



# Introduction to probability theory and statistical inference

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# Chapter 1

## Introduction

In the following pages one will find an introductory course to probability and statistical inference, aiming to cover both foundations and basic mathematical concepts, but also modern tools to deal with modern problems. The text is composed by six chapters, together with some appendix reviewing basic mathematical concepts, and a bibliographic note. The purpose of this lecture notes is to make both probability and statistical analysis an easy, interesting and engaging topic for anyone interested, without the need for prior experience with mathematical training.

First, we will introduce and explore the concept of probability itself, and we will discuss how to model information and chance. Then we will discuss a series of mathematical approaches to such quantities and formally define random processes, also referred to as *stochastic*. We will introduce the idea of a function and how functions need to be adapted to implement uncertainty when discussing random events. In the second part we will address the difference between prediction and inference, and discuss a set of subjects normally grouped under the name of *hypothesis testing*. Here we will introduce how to quantify certainty and bias, how to model significance and the idea of hypothesis tests. Finally, we will briefly discuss more modern topics, such as bayesian statistics, stochasticity and Markov processes.

Probability theory is the mathematical framework for quantifying uncertainty and randomness. It provides the foundation for understanding and modeling various real-world phenomena, ranging from gambling and statistical inference to machine learning and quantum mechanics. At its core, probability assigns numerical values to the likelihood of different outcomes in an experiment. The fundamental concepts include sample spaces, events, and probability measures that adhere to axioms established by Andrey Kolmogorov.

The idea of stochasticity and randomness has deep historical roots. Ancient civilizations, including the Babylonians, Egyptians, and Greeks, grappled with the concept of uncertainty in games of chance, commerce, and divination. The oldest known dice date back over 5,000 years, indicating an early human fascination with randomness. While these cultures did not develop formal mathematical probability, they recognized patterns in random events and attempted to predict outcomes based on empirical observations and superstitions. Greek philosophers such as Democritus and Aristotle debated the nature of chance and determinism. The Roman philosopher Cicero distinguished between chance events and those governed by fate, foreshadowing later discussions on probability. In medieval times, scholars like Gerolamo Cardano (1501–1576) made early contributions by analyzing gambling problems and laying the groundwork for probability theory. The formalization of probability as a mathematical discipline began in the 17th century with the correspondence between Blaise Pascal and Pierre de Fermat, who devised combinatorial methods to solve problems related to games of chance. Their work introduced fundamental ideas such as expected value and laid the foundation for later advances by Christiaan Huygens, Jacob Bernoulli, and Abraham de Moivre. Bernoulli's *Ars Conjectandi* (1713) introduced the Law of Large Numbers, establishing that observed frequencies converge to theoretical probabilities over many trials.

A stochastic process extends probability theory by modeling systems that evolve randomly over time.

Unlike deterministic processes, where the outcome is fixed by initial conditions, stochastic processes incorporate uncertainty at each step. These models are essential in diverse fields such as finance (stock price fluctuations), physics (Brownian motion), and engineering (signal processing). A stochastic process is defined as a collection of random variables indexed by time or space, commonly represented as  $\{X_t\}_{t \in T}$ , where  $T$  is an index set.

One of the most fundamental stochastic processes is the Markov process, which exhibits the Markov property: the future state depends only on the present state, not on past history. This property makes Markov chains particularly useful in modeling systems with memoryless transitions, such as queueing networks and genetic sequences. Another significant class of stochastic processes is the Poisson process, which describes the occurrence of rare events over time, such as radioactive decay or network traffic.

Information theory, developed by Claude Shannon, is deeply intertwined with probability and stochastic processes. It quantifies the amount of uncertainty or surprise in a system and provides a mathematical foundation for data compression and communication. The fundamental measure in information theory is entropy, defined as:

$$H(X) = - \sum_i P(x_i) \log P(x_i), \quad (1.1)$$

where  $P(x_i)$  is the probability of observing outcome  $x_i$ . Entropy captures the unpredictability of a source of information, with higher entropy indicating greater uncertainty.

Shannon also introduced the concept of mutual information, which measures the reduction in uncertainty about one random variable given knowledge of another. This concept is crucial in signal processing, machine learning, and cryptography, where efficient information transfer and encoding are essential.

Together, probability theory, stochastic processes, and information theory form a powerful toolkit for modelling and analyzing uncertainty. Their applications span numerous disciplines, from physics and biology to artificial intelligence and cybersecurity. Understanding these concepts allows for the development of efficient algorithms, accurate predictions, and optimized decision-making strategies in uncertain environments.

Here are three important textbooks in the field of probability and statistics:

- A simple, intuitive introduction to statistics with few mathematical concepts is provided in Spiegelhalter's *The Art of Statistics: How to Learn from Data* [1].
- A more foundational textbook, with more advanced mathematical approach, can be found at DeGroot and Schervish's *Probability and Statistics* [2].
- For a philosophical and historical perspective on probability and statistics, please find McFadden's *The Philosophy of Statistics* [3].



## Chapter 2

# Introduction to probability and random events

### 2.1 What is probability?

As already mentioned in the introduction, probability theory is one of the oldest subjects within mathematical studies. Ideas such as probability or chance, together with measurement, information, inference, can be traced back to ancient times. Paradoxically, almost every topic explained nowadays in modern courses of statistics is extremely new, ranging broadly a century. Concepts like distributions, gaussian behaviour, p-values, hypothesis testing or normalization, are introduced and formalized in the XXth century by mathematicians such as Pearson and Fisher. For the purpose of this course, we will assume a specific framework, where we will understand probability as a number representing information, or *surprise*. For a detailed discussion on foundations of these topics, please see [...]. For more mathematically advanced texts, check [...] and [...].

Broadly speaking, probability, and later statistical inference, are branches of mathematics dealing with chance, also referred to as *random* events, or *stochastic* processes. Indeed, the word stochastic comes from no other than the greek word *στοχαστικός*, which literally means *to guess*. Let's try to briefly introduce the idea of probability, as a quantity that allows us to describe such random events.

So let's first ask ourselves the question. What *is* probability in the first place? What do we mean by it and what does it describe? Probability is nothing more, and nothing less, than a number we make up, a quantity we come up with, to quantify certainty in a process whose outcome we ignore. A number we will use to describe the amount of information we have about a random, or stochastic, event. For simplicity, we can make it range from 0 to 1, in the following way.

- If I'm sure A will never happen,  $P(A) = 0$ .
- If I'm sure A will always happen,  $P(A) = 1$ .
- For anything in between, there is a level of surprise, and hence  $P(A)$  will be a number between 0 and 1.

We will denote all possible outcomes of an experiment  $x_1, x_2, \dots, x_n$ . And we will require that the sum of probabilities of all possible outcomes add up to 1. This is a crucial property we will refer to as *normalization*

$$\sum_{i=1}^n p(x_i) = 1 \tag{2.1}$$

Once we have a definition for probability in the abstract case, we should have a way to compute for particular cases. A way of doing that, referred to as frequentist approach, is by dividing the number of favorable outcomes by the total number of outcomes.

$$P(\text{A happening}) = \frac{\text{Number of times A happens}}{\text{Total number of trials}} \quad (2.2)$$

Probabilities must follow a property we call unitarity. Unitarity ensures that, if we consider and add up the probabilities for all possible events in a given experiment, we get the total. That means, at least one of the scenarios will happen.

Indeed, the literal meaning of probability comes from latin *probabilis*. American logician and philosopher Richard Jeffrey, "Before the middle of the seventeenth century, the term "probable" (Latin *probabilis*) meant just approvable, and was applied in that sense, univocally, to opinion and to action. A probable action or opinion was one such as sensible people would undertake or hold, in the circumstances." [12] However, in legal contexts especially, "probable" could also apply to propositions for which there was good evidence.

The sixteenth-century Italian polymath Girolamo Cardano demonstrated the efficacy of defining odds as the ratio of favourable to unfavourable outcomes (which implies that the probability of an event is given by the ratio of favourable outcomes to the total number of possible outcomes [14]). Aside from the elementary work by Cardano, the doctrine of probabilities dates to the correspondence of Pierre de Fermat and Blaise Pascal (1654). Christiaan Huygens (1657) gave the earliest known scientific treatment of the subject. [15] Jakob Bernoulli's *Ars Conjectandi* (posthumous, 1713) and Abraham de Moivre's *Doctrine of Chances* (1718) treated the subject as a branch of mathematics. [16] See Ian Hacking's *The Emergence of Probability* [10] and James Franklin's *The Science of Conjecture* [17] for histories of the early development of the very concept of mathematical probability.

Like other theories, the theory of probability is a representation of its concepts in formal terms – that is, in terms that can be considered separately from their meaning. These formal terms are manipulated by the rules of mathematics and logic, and any results are interpreted or translated back into the problem domain.

There have been at least two successful attempts to formalize probability, namely the Kolmogorov formulation and the Cox formulation. In Kolmogorov's formulation (see also probability space), sets are interpreted as events and probability as a measure on a class of sets. In Cox's theorem, probability is taken as a primitive (i.e., not further analyzed), and the emphasis is on constructing a consistent assignment of probability values to propositions. In both cases, the laws of probability are the same, except for technical details.

## 2.2 Discrete and continuous

Once we have an insight on random events, and a mathematical quantity representing that uncertainty, we are ready to deal with real problems. From tossing coins, to rolling dice, to making measurements, the first thing we realize is that not *all* random events are equal. In some cases, like rolling a fair dice, all outcomes are equally probable, and in other cases, such as counting, we may encounter some results which happen much more often than others. The main criteria we will use for differentiate among random events, is what we will call their *distribution*.

We will distinguish two main families of random events. These in which the number of possible outcomes is finite, or *countable*, and the ones where the number of outcomes is *uncountable*. The first ones will be named as *discrete* events, while the second are normally referred to as *continuous*.

## 2.3 Probability distributions

Once we are comfortable with the idea of random events, and we have been introduced to probability as a number to quantify surprise, we can agree that not all random phenomena are equal. A basic way to classify and separate random events is according to how their probabilities are distributed.

### 2.3.1 Binomial distribution

The binomial distribution models the number of successes in a fixed number of independent trials, each with the same probability of success. It was developed by Jacob Bernoulli in the 17th century while studying the probability of repeated Bernoulli trials. His work laid the foundation for the Law of Large Numbers.

Intuitively, this distribution is useful when considering repeated experiments with two possible outcomes (success or failure). For example, flipping a fair coin multiple times follows a binomial pattern.

The probability mass function is given by:

$$P(x; n, p) = \binom{n}{x} p^x (1-p)^{n-x}, \quad (2.3)$$

where  $n$  is the number of trials and  $p$  is the probability of success.

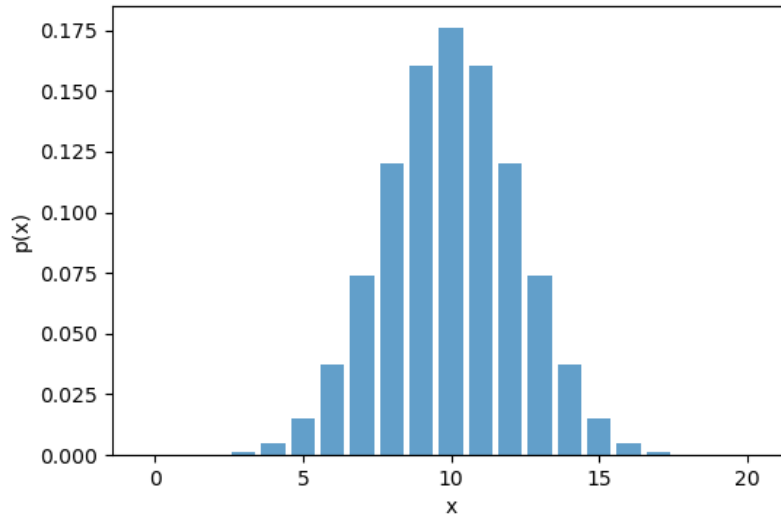


Figure 2.1: Representation of the binomial distribution of a random variable  $x$ , given the total number of trials  $n$  and the individual probability of success  $p$ .

**Example 1:** Suppose we flip a fair coin 5 times ( $n = 5$ ) and want to find the probability of getting exactly 3 heads ( $p = 0.5$ ):

$$P(X = 3) = \binom{5}{3} (0.5)^3 (0.5)^2 = 10 \times 0.125 \times 0.25 = 0.3125. \quad (2.4)$$

**Example 2:** Suppose we flip a fair coin 5 times ( $n = 5$ ) and want to find the probability of getting exactly 3 heads ( $p = 0.5$ ):

$$P(X = 3) = \binom{5}{3} (0.5)^3 (0.5)^2 = 10 \times 0.125 \times 0.25 = 0.3125. \quad (2.5)$$

**Example 3:** Suppose we flip a fair coin 5 times ( $n = 5$ ) and want to find the probability of getting exactly 3 heads ( $p = 0.5$ ):

$$P(X = 3) = \binom{5}{3} (0.5)^3 (0.5)^2 = 10 \times 0.125 \times 0.25 = 0.3125. \quad (2.6)$$

### 2.3.2 Poisson distribution

Named after Siméon Denis Poisson, this distribution was introduced in the early 19th century to model rare events. It is particularly useful for counting occurrences over a fixed interval of time or space.

Intuitively, the Poisson distribution applies to events happening randomly but with a known average rate, such as the number of emails received per hour.

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Intuitively, the Poisson distribution applies to events happening randomly but with a known average rate, such as the number of emails received per hour.

The probability mass function is:

$$P(x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}, \quad (2.7)$$

where  $\lambda$  is the expected number of occurrences.

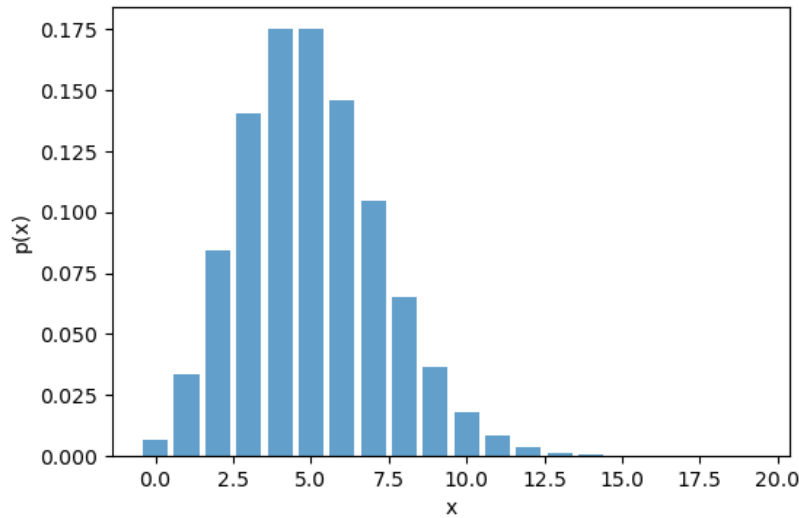


Figure 2.2: Representation of the Poisson distribution of a random variable  $x$ , given the number of observations  $\lambda$  as a parameter.

**Example 1:** If a bookstore sells an average of 3 books per hour ( $\lambda = 3$ ), the probability of selling exactly 5 books in an hour is:

$$P(x = 5) = \frac{3^5 e^{-3}}{5!} = \frac{243e^{-3}}{120} \approx 0.1008. \quad (2.8)$$

**Example 2:** If a bookstore sells an average of 3 books per hour ( $\lambda = 3$ ), the probability of selling exactly 5 books in an hour is:

$$P(x = 5) = \frac{3^5 e^{-3}}{5!} = \frac{243e^{-3}}{120} \approx 0.1008. \quad (2.9)$$

**Example 3:** If a bookstore sells an average of 3 books per hour ( $\lambda = 3$ ), the probability of selling exactly 5 books in an hour is:

$$P(x = 5) = \frac{3^5 e^{-3}}{5!} = \frac{243e^{-3}}{120} \approx 0.1008. \quad (2.10)$$

### 2.3.3 Uniform distribution

The uniform distribution represents a scenario where all outcomes in an interval  $[a, b]$  are equally likely. This distribution has been used since antiquity, especially in early probability and gambling studies.

Intuitively, it is useful when every possible outcome is equally probable, such as rolling a fair die.

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Intuitively, it is useful when every possible outcome is equally probable, such as rolling a fair die.

The probability density function is:

$$f(x) = \frac{1}{b-a}, \quad a \leq x \leq b. \quad (2.11)$$

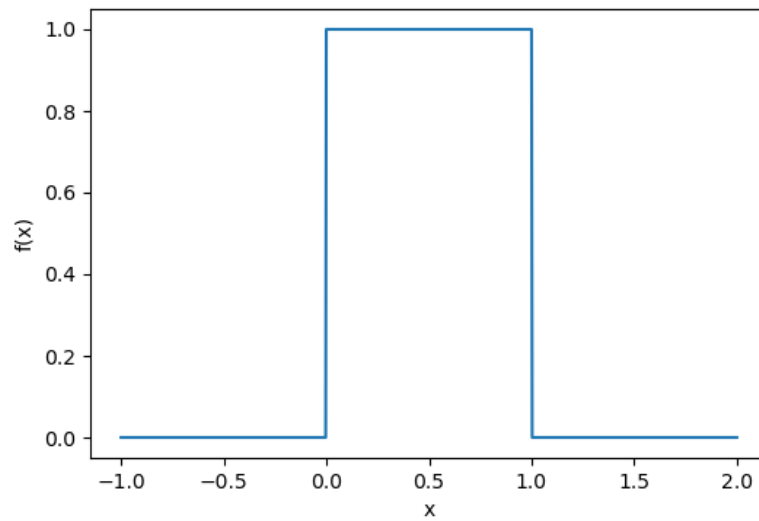


Figure 2.3: Representation of the uniform distribution of a random variable  $x$ , given the boundary parameters  $a$ ,  $b$ .

**Example 1:** If a random number is chosen from the interval  $[2, 10]$ , the probability density is:

$$f(x; a, b) = \frac{1}{10 - 2} = 0.125. \quad (2.12)$$

**Example 2:** If a random number is chosen from the interval  $[2, 10]$ , the probability density is:

$$f(x; a, b) = \frac{1}{10 - 2} = 0.125. \quad (2.13)$$

**Example 3:** If a random number is chosen from the interval  $[2, 10]$ , the probability density is:

$$f(x; a, b) = \frac{1}{10 - 2} = 0.125. \quad (2.14)$$

### 2.3.4 Gaussian distribution

Introduced by Carl Friedrich Gauss, the normal distribution became central to statistics due to the Central Limit Theorem (CLT). It describes how averages of large samples tend to form a bell-shaped curve.

Intuitively, many natural and social phenomena follow a normal distribution, such as human heights and test scores.

Introduced by Carl Friedrich Gauss, the normal distribution became central to statistics due to the Central Limit Theorem (CLT). It describes how averages of large samples tend to form a bell-shaped curve.

Intuitively, many natural and social phenomena follow a normal distribution, such as human heights and test scores.

The probability density function is:

$$f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \quad (2.15)$$

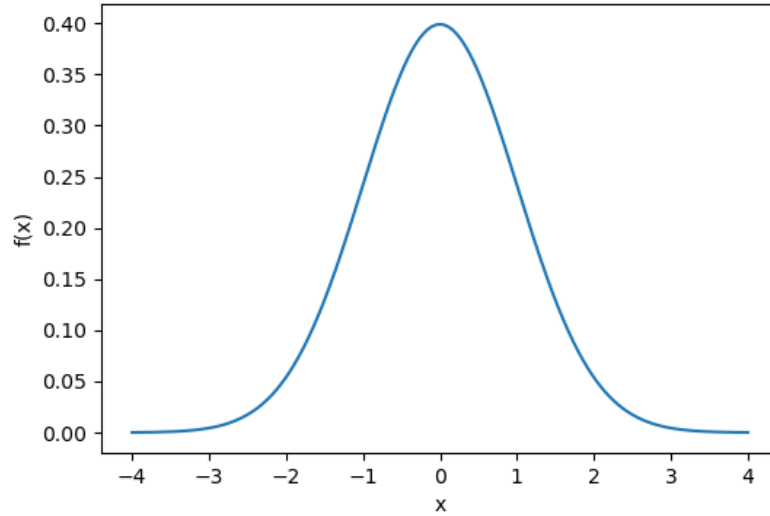


Figure 2.4: Representation of the gaussian distribution of a random variable  $x$ , given the mean value  $\mu$  and standard deviation  $\sigma$  parameters.

**Example 1:** If human heights are normally distributed with mean  $\mu = 170$  cm and standard deviation  $\sigma = 10$  cm, the probability density of someone being exactly 180 cm is:

$$f(180) = \frac{1}{10\sqrt{2\pi}} e^{-\frac{(180-170)^2}{2(10)^2}} \approx 0.0242. \quad (2.16)$$

**Example 2:** If human heights are normally distributed with mean  $\mu = 170$  cm and standard deviation  $\sigma = 10$  cm, the probability density of someone being exactly 180 cm is:

$$f(180) = \frac{1}{10\sqrt{2\pi}} e^{-\frac{(180-170)^2}{2(10)^2}} \approx 0.0242. \quad (2.17)$$

**Example 3:** If human heights are normally distributed with mean  $\mu = 170$  cm and standard deviation  $\sigma = 10$  cm, the probability density of someone being exactly 180 cm is:

$$f(180) = \frac{1}{10\sqrt{2\pi}} e^{-\frac{(180-170)^2}{2(10)^2}} \approx 0.0242. \quad (2.18)$$

### 2.3.5 Exponential distribution

The exponential distribution models waiting times between Poisson process events. It has been widely applied in reliability analysis and survival studies.

Intuitively, it describes situations where the probability of waiting a certain time between events remains constant, such as time between bus arrivals.

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The probability density function is:

$$f(x; \lambda) = \lambda e^{-\lambda x}, \quad x \geq 0. \quad (2.19)$$

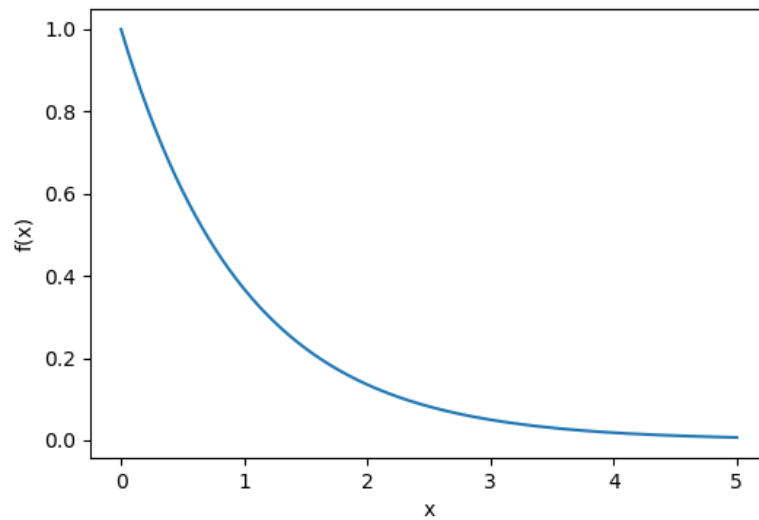


Figure 2.5: Representation of the exponential distribution of a random variable  $x$ , given the decay rate  $\lambda$ .

**Example 1:** If a call center receives calls at an average rate of  $\lambda = 2$  per minute, the probability that the next call arrives after more than 2 minutes is:

$$P(X > 2) = e^{-2(2)} = e^{-4} \approx 0.0183. \quad (2.20)$$

**Example 2:** If a call center receives calls at an average rate of  $\lambda = 2$  per minute, the probability that the next call arrives after more than 2 minutes is:

$$P(X > 2) = e^{-2(2)} = e^{-4} \approx 0.0183. \quad (2.21)$$

**Example 3:** If a call center receives calls at an average rate of  $\lambda = 2$  per minute, the probability that the next call arrives after more than 2 minutes is:

$$P(X > 2) = e^{-2(2)} = e^{-4} \approx 0.0183. \quad (2.22)$$





## Chapter 3

# Parameter estimation

### 3.1 Prediction vs inference

In the previous chapters we have introduced the mathematical theory of probability. That is, we have developed a series of tools, a *theory*, which enables us to make predictions in stochastic processes. But, contrary to what is normally explain in introductory courses, science is not always headed in the theory and experiment direction. There can be cases, as we will soon see, where hypothesis are formulated for a given phenomena, and no prediction is made. In such cases, it is from measurement that we will try to see, or *infer* if our hypothesis are compatible with given data. Indeed, most modern data analysis and hypothesis testing lie in the inferential statistics, rather than predictive probability.

The difference between prediction and inference has been a topic of interest in statistics and data science for centuries. While both concepts involve drawing conclusions from data, their goals, methodologies, and historical development differ significantly.

The roots of inference trace back to classical statistics, particularly the work of Pierre-Simon Laplace (1749–1827) and Carl Friedrich Gauss (1777–1855), who developed probability theory and the method of least squares. Their work laid the foundation for statistical inference, which aims to understand relationships between variables and make generalizable conclusions about populations from samples.

For example, Laplace used probability theory to estimate the population of France, introducing Bayesian inference, which provides a framework for updating beliefs based on observed data. Gauss contributed the normal distribution and least squares estimation, which became essential for making inferences about unknown parameters.

On the other hand, prediction as a primary goal gained traction much later, particularly in the 20th century with the rise of machine learning. The focus shifted from understanding relationships to optimizing models that generalize well to unseen data. In 2001, Leo Breiman, in his seminal paper "Statistical Modeling: The Two Cultures," highlighted the distinction, arguing that traditional statistics emphasized inference, whereas modern machine learning prioritized prediction.

Inference seeks to explain why and how variables relate. The key idea is causality and interpretability: given a dataset, inference aims to answer questions such as: Does smoking cause lung cancer, or is the correlation due to other confounding factors? How does an increase in temperature affect ice cream sales? What are the most significant predictors of house prices? Statistical techniques such as hypothesis testing, confidence intervals, and regression analysis help researchers understand these relationships. The emphasis is on estimating parameters and determining statistical significance rather than simply making accurate predictions. A classic example is Sir Ronald Fisher (1890–1962), who developed maximum likelihood estimation (MLE) to infer parameters of probability distributions. Fisher's work allowed statisticians to estimate relationships between variables and quantify uncertainty.

Prediction focuses on accuracy and generalization rather than explaining causality. The goal is to create a model that performs well on new, unseen data, even if the underlying relationships between variables are not fully understood. For example, in modern deep learning, neural networks can recognize faces with high accuracy but offer little interpretability in how they make decisions. Unlike inference, which aims to understand why a pattern exists, prediction is about making the best possible guess given the available data. A key contributor to predictive modeling was Andrey Kolmogorov (1903–1987), who formalized probability theory and stochastic processes. His work laid the foundation for modern probabilistic models used in machine learning and artificial intelligence. Later, Vapnik and Chervonenkis (1971) developed statistical learning theory, which introduced VC dimension, a measure of a model’s ability to generalize. This work led to the development of Support Vector Machines (SVMs), a key predictive tool in machine learning.

While Breiman’s paper emphasized the divide between the two approaches, modern data science integrates both. In many cases, understanding causal relationships (inference) can improve predictive performance, and accurate prediction can guide further investigations into causality. For example, epidemiologists use inference to understand how diseases spread, but they also use predictive models to forecast outbreaks. In finance, analysts infer factors affecting stock prices while using machine learning to predict market trends. By combining both approaches, we gain a more comprehensive understanding of data, allowing for both insightful interpretations and powerful predictions.

## 3.2 Parameter estimation

Another key difference we will discuss now, and quite a subtle one from the mathematical perspective, is that one between a *variable* and a *parameter*. Consider the example of a binomial experiment, e.g. tossing coins and asking for the probability of measuring a specific number of heads. There, we would write it as

$$P(x; n, p) = \binom{n}{x} p^x (1 - p)^{n-x}, \quad (3.1)$$

where  $n$  is the number of trials and  $p$  is the probability of success.

In our previous examples, we have treated just  $x$  as our variable of interest, but we could think about  $P$  as a function of three independent variables. The number of times we want to observe heads, the total number of trials, and the probability of success for each toss. Normally, we will call *parameters*, to all these variables we will freeze for the purpose of our calculations, and either consider them either known, or fit them from data (...).

### 3.3 Law of Large Numbers (LLN)

#### 3.3.1 Introduction

The Law of Large Numbers (LLN) is one of the fundamental theorems of probability theory. It was first formulated by Jacob Bernoulli in the late 17th century and later refined by other mathematicians, including Pafnuty Chebyshev. Bernoulli's work aimed to formalize how relative frequencies of events stabilize as the number of trials increases, providing the foundation for statistical inference. LLN plays a crucial role in statistics, finance, and machine learning, ensuring that averages computed from large samples are reliable estimates of expected values.

#### 3.3.2 Definition

The Law of Large Numbers states that as the sample size increases, the sample mean approaches the expected value. Formally, if  $X_1, X_2, \dots, X_n$  are independent and identically distributed (i.i.d.) random variables with expected value  $\mathbb{E}[X] = \mu$ , then:

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \rightarrow \mu \quad \text{as } n \rightarrow \infty. \quad (3.2)$$

#### 3.3.3 Intuition

Consider flipping a fair coin multiple times. The proportion of heads observed converges to 0.5 as the number of flips increases. This illustrates that the observed average stabilizes around the theoretical probability.

#### 3.3.4 Types of LLN

- **Weak Law of Large Numbers (WLLN):** Convergence in probability, i.e., for any  $\epsilon > 0$ ,

$$P(|\bar{X}_n - \mu| \geq \epsilon) \rightarrow 0 \quad \text{as } n \rightarrow \infty. \quad (3.3)$$

- **Strong Law of Large Numbers (SLLN):** Almost sure convergence, i.e.,

$$P\left(\lim_{n \rightarrow \infty} \bar{X}_n = \mu\right) = 1. \quad (3.4)$$

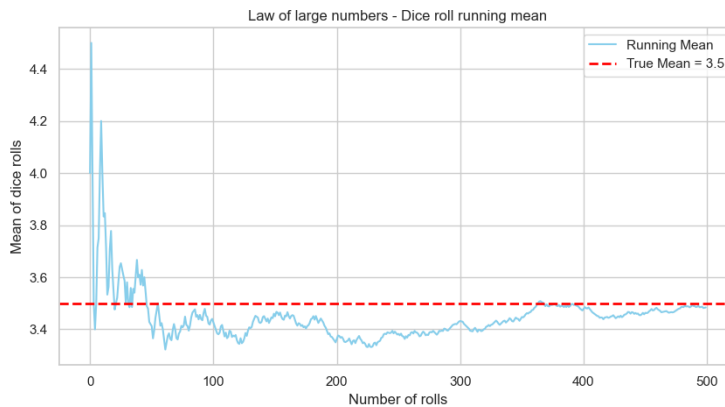


Figure 3.1: Representation of the law of large numbers. The sample mean tends to the population mean as the number of rolls  $n$  increases.

### 3.3.5 Example

Suppose we roll a fair six-sided die multiple times. The expected value of a roll is:

$$\mathbb{E}[X] = \frac{1 + 2 + 3 + 4 + 5 + 6}{6} = 3.5. \quad (3.5)$$

As we roll more dice, the sample mean of observed values gets closer to 3.5.

## 3.4 Central Limit Theorem (CLT)

### 3.4.1 Introduction

The Central Limit Theorem (CLT) was first discovered in the 18th century by Abraham de Moivre and later developed by Pierre-Simon Laplace and Carl Friedrich Gauss. It formalizes the idea that the distribution of sample means tends toward a normal distribution, regardless of the shape of the original population distribution. The CLT is fundamental in inferential statistics, allowing researchers to make predictions and construct confidence intervals for population parameters based on sample data.

### 3.4.2 Definition

The Central Limit Theorem states that for a large enough sample size, the sampling distribution of the sample mean follows a normal distribution, regardless of the original population distribution. Formally, if  $X_1, X_2, \dots, X_n$  are i.i.d. random variables with mean  $\mu$  and variance  $\sigma^2$ , then the standardized sample mean:

$$Z = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \quad (3.6)$$

converges in distribution to a standard normal distribution  $\mathcal{N}(0, 1)$  as  $n \rightarrow \infty$ .

### 3.4.3 Intuition

No matter the shape of the original distribution, when we take many samples and compute their means, the histogram of these sample means will resemble a normal curve as the sample size grows.

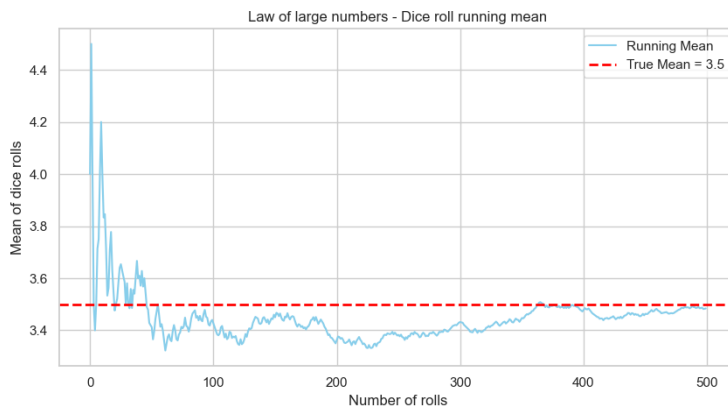


Figure 3.2: Representation of the law of large numbers. The sample mean follows a gaussian distribution as the sample size  $n$  increases.

### 3.4.4 Example

Consider rolling a fair six-sided die multiple times and computing the average outcome for groups of  $n$  rolls. As  $n$  increases, the distribution of these sample means approaches a normal distribution, centered at  $\mu = 3.5$ .

### 3.4.5 Applications

- Used in inferential statistics to approximate sampling distributions.
- Forms the basis for hypothesis testing and confidence intervals.

- Justifies the normality assumption in many statistical models.

## Chapter 4

# Introduction to statistical inference

### 4.1 Prediction vs inference

In the previous chapters we have introduced the mathematical theory of probability. That is, we have developed a series of tools, a *theory*, which enables us to make predictions in stochastic processes. But, contrary to what is normally explain in introductory courses, science is not always headed in the theory and experiment direction. There can be cases, as we will soon see, where hypothesis are formulated for a given phenomena, and no prediction is made. In such cases, it is from measurement that we will try to see, or *infer* if our hypothesis are compatible with given data. Indeed, most modern data analysis and hypothesis testing lie in the inferential statistics, rather than predictive probability.

### 4.2 Hypothesis testing

Probability theory is one of the oldest subjects within mathematical studies. Paradoxically, almost every topic explained nowadays in modern courses of statistics is extremely new, ranging broadly a century. (...)

So let's first ask ourselves the question. What is probability in the first place? What do we mean by it and what does it describe? Probability is nothing more, and nothing less, that a number we make up, a quantity we come up with, to quantify certainty. A number we will use to describe the amount of information we have about a random, or stochastic, event. For simplicity, we can make it range from 0 to 1, in the following way.

### 4.3 Statistic tests

Statistic tests

### 4.4 P-values and significance

P-values and significance

#### Compare sample mean with hypothesized value - One sample t-test

The one-sample t-test is used to determine whether the mean of a single sample differs significantly from a known or hypothesized population mean. It assumes that the sample data are drawn from a normally distributed population. The test statistic is given by:

$$t = \frac{\bar{x} - \mu}{s/\sqrt{n}},$$

where  $\bar{x}$  is the sample mean,  $\mu$  is the population mean,  $s$  is the sample standard deviation, and  $n$  is the sample size.



Compare sample means of two groups - Two sample t-test

Compare sample variances of two groups - Fisher test

Compare more than two groups - ANOVA

Compare distributions -  $\chi^2$  test

## 4.5 Parametric and non-parametric

## 4.6 Comparing data and normalization

Comparing data and normalization



## Chapter 5

# Introduction to bayesian statistics

### 5.1 The Bayes' theorem

The Bayes' theorem.

### 5.2 Bayesian vs frequentist

Bayesian vs frequentist.

### 5.3 Bayesian statistics

Bayesian statistics.



## Chapter 6

# Stochasticity and Markov processes

6.1 Stochasticity and Markov processes

6.2 Markov chains and hidden Markov models

6.3 Modern applications



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