It is remarkable that a science which began with the consideration of games of chance should become the most important object of human knowledge . . . The most important questions of life are, for the most part, really only problems of probability . . .

The theory of probabilities is at bottom nothing but common sense reduced to calculus.

– Pierre Simon de Laplace [1812]

Learning Objectives

At the end of the class you should be able to:

- justify the use and semantics of probability
- know how to compute marginals and apply Bayes' theorem
- identify conditional independence
- build a belief network for a domain

Using Uncertain Knowledge

- Agents don't have complete knowledge about the world.
- Agents need to make (informed) decisions given their uncertainty.
- It isn't enough to assume what the world is like.
  Example: wearing a seat belt.
- An agent needs to reason about its uncertainty.

Why Probability?

- There is lots of uncertainty about the world, but agents still need to act.
- Predictions are needed to decide what to do:
  - definitive predictions: you will (not) be run over tomorrow
  - point probabilities: probability you will be run over tomorrow is 0.002
  - probability ranges: you will be run over with probability in range [0.001,0.34]
- Acting is gambling: agents who don't use probabilities will lose to those who do — Dutch books.
- Probabilities can be learned from data.
  Bayes' rule specifies how to combine data and prior knowledge.

Numerical Measures of Belief

- Belief in proposition, f, can be measured in terms of a number between 0 and 1 — this is the probability of f.
  - The probability f is 0 means that f is believed to be definitely false.
  - The probability f is 1 means that f is believed to be definitely true.
- Using 0 and 1 is purely a convention.
- f has a probability between 0 and 1, means the agent is ignorant of its truth value.
- Probability is a measure of an agent's ignorance.
- Probability is *not* a measure of degree of truth.

Possible World Semantics

- Ω is a (possibly infinite) set of possible worlds.
- A random variable is a function possible worlds
- A random variable with a countable (or finite) range is a discrete random variable.
- A variable with range $\{true, false\}$ is a Boolean random variable.
- A variable with range the real numbers is a continuous random variable.
- $\omega \models X = v$ means variable X has value v in world ω.
- $\omega \models X > v$ means variable X is greater than v in world ω.
- Logical connectives have their standard meaning:

$$\omega \models \alpha \wedge \beta \text{ if } \omega \models \alpha \text{ and } \omega \models \beta$$

$$\omega \models \alpha \vee \beta \text{ if } \omega \models \alpha \text{ or } \omega \models \beta$$

$$\omega \models \neg\alpha \text{ if } \omega \not\models \alpha$$

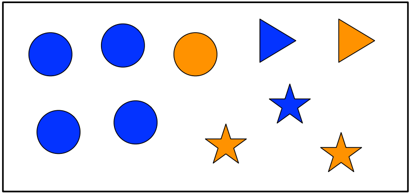
(Sometimes the range of a random variable is called it's domain – it is the domain of a function on random variables.)

Semantics of Probability

- Probability defines a measure on sets of possible worlds. (Not all sets have measures; just those than can be described.)
- A probability measure is a function μ from sets of worlds into the non-negative real numbers such that:
  - $\mu(\Omega) = 1$
  - $\mu(S_1 \cup S_2) = \mu(S_1) + \mu(S_2)$ if $S_1 \cap S_2 = \{\}$.
    Extended to countable unions (σ-additivity):
    $$\mu(\bigcup_i S_i) = \sum_i \mu(S_i) \text{ if } S_i \cap S_j = \{\} \text{ for } i \neq j$$
- $P(\alpha) = \mu(\{\omega \mid \omega \models \alpha\})$.

Semantics

Possible Worlds:



Suppose the measure of each singleton world is 0.1.

- What is the probability of circle?
- What us the probability of star?
- What is the probability of orange?
- What is the probability of orange and star?
- What is the probability of orange and circle?

Note that $P(\alpha \wedge \beta)$ is not a function of $P(\alpha)$ and $P(\beta)$.

Expected Value

- The expected value of numerical random variable X with respect to probability P is

$$\mathbb{E}_P(X) = \sum_{v \in domain(X)} v * P(X{=}v)$$

  when the domain is X is finite or countable.

- When the domain is continuous, the sum becomes an integral.
- If α is a proposition, treating *true* as 1 and *false* as 0:

$$\mathbb{E}_P(\alpha) = P(\alpha)$$

Conditioning

- Probabilistic conditioning specifies how to revise beliefs based on new information.
- An agent builds a probabilistic model taking all background information into account.
  This gives the prior probability.
- All other information must be conditioned on.
- If evidence e is the all of the information obtained subsequently, the conditional probability $P(h \mid e)$ of h given e is the posterior probability of h.

Semantics of Conditional Probability

- Evidence e rules out possible worlds incompatible with e.
- Evidence e induces a new measure, μ_e, over possible worlds:

$$\mu_e(S) = \begin{cases} c * \mu(S) & \text{if } \omega \models e \text{ for all } \omega \in S \\ 0 & \text{if } \omega \not\models e \text{ for all } \omega \in S \end{cases}$$

  To derive c:

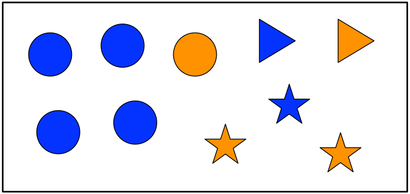
$$\begin{aligned} \mu_e(\Omega) &= \mu_e(\{\omega \mid \omega \models e\}) + \mu_e(\{\omega \mid \omega \not\models e\}) \\ &= c * P(e) \end{aligned}$$

  therefore $c = \frac{1}{P(e)}$.
- The conditional probability of formula h given evidence e is

$$\begin{aligned} P(h \mid e) &= \mu_e(\{\omega : \omega \models h\}) \\ &= \frac{P(h \wedge e)}{P(e)} \end{aligned}$$

Conditioning

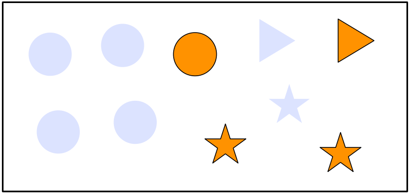
Possible Worlds:



$P(Shape{=}star) = 0.3$

$P(Shape{=}circle) = 0.5$

Observe *Color=orange*:



$P(Shape{=}star \mid Color{=}orange) = 0.5$

$P(Shape{=}circle \mid Color{=}orange) = 0.25$

Chain Rule: probability of conjunctions

$$P(h \mid e) = \frac{P(h \wedge e)}{P(e)}$$

Therefore

$$P(h \wedge e) = P(h \mid e) * P(e)$$

Chain Rule

Semantics of conditioning gives: $P(h \wedge e) = P(h \mid e) * P(e)$

$$
\begin{aligned}
& P(f_n \wedge f_{n-1} \wedge \ldots \wedge f_1) \\
= \;& P(f_n \mid f_{n-1} \wedge \cdots \wedge f_1) * \\
& P(f_{n-1} \wedge \cdots \wedge f_1) \\
= \;& P(f_n \mid f_{n-1} \wedge \cdots \wedge f_1) * \\
& P(f_{n-1} \mid f_{n-2} \wedge \cdots \wedge f_1) * \\
& P(f_{n-2} \wedge \cdots \wedge f_1) \\
= \;& P(f_n \mid f_{n-1} \wedge \cdots \wedge f_1) * \\
& P(f_{n-1} \mid f_{n-2} \wedge \cdots \wedge f_1) \\
& * \cdots * P(f_3 \mid f_2 \wedge f_1) * P(f_2 \mid f_1) * P(f_1) \\
= \;& \prod_{i=1}^{n} P(f_i \mid f_1 \wedge \cdots \wedge f_{i-1})
\end{aligned}
$$

Bayes' theorem

The chain rule and commutativity of conjunction ($h \wedge e$ is equivalent to $e \wedge h$) gives us:

$$
\begin{aligned}
P(h \wedge e) &= P(h \mid e) * P(e) \\
&= P(e \mid h) * P(h).
\end{aligned}
$$

If $P(e) \neq 0$, divide the right hand sides by $P(e)$:

$$
P(h \mid e) = \frac{P(e \mid h) * P(h)}{P(e)}.
$$

This is Bayes' theorem.

Why is Bayes' theorem interesting?

- Often you have causal knowledge:
  $P(\mathit{symptom} \mid \mathit{disease})$
  $P(\mathit{light\ is\ off} \mid \mathit{status\ of\ switches\ and\ switch\ positions})$
  $P(\mathit{alarm} \mid \mathit{fire})$
  $P($*image looks like*  $\mid \mathit{a\ tree\ is\ in\ front\ of\ a\ car})$
- and want to do evidential reasoning:
  $P(\mathit{disease} \mid \mathit{symptom})$
  $P(\mathit{status\ of\ switches} \mid \mathit{light\ is\ off\ and\ switch\ positions})$
  $P(\mathit{fire} \mid \mathit{alarm})$
  $P(\mathit{a\ tree\ is\ in\ front\ of\ a\ car} \mid$ *image looks like*  $)$