Probabilistic Graphical Models

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Syllabus

Organization

- 16 x 1h15 : courses + tutorial
- final exam

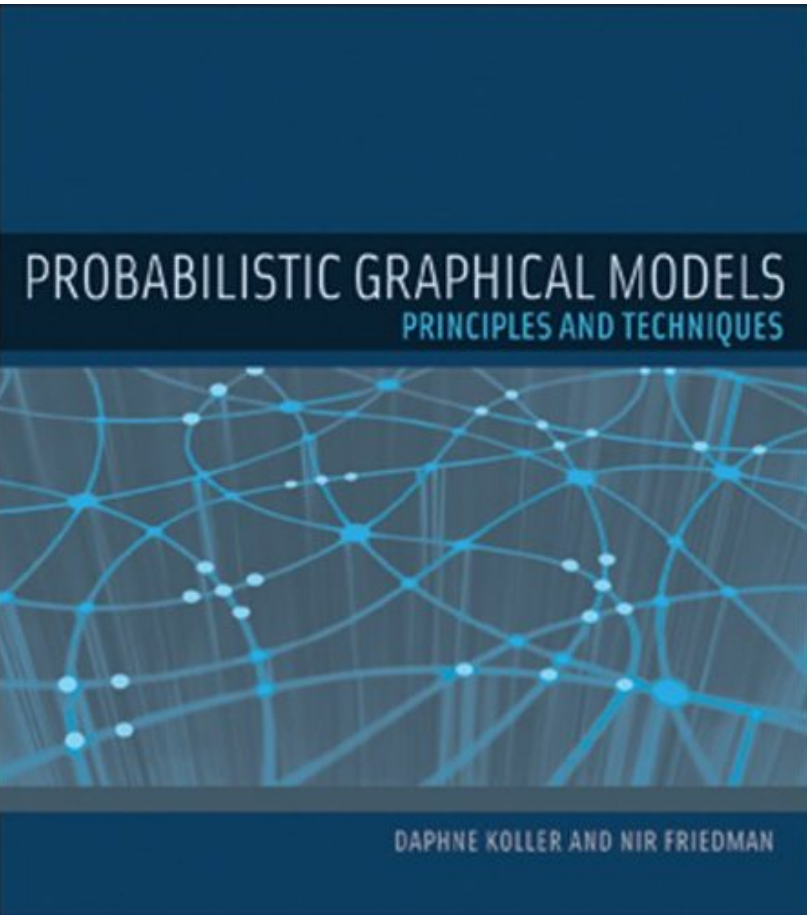
Content

- Bayesian networks : definition and inference (PhL)
- Bayesian networks : learning (PhL)
- Probabilistic relational models (PhL)
- Markov logic networks (HLC)

Philippe Leray

Hoel Le Capitaine

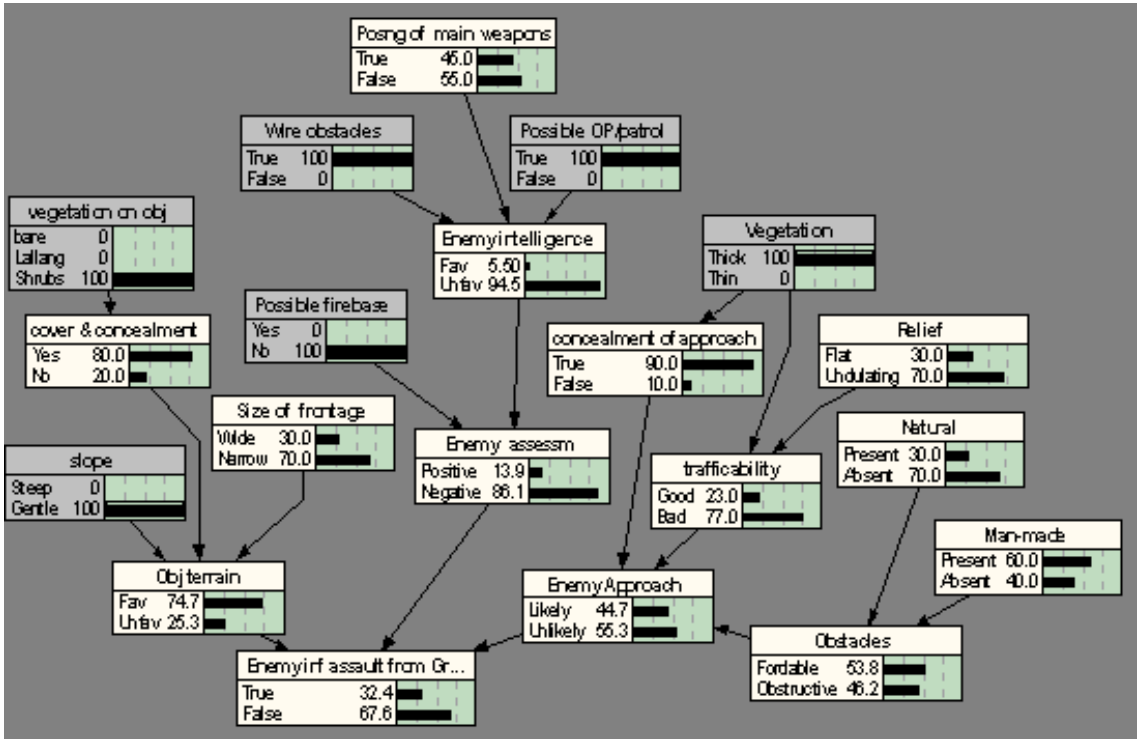
Introduction



Probabilistic Graphical Models

- Marriage between Graph theory and Probability theory
- Powerful framework for representing complex domains using probability distributions
- Numerous applications in machine learning, computer vision, natural language processing, computational biology, ...

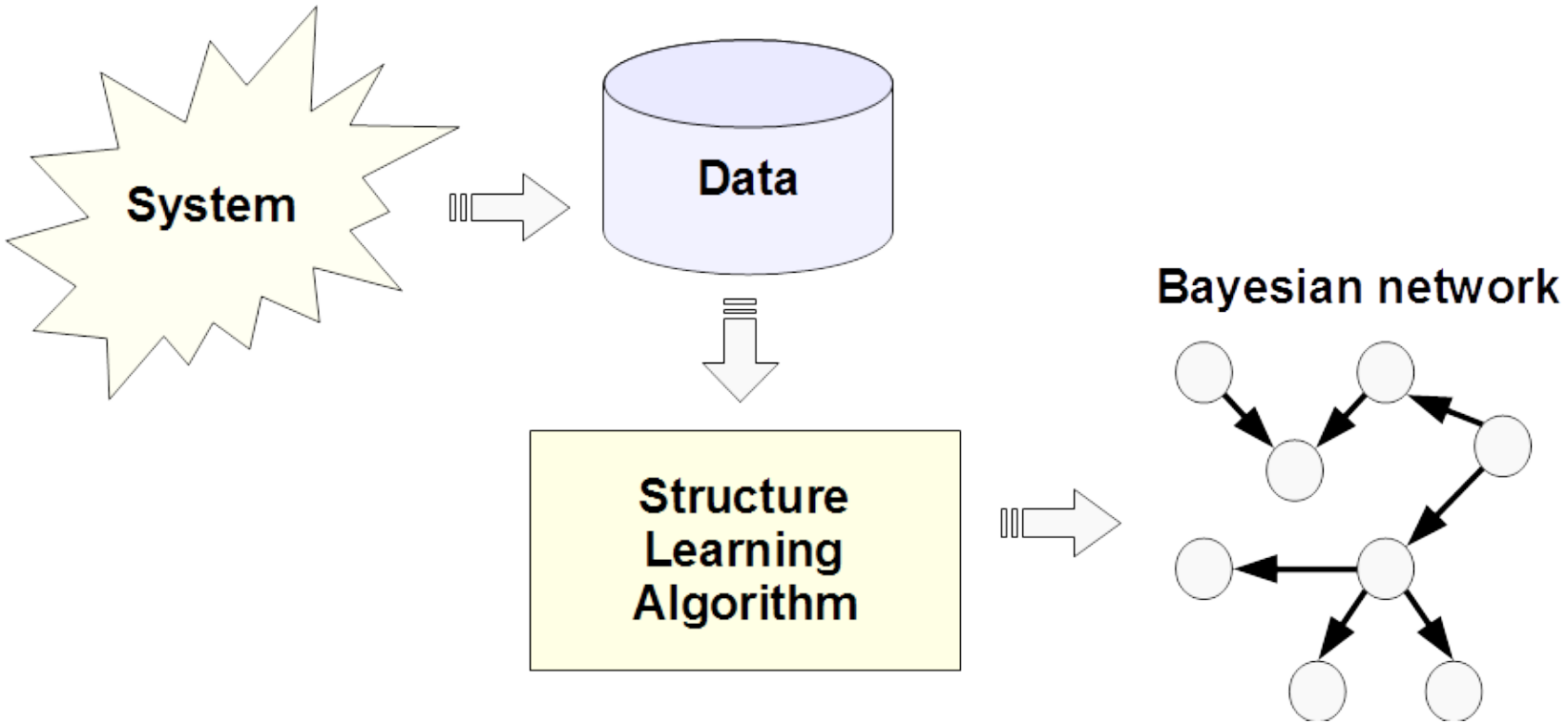
Bayesian networks for knowledge modeling and reasoning



Advantages

- Modeling uncertain relationships
- Reasoning from incomplete observations

Bayesian networks for knowledge discovery

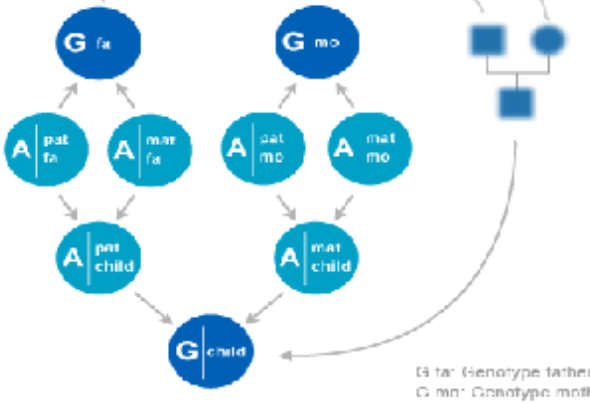


Advantages

- Structure learning from data
- Graphical interpretation

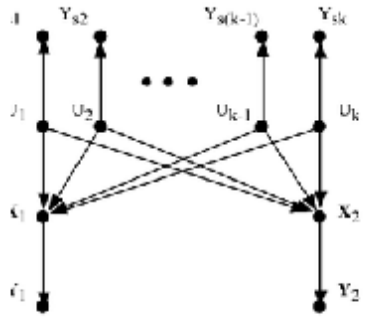
Bayesian networks applications

Victim identification system



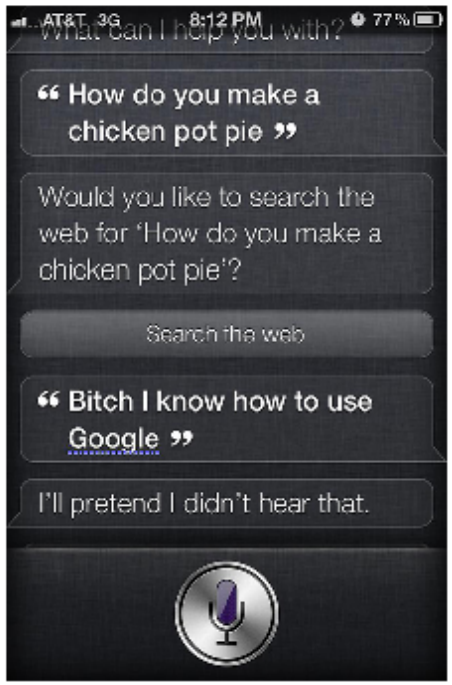
G fa: Genotype father
G mo: Genotype mother
G child: Genotype child
A pat: Paternal Mother Allele
A mat: Maternal Mother Allele

Turbo-codes (GSM, ...)

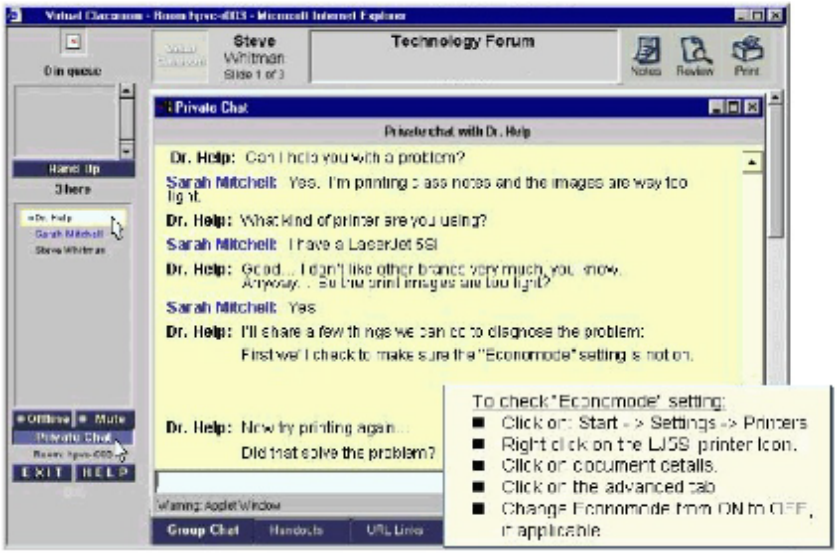


Anti Spam

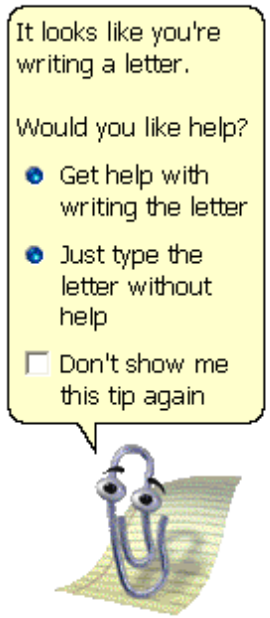
Assistant iPhone SIRI



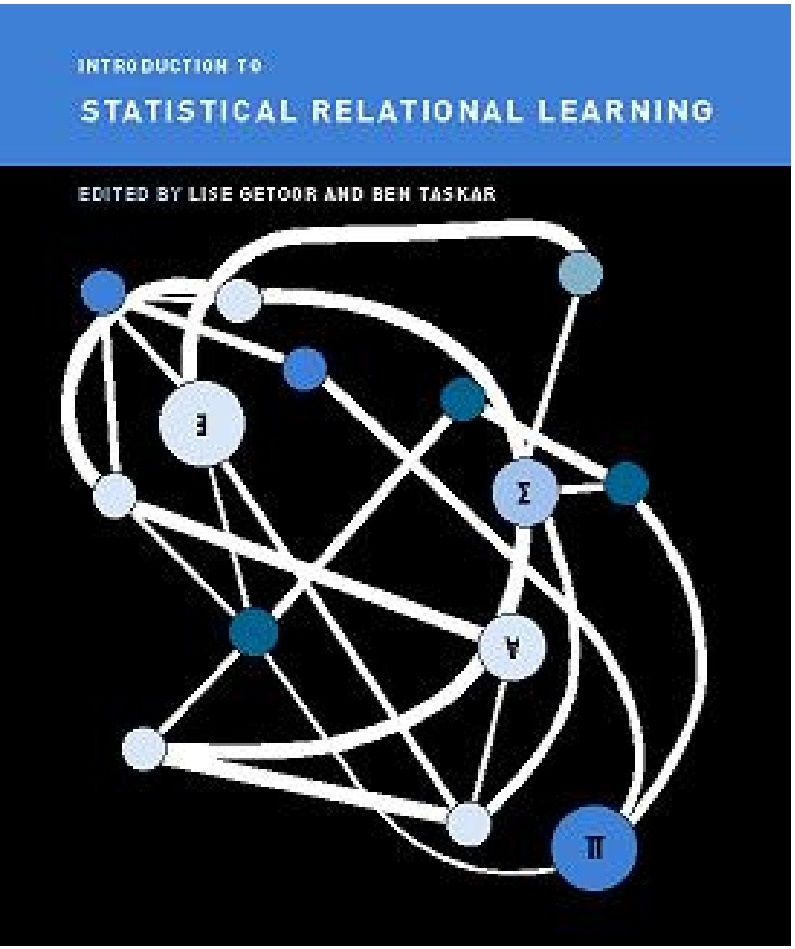
After-sale services



MS Office assistant



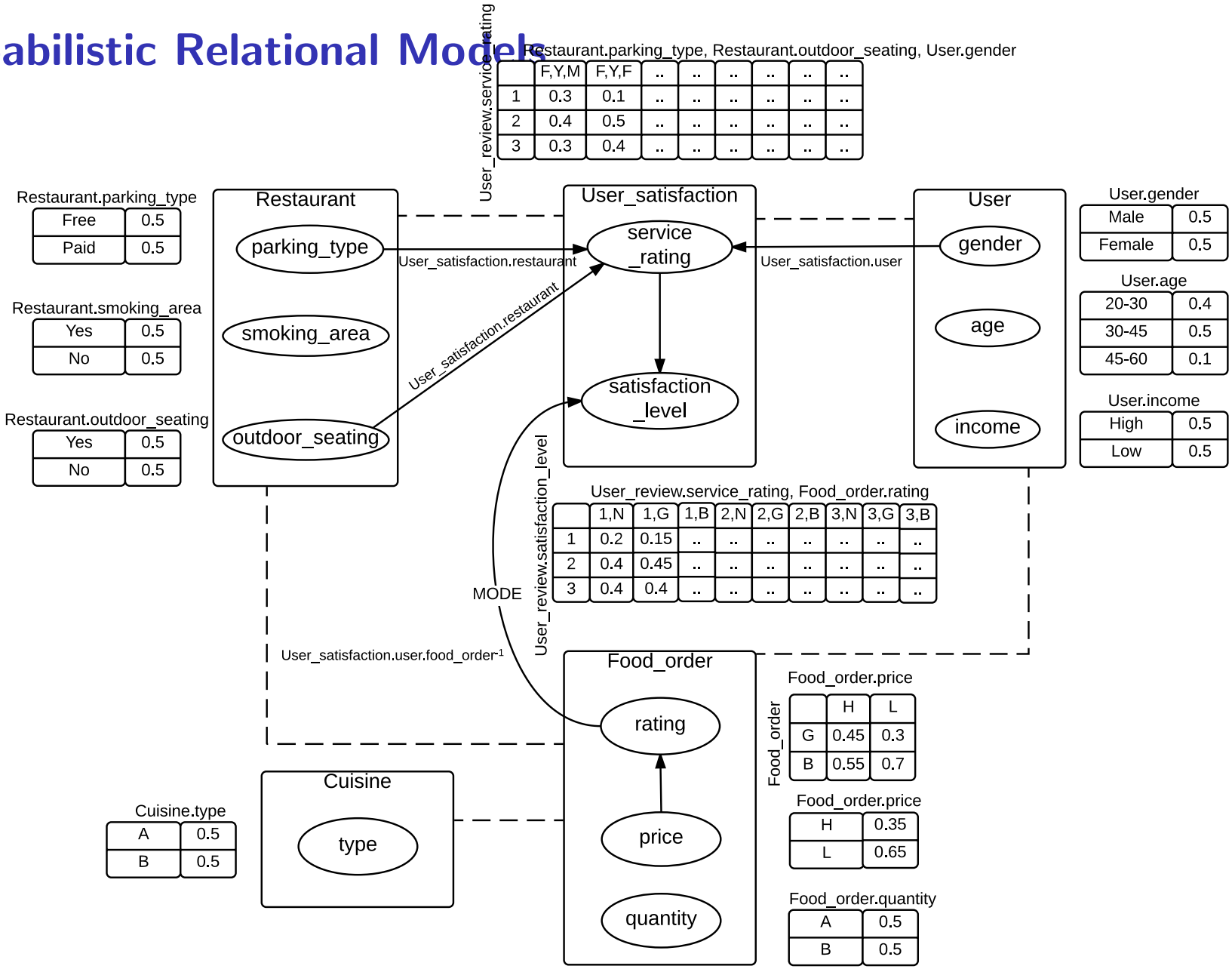
Some other PGMs



Extensions to relational domains

- Adding relations to probabilistic models : Probabilistic relational models
- Adding probability to logical/relational models : Markov logic networks

Probabilistic Relational Model



Markov Logic Networks

1.5	$\forall x\ Smokes(x) \Rightarrow Cancer(x)$
1.1	$\forall x, y\ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$

Two constants: **Anna** (A) and **Bob** (B)