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ESTADOS UNIDOS MEXICANOS

TECNOLÓGICO NACIONAL DE MÉXICO

INSTITUTO TECNOLÓGICO DE CIUDAD GUZMÁN

Aprendizaje por Refuerzo

Maestría en Ciencias Computacionales
2do Semestre

Presenta
Dr. Julio Alberto García Rodríguez

Ciudad Guzmán, Enero de 2026

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SITIO OFICIAL

https://cdguzman.tecnm.mx/pag/

ENCUADRE DE LA MATERIA

- Actividades de aprendizaje 30%
  (Tareas, Ejercicios de clase, Investigaciones, Prácticas, Exposiciones)
- Instrumento de Evaluación: Examen escrito 40%
- Proyecto de Asignatura 30%

A través del presente escrito CONFIRMO que conozco el ENCUADRE y el PROGRAMA DE ESTUDIOS de la materia de APRENDIZAJE POR REFUERZO

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Nombre completo y firma Fecha

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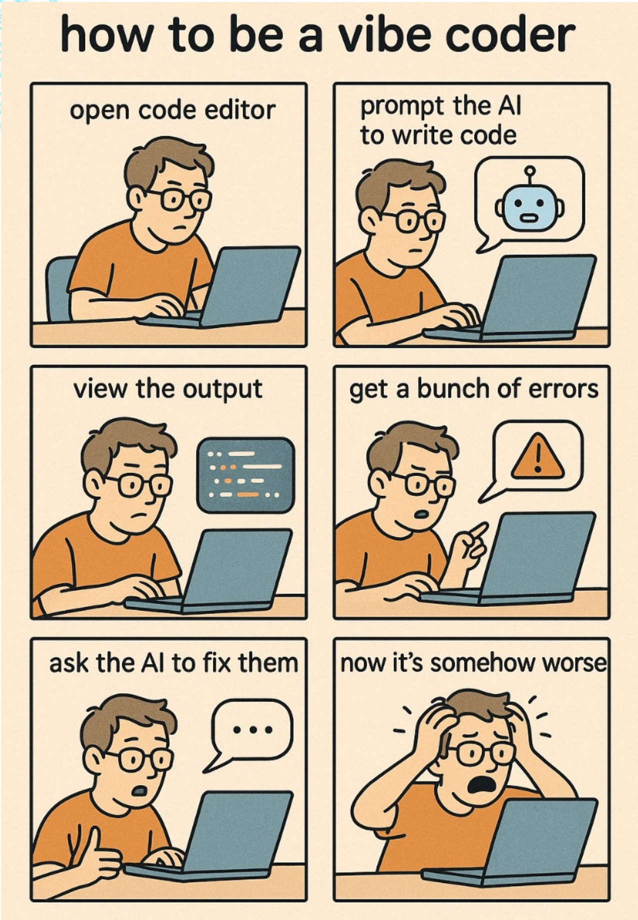
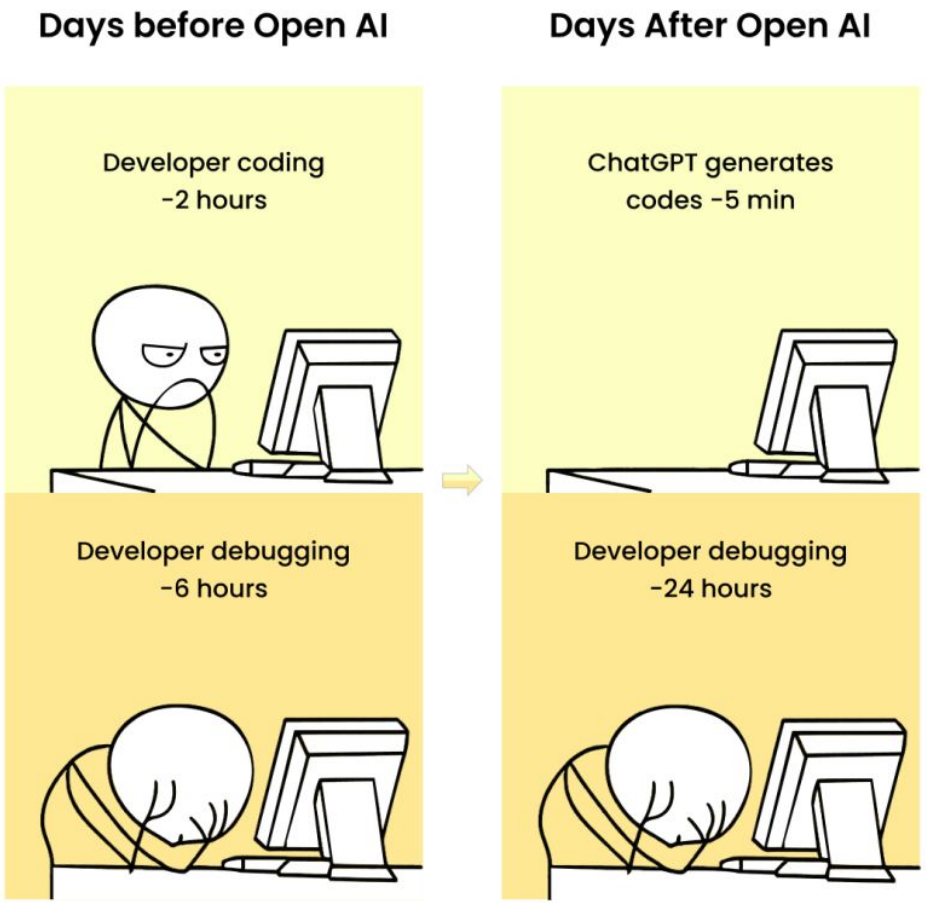
Class Best practices

- Limited Smartphone use. Emergencies only.
- Put attention in class, avoid distractors as Social Networks.
- Ask when you feel lost.
- Remember that Natural Intelligence is still better than Artificial Intelligence. Use AI tools wisely, responsibly, and ethically.
- The class focuses on **developing logical, mathematical, and computational thinking skills**. It is not focused on developing thousands of lines of code that even the student doesn't understand.

Class Best practices





1. Introducción al AR

Learning by Interacting with the World

The idea that we learn by interacting with our environment is probably the first to occur to us when we think about the nature of learning.

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1.1 Introducción al AR

Learning by Interacting with the World

When an infant plays, waves its arms, or looks about, it has no explicit teacher, but it does have a direct sensorimotor connection to its environment. Exercising this connection produces a wealth of information about cause and effect, about the consequences of actions, and about what to do in order to achieve goals.

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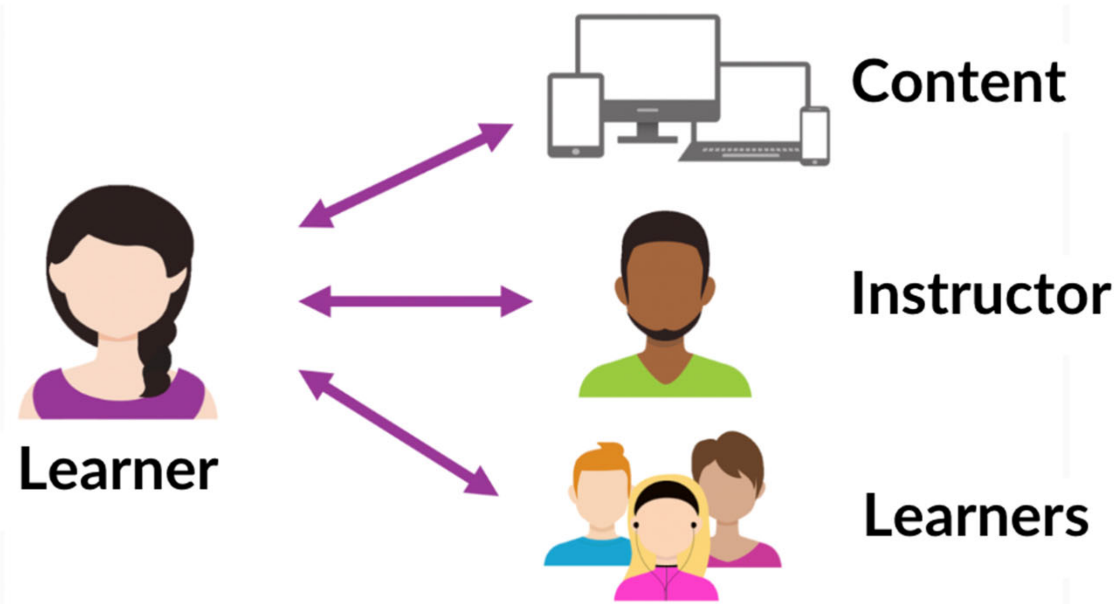
1.1 Introducción al AR

Learning by Interacting with the World

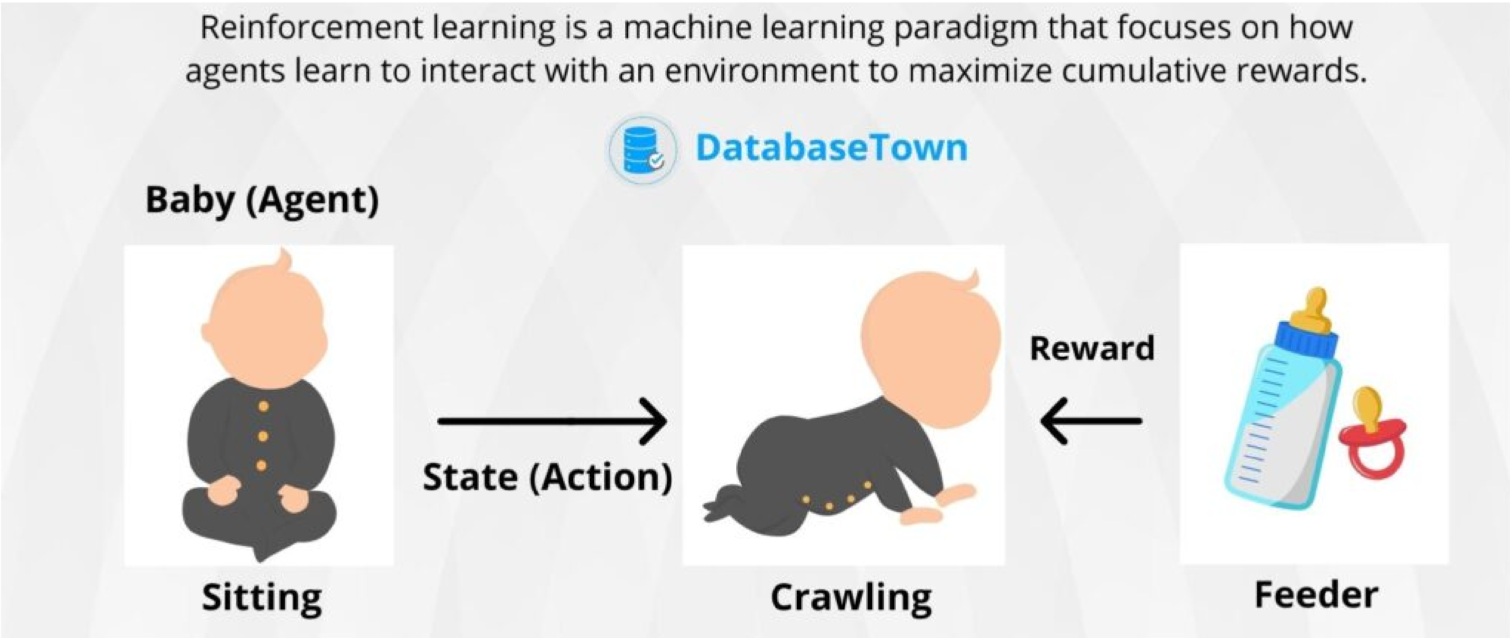
Learning from interaction is a foundational idea underlying nearly all theories of learning and intelligence.



1.1 Introducción al AR

Learning by Interacting with the World

Reinforcement Learning (RL) explores <u>a computational approach to learning from interaction where an agent seeks to achieve goals by navigating an uncertain environment.</u>



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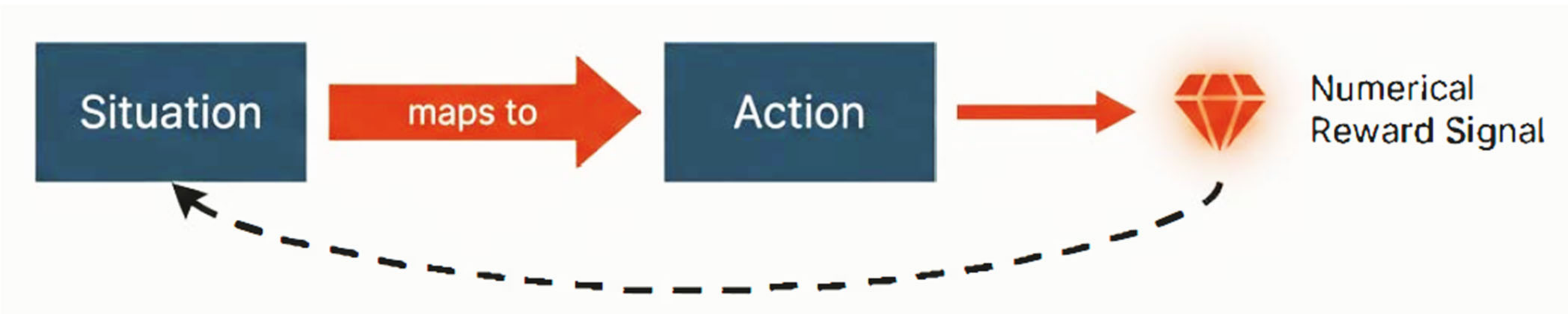
1.1 Introducción al AR

Learning by Interacting with the World

Reinforcement learning is
- Learning what to do
- How to map situations to actions
- So as to maximize a numerical reward signal.



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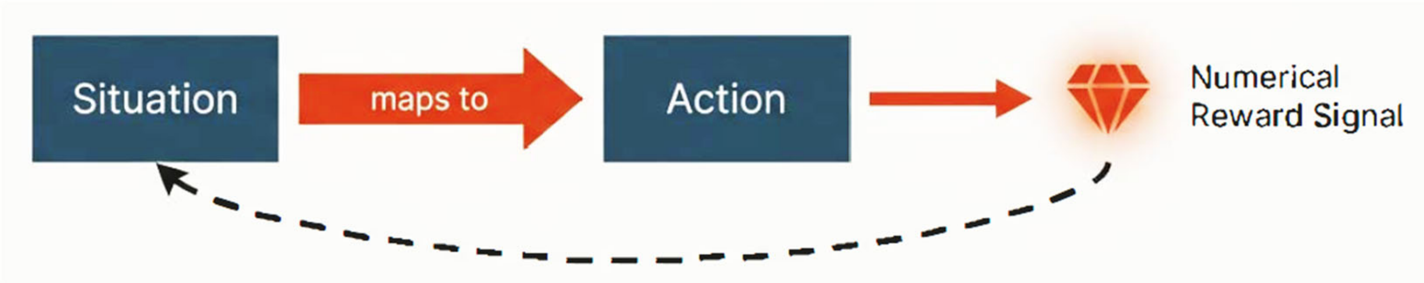
1.1 Introducción al AR

Learning by Interacting with the World



Trial-and-Error Search

The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.

Delayed Reward

Actions may affect not only the immediate reward but also all subsequent rewards.

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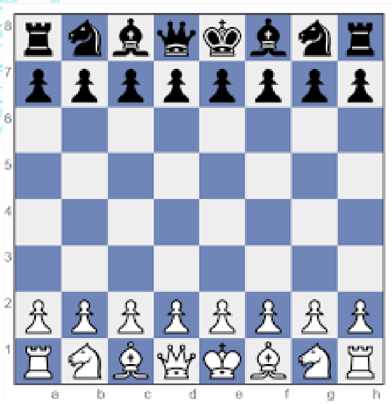
1.1 Introducción al AR

Learning by Interacting with the World



Chess

Shogi

Go

1.1 Introducción al AR

Learning by Interacting with the World

The Game of Go

A few years ago, AlphaGo beat Lee Sedol, a world champion in Go (a feat experts didn't think would happen for another decade) Now, AlphaZero learns to become superhuman without ever considering human strategy.

AlphaGo → AlphaGo Zero → AlphaZero

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1.1 Introducción al AR

Learning by Interacting with the World

Lee Sedol

27 languages

Article Talk   Read Edit View history Tools

From Wikipedia, the free encyclopedia

In this Korean name, the family name is Lee.

Lee Sedol (Korean: 이세돌; born 2 March 1983), or **Lee Se-dol**, is a South Korean former professional Go player of 9 dan rank.[1] As of February 2016, he ranked second in international titles (18), behind only Lee Chang-ho (21). His nickname is "The Strong Stone" ("Ssen-dol"). In March 2016, he played a notable series of matches against the program AlphaGo that ended in Lee losing 1–4.[2]

Lee announced his retirement from professional play in November 2019, stating he could never be the top overall player of Go due to the increasing dominance of AI, which he called "an entity that cannot be defeated".[3] Lee shared in a 2024 interview, "losing to AI, in a sense, meant my entire world was collapsing. ... I could no longer enjoy the game. So I retired."[4]

Lee Sedol

1.1 Introducción al AR

Learning by Interacting with the World

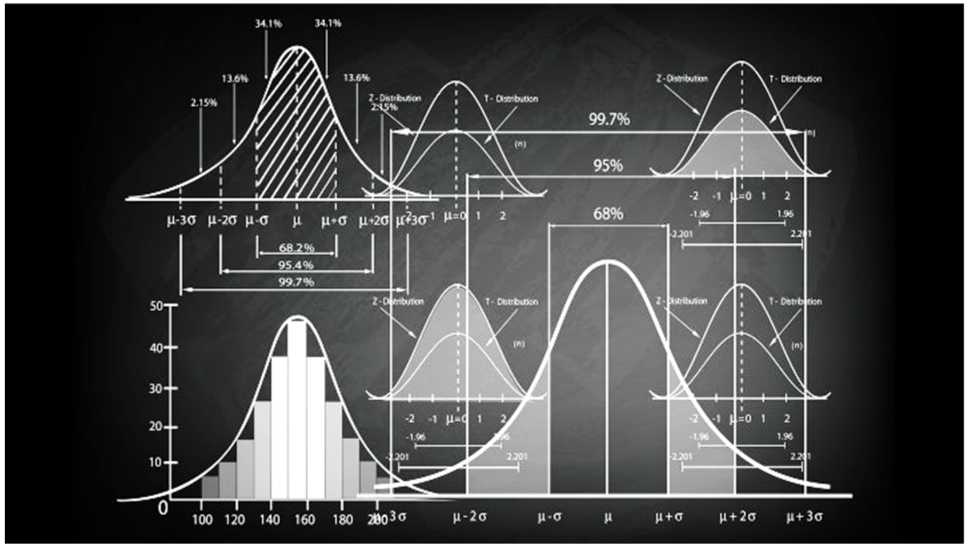
https://deepmind.google/research/alphazero-and-muzero/

https://www.youtube.com/watch?v=7L2sUGcOgh0&t=26s

1.2 El rol de la probabilidad y estadística

Probability and statistics are not just important for Reinforcement Learning (RL), they are the engine room of the entire field.

They serves as the essential mathematical framework for making decisions in uncertain, dynamic environments.



1.2 El rol de la probabilidad y estadística

Statistics

Researchers and practitioners apply and extend statistical methodology, contributing new ideas and methods for conducting data analysis.

1.2 El rol de la probabilidad y estadística

Statistics

Evolving and dynamic field -> Emerging challenges and opportunities

- **Properties** of statistical methods are under **continuing study**.
- New application areas → **development** of new analytic methods.
- New types of sensors → **new types of data**.
- Advances in **computing** → sophisticated analyses on Big Data.

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1.2 El rol de la probabilidad y estadística

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Statistics

Statistics is a “big tent” discipline. Incorporates new ideas from theory, practice, allied fields.

Different Perspectives:

- “art of summarizing data”
- “science of uncertainty”
- “science of decisions”
- “science of variation”
- “art of forecasting”
- “science of measurement”
- “basis for principled data collection”

1.2 El rol de la probabilidad y estadística

Statistics as the "science of uncertainty"

- Data can be **misleading.**
- Statistics provides framework for **assessing whether claims based on data are meaningful.**

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1.2 El rol de la probabilidad y estadística

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Statistics as the "science of uncertainty"

- Uncertainty is inevitable, but it is highly desirable to **quantify how far our reported findings may fall from “the truth”.**

Many public opinion polls report **± margin of error**

→ potential discrepancy between
reported and actual states of public opinion

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1.2 El rol de la probabilidad y estadística

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Statistics as the "science of decisions"

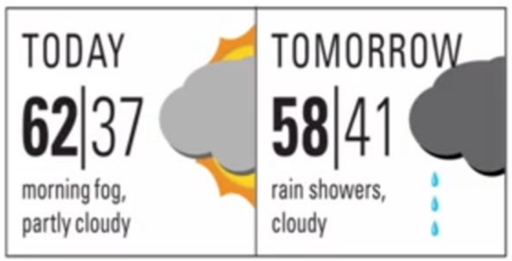
- **Understanding data** is important → only consequential if we act on what we have learned.
- **Decision-making** = ultimate goal of any statistical analysis.
- We make decisions in face of uncertainty!
  What are costs and benefits of different approaches?

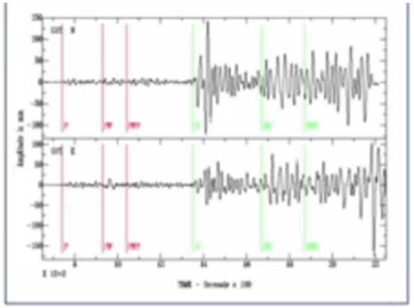
→ at higher than average risk for cancer…
should they undergo preventative procedure?

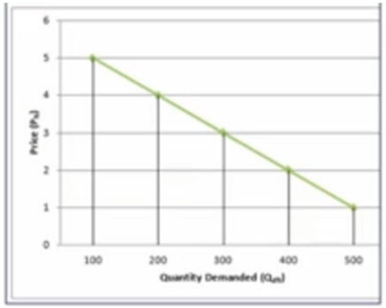
1.2 El rol de la probabilidad y estadística

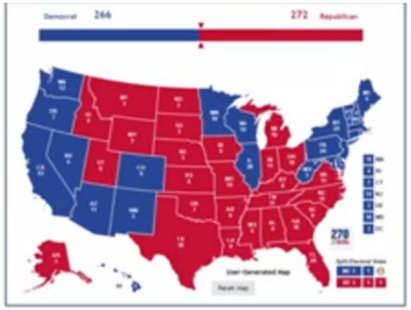
Statistics as the “art of forecasting"

- **Forecasting or prediction** = central tasks in statistics.
- We **cannot** know the future with absolute certainty, but efficient use of available data.
  → **can** sometimes make accurate predictions about the future.









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1.2 El rol de la probabilidad y estadística

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Statistics as the "science of measurement"

- **High accuracy:** age or height of a person.
- **More difficult**: blood pressure (varies minute to minute).
- **Harder:** "mood," "political ideology," "personality".

Statistics: major role in **constructing and evaluating rigorous approaches for measuring difficult-to-define concepts** and in **assessing quality**.

1.2 El rol de la probabilidad y estadística

Statistics as the "basis for principled data collection "

- Data often expensive and difficult to collect.
- Resource limitations → collect least data possible.

Statistics: provides a rational way to manage this trade-off

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1.2 El rol de la probabilidad y estadística

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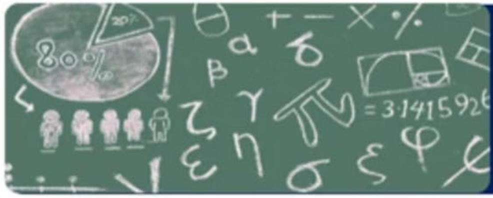
"Statistics and Its Allied Fields"

Computer science: algorithms, data structures for working with data, programming languages for manipulating data.



Mathematics: language and notation for expressing statistical concepts concisely, tools for understanding properties of statistical methods.

1.2 El rol de la probabilidad y estadística

"Statistics and Its Allied Fields"

Probability theory: branch of mathematics ~ crucial part of foundations of statistics – to express ideas about randomness and uncertainty.

Data Science: database management, machine learning, computational infrastructure to carry out data analysis.

1.2 El rol de la probabilidad y estadística

Resources

https://www.youtube.com/watch?v=WMDAR2bZEp0

1.2 El rol de la probabilidad y estadística

DRV

Discrete Random Variables

When working on a data analysis problem, one of the biggest challenges is the disparity between the theoretical tools we learn in school and the *actual data* our boss hands to us. By actual data, we mean a collection of numbers, perhaps organized or perhaps not. When we are given the dataset, the first thing we do would certainly not be to define the Borel σ-field and then define the measure. Instead, we would normally compute the mean, the standard deviation, and perhaps some scores about the skewness.

1.2 El rol de la probabilidad y estadística

The situation is best explained by the landscape shown in Figure 3.1. On the one hand, we have well-defined probability tools, but on the other hand, we have a set of practical “battle skills” for processing data. Often we view them as two separate entities. As long as we can pull the statistics from the dataset, why bother about the theory? Alternatively, we have a set of theories, but we will never verify them using the actual datasets. How can we bridge the two? What are the missing steps in the probability theory we have learned so far? The goal of this chapter (and the next) is to fill this gap.

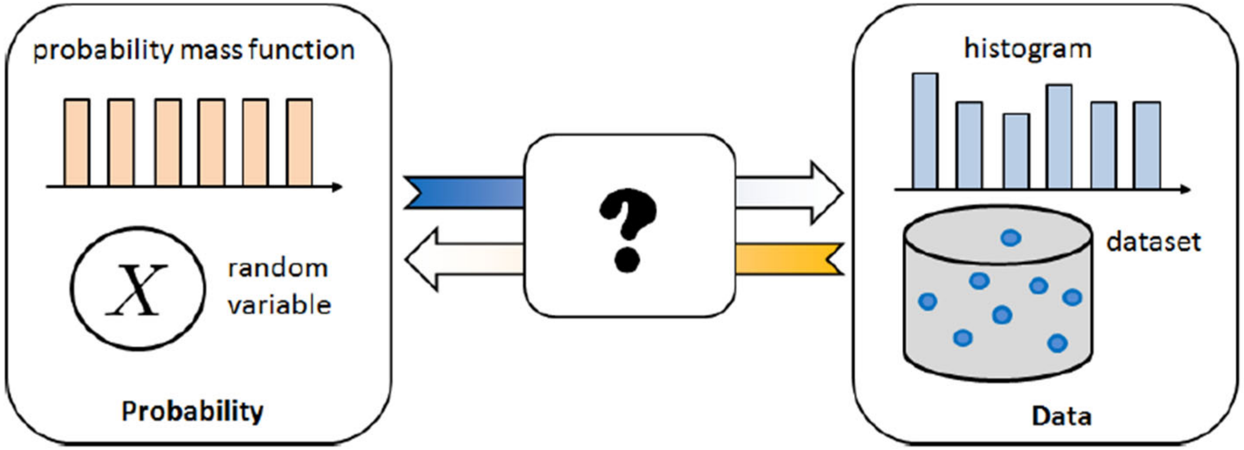


Figure 3.1: The landscape of probability and data. Often we view probability and data analysis as two different entities. However, probability and data analysis are inseparable. The goal of this chapter is to link the two.

DRV

Discrete Random Variables

The first step is to recognize that the sample space and the event space are all based on *statements*, for example, "getting a head when flipping a coin" or "winning the game." These statements are not numbers, but we (engineers) love numbers. Therefore, we should ask a very basic question: How do we convert a statement to a number? The answer is the concept of **random variables**.

> **Key Concept 1: What are random variables?**
>
> Random variables are mappings from events to numbers.

1.2 El rol de la probabilidad y estadística

DRV

Discrete Random Variables

Now, suppose that we have constructed a random variable that translates statements to numbers. The next task is to endow the random variable with probabilities. More precisely, we need to assign probabilities to the random variable so that we can perform computations. This is done using the concept called **probability mass function** (PMF).

Key Concept 2: What are probability mass functions (PMFs)?

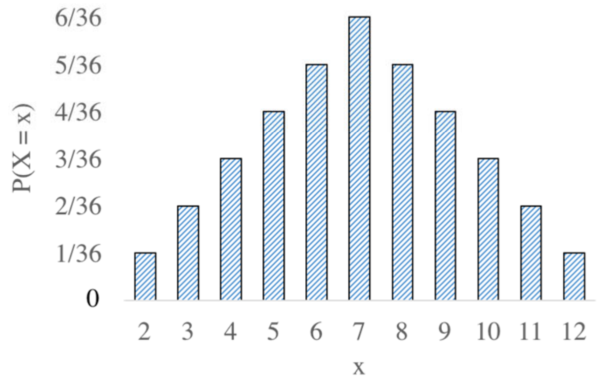
Probability mass functions are the ideal histograms of random variables.

1.2 El rol de la probabilidad y estadística

DRV

Discrete Random Variables

The best way to think about a PMF is a histogram, something we are familiar with. A histogram has two axes: The x-axis denotes the set of **states** and the y-axis denotes the **probability**. For each of the states that the random variable possesses, the histogram tells us the probability of getting a particular state. The PMF is the *ideal* histogram of a random variable. It provides a complete characterization of the random variable. If you have a random variable, you must specify its PMF. Vice versa, if you tell us the PMF, you have specified a random variable.



1.2 El rol de la probabilidad y estadística

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Discrete Random Variables

We ask the third question about pulling information from the probability mass function, such as the mean and standard deviation. How do we obtain these numbers from the PMF? We are also interested in operations on the mean and standard deviations. For example, if a professor offers ten bonus points to the entire class, how will it affect the mean and standard deviation? If a store provides 20% off on all its products, what will happen to its mean retail price and standard deviation? However, the biggest question is perhaps the difference between the mean we obtain from a PMF and the mean we obtain from a histogram. Understanding this difference will immediately help us build a bridge from theory to practice.

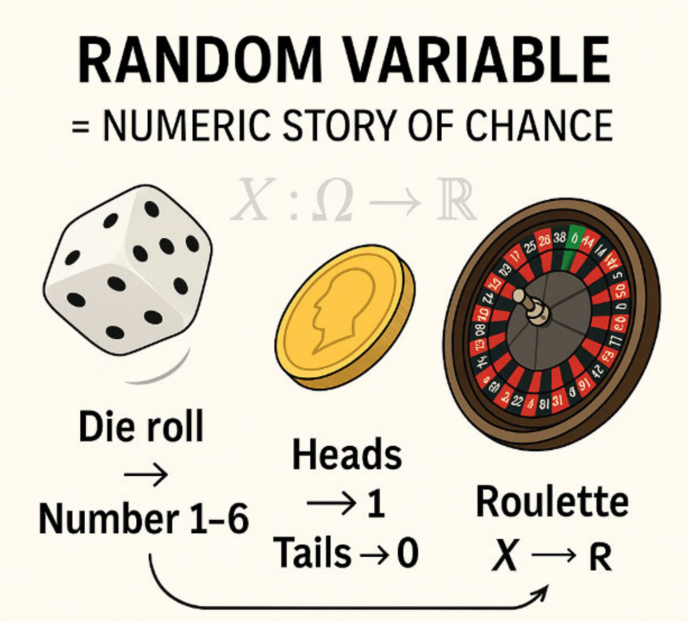
Key Concept 3: What is expectation?

Expectation = Mean = Average computed from a PMF.

1.2 El rol de la probabilidad y estadística

Definition of RV

Definition 3.1. *A* random variable X *is a function* $X : \Omega \to \mathbb{R}$ *that maps an outcome* $\xi \in \Omega$ *to a number* $X(\xi)$ *on the real line.*



Definition of RV

Definition 3.1. *A* **random variable** X *is a function* $X : \Omega \to \mathbb{R}$ *that maps an outcome* $\xi \in \Omega$ *to a number* $X(\xi)$ *on the real line.*

Symbol	Meaning
Ω	sample space = the set containing $\clubsuit, \diamondsuit, \heartsuit, \spadesuit$
ξ	an element in the sample space, which is one of $\clubsuit, \diamondsuit, \heartsuit, \spadesuit$
X	a function that maps $\clubsuit$ to the number 1, $\diamondsuit$ to the number 2, etc
$X(\xi)$	a number on the real line, e.g., $X(\clubsuit) = 1$

Definition of RV

The random variable X is a *function*. The input to the function is an outcome of the sample space, whereas the output is a number on the real line. This type of function is somewhat different from an ordinary function that often translates a number to another number. Nevertheless, X is a function.

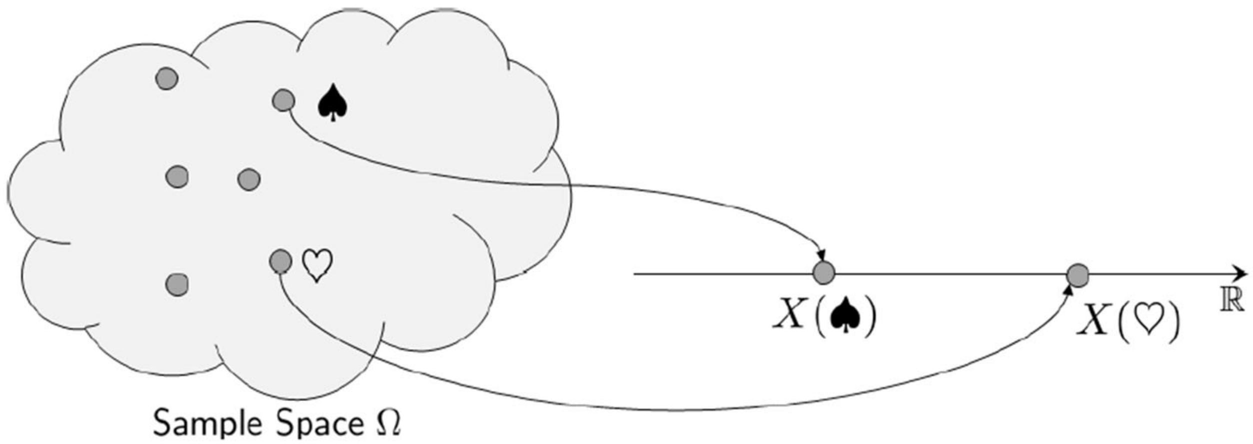


Figure 3.2: A random variable is a mapping from the outcomes in the sample space to numbers on the real line. We can think of a random variable X as a translator that translates a statement to a number.

1.2 El rol de la probabilidad y estadística

Exercise 1 of RV

Example 3.1. Suppose we flip a fair coin so that $\Omega = \{\text{head}, \text{tail}\}$. We can define the random variable $X : \Omega \to \mathbb{R}$ as

$$X(\text{head}) = 1, \qquad \text{and} \qquad X(\text{tail}) = 0.$$

Find

$\mathbb{P}[X = 1]$ $\qquad$ $\mathbb{P}[\{\text{head}\}]$

Explanation

Exercise 2 of RV

Example 3.2. Flip a coin 2 times. The sample space Ω is

$$\Omega = \{(\text{head}, \text{head}), (\text{head}, \text{tail}), (\text{tail}, \text{head}), (\text{tail}, \text{tail})\}.$$

Suppose that X is a random variable that maps an outcome to a number representing the sum of "head," i.e.,

$$X(\cdot) = \text{number of heads}.$$

Then, for the 4 ξ's in the sample space there are only 3 distinct numbers. More precisely, if we let $\xi_1 = (\text{head}, \text{head})$, $\xi_2 = (\text{head}, \text{tail})$, $\xi_3 = (\text{tail}, \text{head})$, $\xi_4 = (\text{tail}, \text{tail})$, then,

Find the mathematical representation of the RV and draw an illustration of the mapping