

# COMP30027 MACHINE LEARNING TUTORIAL

## Workshop - 2



**Head**



**Tail**



# Navigating the World of Probability

Welcome to our exploration of probability. We'll journey from basic definitions to probability distributions





# Understanding Basic Probability

## Definition

Probability measures the likelihood of an event occurring. It ranges from 0 (impossible) to 1 (certain).

## Basic Rules

The sum of all probabilities in a sample space equals 1. The probability of impossible events is 0.

## Deck of Card Example

$$P(\text{red card}) = P(\text{black card}) = 26/52 = 0.5$$

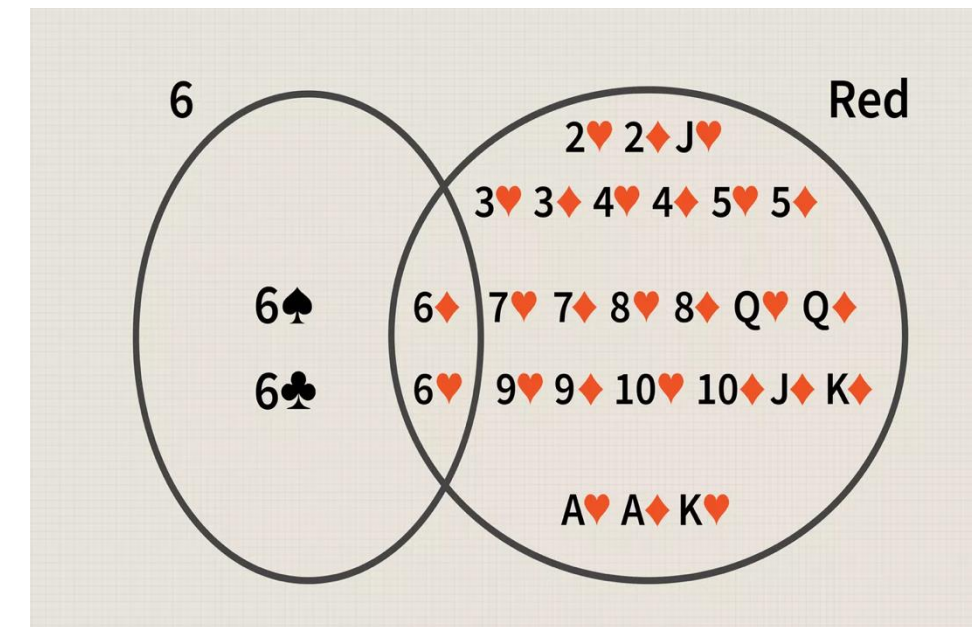
# Joint Probability

## Definition

Joint probability is the likelihood of two events occurring together. It's denoted as  $P(A \text{ and } B)$  or  $P(A \cap B)$ .

## Formula

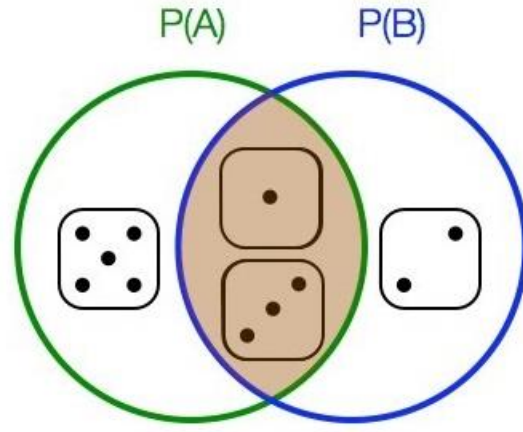
For independent events:  $P(A \text{ and } B) = P(A) \times P(B)$ . For dependent events, we use the conditional probability formula.



## Card Example

The probability of drawing a red '6' card is

$$P(6 \cap \text{red}) = P(6) \times P(\text{red}) = 4/52 \times 26/52 = 1/26$$



What is the Probability of  
rolling a dice and it's  
value is less than 4

$$P(B | A) = \frac{P(A \cap B)}{P(A)}$$

knowing that the value is  
an odd number

# Conditional Probability

1

## Definition

The probability of event A occurring given that event B has occurred. It represents updated probabilities with new information.

2

## Formula

$P(A|B) = P(A \text{ and } B) / P(B)$ , where  $P(B) > 0$ .

3

## Example





# Marginal Probability

## Definition

Marginal probability is the probability of an event occurring regardless of the outcome of another variable.

## Calculation

Found by summing joint probabilities across all values of the other variable.

## Class Example

If 40% of students are male,  $P(\text{Male}) = 0.4$  is a marginal probability, regardless of other student attributes.

Q1

Approximately 1% of women aged between 40 and 50 have breast cancer. 80% of mammogram screening tests detect breast cancer when it is there. 90% of mammograms DO NOT show breast cancer when it's NOT there. Use this information to complete the following table with:

- the **joint probabilities**  $P(\text{Cancer}, \text{Test})$  for each possible pair of cancer status and test result
- the **conditional probabilities**  $P(\text{Test}|\text{Cancer})$  for each test result given cancer status

Cancer	Test	Joint prob.	Conditional prob.
Yes	Positive		80%
Yes	Negative		
No	Positive		
No	Negative		90%



Compute the Conditional Probabilities

Cancer	Test	Joint prob.	Conditional prob.
Yes	Positive		80%
Yes	Negative		20%
No	Positive		10%
No	Negative		90%

- This method ensures each row sums to 100%.
- It's a simple subtraction method: 100% - Known Probability = Other Probability.

1. If a person has cancer:

- $P(Positive|Cancer) = 80\%$
- $P(Negative|Cancer) = 100\% - 80\% = 20\%$

2. If a person does NOT have cancer:

- $P(Negative|NoCancer) = 90\%$
- $P(Positive|NoCancer) = 100\% - 90\% = 10\%$

### Formula for Joint Probability

$$P(A, B) = P(B|A) \times P(A)$$

where:

- $A$  is the cancer status (Yes or No)
- $B$  is the test result (Positive or Negative)

Cancer	Test	Joint prob.	Conditional prob.
Yes	Positive	0.8%	80%
Yes	Negative	0.2%	20%
No	Positive	9.9%	10%
No	Negative	89.1%	90%

#### (1) Probability of having cancer and a positive test result

$$\begin{aligned} P(Cancer, Positive) &= P(Positive|Cancer) \times P(Cancer) \\ &= 0.80 \times 0.01 = 0.008 \end{aligned}$$

#### (2) Probability of having cancer and a negative test result

$$\begin{aligned} P(Cancer, Negative) &= P(Negative|Cancer) \times P(Cancer) \\ &= 0.20 \times 0.01 = 0.002 \end{aligned}$$

#### (3) Probability of not having cancer and a positive test result

$$\begin{aligned} P(NoCancer, Positive) &= P(Positive|NoCancer) \times P(NoCancer) \\ &= 0.10 \times 0.99 = 0.099 \end{aligned}$$

#### (4) Probability of not having cancer and a negative test result

$$\begin{aligned} P(NoCancer, Negative) &= P(Negative|NoCancer) \times P(NoCancer) \\ &= 0.90 \times 0.99 = 0.891 \end{aligned}$$

Q2

Given the table above, compute the **marginal probability** of a positive result in the mammogram screening test.

The **marginal probability** is the total probability of a positive result:

$$P(\text{Test} == \text{Positive} | \text{Cancer} == \text{No})P(\text{Cancer} == \text{No}) + P(\text{Test} == \text{Positive} | \text{Cancer} == \text{Yes})P(\text{Cancer} == \text{Yes})$$

this is the sum of the two joint probabilities in the table above:

$$P(\text{Test} == \text{Positive}, \text{Cancer} == \text{No}) + P(\text{Test} == \text{Positive}, \text{Cancer} == \text{Yes})$$

=> 0.8 + 9.9 = 10.7%

Cancer	Test	Joint prob.	Conditional prob.
Yes	Positive	0.8%	80%
Yes	Negative	0.2%	20%
No	Positive	9.9%	10%
No	Negative	89.1%	90%

### Q3

Suppose a woman in this age group receives a positive test result. Compute the **conditional probability**  $P(\text{Cancer} == \text{Yes} | \text{Test} == \text{Positive})$ .

This is equivalent to the joint probability  $P(\text{Test} == \text{Positive}, \text{Cancer} == \text{Yes})$  over the total probability of a positive result:

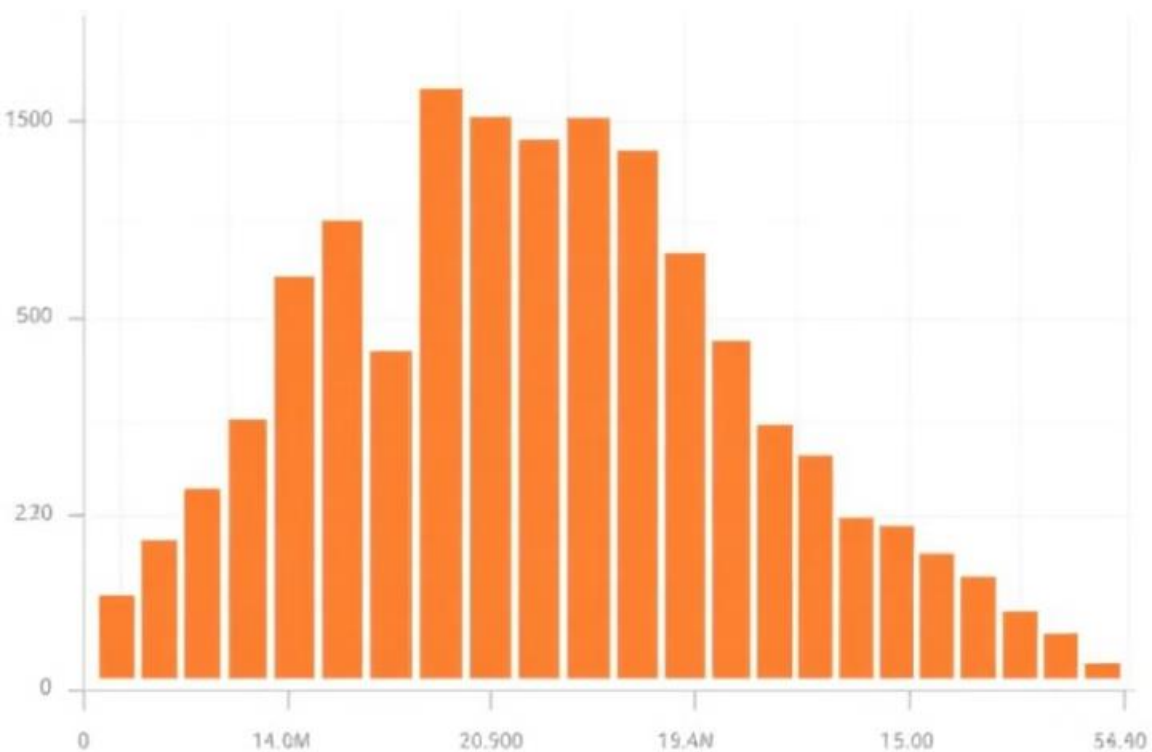
$$P(\text{Test} == \text{Positive}, \text{Cancer} == \text{Yes}) / P(\text{Test} == \text{Positive})$$

$$0.8 / 10.7 = 7.5\%$$

This result shows that even if a screening test returns a positive result, the actual chance of cancer is only 7.5%.



# Empirical Probability Distribution



## Data Collection

Gather observations from real-world experiments or surveys.  
Record frequencies of each outcome.

## Frequency Analysis

Count occurrences of each value. Divide by total observations to get relative frequencies.

## Distribution Creation

Plot these relative frequencies. They approximate the true probability distribution as sample size increases.

# Binomial Distribution



## Definition

Models the number of successes in  $n$  independent trials, each with probability  $p$  of success.



## Formula

$P(X = k) = C(n, k) \times p^k \times (1-p)^{(n-k)}$  where  $C(n, k)$  is the binomial coefficient.



## Coin Example

For 3 heads in 5 flips:  
 $P(X = 3) = C(5, 3) \times (0.5)^3 \times (0.5)^2 = 10 \times 0.03125 = 0.3125$ .



## Q4

Suppose you flip a fair coin 10 times. What are the odds that you will get exactly  $K$  heads, for each possible value of  $K$  (0,1,...10)? Write a function to simulate this experiment and empirically estimate the probability distribution.

- Simulate flipping coin 10 time
- Count number of heads in each experiment
- Plot the probability distribution



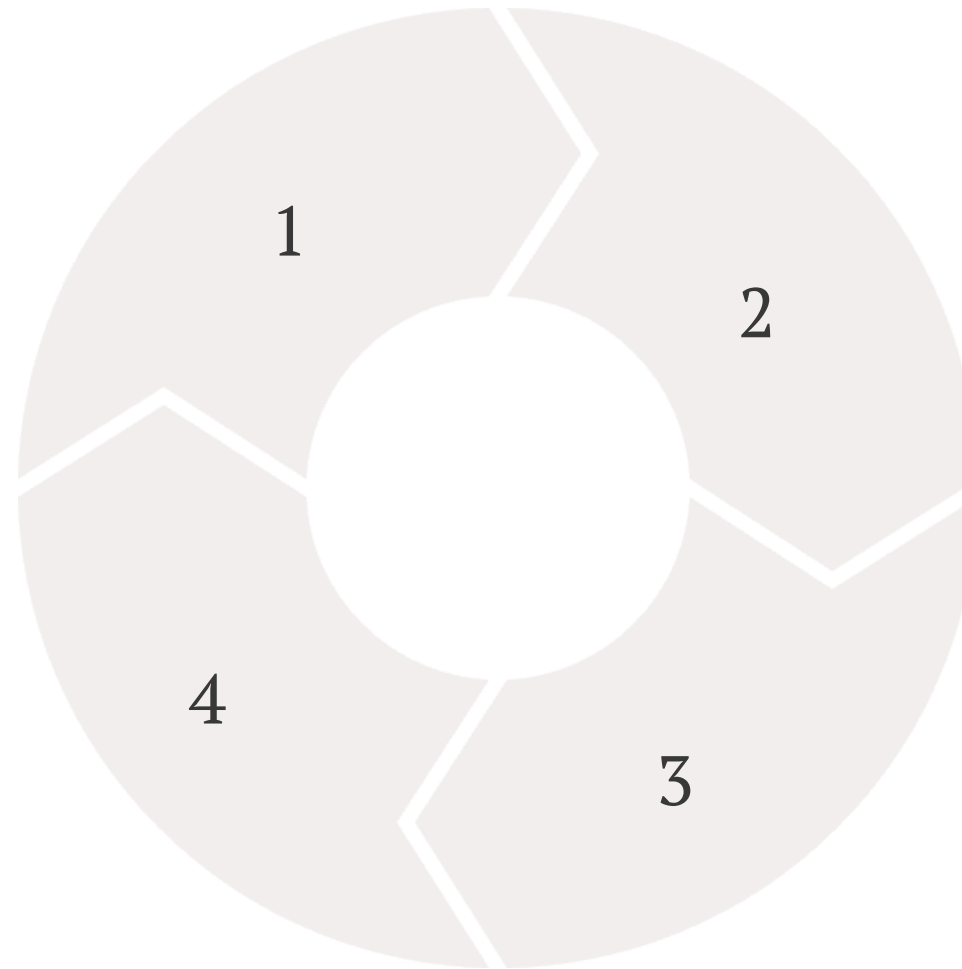
# Probability Density Function

## Definition

A function whose integral gives probabilities for continuous random variables.

## Interpretation

The PDF value itself isn't a probability.  
Probabilities come from areas under the curve.



## Properties

PDFs must be non-negative and integrate to 1 over the entire domain.

## Normal Distribution

The bell curve with PDF  $f(x) = \frac{1}{\sigma\sqrt{2\pi}} \times e^{-(x-\mu)^2/2\sigma^2}$  is the most common example.



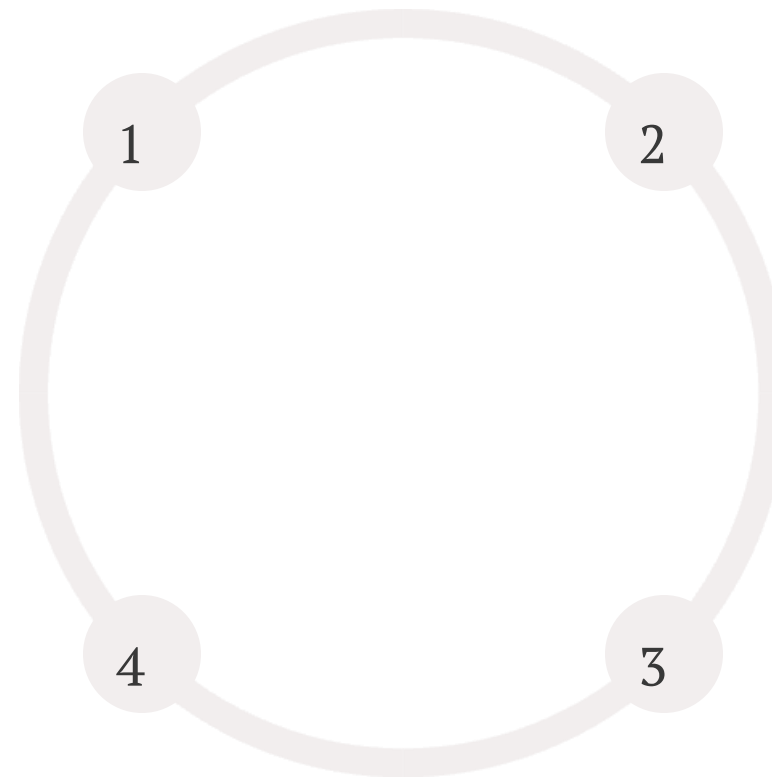
# Entropy in Probability

## Definition

Entropy measures uncertainty or information content in a probability distribution.

## Properties

Entropy is maximized when all outcomes are equally likely. It quantifies unpredictability.



## Formula

$H(X) = -\sum P(x_i) \times \log_2(P(x_i))$  for all possible outcomes  $x_i$ .

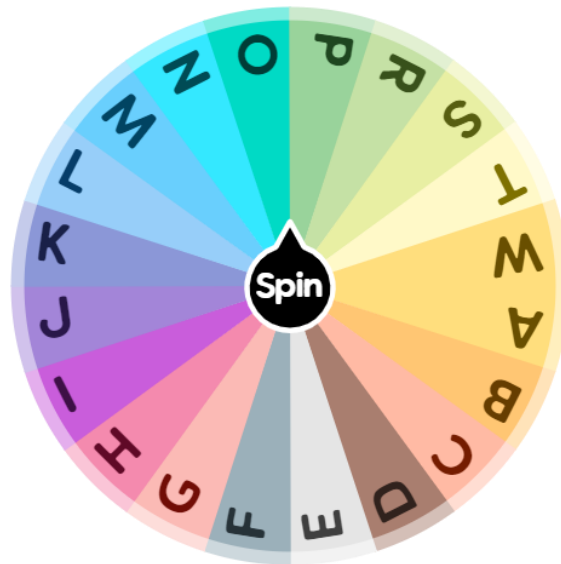
## Coin Example

For a fair coin:  $H(X) = -(0.5 \times \log_2(0.5) + 0.5 \times \log_2(0.5)) = 1$  bit.

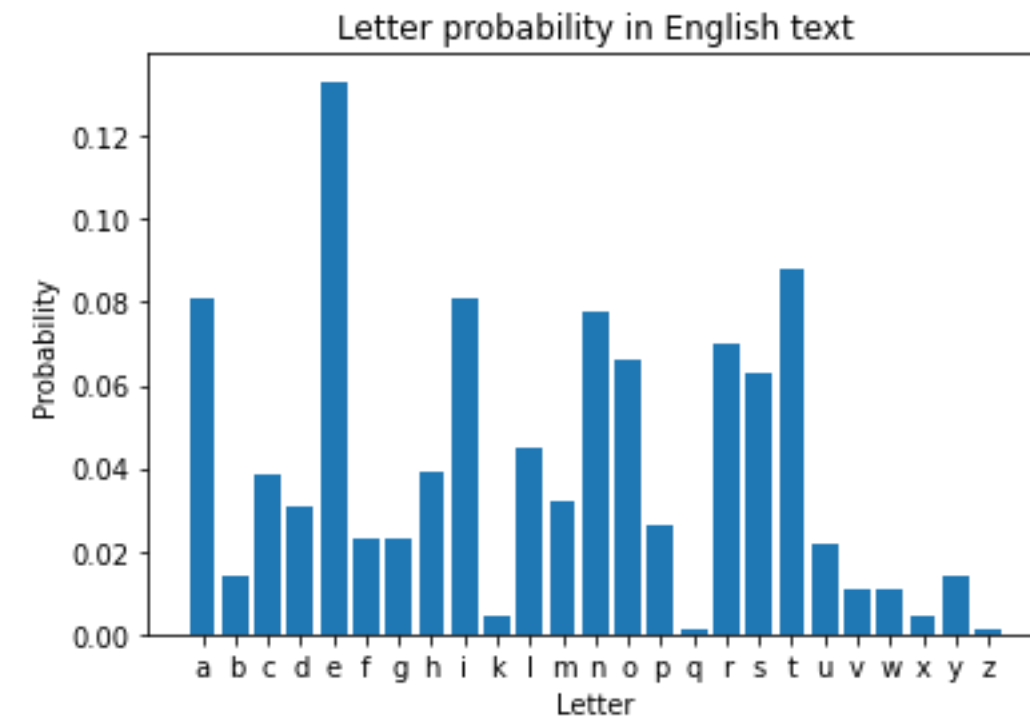
## Q6

Compute the entropy of a random letter generator which can generate any of the 26 English letters (a-z), each with equal probability.

$$H(X) = - \sum_{x \in X} p(x) \log_2 p(x)$$

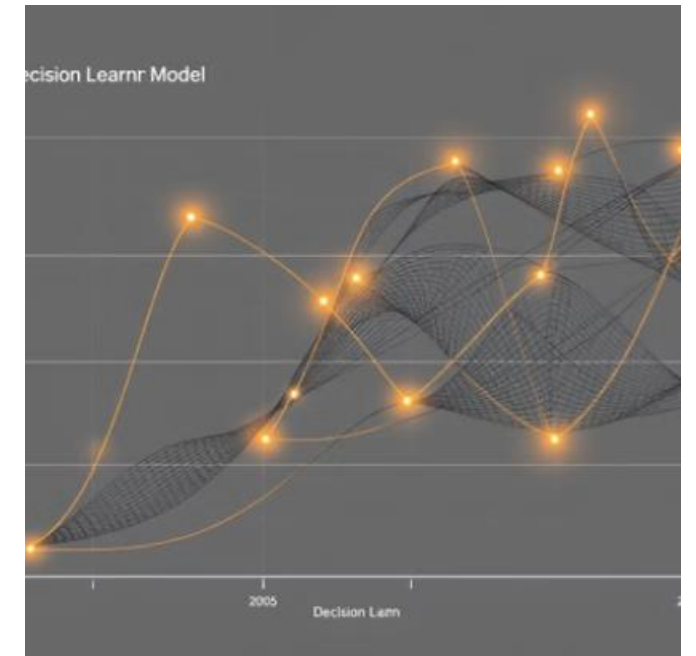
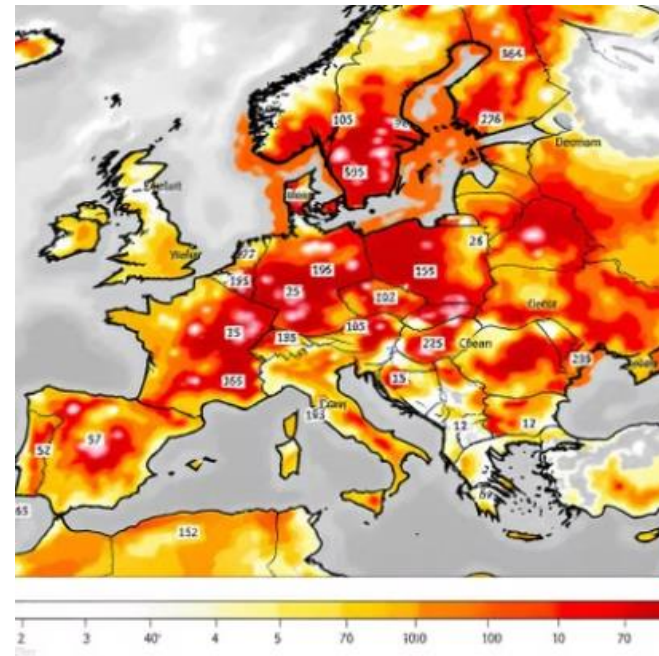


- All letters (A–Z) are **equally likely**
- Probability of each letter =  $1/26$
- Entropy is **maximum**
- High **uncertainty**: each letter is a total surprise



- Letters are **not equally likely** (e.g., E is common, Z is rare)
- More **predictable** due to patterns
- Entropy is **lower**
- Some information is **redundant** (due to structure and grammar)

# Real-world Applications of Probability



Probability concepts power financial risk assessment, weather forecasting, medical diagnostics, and AI systems. They help us navigate uncertainty in virtually every field.

