

# Lecture 1

# PART I. PROBABILITY THEORY

## Chapter 1. Probability Space

There are three approaches to the notion of *probability*:

- **classical**: intuitive, what most people are familiar with and think of when they hear the word “probability”;
- **geometrical**: a natural extension of classical probability, for the case of infinite numbers of cases;
- **axiomatic**: rigorous, mathematical, enables proving probability formulas.

# 1. Experiments and Events

- An **experiment** is any process or action whose outcome is not known (is random).
- The **sample space**, denoted by  $S$ , is the set of all possible outcomes of an experiment. Its elements are called **elementary events** (denoted by  $e_i, i \in \mathbb{N}$ ).
- An **event** is a collection of elementary events, i.e. it is a **subset** of  $S$  (events are denoted by capital letters,  $A_i, i \in \mathbb{N}$ ).

Since events are defined as **sets**, we can employ set theory in describing them.

- two special events associated with every experiment:
  - the **impossible** event, denoted by  $\emptyset$  (“never happens”);
  - the **sure (certain)** event, denoted by  $S$  (“surely happens”).
- for each event  $A \subseteq S$ , we define the event  $\bar{A}$ , the **complementary** event, to mean that  $\bar{A}$  occurs if and only if  $A$  does not occur;  $\overline{\bar{A}} = A$ ;
- we say that event  $A$  **implies (induces)** event  $B$ ,  $A \subseteq B$ , if every element of  $A$  is also an element of  $B$ , or in other words, if the occurrence of  $A$  induces (implies) the occurrence of  $B$ ;  $A$  and  $B$  are **equal (equivalent)**,  $A = B$ , if  $A$  implies  $B$  and  $B$  implies  $A$ ;

- for any two events  $A, B \subseteq S$ , we define the following events:
  - **union** of  $A$  and  $B$ ,

$$A \cup B = \{e \in S \mid e \in A \text{ or } e \in B\},$$

the event that occurs if either  $A$  or  $B$  or both occur;

- **intersection** of  $A$  and  $B$ ,

$$A \cap B = \{e \in S \mid e \in A \text{ and } e \in B\},$$

the event that occurs if both  $A$  and  $B$  occur;

- **difference** of  $A$  and  $B$ ,

$$A \setminus B = \{e \in S \mid e \in A \text{ and } e \notin B\} = A \cap \overline{B},$$

the event that occurs if  $A$  occurs and  $B$  does not;

- **symmetric difference** of  $A$  and  $B$ ,

$$A \Delta B = (A \setminus B) \cup (B \setminus A) = (A \cup B) \setminus (A \cap B),$$

the event that occurs if  $A$  or  $B$  occur, but not both.

The operations of union, intersection and symmetric difference are

– **commutative:**

$$A \cup B = B \cup A, \quad A \cap B = B \cap A, \quad A \Delta B = B \Delta A;$$

– **associative:**

$$(A \cup B) \cup C = A \cup (B \cup C), \quad (A \cap B) \cap C = A \cap (B \cap C),$$

$$(A \Delta B) \Delta C = A \Delta (B \Delta C);$$

– **distributive:**

$$(A \cup B) \cap C = (A \cap C) \cup (B \cap C), \quad (A \cap B) \cup C = (A \cup C) \cap (B \cup C),$$

$$A \cap (B \Delta C) = (A \cap B) \Delta (A \cap C).$$

## Definition 1.1.

- Two events  $A$  and  $B$  are said to be **mutually exclusive (disjoint, incompatible)** if  $A$  and  $B$  cannot occur at the same time, i.e.  $A \cap B = \emptyset$ ;
- Three or more events are mutually exclusive if **any two of them are**, i.e.

$$A_i \cap A_j = \emptyset, \forall i \neq j;$$

- A collection of events  $\{A_i\}_{i \in I}$  from  $S$  is said to be **(collectively) exhaustive** if

$$\bigcup_{i \in I} A_i = S;$$

- A collection of events  $\{A_i\}_{i \in I}$  from  $S$  is said to be a **partition** of  $S$  if the events are collectively exhaustive and mutually exclusive, i.e.

$$\bigcup_{i \in I} A_i = S, \quad A_i \cap A_j = \emptyset, \forall i, j \in I, i \neq j.$$

**Example 1.2.**

Consider the experiment of rolling a die. Then the sample space is

$$S = \{e_1, e_2, e_3, e_4, e_5, e_6\},$$

where the elementary events (outcomes) are  $e_i$ ,  $i = \overline{1, 6}$ , with  $e_i$  being the event that the face  $i$  shows on the die.

Consider the following events:

$A$ : face 1 shows,

$B$ : face 2 shows,

$C$ : an even number shows,

$D$ : a prime number shows,

$E$ : a composite number shows.

Then we have

$$A = \{e_1\}, B = \{e_2\}, C = \{e_2, e_4, e_6\}, D = \{e_2, e_3, e_5\}, E = \{e_4, e_6\}.$$



We also have

$$B \subseteq C, A \cap B = \emptyset, A \cap D = \emptyset, A \cap E = \emptyset, D \cap E = \emptyset,$$

$$C \cap D = B, A \cup D \cup E = S.$$

So, for example, events  $\{A, B\}$  and  $\{A, D, E\}$  are *mutually exclusive*. In fact, these last three are also *collectively exhaustive*. Thus, events  $\{A, D, E\}$  form a **partition** of  $S$ .

### Proposition 1.3.

For every collection of events  $\{A_i\}_{i \in I}$ , **De Morgan's laws** hold:

$$a) \overline{\bigcup_{i \in I} A_i} = \bigcap_{i \in I} \bar{A}_i,$$

$$b) \overline{\bigcap_{i \in I} A_i} = \bigcup_{i \in I} \bar{A}_i.$$

## 2. Sigma Fields, Probability and Rules of Probability

### Definition 2.1.

A collection  $\mathcal{K}$  of events from  $S$  is said to be a  **$\sigma$ -field** ( **$\sigma$ -algebra**) over  $S$  if it satisfies the following conditions:

- (i)  $\mathcal{K} \neq \emptyset$ ;
- (ii) if  $A \in \mathcal{K}$ , then  $\bar{A} \in \mathcal{K}$ ;
- (iii) if  $A_n \in \mathcal{K}$  for all  $n \in \mathbb{N}$ , then  $\bigcup_{n=1}^{\infty} A_n \in \mathcal{K}$ .

If  $\mathcal{K}$  is a  $\sigma$ -field over the sample space  $S$ , then the pair  $(S, \mathcal{K})$  is called a **measurable space**.

### Example 2.2.

The **power set**  $\mathcal{P}(S) = \{S' | S' \subseteq S\}$  is a  $\sigma$ -field over  $S$ .

**Theorem 2.3.**

Let  $\mathcal{K}$  be a  $\sigma$ -field over  $S$ . Then the following properties hold:

a)  $\emptyset, S \in \mathcal{K}$ .

b) for all  $A, B \in \mathcal{K}$ ,  $A \cap B, A \setminus B, A \Delta B \in \mathcal{K}$ .

c) if  $A_n \in \mathcal{K}$ , for all  $n \in \mathbb{N}$ , then  $\bigcap_{n=1}^{\infty} A_n \in \mathcal{K}$ .

**Definition 2.4.**

Let  $\mathcal{K}$  be a  $\sigma$ -field over  $S$ . A mapping  $P : \mathcal{K} \rightarrow \mathbb{R}$  is called **probability** if it satisfies the following conditions:

- (i)  $P(S) = 1$ ;
- (ii)  $P(A) \geq 0$ , for all  $A \in \mathcal{K}$ ;
- (iii) for any sequence  $\{A_n\}_{n \in \mathbb{N}} \subseteq \mathcal{K}$  of **mutually exclusive** events,

$$P\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} P(A_n), \quad (2.1)$$

( $P$  is  $\sigma$ -additive).

The triplet  $(S, \mathcal{K}, P)$  is called a **probability space**.

**Theorem 2.5.**

Let  $(S, \mathcal{K}, P)$  be a probability space, and let  $A, B \in \mathcal{K}$ . Then the following properties hold:

- a)  $P(\bar{A}) = 1 - P(A)$  and  $0 \leq P(A) \leq 1$ .
- b)  $P(\emptyset) = 0$ .
- c)  $P(A \setminus B) = P(A) - P(A \cap B)$ .
- d) If  $A \subseteq B$ , then  $P(A) \leq P(B)$ , i.e.  $P$  is *monotonically increasing*.
- e)  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ .

## Proof.

a)  $A, \bar{A} \in \mathcal{K}$ ,  $A \cup \bar{A} = S$  and  $A, \bar{A}$  are **mutually exclusive**. Then

$$1 = P(S) = P(A \cup \bar{A}) \stackrel{(2.1)}{=} P(A) + P(\bar{A}),$$

i.e.  $P(\bar{A}) = 1 - P(A)$ .

Since  $P(\bar{A}) \geq 0$ , it follows that  $P(A) \leq 1$ , so  $0 \leq P(A) \leq 1$ .

b)  $P(\emptyset) = P(\bar{S}) = 1 - P(S) = 0$ .

c)  $A = (A \cap B) \cup (A \setminus B)$  and  $A \cap B, A \setminus B$  are **mutually exclusive**. Thus

$$P(A) \stackrel{(2.1)}{=} P(A \cap B) + P(A \setminus B),$$

so  $P(A \setminus B) = P(A) - P(A \cap B)$ . □

## Proof.

d) Since  $A \subseteq B$ ,  $A = A \cap B$ . Then by c), we have

$$0 \leq P(B \setminus A) = P(B) - P(A),$$

which means  $P(A) \leq P(B)$ .

e) We have  $A \cup B = A \cup (B \setminus (A \cap B))$  and  $A, B \setminus (A \cap B)$  are **mutually exclusive**. Then using part c),

$$\begin{aligned} P(A \cup B) &\stackrel{(2.1)}{=} P(A) + P(B \setminus (A \cap B)) \\ &\stackrel{c)}{=} P(A) + P(B) - P(B \cap (A \cap B)) \\ &= P(A) + P(B) - P(A \cap B). \end{aligned}$$



Part e) of Theorem 2.5 can be generalized to more than two events.

## Theorem 2.6.

Let  $(S, \mathcal{K}, P)$  be a probability space and  $(A_n)_{n \in \mathbb{N}} \subseteq \mathcal{K}$  a sequence of events. Then **Poincaré's formula (the inclusion-exclusion principle)** holds

$$\begin{aligned}
 P\left(\bigcup_{i=1}^n A_i\right) &= \sum_{i=1}^n P(A_i) - \sum_{1 \leq i < j \leq n} P(A_i \cap A_j) \\
 &+ \sum_{1 \leq i < j < k \leq n} P(A_i \cap A_j \cap A_k) \\
 &+ \dots + (-1)^{n-1} P\left(\bigcap_{i=1}^n A_i\right),
 \end{aligned} \tag{2.2}$$

for all  $n \in \mathbb{N}$ . As a consequence,

$$P\left(\bigcup_{n=1}^{\infty} A_n\right) \leq \sum_{n=1}^{\infty} P(A_n), \text{ i.e. } P \text{ is subadditive.}$$



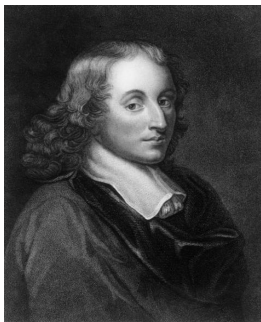
**Example 2.7.**

Let us write formula (2.2) for three events  $A, B, C \in \mathcal{K}$ .

$$\begin{aligned} P(A \cup B \cup C) &= P(A) + P(B) + P(C) \\ &\quad - \left( P(A \cap B) + P(A \cap C) + P(B \cap C) \right) \\ &\quad + P(A \cap B \cap C). \end{aligned}$$

### 3. Classical Definition of Probability

Intuitively, each event has an associated quantity which characterizes *how likely* its occurrence is; this is called the **probability** of the event. The classical definition of probability was given independently by B. Pascal and P. Fermat in the 17th century.



Blaise Pascal (1623 - 1662)



Pierre de Fermat (1607 - 1665)

### Definition 3.1.

Consider an experiment whose outcomes are finite and equally likely. Then the **probability of the occurrence of the event**  $A$  is given by

$$P(A) = \frac{\text{number of favorable outcomes for the occurrence of } A}{\text{total number of possible outcomes of the experiment}} \stackrel{\text{not}}{=} \frac{N_f}{N_t}. \quad (3.1)$$

### Remark 3.2.

This approach can be used only when it is reasonable to assume that the possible outcomes of an experiment are **equally likely** (fair die, fair coin). Also, the two numbers have to be **finite**. When that is not the case, *geometrical probability* is used, when some *continuous measure* of a set is used (instead of the cardinality):

$$P(A) = \frac{\mu(A)}{\mu(S)}.$$

**Remark 3.3.**

This notion is closely related to that of *relative frequency* of an event  $A$ : repeat an experiment a number of times  $N$  and count the number of times event  $A$  occurs,  $N_A$ . Then the **relative frequency** of the event  $A$  is defined by

$$f_A = \frac{N_A}{N}.$$

Such a number is often used as an approximation to the probability of  $A$ . This is justified by the fact that

$$f_A \xrightarrow{N \rightarrow \infty} P(A).$$

The relative frequency is used in computer simulations of random phenomena.

**Example 3.4.**

Two dice are rolled. Find the probability of the events

*A*: a double appears;

*B*: the sum of the two numbers obtained is less than or equal to 5.

**Solution.** We begin by computing the denominator in formula (3.1), because that number is *common* to both probabilities. The **total number of possible outcomes** is the number of elements of the sample space. The sample space is

$$S = \{e_{ij} \mid i, j = \overline{1, 6}\},$$

where  $e_{ij}$  (identified by the pair  $(i, j)$ , for simplicity) represents the event that number  $i$  showed on the first die and number  $j$  on the second. Hence,

$$N_t = 36.$$

For event  $A$ ,  $N_f = 6$  (there are six doubles out of 36 possible outcomes), so

$$P(A) = \frac{1}{6}.$$

For event  $B$ , we count the number of favorable outcomes, i.e. the number of pairs  $(i, j)$  for which  $i + j \leq 5$ . We have

$$\left. \begin{array}{cccc} (1, 1) & (1, 2) & (1, 3) & (1, 4) \\ & (2, 2) & (2, 3) & \end{array} \right\} 6 \text{ outcomes}$$

By *symmetry*, we have  $6 \times 2 = 12$ , but two of the pairs were *already symmetric*, so  $N_f = 12 - 2 = 10$  cases. Thus,

$$P(B) = \frac{5}{18}.$$

