

# Informatics 2D – Reasoning and Agents

## Semester 2, 2011-12

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Lecture 22 – Probabilities and Bayes' Rule  
13th March 2012  
adapted from slides by Michael Rovatsos

## Where are we?

Last time ...

- ▶ Introduced basics of decision theory (probability theory + utility)
- ▶ Talked about random variables, probability distributions
- ▶ Introduced basic probability notation and axioms

Today ...

- ▶ **Probabilities and Bayes' Rule**

## Inference with joint probability distributions

- ▶ Last time we talked about joint probability distributions (JPDs) but didn't present a method for **probabilistic inference** using them
- ▶ Problem: Given some observed evidence and a query proposition, how can we compute the **posterior probability** of that proposition?
- ▶ We will first discuss a simple method using a JPD as "knowledge base"
- ▶ Although not very useful in practice, it helps us to discuss interesting issues along the way

## Example

- ▶ Domain consisting only of Boolean variables *Toothache*, *Cavity* and *Catch* (steel probe catches in tooth)
- ▶ Consider the following JPD:

	<i>toothache</i>		$\neg$ <i>toothache</i>	
	<i>catch</i>	$\neg$ <i>catch</i>	<i>catch</i>	$\neg$ <i>catch</i>
<i>cavity</i>	0.108	0.012	0.072	0.008
$\neg$ <i>cavity</i>	0.016	0.064	0.144	0.576

- ▶ Probabilities (table entries) sum to 1
- ▶ We can compute probability of any proposition, e.g.  
 $P(\textit{catch} \vee \textit{cavity}) =$   
 $0.108 + 0.016 + 0.072 + 0.144 + 0.012 + 0.008 = 0.36$

## Marginalisation, conditioning & normalisation

- ▶ Extracting distribution of subset of variables is called **marginalisation**:  $\mathbf{P}(\mathbf{Y}) = \sum_{\mathbf{z}} \mathbf{P}(\mathbf{Y}, \mathbf{z})$
- ▶ Example:

$$\begin{aligned} P(\text{cavity}) &= P(\text{cavity}, \text{toothache}, \text{catch}) + P(\text{cavity}, \text{toothache}, \neg \text{catch}) \\ &\quad + P(\text{cavity}, \neg \text{toothache}, \text{catch}) + P(\text{cavity}, \neg \text{toothache}, \neg \text{catch}) \\ &= 0.108 + 0.012 + 0.072 + 0.008 = 0.2 \end{aligned}$$

- ▶ **Conditioning** – variant using the product rule:

$$\mathbf{P}(\mathbf{Y}) = \sum_{\mathbf{z}} \mathbf{P}(\mathbf{Y}|\mathbf{z})P(\mathbf{z})$$

## Marginalisation, conditioning & normalisation

- ▶ Computing conditional probabilities:

$$\begin{aligned}
 P(\text{cavity}|\text{toothache}) &= \frac{P(\text{cavity} \wedge \text{toothache})}{P(\text{toothache})} \\
 &= \frac{0.108 + 0.012}{0.108 + 0.012 + 0.016 + 0.064} = 0.6
 \end{aligned}$$

- ▶ **Normalisation** ensures probabilities sum to 1, normalisation constants often denoted by  $\alpha$
- ▶ Example:

$$\begin{aligned}
 \mathbf{P}(\text{Cavity}|\text{toothache}) &= \alpha \mathbf{P}(\text{Cavity}, \text{toothache}) \\
 &= \alpha [\mathbf{P}(\text{Cavity}, \text{toothache}, \text{catch}) + \mathbf{P}(\text{Cavity}, \text{toothache}, \neg \text{catch})] \\
 &= \alpha [\langle 0.108, 0.016 \rangle + \langle 0.012, 0.064 \rangle] = \alpha \langle 0.12, 0.08 \rangle = \langle 0.6, 0.4 \rangle
 \end{aligned}$$

## A general inference procedure

- ▶ Let  $X$  be a query variable (e.g. *Cavity*),  $\mathbf{E}$  set of evidence variables (e.g.  $\{Toothache\}$ ) and  $\mathbf{e}$  their observed values,  $\mathbf{Y}$  remaining unobserved variables
- ▶ Query evaluation:  $\mathbf{P}(X|\mathbf{e}) = \alpha \mathbf{P}(X, \mathbf{e}) = \alpha \sum_{\mathbf{y}} \mathbf{P}(X, \mathbf{e}, \mathbf{y})$
- ▶ Note that  $X$ ,  $\mathbf{E}$ , and  $\mathbf{Y}$  constitute complete set of variables, i.e.  $\mathbf{P}(x, \mathbf{e}, \mathbf{y})$  simply a subset of probabilities from the JPD
- ▶ For every value  $x_i$  of  $X$ , sum over all values of every variable in  $\mathbf{Y}$  and normalise the resulting probability vector
- ▶ Only theoretically relevant, it requires  $O(2^n)$  steps (and entries) for  $n$  Boolean variables (and we don't have these values)
- ▶ Basically, all methods we will talk about deal with tackling this problem!

## Independence

- ▶ Suppose we extend our example with the variable *Weather*
- ▶ What is the relationship between old and new JPD?
- ▶ Can compute  $P(\textit{toothache}, \textit{catch}, \textit{cavity}, \textit{Weather} = \textit{cloudy})$  as:

$$P(\textit{Weather} = \textit{cloudy} | \textit{toothache}, \textit{catch}, \textit{cavity}) P(\textit{toothache}, \textit{catch}, \textit{cavity})$$

- ▶ And since the weather does not depend on dental stuff, we expect that

$$P(\textit{Weather} = \textit{cloudy} | \textit{toothache}, \textit{catch}, \textit{cavity}) = P(\textit{Weather} = \textit{cloudy})$$

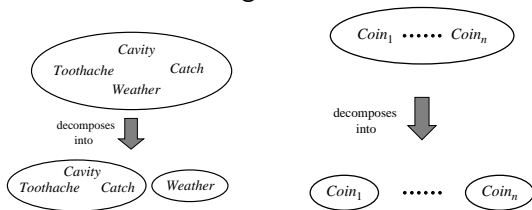
- ▶ So

$$P(\textit{toothache}, \textit{catch}, \textit{cavity}, \textit{Weather} = \textit{cloudy}) = \\ P(\textit{Weather} = \textit{cloudy}) P(\textit{toothache}, \textit{catch}, \textit{cavity})$$

- ▶ One 8-element and one 4-element table rather than a 32-table!

## Independence

- ▶ This is called **independence**, usually written as  
 $P(X|Y) = P(X)$  or  $P(Y|X) = P(Y)$  or  $P(X, Y) = P(X)P(Y)$
- ▶ Depends on domain knowledge; can factor distributions



- ▶ Such independence assumptions can help to dramatically reduce complexity
- ▶ Independence assumptions are sometimes *necessary* even when not entirely justified, so as to make probabilistic reasoning in the domain practical (more later).

## Bayes' rule

- ▶ **Bayes' rule** is derived by writing the product rule in two forms and equating them:

$$\left. \begin{array}{l} P(a \wedge b) = P(a|b)P(b) \\ P(a \wedge b) = P(b|a)P(a) \end{array} \right\} \Rightarrow P(b|a) = \frac{P(a|b)P(b)}{P(a)}$$

- ▶ General case for multivaried variables using background evidence  $\mathbf{e}$ :

$$P(Y|X, \mathbf{e}) = \frac{P(X|Y, \mathbf{e})P(Y|\mathbf{e})}{P(X|\mathbf{e})}$$

- ▶ Useful because often we have good estimates for three terms on the right and are interested in the fourth

## Applying Bayes' rule

- ▶ Example: meningitis causes stiff neck with 50%, probability of meningitis ( $m$ )  $1/50000$ , probability of stiff neck ( $s$ )  $1/20$

$$P(m|s) = \frac{P(s|m)P(m)}{P(s)} = \frac{\frac{1}{2} \times \frac{1}{50000}}{\frac{1}{20}} = \frac{1}{5000}$$

- ▶ Previously, we were able to avoid calculating probability of evidence ( $P(s)$ ) by using normalisation
- ▶ With Bayes' rule:  $\mathbf{P}(M|s) = \alpha \langle P(s|m)P(m), P(s|\neg m)P(\neg m) \rangle$
- ▶ Usefulness of this depends on whether  $P(s|\neg m)$  is easier to calculate than  $P(s)$
- ▶ Obvious question: why would conditional probability be available in one direction and not in the other?
- ▶ Diagnostic knowledge (from symptoms to causes) is often fragile  
(e.g.  $P(m|s)$  will go up if  $P(m)$  goes up due to epidemic)

## Combining evidence

- ▶ Attempting to use additional evidence is easy in the JPD model

$$\mathbf{P}(Cavity|toothache \wedge catch) = \alpha \langle 0.108, 0.016 \rangle \approx \langle 0.871, 0.129 \rangle$$

but requires additional knowledge in Bayesian model:

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

- ▶ This is basically almost as hard as JPD calculation
- ▶ Refining idea of independence: *Toothache* and *Catch* are independent given presence/absence of *Cavity* (both caused by cavity, no effect on each other)

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

## Conditional independence

- ▶ Two variables  $X$  and  $Y$  are conditionally independent given  $Z$  if  $\mathbf{P}(X, Y|Z) = \mathbf{P}(X|Z)\mathbf{P}(Y|Z)$
- ▶ Equivalent forms  $\mathbf{P}(X|Y, Z) = \mathbf{P}(X|Z)$ ,  
 $\mathbf{P}(Y|X, Z) = \mathbf{P}(Y|Z)$
- ▶ So in our example:

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

- ▶ As before, this allows us to decompose large JPD tables into smaller ones, grows as  $O(n)$  instead of  $O(2^n)$
- ▶ This is what makes probabilistic reasoning methods scalable at all!

## Conditional independence

- ▶ Conditional independence assumptions much more often reasonable than absolute independence assumptions
- ▶ **Naive Bayes model:**

$$\mathbf{P}(Cause, Effect_1, \dots, Effect_n) = \mathbf{P}(Cause) \prod_i \mathbf{P}(Effect_i | Cause)$$

- ▶ Based on the idea that all effects are conditionally independent given the cause variable
- ▶ Also called **Bayesian classifier** or (by some) even “**idiot Bayes model**”
- ▶ Works surprisingly well in many domains despite its simplicity!

## Summary

- ▶ Probabilistic inference with full JPDs
- ▶ Independence and conditional independence
- ▶ Bayes' rule and its applications problems with fairly simple techniques
- ▶ Next time: **Probabilistic Reasoning with Bayesian Networks**