

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.

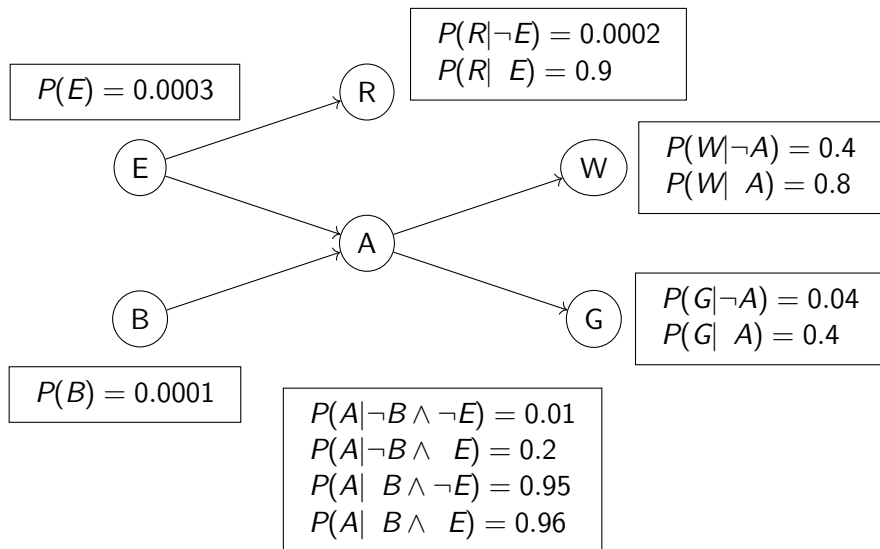
Learning Goals

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?

$$P(B = b | W = t \wedge G = t), b \in \{t, f\}$$

Shorthand notation:

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

B can be true or false

b: B is true.

$\neg b$: B is false.

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

Answering the query

$$\frac{P(B \wedge w \wedge g)}{P(w \wedge g)}$$

$$\underline{P(B|w \wedge g)} = \frac{P(B \wedge w \wedge g)}{\underbrace{P(b \wedge w \wedge g)}_{(1)} + \underbrace{P(\neg b \wedge w \wedge g)}_{(2)}}$$

$$\begin{aligned}
 & P(B \wedge w \wedge g) \\
 &= \sum_a \sum_e \sum_r P(B \wedge e \wedge a \wedge w \wedge g \wedge r) \\
 &= \sum_a \sum_e \sum_r P(B) P(e) P(r|e) P(a|B \wedge e) P(w|a) P(g|a) \\
 &= P(B) \sum_a P(w|a) P(g|a) \sum_e P(e) P(a|B \wedge e) \boxed{\sum_r P(r|e)} \\
 &\quad \quad \quad = 1
 \end{aligned}$$

Number of operations

How many addition and multiplication operations do we need to perform to evaluate the following expression?

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

Handwritten annotations for the expression above:

- $P(B)$ is highlighted in cyan with "1" below it and "8 times" above it with a downward arrow.
- $P(e)$ is highlighted in cyan with "2" below it.
- $P(r|e)$ is highlighted in cyan with "3" below it.
- $P(a|B \wedge e)$ is highlighted in cyan with "4" below it.
- $P(w|a)$ is highlighted in cyan with "5" below it.
- $P(g|a)$ is highlighted in green with "8 times" above it and a downward arrow.
- A bracket under the first three terms ($P(B)P(e)P(r|e)$) is labeled "2 times".
- A bracket under the last three terms ($P(a|B \wedge e)P(w|a)P(g|a)$) is labeled "1 time".
- A large blue bracket under the entire product of probabilities is labeled "7 additions".

(A) ≤ 10

(B) 11-20

(C) 21-40

(D) 41-60

(E) ≥ 61

7 additions.

$5 * 8 = 40$ multiplications.

47 operations.

Number of operations

How many addition and multiplication operations do we need to perform to evaluate the following expression?

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

Handwritten annotations:

- 1 multiplication (pointing to $P(B)$)
- 2 multiplications, 1 addition (pointing to the inner sum $\sum_e P(e) P(a|B \wedge e)$)
- 10 operations, 1 addition (pointing to the entire expression)

(A) ≤ 10

(B) 11-20

(C) 21-40

(D) 41-60

(E) ≥ 61

12 operations.

Learning Goals

Why Use the Variable Elimination Algorithm

The Variable Elimination Algorithm

Revisiting the Learning goals

Introducing the Variable Elimination Algorithm

- ▶ Performing probabilistic inference is challenging.
 - calculating the posterior distribution of one or more query variables given some evidence is #NP.
 - no general efficient implementation available.
- ▶ Exact and approximate inferences.
 - naive approach for exact inference: enumerate all the worlds consistent w/ evidence.
 - can do better w/ \rightarrow
- ▶ The variable elimination algorithm uses dynamic programming and exploits the conditional independence.
 \downarrow
do the calculations once and save the results for later.

VEA = factors + operations on factors
(restrict, sum out, multiply, normalize.)

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.

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

$$P(B), P(E), P(A|B \wedge E), P(R|E), P(W|A), P(G|A)$$

$$f_1(B), f_2(E), f_3(A, B, E), f_4(R, E), f_5(W, A), f_6(G, A).$$

Restrict a factor

Restrict a factor by assigning a value to the variable in the factor.

- ▶ For each observed variable, restrict the factor to the observed value.
- ▶ Restricting $f(X_1, X_2, \dots, X_j)$ to $X_1 = v_1$, $f'(X_2, \dots, X_j)$, 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. $f^*(\cdot)$

$$P(B \wedge W \wedge g) = P(B) \sum_a P(W|a) P(g|a) \sum_e P(e) P(a|B \wedge e).$$

$\uparrow \quad \uparrow$

Restrict $f_5(W, A)$ to $W = w. \Rightarrow f_7(A)$

Restrict $f_6(G, A)$ to $G = g \Rightarrow f_8(A)$

Restrict a factor

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

$f_1(X, Y, Z)$:

	Y	Z	val
$f_2(Y, Z)$:	t	t	0.1
	t	f	0.9
	f	t	0.2
	f	f	0.8

	Y	val
$f_3(Y)$:	t	0.9
	f	0.8

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


$f_4() : 0.8$

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:

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



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

Sum out e first, and a next.

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

$f_2(X, Z)$

X	Z	val
t	t	0.57
t	f	0.43
f	t	0.54
f	f	0.46

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

Multiplying factors

3 cases: f_1 and f_2 have same variables.

f_1 and f_2 have a subset of variables in common.

f_1 and f_2 have no variable in common.

Multiply two factors together.

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

element-wise multiplication

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

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

Multiplying factors

$\{X, Y\}$

f_1 :

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

$\{Y, Z\}$

f_2 :

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

$f_1 \times f_2$

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

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

f_2 :

Y	val
t	0.25
f	0.75

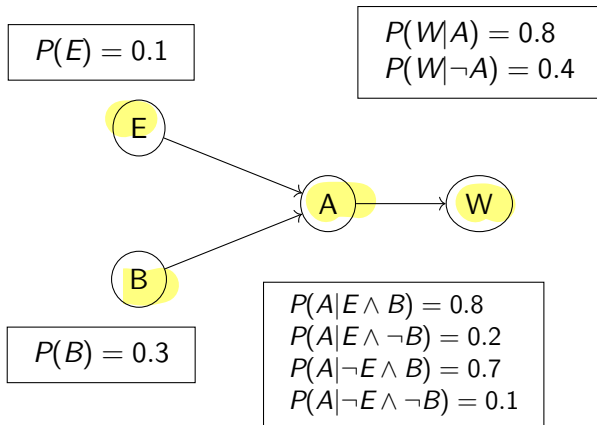
Variable elimination algorithm

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

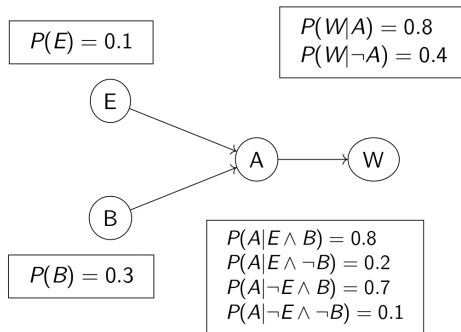
- ▶ **Construct a factor** for each conditional probability distribution.
- ▶ **Restrict** the observed variables to their observed values.
- ▶ Eliminate each hidden variable X_{h_j} . *based on some order.*
 - ▶ **Multiply** all the factors that contain X_{h_j} to get new factor g_j .
 - ▶ **Sum out**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



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



$$P(B|\neg a) = \sum_e \sum_w P(B) P(e) P(\neg a|B \wedge e) P(W|\neg a)$$

$$= P(B) \sum_e P(e) P(\neg a|B \wedge e) \sum_w P(W|\neg a)$$

query variable: B

evidence variable: A

hidden variables: E, W

① define factors:

$P(B)$ $P(E)$ $P(A|B \wedge E)$ $P(W|A)$

$f_1(B)$ $f_2(E)$ $f_3(A, B, E)$ $f_4(W, A)$

② restrict factors:

restrict $f_3(A, B, E)$ to $A = \neg a$ to get $f_5(B, E)$

restrict $f_4(W, A)$ to $A = \neg a$ to get $f_6(W)$

new factor list: $f_1(B), f_2(E), f_5(B, E), f_6(W)$

③ Get rid of hidden variables E and W .
Sum out W first and then E .

(1) multiply all the factors containing W : $f_6(W)$.

sum out W from $f_6(W)$ to get $f_7()$.

(2) multiply all the factors containing E : $f_2(E) \times f_3(B, E) = f_7(B, E)$

sum out E from $f_7(B, E)$ to get $f_8(B)$.

new factor list: $f_1(B), f_8(B), f_7()$.

④ multiply all remaining factors.

$$f_1(B) \times f_8(B) \times f_7() = f_9(B).$$

new factor list: $f_9(B)$.

⑤ normalize $f_9(B)$ to get $f_{10}(B)$.

B	val
t	
f	

QED

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