

# Using Uncertain Knowledge

- Agents don't have complete knowledge about the world.
- Agents need to make decisions based on 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.
- When an agent makes an action under uncertainty, it is gambling  $\implies$  probability.

# Probability

- Probability is an agent's measure of belief in some proposition — **subjective probability.**
- **Example:** Your probability of a bird flying is your measure of belief in the flying ability of an individual based only on the knowledge that the individual is a bird.
  - ▶ Other agents may have different probabilities, as they may have had different experiences with birds or different knowledge about this particular bird.
  - ▶ An agent's belief in a bird's flying ability is affected by what the agent knows about that bird.

# 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, doesn't mean  $f$  is true to some degree, but means you are ignorant of its truth value. Probability is a measure of your ignorance.

# Random Variables

- A **random variable** is a term in a language that can take one of a number of different values.
- The **domain** of a variable  $X$ , written  $dom(X)$ , is the set of values  $X$  can take.
- A tuple of random variables  $\langle X_1, \dots, X_n \rangle$  is a complex random variable with domain  $dom(X_1) \times \dots \times dom(X_n)$ . Often the tuple is written as  $X_1, \dots, X_n$ .
- Assignment  **$X = x$**  means variable  $X$  has value  $x$ .
- A **proposition** is a Boolean formula made from assignments of values to variables.

# Possible World Semantics

- A **possible world** specifies an assignment of one value to each random variable.
- $\omega \models X = x$   
means variable  $X$  is assigned value  $x$  in world  $\omega$ .
- Logical connectives have their standard meaning:
  - $\omega \models \alpha \wedge \beta$  if  $\omega \models \alpha$  and  $\omega \models \beta$
  - $\omega \models \alpha \vee \beta$  if  $\omega \models \alpha$  or  $\omega \models \beta$
  - $\omega \models \neg\alpha$  if  $\omega \not\models \alpha$
- Let  $\Omega$  be the set of all possible worlds.

# Semantics of Probability: finite case

For a finite number of possible worlds:

- Define a nonnegative measure  $\mu(\omega)$  to each world  $\omega$  so that the measures of the possible worlds sum to 1.  
The measure specifies how much you think the world  $\omega$  is like the real world.
- The **probability** of proposition  $f$  is defined by:

$$P(f) = \sum_{\omega \models f} \mu(\omega).$$

# Axioms of Probability: finite case

Three axioms define what follows from a set of probabilities:

**Axiom 1**  $0 \leq P(f)$  for any formula  $f$ .

**Axiom 2**  $P(\tau) = 1$  if  $\tau$  is a tautology.

**Axiom 3**  $P(f \vee g) = P(f) + P(g)$  if  $\neg(f \wedge g)$  is a tautology.

- These axioms are sound and complete with respect to the semantics.

# Semantics of Probability: general case

In the general case, probability defines a measure on sets of possible worlds. We define  $\mu(S)$  for some sets  $S \subseteq \Omega$  satisfying:

- $\mu(S) \geq 0$
- $\mu(\Omega) = 1$
- $\mu(S_1 \cup S_2) = \mu(S_1) + \mu(S_2)$  if  $S_1 \cap S_2 = \{\}$ .

Or sometimes  $\sigma$ -additivity:

$$\mu\left(\bigcup_i S_i\right) = \sum_i \mu(S_i) \text{ if } S_i \cap S_j = \{\} \text{ for } i \neq j$$

Then  $P(\alpha) = \mu(\{\omega \mid \omega \models \alpha\})$ .

# Probability Distributions

- A probability distribution on a random variable  $X$  is a function  $dom(X) \rightarrow [0, 1]$  such that

$$x \mapsto P(X = x).$$

This is written as  $P(X)$ .

- This also includes the case where we have tuples of variables. E.g.,  $P(X, Y, Z)$  means  $P(\langle X, Y, Z \rangle)$ .
- When  $dom(X)$  is infinite sometimes we need a probability density function...

# Conditioning

- Probabilistic conditioning specifies how to revise beliefs based on new information.
- You build 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**  $P(h|e)$  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,  $\mu_e$ , over possible worlds

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

We can show  $c = \frac{1}{P(e)}$ .

The conditional probability of formula  $h$  given evidence  $e$  is

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

# Chain Rule

$$\begin{aligned} & P(f_1 \wedge f_2 \wedge \dots \wedge f_n) \\ &= P(f_n | f_1 \wedge \dots \wedge f_{n-1}) \times \\ &\quad P(f_1 \wedge \dots \wedge f_{n-1}) \\ &= P(f_n | f_1 \wedge \dots \wedge f_{n-1}) \times \\ &\quad P(f_{n-1} | f_1 \wedge \dots \wedge f_{n-2}) \times \\ &\quad P(f_1 \wedge \dots \wedge f_{n-2}) \\ &= P(f_n | f_1 \wedge \dots \wedge f_{n-1}) \times \\ &\quad P(f_{n-1} | f_1 \wedge \dots \wedge f_{n-2}) \\ &\quad \times \dots \times P(f_3 | f_1 \wedge f_2) \times P(f_2 | f_1) \times P(f_1) \\ &= \prod_{i=1}^n P(f_i | f_1 \wedge \dots \wedge f_{i-1}) \end{aligned}$$

# Bayes' theorem

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

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

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

$$P(h|e) = \frac{P(e|h) \times P(h)}{P(e)}.$$

This is **Bayes' theorem.**

# Why is Bayes' theorem interesting?

- Often you have causal knowledge:  
 $P(\textit{symptom} \mid \textit{disease})$   
 $P(\textit{light is off} \mid \textit{status of switches and switch positions})$   
 $P(\textit{alarm} \mid \textit{fire})$   
 $P(\textit{image looks like } \img alt="stick figure" data-bbox="400 450 440 510" \mid \textit{a tree is in front of a car})$
- and want to do evidential reasoning:  
 $P(\textit{disease} \mid \textit{symptom})$   
 $P(\textit{status of switches} \mid \textit{light is off and switch positions})$   
 $P(\textit{fire} \mid \textit{alarm})$ .  
 $P(\textit{a tree is in front of a car} \mid \textit{image looks like } \img alt="stick figure" data-bbox="760 740 800 800" )$