Lecture 5
Baysian Networks

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Course Overview

- ✓ Introduction
  - ✓ Artificial Intelligence
  - ✓ Intelligent Agents
- ✓ Search
  - ✓ Uninformed Search
  - ✓ Heuristic Search
- Uncertain knowledge and Reasoning
  - Probability and Bayesian approach
  - Bayesian Networks
  - Hidden Markov Chains
  - Kalman Filters
- Learning
  - Supervised
    Learning Bayesian Networks, Neural Networks
  - Unsupervised
    EM Algorithm
- Reinforcement Learning
- Games and Adversarial Search
  - Minimax search and Alpha-beta pruning
  - Multiagent search
- Knowledge representation and Reasoning
  - Propositional logic
  - First order logic
  - Inference
  - Plannning

Outline

1. Probability Basis
2. Bayesian networks

Summary

Probability is a rigorous formalism for uncertain knowledge

Joint probability distribution specifies probability of every atomic event
Queries can be answered by summing over atomic events

For nontrivial domains, we must find a way to reduce the joint size

Independence and conditional independence provide the tools

Outline

1. Probability Basis
2. Bayesian networks

Outline

- ♢ Syntax
- ♢ Semantics
- ♢ Parameterized distributions

Bayesian networks

Definition

A simple, graphical notation for conditional independence assertions and hence for compact specification of full joint distributions

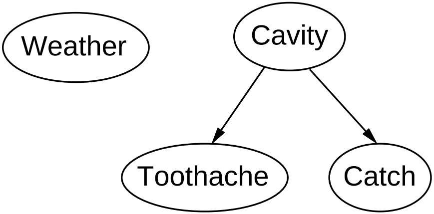
Syntax:

a set of nodes, one per variable
a directed, acyclic graph (link ≈ "directly influences")
a conditional distribution for each node given its parents:
$\Pr(X_i \mid Parents(X_i))$

In the simplest case, conditional distribution represented as a conditional probability table (CPT) giving the distribution over X_i for each combination of parent values

Example

Topology of network encodes conditional independence assertions:



Weather is independent of the other variables
Toothache and *Catch* are conditionally independent given *Cavity*

Example

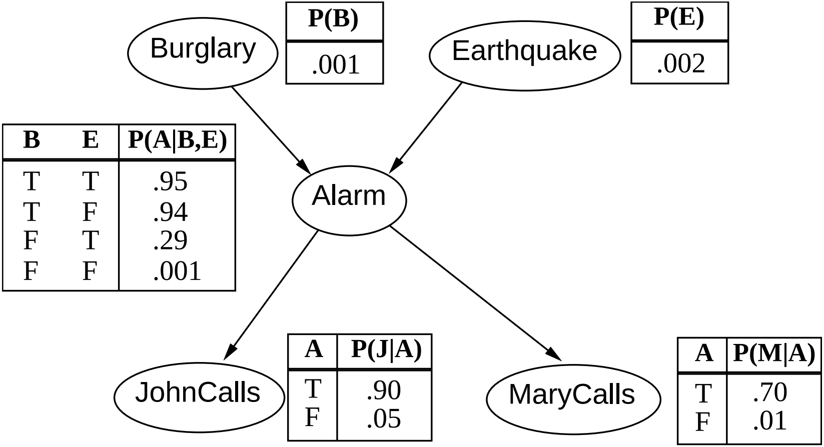
I'm at work, neighbor John calls to say my alarm is ringing, but neighbor Mary doesn't call. Sometimes it's set off by minor earthquakes. Is there a burglar?

Variables: *Burglar*, *Earthquake*, *Alarm*, *JohnCalls*, *MaryCalls*

Network topology reflects "causal" knowledge:

- A burglar can set the alarm off
- An earthquake can set the alarm off
- The alarm can cause Mary to call
- The alarm can cause John to call

Example contd.



P(B)
.001

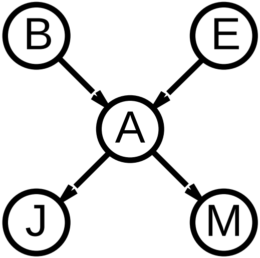
P(E)
.002

B	**E**	**P(A|B,E)**
T	T	.95
T	F	.94
F	T	.29
F	F	.001

A	**P(J|A)**
T	.90
F	.05

A	**P(M|A)**
T	.70
F	.01

Compactness



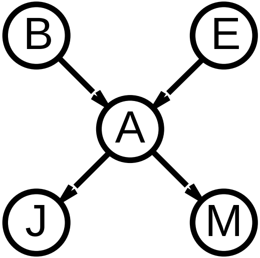
A CPT for Boolean X_i with k Boolean parents has 2^k rows for the combinations of parent values

Each row requires one number p for $X_i = true$
(the number for $X_i = false$ is just $1 - p$)
If each variable has no more than k parents,
the complete network requires $O(n \cdot 2^k)$ numbers

I.e., grows linearly with n, vs. $O(2^n)$ for the full joint distribution

For burglary net, $1 + 1 + 4 + 2 + 2 = 10$ numbers
(vs. $2^5 - 1 = 31$)

Global semantics



"Global" semantics defines the full joint distribution as the product of the local conditional distributions:

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid parents(X_i))$$

e.g., $P(j \wedge m \wedge a \wedge \neg b \wedge \neg e)$

$$\begin{aligned} &= P(j \mid a)P(m \mid a)P(a \mid \neg b, \neg e)P(\neg b)P(\neg e) \\ &= 0.9 \times 0.7 \times 0.001 \times 0.999 \times 0.998 \\ &\approx 0.00063 \end{aligned}$$

Constructing Bayesian networks

Need a method such that a series of locally testable assertions of conditional independence guarantees the required global semantics

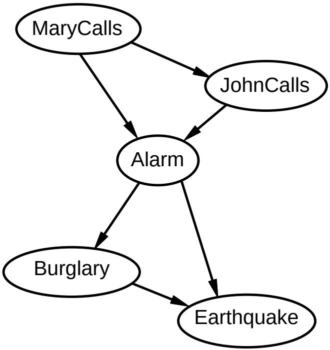
- Choose an ordering of variables $X_1, \ldots, X_n$
- For $i = 1$ to n
  add X_i to the network
  select parents from $X_1, \ldots, X_{i-1}$ such that
  $\Pr(X_i \mid Parents(X_i)) = \Pr(X_i \mid X_1, \ldots, X_{i-1})$

This choice of parents guarantees the global semantics:

$$\begin{aligned}\Pr(X_1, \ldots, X_n) &= \prod_{i=1}^{n} \Pr(X_i \mid X_1, \ldots, X_{i-1}) \quad \text{(chain rule)} \\ &= \prod_{i=1}^{n} \Pr(X_i \mid Parents(X_i)) \quad \text{(by construction)}\end{aligned}$$

Example

Suppose we choose the ordering M, J, A, B, E



$P(J \mid M) = P(J)$? No
$P(A \mid J, M) = P(A \mid J)$?
$P(A \mid J, M) = P(A)$? No
$P(B \mid A, J, M) = P(B \mid A)$? Yes
$P(B \mid A, J, M) = P(B)$? No
$P(E \mid B, A, J, M) = P(E \mid A)$? No
$P(E \mid B, A, J, M) = P(E \mid A, B)$?
Yes

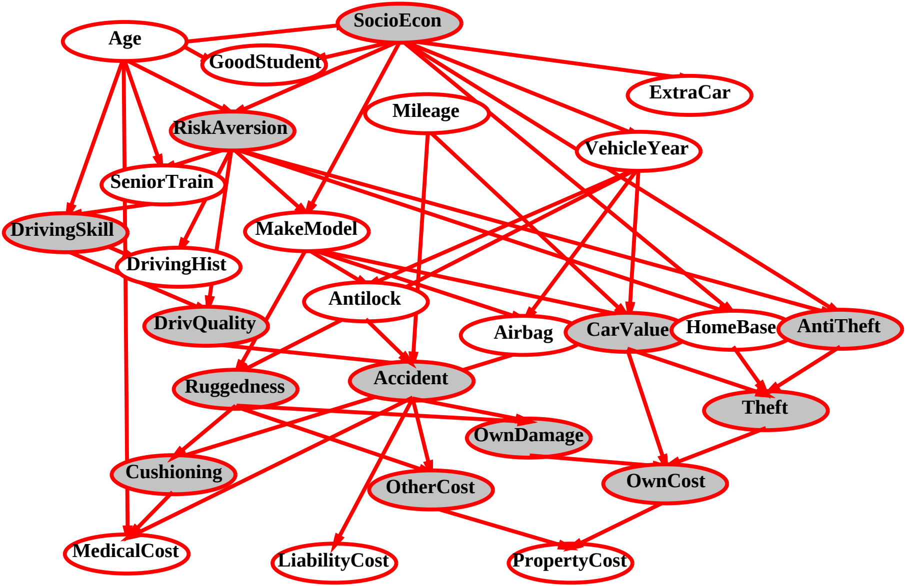
Deciding conditional independence is hard in noncausal directions

(Causal models and conditional independence seem hardwired for humans!)

Assessing conditional probabilities is hard in noncausal directions

Network is less compact:
$1 + 2 + 4 + 2 + 4 = 13$ numbers needed

Example: Car insurance



Compact conditional distributions

CPT grows exponentially with number of parents
CPT becomes infinite with continuous-valued parent or child

Solution:
canonical distributions that are defined compactly

Deterministic nodes are the simplest case:
$X = f(Parents(X))$ for some function f

E.g., Boolean functions
$NorthAmerican \Leftrightarrow Canadian \lor US \lor Mexican$

E.g., numerical relationships among continuous variables

$$\frac{\partial Level}{\partial t} = \text{ inflow + precipitation - outflow - evaporation}$$

Compact conditional distributions contd.

Noisy-OR distributions model multiple noninteracting causes

1) Parents $U_1 \ldots U_k$ include all causes (can add leak node)

2) Independent failure probability q_i for each cause alone

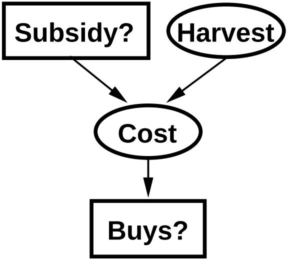
$$\Longrightarrow P(X \mid U_1 \ldots U_j, \neg U_{j+1} \ldots \neg U_k) = 1 - \prod_{i=1}^{j} q_i$$

Cold	*Flu*	*Malaria*	$P(Fever)$	$P(\neg Fever)$
F	F	F	**0.0**	1.0
F	F	T	0.9	**0.1**
F	T	F	0.8	**0.2**
F	T	T	0.98	$0.02 = 0.2 \times 0.1$
T	F	F	0.4	**0.6**
T	F	T	0.94	$0.06 = 0.6 \times 0.1$
T	T	F	0.88	$0.12 = 0.6 \times 0.2$
T	T	T	0.988	$0.012 = 0.6 \times 0.2 \times 0.1$

Number of parameters **linear** in number of parents

Hybrid (discrete+continuous) networks

Discrete (*Subsidy?* and *Buys?*); continuous (*Harvest* and *Cost*)



Option 1: discretization—possibly large errors, large CPTs
Option 2: finitely parameterized canonical families
1) Continuous variable, discrete+continuous parents (e.g., *Cost*)
2) Discrete variable, continuous parents (e.g., *Buys?*)

Continuous child variables

Need one conditional density function for child variable given continuous parents, for each possible assignment to discrete parents

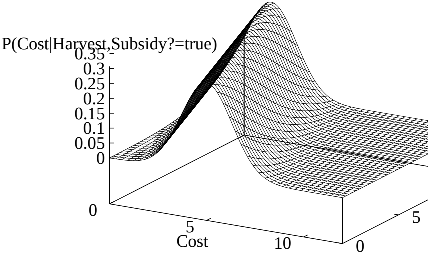
Most common is the linear Gaussian model, e.g.,:

$$
\begin{aligned}
&P(\mathit{Cost} = c \mid \mathit{Harvest} = h, \mathit{Subsidy} = \mathit{true}) \\
&\quad = \quad N(a_t h + b_t, \sigma_t) \\
&\quad = \quad \frac{1}{\sigma_t \sqrt{2\pi}} \mathit{exp} \left(-\frac{1}{2} \left(\frac{c - (a_t h + b_t)}{\sigma_t} \right)^2 \right)
\end{aligned}
$$

Mean *Cost* varies linearly with *Harvest*, variance is fixed

⇝Linear variation is unreasonable over the full range
but works OK if the **likely** range of *Harvest* is narrow

Continuous child variables

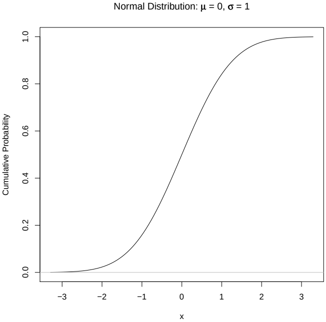


All-continuous network with linear Gaussian distributions
⟹ full joint distribution is a multivariate Gaussian

Discrete+continuous linear Gaussian network is a conditional Gaussian network i.e., a multivariate Gaussian over all continuous variables for each combination of discrete variable values

Discrete variable w/ continuous parents

Probability of *Buys?* given *Cost* should be a “soft” threshold:



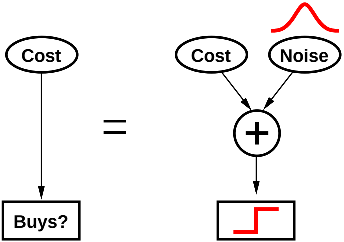
Probit distribution uses integral of Gaussian:

$$\Phi(x) = \int_{-\infty}^{x} N(0,1)(x)dx$$

$$P(Buys? = true \mid Cost = c) = \Phi((-c + \mu)/\sigma)$$

Why the probit?

1. It's sort of the right shape
2. Can be viewed as hard threshold whose location is subject to noise

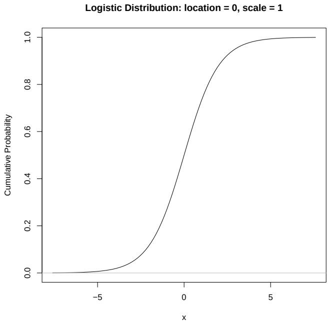


Discrete variable contd.

Sigmoid (or logit) distribution also used in neural networks:

$$P(Buys? = true \mid Cost = c) = \frac{1}{1 + exp(-2\frac{-c+\mu}{\sigma})}$$

Sigmoid has similar shape to probit but much longer tails:



Summary

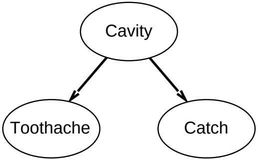
- Bayes nets provide a natural representation for (causally induced) conditional independence
- Topology + CPTs = compact representation of joint distribution
- Generally easy for (non)experts to construct
- Canonical distributions (e.g., noisy-OR) = compact representation of CPTs
- Continuous variables $\Longrightarrow$ parameterized distributions (e.g., linear Gaussian)

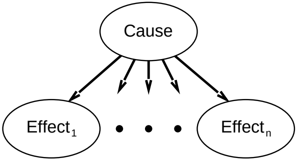
Bayes' Rule and conditional independence

$$\begin{aligned}
&\Pr(\mathit{Cavity} \mid \mathit{toothache} \wedge \mathit{catch}) \\
&\quad = \quad \alpha \Pr(\mathit{toothache} \wedge \mathit{catch} \mid \mathit{Cavity}) \Pr(\mathit{Cavity}) \\
&\quad = \quad \alpha \Pr(\mathit{toothache} \mid \mathit{Cavity}) \Pr(\mathit{catch} \mid \mathit{Cavity}) \Pr(\mathit{Cavity})
\end{aligned}$$

This is an example of a naive Bayes model:

$$\Pr(\mathit{Cause}, \mathit{Effect}_1, \ldots, \mathit{Effect}_n) = \Pr(\mathit{Cause}) \prod_i \Pr(\mathit{Effect}_i \mid \mathit{Cause})$$

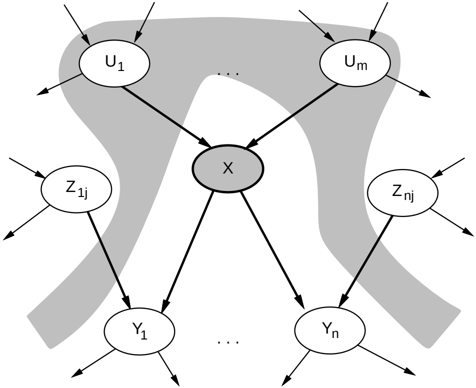




Total number of parameters is **linear** in n

Local semantics

Local semantics: each node is conditionally independent of its nondescendants given its parents



Theorem: Local semantics ⇔ global semantics

Markov blanket

Each node is conditionally independent of all others given its Markov blanket: parents + children + children's parents