# Probability

Modeling uncertainty

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#### Random experiment (random variable)

Elements of probability theory

#### Sample space

**Definition**. For a "random experiment", the sample space  $\Omega$  is the set of possible outcomes of the random experiment.

#### **Events**

**Definition**. An event of a random variable with sample space  $\Omega$  is a subset  $E \subset \Omega$ .

#### Distribution

**Definition**. A distribution  $\pi : \mathcal{P}(\Omega) \to \mathbb{R}$  over a sample space  $\Omega$  is a function of subsets of  $\Omega$  that satisfies the following properties:

- 1. "Normalization":  $\pi(\emptyset) = 0$ ,  $\pi(\Omega) = 1$ .
- 2. "Monotonicity":  $A \subset B \Rightarrow \pi(A) \leq \pi(B)$ .
- 3. "A dditivity":  $A \cap B = \emptyset \Rightarrow \pi(A \cup B) = \pi(A) + \pi(B)$ .

#### Measure-theoretic definition

#### 1 Probability Spaces and Random Variables

Let  $(\Omega, \mathcal{H}, \mathbb{P})$  be a probability space. The set  $\Omega$  is called the *sample space*; its elements are called *outcomes*. The  $\sigma$ -algebra  $\mathcal{H}$  may be called the grand *history*; its elements are called *events*. We repeat the properties of the probability measure  $\mathbb{P}$ ; all sets here are events:

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1.1 Norming: \mathbb{P}(\emptyset) = 0, \mathbb{P}(\Omega) = 1.
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Monotonicity:  $H \subset K \Rightarrow \mathbb{P}(H) \leq \mathbb{P}(K)$ .

Finite additivity:  $H \cap K = \emptyset \implies \mathbb{P}(H \cup K) = \mathbb{P}(H) + \mathbb{P}(K)$ .

Countable additivity:  $(H_n)$  disjointed  $\Rightarrow \mathbb{P}(\bigcup_n H_n) = \sum_n \mathbb{P}(H_n)$ .

Sequential continuity:  $H_n \nearrow H \implies \mathbb{P}(H_n) \nearrow \mathbb{P}(H)$ ,

 $H_n \searrow H \quad \Rightarrow \quad \mathbb{P}(H_n) \searrow \mathbb{P}(H).$ 

Boole's inequality:  $\mathbb{P}(\bigcup_n H_n) \leq \sum_n \mathbb{P}(H_n)$ .

Erhan Çinlar, Probability and Stochastics (you will not be tested on this)

#### Distribution (notes)

**Definition**. A distribution  $\mathbb{P}: \mathcal{P}(\Omega) \to \mathbb{R}$  over a sample space  $\Omega$  is a function of subsets of  $\Omega$ , first defined over the singletons  $\{a\}, a \in \Omega \text{ such that:}$ 

- 1.  $\mathbb{P}(A) = \sum_{a \in A} \mathbb{P}(a)$ ,
- 2.  $0 \leq \mathbb{P}(a) \leq 1$  for all  $a \in \Omega$ ,
- 3.  $\mathbb{P}(\Omega) = \sum_{a \in \Omega} \mathbb{P}(a) = 1$ .

# Equivalence of definitions

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#### Random variables

**Definition.** A random variable is a double  $X = (\Omega, \pi)$ , where  $\Omega$  is the sample space of X, and  $\pi$  is the distribution of X.

## Examples of random variables

# Example: balls and bins

Example: "birthday paradox"

## Example: Monty Hall problem