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## 1 Naive Bayes

### 1.1 1. Overarching Goals

- We want to assign each  $\bar{x} \in X$  to its correct class  $C_k$ ,  $k \in 1, \dots, K$
- We ask: **Given**  $\bar{x} \in X$ , what is its most **probable class**  $C_k$ ?

### 1.2 Understanding Conditional Probability

- Sample space ( $\Omega$ ) contains events whose probability of occurring is proportional to its area w.r.t the sample space
- In a fair coin flip,  $\mathbb{P}(\text{heads}) = \mathbb{P}(H) = \mathbb{P}(\text{tails}) = \mathbb{P}(T) = 0.5$
- Say we have the events  $H$ ,  $T$ , and  $N$ , where  $H$  is the event that Hillary Clinton is elected president,  $T$  is the probability that Trump is, and  $N$  is the probability that a nuclear winter occurs during the next presidency.
- see figure one
- If we want to talk about the probability of a nuclear winter happening ( $\mathbb{P}(N)$ ) given that Donald Trump is elected president ( $\mathbb{P}(T)$ ), we express it as  $\mathbb{P}(N|T)$ .
  - $\mathbb{P}(N|T)$  is read as "probability of a nuclear winter given that Trump is elected"
- $\mathbb{P}(N|T) = \frac{\mathbb{P}(N \cap T)}{\mathbb{P}(T)}$ .
  - Note that the probability of event  $T$  occurring is in the denominator, think of this as the new sample space that has been reduced.
  - We then find the probability of  $\mathbb{P}(N \cap T)$  over this new, reduced sample space. This is equivalent to  $\mathbb{P}(N|T) = \frac{\mathbb{P}(N \cap T)}{\mathbb{P}(T)}$ .
  - see figure 2

### 1.3 Bayes' Theorem

- We can represent the entire sample space  $\Omega$  in terms of conditional probabilities.
- see figure 3
- As a reminder: we want to assign each  $\bar{x} \in X$  to its correct class  $C_k$ ,  $k \in 1, \dots, K$
- We ask: **Given**  $\bar{x} \in X$ , what is its most **probable class**  $C_k$ ?
- $P(C_k|\bar{x}) = \frac{P(\bar{x}|C_k) \cdot P(C_k)}{P(\bar{x})}$
- $P(C_k|\bar{x}) = \frac{P(C_k \cap \bar{x})}{P(\bar{x})} = \frac{P(C_k, \bar{x})}{P(\bar{x})}$ 
  - $= \frac{P(x_1, x_2, \dots, x_n, C_k)}{P(\bar{x})}$

$$\begin{aligned}
- &= \frac{P(x_1|x_2, \dots, x_n, C_k) \cdot P(x_2, \dots, x_n, C_n)}{P(\bar{x})} \\
- &= \frac{P(x_1|x_2, \dots, C_k) \cdot P(x_2|x_3, \dots, C_k) \dots P(x_n|C_k)P(C_k)}{P(\bar{x})}
\end{aligned}$$

- See figure 4.

## 1.4 Terminology / Glossary

- Sample Space ( $\Omega$ ) - set of all possible outcomes of an experiment
- $A, B$  - events that are subsets of the sample space
- $\mathbb{P}(A)$  - Probability of event  $A$  occurring.
- $\mathbb{P}(-A)$  (or  $\mathbb{P}(A^c)$ ) - Probability of  $A$ 's complement ("not  $A$ ") occurring.
- $\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(A) \cdot \mathbb{P}(B|A)}{\mathbb{P}(B)}$
- $A \perp B$  -  $A$  is independent of  $B$  if and only if the (non-)occurrence of  $B$  has no effect on the (non-)occurrence of  $A$ , and vice versa.
  - Corollary: If  $A \perp B$ ,  $\mathbb{P}(A|B) = \mathbb{P}(A)$
  - Technical definition:  $A \perp B$  if and only if  $\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$

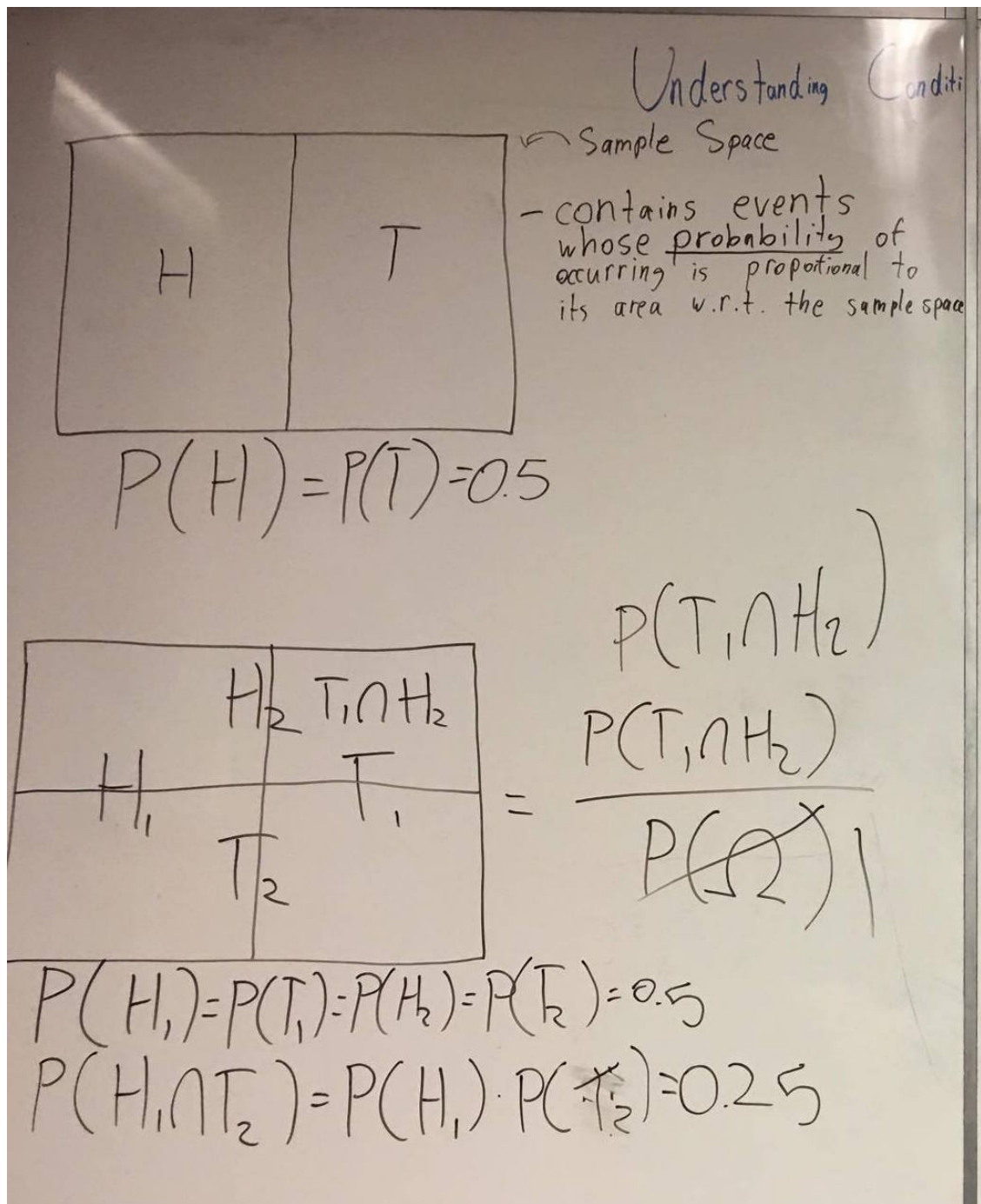


Figure 1: A visual representation of the sample space in the case of one and two coin flips.

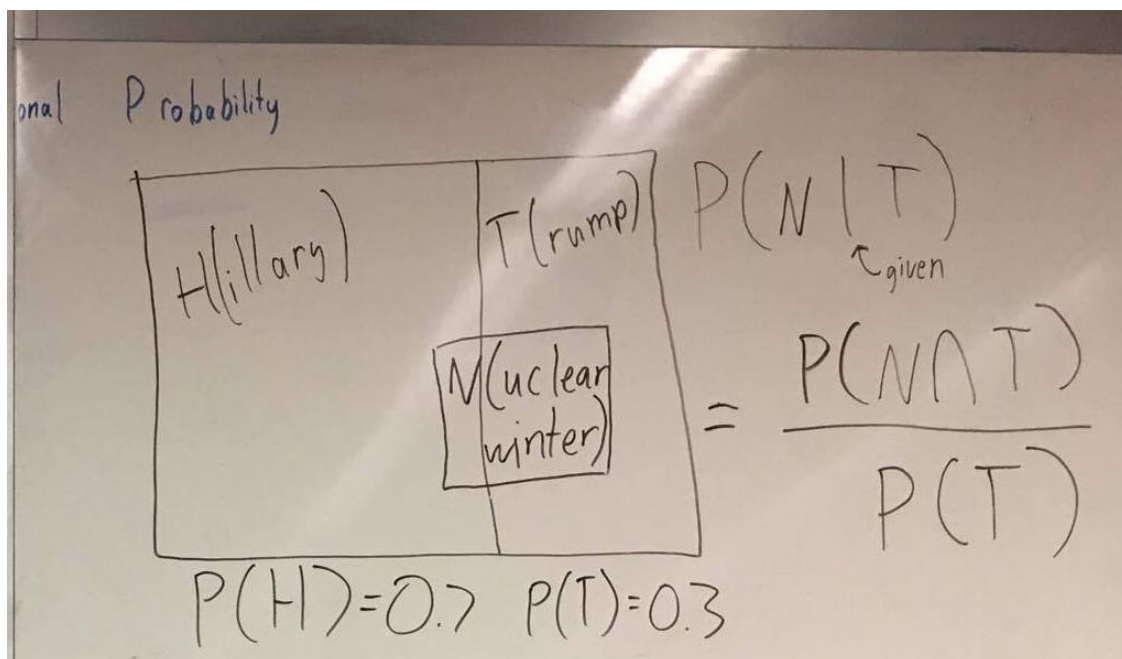


Figure 2: A visual representation of the sample space in conditional probability.

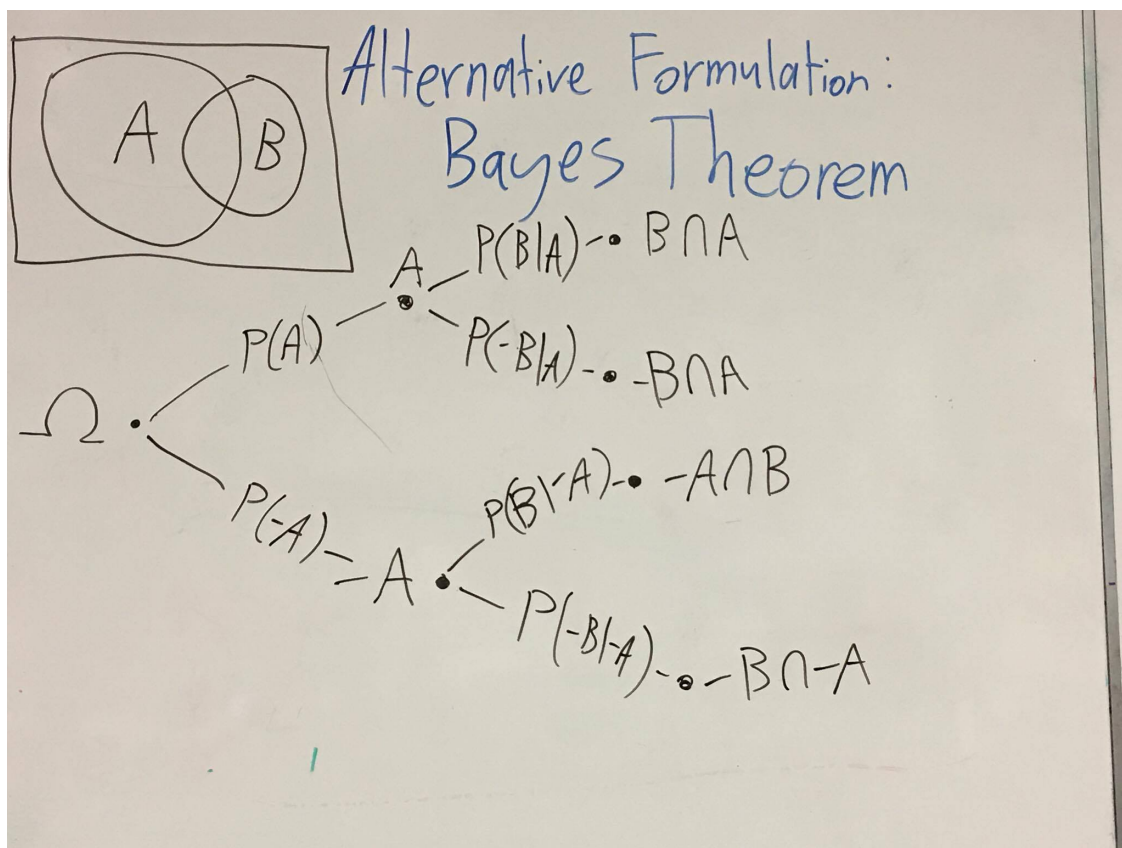


Figure 3: A visual representation of the sample space as conditional probabilities

Naive Bayes

GOAL: want to assign each  $\vec{x} \in X$  to its correct class  $C_k$ ,  $k \in \{1, \dots, K\}$

We ask: Given  $\vec{x} \in X$ , what is its most probable class  $C_k$ ?

$$P(C_k | \vec{x}) = \frac{P(\vec{x} | C_k) P(C_k)}{P(\vec{x})}$$

**FAIL**

$$P(C_k | \vec{x}) = \frac{P(C_k \cap \vec{x})}{P(\vec{x})} = \frac{P(C_k, \vec{x})}{P(\vec{x})} \quad (\text{notation})$$

$$= \frac{P(x_1, x_2, \dots, x_n, C_k)}{P(\vec{x})} \quad (\text{expansion})$$

$$= \frac{P(x_1 | x_2, \dots, x_n, C_k) P(x_2, \dots, x_n, C_k)}{P(\vec{x})}$$

$$= \frac{P(x_1 | x_2, \dots, C_k) P(x_2 | x_3, \dots, C_k) \dots P(x_n | C_k) P(C_k)}{P(\vec{x})}$$

Term

- ① Sample Space
- ② A, B - events +
- ③  $P(A)$  - Probability
- ④  $P(A)$  or  $P(A^c)$  -
- ⑤  $P(A|B) = P$
- ⑥  $ALB-A$  is of of Co To
- ⑦  $P(A, B)$  chain

Figure 4: The expansion of bayes' theorem