frac{d-c}{\beta-\alpha}$$

with $\alpha < \mathbf{c} < \mathbf{d} < \beta$

$$F(x) = \begin{cases} 0 & \text{if } x < \alpha \\ \frac{x - \alpha}{\beta - \alpha} & \text{if } \alpha \le x \le \beta \\ 1 & \text{if } x > \beta \end{cases}$$

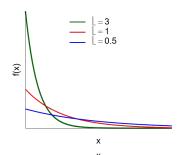
Exponential distribution

The exponential distribution is a continuous probability distribution that describes the time between events in a Poisson process, where events occur continuously and independently at a constant average rate.

It has rate parameter λ and is defined as:

$$f(x) = \lambda e^{-\lambda x}$$

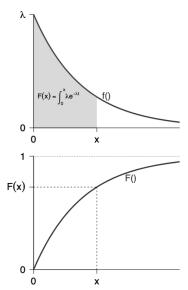
for x > 0 and $\lambda > 0$.



Exponential distribution

The cumulative distribution function is:

$$F(x) = \int_0^x \lambda e^{-\lambda t} dt$$
$$= [-e^{-\lambda t}]_0^x$$
$$= 1 - e^{-\lambda x}$$



Expected value and variance

Let f(x) be the probability density function of a continuous random variable X.

$$E(X) = \int xf(x)dx$$

$$E(h(X)) = \int h(x)f(x)dx$$

$$V(X) = \int (x - E(X))^2 f(x)dx$$

Moreover, the following properties hold (using the properties of the integrals)

- ► E(aX + b) = aE(X) + b
- $V(X) = E(X^2) [E(X)]^2$
- $V(aX + b) = a^2V(X)$

Uniform dist.: expected value and variance

Let X be a random variable following the Uniform distribution between α and β , thus

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \text{if } \alpha \le x \le \beta \\ 0 & \text{otherwise} \end{cases}$$

then

$$E(X) = \int_{\alpha}^{\beta} \frac{x}{\beta - \alpha} dx = \frac{1}{\beta - \alpha} \left[\frac{x^2}{2} \right]_{\alpha}^{\beta} = \frac{1}{\beta - \alpha} \frac{\beta^2 - \alpha^2}{2} = \frac{\alpha + \beta}{2}$$

$$E(X^2) = \int_{\alpha}^{\beta} \frac{x^2}{\beta - \alpha} dx = \frac{1}{\beta - \alpha} \left[\frac{x^3}{3} \right]_{\alpha}^{\beta} = \frac{1}{\beta - \alpha} \frac{\beta^3 - \alpha^3}{3} = \frac{\beta^2 + \alpha\beta + \alpha\beta}{3}$$

$$V(X) = E(X^{2}) - (E(X))^{2} = \frac{\beta^{2} + \alpha\beta + \alpha^{2}}{3} - \left(\frac{\alpha + \beta}{2}\right)^{2} = \frac{(\beta - \alpha)^{2}}{12}$$

Exponential distr: expected value and variance

Let X be a random variable following the Exponential distribution with rate parameter $\lambda>0$, thus

$$f(x) = \lambda e^{-\lambda x}$$

for $x \ge 0$, then, by integration by parts,

$$E(X) = \int_0^\infty x \lambda e^{-\lambda x} dx = [-xe^{-\lambda x}]_0^\infty + \int_0^\infty e^{-\lambda x} dx = [-\frac{e^{-\lambda x}}{\lambda}]_0^\infty = \frac{1}{\lambda}$$

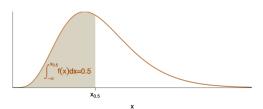
$$E(X^2) = \int_0^\infty x^2 \lambda e^{-\lambda x} dx = [-x^2 e^{-\lambda x}]_0^\infty + \int_0^\infty 2x e^{-\lambda x} dx = \frac{2}{\lambda^2}$$

$$V(X) = E(X^2) - (E(X))^2 = \frac{2}{\lambda^2} - \left(\frac{1}{\lambda}\right)^2 = \frac{1}{\lambda^2}$$

Median

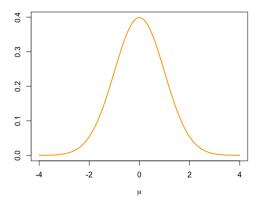
We define the **median** of a continuous random variable X with pdf f(x) the value Me(X) or $x_{0.5}$ such that:

$$F(Me(X)) = \int_{-\infty}^{Me(X)} f(x) dx = 0.5$$



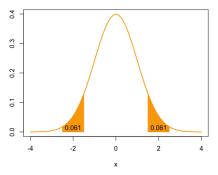
Normal distribution

The most popular continuous distribution is the Normal (or Gaussian) distribution and its density has the following shape.



Normal distribution

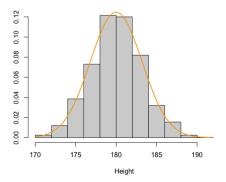
The most popular continuous distribution is the Normal (or Gaussian) distribution and its density has the following shape.



- ► The most likely values to occur are the ones around the center (the mean)
- ► It is symmetric, then symmetric deviations on the right and left have the same probability

Example

The distribution of the male students' height.



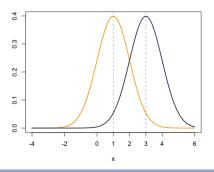
Normal distribution: parameters

The probability density function of the normal distribution is:

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Thus if a r.v. X follows a normal distribution we write:

$$X \sim N(\mu, \sigma^2)$$



- \blacktriangleright μ is the mean of the distribution
- For different μ values, the distribution shifts on the x axis

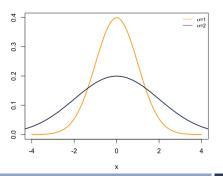
Normal distribution: parameters

The probability density function of the normal distribution is:

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Thus if a r.v. X follows a normal distribution we write:

$$X \sim N(\mu, \sigma^2)$$



- $ightharpoonup \sigma^2$ is the variance of the distribution
- For different σ values, the distribution remains centered on the same value but becomes wider: larger values (in absolute values) of the r.v. are more likely

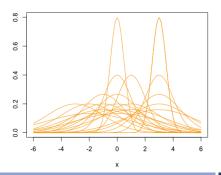
Normal distribution: parameters

The probability density function of the normal distribution is:

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

Thus if a r.v. X follows a normal distribution we write:

$$X \sim N(\mu, \sigma^2)$$



Varying μ and σ , we can obtain an infinite number of distributions.

Normal distribution: probabilities

Assume that $X \sim N(\mu, \sigma^2)$, then its pdf is:

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

we can use it to compute probabilities of a Normal rv

$$p = P(a \le X \le b)$$

where

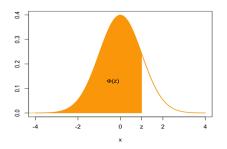
$$p = \int_a^b f(t)dt = F(b) - F(a)$$

Unfortunately, we do not have a closed form to compute this probability, but we can refer to a particular normal distribution...

Standard Normal distribution

The standard normal distribution, that is $\mu=0$ and $\sigma=1$, plays an important role.

$$Z \sim N(0,1) \rightarrow f(z;0,1) = \frac{1}{\sqrt{2\pi}}e^{-z^2/2}$$



We define:

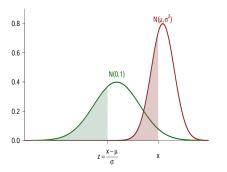
$$\Phi(z) = P(Z \le z)$$

the area under the curve between $-\infty$ and z. Note that with Φ we call the cumulative distribution function of the standard normal distribution

Standard Normal vs Normal (μ, σ)

If $X \sim N(\mu, \sigma^2)$, then

$$P(X \le x) = P\left(\frac{X - \mu}{\sigma} \le \frac{x - \mu}{\sigma}\right) = P\left(Z \le \frac{x - \mu}{\sigma}\right) = \Phi\left(\frac{x - \mu}{\sigma}\right)$$



That is, the red area (equal to $P(X \le x)$) is equal to the green one. Knowing $\Phi(z)$, we can compute any probability associated with a generic normal distribution $N(\mu, \sigma^2)$.

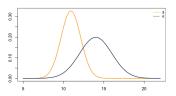
Normal distribution: transformations

Let X be distributed as a normal distribution $N(\mu, \sigma^2)$, and let a, and b be two real numbers, then:

$$Y = aX + b$$

follows a normal distribution:

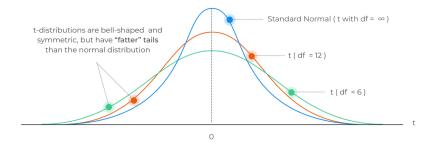
$$Y \sim N(a\mu + b, a^2\sigma^2)$$



As an example, if the stock price on a given day expressed in euros follows a Normal distribution $N(14, \sigma^2 = 2)$, then the value in dollars (1\$ = 0.78 euros) is still distributed as a Normal with mean 0.78×14 and variance $2 \times (0.78)^2$.

Normal vs Student's t

Another relevant continuous distribution is the **Student't** distribution t_{ν} , governed by the parameter ν (the degrees of freedom).



It is closely related to the Standard Normal (when $\nu \to \infty,\ t_{\nu} \stackrel{approx}{\sim} \mathcal{N}(0,1)$ but, in general, it has heavier tails. It is widely used in statistical inference.