CS 730/730W/830: Intro AI

Bayesian Networks

Approx. Inference

Exact Inference

1 handout: slides final blog entries were due

Bayesian Networks

- **■** Example
- Reminder

Approx. Inference

Exact Inference

Bayesian Networks

The Alarm Domain

Bayesian Networks

■ Example

■ Reminder

Approx. Inference

Exact Inference

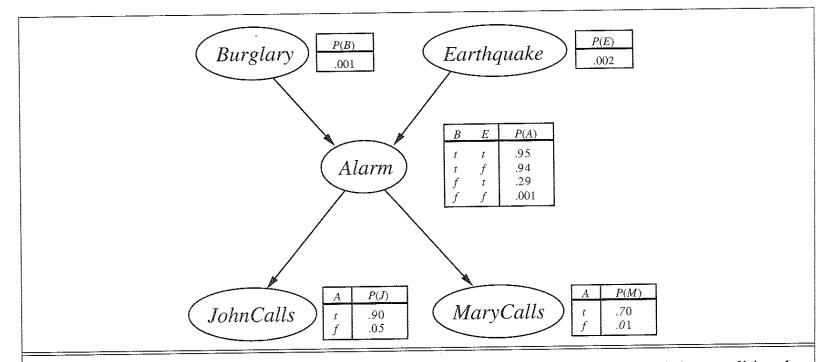


Figure 14.2 A typical Bayesian network, showing both the topology and the conditional probability tables (CPTs). In the CPTs, the letters B, E, A, J, and M stand for Burglary, Earthquake, Alarm, JohnCalls, and MaryCalls, respectively.

Bayes Nets Reminder

Bayesian Networks

 \blacksquare Example

■ Reminder

Approx. Inference

Exact Inference

In general:

$$P(x_1, \dots, x_n) = P(x_n | x_{n-1}, \dots, x_1) P(x_{n-1}, \dots, x_1)$$

Bayes Nets Reminder

Bayesian Networks

■ Example

Reminder

Approx. Inference

Exact Inference

In general:

$$P(x_1, \dots, x_n) = P(x_n | x_{n-1}, \dots, x_1) P(x_{n-1}, \dots, x_1)$$
$$= \prod_{i=1}^n P(x_i | x_{i-1}, \dots, x_1)$$

Bayes Net specifies independence:

$$P(X_i|X_{i-1},\ldots,X_1) = P(X_i|parents(X_i))$$

joint distribution:

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

What is distribution of X given evidence e and unobserved Y?

Bayesian Networks

Approx. Inference

- Basic Sampling
- Rej. Sampling
- Likelihood Wting
- Break

Exact Inference

Approximate Inference

Sampling According to the Joint Distribution

Bayesian Networks

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Basic Sampling
Rej. Sampling
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Break

Exact Inference

sample values for variables, working top down

directly implements the semantics of the network 'generative model'

each sample is linear time

Rejection Sampling

Bayesian Networks

Approx. Inference

Basic Sampling

Rej. Sampling

Likelihood Wting

Break

Exact Inference

What is distribution of X given evidence e and unobserved Y?

Draw worlds from the joint, rejecting those that do not match e. Look at distribution of X.

each sample is linear time, but overall slow if e is unlikely

Likelihood Weighting

Bayesian Networks

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Exact Inference

What is distribution of X given evidence e and unobserved Y?

ChooseSample (e)

$$w \leftarrow 1$$
 for each variable V_i in topological order:

if
$$(V_i = v_i) \in e$$
 then $w \leftarrow w \cdot P(v_i | parents(v_i))$

else

 $v_i \leftarrow \mathsf{sample} \ \mathsf{from} \ P(V_i | parents(V_i))$

(afterwards, normalize samples so all w's sum to 1)

uses all samples, but needs lots of samples if e are late in ordering

Break

Bayesian Networks

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Exact Inference

- exam 3: calculator, review session May 4
- projects

Bayesian Networks

Approx. Inference

Exact Inference

- **■** Enumeration
- **■** Example
- Var. Elim. 1
- Var. Elim. 2
- **■** EOLQs

Exact Inference in Bayesian Networks

Enumeration Over the Joint Distribution

Bayesian Networks

Approx. Inference

Exact Inference

- Enumeration
- **■** Example
- Var. Elim. 1
- Var. Elim. 2
- **■** EOLQs

What is distribution of X given evidence e and unobserved Y?

$$P(X|e) = \frac{P(e|X)P(X)}{P(e)}$$

$$= \alpha P(X,e)$$

$$= \alpha \sum_{y} P(X,e,y)$$

$$= \alpha \sum_{y} \prod_{i=1}^{n} P(V_i|parents(V_i))$$

Example

Bayesian Networks

Approx. Inference

Exact Inference

■ Enumeration

■ Example

- Var. Elim. 1
- Var. Elim. 2
- **■** EOLQs

$$P(B|j,m) = \frac{P(j,m|B)P(B)}{P(j,m)}$$

$$= \alpha P(B,j,m)$$

$$= \alpha \sum_{e} \sum_{a} P(B,e,a,j,m)$$

$$= \alpha \sum_{e} \sum_{a} \prod_{i=1}^{n} P(V_{i}|parents(V_{i}))$$

$$P(b|j,m) = \alpha \sum_{e} \sum_{a} P(b)P(e)P(a|b,e)P(j|a)P(m|a)$$

$$= \alpha P(b) \sum_{e} P(e) \sum_{a} P(a|b,e)P(j|a)P(m|a)$$

[draw tree]

Variable Elimination

Bayesian Networks

Approx. Inference

Exact Inference

- **■** Enumeration
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- Var. Elim. 2
- **■** EOLQs

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

factors = tables = $f_{varsused}(dimensions)$.

eg: $f_A(A, B, E)$, $f_M(A)$

multiplying factors: table with union of variables summing reduces table

Variable Elimination

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- **■** Enumeration
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- **■** EOLQs

eliminating variables: eg P(J|b)

$$P(J|b) = \alpha P(b) \sum_{e} P(e) \sum_{a} P(a|b,e) P(J|a) \sum_{m} P(m|a)$$

all vars not ancestor of query or evidence are irrelevant!

EOLQs

Bayesian Networks

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- **■** Enumeration
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- Var. Elim. 1
- Var. Elim. 2
- EOLQs

- What question didn't you get to ask today?
- What's still confusing?
- What would you like to hear more about?

Please write down your most pressing question about AI and put it in the box on your way out.

Thanks!