Bayesian Inference

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Determinism and its Limits

Why do we need Probabilities?

Determinism

- Every event is determined by past events.
- assumed in Classical Mechanics
- contradicted in Quantum Mechanics?

Reality

- limited knowledge, e.g. friction
- ▶ limited control over initial state, e.g. in chaotic systems

Example: Throwing dice: Initial angle and velocity are unknown or difficult to control. It is unknown if the dice are fair.

⇒ Thus, we need probabilities to predict events!





Frequentist statistics

Probabilities are determined by distributions of random events. They are characterized by the frequency of occurring events.

	1	2	3	4	5	6	\sum
frequency	10	5	7	6	9	7	44
probability [%]	23	11	16	14	20	16	100

results of dice rolls; expected PMF $p(i)=1/6=16.\bar{6}\,\%$

- Probability Mass Function (PMF) (discrete)
- Probability Density Function (PDF) (continuous)
- Cumulative Distribution Function (CDF) (integrated PDF)

 $p(6) = \frac{1}{6} \Rightarrow I$ expect that every 6th dice roll shows a 6, on average.





Bayesian statistics

Bayesian statistics describes the credibility of hypotheses.

- hypothesis H: falsifiable assumption that a specific statement is true, e.g. it will rain today.
- ▶ credibility $C(H) \in [0,1]$: strength of belief in H
- mathematically, credibilities and probabilities are identical
- difference is conceptual
- ightharpoonup C(H) can be updated with new data

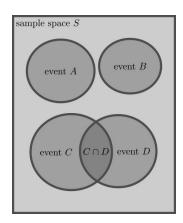
 $p(6) = \frac{1}{6} \Rightarrow I$ believe the hypothesis H "the die roll shows a 6" with a credibility of $C(H) = \frac{1}{6}$.



Conditional Probability

P(A|B) describes the probability of event A with the assumption that event B takes place.

- ightharpoonup read: P(A given that B)
- filters sets of possible events
- ▶ joint probability: both A and B: $P(A \cap B) = P(A)P(B|A)$
- \Rightarrow only when A and B independent: $P(A \cap B) = P(A)P(B)$
- ▶ joint probability: any A or B: $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- \Rightarrow A and B mutually exclusive: $P(A \cup B) = P(A) + P(B)$





Probability & Likelihood

Recap from the talk The Maximum Likelihood Principle by Maja Korbmacher.

- Probability P: tool for prediction of events
- Likelihood L: tool for modelling
- equal for given hypothesis H and events E
- but only if no prior knowledge is available
- Bayes' theorem generalizes this, using prior knowledge

$$L(H|E) \stackrel{?}{=} P(E|H) \tag{1}$$



Bayes' Theorem

Bayes' theorem describes the procedure of updating a hypothesis H, given that new evidence E is available. It is the scientific method of changing beliefs.

- Hypothesis H
- Evidence E
- ▶ follows from joint probability $P(E \cap H)$
- ightharpoonup overall likelihood P(E) (law of total probability)

$$P_2(H|E) = \frac{P(E|H)P_1(H)}{P(E)}$$
 (2)

$$\Rightarrow L(H|E) = P(E|H) \cdot \frac{P(H)}{P(E)}$$
 (3)

$$P(E) = P(E|H)P(H) + P(E|\neg H)P(\neg H)$$
 (4)

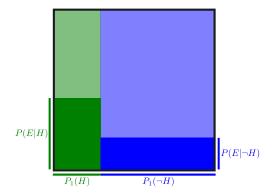




Bayes' Theorem

Geometric Interpretation

- ▶ square: probability 1
- ightharpoonup prior $P_1(H)$



The black square with side length 1 contains all probabilities.





Updating Credibilities

with Bayes' Theorem

$$P_2(H|E) = \frac{P(E|H)P_1(H)}{P(E)}$$

How to update the credibility of a hypothesis H:

- 1. assert prior $P_1(H)$
- 2. evaluate evidence $E: \rightarrow$ likelihood P(E|H)
- 3. calculate overall likelihood P(E)
- 4. calculate posterior probability $P_2(H|E)$





Updating Credibilities

The Posterior Odds ratio

The Posterior Odds ratio compares the posterior probabilities P_2 for two different hypotheses $H_{A,B}$.

- relative probability: compare probabilities
- absolute probabilities have limited use
- $ightarrow rac{P(A)}{P(B)} = rac{1}{2}$ tells event B occurs twice as often as event A, for e.g. P(A) = 0.1, P(B) = 0.2 or P(A) = 0.3, P(B) = 0.6.
- ightharpoonup overall likelihood P(E) becomes irrelevant

$$\frac{P_2(H_A|E)}{P_2(H_B|E)} = \frac{P(E|H_A)}{P(E|H_B)} \frac{P_1(H_A)}{P_1(H_B)}$$
(5)

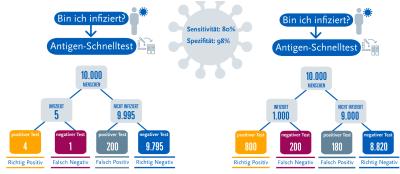




Example

rapid antigen tests

Assume a COVID rapid test with a sensitivity of 80%, causing 20% false-negative results, and a specificity of 98%, causing 2% false-positive results.



Source: Robert Koch Institute





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Thank you for your attention!



