

Structure-based Categorisation of Bayesian Network Parameters

Janneke H. Bolt & Silja Renooij

Department of Information and Computing Sciences
Utrecht University, The Netherlands



Universiteit Utrecht

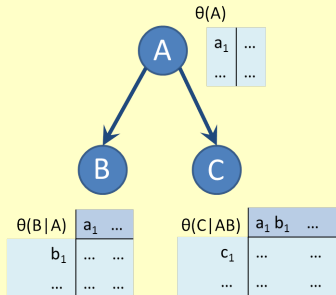
ECSQARU 2017, Lugano

Context I

Multi-parameter tuning in Bayesian networks

[Bolt & van der Gaag, ECSQARU 2015]

- ▷ change $\Pr(\mathbf{h}|\mathbf{e})$ by changing $\theta_1, \dots, \theta_n$ **simultaneously**
- ▷ most effective if parameters work in same direction



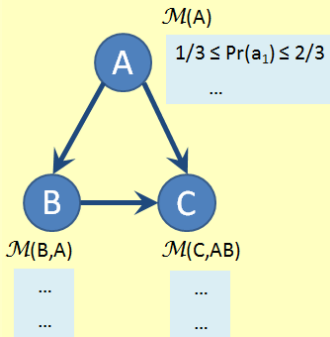
Exploitable knowledge: qualitative effect ('+', '-') on $\Pr(\mathbf{h}|\mathbf{e})$ of change in θ_i for any value $\theta_j \neq \theta_i$

Context II

Pre-processing for inference in credal networks

[Bolt, De Bock & Renooij, ECAI 2016]

- ▷ inference: compute $\overline{\Pr}(\mathbf{h}|\mathbf{e})$ and $\underline{\Pr}(\mathbf{h}|\mathbf{e})$
- ▷ simplify computation: replace credal set $\mathcal{M}(V, pa(V))$ with single $\theta(V|pa(V))$



Exploitable knowledge: qualitative effect ('+', '-') on $\Pr(\mathbf{h}|\mathbf{e})$ for choice of $\theta(v|pa(V))$

Relating parameters to output probabilities

This is exactly what **sensitivity functions** for Bayesian networks \mathcal{B} do:

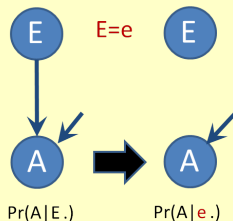
$$\Pr(\mathbf{h}|\mathbf{e}) = \frac{\Pr(\mathbf{h}, \mathbf{e})}{\Pr(\mathbf{e})} = \frac{\sum_{\mathbf{R}} \prod_V \theta(v|\boldsymbol{\pi})}{\sum_{\mathbf{H}, \mathbf{R}} \prod_V \theta(v|\boldsymbol{\pi})}$$

- fraction of multi-linear expressions in the parameters
- exact function $f_{\Pr(\mathbf{h}|\mathbf{e})}(\boldsymbol{\theta})$ **depends** on (fixed) values of other parameters
- whether $f(\boldsymbol{\theta})$ is **increasing** or **decreasing** may be **independent** of those other parameters

Which parameters are **not** used?

We consider parameters in the **query-dependent backbone** \mathcal{B}_q of \mathcal{B} :

- no d-separated nodes (V_i s.t. $\langle V_i, \mathbf{H} | \mathbf{E} \rangle_d$)
- no barren nodes
($V_i \in \mathbf{R}$ s.t. V_i is leaf or $de(V_i) \subseteq \text{barren}$)
- evidence absorption
($\implies \forall V_i : pa(V_i) \cap \mathbf{E} = \emptyset$)



Which parameters *are* used?

$$\Pr(\mathbf{h}, \mathbf{e}) = \sum_{\mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi}) \quad \Bigg| \quad \Pr(\mathbf{e}) = \sum_{\mathbf{H}, \mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi})$$

Computations include parameters $\theta(v | \boldsymbol{\pi})$ obeying

- in general: $v \sim \text{her}$ and $\boldsymbol{\pi} \sim \text{her}$

Which parameters *are* used?

$$\Pr(\mathbf{h}, \mathbf{e}) = \sum_{\mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi}) \quad \Bigg| \quad \Pr(\mathbf{e}) = \sum_{\mathbf{H}, \mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi})$$

Computations include parameters $\theta(v | \boldsymbol{\pi})$ obeying

- in general: $v \sim \text{her}$ and $\boldsymbol{\pi} \sim \text{her}$
- !note: **always** $\exists \mathbf{r}(\mathbf{h}^*) : v \sim \mathbf{r}(\mathbf{h}^*)$ and $\boldsymbol{\pi} \sim \mathbf{r}(\mathbf{h}^*)$

Which parameters *are* used?

$$\Pr(\mathbf{h}, \mathbf{e}) = \sum_{\mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi}) \quad \Bigg| \quad \Pr(\mathbf{e}) = \sum_{\mathbf{H}, \mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi})$$

Computations include parameters $\theta(v | \boldsymbol{\pi})$ obeying

- in general: $v \sim \mathbf{h} \mathbf{e} \mathbf{r}$ and $\boldsymbol{\pi} \sim \mathbf{h} \mathbf{e} \mathbf{r}$
- **!note: always** $\exists \mathbf{r}(\mathbf{h}^*) : v \sim \mathbf{r}(\mathbf{h}^*)$ and $\boldsymbol{\pi} \sim \mathbf{r}(\mathbf{h}^*)$
- more specifically:

$$\begin{array}{l|l} V \in \mathbf{E}: v \sim \mathbf{e} \text{ and } \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{E}: v \sim \mathbf{e} \\ V \in \mathbf{H}: v \sim \mathbf{h} \text{ and } \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{H}: \\ V \in \mathbf{R}: \quad \quad \quad \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{R}: \end{array}$$

Which parameters *are* used?

$$\Pr(\mathbf{h}, \mathbf{e}) = \sum_{\mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi}) \quad \left| \quad \Pr(\mathbf{e}) = \sum_{\mathbf{H}, \mathbf{R}} \prod_V \theta(v | \boldsymbol{\pi})$$

Computations include parameters $\theta(v | \boldsymbol{\pi})$ obeying

- in general: $v \sim \mathbf{h} \mathbf{e} \mathbf{r}$ and $\boldsymbol{\pi} \sim \mathbf{h} \mathbf{e} \mathbf{r}$
- **!note: always** $\exists \mathbf{r}(\mathbf{h}^*) : v \sim \mathbf{r}(\mathbf{h}^*)$ and $\boldsymbol{\pi} \sim \mathbf{r}(\mathbf{h}^*)$
- more specifically:

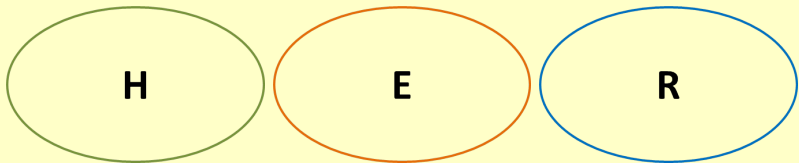
$$\begin{array}{l|l} V \in \mathbf{E}: v \sim \mathbf{e} \text{ and } \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{E}: v \sim \mathbf{e} \\ V \in \mathbf{H}: v \sim \mathbf{h} \text{ and } \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{H}: \\ V \in \mathbf{R}: \quad \quad \quad \boldsymbol{\pi} \sim \mathbf{h} & V \in \mathbf{R}: \end{array}$$

Roughly speaking:

more constraints \rightarrow more knowledge of $f_{\Pr(\mathbf{h}|\mathbf{e})}(\theta)$

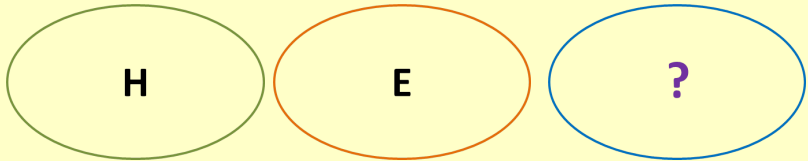
Qualitative effects of parameters

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and all variables V in \mathcal{B}_q :



Qualitative effects of parameters

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and all variables V in \mathcal{B}_q :

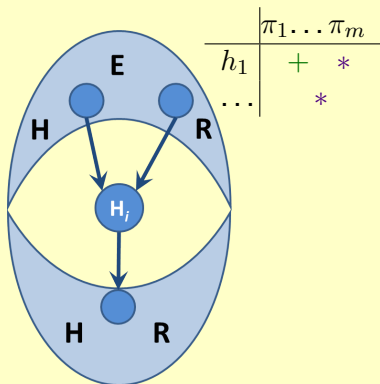


For parameters of $V \in \mathbb{R}$ the qualitative effect is *unknown*

(▷ i.e. cannot be established from merely structural properties)

Parameters of variables in \mathbf{H} (I)

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = H_i \in \mathbf{H}$



Assume $de(H_i) \cap \mathbf{E} = \emptyset$

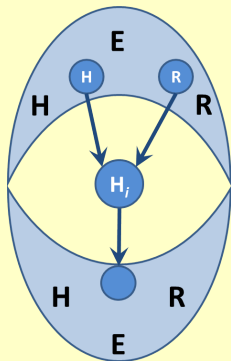
- H_i 's parameters are **not** used for computing $\Pr(\mathbf{e})$
- if $v \sim \mathbf{h}$ and $\boldsymbol{\pi} \sim \mathbf{h}$
→ **category** +¹
- otherwise, H_i 's parameters are **not** used for computing $\Pr(\mathbf{h}, \mathbf{e})$ either
→ **category** *

¹ Proof: sign of first derivative of sensitivity function under given constraints

Parameters of variables in \mathbf{H} (II)

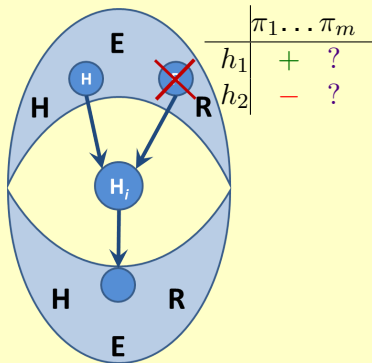
Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = H_i \in \mathbf{H}$

Assume H_i is binary-valued



Parameters of variables in \mathbf{H} (II)

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = H_i \in \mathbf{H}$



Assume H_i is binary-valued

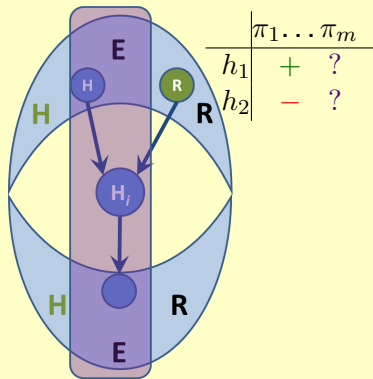
If $\boldsymbol{\pi} \sim \mathbf{h}$ then

- if $pa(H_i) \cap \mathbf{R} = \emptyset$ [ECAI 2016]
 - ▷ $v \sim \mathbf{h} \rightarrow$ category +
 - ▷ $v \approx \mathbf{h} \rightarrow$ category -

Otherwise: category ?

Parameters of variables in \mathbf{H} (II)

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = H_i \in \mathbf{H}$



Assume H_i is binary-valued

If $\boldsymbol{\pi} \sim \mathbf{h}$ then

- if $pa(H_i) \cap \mathbf{R}$ d-separated²
 - ▷ $v \sim \mathbf{h} \rightarrow$ category +
 - ▷ $v \not\sim \mathbf{h} \rightarrow$ category -

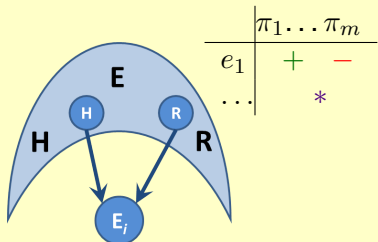
Otherwise: category ?

² $pa(H_i) \cap \mathbf{R}$ and $\mathbf{H} \setminus (\{H_i\} \cup pa(H_i))$ d-sep given $\mathbf{E} \cup ((\{H_i\} \cup pa(H_i)) \cap \mathbf{H})$

Parameters of variables in \mathbf{E}

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = E_i \in \mathbf{E}$

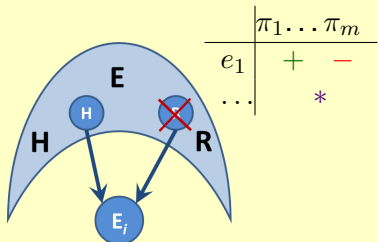
- If $v \approx \mathbf{e}$ then E_i 's parameters are **not** used for computing $\Pr(\mathbf{h}, \mathbf{e})$ or $\Pr(\mathbf{e}) \rightarrow$ **category** * [ECAI 2016]
- If $v \sim \mathbf{e}$ and $\boldsymbol{\pi} \approx \mathbf{h}$ then E_i 's parameters are **only** used for computing $\Pr(\mathbf{e}) \rightarrow$ **category** - [ECAI 2016]



Parameters of variables in \mathbf{E}

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = E_i \in \mathbf{E}$

- If $v \approx \mathbf{e}$ then E_i 's parameters are **not** used for computing $\Pr(\mathbf{h}, \mathbf{e})$ or $\Pr(\mathbf{e}) \rightarrow$ **category** *
- If $v \sim \mathbf{e}$ and $\boldsymbol{\pi} \approx \mathbf{h}$ then E_i 's parameters are **only** used for computing $\Pr(\mathbf{e}) \rightarrow$ **category** -



If $v \sim \mathbf{e}$ and $\boldsymbol{\pi} \sim \mathbf{h}$ then

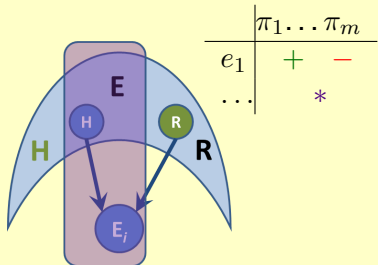
- if $pa(E_i) \cap \mathbf{R} = \emptyset$ [ECAI 2016]
 \rightarrow **category** +

Otherwise: **category** ?

Parameters of variables in \mathbf{E}

Consider $\Pr(\mathbf{h}|\mathbf{e})$ and $\theta(v|\boldsymbol{\pi})$ for $V = E_i \in \mathbf{E}$

- If $v \approx \mathbf{e}$ then E_i 's parameters are **not** used for computing $\Pr(\mathbf{h}, \mathbf{e})$ or $\Pr(\mathbf{e}) \rightarrow$ **category ***
- If $v \sim \mathbf{e}$ and $\boldsymbol{\pi} \approx \mathbf{h}$ then E_i 's parameters are **only** used for computing $\Pr(\mathbf{e}) \rightarrow$ **category -**



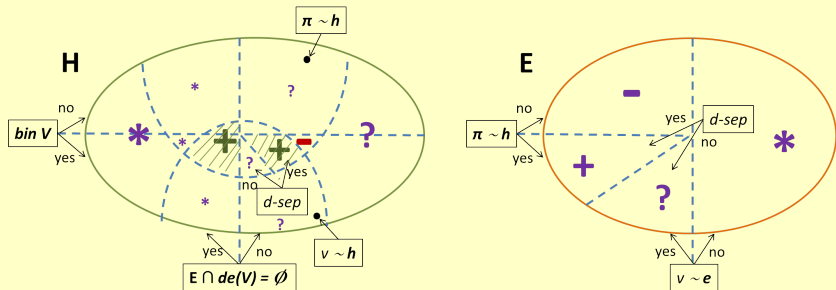
If $v \sim \mathbf{e}$ and $\boldsymbol{\pi} \sim \mathbf{h}$ then

- if $pa(E_i) \cap \mathbf{R}$ **d-separated**³
 \rightarrow **category +**

Otherwise: **category ?**

³ $pa(E_i) \cap \mathbf{R}$ and $\mathbf{H} \setminus pa(H_i)$ d-sep given $\mathbf{E} \cup (pa(H_i) \cap \mathbf{H})$

Summary and conclusions



Recall: qualitative effect on $\Pr(h|e)$ for choice of $\theta(v|pa(V))$ is **exploitable knowledge**

- all network parameters are now categorised
- more parameters have a meaningful category ($\neq ?$)
- category ? leaves some room for further study