

Planning, Learning and Decision Making

Lecture 1

What is probability?

- Has roots in games of chance
- Used to **measure** the likelihood of occurrence of events



Natural tool to model uncertainty

What is probability?

- Classical definition of probability of event A
 - N possible events
 - N_A ways by which A can occur

$$\mathbb{P}[A] = \frac{N_A}{N}$$

- Examples:
 - Throw a die 10 times: 1, 2, 3, 2, 3, 5, 4, 6, 2, 1
 - What is the probability of drawing an even number in a die?

What is probability?

- Frequentist definition of probability of event A
 - Relative frequency of event A
 - N observed events
 - N_A times that event A occurred

$$\mathbb{P}[A] = \lim_{N \rightarrow \infty} \frac{N_A}{N}$$

- Examples:
 - What is the probability of drawing a ♠ in a card deck?

What is probability?

- Subjective definition of probability of event A
 - *Degree of belief* that event A may occur
- Example:
 - Probability that Robert de Niro has won three Oscars

Formally, ...

- **Probability space is a triplet (Ω, \mathcal{F}, P) where:**

- Ω is the *sample space* ← Things that can happen
- \mathcal{F} is the set of events ← Things we want to measure
- **P** is a probability measure ← Way to measure them

Formally, ...

- **Sample space Ω**

- Space of possible *outcomes*

- Each and every thing that may happen

- Example:

In a die throw, the possible outcomes are $\{1, 2, 3, 4, 5, 6\}$

- Example:

When drawing a card, the possible outcomes are $\{A\spadesuit, 2\spadesuit, \dots, J\diamondsuit, Q\diamondsuit, K\diamondsuit\}$

Formally, ...

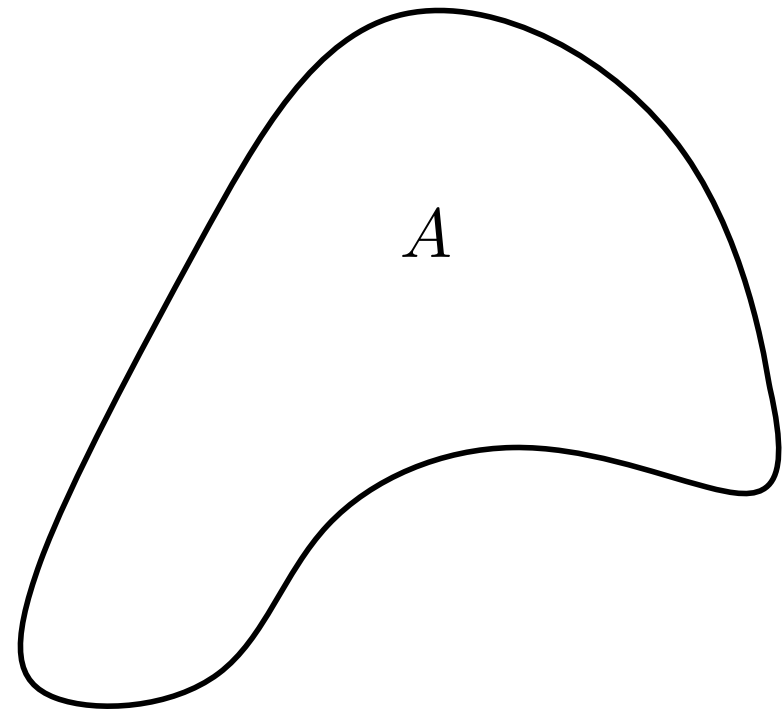
- **Set of events, \mathcal{F}**
 - Subsets of Ω that we can “measure”, i.e., assign a probability
 - Includes the empty set \emptyset and the full set Ω
 - Examples of events (die throw):
 - Drawing an even number: $\{2, 4, 6\}$
 - Drawing a number larger than 3: $\{4, 5, 6\}$
 - Drawing no number: \emptyset

Formally, ...

- **Set of events, \mathcal{F}**
 - Subsets of Ω that we can “measure”, i.e., assign a probability
 - Includes the empty set \emptyset and the full set Ω
 - Examples of events (card draw):
 - Drawing a spade: $\{A\spadesuit, 2\spadesuit, 3\spadesuit, 4\spadesuit, 5\spadesuit, 6\spadesuit, 7\spadesuit, 8\spadesuit, 9\spadesuit, 10\spadesuit, J\spadesuit, Q\spadesuit, K\spadesuit\}$
 - Drawing a figure: $\{J\spadesuit, Q\spadesuit, K\spadesuit, J\clubsuit, Q\clubsuit, K\clubsuit, J\heartsuit, Q\heartsuit, K\heartsuit, J\diamondsuit, Q\diamondsuit, K\diamondsuit\}$

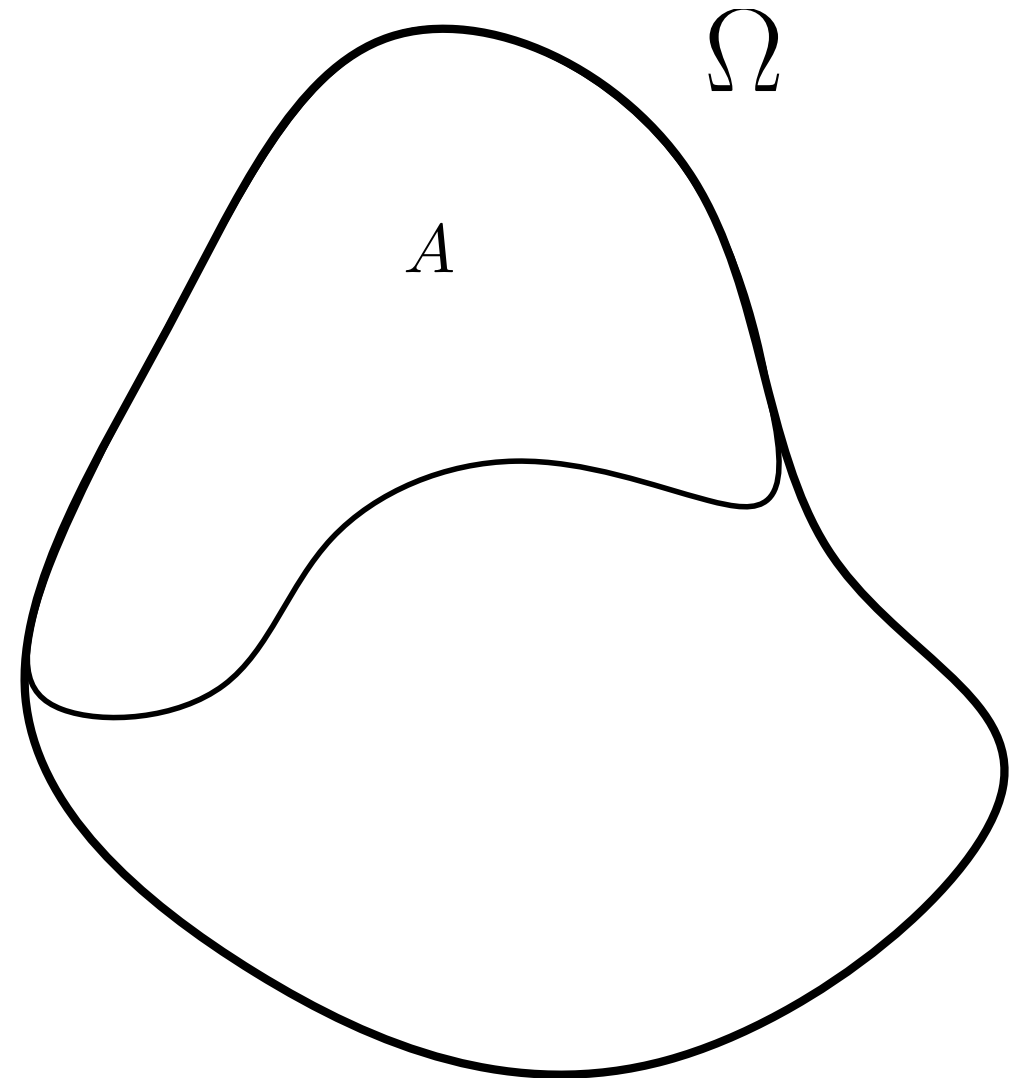
Formally, ...

- **Probability, P**
 - “Measures” each event in \mathcal{F}
 - Axioms of probability:
 - **$P(A) \geq 0$**



Formally, ...

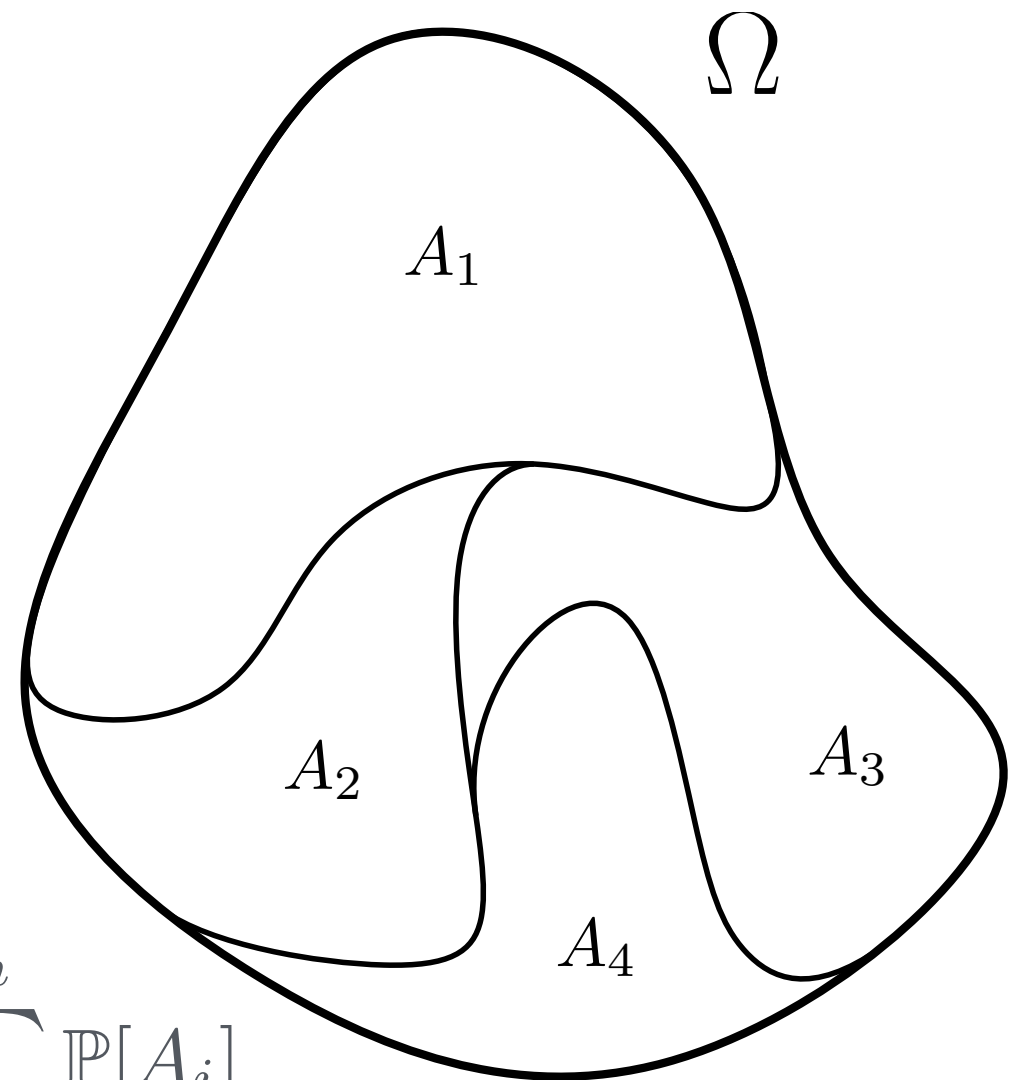
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 - $P(A) \geq 0$
 - $P(\Omega) = 1$



Formally, ...

- **Probability, P**
 - “Measures” each event in \mathcal{F}
 - Axioms of probability:
 - $P(A) \geq 0$
 - $P(\Omega) = 1$
 - Given disjoint events A_1, \dots, A_n

$$\mathbb{P}[A_1 \cup \dots \cup A_n] = \sum_{i=1}^n \mathbb{P}[A_i]$$



- $\mathbf{P}(A) \geq 0$
- $\mathbf{P}(\Omega) = 1$
- $\mathbb{P}[A_1 \cup \dots \cup A_n] = \sum_{i=1}^n \mathbb{P}[A_i]$

Can you show:

- $\mathbf{P}(\emptyset) = 0$
- $P(\Omega) = 1 = P(\Omega \cup \emptyset) = P(\Omega) + P(\emptyset).$
- Then $P(\emptyset) = 1 - P(\Omega) = 0.$

Conditional probability

- Conditional probability of event A given B :
- Probability of A occurring, given that B occurred

$$\mathbb{P}[A \mid B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$

... assuming $\mathbf{P}(B) > 0$.

- Verifies all axioms of probability

Conditional probability

- **Important properties:**
- Independent events: $\mathbb{P}[A \mid B] = \mathbb{P}[A]$
- Law of total probability: given disjoint events A_1, \dots, A_n , with

$$A_1 \cup \dots \cup A_n = \Omega,$$

$$\mathbb{P}[B] = \sum_{i=1}^n \mathbb{P}[B \mid A_i] \cdot \mathbb{P}[A_i]$$

Conditional probability

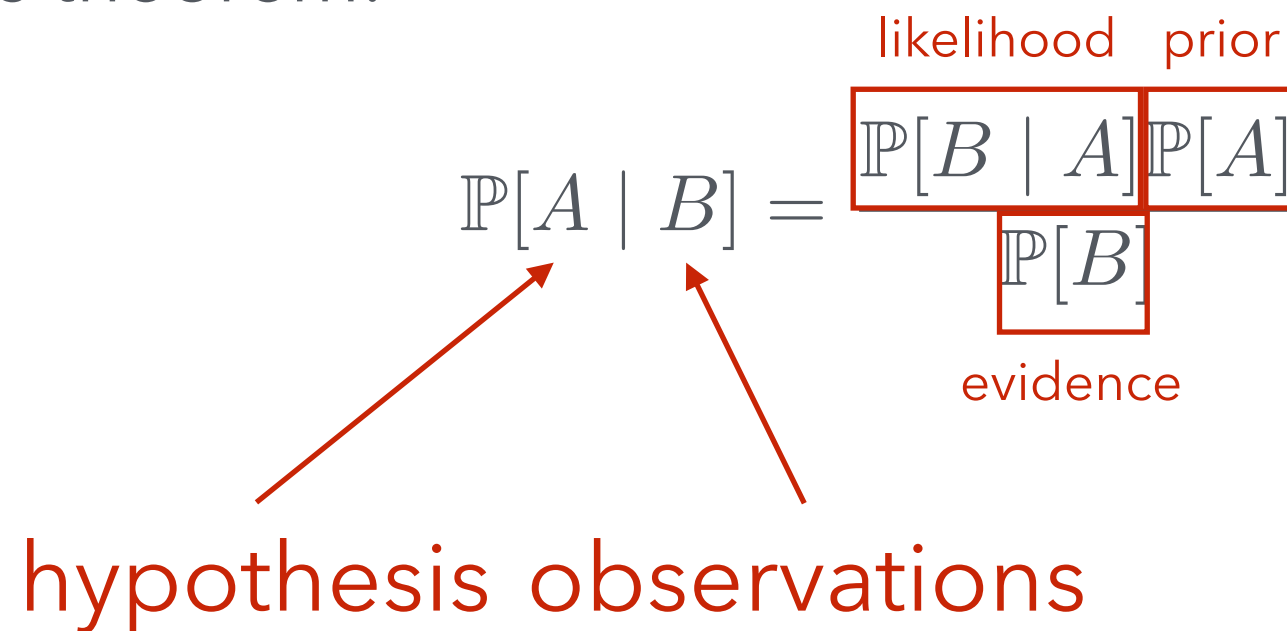
- **Important properties:**
- Bayes theorem:

$$\mathbb{P}[A \mid B] = \frac{\mathbb{P}[B \mid A] \mathbb{P}[A]}{\mathbb{P}[B]}$$

likelihood prior

evidence

hypothesis observations



The diagram illustrates Bayes' theorem with the equation $\mathbb{P}[A \mid B] = \frac{\mathbb{P}[B \mid A] \mathbb{P}[A]}{\mathbb{P}[B]}$. Red boxes highlight the components: $\mathbb{P}[B \mid A]$ is labeled 'likelihood', $\mathbb{P}[A]$ is labeled 'prior', and $\mathbb{P}[B]$ is labeled 'evidence'. Two red arrows point from the text 'hypothesis' to A and 'observations' to B in the conditional probability $\mathbb{P}[A \mid B]$.

Random variable

- Given a probability space $(\Omega, \mathcal{F}, \mathbf{P})$,
 - Sometimes Ω is a cumbersome set to work with
 - It would be more convenient to instead work in some other space, more mathematically convenient (for example, \mathbf{R})
- A **random variable** X is a map $X : \Omega \longrightarrow E$, where E is some convenient space (usually \mathbf{R})
- We usually work with random variables, ignoring the underlying probability space

Random variable

- We write $\mathbf{P}(X = x)$ to represent

$$\mathbb{P}[X = x] = \mathbb{P}[\{\omega \in \Omega : X(\omega) = x\}]$$

- If the r.v. takes values in a discrete set, we call it a *discrete random variable*
- If the r.v. takes values in a continuous set, we call it a *continuous random variable*

Expectation

- Given a r.v. X and a function $f : X \longrightarrow \mathbf{R}$, the *expectation* of f is the quantity

$$\mathbb{E}[f(X)] = \sum_x f(x) \mathbb{P}[X = x]$$

- We can have conditional expectations:

$$\mathbb{E}[f(X) \mid Y = y] = \sum_x f(x) \mathbb{P}[X = x \mid Y = y]$$

Properties

- Law of total probability with expectations:

$$\mathbb{E}[f(X)] = \sum_y \mathbb{E}[f(X) \mid Y = y] \mathbb{P}[Y = y]$$

- Conditioning “eliminates” expectation:

$$\mathbb{E}[f(X) \mid X = x] = f(x)$$

Some useful results

- **Law of large numbers:** Given i.i.d. real-valued r.v.s X_1, \dots, X_n , such that

$$\mathbb{E}[X_1] = \mathbb{E}[X_2] = \dots = \mathbb{E}[X_N] = \mu$$

then

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N X_i \stackrel{a.s.}{=} \mu$$

Some useful results

- **Jensen's inequality:** Given a real-valued r.v. X and a convex function f , then

$$f(\mathbb{E}[X]) \leq \mathbb{E}[f(X)]$$

