

Inference by Enumeration



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Bayesian Networks

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Bayesian Networks

- Okay, so what can we do with Bayesian Networks?
- They are useful for inference (a conclusion reached on the basis of evidence and reasoning)

Inference tasks

- **Simple queries:** compute posterior marginal $\mathbf{P}(X_i|\mathbf{E} = e)$
 $\mathbf{P}(\textit{Listening} = \textit{true}|\textit{Status} = \textit{excited})$
- **Conjunctive queries**
 $\mathbf{P}(X_i, X_j|\mathbf{E} = \mathbf{e}) = \mathbf{P}(X_i|\mathbf{E} = e)\mathbf{P}(X_j|X_i, \mathbf{E} = e)$
- **Optimal decisions:** decision networks include utility information; probabilistic inference required for $P(\textit{outcome}|\textit{action}, \textit{evidence})$
- **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 tasks

- We will focus on simple queries:
- Compute posterior marginal
$$\mathbf{P}(X_i|\mathbf{E} = e)$$
$$\mathbf{P}(\textit{Listening} = \textit{true}|\textit{Status} = \textit{excited})$$
- We will look a several ways of doing this.
 1. Enumeration
 2. Rejection sampling (using prior sampling)
 3. Likelihood weighting
 4. Gibbs sampling

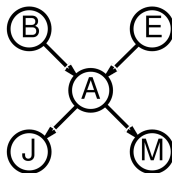
Inference by enumeration

- Simplest approach to evaluating the network is to do just as we did for the dentist example
- Difference is that we use the structure of the network to tell us which sets of joint probabilities to use.
 - Thanks Professor Markov
- Gives us a slightly intelligent way to sum out variables from the joint without actually constructing its explicit representation

Inference by enumeration

- Simple query on the burglary network.

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



- Rewrite full joint entries taking network into account:

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

Inference by enumeration

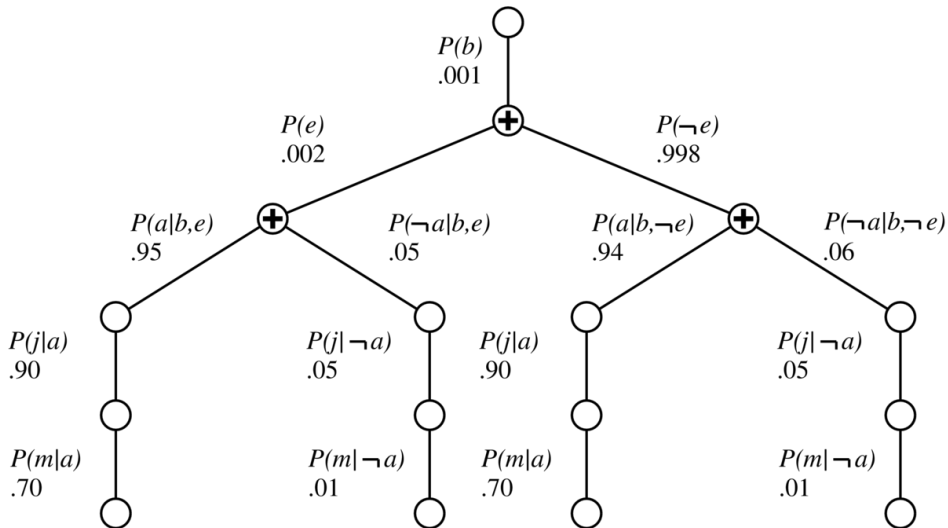
- We evaluate this expression

$$\mathbf{P}(B|j, m) = \alpha \mathbf{P}(B) \sum_e P(e) \sum_a \mathbf{P}(a|B, e) P(j|a) P(m|a)$$

by going through the variables in order, multiplying CPT entries along the way.

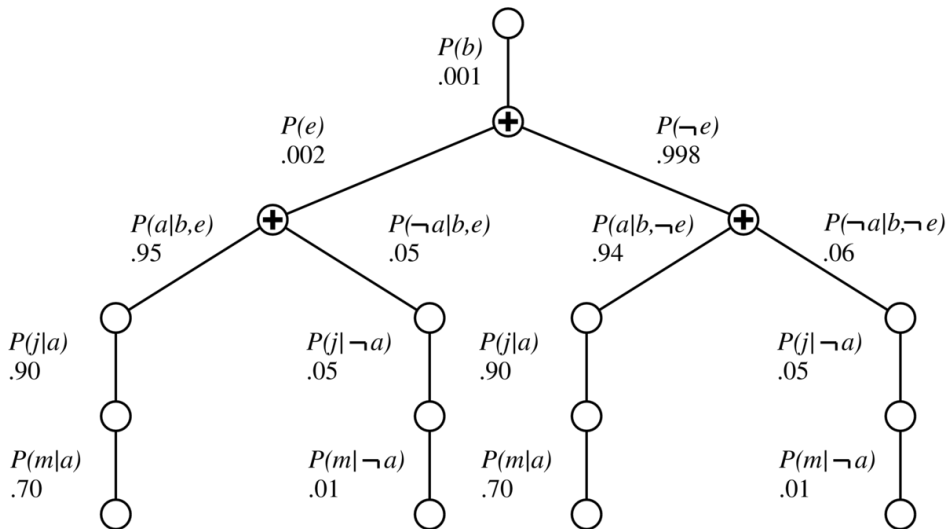
- At each point, we need to loop through the possible values of the variable.
- Involves a lot of repeated calculations.

Evaluation tree



$$\mathbf{P}(B|j,m) = \alpha \mathbf{P}(B) \sum_e P(e) \sum_a \mathbf{P}(a|B,e) P(j|a) P(m|a)$$

Evaluation tree



Inefficient: computes $P(j|a)P(m|a)$ for each value of e

Enumeration algorithm

function ENUMERATION-ASK(X, \mathbf{e}, bn) **returns** a distribution over X

inputs: X , the query variable

\mathbf{e} , observed values for variables \mathbb{E}

bn , a Bayesian network $\{X\} \cup \mathbb{E} \cup \mathbf{Y}$

$Q(X) \leftarrow$ a distribution over X , initially empty

for each value x_i of X **do**

 extend \mathbf{e} with value x_i for X

$Q(x_i) \leftarrow \text{ENUMERATE-ALL}(\text{VARS}[bn], \mathbf{e})$

return NORMALIZE($Q(X)$)

Enumeration algorithm

function **ENUMERATE-ALL**($vars, \mathbf{e}$) **returns** a real number
 if **EMPTY?**($vars$) **then return** 1.0
 $Y \leftarrow \text{FIRST}(vars)$
 if Y has value y in \mathbf{e}
 then return $P(y \mid Pa(Y))$
 $\times \text{ENUMERATE-ALL}(\text{REST}(vars), \mathbf{e})$
 else return $\sum_y P(y \mid Pa(Y))$
 $\times \text{ENUMERATE-ALL}(\text{REST}(vars), \mathbf{e}_y)$
 where \mathbf{e}_y is \mathbf{e} extended with $Y = y$

Other exact approaches

- We can improve on enumeration.
- **Variable elimination** evaluates the enumeration tree bottom up, remembering intermediate values.
 - Simple and efficient for single queries
- **Clustering algorithms** can be more efficient for multiple queries
 - Group variables together strategically.
- However, *all* exact inference can be computationally intractable.

Complexity of exact inference

- **Singly connected** networks (or **polytrees**)
- Any two nodes are connected by at most one (undirected) path
- Time and space cost of variable elimination are:

$$O(d^k n)$$

for k parents, d values.

Complexity of exact inference

- **Multiply connected** networks.
- Exponential time and space complexity, even when number of parents of a node is bounded.
- Inference is NP-hard.
- In fact, #P-complete.

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

