# Probabilistic graphical models: current research activities

Jirka Vomlel

Institute of Information Theory and Automation Academy of Sciences of the Czech Republic http://www.utia.cz/vomlel

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### A simple Bayesian network model - Chest Clinic



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Conditional probability tables (CPTs)

 $\begin{array}{ll} P({\sf Visit to Asia}) & P({\sf Smoker}) \\ P({\sf Tuberculosis} \mid {\sf Visit to Asia}) & P({\sf Cancer} \mid {\sf Smoker}) \\ P({\sf Bronchitis} \mid {\sf Smoker}) & P({\sf RTG} \mid {\sf Tuberculosis, Cancer}) \\ P({\sf Dyspnoea} \mid {\sf Tuberculosis, Cancer, Bronchitis}) \end{array}$ 



#### P(X|Smoker=true)



#### $P(X|\mathsf{Smoker}=\mathsf{true}, \mathsf{Dyspnoea}=\mathsf{true})$



P(X|Smoker=true, Dyspnoea=true, RTG=true)



P(X|Smoker=true, Dyspnoea=true, RTG=true, Visit to Asia=true)

First, assume a deterministic function. RTG is positive iff the patient has tuberculosis or cancer.

RTG	Tuberculosis	Cancer	p
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	0
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1

RTG can have other reasons for being positive and RTG need not be positive even if the patient has tuberculosis or cancer.

RTG	Tuberculosis	Cancer	p	p'	
0	0	0	1	$p_0$	0.95
0	0	1	0	$p_0 * p_1$	0.019
0	1	0	0	$p_0 * p_2$	0.019
0	1	1	0	$p_0 * p_1 * p_2$	0.00038
1	0	0	0	$1 - p_0$	0.05
1	0	1	1	$1 - p_0 * p_1$	0.981
1	1	0	1	$1 - p_0 * p_2$	0.981
1	1	1	1	$1 - p_0 * p_1 * p_2$	0.99962
				$p_0, p_1, p_2 \in \langle 0, 1 \rangle$	

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Let k be the number of parents. We need to specify k + 1 values  $p_0, p_1, \ldots, p_k$  instead of  $2^k$  in a general CPT.

• Model elicitation

- Model elicitation
  - learning models from data (using Integer Programming)
  - learning models with local structure of a noisy-or like type.
  - combination of expert knowledge and data (biological pathways and experimental data)

- Model elicitation
- Efficient inference with special types of probabilistic models

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- Efficient inference with special types of probabilistic models
  - exploiting determinism
  - exploiting local structure of CPTs

- Model elicitation
- Efficient inference with special types of probabilistic models
- Methods of approximate inference

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- Methods of approximate inference
  - iterative refinement
  - anytime inference methods

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- Methods of approximate inference
- Other types of probabilistic graphical models:

- Model elicitation
- Efficient inference with special types of probabilistic models
- Methods of approximate inference
- Other types of probabilistic graphical models:
  - models with continuous variables (other than Gaussian)
  - models with causal interpretation of directed edges
  - models with both directed and undirected edges in the model (e.g. chain graphs)
  - modeling temporal and spatial information.

- Model elicitation
- Efficient inference with special types of probabilistic models
- Methods of approximate inference
- Other types of probabilistic graphical models:
- Finding good strategies with the help of a BN:

- Model elicitation
- Efficient inference with special types of probabilistic models
- Methods of approximate inference
- Other types of probabilistic graphical models:
- Finding good strategies with the help of a BN:
  - Decision-Theoretic Troubleshooting
  - Adaptive Testing

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- Methods of approximate inference
- Other types of probabilistic graphical models:
- Finding good strategies with the help of a BN:
- Classification and regression for medical applications:

- Model elicitation
- Efficient inference with special types of probabilistic models
- Methods of approximate inference
- Other types of probabilistic graphical models:
- Finding good strategies with the help of a BN:
- Classification and regression for medical applications:
  - mortality prediction
  - prediction of medical care costs