

II-Probabilities

Probabilistic Reasoning

Logik für Erklärbare KI: Technische Einführung in das ENEXA Projekt

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Example: Being at a dentist

We are reasoning about a factored system with three variables:

- ▶ **Toothache** $i \in [2]$, whether your tooth hurts
- ▶ **Cavity** $j \in [2]$, whether there is a cavity in your tooth
- ▶ **Catch** $k \in [2]$, whether the dentist catches in your tooth

	<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

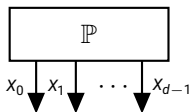
Definition (Probability Tensor)

Let there be a factored system \mathcal{F} defined by variables X_k taking values in $[m_k]$. A probability distribution over the states of \mathcal{F} is a map

$$\mathbb{P} : \bigtimes_{k \in [d]} [m_k] \rightarrow [0, \infty)$$

such that $\sum_{i_0, \dots, i_{d-1}} \mathbb{P}(i_0, \dots, i_{d-1}) = 1$.

We depict



We depict the condition, that coordinate sums are one, by directions on the legs.

Definition (Directed Tensor)

A tensor

$$T \in \bigotimes_{v \in \mathcal{V}} \mathbb{R}^{m_v}$$

is said to be directed with incoming variables \mathcal{V}^{in} and outgoing variables \mathcal{V}^{out} , where $\mathcal{V} = \mathcal{V}^{\text{in}} \dot{\cup} \mathcal{V}^{\text{out}}$, when

$$\mathcal{C}(\{T\}, \mathcal{V}^{\text{in}}) = \mathbb{I}^{\mathcal{V}^{\text{in}}}$$

where $\mathbb{I}^{\mathcal{V}^{\text{in}}}$ denoted the trivial tensor in $\bigotimes_{v \in \mathcal{V}^{\text{in}}} \mathbb{R}^{m_v}$ which coordinates are all 1.

Example: Marginal Distributions

What is the probability that there is a cavity?

$$\mathbb{P}^{\text{Dentist, Cavity}}[\text{Cavity}] = \sum_{j \in [2]} \sum_{k \in [2]} \mathbb{P}^{\text{Dentist}}(:, j, k) \quad (1)$$

This is called a **marginal** distribution.

Exercise

Calculate the marginal probability of **Cavity** given the probability tensor $\mathbb{P}^{\text{Dentist}}$.

	<i>toothache</i>		<i>¬toothache</i>	
	<i>catch</i>	<i>¬catch</i>	<i>catch</i>	<i>¬catch</i>
<i>cavity</i>	0.108	0.012	0.072	0.008
<i>¬cavity</i>	0.016	0.064	0.144	0.576

Definition (Marginal Probability)

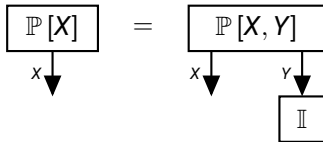
Given a distribution \mathbb{P} of the categorical variables X and Y the marginal distribution of the categorical variable X is defined for each i_X as

$$\mathbb{P}[X = i_X] = \sum_{i_Y \in [m_Y]} \mathbb{P}[X = i_X, Y = i_Y] .$$

Marginal probabilities are contractions

$$\mathbb{P}[X] = \mathcal{C}(\{\mathbb{P}\}, \{X\})$$

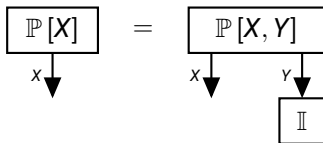
depicted by



Marginal Distributions in Contraction Formalism

Contractions are useful to

- Specify the Probability Tensor, or a decomposition of it
- Specify the variables to marginalize over as the ones left open



Directed notation preserved: Marginal probabilities are again probability distributions, since

$$\sum_{i \in [2]} \mathbb{P}^{\text{Dentist, Cavity}}[i] = \sum_{i \in [2]} \sum_{j \in [2]} \sum_{k \in [2]} \mathbb{P}_{i,j,k}^{\text{Dentist}} = 1. \quad (2)$$

Example: Conditional Distributions

What is the probability of having a cavity when having a toothache?

$$\mathbb{P}^{\text{Dentist}}[\text{Cavity}|\text{Toothache}] = \frac{\sum_{j \in [2]} \mathbb{P}^{\text{Dentist}}_{:,j,:}}{\sum_{j,k \in [2]} \mathbb{P}^{\text{Dentist}}_{:,j,k}} \quad (3)$$

This is called a **conditional** distribution.

Exercise

Calculate the probability of **Cavity** conditioned on **Toothache**.

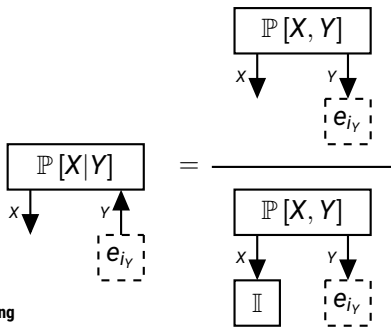
	<i>toothache</i>		<i>¬toothache</i>	
	<i>catch</i>	<i>¬catch</i>	<i>catch</i>	<i>¬catch</i>
<i>cavity</i>	0.108	0.012	0.072	0.008
<i>¬cavity</i>	0.016	0.064	0.144	0.576

Formal Definition of Conditional Distributions

Definition (Conditional Probability)

Given a distribution \mathbb{P} of the categorical variables X and Y , the conditioned distribution of X is defined by

$$\mathbb{P}[X = i_X | Y = i_Y] = \frac{\mathbb{P}[X = i_X, Y = i_Y]}{\mathbb{P}[Y = i_Y]}.$$



Definition (Normation of Tensor Networks)

A tensor network \mathcal{T} on variables \mathcal{V} can be normed on $\tilde{\mathcal{V}}$, if the coordinates of no slice with respect to $\tilde{\mathcal{V}}$ sum to 0. Then we define the normed tensor

$$\mathcal{N}(\mathcal{T}, \mathcal{V}^{\text{out}}, \mathcal{V}^{\text{in}}) \in \left(\bigotimes_{v \in \mathcal{V}^{\text{in}}} \mathbb{R}^{m_v} \right) \otimes \left(\bigotimes_{v \in \mathcal{V}^{\text{out}}} \mathbb{R}^{m_v} \right)$$

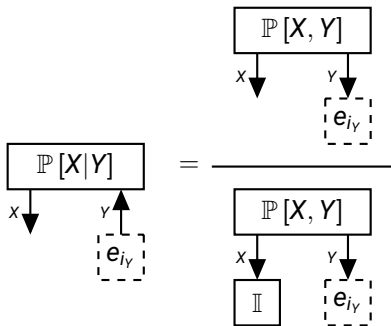
by

$$\mathcal{N}(\mathcal{T}, \mathcal{V}^{\text{out}}, \mathcal{V}^{\text{in}}) = \sum_{i_{\mathcal{V}^{\text{in}}} \in \prod_{v \in \mathcal{V}^{\text{in}}} m_v} \mathbf{e}_{i_{\mathcal{V}^{\text{in}}}} \otimes \frac{\mathcal{C}(\mathcal{T} \cup \{\mathbf{e}_{i_{\mathcal{V}^{\text{in}}}\}, \mathcal{V}^{\text{out}}\})}{\mathcal{C}(\mathcal{T} \cup \{\mathbf{e}_{i_{\mathcal{V}^{\text{in}}}\}, \emptyset\})}.$$

Conditioning is the normation

$$\mathbb{P}[X|Y] = \mathcal{N}(\{\mathbb{P}\}, \{X\}, \{Y\})$$

depicted by



The directed notation highlights **Conditions** by incoming legs and **Distributions** by outgoing legs.

The Bayes Theorem relates conditional probabilities:

Theorem (Bayes Theorem)

For any joint distribution of two categorical variables X and Y it holds that

$$\mathbb{P}[X|Y] = \frac{\mathbb{P}[X, Y]}{\mathbb{P}[Y]} = \frac{\mathbb{P}[Y|X] \mathbb{P}[X]}{\mathbb{P}[Y]}.$$

Directions of Reasoning

- ▶ **Causal direction:** Toothache is caused by cavity
- ▶ **Diagnostic direction:** Cavity is probable because of toothache

Bayes Theorem allows us to reason in diagnostic direction, given an underlying causal influence:

$$\begin{aligned} \mathbb{P}^{\text{Dentist}}[\text{Cavity}|\text{Toothache}] \\ = \mathbb{P}^{\text{Dentist}}[\text{Toothache}|\text{Cavity}] \frac{\mathbb{P}^{\text{Dentist}}[\text{Cavity}]}{\mathbb{P}^{\text{Dentist}}[\text{Toothache}]} \end{aligned}$$

Probabilistic queries can be answered by contractions

- Marginal probabilities

$$\mathbb{P}[X] = \mathcal{C}(\{\mathbb{P}\}, \{X\})$$

- Conditional probabilities

$$\mathbb{P}[X|Y] = \mathcal{N}(\{\mathbb{P}\}, \{X\}, \{Y\})$$

Outlook: **Tensor network decompositions of \mathbb{P}** increase the execution efficiency!