

Representing Uncertainty

CSE 573

Many Techniques Developed

- Fuzzy Logic
- Certainty Factors
- Non-monotonic logic
- Probability

- Only one has stood the test of time!

Aspects of Uncertainty

- Suppose you have a flight at 12 noon
- When should you leave for SEATAC
 - What are traffic conditions?
 - How crowded is security?
- Leaving 18 hours early may get you there
 - But ... ?

Decision Theory = Probability + Utility Theory

Min before noon	P(arrive-in-time)
20 min	0.05
30 min	0.25
45 min	0.50
60 min	0.75
120 min	0.98
1080 min	0.99

Depends on your *preferences*
Utility theory: representing & reasoning
about preferences

What Is Probability?

- **Probability**: Calculus for dealing with nondeterminism and uncertainty
- Cf. Logic
- **Probabilistic model**: Says how often we expect different things to occur
- Cf. Function

What Is Statistics?

- **Statistics 1**: Describing data
- **Statistics 2**: Inferring probabilistic models from data
 - Structure
 - Parameters

Why Should You Care?

- The world is full of uncertainty
 - Logic is not enough
 - Computers need to be able to handle uncertainty
- Probability: new foundation for AI (& CS!)
- Massive amounts of data around today
 - Statistics and CS are both about data
 - Statistics lets us summarize and understand it
 - Statistics is the basis for most learning
- Statistics lets data do our work for us

© Daniel S. Weld

7

Outline

- Basic notions
 - Atomic events, probabilities, joint distribution
 - Inference by enumeration
 - Independence & conditional independence
 - Bayes' rule
- Bayesian networks
- Statistical learning
- Dynamic Bayesian networks (DBNs)
- Markov decision processes (MDPs)

© Daniel S. Weld

8

Logic vs. Probability

Symbol: Q, R ...	Random variable: Q ...
Boolean values: T, F	Domain: you specify e.g. {heads, tails} [1, 6]
State of the world: Assignment to Q, R ... Z	Atomic event: complete specification of world: Q... Z <ul style="list-style-type: none"> • Mutually exclusive • Exhaustive
	Prior probability (aka Unconditional prob: P(Q)
	Joint distribution: Prob. of every atomic event

© Daniel S. Weld

9

Syntax for Propositions

Propositional or Boolean random variables
e.g., *Cavity* (do I have a cavity?)

Discrete random variables (*finite* or *infinite*)
e.g., *Weather* is one of {*sunny*, *rain*, *cloudy*, *snow*}
Weather = rain is a proposition
Values must be exhaustive and mutually exclusive

Continuous random variables (*bounded* or *unbounded*)
e.g., *Temp* = 21.6; also allow, e.g., *Temp* < 22.0.

Arbitrary Boolean combinations of basic propositions

© Daniel S. Weld

10

Propositions

- Assume Boolean variables
 - Propositions:
 - A = true
 - B = false
 - $a \vee b$
- Proposition = disjunction of atomic events in which it is true
e.g., $(a \vee b) \equiv (\neg a \wedge b) \vee (a \wedge \neg b) \vee (a \wedge b)$
 $\Rightarrow P(a \vee b) = P(\neg a \wedge b) + P(a \wedge \neg b) + P(a \wedge b)$

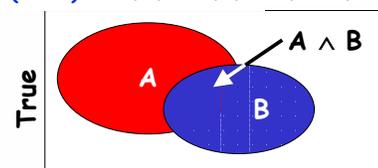
© Daniel S. Weld

11

Why Use Probability?

The definitions imply that certain logically related events must have related probabilities

$$\text{E.g. } P(A \vee B) = P(A) + P(B) - P(A \wedge B)$$



de Finetti (1931): an agent who bets according to probabilities that violate these axioms can be forced to bet so as to lose money regardless of outcome.

© Daniel S. Weld

12

Prior Probability

Prior or unconditional probabilities of propositions

e.g., $P(\text{Cavity} = \text{true}) = 0.1$ and $P(\text{Weather} = \text{sunny}) = 0.72$ correspond to belief prior to arrival of any (new) evidence

Probability distribution gives values for all possible assignments:

$P(\text{Weather}) = (0.72, 0.1, 0.08, 0.1)$ (normalized, i.e., sums to 1)

Joint probability distribution for a set of r.v.s gives the probability of every atomic event on those r.v.s

$P(\text{Weather}, \text{Cavity}) = a 4 \times 2$ matrix of values:

Weather =	sunny	rain	cloudy	snow
Cavity = true	0.144	0.02	0.016	0.02
Cavity = false	0.576	0.08	0.064	0.08

Any question can be answered by the joint distribution

© Daniel S. Weld

13

Conditional Probability

Conditional or posterior probabilities

e.g., $P(\text{cavity}|\text{toothache}) = 0.8$

i.e., given that *toothache* is all I know

NOT "if *toothache* then 80% chance of *cavity*"

(Notation for conditional distributions:

$P(\text{Cavity}|\text{Toothache}) = 2$ -element vector of 2-element vectors)

If we know more, e.g., *cavity* is also given, then we have

$P(\text{cavity}|\text{toothache}, \text{cavity}) = 1$

Note: the less specific belief *remains valid* after more evidence arrives, but is not always *useful*

New evidence may be irrelevant, allowing simplification, e.g.,

$P(\text{cavity}|\text{toothache}, \text{A9ersWin}) = P(\text{cavity}|\text{toothache}) = 0.8$

This kind of inference, sanctioned by domain knowledge, is crucial

© Daniel S. Weld

14

Conditional Probability

Def: $P(a|b) = \frac{P(a \wedge b)}{P(b)}$ if $P(b) \neq 0$

Product rule gives an alternative formulation:

$$P(a \wedge b) = P(a|b)P(b) = P(b|a)P(a)$$

A general version holds for whole distributions, e.g.,

$$P(\text{Weather}, \text{Cavity}) = P(\text{Weather}|\text{Cavity})P(\text{Cavity})$$

(View as a 4×2 set of equations, *not* matrix mult.)

Chain rule is derived by successive application of product rule:

$$\begin{aligned} P(X_1, \dots, X_n) &= P(X_1, \dots, X_{n-1}) P(X_n|X_1, \dots, X_{n-1}) \\ &= P(X_1, \dots, X_{n-2}) P(X_{n-1}|X_1, \dots, X_{n-2}) P(X_n|X_1, \dots, X_{n-1}) \\ &= \dots \\ &= \prod_{i=1}^n P(X_i|X_1, \dots, X_{i-1}) \end{aligned}$$

© Daniel S. Weld

15

Inference by Enumeration

Start with the joint distribution:

	toothache		\neg toothache	
	catch	\neg catch	catch	\neg catch
cavity	.108	.012	.072	.008
\neg cavity	.016	.064	.144	.576

For any proposition ϕ , sum the atomic events where it is true:

$$P(\phi) = \sum_{\omega:\omega\models\phi} P(\omega)$$

$$\begin{aligned} P(\text{toothache}) &= .108 + .012 + .016 + .064 \\ &= .20 \text{ or } 20\% \end{aligned}$$

This process is called "Marginalization"

© Daniel S. Weld

16

Inference by Enumeration

Start with the joint distribution:

	toothache		\neg toothache	
	catch	\neg catch	catch	\neg catch
cavity	.108	.012	.072	.008
\neg cavity	.016	.064	.144	.576

For any proposition ϕ , sum the atomic events where it is true:

$$P(\phi) = \sum_{\omega:\omega\models\phi} P(\omega)$$

$$\begin{aligned} P(\text{toothache} \vee \text{cavity}) &= .20 + .072 + .008 \\ &= .28 \end{aligned}$$

© Daniel S. Weld

17

Inference by Enumeration

Start with the joint distribution:

	toothache		\neg toothache	
	catch	\neg catch	catch	\neg catch
cavity	.108	.012	.072	.008
\neg cavity	.016	.064	.144	.576

Can also compute conditional probabilities:

$$\begin{aligned} P(\neg \text{cavity}|\text{toothache}) &= \frac{P(\neg \text{cavity} \wedge \text{toothache})}{P(\text{toothache})} \\ &= \frac{0.016 + 0.064}{0.108 + 0.012 + 0.016 + 0.064} = 0.4 \end{aligned}$$

© Daniel S. Weld

18

Problems ??

- Worst case time: $O(n^d)$
Where d = max arity
And n = number of random variables
- Space complexity also $O(n^d)$
Size of joint distribution
- How get $O(n^d)$ entries for table??

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

Value of cavity &
catch irrelevant -
When computing
 $P(\text{toothache})$