

# Inferences in Bayesian Networks

## Variable Elimination Algorithm

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Lecture 15

Based on work by K. Leyton-Brown, K. Larson, and P. van Beek

# Outline

Learning Goals

A Query for the Holmes Scenario

The Variable Elimination Algorithm

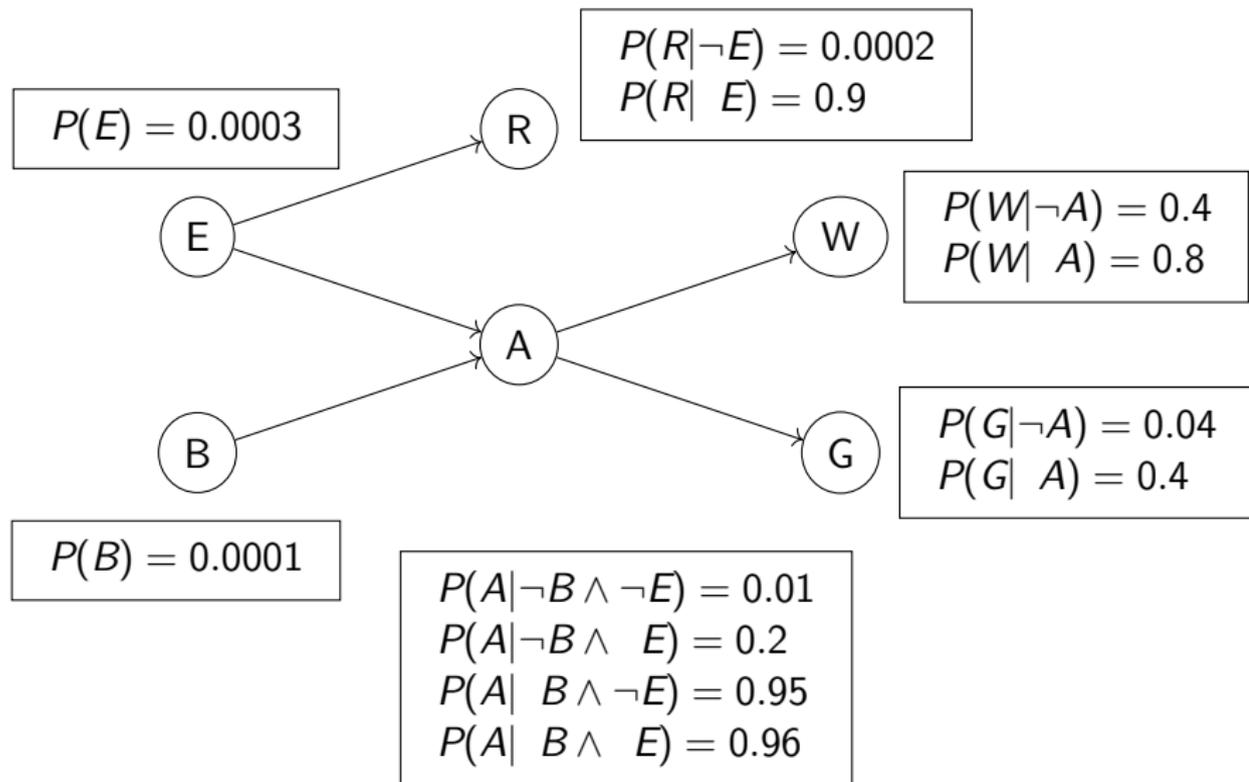
Revisiting the Learning goals

# Learning Goals

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

- ▶ Define factors. Manipulate factors using operations restrict, sum out, multiply and normalize.
- ▶ Compute a prior or a posterior probability given a Bayesian network.
- ▶ Describe/trace/implement the variable elimination algorithm for calculating a prior or a posterior probability given a Bayesian network.

# 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?*

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

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

## Number of operations

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

$$\begin{aligned} &P(B = t \wedge W = t \wedge G = t) \\ &= \sum_{a \in \{t, f\}} \sum_{e \in \{t, f\}} \sum_{r \in \{t, f\}} P(B = t)P(E = e)P(A = a|B = t \wedge E = e) \\ &\quad P(R = r|E = e)P(G = t|A = a)P(W = t|A = a) \end{aligned}$$

- (A) Less than 10
- (B) 10-25
- (C) 26-40
- (D) 41-55
- (E) More than 55

## Number of operations

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

$$\begin{aligned} &P(B = t \wedge W = t \wedge G = t) \\ &= P(B = t) \sum_{a \in \{t, f\}} P(G = t | A = a) P(W = t | A = a) \\ &\quad \sum_{e \in \{t, f\}} P(E = e) P(A = a | B = t \wedge E = e) \end{aligned}$$

- (A) Less than 10
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- (D) 41-55
- (E) More than 55

# Factors

- ▶ A **factor** is a representation of a function from a tuple of random variables into a number.
- ▶ We will write factor  $f$  on variables  $X_1, \dots, X_j$  as  $f(X_1, \dots, X_j)$ .
- ▶ A factor denotes a distribution over the given tuple of variables in some (unspecified) context
  - ▶ e.g.,  $P(X_1, X_2)$  is a factor  $f(X_1, X_2)$
  - ▶ e.g.,  $P(X_1, X_2, X_3 = v_3)$  is a factor  $f(X_1, X_2)$
  - ▶ e.g.,  $P(X_1, X_3 = v_3 | X_2)$  is a factor  $f(X_1, X_2)$

## Restrict a factor

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

- ▶  $f(X_1 = v_1, X_2, \dots, X_j)$ , where  $v_1 \in \text{dom}(X_1)$ , is a factor on  $X_2, \dots, X_j$ .
- ▶  $f(X_1 = v_1, X_2 = v_2, \dots, X_j = v_j)$  is a number that is the value of  $f$  when each  $X_i$  has value  $v_i$ .

## 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  $f_2(Y, Z) = f_1(X = t, Y, Z)$ ?
- ▶ What is  $f_3(Y) = f_2(Y, Z = f)$ ?
- ▶ What is  $f_4() = f_3((Y = f))$ ?

## Sum out a variable

**Sum out** a variable, say  $X_1$  with domain  $\{v_1, \dots, v_k\}$ , from factor  $f(X_1, \dots, X_j)$ , resulting in a factor on  $X_2, \dots, X_j$  defined by:

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

## 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  $f_2(X, Z) = \sum_B f_1(X, Y, Z)$ ?

# Multiplying factors

**Multiply** two factors together.

- ▶ The **product** of factor  $f_1(X, Y)$  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

$f_1(A, B)$ :

$A$	$B$	val
t	t	0.1
t	f	0.9
f	t	0.2
f	f	0.8

$f_2(B, C)$ :

$B$	$C$	val
t	t	0.3
t	f	0.7
f	t	0.6
f	f	0.4

What is  $f_1(A, B) \times f_2(B, C)$ ?

# 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.

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