

# Graphical Models for Decision Making

Lesson 1, week 12, class 23

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## 1 Introduction

# Outline of Contents

## 1 Introduction

# Graphical Models for Decision Making

## Decision Analysis

### Decision Analysis → Decision Support Systems

- Complex problems: uncertainty, risk, (multi)objectives, dependencies among variables, preferences over outcomes, ...
- The Models are a tool for problem representation, (computational) evaluation and (deep) understanding to think on the problem.
- Prescriptive approach: Descriptive + Normative.
- Better decisions: coherent and rational process. Not guess the future or improve our luck.

Inmanuel Kant

"All our knowledge begins from sense (Observation), passes understanding (description and modeling) and ends in reason (inference)"

# Graphical Models for Decision Making

## Decision Analysis

### Decision Analysis Cycle

Dialogue between analyst and decision maker (DM)

- 1 Problem Identification
- 2 Tree of Goals (Static or Dynamic)
- 3 Decision Alternative set
- 4 Decision Model
  - i Structure
  - ii Uncertatinty
  - iii Preferences
- 5 Optimal Alternative Evaluation
- 6 Sensitivity Analysis
- 7 Validation No {goto 1,2,3 or 4} / Yes {next}
- 8 Optimal Alternative Implementation

A. Einstein

"Everything should be made as simple as possible, but not one bit simpler"

# Graphical Models for Decision Making

Uncertainty → Probability (Frequentist and Subjective)

## Frequentist Probability

Experiments: repetitive framework, Assessing using data

## Subjective Probability

Bets: degree of belief, personal judgment, Assessing by experts (Cognitive heuristics → biased assignments)

## Bayes Theorem → Belief Revision (Learning)

- Diagnostic test (+/-) over a process or outcome

	present	absent
+	TP	FP
-	FN	TN

- Sensitivity ( $TPR = P(+|present) = TP/(TP + FN)$ ) and Specificity ( $TNR = P(-|absent) = TN/(TN + FP)$ );  $FNR = 1 - TPR$ ,  $FPR = 1 - TNR$
- Bayes: posterior probability,

$$P(present|+) = \frac{P(+|present)P(present)}{P(+|present)P(present) + P(+|absent)P(absent)}$$

# Graphical Models for Decision Making

Preferences  $\rightarrow$  Utility

## Utility

DM should balance preferences over consequences and uncertainty over outcomes. Our utility model is for discrete variables and it is a table over the attributes

- Utility Theory: Axioms (A1-A7), Properties (scale, positive affine transformations,  $u(x_1) = 1, u(x_n) = 0$ )
- $X, x_i \succsim x_j \Leftrightarrow u(x_i) \geq u(x_j) \forall x_i, x_j \in X$
- Under uncertainty the decision maker must choose between lotteries for each alternative and the consequences (prizes)
- Assessing utility function, compare sure prizes  $\langle 1, x_s \rangle$  and reference lottery  $\langle p, x_1; 1 - p, x_n \rangle$ , Methods:
  - certainty equivalence: search for  $x_s$
  - probability equivalence: search for  $p$
- Assessing multi-attribute Utility

A. Machado

"Every fool confuses value with price"

# Graphical Models for Decision Making

## Probabilistic graphical models: Graph theory + Probability Theory + Decision Theory

Probabilistic graphical models are an elegant framework which combines uncertainty (probabilities) and logical structure (independence constraints) to compactly represent complex, real-world phenomena. The framework is quite general in that many of the commonly proposed statistical models (Kalman filters, hidden Markov models, Ising models) can be described as graphical models.

Graphical models have enjoyed a surge of interest in the last two decades, due both to the flexibility and power of the representation and to the increased ability to effectively learn and perform inference in large networks. (Daphne Koller, Nir Friedman, Lise Getoor and Ben Taskar)

- Decision Tables (Decision, one)
- Decision Trees (Decision, sequential)
- Bayesian Networks (Diagnosis, aposteriori)
- Influence Diagrams (Decision, general,  $ID = BN + Decisions + Utility$ )
- ...



# Graphical Models for Decision Making

## References and Software Tools

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References and software tools

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# Graphical Models for Decision Making

References and software tools

## Software Tools

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Packages:

bnlearn, deal, pcalg, catnet, mugnet, bayesclass → learning  
gRbase, gRain → inference

- GeNie
- Bayesia
- Netica
- Hugin
- ...

# Graphical Models for Decision Making

## Outline

- Introduction
- Decision tables and decision trees.
- Bayesian networks
- Influence diagrams
- Practice: problems + models + evaluation + analysis
- Qualification: deliver solution of practical exercises

# ¿Remarks and Questions?

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12/01/2015, CIG