

Inferences in Bayesian Networks

Variable Elimination Algorithm

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Lecture 13

Readings: RN 14.4. PM 8.4.

Outline

Learning Goals

Why Use the Variable Elimination Algorithm

The Variable Elimination Algorithm

Revisiting the Learning goals

Learning Goals

By the end of the lecture, you should be able to

- ▶ Explain how we can perform probabilistic inference more efficiently using the variable elimination algorithm.
- ▶ Define factors. Manipulate factors using operations restrict, sum out, multiply and normalize.
- ▶ Describe/trace/implement the variable elimination algorithm for calculating a prior or a posterior probability given a Bayesian network.
- ▶ Explain how the elimination ordering affects the complexity of the variable elimination algorithm.
- ▶ Identify the variables that are irrelevant to a query.

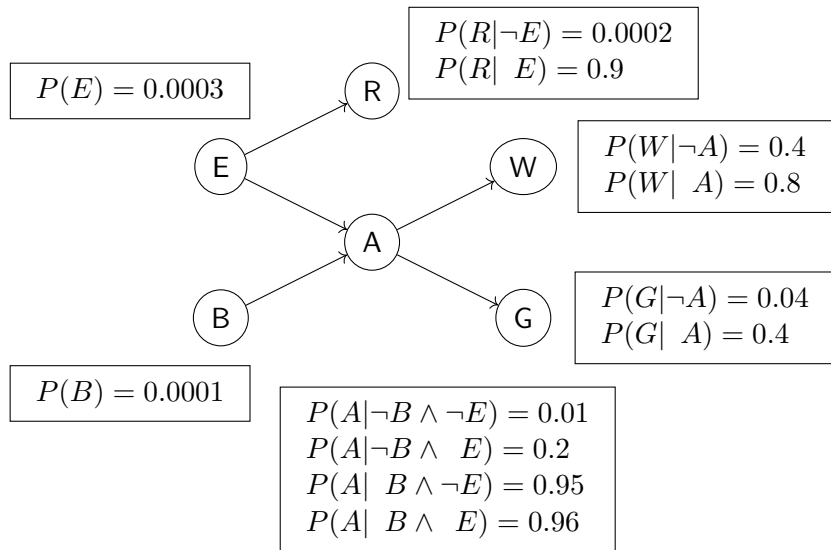
Learning Goals

Why Use the Variable Elimination Algorithm

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Revisiting the Learning goals

A Bayesian Network for the Holmes Scenario



Answering a Question

What is the probability that a burglary is happening given that Dr. Watson and Mrs. Gibbon both call?

$$P(B|w \wedge g)$$

- ▶ Query variables: B
- ▶ Evidence variables: W and G
- ▶ Hidden variables: E , A , and R .

Answering the query using the joint distribution

$$P(B|w \wedge g) =$$

Number of operations using the joint distribution

How many addition and multiplication operations do we need to calculate the expression below?

$$\sum_e \sum_a \sum_r P(B)P(e)P(a|B \wedge e)P(w|a)P(g|a)P(r|e)$$

- (A) ≤ 10
- (B) 11-20
- (C) 21-40
- (D) 41-60
- (E) ≥ 61

Answering the query using variable elimination algorithm

$$\sum_e \sum_a \sum_r P(B)P(e)P(a|B \wedge e)P(w|a)P(g|a)P(r|e)$$

Number of operations via the variable elimination algorithm

How many addition and multiplication operations do we need to calculate the expression below?

$$P(B) \sum_e P(e) \sum_a P(a|B \wedge e)P(w|a)P(g|a)$$

- (A) ≤ 10
- (B) 11-20
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- (D) 41-60
- (E) ≥ 61

Learning Goals

Why Use the Variable Elimination Algorithm

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Revisiting the Learning goals

Introducing the Variable Elimination Algorithm

- ▶ Performing probabilistic inference is challenging.
- ▶ Exact and approximate inferences.
- ▶ The variable elimination algorithm uses dynamic programming and exploits the conditional independence.

Factors

- ▶ A function from some random variables to a number.
- ▶ $f(X_1, \dots, X_j)$: a factor f on variables X_1, \dots, X_j .
- ▶ A factor can represent a joint or a conditional distribution.
For example, $f(X_1, X_2)$ can represent $P(X_1 \wedge X_2)$, $P(X_1|X_2)$ or $P(X_1 \wedge X_3 = v_3|X_2)$.
- ▶ Define a factor for every conditional probability distribution in the Bayes net.

Restrict a factor

Restrict a factor.

- ▶ Assign each evidence variable to its observed value.
- ▶ Restricting $f(X_1, X_2, \dots, X_j)$ to $X_1 = v_1$, produces a new factor $f(X_1 = v_1, X_2, \dots, X_j)$ on X_2, \dots, X_j .
- ▶ $f(X_1 = v_1, X_2 = v_2, \dots, X_j = v_j)$ is a number.

Restrict a factor

$f_1(X, Y, Z)$:

X	Y	Z	val
t	t	t	0.1
t	t	f	0.9
t	f	t	0.2
t	f	f	0.8
f	t	t	0.4
f	t	f	0.6
f	f	t	0.3
f	f	f	0.7

- ▶ What is $f_2(Y, Z) = f_1(x, Y, Z)$?
- ▶ What is $f_3(Y) = f_2(Y, \neg z)$?
- ▶ What is $f_4() = f_3(\neg y)$?

Sum out a variable

Sum out a variable.

Summing out X_1 with domain $\{v_1, \dots, v_k\}$ from factor $f(X_1, \dots, X_j)$, produces a factor on X_2, \dots, X_j defined by:

$$\left(\sum_{X_1} f\right)(X_2, \dots, X_j) = f(X_1 = v_1, \dots, X_j) + \dots + f(X_1 = v_k, \dots, X_j)$$

Sum out a variable

$f_1(X, Y, Z)$:

X	Y	Z	val
t	t	t	0.03
t	t	f	0.07
t	f	t	0.54
t	f	f	0.36
f	t	t	0.06
f	t	f	0.14
f	f	t	0.48
f	f	f	0.32

What is $f_2(X, Z) = \sum_Y f_1(X, Y, Z)$?

Multiplying factors

Multiply two factors together.

The **product** of factors $f_1(X, Y)$ and $f_2(Y, Z)$, where Y are the variables in common, is the factor $(f_1 \times f_2)(X, Y, Z)$ defined by:

$$(f_1 \times f_2)(X, Y, Z) = f_1(X, Y) * f_2(Y, Z).$$

Multiplying factors

f_1 :

X	Y	val
t	t	0.1
t	f	0.9
f	t	0.2
f	f	0.8

f_2 :

Y	Z	val
t	t	0.3
t	f	0.7
f	t	0.6
f	f	0.4

What is $f_1(X, Y) \times f_2(Y, Z)$?

Normalize a factor

- ▶ Convert it to a probability distribution.
- ▶ Divide each value by the sum of all the values.

f_1 :

Y	val
t	0.2
f	0.6

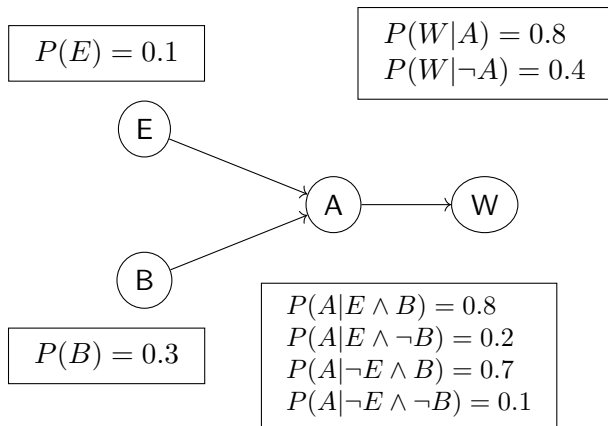
Variable elimination algorithm

To compute $P(X_q | X_{o_1} = v_1 \wedge \dots \wedge X_{o_j} = v_j)$:

- ▶ **Construct a factor** for each conditional probability distribution.
- ▶ **Restrict** the observed variables to their observed values.
- ▶ Eliminate each hidden variable X_{h_j} .
 - ▶ **Multiply** all the factors that contain X_{h_j} to get new factor g_j .
 - ▶ **Sum out** the variable X_{h_j} from the factor g_j .
- ▶ **Multiply** the remaining factors.
- ▶ **Normalize** the resulting factor.

Example of VEA

Given a portion of the Holmes network below, calculate $P(B|\neg A)$ using the variable elimination algorithm.



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