Credal Networks under Epistemic Irrelevance: Theory and Algorithms

Jasper De Bock

13 May 2015, Ghent, Belgium

For the second part of the proof, we start by considering the following collection of gambles on $\mathscr{X}_K$:

$$\mathscr{A}^*_{K\rfloor x_{P(K)}} := \Big\{ \mathbb{I}_{\{z_{PN(s)\cap K_1}\}} f_{s,z_{PN(s)}} : s \in K,\ z_{PN(s)} \in \mathscr{X}_{PN(s)}, \\ z_{P(s)\setminus P_K(s)} = x_{P(s)\setminus P_K(s)},\ P(s) \cap K \subseteq K_1 \subseteq K, \\ f_{s,z_{PN(s)}} \neq 0 \Big\},$$

which is a finite subset of $\mathscr{D}^{\mathrm{irr}}_{K\rfloor x_{P(K)}} := \operatorname{posi}(\mathscr{A}^{\mathrm{irr}}_{K\rfloor x_{P(K)}})$. To see why, first notice that because $PN_K(s) = PN(s) \cap K$ due to Lemma 79(iii)$_{184}$, $\mathbb{I}_{\{z_{PN(s)\cap K_1}\}}$ is clearly the (finite) sum of all indicators $\mathbb{I}_{\{y_{PN_K(s)}\}}$ such that $y_{PN_K(s)} \in \mathscr{X}_{PN_K(s)}$ and $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$. By definition of the posi operator, we are now left to show that for any $y_{PN_K(s)} \in \mathscr{X}_{PN_K(s)}$ such that $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$, we have $\mathbb{I}_{\{y_{PN_K(s)}\}} f_{s,z_{PN(s)}} \in \mathscr{A}^{\mathrm{irr}}_{K\rfloor x_{P(K)}}$. By construction of $\mathscr{A}^*_{K\rfloor x_{P(K)}}$, we know that $z_{P(s)\setminus P_K(s)} = x_{P(s)\setminus P_K(s)}$, and it therefore suffices to show that $y_{P_K(s)} = z_{P_K(s)}$. To see why this last equality holds, first notice that $P_K(s) = P(s) \cap K$ due to Lemma 76$_{181}$. Also, $P(s) \cap K \subseteq PN(s) \cap K_1$ because $P(s) \cap K \subseteq K_1$ by construction of $\mathscr{A}^*_{K\rfloor x_{P(K)}}$ and $P(s) \cap K \subseteq PN(s)$ by definition of $PN(s)$. Therefore, we find that $P_K(s) \subseteq PN(s) \cap K_1$, implying that $y_{P_K(s)} = z_{P_K(s)}$ is a direct consequence of $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$.

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Bayesian

~~Credal~~ $\boxed{\text{Networks}}$ under Epistemic Irrelevance: Theory and Algorithms

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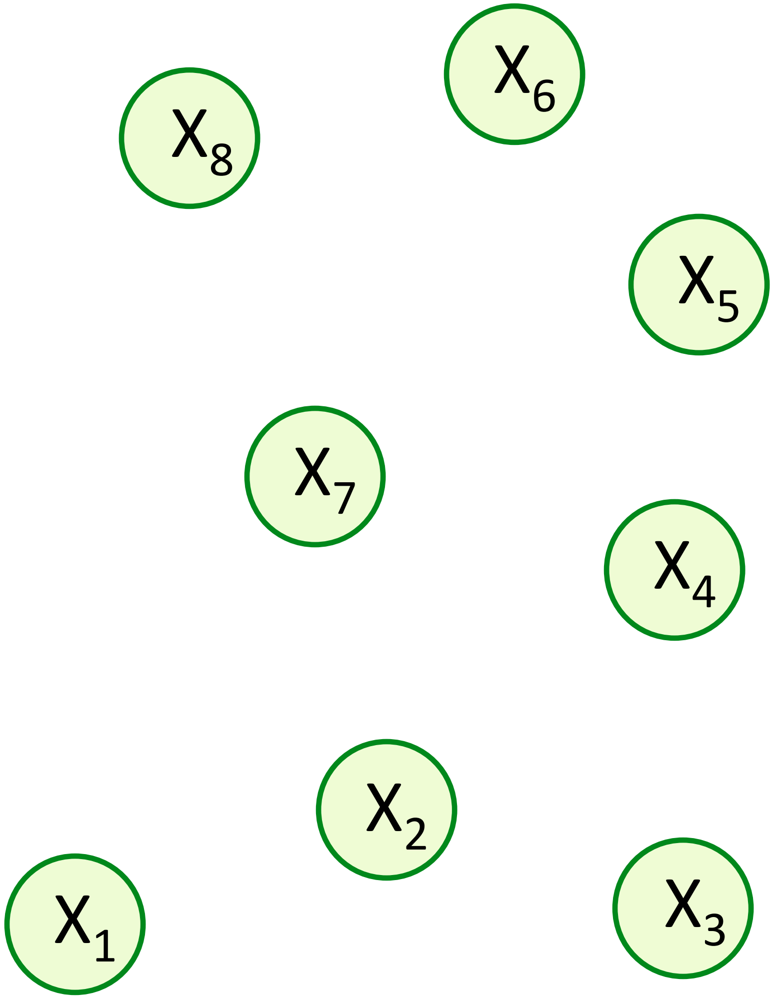
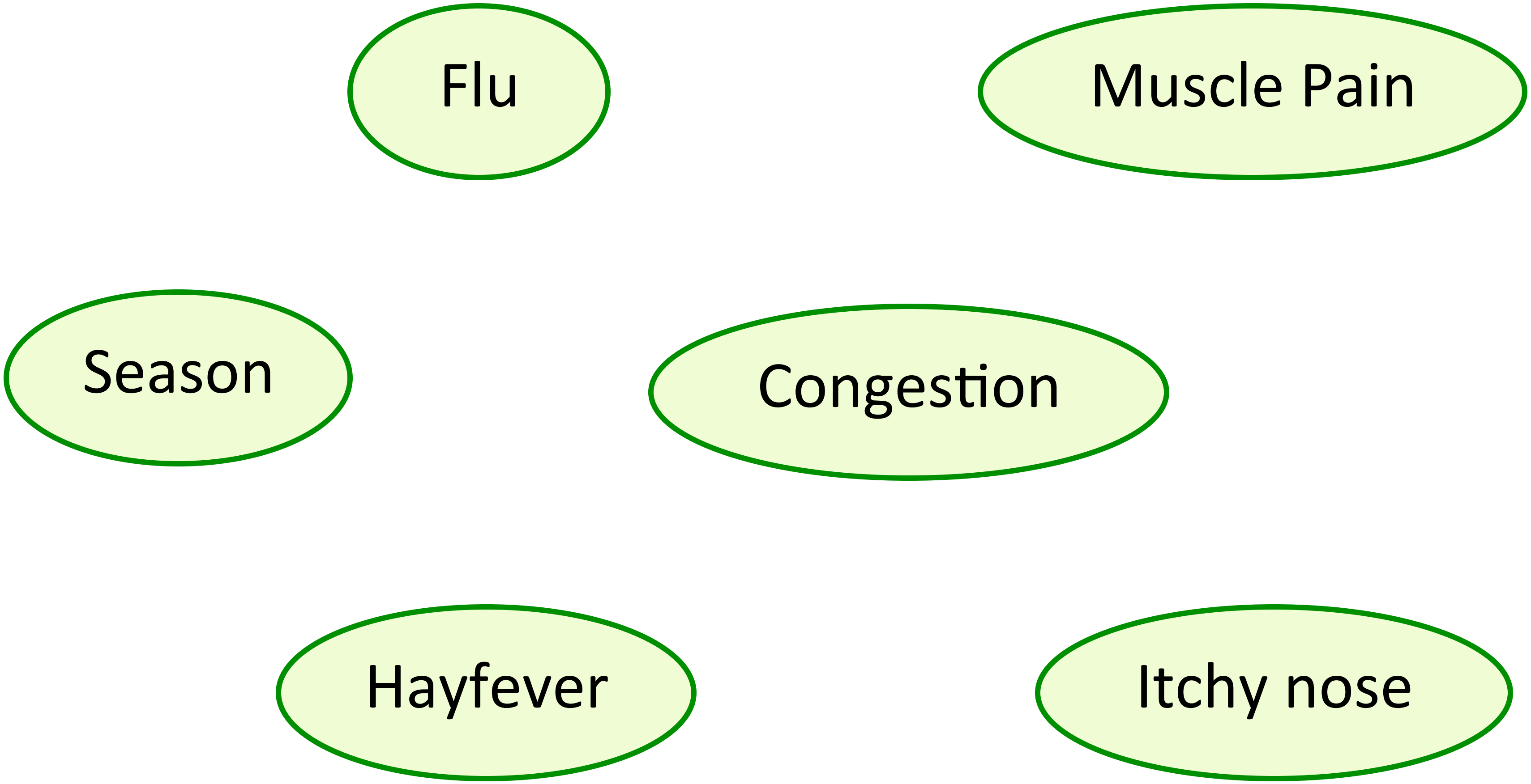
Bayesian networks: variables

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$

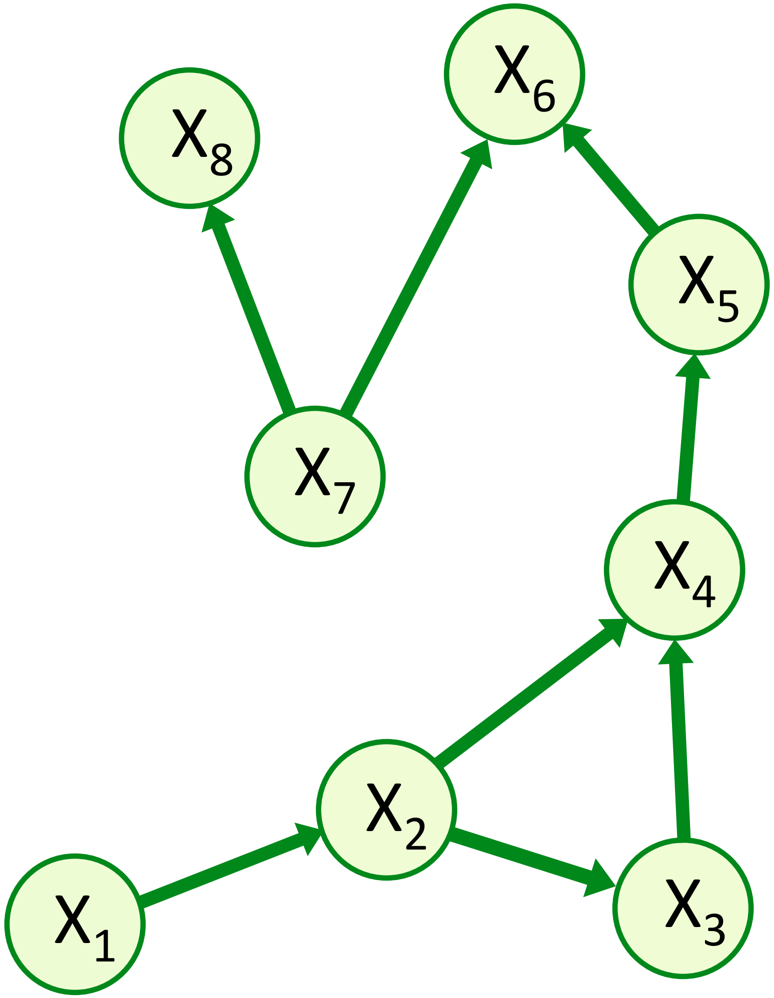


Bayesian networks: variables

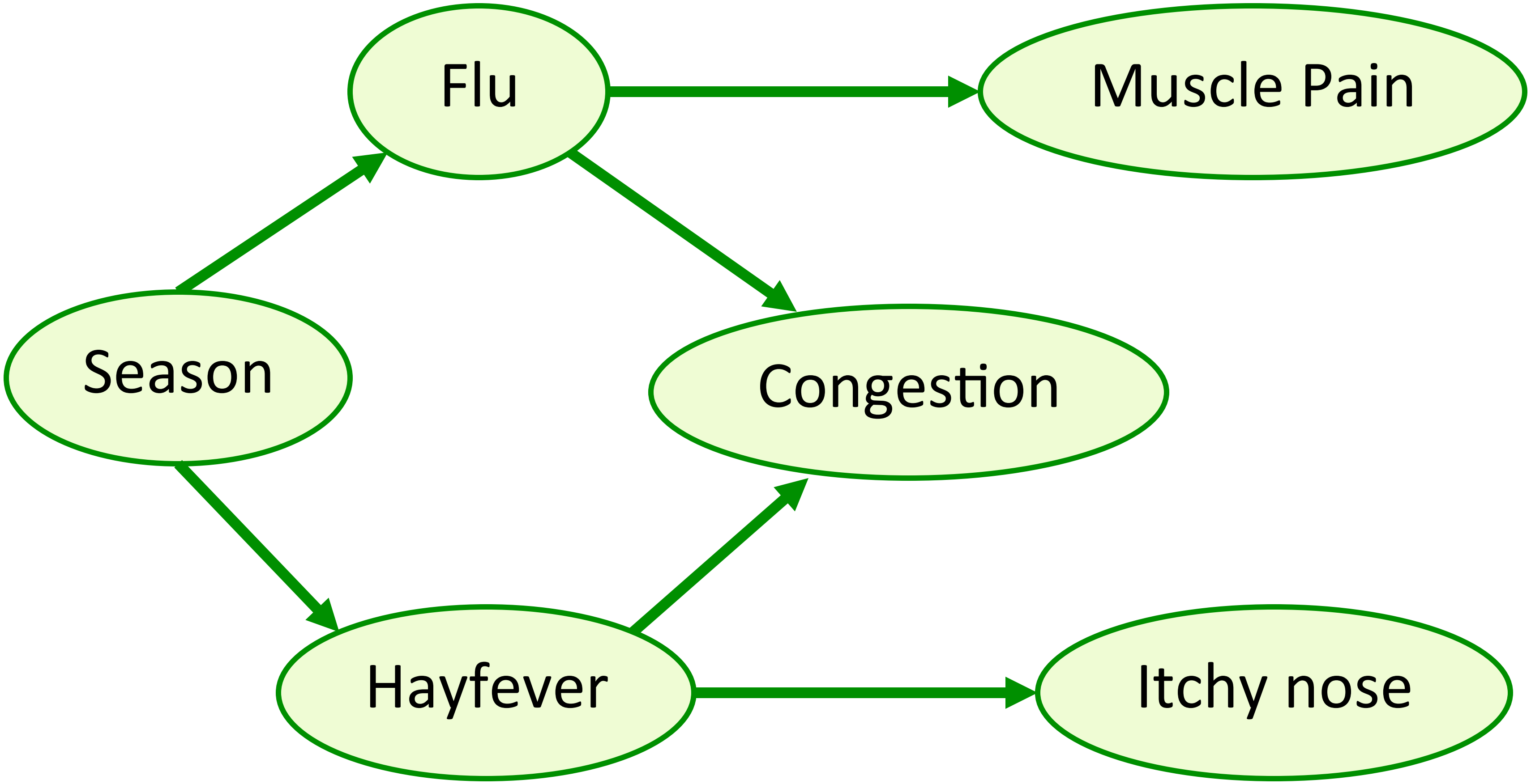


Bayesian networks: graphical structure

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG



Bayesian networks: graphical structure

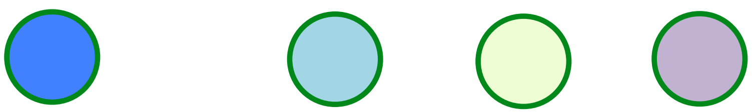


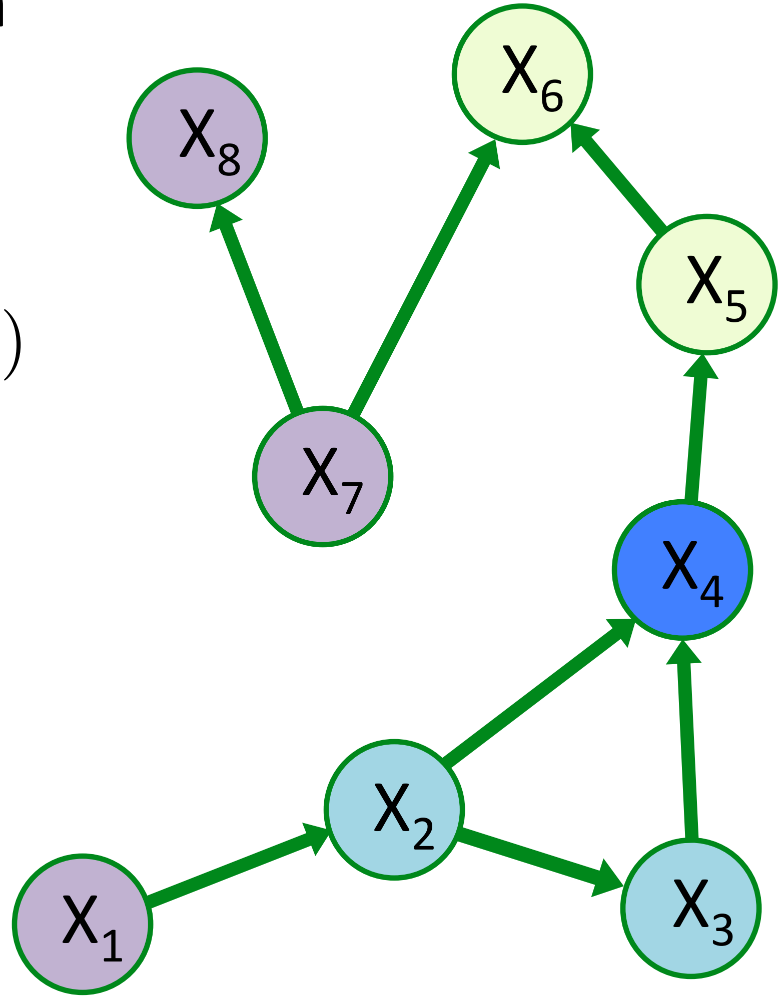
Bayesian networks: graphical structure

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$

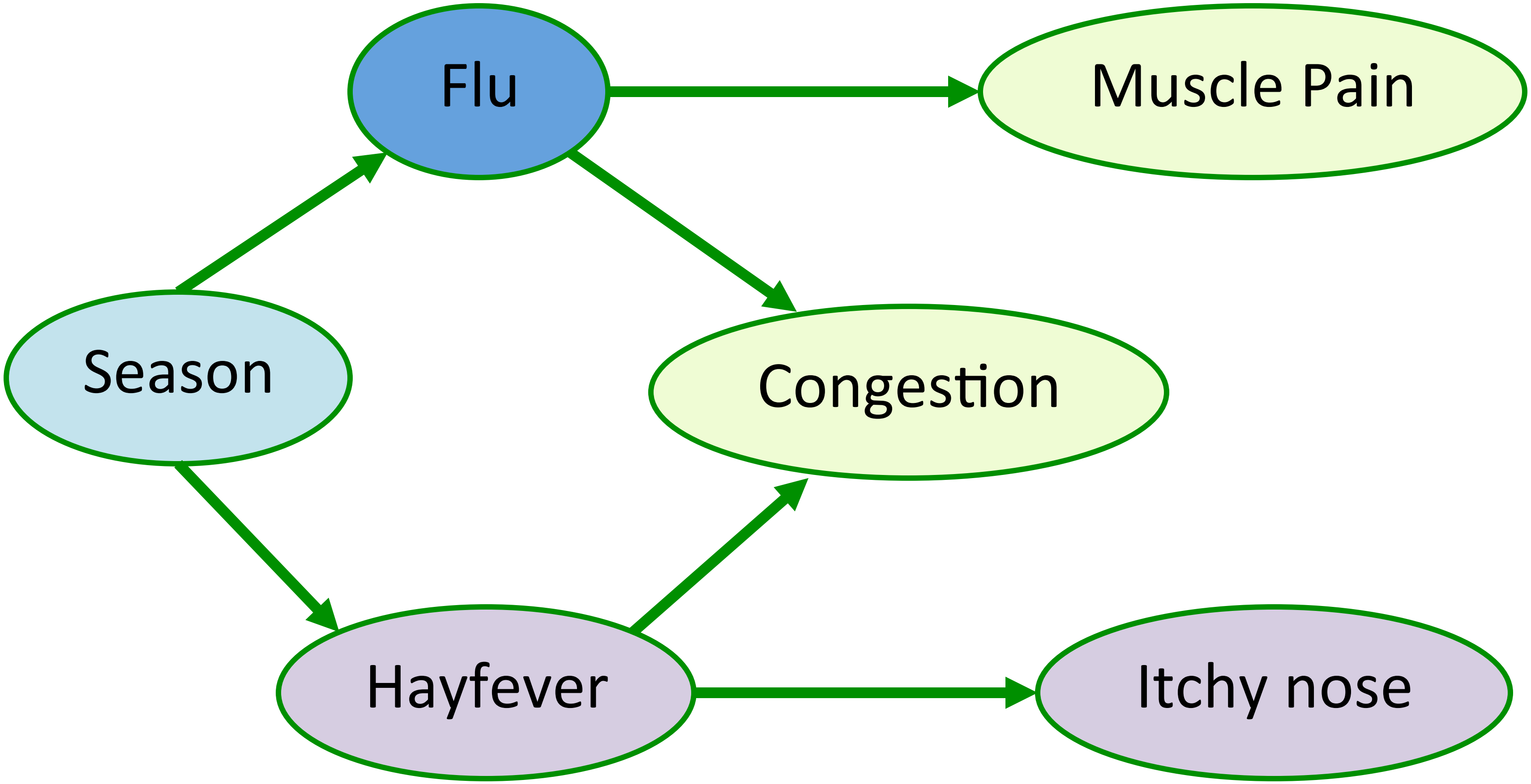
- Graphical structure: DAG

$\Rightarrow \forall s \in G: \; P(s), D(s), N(s)$

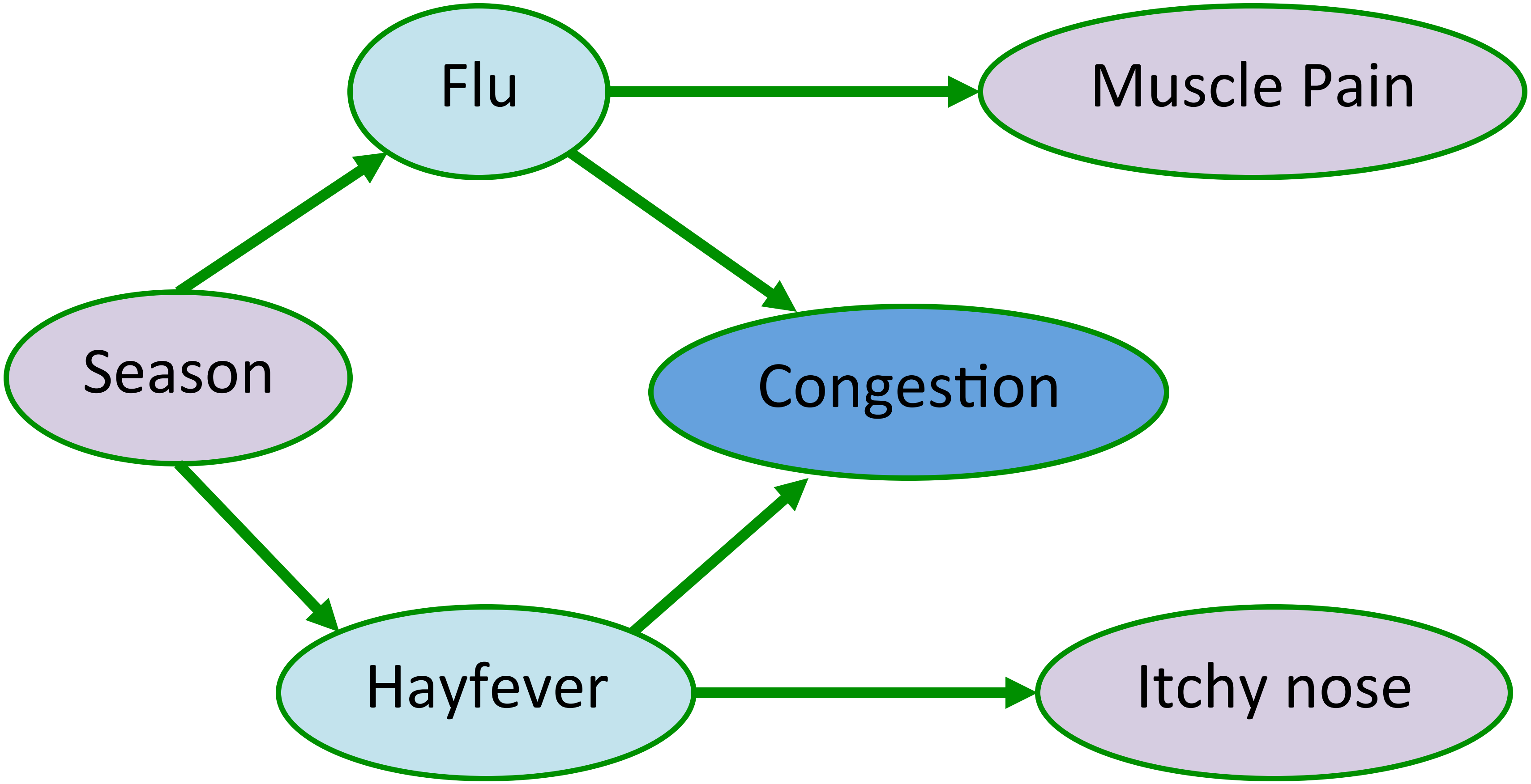




Bayesian networks: graphical structure

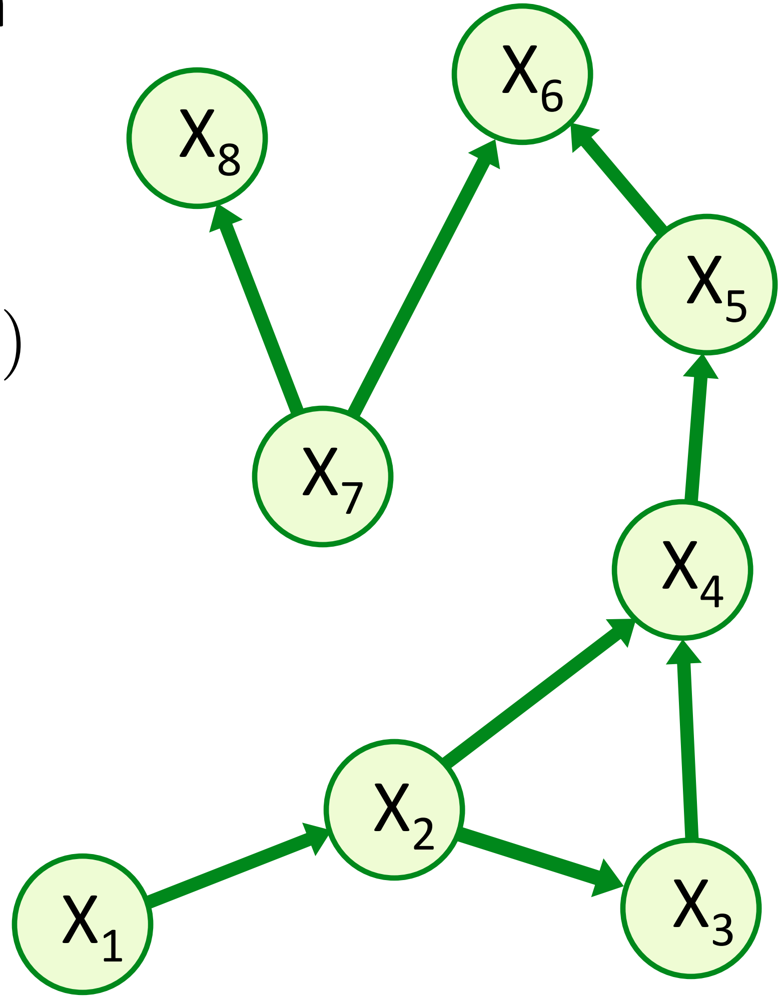


Bayesian networks: graphical structure



Bayesian networks: local models

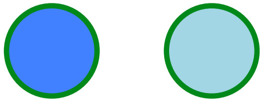
- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G: P(s), D(s), N(s)$
- Local uncertainty models

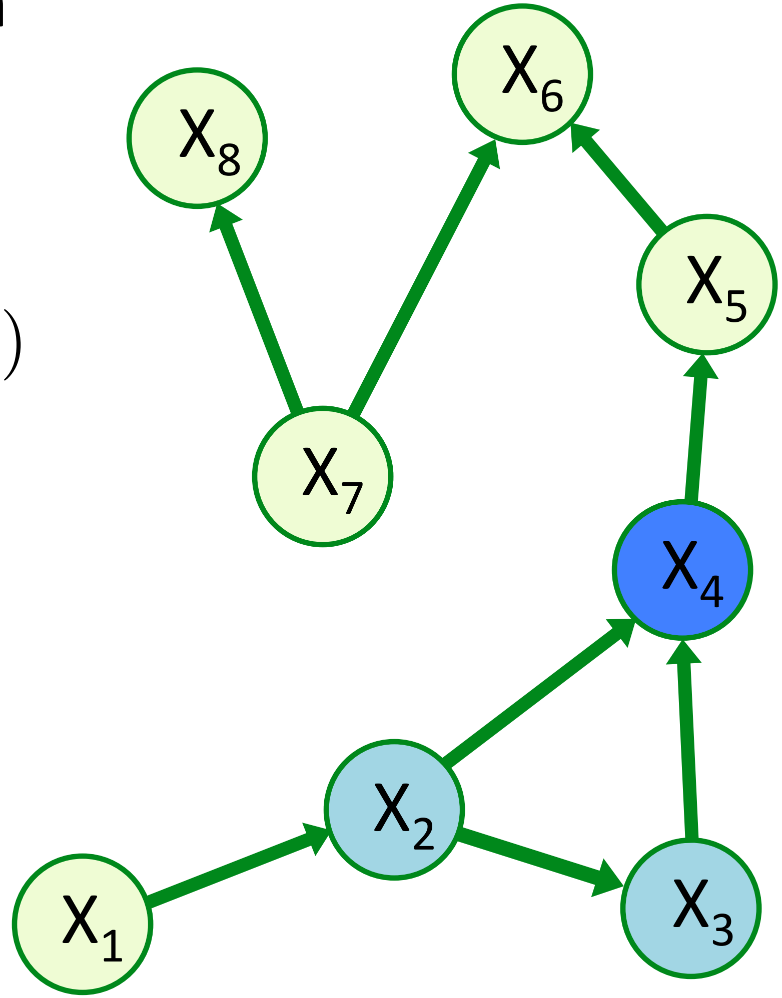


Bayesian networks: local models

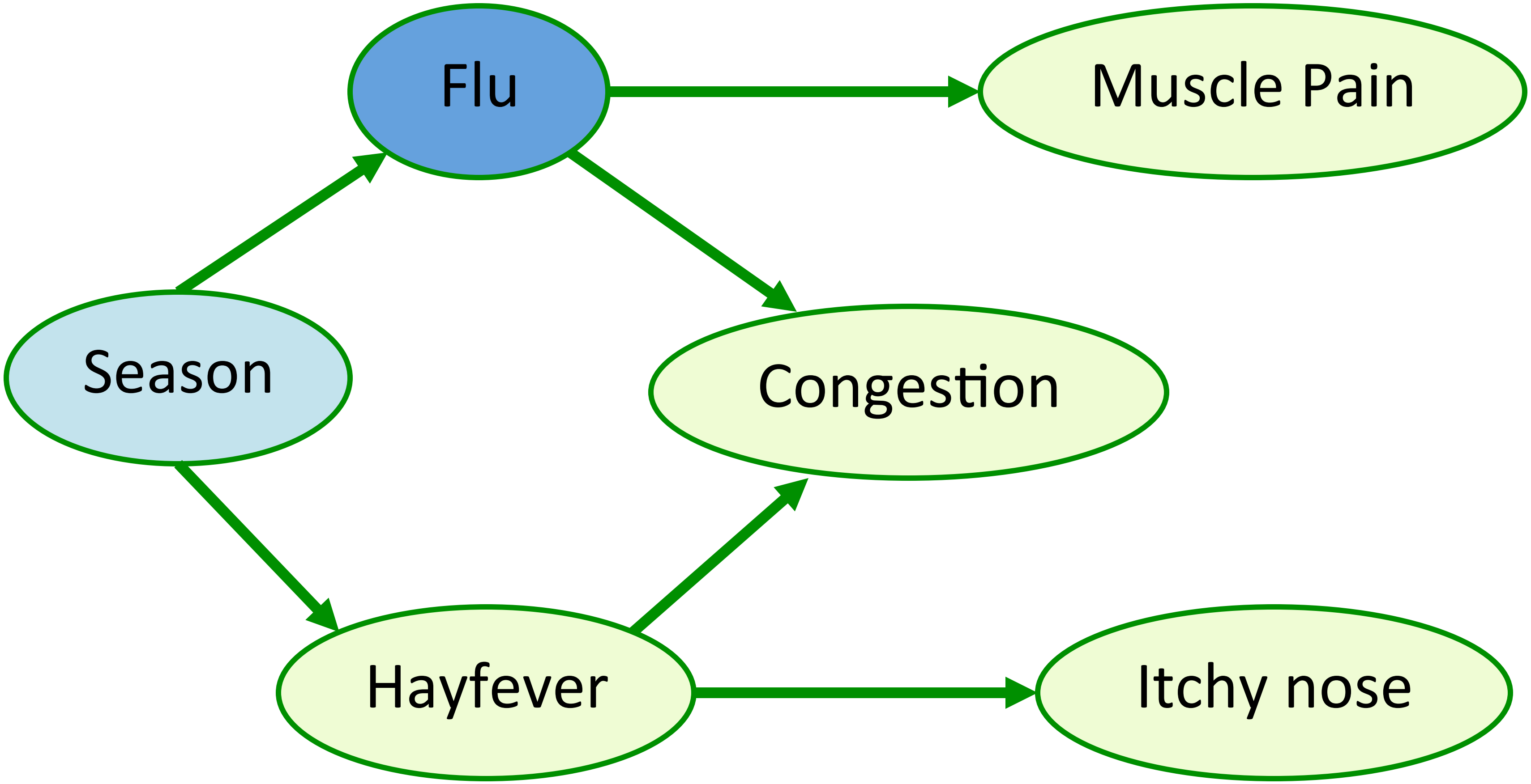
- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon\ P(s), D(s), N(s)$
- Local uncertainty models: mass functions $p_{s\rfloor x_{P(s)}}$

Example: $p_{4\rfloor x_{\{2,3\}}}$

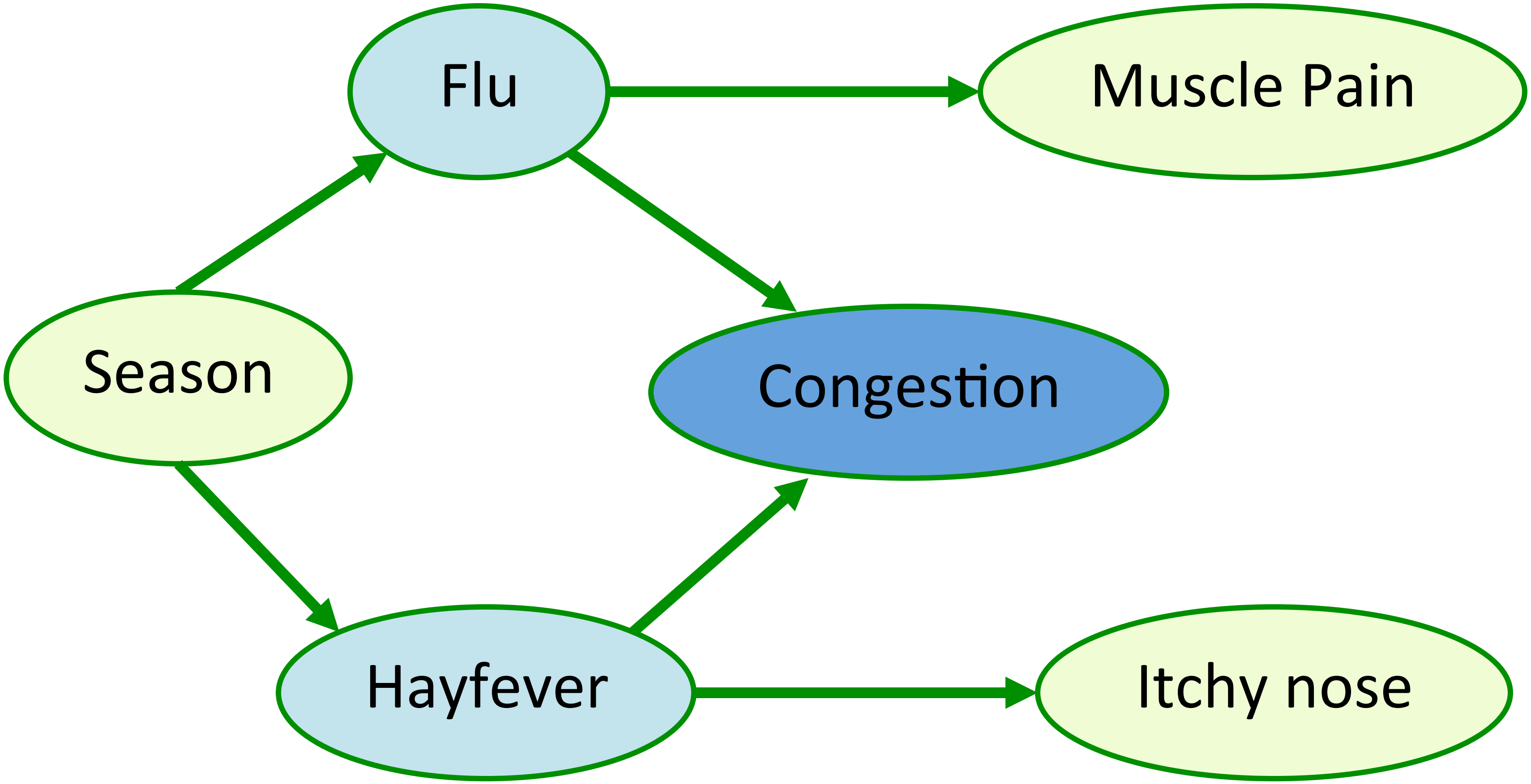




Bayesian networks: local models

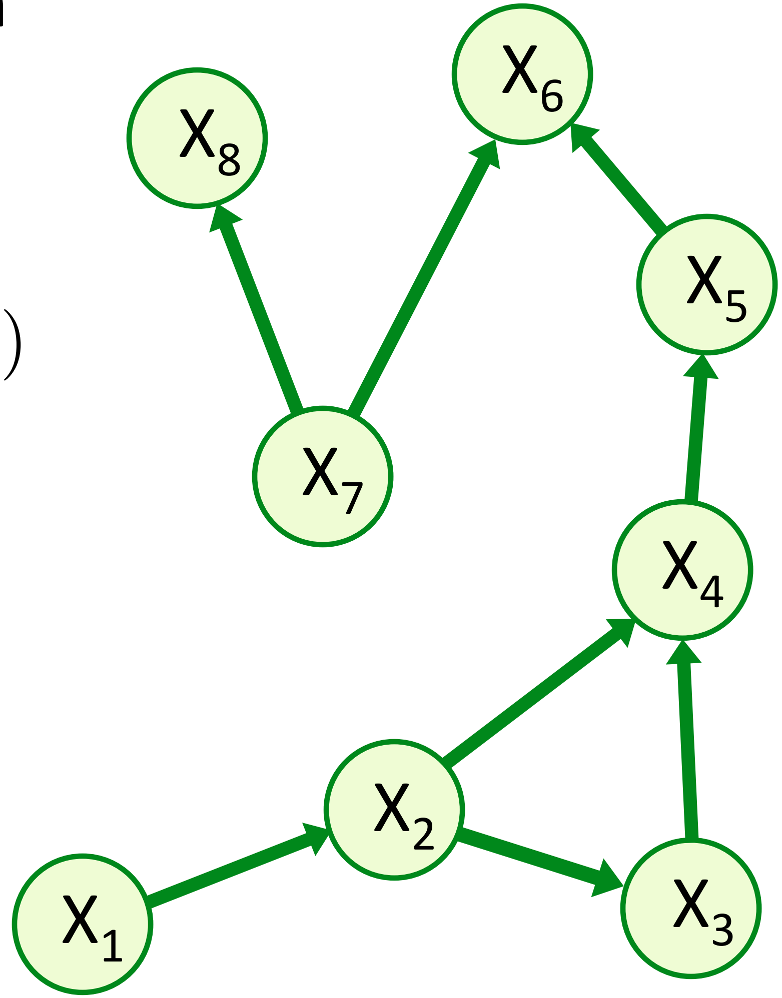


Bayesian networks: local models



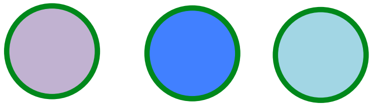
Bayesian networks: independence

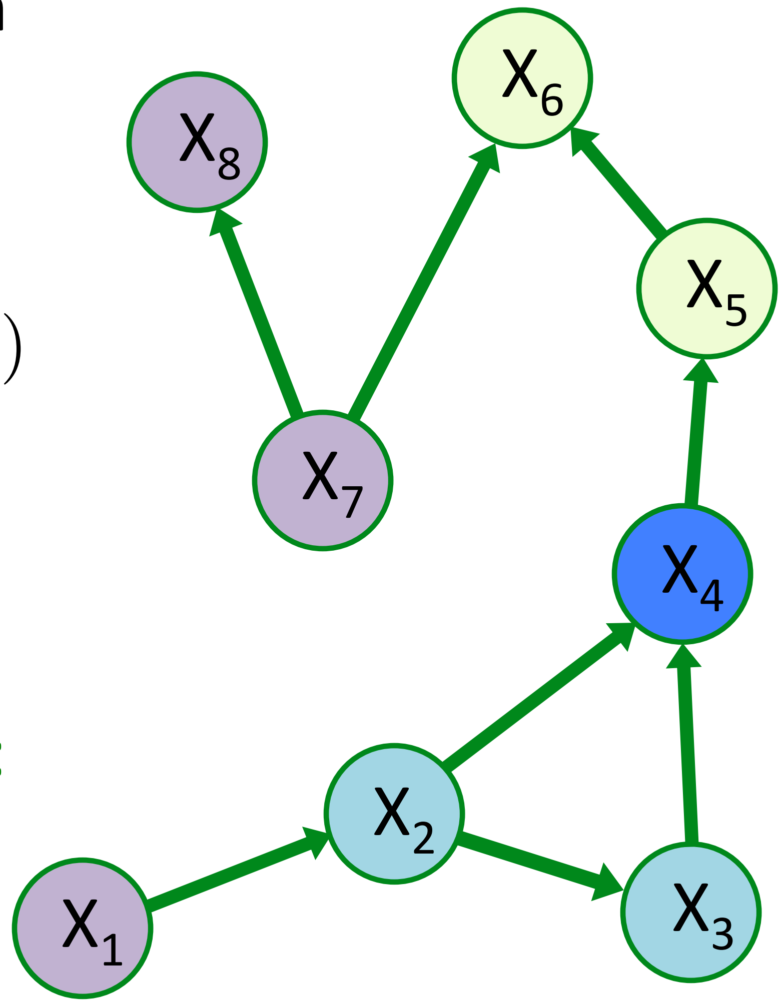
- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon P(s), D(s), N(s)$
- Local uncertainty models: mass functions $p_{s \rfloor x_{P(s)}}$
- Independence assumptions



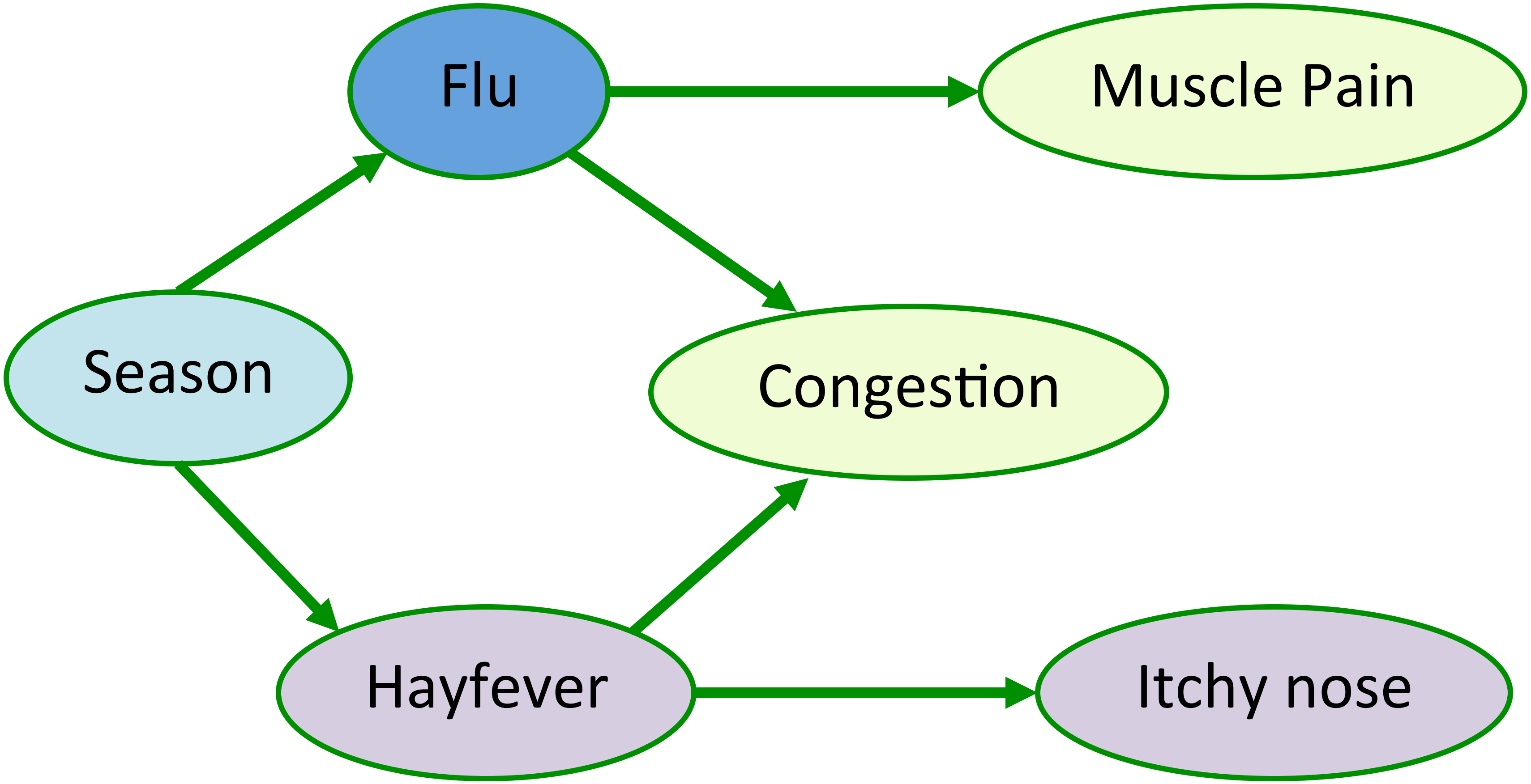
Bayesian networks: independence

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon P(s), D(s), N(s)$
- Local uncertainty models: mass functions $p_{s\rfloor x_{P(s)}}$
- Independence assumptions:
  $\forall s \in G\colon I(N(s), s\,|\,P(s))$

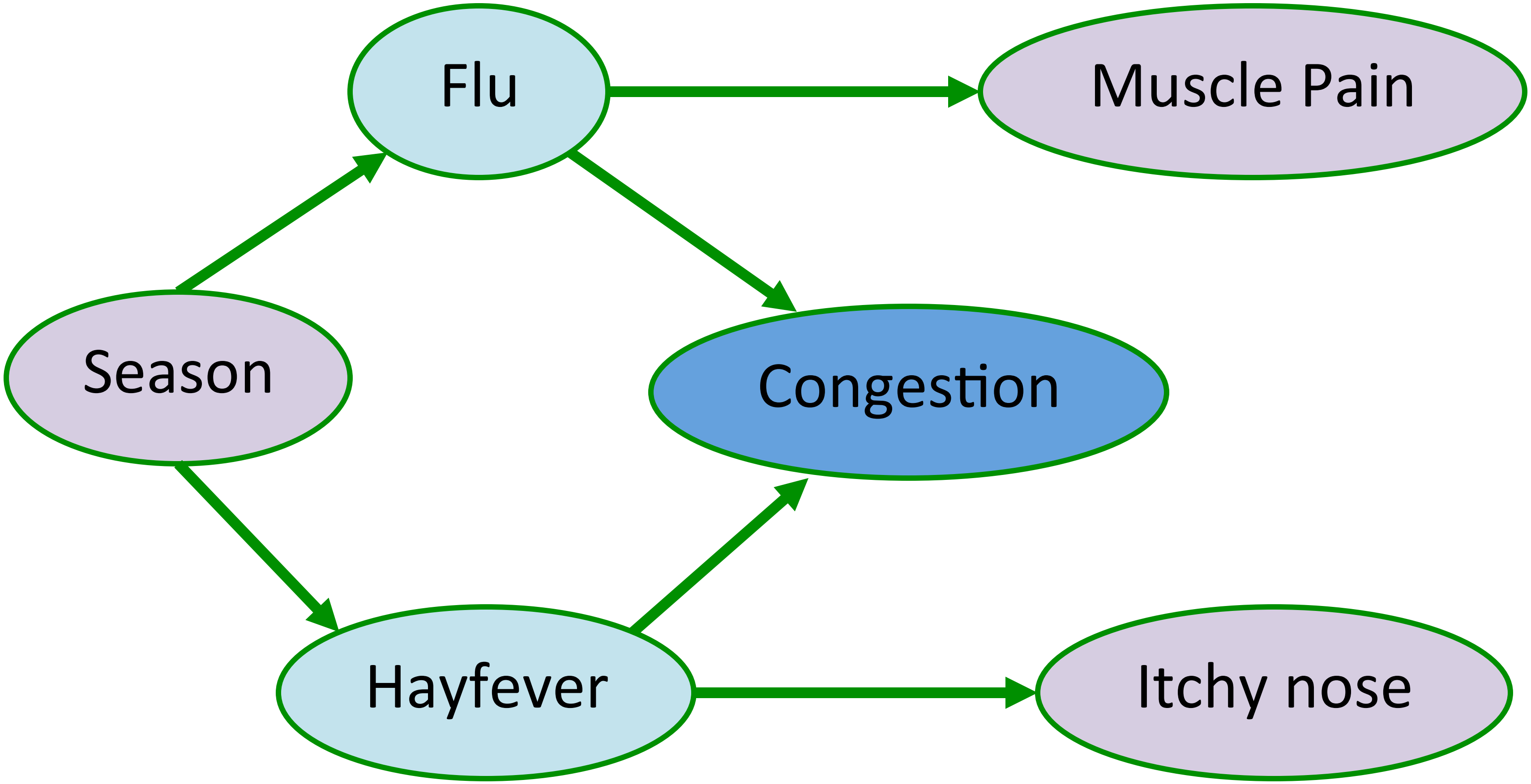




Bayesian networks: independence

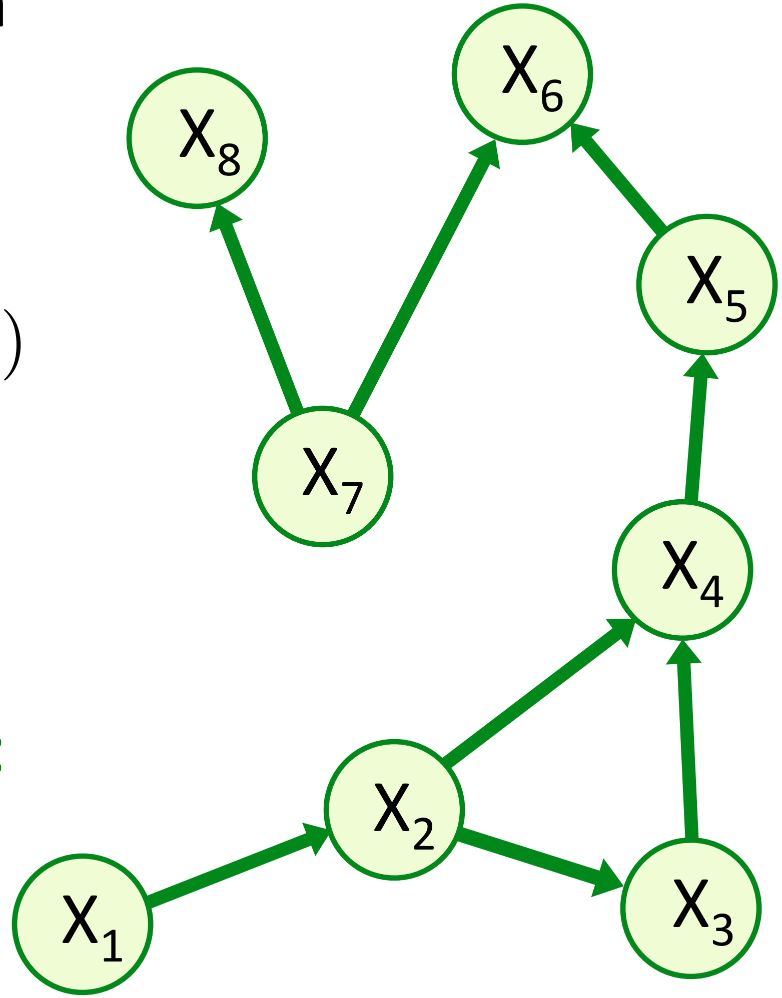


Bayesian networks: independence



Bayesian networks: basic setup

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon P(s), D(s), N(s)$
- Local uncertainty models: mass functions $p_{s \rfloor x_{P(s)}}$
- Independence assumptions:
  $\forall s \in G\colon I(N(s), s \,|\, P(s))$



Bayesian networks: the global model

$$p(x_s | x_{P(s)}, x_{N(s)}) = p(x_s | x_{P(s)})$$

Independence assumptions:

$$\forall s \in G: I(N(s), s \,|\, P(s))$$

Bayesian networks: the global model

$$p(x_s \rfloor x_{P(s)}, x_{N(s)}) = \boxed{p(x_s \rfloor x_{P(s)}) = p_{s\rfloor x_{P(s)}}(x_s)}$$

Local uncertainty models:
mass functions $p_{s\rfloor x_{P(s)}}$

Independence assumptions:
$\forall s \in G \colon I(N(s), s \,|\, P(s))$

Bayesian networks: the global model

$$\boxed{p(x_s \rfloor x_{P(s)}, x_{N(s)}) = p(x_s \rfloor x_{P(s)}) = p_{s \rfloor x_{P(s)}}(x_s)}$$

Local uncertainty models:
mass functions $p_{s \rfloor x_{P(s)}}$

Independence assumptions:
$\forall s \in G\colon I(N(s), s \,|P(s))$

Bayesian networks: the global model

$$p(x_s \rfloor x_{P(s)}, x_{N(s)}) = p(x_s \rfloor x_{P(s)}) = p_{s \rfloor x_{P(s)}}(x_s)$$

$$p(x_G) = \prod_{s \in G} p_{s \rfloor x_{P(s)}}(x_s)$$

Bayesian networks: the global model

$$p(x_G) = \prod_{s \in G} p_{s \rfloor x_{P(s)}}(x_s)$$

Bayesian networks: inference

$$p(x_S) = \sum_{x_{G\setminus S}} p(x_S, x_{G\setminus S})$$

$$p(x_G) = \prod_{s\in G} p_{s\rfloor x_{P(s)}}(x_s)$$

Bayesian networks: inference

$$p(x_S) = \sum_{x_{G \setminus S}} p(x_S, x_{G \setminus S})$$

$$p(x_Q \rfloor x_E) = \frac{p(x_{Q \cup E})}{p(x_E)}$$

$$p(x_G) = \prod_{s \in G} p_{s \rfloor x_{P(s)}}(x_s)$$

Bayesian networks: inference

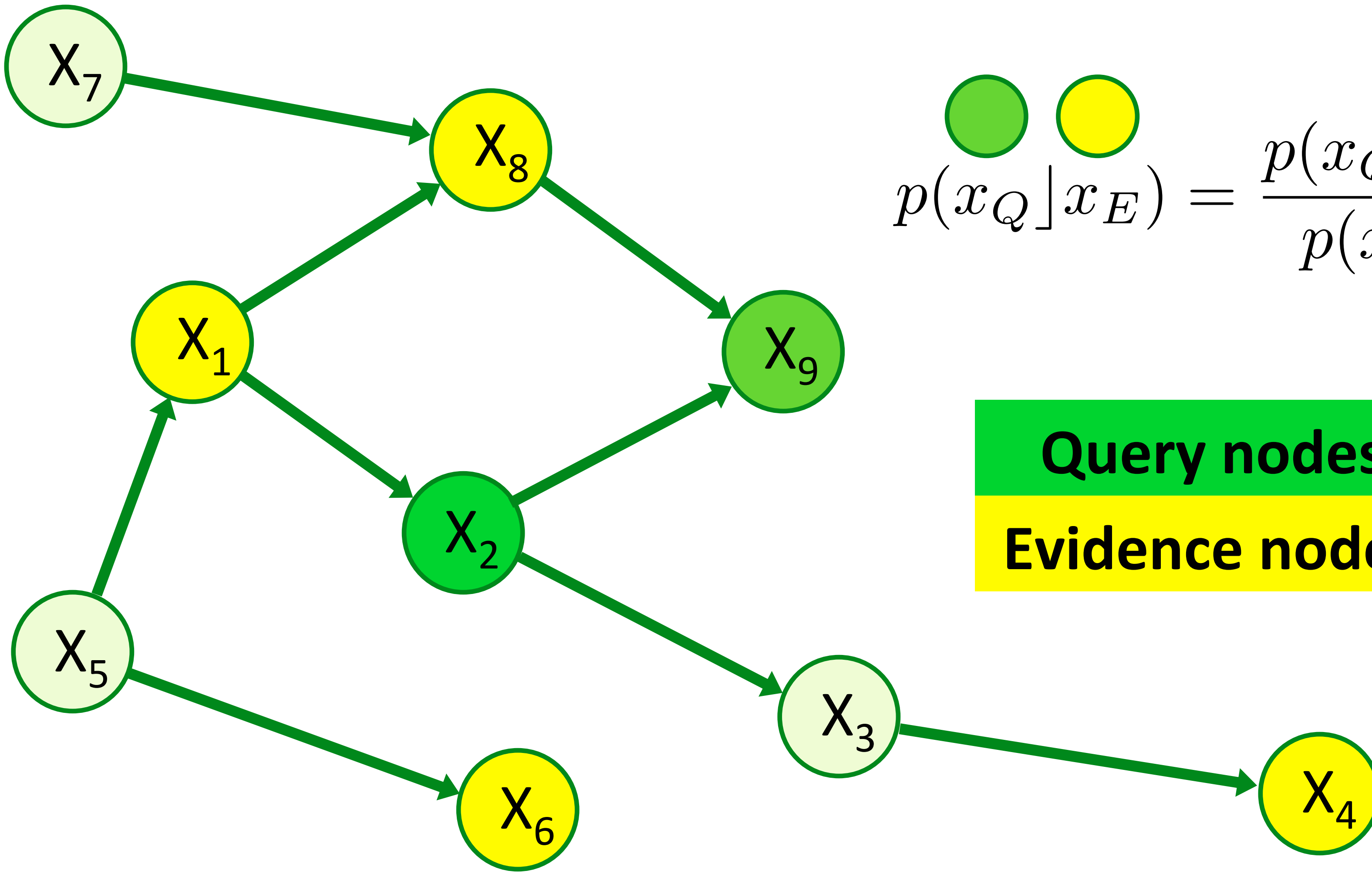
$$p(x_S) = \sum_{x_{G \setminus S}} p(x_S, x_{G \setminus S})$$

$$p(x_Q | x_E) = \frac{p(x_{Q \cup E})}{p(x_E)}$$

Decision making

$$p(x_G) = \prod_{s \in G} p_{s | x_{P(s)}}(x_s)$$

Bayesian networks: **inference**

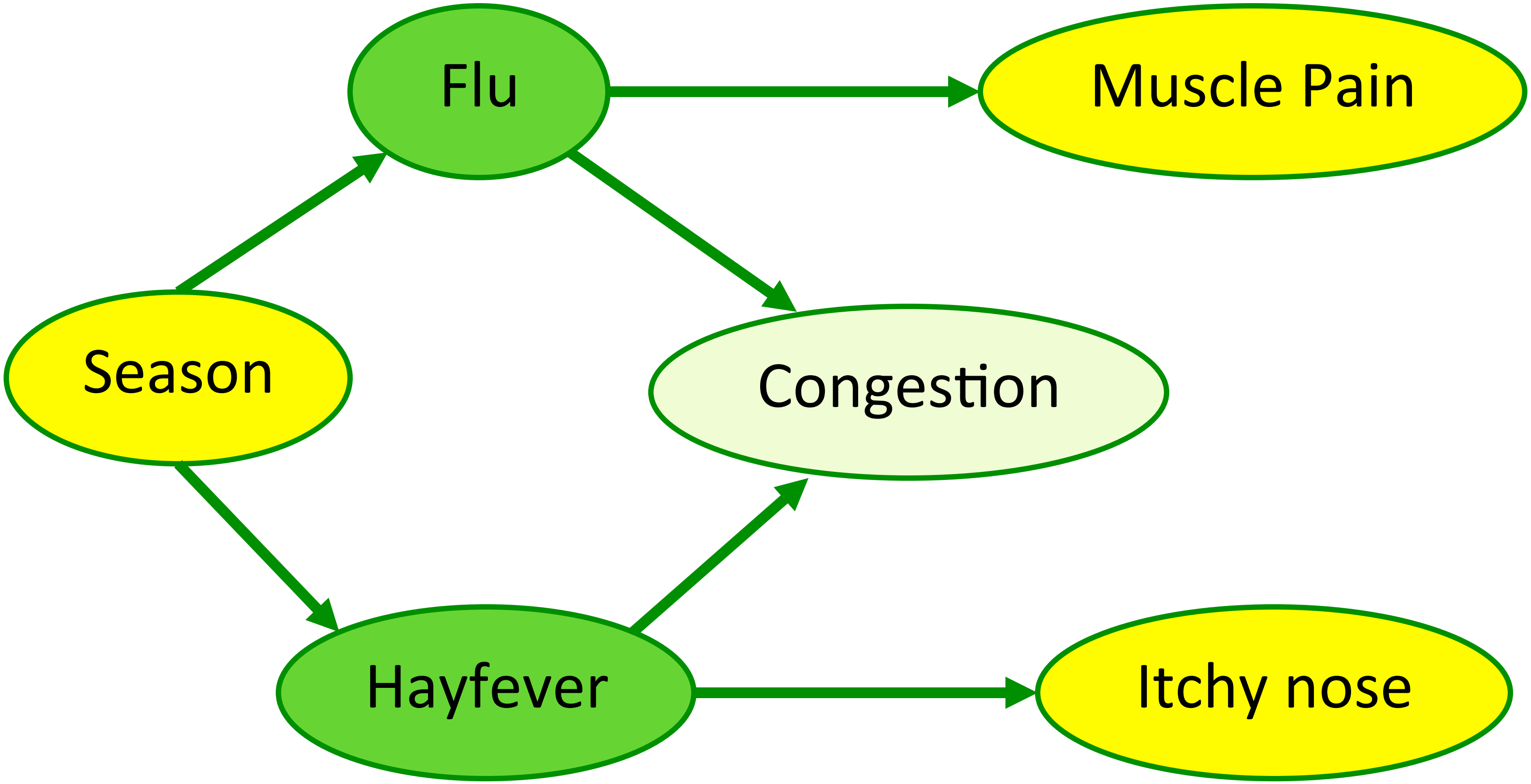


$$p(x_Q \mid x_E) = \frac{p(x_{Q \cup E})}{p(x_E)}$$

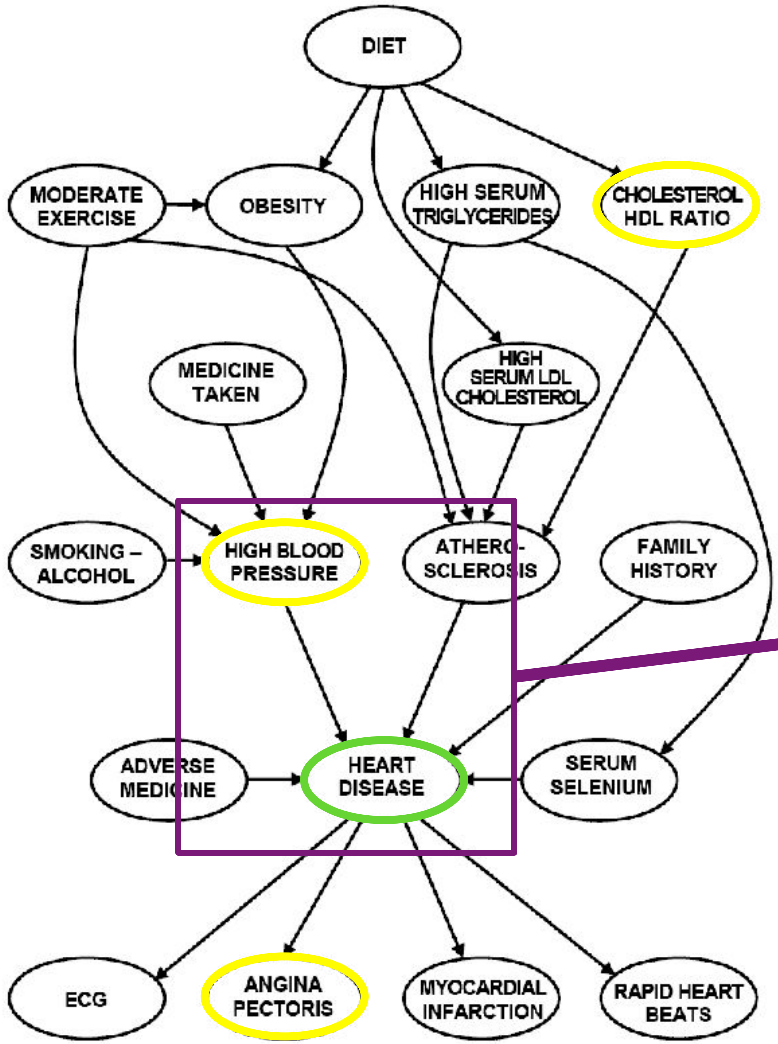
Query nodes

Evidence nodes

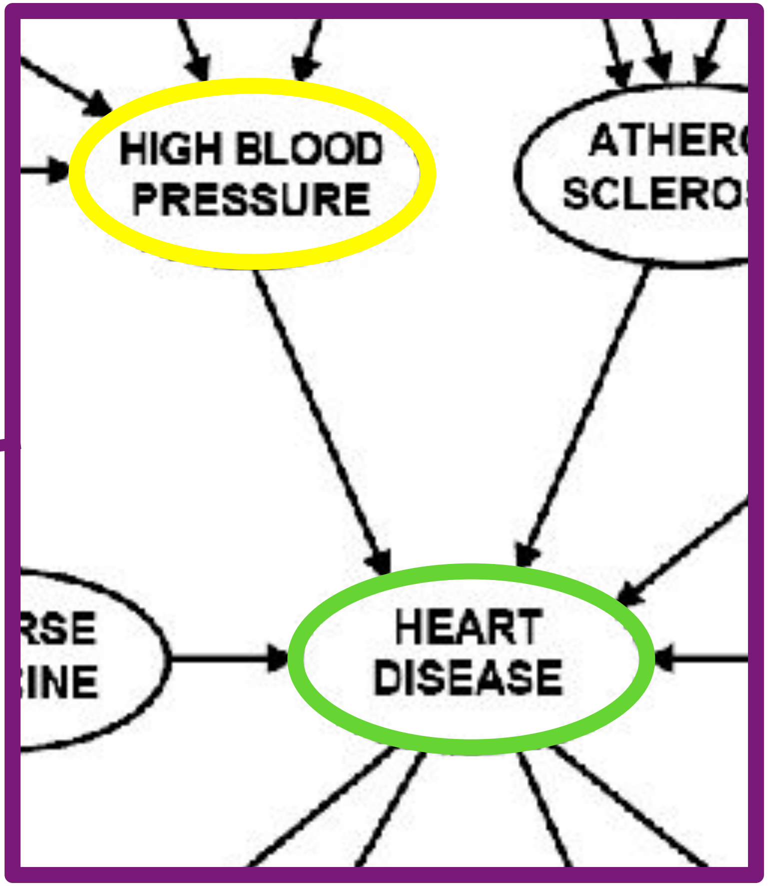
Bayesian networks: inference



Bayesian networks: examples

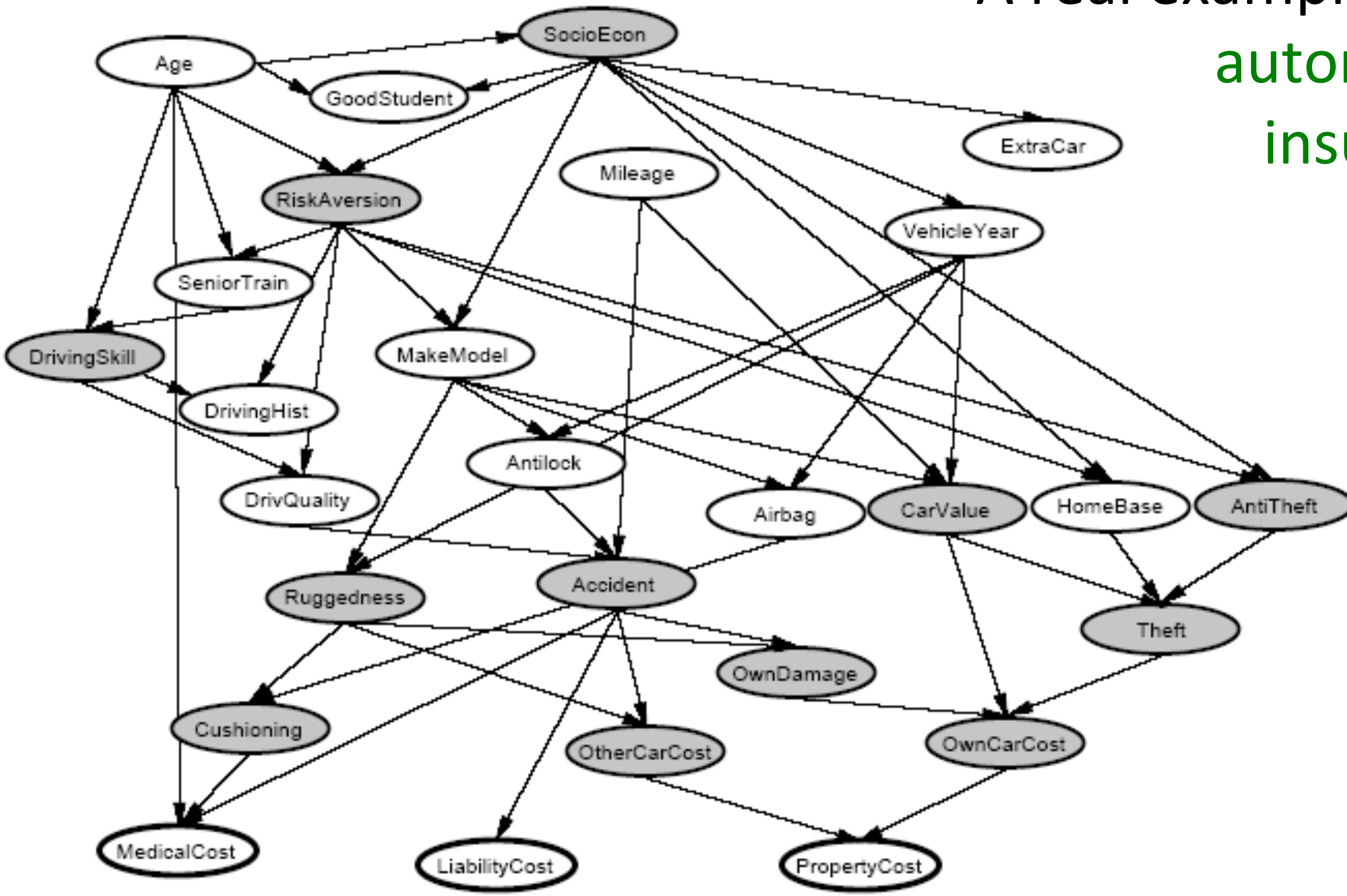


A real medical example

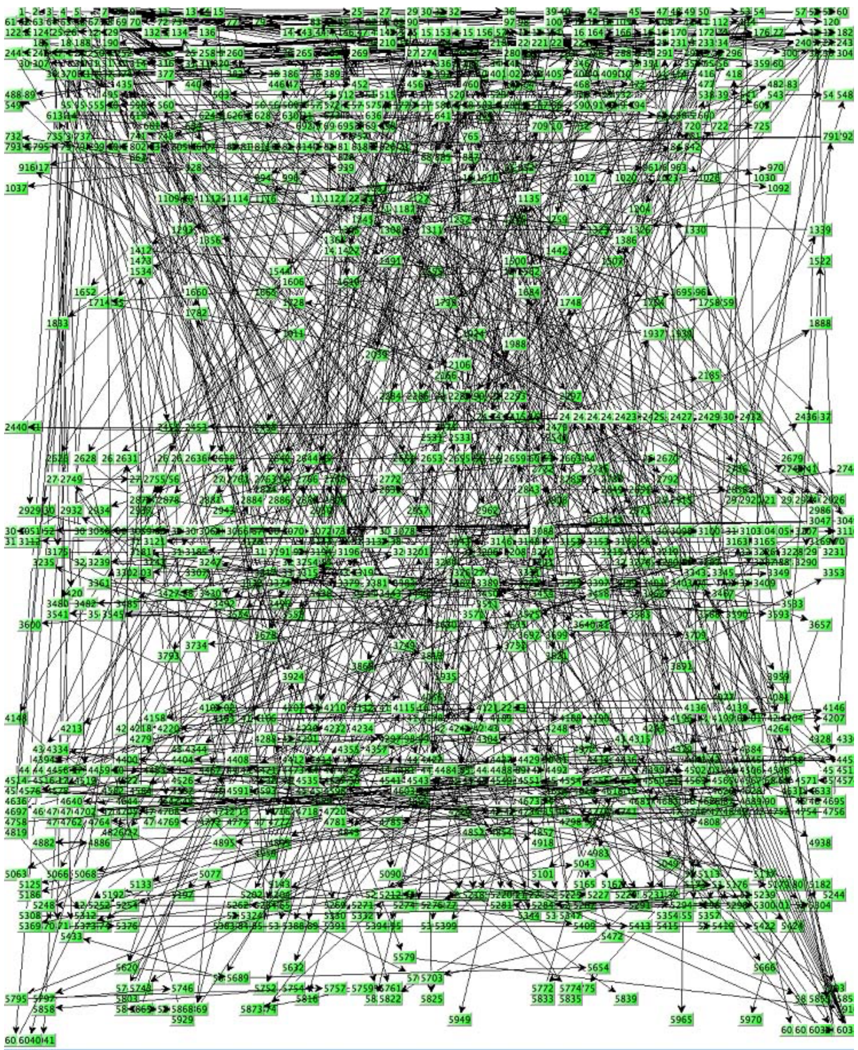


Bayesian networks: examples

A real example from automobile insurance



Bayesian networks: examples

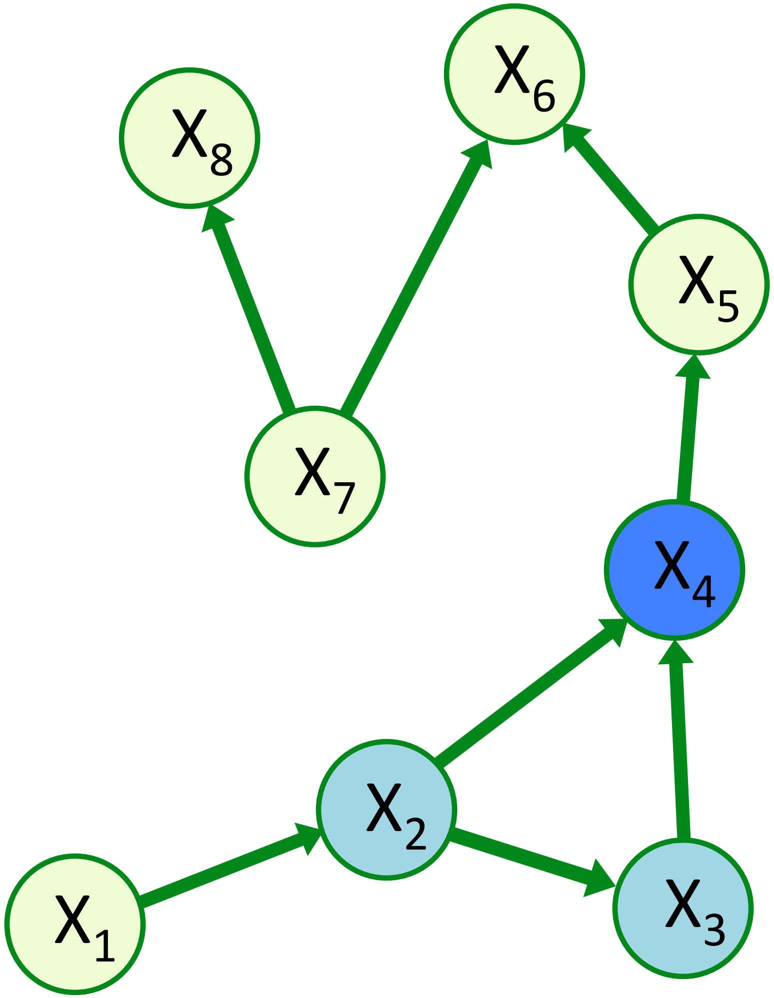


A real example in advertisement, used to optimise and individualise the advertisments that are shown on websites

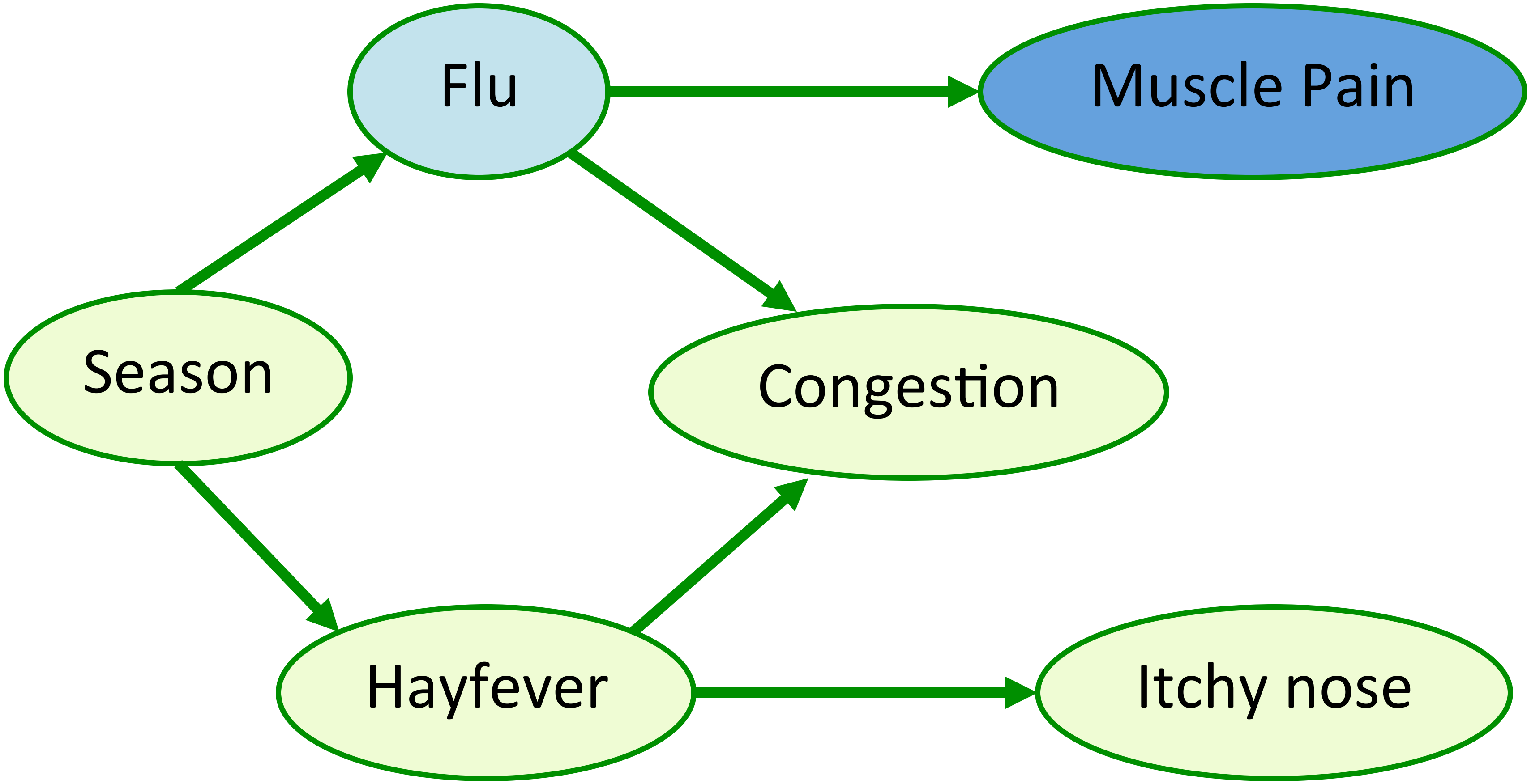
Bayesian networks: in a perfect world…

What if we don't know them exactly?

Local uncertainty models:
mass functions $p_{s\rfloor x_{P(s)}}$

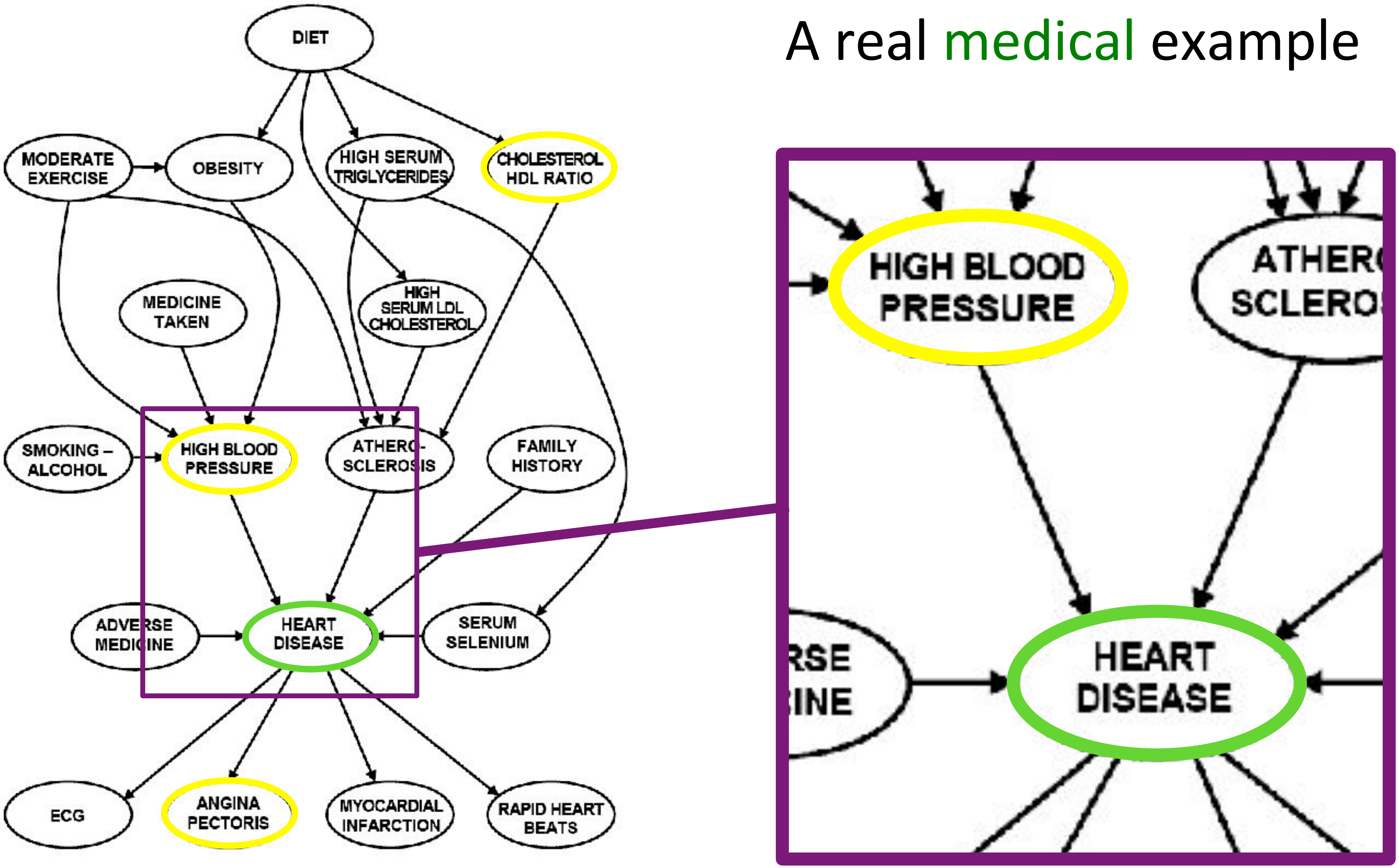


Bayesian networks: in a perfect world…



Bayesian networks: in a perfect world…

A real medical example



Bayesian

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$\boxed{\text{Credal Networks}}$ under Epistemic Irrelevance: Theory and Algorithms

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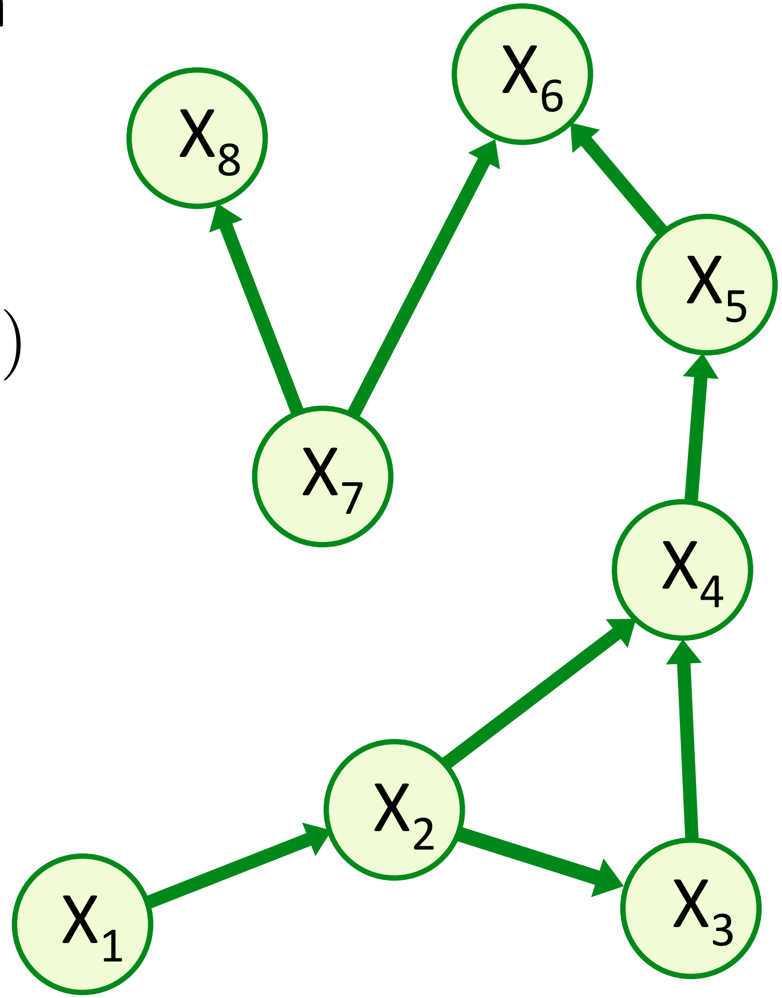
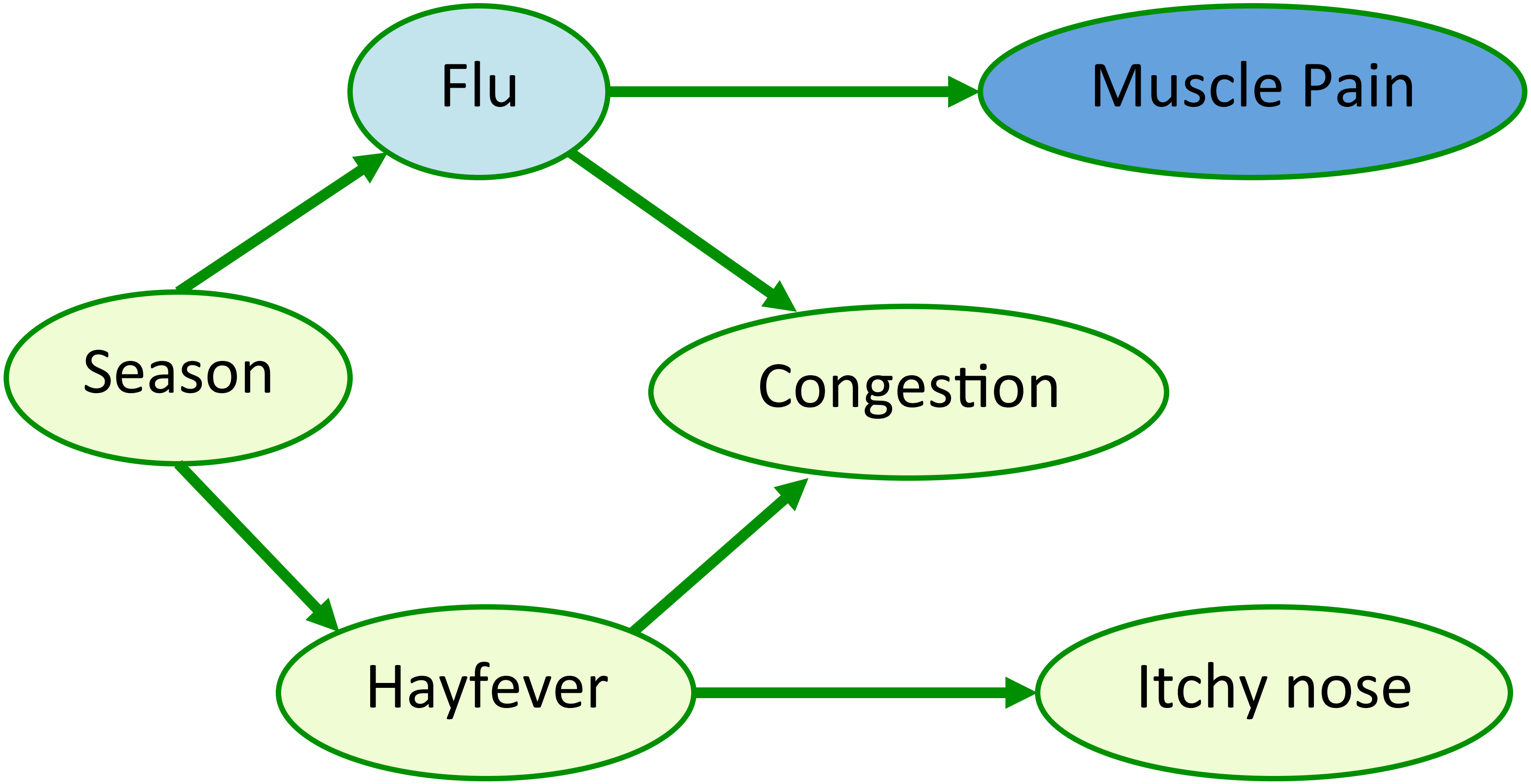
Credal networks: credal sets

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G: P(s), D(s), N(s)$
- Local uncertainty models: credal sets $\mathcal{F}_{s \rfloor x_{P(s)}}$



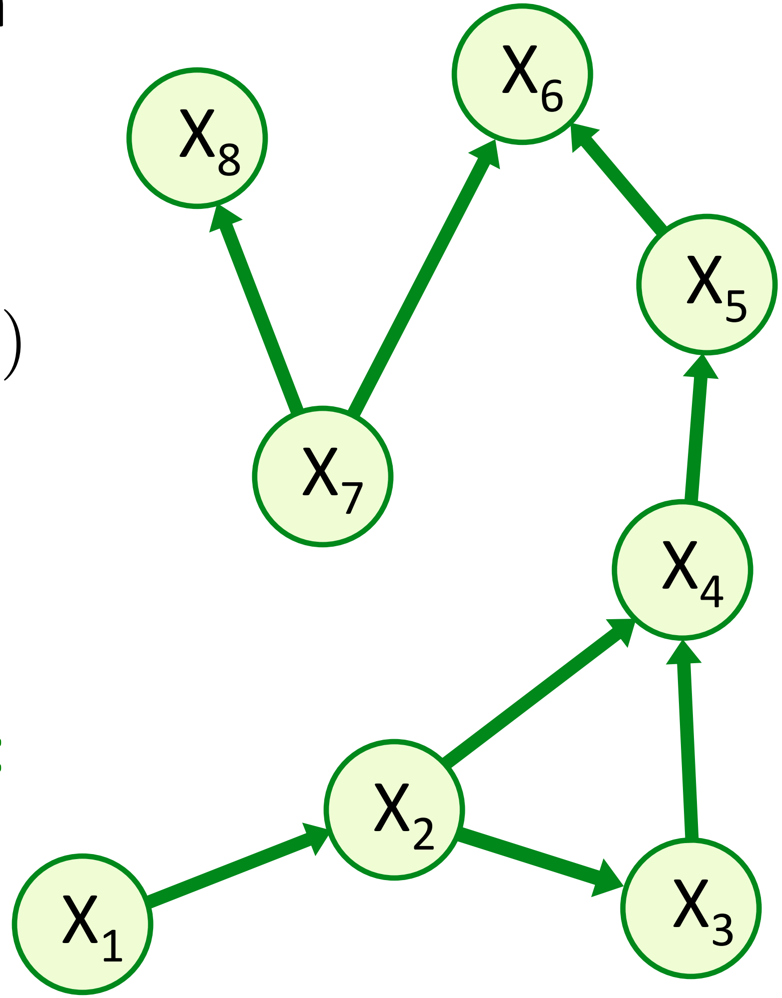
Credal networks: credal sets



Credal networks: independence?

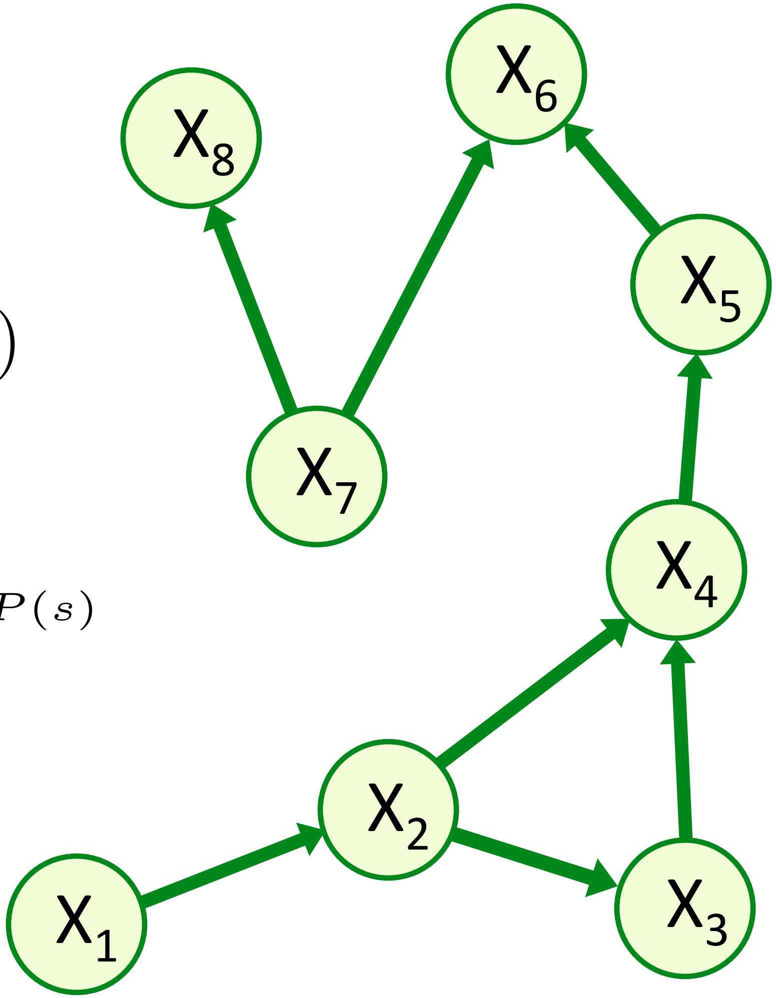
- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G: P(s), D(s), N(s)$
- Local uncertainty models: credal sets $\mathcal{F}_{s \rfloor x_{P(s)}}$
- Independence assumptions:

  ?



Credal networks: complete independence

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon P(s), D(s), N(s)$
- Local uncertainty models:
  credal sets $\mathcal{F}_{s\rfloor x_{P(s)}} \ni p_{s\rfloor x_{P(s)}}$
- Independence assumptions:
  $\forall s \in G\colon I(N(s), s\,|P(s))$



Credal networks: complete independence

$$p(x_G) = \prod_{s \in G} p_{s \rfloor x_{P(s)}}(x_s)$$

$$\in \mathcal{F}_{s \rfloor x_{P(s)}}$$

Credal networks: inference

$$p(x_S) = \sum_{x_{G\setminus S}} p(x_S, x_{G\setminus S})$$

?

$$p(x_Q \rfloor x_E) = \frac{p(x_{Q\cup E})}{p(x_E)}$$

$$p(x_G) = \prod_{s\in G} p_{s\rfloor x_{P(s)}}(x_s)$$

$$\in \mathcal{F}_{s\rfloor x_{P(s)}}$$

Credal networks: inference

$$p(x_S) = \sum_{x_{G\setminus S}} p(x_S, x_{G\setminus S})$$

Lower and upper bounds!

$$p(x_Q \rfloor x_E) = \frac{p(x_{Q\cup E})}{p(x_E)}$$

$$p(x_G) = \prod_{s\in G} p_{s\rfloor x_{P(s)}}(x_s)$$

$$\boxed{\in \mathcal{F}_{s\rfloor x_{P(s)}}}$$

Credal networks: **inference**

Lower and upper bounds!

$$p(x_S) = \sum_{x_{G\setminus S}} p(x_S, x_{G\setminus S})$$

$$p(x_Q | x_E) = \frac{p(x_{Q\cup E})}{p(x_E)}$$

Decision making

?

$$p(x_G) = \prod_{s\in G} p_{s|x_{P(s)}}(x_s)$$

$$\in \mathcal{F}_{s|x_{P(s)}}$$

Credal networks: inference

$$p(x_S) = \sum_{x_{G \setminus S}} p(x_S, x_{G \setminus S})$$

Lower and upper bounds!

$$p(x_Q \rfloor x_E) = \frac{p(x_{Q \cup E})}{p(x_E)}$$

Decision making

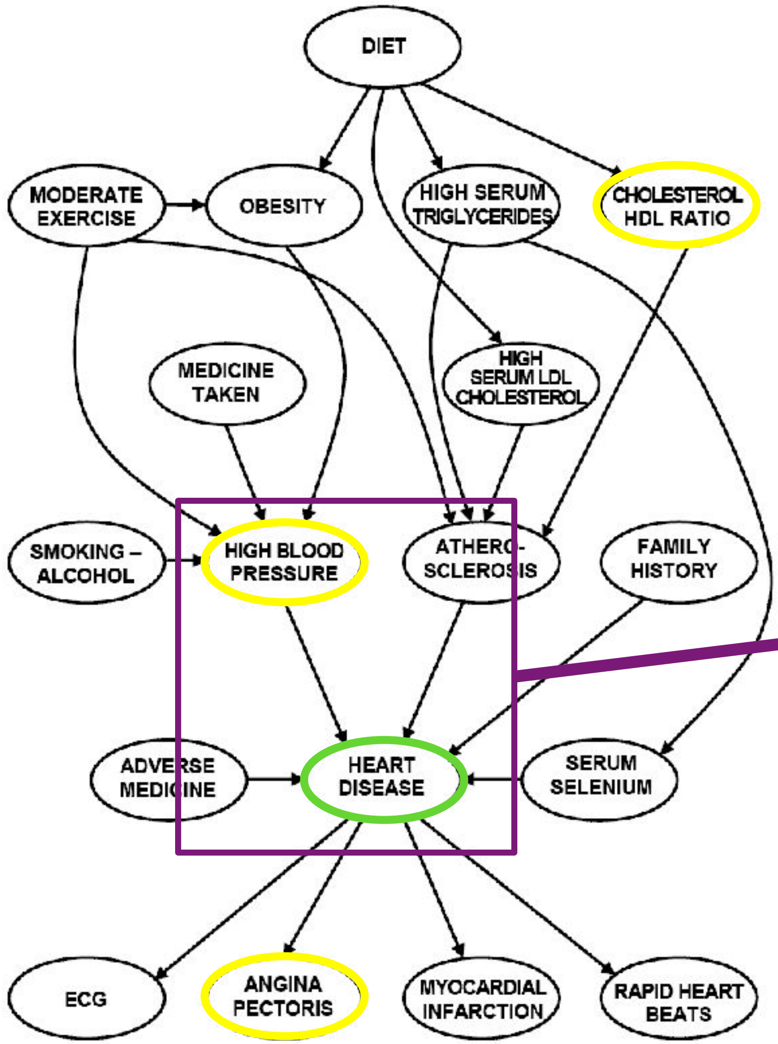
Multiple decisions!

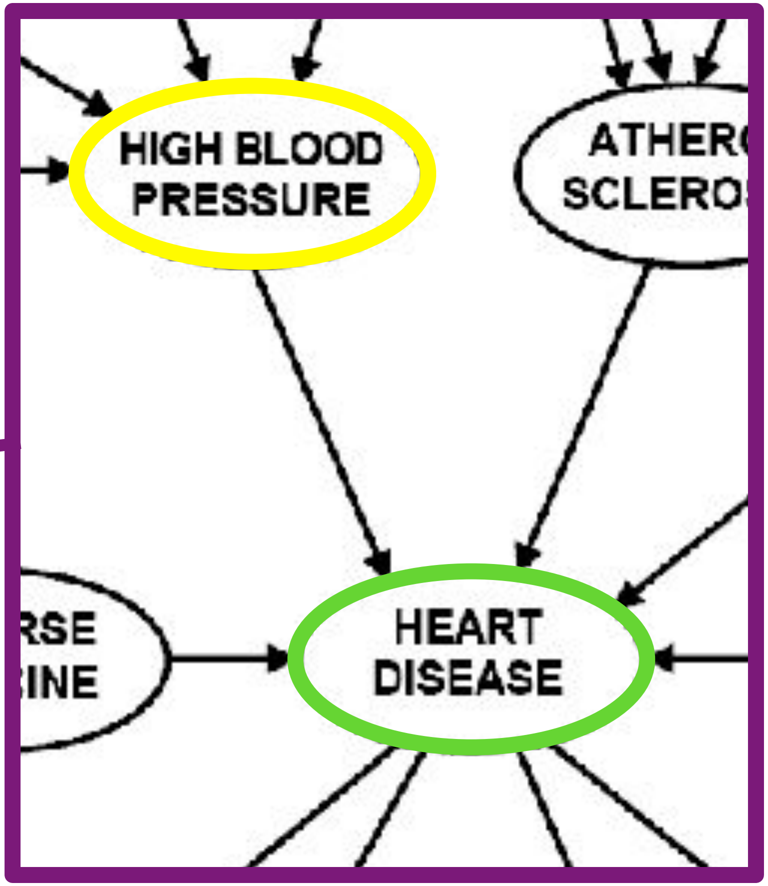
$$p(x_G) = \prod_{s \in G} p_{s \rfloor x_{P(s)}}(x_s)$$

$$\boxed{\in \mathcal{F}_{s \rfloor x_{P(s)}}}$$

Credal networks: inference

A real medical example





Credal networks: in a perfect world...

Are you sure they are completely independent?

Maybe they are almost independent?

What does `almost' mean?

Independence assumptions:
$\forall s \in G : I(N(s), s \,|\, P(s))$

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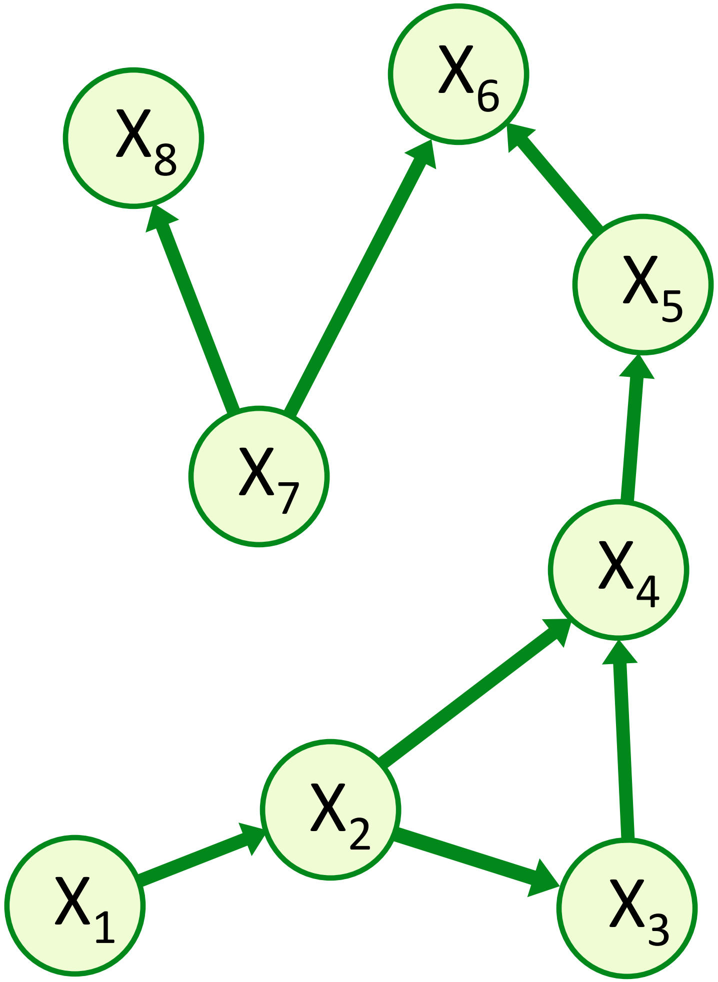
Credal networks: epistemic irrelevance

- Variables X_s take values x_s in a finite non-empty set $\mathcal{X}_s$
- Graphical structure: DAG
  $\Rightarrow \forall s \in G\colon P(s), D(s), N(s)$
- Local uncertainty models: credal sets $\mathcal{F}_{s \rfloor x_{P(s)}}$
- Epistemic irrelevance:
  $\forall s \in G\colon IR(N(s), s \,|\, P(s))$



Credal networks: epistemic irrelevance

$$\mathcal{F}_{s\rfloor x_{P(s)},x_{N(s)}} = \mathcal{F}_{s\rfloor x_{P(s)}}$$

Epistemic irrelevance:

$\forall s \in G\colon IR(N(s), s\,|P(s))$

Credal networks: epistemic irrelevance

$$
\begin{array}{ccc}
\mathcal{F}_{s \rfloor x_{P(s)}, x_{N(s)}} & = & \mathcal{F}_{s \rfloor x_{P(s)}} \\
\rotatebox{90}{$\in$} & & \rotatebox{90}{$\in$} \\
p(x_s \rfloor x_{P(s)}, x_{N(s)}) & \cancel{=} & p(x_s \rfloor x_{P(s)})
\end{array}
$$

Almost independence!

Credal networks: epistemic irrelevance

$$
\begin{array}{ccc}
\mathcal{F}_{s \rfloor x_{P(s)}, x_{N(s)}} & = & \mathcal{F}_{s \rfloor x_{P(s)}} \\
\rotatebox{90}{$\in$} & & \rotatebox{90}{$\in$} \\
p(x_s \rfloor x_{P(s)}, x_{N(s)}) & \cancel{=} & p(x_s \rfloor x_{P(s)})
\end{array}
$$

Almost independence!

What is probability?	What is independence?	What is uncertainty?

Credal networks: epistemic irrelevance

$$\mathcal{M}_{s\rfloor x_{P(s)},x_{N(s)}} = \mathcal{M}_{s\rfloor x_{P(s)}}$$

$$\mathcal{F}_{s\rfloor x_{P(s)},x_{N(s)}} = \mathcal{F}_{s\rfloor x_{P(s)}}$$

$$\mathcal{D}_{s\rfloor x_{P(s)},x_{N(s)}} = \mathcal{D}_{s\rfloor x_{P(s)}}$$

$$\underline{P}_{s\rfloor x_{P(s)},x_{N(s)}} = \underline{P}_{s\rfloor x_{P(s)}}$$

What is probability?

What is independence?

What is uncertainty?

Credal networks: epistemic irrelevance

$$
\begin{array}{ccc}
\mathcal{F}_{s \rfloor x_{P(s)}, x_{N(s)}} & = & \mathcal{F}_{s \rfloor x_{P(s)}} \\
\Cup & & \Cup \\
p(x_s \rfloor x_{P(s)}, x_{N(s)}) & \cancel{=} & p(x_s \rfloor x_{P(s)})
\end{array}
$$

Almost independence!

Credal networks: the global model?

$$\boxed{\begin{array}{ccc} \mathcal{F}_{s \rfloor x_{P(s)}, x_{N(s)}} & = & \mathcal{F}_{s \rfloor x_{P(s)}} \\ \Cup & & \Cup \\ p(x_s \rfloor x_{P(s)}, x_{N(s)}) & \cancel{=} & p(x_s \rfloor x_{P(s)}) \end{array}}$$

? $$p(x_G) = \prod_{s \in G} \cancel{p_{s \rfloor x_{P(s)}}(x_s)}$$

$$\cancel{\boxed{\in \mathcal{F}_{s \rfloor x_{P(s)}}}}$$

The irrelevant natural extension

$$
\begin{array}{ccc}
\mathcal{F}_{s\rfloor x_{P(s)},x_{N(s)}} & = & \mathcal{F}_{s\rfloor x_{P(s)}} \\
\rotatebox{90}{$\in$} & & \rotatebox{90}{$\in$} \\
p(x_s\rfloor x_{P(s)},x_{N(s)}) & \cancel{=} & p(x_s\rfloor x_{P(s)})
\end{array}
$$

the set of all global probability mass functions that are compatible with our assessments

The irrelevant natural extension: inference?

? $$p(x_S) = \sum_{x_{G\setminus S}} p(x_S, x_{G\setminus S})$$

Lower and upper bounds!

$$p(x_Q | x_E) = \frac{p(x_{Q\cup E})}{p(x_E)}$$?

Decision making

Multiple ? decisions!

the set of all global probability mass functions that are compatible with our assessments

The irrelevant natural extension

The **global model** can be described in terms of linear constraints

(Cozman, 2000)

Inference can be performed using linear programming techniques

The irrelevant natural extension

The **global model** can be described in terms of linear constraints

(Cozman, 2000)

Inference can be performed using linear programming techniques

- Without a positivity assumption!
- Equally simple representations in terms of three other frameworks!

The irrelevant natural extension

The **global model** can be described in terms of linear constraints

(Cozman, 2000)

Inference can be performed using linear programming techniques

- Without a positivity assumption!
- Equally simple representations in terms of three other frameworks!

 # constraints is exponential in the size of the network!

Credal Networks under Epistemic Irrelevance: $\boxed{\text{Theory and Algorithms}}$

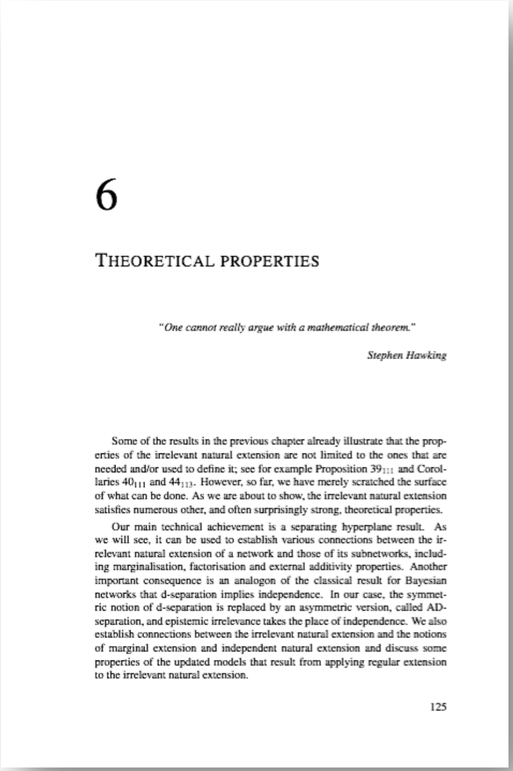
Jasper De Bock

13 May 2015, Ghent, Belgium

The irrelevant natural extension

Theoretical properties

- Connections with marginal and independent natural extension
- Marginalisation properties
- AD-separation implies epistemic irrelevance
- …



6

THEORETICAL PROPERTIES

"One cannot really argue with a mathematical theorem."

Stephen Hawking

Some of the results in the previous chapter already illustrate that the properties of the irrelevant natural extension are not limited to the ones that are needed and/or used to define it; see for example Proposition 39_{111} and Corollaries 40_{111} and 44_{113}. However, so far, we have merely scratched the surface of what can be done. As we are about to show, the irrelevant natural extension satisfies numerous other, and often surprisingly strong, theoretical properties.

Our main technical achievement is a separating hyperplane result. As we will see, it can be used to establish various connections between the irrelevant natural extension of a network and those of its subnetworks, including marginalisation, factorisation and external additivity properties. Another important consequence is an analogon of the classical result for Bayesian networks that d-separation implies independence. In our case, the symmetric notion of d-separation is replaced by an asymmetric version, called AD-separation, and epistemic irrelevance takes the place of independence. We also establish connections between the irrelevant natural extension and the notions of marginal extension and independent natural extension and discuss some properties of the updated models that result from applying regular extension to the irrelevant natural extension.

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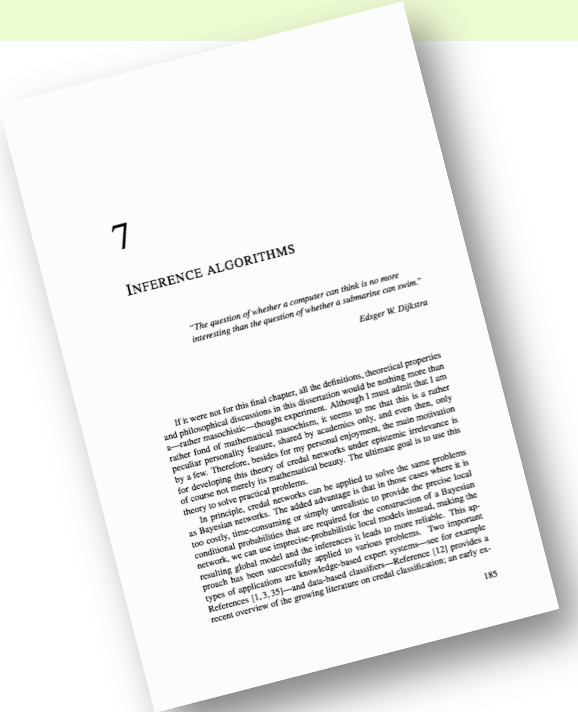
The irrelevant natural extension

Inference algorithms

- For recursively decomposable networks, inference is very efficient!

  For trees: (Cooman et al., 2010)



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INFERENCE ALGORITHMS

"The question of whether a computer can think is no more interesting than the question of whether a submarine can swim."

Edsger W. Dijkstra

If it were not for this final chapter, all the definitions, theoretical properties and philosophical discussions in this dissertation would be nothing more than a—rather masochistic—thought experiment. Although I must admit that I am rather fond of mathematical masochism, it seems to me that this is a rather peculiar personality feature, shared by academics only, and even then, only by a few. Therefore, besides for my personal enjoyment, the main motivation for developing this theory of credal networks under epistemic irrelevance is of course not merely its mathematical beauty. The ultimate goal is to use this theory to solve practical problems.

In principle, credal networks can be applied to solve the same problems as Bayesian networks. The added advantage is that in those cases where it is too costly, time-consuming or simply unrealistic to provide the precise local conditional probabilities that are required for the construction of a Bayesian network, we can use imprecise-probabilistic local models instead, making the resulting global model and the inferences it leads to more reliable. This approach has been successfully applied to various problems. Two important types of applications are knowledge-based expert systems—see for example References [1, 3, 35]—and data-based classifiers—Reference [12] provides a recent overview of the growing literature on credal classification; an early ex-

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- Non-decomposable networks can also be dealt with (on a case by case basis)
- Complex types of inference are possible!
- …

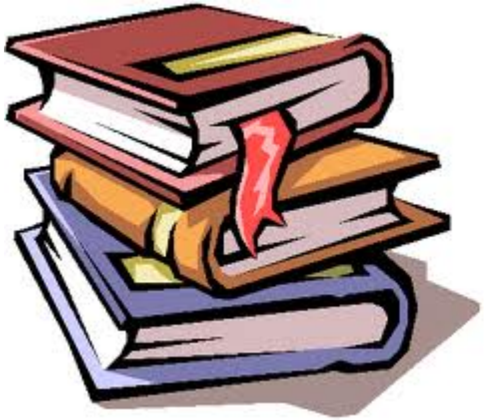
For the second part of the proof, we start by considering the following collection of gambles on $\mathscr{X}_K$:

$$\mathscr{A}^*_{K\rfloor x_{P(K)}} := \Big\{ \mathbb{I}_{\{z_{PN(s)\cap K_1}\}} f_{s,z_{PN(s)}} : s \in K,\ z_{PN(s)} \in \mathscr{X}_{PN(s)}, \\ z_{P(s)\setminus P_K(s)} = x_{P(s)\setminus P_K(s)},\ P(s)\cap K \subseteq K_1 \subseteq K, \\ f_{s,z_{PN(s)}} \neq 0 \Big\},$$

which is a finite subset of $\mathscr{D}^{\mathrm{irr}}_{K\rfloor x_{P(K)}} := \operatorname{posi}(\mathscr{A}^{\mathrm{irr}}_{K\rfloor x_{P(K)}})$. To see why, first notice that because $PN_K(s) = PN(s)\cap K$ due to Lemma 79(iii)$_{184}$, $\mathbb{I}_{\{z_{PN(s)\cap K_1}\}}$ is clearly the (finite) sum of all indicators $\mathbb{I}_{\{y_{PN_K(s)}\}}$ such that $y_{PN_K(s)} \in \mathscr{X}_{PN_K(s)}$ and $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$. By definition of the posi operator, we are now left to show that for any $y_{PN_K(s)} \in \mathscr{X}_{PN_K(s)}$ such that $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$, we have $\mathbb{I}_{\{y_{PN_K(s)}\}} f_{s,z_{PN(s)}} \in \mathscr{A}^{\mathrm{irr}}_{K\rfloor x_{P(K)}}$. By construction of $\mathscr{A}^*_{K\rfloor x_{P(K)}}$, we know that $z_{P(s)\setminus P_K(s)} = x_{P(s)\setminus P_K(s)}$, and it therefore suffices to show that $y_{P_K(s)} = z_{P_K(s)}$. To see why this last equality holds, first notice that $P_K(s) = P(s)\cap K$ due to Lemma 76$_{181}$. Also, $P(s)\cap K \subseteq PN(s)\cap K_1$ because $P(s)\cap K \subseteq K_1$ by construction of $\mathscr{A}^*_{K\rfloor x_{P(K)}}$ and $P(s)\cap K \subseteq PN(s)$ by definition of $PN(s)$. Therefore, we find that $P_K(s) \subseteq PN(s)\cap K_1$, implying that $y_{P_K(s)} = z_{P_K(s)}$ is a direct consequence of $y_{PN(s)\cap K_1} = z_{PN(s)\cap K_1}$.


Cosa si può fare con esso?

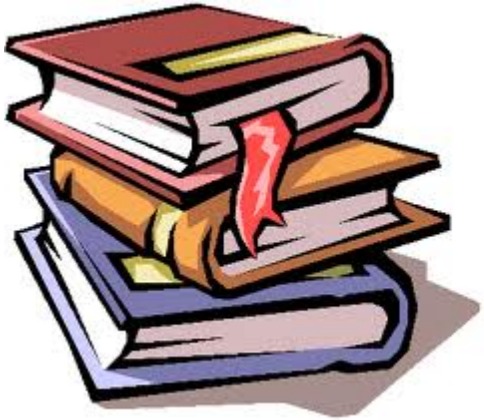
An application: correcting OCR errors



Scan and apply
Optical Character
Recognition
software

An application: correcting OCR errors

DOCTORAAT

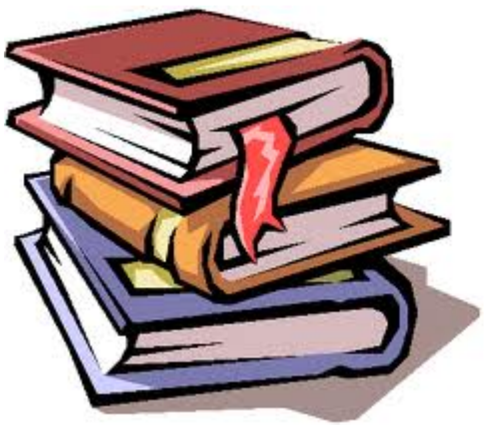


Scan and apply
Optical Character
Recognition
software

DOCTQRAAT

An application: correcting OCR errors

DOCTORAAT



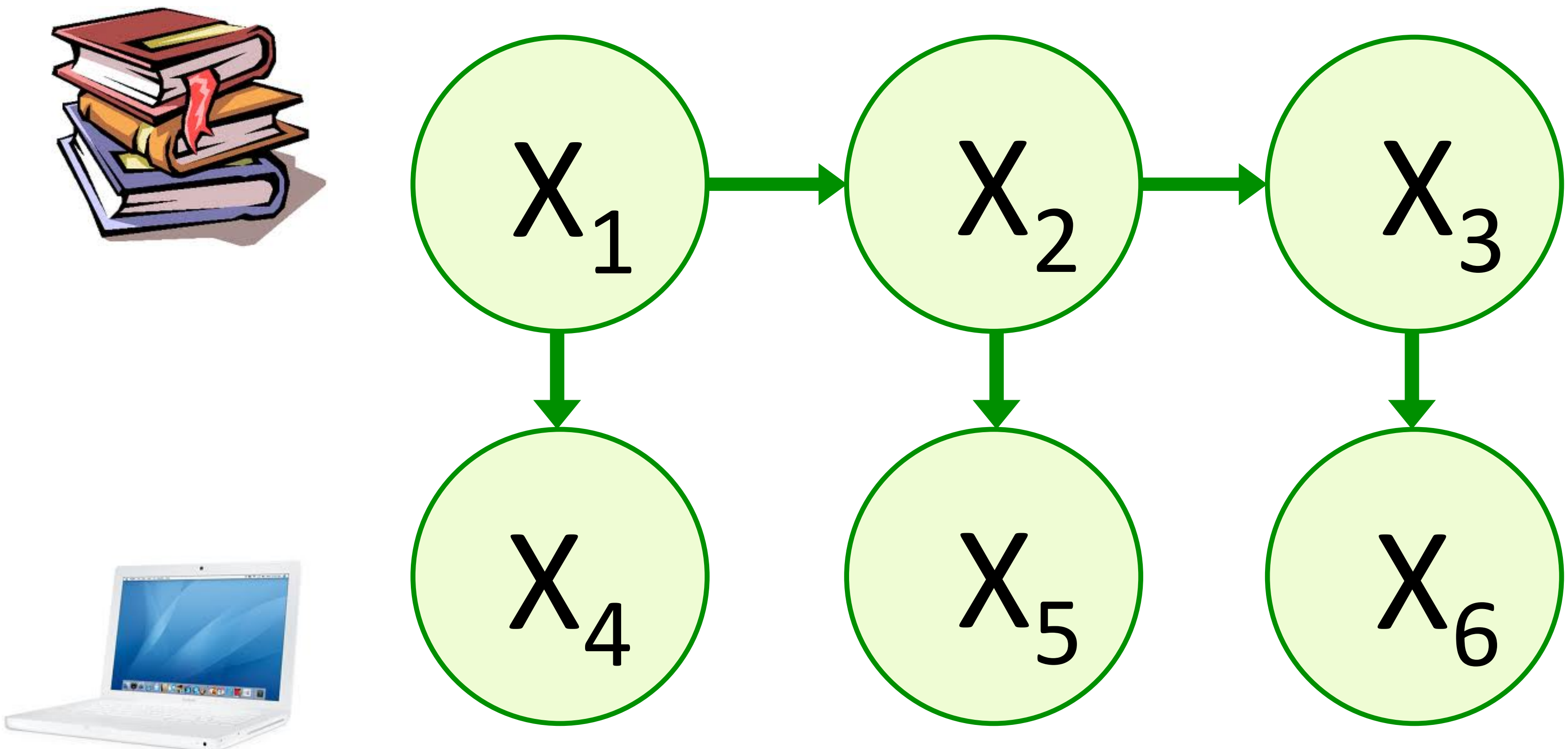
Scan and apply Optical Character Recognition software

DOCTQRAAT

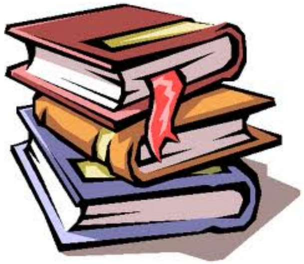
Correct errors

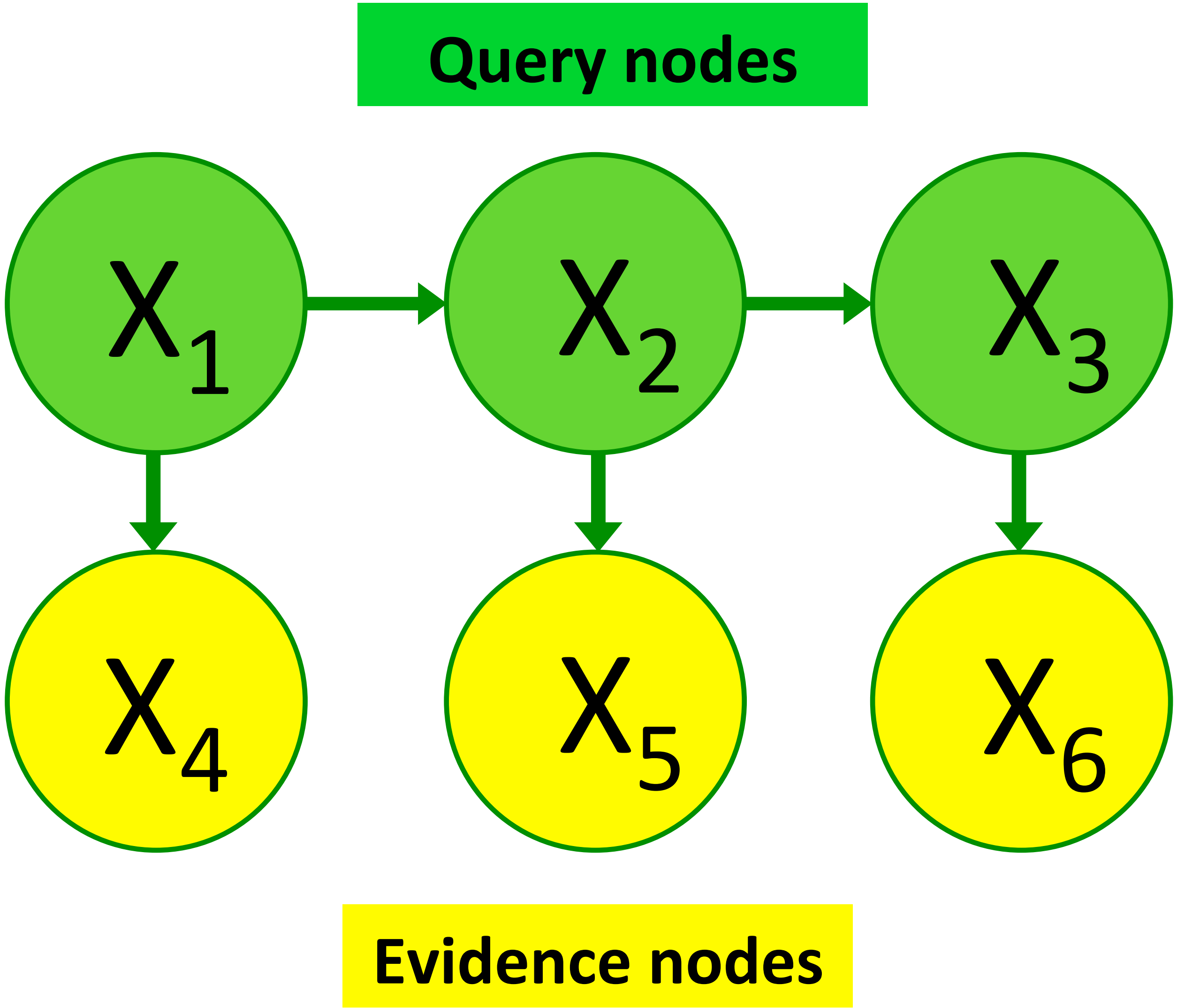
Bayesian or credal networks

An application: correcting OCR errors



An application: correcting OCR errors





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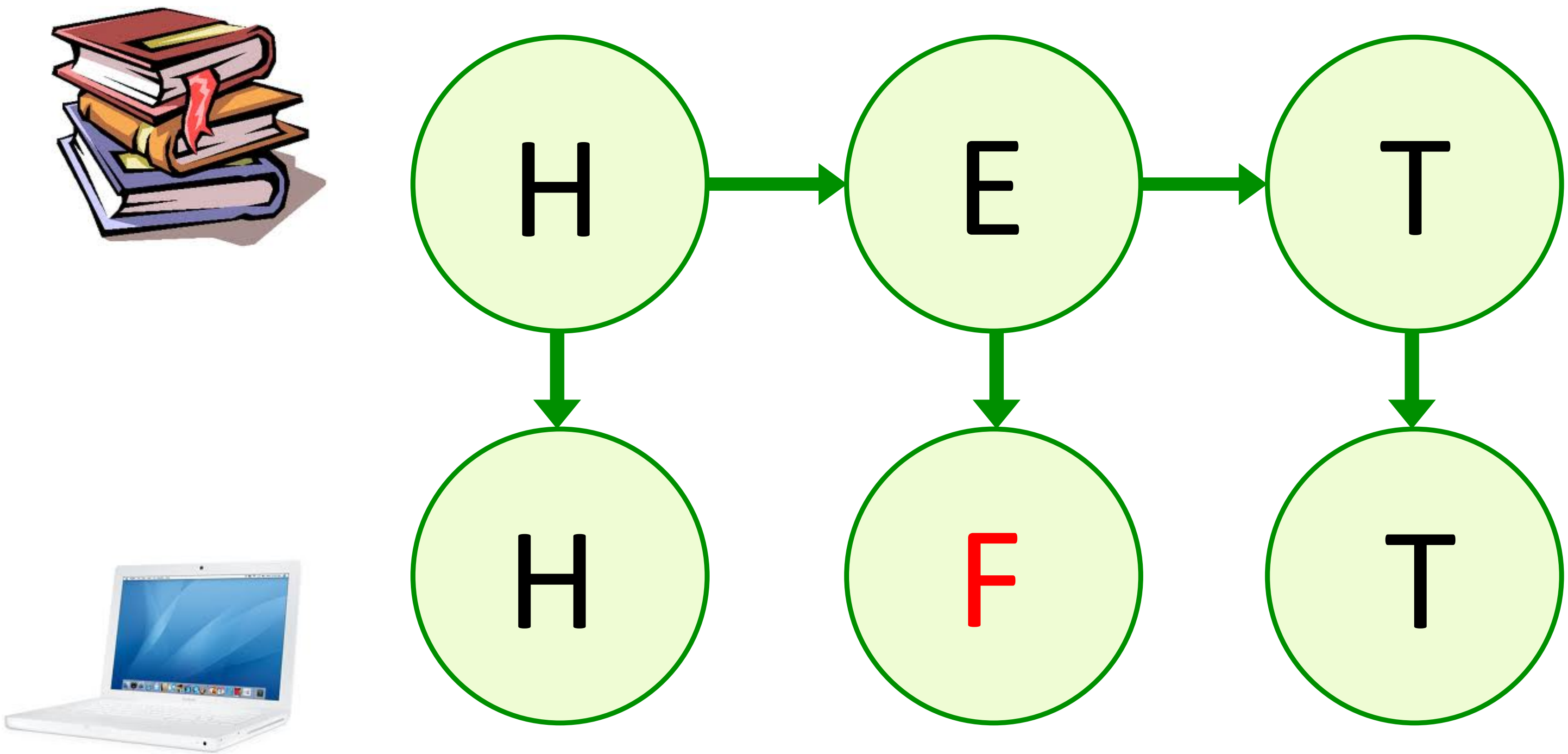
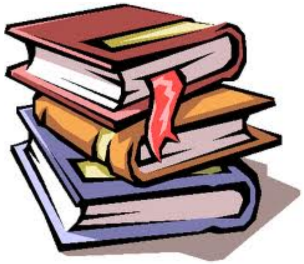
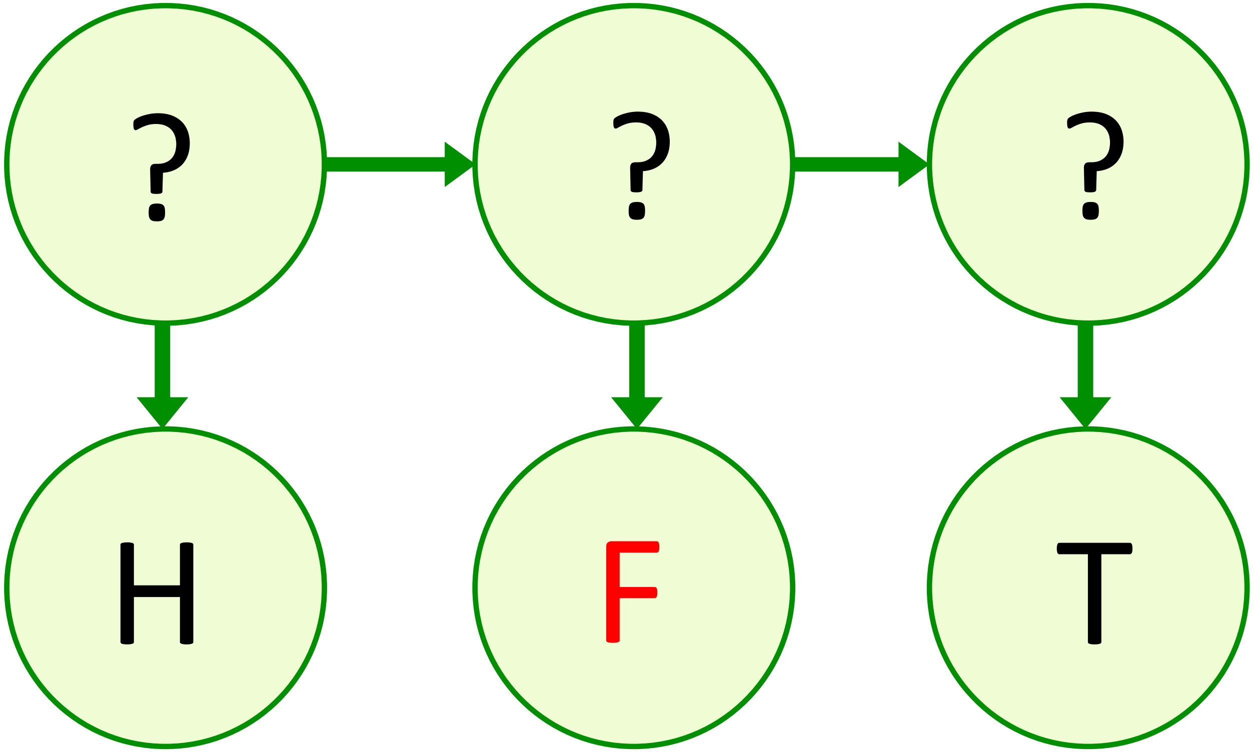
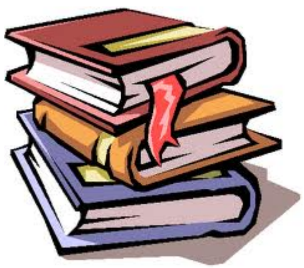


An application: correcting OCR errors

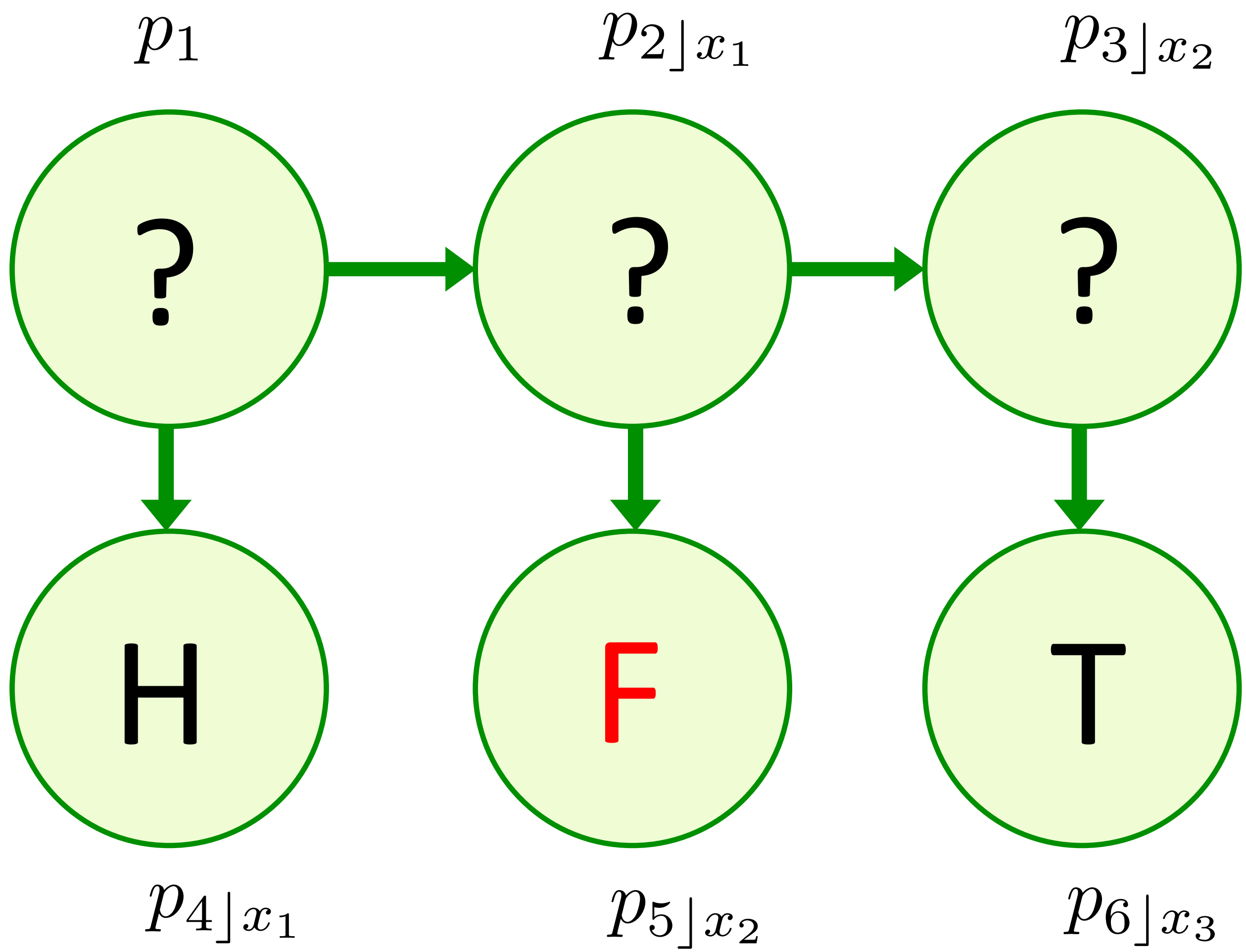




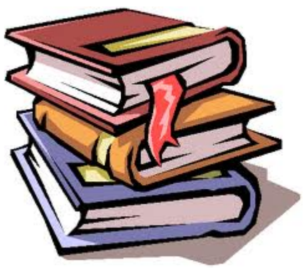
An application: correcting OCR errors



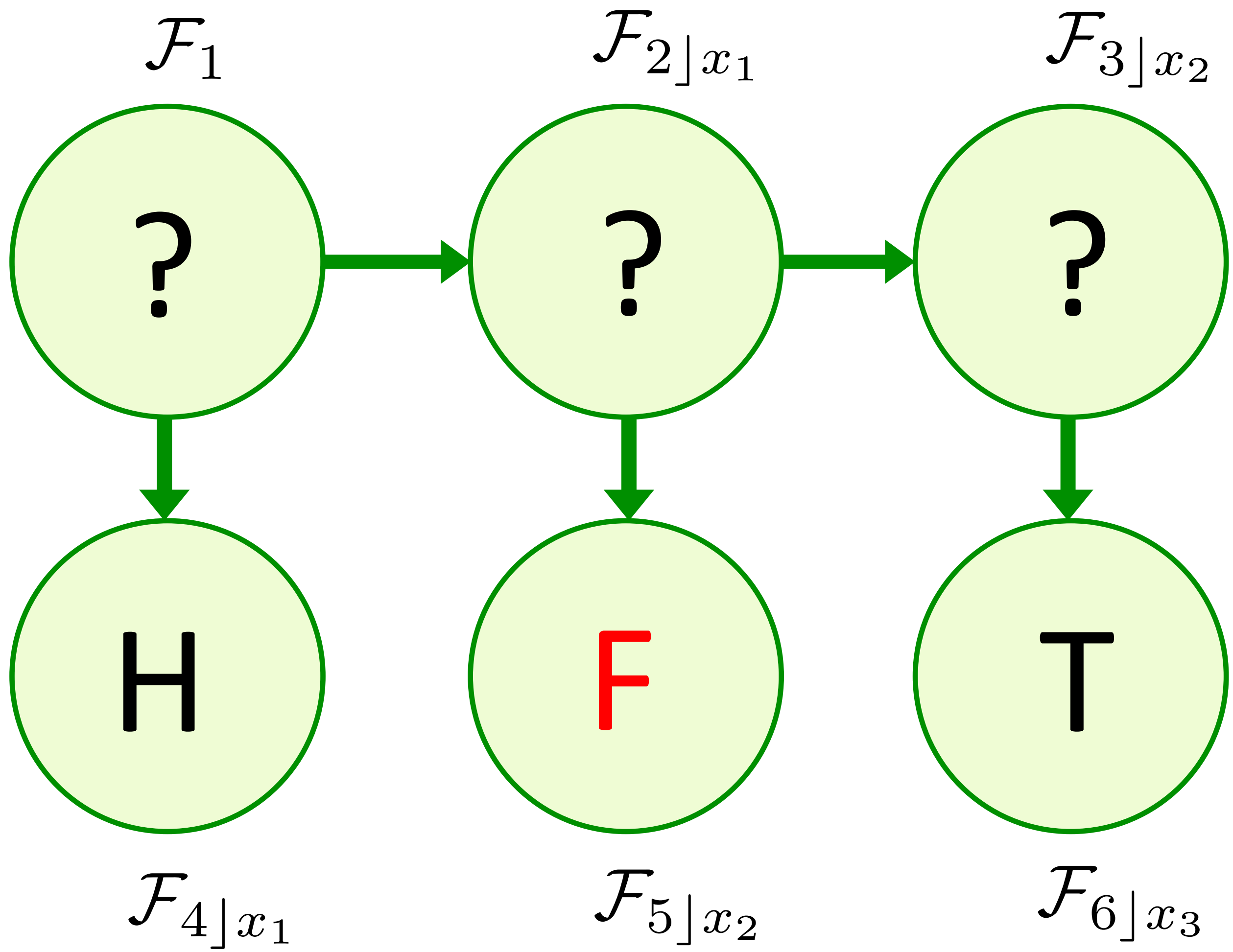
Bayesian network



An application: correcting OCR errors



Credal network



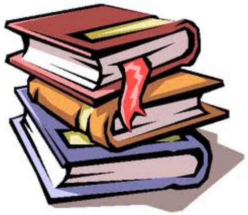
An application: correcting OCR errors

La Divina Commedia

Data is scarce (or expensive)

Obtaining accurate probabilities is unrealistic

An application: correcting OCR errors



original

VITA

correctly read

digital

VITA

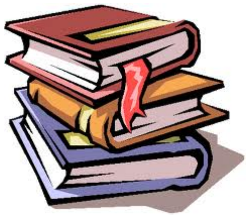
Solution Bayesian network

VITA

Solution(s) credal network

VITA

An application: correcting OCR errors



original

CON

incorrectly read

digital

CCN

Solution Bayesian network

CON

Solution(s) credal network

CON

An application: correcting OCR errors

original

CHE

incorrectly read

digital

CNE

Solution Bayesian network

ONE

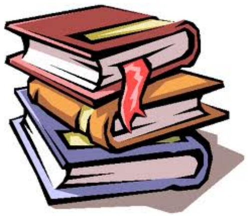
Solution(s) credal network

CBE CHE

CNE CZE

ONE

An application: correcting OCR errors



original

EH

correctly read

digital

EH

Solution Bayesian network

EN

Solution(s) credal network

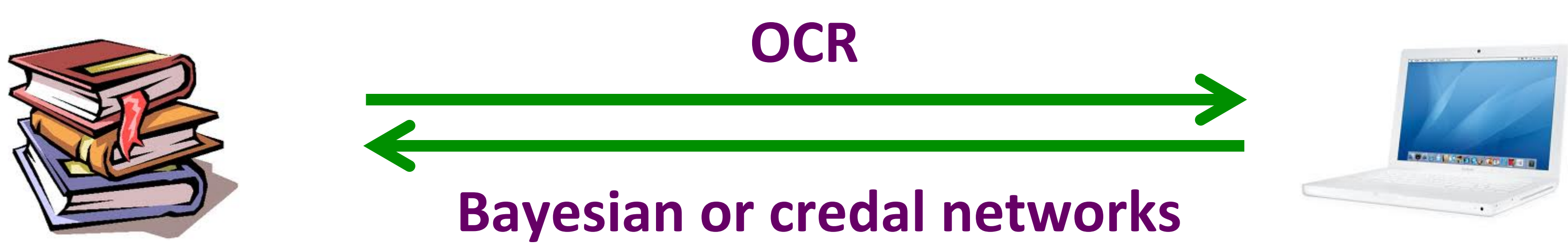
CH

EH

EN

An application: correcting OCR errors

	TOTAL	OCR correct	OCR wrong
TOTAL	200 (100%)	137 (68.5%)	63 (31.5%)
Credal network			
Includes correct answer	172 (86%)	137	35
Only wrong answers	28 (14%)	0	28
Bayesian network			
Correct answer	157 (78.5%)	132	25
Wrong answer	43 (21.5%)	5	38



An application: correcting OCR errors

Words for which the credal network suggests multiple answers

	TOTAL	OCR correct	OCR wrong
TOTAL	45 (100%)	8 (17.8%)	37 (82.2%)
Credal network			
Includes correct answer	38 (84.4%)	8	30
Only wrong answers	7 (15.6%)	0	7
Bayesian network			
Correct answer	23 (51.1%)	3	20
Wrong answer	22 (48.9%)	5	17


Cosa si può fare con esso?


Ci sono domande?