Uncertainty

LESSON 11

Reading

Chapter 13

Outline

Uncertainty

Probability

Syntax and Semantics

Inference

Independence and Bayes' Rule

Uncertainty

Let action A_t = leave for airport $_t$ minutes before flight

Will A_t get me there on time? Problems:

1. partial observability (road state, other drivers' plans, etc.)
2. noisy sensors (traffic reports)
3. uncertainty in action outcomes (flat tire, etc.)
4. immense complexity of modeling and predicting traffic

Hence a purely logical approach either

1. risks falsehood: "A_{25} will get me there on time", or
2. leads to conclusions that are too weak for decision making:

"A_{25} will get me there on time if there's no accident on the bridge and it doesn't rain and my tires remain intact etc etc."

(A_{1440} might reasonably be said to get me there on time but I'd have to stay overnight in the airport …)

Methods for handling uncertainty

Default or nonmonotonic logic:

- Assume my car does not have a flat tire
- Assume A_{25} works unless contradicted by evidence

Issues: What assumptions are reasonable? How to handle contradiction?

Rules with fudge factors:

- A_{25} $|\rightarrow_{0.3}$ get there on time
- *Sprinkler* $|\rightarrow_{0.99}$ *WetGrass*
- *WetGrass* $|\rightarrow_{0.7}$ *Rain*

Issues: Problems with combination, e.g., *Sprinkler* causes *Rain*??

Probability

- Model agent's degree of belief
- Given the available evidence,
- A_{25} will get me there on time with probability 0.04
-

Probability

Probabilistic assertions summarize effects of

- laziness: failure to enumerate exceptions, qualifications, etc.
- ignorance: lack of relevant facts, initial conditions, etc.

Subjective probability:

Probabilities relate propositions to agent's own state of knowledge

e.g., $P(A_{25} \mid \text{no reported accidents}) = 0.06$

These are not assertions about the world

Probabilities of propositions change with new evidence:

e.g., $P(A_{25} \mid \text{no reported accidents, 5 a.m.}) = 0.15$

Making decisions under uncertainty

Suppose I believe the following:

$P(A_{25}$ gets me there on time | …) = 0.04

$P(A_{90}$ gets me there on time | …) = 0.70

$P(A_{120}$ gets me there on time | …) = 0.95

$P(A_{1440}$ gets me there on time | …) = 0.9999

Which action to choose?

Depends on my preferences for missing flight vs. time spent waiting, etc.

- Utility theory is used to represent and infer preferences
- Decision theory = probability theory + utility theory

Syntax

Basic element: random variable

Similar to propositional logic: possible worlds defined by assignment of values to random variables.

Boolean random variables

e.g., *Cavity* (do I have a cavity?)

Discrete random variables

e.g., *Weather* is one of <*sunny,rainy,cloudy,snow*>

Domain values must be exhaustive and mutually exclusive

Elementary proposition constructed by assignment of a value to a

random variable: e.g., *Weather = sunny*, *Cavity = false*

(abbreviated as $\neg$*cavity*)

Complex propositions formed from elementary propositions and standard logical connectives e.g., *Weather = sunny* $\vee$ *Cavity = false*

Syntax

Atomic event: A complete specification of the state of the world about which the agent is uncertain

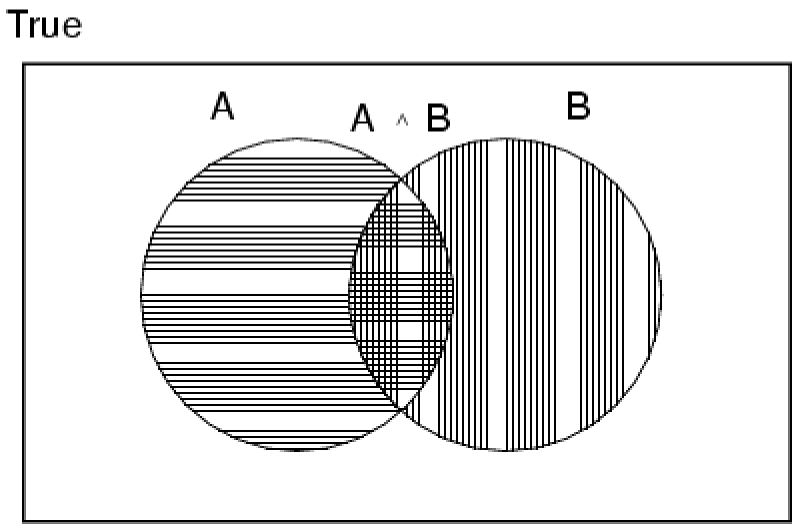
E.g., if the world consists of only two Boolean variables *Cavity* and *Toothache*, then there are 4 distinct atomic events:

Cavity = false $\wedge$ *Toothache = false*
Cavity = false $\wedge$ *Toothache = true*
Cavity = true $\wedge$ *Toothache = false*
Cavity = true $\wedge$ *Toothache = true*

Atomic events are mutually exclusive and exhaustive

Axioms of probability

For any propositions *A, B*

- $0 \leq P(A) \leq 1$
- $P(true) = 1$ and $P(false) = 0$
- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$
- 

Prior probability

Prior or unconditional probabilities of propositions

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

Probability distribution gives values for all possible assignments:

P(*Weather*) = <0.72,0.1,0.08,0.1> (normalized, i.e., sums to 1)

Joint probability distribution for a set of random variables gives the probability of every atomic event on those random variables

P(*Weather,Cavity*) = a 4 × 2 matrix of values:

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

Every question about a domain can be answered by the joint distribution

Conditional probability

Conditional or posterior probabilities

e.g., $P(cavity \mid toothache) = 0.8$

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

(Notation for conditional distributions:

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

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

$P(cavity \mid toothache, cavity) = 1$

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

$P(cavity \mid toothache, sunny) = P(cavity \mid toothache) = 0.8$

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

Conditional probability

Definition of conditional probability:

$P(a \mid b) = P(a \wedge b) / P(b)$ if $P(b) > 0$

Product rule gives an alternative formulation:

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

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

$\mathbf{P}(Weather, Cavity) = \mathbf{P}(Weather \mid Cavity)\, \mathbf{P}(Cavity)$

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

Chain rule is derived by successive application of product rule:

$$
\begin{aligned}
\mathbf{P}(X_1, \ldots, X_n) &= \mathbf{P}(X_1,\ldots,X_{n-1})\, \mathbf{P}(X_n \mid X_1,\ldots,X_{n-1}) \\
&= \mathbf{P}(X_1,\ldots,X_{n-2})\, \mathbf{P}(X_{n-1} \mid X_1,\ldots,X_{n-2})\, \mathbf{P}(X_n \mid X_1,\ldots,X_{n-1}) \\
&= \ldots \\
&= \pi_{i=1}\text{^}n\, \mathbf{P}(X_i \mid X_1, \ldots, X_{i-1})
\end{aligned}
$$

Inference by enumeration

Start with the joint probability distribution:

	toothache		*¬ toothache*	
	catch	*¬ catch*	*catch*	*¬ catch*
cavity	.108	.012	.072	.008
¬ cavity	.016	.064	.144	.576

For any proposition ϕ, sum the atomic events where it is true:
$P(\phi) = \Sigma_{\omega:\omega \models \phi} P(\omega)$

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Can also compute conditional probabilities:

$$P(\neg cavity \mid toothache) = \frac{P(\neg cavity \wedge toothache)}{P(toothache)}$$

$$= \frac{0.016+0.064}{0.108 + 0.012 + 0.016 + 0.064}$$

$$= 0.4$$

Normalization

	toothache		*¬ toothache*	
	catch	*¬ catch*	*catch*	*¬ catch*
cavity	.108	.012	.072	.008
¬ cavity	.016	.064	.144	.576

Denominator can be viewed as a normalization constant α

$\mathbf{P}(\mathit{Cavity} \mid \mathit{toothache}) = \alpha,\ \mathbf{P}(\mathit{Cavity}, \mathit{toothache})$

$= \alpha,\ [\mathbf{P}(\mathit{Cavity}, \mathit{toothache}, \mathit{catch}) + \mathbf{P}(\mathit{Cavity}, \mathit{toothache}, \neg\, \mathit{catch})]$

$= \alpha,\ [<0.108, 0.016> + <0.012, 0.064>]$

$= \alpha,\ <0.12, 0.08> = <0.6, 0.4>$

General idea: compute distribution on query variable by fixing evidence variables and summing over hidden variables

Inference by enumeration, contd.

Typically, we are interested in

the posterior joint distribution of the query variables **Y**

given specific values **e** for the evidence variables **E**

Let the hidden variables be **H** = **X** - **Y** - **E**

Then the required summation of joint entries is done by summing out the hidden variables:

$$\mathbf{P}(\mathbf{Y} \mid \mathbf{E} = \mathbf{e}) = \alpha\mathbf{P}(\mathbf{Y},\mathbf{E} = \mathbf{e}) = \alpha\Sigma_h\mathbf{P}(\mathbf{Y},\mathbf{E}= \mathbf{e}, \mathbf{H} = \mathbf{h})$$

The terms in the summation are joint entries because **Y**, **E** and **H** together exhaust the set of random variables

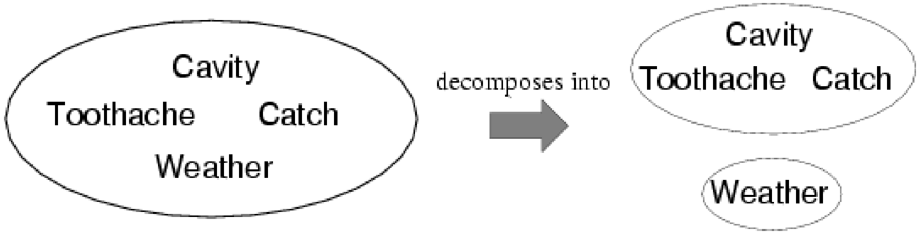
Obvious problems:

1. Worst-case time complexity $O(d^n)$ where d is the largest arity
2. Space complexity $O(d^n)$ to store the joint distribution
3. How to find the numbers for $O(d^n)$ entries?

Independence

A and *B* are independent iff

P(*A*|*B*) = **P**(*A*)



P(*Toothache, Catch, Cavity, Weather*)
= **P**(*Toothache, Catch, Cavity*) **P**(*Weather*)

32 entries reduced to 12; for *n* independent biased coins, $O(2^n) \rightarrow O(n)$

Absolute independence powerful but rare

Dentistry is a large field with hundreds of variables, none of which are independent. What to do?

Conditional independence

$\mathbf{P}(Toothache, Cavity, Catch)$ has $2^3 - 1 = 7$ independent entries

If I have a cavity, the probability that the probe catches in it doesn't depend on whether I have a toothache:

(1) $\mathbf{P}(catch \mid toothache, cavity) = \mathbf{P}(catch \mid cavity)$

The same independence holds if I haven't got a cavity:

(2) $\mathbf{P}(catch \mid toothache, \neg cavity) = \mathbf{P}(catch \mid \neg cavity)$

Catch is conditionally independent of *Toothache* given *Cavity*:

$\mathbf{P}(Catch \mid Toothache, Cavity) = \mathbf{P}(Catch \mid Cavity)$

Equivalent statements:

$\mathbf{P}(Toothache \mid Catch, Cavity) = \mathbf{P}(Toothache \mid Cavity)$

$\mathbf{P}(Toothache, Catch \mid Cavity) = \mathbf{P}(Toothache \mid Cavity)\, \mathbf{P}(Catch \mid Cavity)$

Conditional independence contd.

Write out full joint distribution using chain rule:

P(*Toothache, Catch, Cavity*)

= **P**(*Toothache | Catch, Cavity*) **P**(*Catch, Cavity*)

= **P**(*Toothache | Catch, Cavity*) **P**(*Catch | Cavity*) **P**(*Cavity*)

= **P**(*Toothache | Cavity*) **P**(*Catch | Cavity*) **P**(Cavity)

I.e., 2 + 2 + 1 = 5 independent numbers

In most cases, the use of conditional independence reduces the size of the representation of the joint distribution from exponential in *n* to linear in *n*.

Conditional independence is our most basic and robust form of knowledge about uncertain environments.

Bayes' Rule

Product rule $P(a \wedge b) = P(a \mid b)\, P(b) = P(b \mid a)\, P(a)$

$\Rightarrow$ Bayes' rule: $P(a \mid b) = P(b \mid a)\, P(a) / P(b)$

or in distribution form

$$\mathbf{P}(Y|X) = \mathbf{P}(X|Y)\, \mathbf{P}(Y) / \mathbf{P}(X) = \alpha \mathbf{P}(X|Y)\, \mathbf{P}(Y)$$

Useful for assessing diagnostic probability from causal probability:

- P(Cause|Effect) = P(Effect|Cause) P(Cause) / P(Effect)

E.g., let *M* be meningitis, *S* be stiff neck:

$P(m|s) = P(s|m)\, P(m) / P(s) = 0.8 \times 0.0001 / 0.1 = 0.0008$

- Note: posterior probability of meningitis still very small!

Bayes' Rule and conditional independence

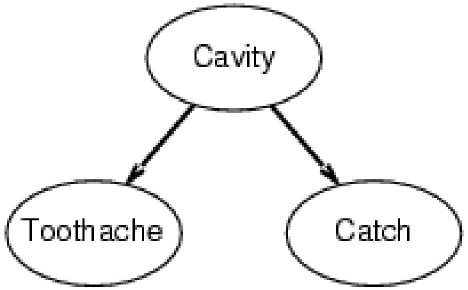
$\mathbf{P}(Cavity \mid toothache \wedge catch)$

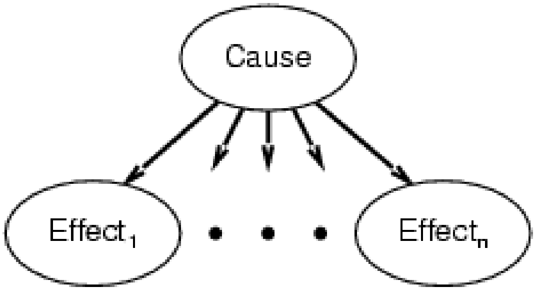
$= \alpha \mathbf{P}(toothache \wedge catch \mid Cavity)\, \mathbf{P}(Cavity)$

$= \alpha \mathbf{P}(toothache \mid Cavity)\, \mathbf{P}(catch \mid Cavity)\, \mathbf{P}(Cavity)$

This is an example of a naïve Bayes model:

$\mathbf{P}(\text{Cause}, \text{Effect}_1, \ldots, \text{Effect}_n) = \mathbf{P}(\text{Cause})\, \pi_i \mathbf{P}(\text{Effect}_i \mid \text{Cause})$





Total number of parameters is linear in n

Summary

Probability is a rigorous formalism for uncertain knowledge

Joint probability distribution specifies probability of every atomic event

Queries can be answered by summing over atomic events

For nontrivial domains, we must find a way to reduce the joint size

Independence and conditional independence provide the tools