

# Discrete Mathematics and Its Applications 2 (CS147)

*Lecture 9: Conditional probability, independence*

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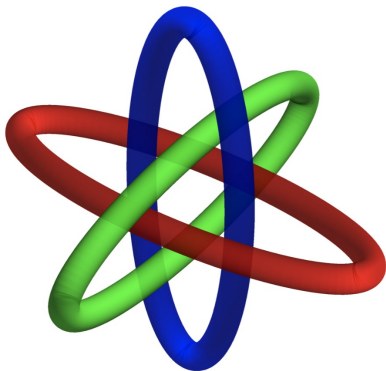


Figure: Borromean rings.

## Recall Probability...

- a metric/measure/function  $f$  of “event  $A$  occurs”

### Definition (Probability)

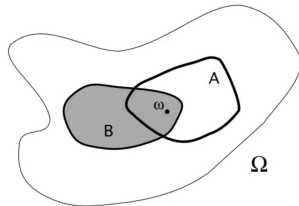
Probability  $\Pr : \mathcal{F} \rightarrow [0, 1]$  is a function that assigns a value to events

- ▶ nonnegativity:  $\Pr(A) \geq 0$
  - ▶ normalization:  $\Pr(\Omega) = 1$
  - ▶ countable additivity: if  $A_i \in \mathcal{F}$  is a countable sequence of disjoint sets, then 
$$\Pr(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \Pr(A_i)$$
- $(\Omega, \mathcal{F})$  is a measurable space
  - $(\Omega, \mathcal{F}, \Pr)$  is a probability space

# Conditional probability

## Problem

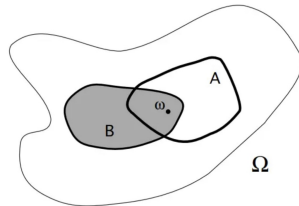
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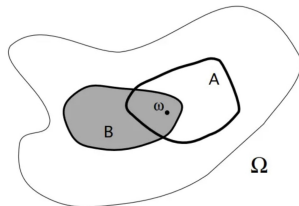


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# Conditional probability

## Problem

*If the event  $B$  occurs, then what is the probability of event  $A$ ?*



**Remark:** Given additional **information**, we infer the outcome of a random trial.

## Definition (Conditional probability)

Consider any two events  $A, B \subseteq \Omega$ , if  $\Pr(B) > 0$ , the conditional probability is

$$\Pr(A|B) = \frac{\Pr(A \cap B)}{\Pr(B)}.$$

**Remark:** the probability of event  $A$  occurs given that event  $B$  occurs.

# Partition theorem

## Definition (Partition)

$\{B_1, \dots, B_n\} \subseteq \Omega$  be a partition of the sample space  $\Omega$  if

- ▶  $\Omega = \cup_{i=1}^n B_i$ .
- ▶  $\Pr(B_i) > 0, \forall i \in [n]$ .
- ▶  $B_i \cap B_j = \emptyset \forall i \neq j$ .

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### Definition (Law of total probability)

Let  $\{B_1, \dots, B_n\} \subseteq \Omega$  be a partition of the sample space  $\Omega$ . Consider any event  $A \subseteq \Omega$ , we have

$$\Pr(A) = \sum_{i=1}^n \Pr(A \cap B_i) = \sum_{i=1}^n \Pr(A|B_i)\Pr(B_i).$$

**Remark:** a special case:  $\Pr(A) = \Pr(A \cap B) + \Pr(A \cap B^c)$ .



## From reason to result, from result to reason...

○ law of total probability: from reason to result

▶  $A$ : result/phenomenon

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- Bayes's theorem: from result to reason

- ▶  $\Pr(B_i|A)$ : event  $A$  occurs, infer the probability that the event is caused by  $B_i$
- ▶  $\Pr(B_i)$ : prior probability

# Bayes's theorem

## Theorem

Let  $\{B_1, \dots, B_n\} \subseteq \Omega$  be a *partition* of the sample space  $\Omega$  such that  $\Pr(B_i) > 0, \forall i \in [n]$ . Consider any event  $A \subseteq \Omega$ , we have

$$\begin{aligned}\Pr(B_i|A) &= \frac{\Pr(B_i \cap A)}{\Pr(A)} = \frac{\Pr(A|B_i)\Pr(B_i)}{\Pr(A)} \\ &= \frac{\Pr(A|B_i)\Pr(B_i)}{\sum_{j=1}^n \Pr(A|B_j)\Pr(B_j)}\end{aligned}$$

**Remark:** special case with  $n = 2$ :  $\Omega = B \cup B^c$ .

$$\Pr(B|A) = \frac{\Pr(A|B)\Pr(B)}{\Pr(A|B)\Pr(B) + \Pr(A|B^c)\Pr(B^c)}$$

## Example

### Example

Consider a disease with an incidence rate of 1 in  $10^5$  among the population. There is a diagnostic test the disease. For one person:

- ▶ If (s)he has this disease, this test is positive with probability at 9/10
- ▶ If (s)he doesn't have this disease, the test is positive with probability at 1/20

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Target: estimate  $\Pr(B|A)$

- ▶ prior:  $\Pr(B) = 10^{-5}$
- ▶  $\Pr(A|B) = 0.9$
- ▶  $\Pr(A|B^c) = 0.05$

## Solutions

- ▶ prior:  $\Pr(B) = 10^{-5}$
- ▶  $\Pr(A|B) = 0.9$
- ▶  $\Pr(A|B^c) = 0.05$

### Solution

Denote  $A =$  event that he/she is tested with positive;  $B =$  event that he/she has this disease.

$$\begin{aligned}\Pr(B|A) &= \frac{\Pr(B \cap A)}{\Pr(A)} = \frac{P(A|B)\Pr(B)}{\Pr(A \cap B) + \Pr(A \cap B^c)} = \frac{P(A|B)\Pr(B)}{P(A|B)\Pr(B) + P(A|B^c)\Pr(B^c)} \\ &= \frac{0.9 \times 10^{-5}}{0.9 \times 10^{-5} + 0.05 \times (1 - 10^{-5})} \approx 0.00018\end{aligned}$$



# Independence

$\Pr(A|B)$  changes when  $B$  changes

## Definition (Independence)

Event  $A$  and  $B$  are **independent** if  $\Pr(A \cap B) = \Pr(A)\Pr(B)$ .

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## Definition (mutually independent)

A collection of events  $A_1, A_2, \dots, A_k \subseteq \Omega$  are independent if and only if

$$\forall I \subseteq [1, k], \quad \Pr(\cap_{j \in I} A_j) = \prod_{j \in I} \Pr(A_j).$$

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## Definition (pairwise independent)

A collection of events  $A_1, A_2, \dots, A_k \subseteq \Omega$  are **pairwise independent** if and only if

$$\forall i, j \subseteq [1, k], i \neq j, \quad \Pr(A_i \cap A_j) = \Pr(A_i)\Pr(A_j).$$

# Relationship between mutually independent and pairwise independent

- mutually independent  $\Rightarrow$  pairwise independent
- pairwise independent  $\not\Rightarrow$  mutually independent

## Statement

*Intuitive idea: two events  $A, B$  occur, leading to the case that  $C$  occurs*

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*mutually independent:  $\Pr(ABC) = \Pr(A)\Pr(B)\Pr(C)$*

*pairwise independent:  $\Pr(ABC) = \Pr(A|BC)\Pr(BC) = \Pr(A|BC)\Pr(B)\Pr(C)$*

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### Example

- ▶ Two independent fair coin tosses
  - $A$ : First toss is H
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$$\Pr(A \cap B) = \frac{1}{4} = \Pr(A)\Pr(B)$$

$$\Pr(A \cap C) = \frac{1}{4} = \Pr(A)\Pr(C) \text{ (similar to } B)$$

$$\Pr(A \cap B \cap C) = \frac{1}{4} \neq \Pr(A)\Pr(B)\Pr(C) = \frac{1}{8}$$

# Union bound

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*We have*

$$\Pr(A \cup B) = \Pr(A) + \Pr(B) - \Pr(A \cap B).$$



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## Definition

Consider any events  $A_1, A_2, \dots, A_k \subseteq \Omega$ , then

$$\Pr(A_1 \cup A_2 \cup \dots \cup A_k) \leq \Pr(A_1) + \Pr(A_2) + \dots + \Pr(A_k).$$

## One example in Seminar

### Problem

*Suppose that in your inbox, 70% of all email is spam, 90% of spam emails contain the word “lottery”, and 5% of non-spam emails contain the word “lottery”. What is the probability that an email selected uniformly at random is actually spam given that it contains the word “lottery”?*

# \*Naive Bayes classifier - Illustration

- o train a binary classifier  $h$  on training data

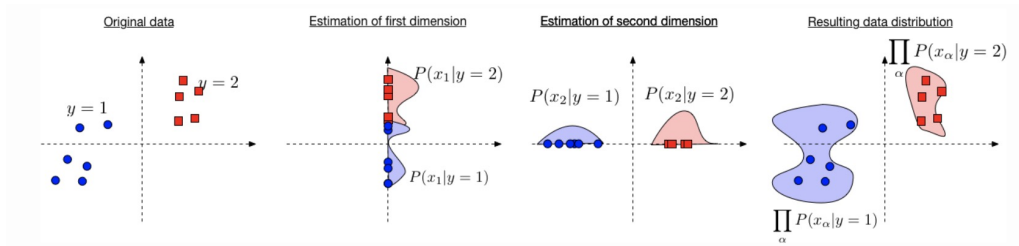


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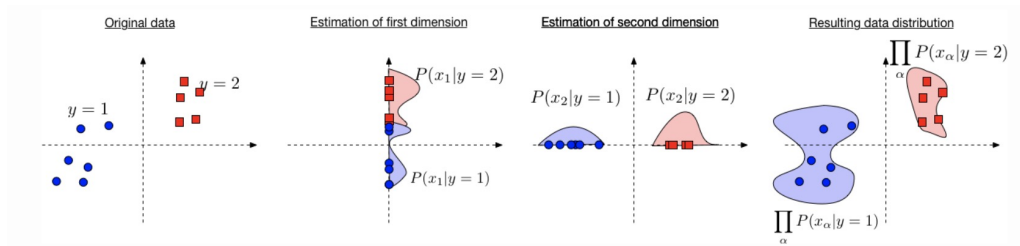


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$$h(\mathbf{x}) = \arg \max_y \Pr(y|\mathbf{x}) = \arg \max_y \frac{\Pr(\mathbf{x}|y)\Pr(y)}{\Pr(\mathbf{x})} = \arg \max_y \prod_{\alpha=1}^d \Pr(x_{\alpha}|y)\Pr(y).$$

- ▶ density estimation for  $\Pr(\mathbf{x}|y)$  → curse of dimensionality
- ▶ Assumption: **features are conditionally independent given the label**