

# Lecture 1, Jan 8, 2024

## Events and Probability

- The *sample space*  $S$  is the set of all outcomes for an experiment
  - An outcome  $s$  is a member of the sample space:  $s \in S$
- An *event* is a set of outcomes that satisfy a certain condition
  - Event  $A$  is a subset of  $S$ :  $A \subseteq S$
- The *complement* of  $A$  is the set of all elements in  $S$  that are not in  $A$ , denoted  $A^c$ ; note  $A \cup A^c = S$  and  $A \cap A^c = \emptyset$
- Given two events  $A$  and  $B$ , the event of either occurring is denoted  $A \cup B$ ; both occurring is  $A \cap B$ 
  - We can break  $A \cup B$  into 3 parts: outcomes in  $A$  only, outcomes in both  $A$  and  $B$ , and outcomes in  $B$  only; these are mutually exclusive
  - $A \cup B = (A \cap B^c) \cup (A^c \cap B) \cup (A \cap B)$
- $C \subseteq A$  means event  $C \implies A$
- Associate with each event a *probability*, satisfying the following:
  1.  $P[A] \geq 0 \forall A$
  2.  $P[S] = 1$
  3.  $A \cap B = \emptyset \iff P[A \cup B] = P[A] + P[B]$ 
    - Note if  $A$  and  $B$  are not mutually exclusive then  $P[A \cup B] = P[A] + P[B] - P[A \cap B]$

## Conditional Probability and Bayes' Rule

- The probability of  $A$  *conditioned on*  $B$  is defined as  $P[A|B] = \frac{P[A \cap B]}{P[B]}$  (assuming  $P[B] \neq 0$ )
  - $P[A|B]$  is known as the *a posteriori* probability
  - By symmetry,  $P[B|A] = \frac{P[A \cap B]}{P[A]}$
- This gives the *product formula*:  $P[A \cap B] = P[A|B]P[B] = P[B|A]P[A]$
- Events  $A$  and  $B$  are *independent* (denoted  $A \perp B$ ) iff  $P[A|B] = P[A]$ , equivalently  $P[A \cap B] = P[A]P[B]$

## Partitioning

- A *partition* of  $S$  is sets  $H_1, \dots, H_n$  such that  $S = H_1 \cup H_2 \dots \cup H_n$  and  $i \neq j \implies H_i \cap H_j = \emptyset$
- Since the  $H$  sets are mutually exclusive,  $A \cap H_i$  are also mutually exclusive
  - Then  $P[A] = P[A \cap H_1] + \dots + P[A \cap H_n] = P[A|H_1]P[H_1] + \dots + P[A|H_n]P[H_n]$
  - This is the *total probability theorem*
- Now we can find  $P[H_i|A] = \frac{P[A \cap H_i]}{P[A]} = \frac{P[A|H_i]P[H_i]}{\sum_j P[A|H_j]P[H_j]}$ 
  - This is the *Bayesian* approach
  - The *frequentist* approach assumes no knowledge about the underlying  $P[H_i]$  so we can only maximize  $P[A|H_i]$