



# CS-323 Artificial Intelligence

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## Lecture 14

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# Probabilistic Reasoning

Chapter 13

(Continued - - -)

# Total Probability Theorem

$$P(B) = P(B|A_1)P(A_1) + P(B|A_2)P(A_2) + P(B|A_3)P(A_3)$$

The result is extendable to any number of events.

$$P(B) = \sum_k P(B|A_k)P(A_k)$$

# Joint Probability Distribution

- Captures probabilities of all possible combinations of a set of random variables.
- Also known as *probabilistic model*.
- E.g.  $\mathbf{P}(\textit{MyGradeInAI}, \textit{MyGradeInCA})$

<i>MyGradeInAI</i>	<i>MyGradeInCA</i>	$\mathbf{P}(\textit{MyGradeInAI}, \textit{MyGradeInCA})$
<i>a</i>	<i>a</i>	0.10
<i>a</i>	<i>b</i>	0.05
$\vdots$	$\vdots$	$\vdots$
<i>d</i>	<i>d</i>	0.00

# Example



	<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

<i>Toothache</i>	<i>Cavity</i>	<i>Catch</i>	<b>P(<i>Toothache</i>, <i>Cavity</i>, <i>Catch</i>)</b>
<i>yes</i>	<i>yes</i>	<i>yes</i>	<b>0.108</b>
<i>yes</i>	<i>yes</i>	<i>no</i>	<b>0.012</b>
<i>yes</i>	<i>no</i>	<i>yes</i>	<b>0.016</b>
<i>yes</i>	<i>no</i>	<i>no</i>	<b>0.064</b>
<i>no</i>	<i>yes</i>	<i>yes</i>	<b>0.072</b>
<i>no</i>	<i>yes</i>	<i>no</i>	<b>0.008</b>
<i>no</i>	<i>no</i>	<i>yes</i>	<b>0.144</b>
<i>no</i>	<i>no</i>	<i>no</i>	<b>0.576</b>

# Example

	<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

$$P(\text{toothache} \vee \text{catch}) = 0.108 + 0.012 + 0.016 + 0.064 + 0.072 + 0.144 = 0.416$$

$$P(\text{toothache} \wedge \text{cavity}) = 0.108 + 0.012 = 0.120$$

$$P(\text{toothache}) = 0.108 + 0.012 + 0.016 + 0.064 = 0.200$$

Marginal  
Probability

Marginalization

$$P(\mathbf{Y}) = \sum_{\mathbf{z} \in \mathbf{Z}} P(\mathbf{Y}, \mathbf{z})$$

Conditioning

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

# Example

	<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

$$P(\text{cavity} \mid \text{toothache}) = \frac{P(\text{cavity}, \text{toothache})}{P(\text{toothache})} = \frac{0.108 + 0.012}{0.200} = 0.60$$

$$P(\neg \text{cavity} \mid \text{toothache}) = \frac{P(\neg \text{cavity}, \text{toothache})}{P(\text{toothache})} = \frac{0.016 + 0.064}{0.200} = 0.40$$

$$\mathbf{P}(\text{Cavity} \mid \text{toothache}) = \langle 0.60, 0.40 \rangle$$

$$\mathbf{P}(\text{Cavity} \mid \text{toothache}) = \frac{1}{P(\text{toothache})} \langle 0.120, 0.080 \rangle = \langle 0.60, 0.40 \rangle$$

  
 $\alpha$ : Normalization Constant



# General Inference Procedure

- Let,
  - ❑  $X$ : query variable
  - ❑  $E$ : set of evidence variables
  - ❑  $e$ : observed values for  $E$
  - ❑  $Y$ : set of unobserved variables (also known as hidden variables)
  - ❑ query:  $\mathbf{P}(X \mid e)$

$$P(X|e) = \alpha P(X, e) = \alpha \sum_y P(X, e, y)$$

Table size for a full joint probability distribution of  $n$  variables each having  $k$  values?  $k^n$

# Reducing the Size of Domain Representation

- Let's add another random variable *Weather* to our dentistry example.
- Suppose *Weather*'s domain is {*sunny, rainy, fog, cloudy*}.

- **Size** of full joint probability distribution table?

$$\checkmark 2 * 2 * 2 * 4 = 32$$

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



# Reducing the Size of Domain Representation

