

E.g. coin, $P(H) = 0.7$
 $\Rightarrow P(\bar{H}) = 0.3$

Conditional probability

Modeling knowledge of uncertainty

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What we aim to model

$P(x|z)$

what we're modelling

Information we know

{52} (1) $P(\text{card} > 7) \approx 0.46$

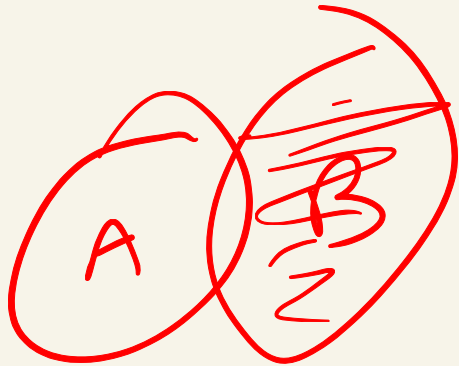
{30} (2) $P(\text{card} > 7)?$ (already drew 22 cards above 7)

(1) : $\frac{|A|}{|\Omega|} \approx 0.46$

(2) : $\frac{|A|}{|\{30\}|} = 0.80$

Conditional probability

Definition. *The conditional probability $\mathbb{P}(A \mid B)$ (read “probability of A given B ”) is defined as the following:*



$$\mathbb{P}(A \mid B) := \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} \leftarrow$$

$$\mathbb{P}(A \cap B) = \mathbb{P}(B) \mathbb{P}(A \mid B)$$

Bayes' Theorem

Theorem. For a distribution \mathbb{P} , the following equation holds:

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

Proof By def, $\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$. Multiply over, we get
 $\mathbb{P}(A \cap B) = \mathbb{P}(A|B) \mathbb{P}(B)$. Since $\mathbb{P}(A \cap B) = \mathbb{P}(B \cap A)$, we get
 $\mathbb{P}(A|B) \mathbb{P}(B) = \mathbb{P}(A \cap B) = \mathbb{P}(B \cap A) = \mathbb{P}(B|A) \mathbb{P}(A)$. Divide
 $\mathbb{P}(B)$ to get desired equation. \square

Why Bayes'?

$$P(I | Pos) = \frac{P(Pos | I) P(I)}{P(Pos)}$$
$$= \frac{P(Pos | I) P(I)}{P(Pos | I) P(I) + P(Pos | \text{not } I) P(\text{not } I)}$$

Partition = $\{I, \text{not } I\}$

$$(P(\text{not } I) = 1 - P(I))$$

A_1, A_2, A_3

$\{A_i\}_{i=1}^n$:= "collection of n sets"

Total probability rule

$\bigcup_{i=1}^n A_i := A_1 \cup A_2 \cup A_3 \cup \dots \cup A_n$

Theorem. Let (Ω, \mathbb{P}) be a random variable. If we have a collection of sets $\{A_i\}_{i=1}^n$ that "partition" the sample space Ω , i.e.:

- \rightarrow 1. $A_i \cap A_j = \emptyset$ for all $i, j \in \{1, \dots, n\}$,
- \rightarrow 2. $\bigcup_{i=1}^n A_i = \Omega$,

Then the following equation holds for any event $B \subset \Omega$:

$$\mathbb{P}(B) = \sum_{i=1}^n \mathbb{P}(B | A_i) \mathbb{P}(A_i).$$

$a \cdot (b + c) = a \cdot b + a \cdot c$
 $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$ "distributive property"

Total probability rule (1)

Proof. We know $\bigcup_{i=1}^n A_i = \Omega$, so since $\Omega \cap B = B$,

$\Rightarrow B = B \cap \left(\bigcup_{i=1}^n A_i\right)$. Distributive property, write

$B = \bigcup_{i=1}^n B \cap A_i$. Since A_i 's ⁽²⁾ disjoint, $\bigcup_{i=1}^n B \cap A_i$ is

a disjoint union, thus use additivity (from lecture) to conclude $P(B) = \sum_{i=1}^n P(B \cap A_i)$. Since

$P(B \cap A_i) = P(B|A_i)P(A_i)$, $\Rightarrow P(B) = \sum_{i=1}^n P(B|A_i)P(A_i)$. \blacksquare

Joint distributions

"Definition": a random variable of the form $(A \times B, \mathbb{R})$
for some sets A, B .

E.g. $A = \{\text{Pos}, \text{Neg}\}$, $B = \{\text{I}, \text{not I}\}$

$P((\text{Pos}, \text{I}))$

	Pos	Neg
I	0.2	0.3
not I	0	0.5

Applying Bayes' Joint Distribution

	I	not I
Pos	A	B
Neg	C	D

1st attempt: solve for unknowns in

$$P(\text{Pos} | I) = \frac{P(\text{Pos} \cap I)}{P(I)} = \frac{A}{A+C} = 0.9$$

$$P(I) = A+C = 0.05$$

$$P(\text{Pos}) = A+B = 0.2$$

Conclusion | Can be done, but hard to solve

for distributions purely algebraically:
this is the power of formulas
like Bayes' Theorem

Simpler, using equations, just plug in:

"5% of US population is affected": $P(I) = 0.05$, $P(\text{not } I) = 0.95$

"40% of affected people test positive": $P(\text{Pos} | I) = 0.4$

"20% of healthy people test positive": $P(\text{Pos} | \text{not } I) = 0.2$

"Probability of being affected": $P(I | \text{Pos})$

$$= \frac{P(\text{Pos} | I) P(I)}{P(\text{Pos} | I) P(I) + P(\text{Pos} | \text{not } I) P(\text{not } I)}$$

$$= \frac{0.4 \cdot 0.05}{0.4 \cdot 0.05 + 0.2 \cdot 0.95}$$

$$= \frac{0.02}{0.02 + 0.19} = 0.09$$