

Bayesian networks

Chapter 14.4–5

Outline

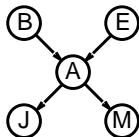
- ▶ Exact inference by enumeration
- ▶ Exact inference by variable elimination
- ▶ Approximate inference by stochastic simulation
- ▶ Approximate inference by Markov chain Monte Carlo


Inference tasks

- ▶ Simple queries: compute posterior marginal $P(X_i | \mathbf{E} = e)$
e.g., $P(\text{NoGas} | \text{Gauge} = \text{empty}, \text{Lights} = \text{on}, \text{Starts} = \text{false})$
- ▶ Conjunctive queries:
$$P(X_i, X_j | \mathbf{E} = e) = P(X_i | \mathbf{E} = e) P(X_j | X_i, \mathbf{E} = e)$$
- ▶ Optimal decisions: decision networks include utility information; probabilistic inference required for $P(\text{outcome} | \text{action}, \text{evidence})$
- ▶ Value of information: which evidence to seek next?
- ▶ Sensitivity analysis: which probability values are most critical?
- ▶ Explanation: why do I need a new starter motor?

Inference by enumeration

- ▶ Slightly intelligent way to sum out variables from the joint without actually constructing its explicit representation
- ▶ Simple query on the burglary network:



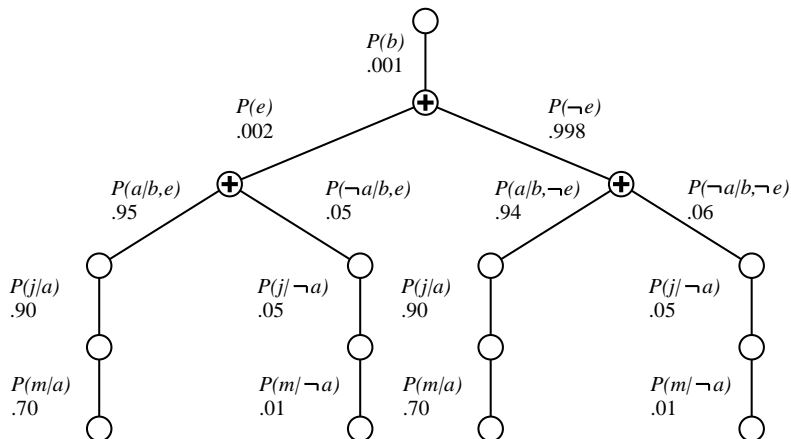

$$\begin{aligned} P(B|j, m) &= \\ &= P(B, j, m) / P(j, m) = \\ &= \alpha P(B, j, m) \\ &= \alpha \sum_e \sum_a P(B, e, a, j, m) \end{aligned}$$

- ▶ Rewrite full joint entries using product of CPT entries:

$$\begin{aligned} P(B|j, m) &= \alpha \sum_e \sum_a P(B) P(e) P(a|B, e) P(j|a) P(m|a) \\ &= \alpha P(B) \sum_e P(e) \sum_a P(a|B, e) P(j|a) P(m|a) \end{aligned}$$

- ▶ Recursive depth-first enumeration: $O(n)$ space, $O(d^n)$ time

Evaluation tree



Enumeration is inefficient: repeated computation e.g., computes $P(j|a)P(m|a)$ for each value of e

Inference by variable elimination

Variable elimination: carry out summations right-to-left, storing intermediate results (**factors**) to avoid re-computation

$$\begin{aligned}P(B|j, m) &= \alpha \underbrace{P(B)}_B \sum_e \underbrace{P(e)}_E \sum_a \underbrace{P(a|B, e)}_A \underbrace{P(j|a)}_J \underbrace{P(m|a)}_M \\&= \alpha P(B) \sum_e P(e) \sum_a P(a|B, e) P(j|a) f_M(a) \\&= \alpha P(B) \sum_e P(e) \sum_a P(a|B, e) f_J(a) f_M(a) \\&= \alpha P(B) \sum_e P(e) \sum_a f_A(a, b, e) f_J(a) f_M(a) \\&= \alpha P(B) \sum_e P(e) f_{AJM}(b, e) (\text{sumout } A) \\&= \alpha P(B) f_{E\bar{A}JM}(b) (\text{sumout } E) \\&= \alpha f_B(b) \times f_{E\bar{A}JM}(b).\end{aligned}$$

Variable elimination: Basic operations

Summing out a variable from a product of factors:

- ▶ move any constant factors outside the summation
- ▶ add up submatrices in pointwise product of remaining factors

$$\sum_x f_1 \times \cdots \times f_k = f_1 \times \cdots \times f_i \sum_x f_{i+1} \times \cdots \times f_k = f_1 \times \cdots \times f_i \times f_{\bar{X}}$$

assuming f_1, \dots, f_i do not depend on X .

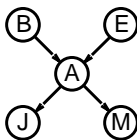
Pointwise product of factors f_1 and f_2 :

$$\begin{aligned} f_1(x_1, \dots, x_j, y_1, \dots, y_k) \times f_2(y_1, \dots, y_k, z_1, \dots, z_l) \\ = f(x_1, \dots, x_j, y_1, \dots, y_k, z_1, \dots, z_l) \end{aligned}$$

E.g., $f_1(a, b) \times f_2(b, c) = f(a, b, c)$

Irrelevant variables

Consider the query $P(\text{JohnCalls} | \text{Burglary} = \text{true})$



$$P(J|b) = \alpha P(b) \sum_e P(e) \sum_a P(a|b, e) P(J|a) \sum_m P(m|a)$$

Sum over m is identically 1; M is **irrelevant** to the query.

Thm 1:

Y is irrelevant to $P(X|\dots)$, unless $Y \in \text{Ancestors}(\{X\} \cup \mathbf{E})$

Here, $X = \text{JohnCalls}$, $\mathbf{E} = \{\text{Burglary}\}$,

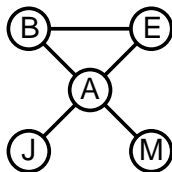
$\text{Ancestors}(\{X\} \cup \mathbf{E}) = \{\text{Alarm}, \text{Earthquake}\}$

$\implies \text{MaryCalls}$ is irrelevant

(Compare this to backward chaining from the query in Horn clause KBs)

Irrelevant variables (continued)

- ▶ **Definition:** moral graph of Bayes net: marry all parents and drop arrows
- ▶ **Definition:** **A** is m-separated from **B** by **C** \iff separated by **C** in the moral graph
- ▶ **Theorem 2:** **Y** is irrelevant if m-separated from **X** by



- ▶ For $P(\text{JohnCalls} | \text{Alarm} = \text{true})$, both *Burglary* and *Earthquake* are irrelevant

Complexity of exact inference –1

- ▶ **Singly connected networks (polytrees)**

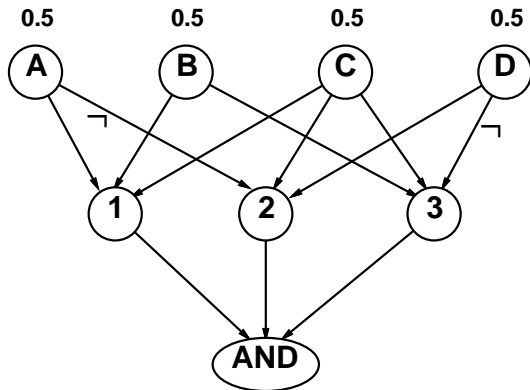
- ▶ any two nodes are connected by at most one (undirected) path
- ▶ time and space cost of variable elimination are $O(d^k n)$

- ▶ **Multiply connected networks**

- ▶ can reduce 3SAT to exact inference \implies NP-hard
- ▶ equivalent to **counting** 3SAT models \implies #P-complete ("number-P hard"), i.e. strictly harder than NP-complete.

Complexity of exact inference – 2

1. $A \vee B \vee C$
2. $C \vee D \vee \neg A$
3. $B \vee C \vee \neg D$



► Basic idea

1. Draw N samples from a sampling distribution



2. Compute an approximate posterior probability \hat{P}
3. Show this converges to the true probability P

► Outline

1. Sampling from an empty network
2. Rejection sampling: reject samples disagreeing with evidence
3. Likelihood weighting: use evidence to weight samples
4. Markov chain Monte Carlo (MCMC): sample from a stochastic process whose stationary distribution is the true posterior

Sampling from an empty network

Prior-Sample(bn): an event sampled from bn

Input: **bn** - a belief network specifying joint distribution

$P(X_1, \dots, X_n)$

x is an event with n elements

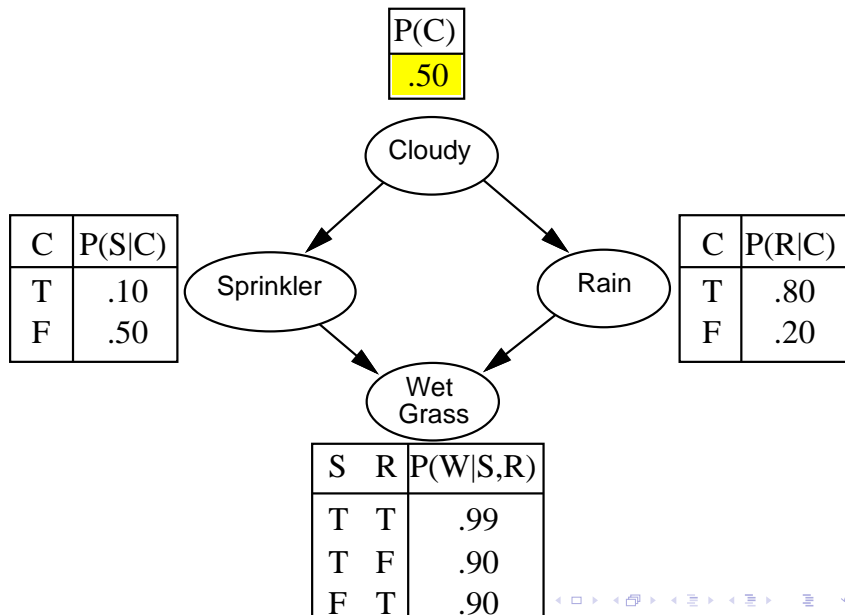
For $i = 1$ to n do

x_i : a random sample from $P(X_i | Parents(X_i))$

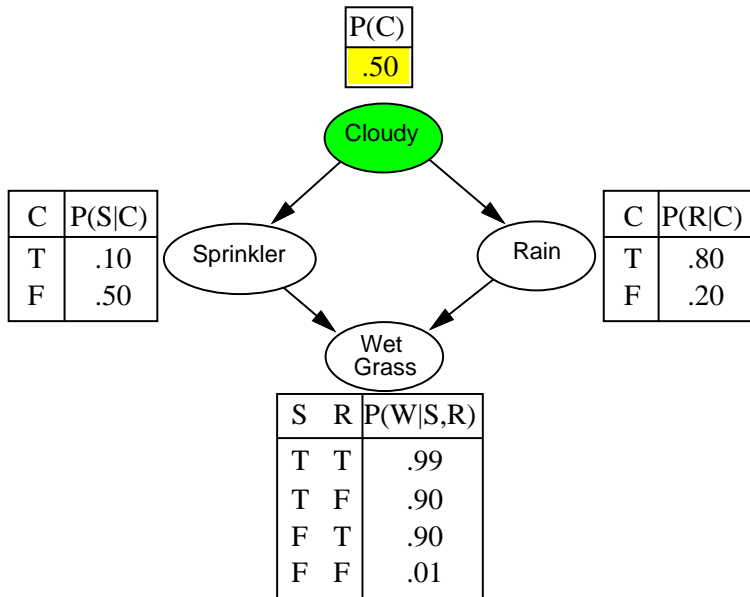
 given the values of $Parents(X_i)$ in x

Return

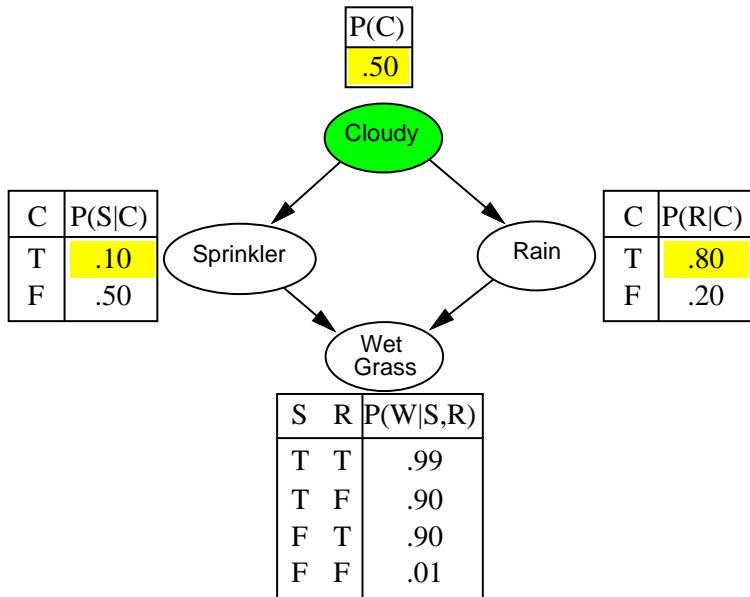
Example



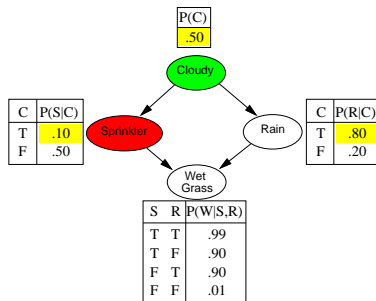
Example



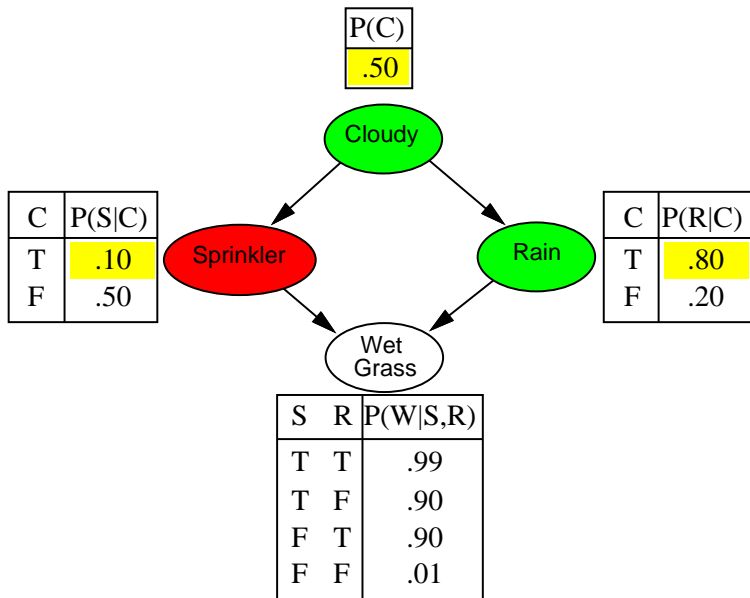
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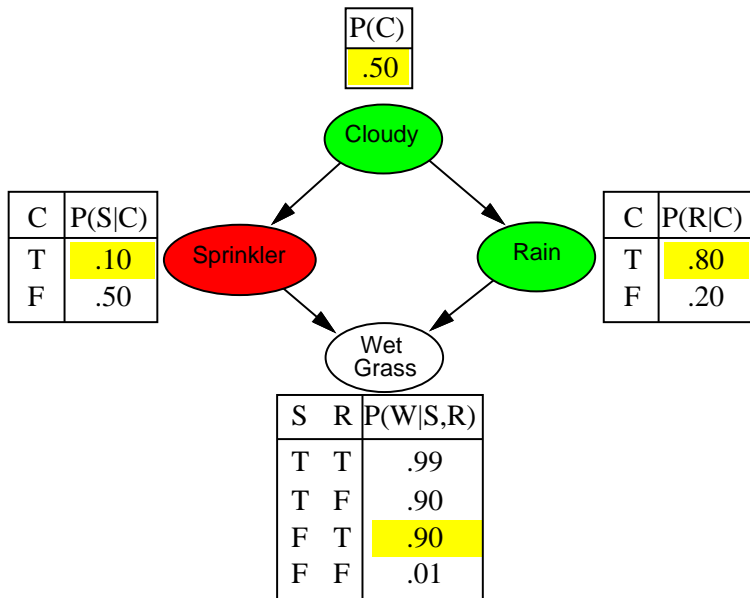
Example



Example



Example



Example

