



# CSC 384 Introduction to Artificial Intelligence

## Uncertainty 4 Variable Elimination Algorithm

Alice Gao and Randy Hickey  
Winter 2023

# Learning Goals

---

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

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

# Outline

---

1. [An Example to Motivate VEA](#)
2. [Variable Elimination Algorithm](#)
3. [A VEA Example](#)

---

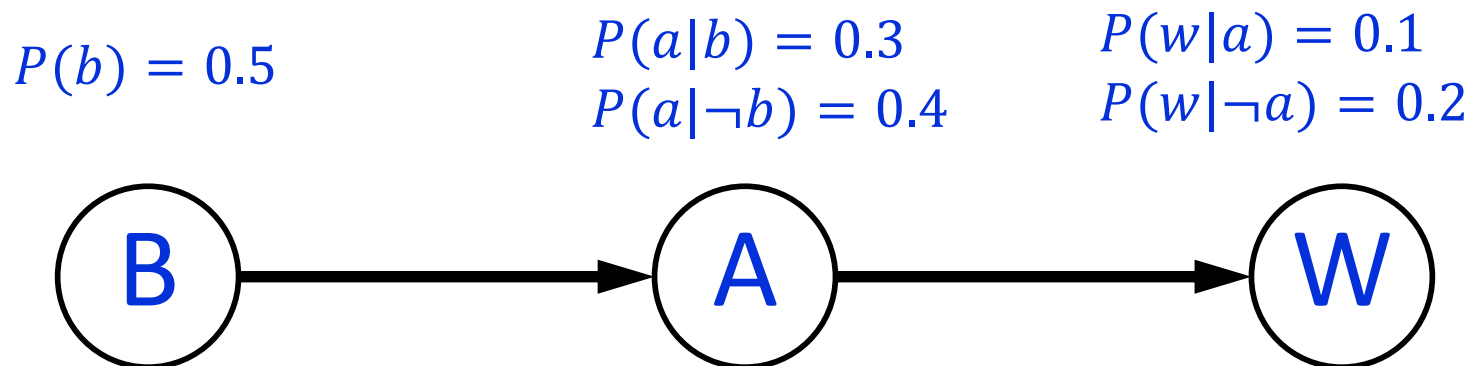
# **AN EXAMPLE TO MOTIVATE VEA**

# An Example to Motivate VEA

---

Calculate  $P(A|\neg w)$

If Dr. Watson does not call  
what is the probability that the alarm is ringing?



# The Probability Tables

---

Goal is to calculate  $P(A|\neg w)$ .

$P(B)$

$P(b)$	0.5
$P(\neg b)$	0.5

$P(A|B)$

$P(a b)$	0.3
$P(\neg a b)$	0.7
$P(a \neg b)$	0.4
$P(\neg a \neg b)$	0.6

$P(W|A)$

$P(w a)$	0.1
$P(\neg w a)$	0.9
$P(w \neg a)$	0.2
$P(\neg w \neg a)$	0.8

# Restrict W

---

Goal is to calculate  $P(A|\neg w)$ .

$P(b)$	0.5
$P(\neg b)$	0.5

$P(a b)$	0.3
$P(\neg a b)$	0.7
$P(a \neg b)$	0.4
$P(\neg a \neg b)$	0.6

<del><math>P(w a)</math></del>	<del>0.1</del>
$P(\neg w a)$	0.9
<del><math>P(w \neg a)</math></del>	<del>0.2</del>
$P(\neg w \neg a)$	0.8



$P(\neg w a)$	0.9
$P(\neg w \neg a)$	0.8

# Calculate the Joint Probabilities

Goal is to calculate  $P(A|\neg w)$ .

$$P(B \wedge A \wedge \neg w) = P(B)P(A|B)P(\neg w|A)$$

$P(b)$	0.5
$P(\neg b)$	0.5

×

$P(a b)$	0.3
$P(\neg a b)$	0.7
$P(a \neg b)$	0.4
$P(\neg a \neg b)$	0.6

×

$P(\neg w a)$	0.9
$P(\neg w \neg a)$	0.8

$$\begin{aligned} &P(b \wedge \neg a \wedge \neg w) \\ &= P(b) P(\neg a|b) P(\neg w|\neg a) \\ &= 0.5 * 0.7 * 0.8 = 0.28 \end{aligned}$$



$P(b \wedge a \wedge \neg w)$	0.135
$P(b \wedge \neg a \wedge \neg w)$	0.28
$P(\neg b \wedge a \wedge \neg w)$	0.18
$P(\neg b \wedge \neg a \wedge \neg w)$	0.24



## Sum Out B

---

Goal is to calculate  $P(A|\neg w)$ .

$$P(A \wedge \neg w) = \sum_B P(B)P(A|B)P(\neg w|A)$$

$$\begin{aligned} P(a \wedge \neg w) &= P(b \wedge a \wedge \neg w) + P(\neg b \wedge a \wedge \neg w) \\ &= 0.135 + 0.18 = 0.315 \end{aligned}$$

$P(b \wedge a \wedge \neg w)$	0.135
$P(b \wedge \neg a \wedge \neg w)$	0.28
$P(\neg b \wedge a \wedge \neg w)$	0.18
$P(\neg b \wedge \neg a \wedge \neg w)$	0.24




$P(a \wedge \neg w)$	0.315
$P(\neg a \wedge \neg w)$	0.52

# Normalize the Probabilities

---

$$P(a|\neg w) = \frac{P(a \wedge \neg w)}{P(a \wedge \neg w) + P(\neg a \wedge \neg w)} \text{ and } = \frac{0.315}{0.315 + 0.52} = 0.377$$

$$P(\neg a|\neg w) = \frac{P(\neg a \wedge \neg w)}{P(a \wedge \neg w) + P(\neg a \wedge \neg w)} = 1 - P(a|\neg w)$$

$P(a \wedge \neg w)$	0.315		$P(a \neg w)$	0.377
$P(\neg a \wedge \neg w)$	0.52		$P(\neg a \neg w)$	0.623

# A Summary of the Calculations

---

$$P(A|\neg w) = \frac{P(A \wedge \neg w)}{P(a \wedge \neg w) + P(\neg a \wedge \neg w)}$$

To calculate  $P(A|\neg w)$ , it is sufficient to

- 4) Calculate the joint probabilities  $P(A \wedge \neg w)$  and
- 5) Normalize them.

$$P(A \wedge \neg w) = \sum_B P(B)P(A|B)P(\neg w|A)$$

To calculate  $P(A \wedge \neg w)$ , we need to

- 1) Restrict the observed variables,
- 2) Calculate the joint probability of all variables, and
- 3) Sum out the hidden variables.

# A Summary of the Steps

---

- 1) Write down the probability tables.
- 2) Restrict the observed variables.
- 3) Calculate the joint probability of all variables.
- 4) Sum out the hidden variables.
- 5) Normalize the probabilities.

---

# VARIABLE ELIMINATION ALGORITHM

# Variable Elimination Algorithm

---

To compute  $P(Q|e_1 \wedge \cdots \wedge e_N)$

- Categorize the variables: query, evidence, and hidden.
- Create a factor for each node in the Bayesian network.
- Restrict each evidence variable to its observed value.
- Eliminate the hidden variables  $h_1, \dots, h_j, \dots, h_M$ .
  - For each hidden variable  $h_j$
  - Multiply all the factors that contain  $h_j$  to create a new factor  $f_j$ .
  - Sum out  $h_j$  from factor  $f_j$ .
- Multiply the remaining factors.
- Normalize the remaining factor.

# Create a Factor

---

Convert each conditional probability table to a factor.

$P(w a)$	0.8
$P(\neg w a)$	0.2
$P(w \neg a)$	0.4
$P(\neg w \neg a)$	0.6



$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

$P(b)$	0.1
$P(\neg b)$	0.9



$b$	0.1
$\neg b$	0.9

# Restrict a Factor

Restrict each evidence variable to its observed value.

$w$	$a$	0.8
$\neg w$	$a$	0.2
<del><math>w</math></del>	<del><math>\neg a</math></del>	<del>0.4</del>
<del><math>\neg w</math></del>	<del><math>\neg a</math></del>	<del>0.6</del>

Restrict  $A$  to be true

<del><math>w</math></del>	<del>0.8</del>
$\neg w$	0.2

Restrict  $W$  to be false

0.2
-----



# Restrict a Factor

---

Restrict each evidence variable to its observed value.

$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

Restrict  $A$  to be true

$w$	0.8
$\neg w$	0.2

Restrict  $W$  to be false

0.2
-----

# Sum out a Variable

---

Sum out a hidden variable from a factor.

$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

Sum out  $A$   $0.8 + 0.4 = 1.2$

$w$	1.2
$\neg w$	0.8

Sum out  $W$   $0.2 + 0.6 = 0.8$

0.6
-----

# Sum out a Variable

---

Sum out a hidden variable from a factor.

$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

Sum out  $A$

$w$	1.2
$\neg w$	0.8

Sum out  $W$

2.0
-----

# Multiply Factors

Multiply factors in an element-wise fashion.

$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

$g$	$a$	0.4
$\neg g$	$a$	0.6
$g$	$\neg a$	0.04
$\neg g$	$\neg a$	0.96

$w$	$a$	$g$	
$\neg w$	$a$	$g$	
$w$	$\neg a$	$g$	$0.4 \times 0.04$
$\neg w$	$\neg a$	$g$	
$w$	$a$	$\neg g$	
$\neg w$	$a$	$\neg g$	
$w$	$\neg a$	$\neg g$	
$\neg w$	$\neg a$	$\neg g$	

# Multiply Factors

---

Multiply two factors in an element-wise fashion.

$w$	$a$	0.8
$\neg w$	$a$	0.2
$w$	$\neg a$	0.4
$\neg w$	$\neg a$	0.6

$g$	$a$	0.4
$\neg g$	$a$	0.6
$g$	$\neg a$	0.04
$\neg g$	$\neg a$	0.96

$w$	$a$	$g$	0.32
$\neg w$	$a$	$g$	0.08
$w$	$\neg a$	$g$	0.016
$\neg w$	$\neg a$	$g$	0.024
$w$	$a$	$\neg g$	0.48
$\neg w$	$a$	$\neg g$	0.12
$w$	$\neg a$	$\neg g$	0.384
$\neg w$	$\neg a$	$\neg g$	0.576

# Normalize a Factor

---

Convert a factor to a probability distribution.

$w$	1.2
$\neg w$	0.8

$w$	0.6
$\neg w$	0.4

$$1.2 / (1.2 + 0.8) = 0.6$$

# Normalize a Factor

---

Convert a factor to a probability distribution.

$w$	1.2
$\neg w$	0.8

$w$	0.6
$\neg w$	0.4

---

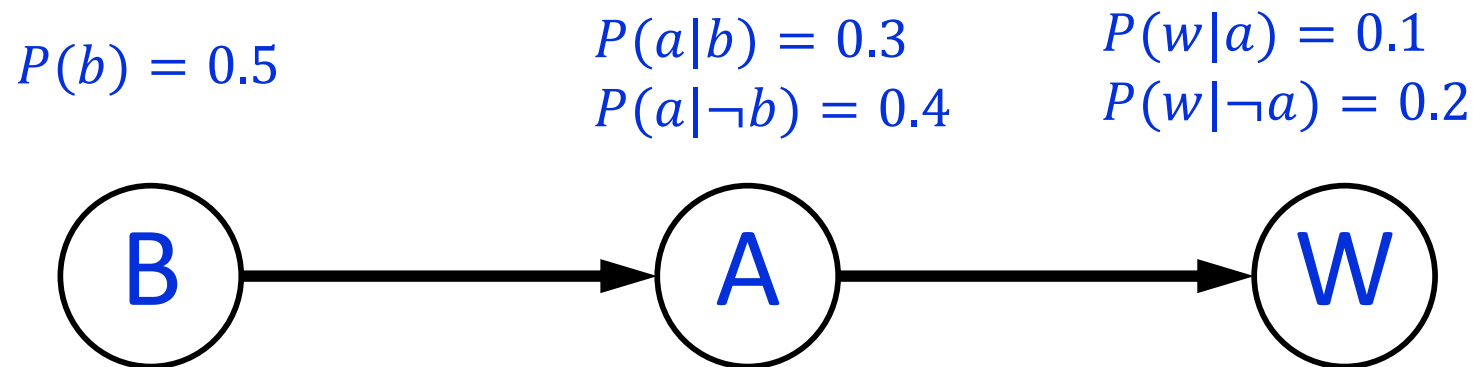
# A FULL VEA EXAMPLE



# A VEA Example

---

Calculate  $P(A|\neg w)$  using variable elimination algorithm.



# Categorize the Variables

---

Calculate  $P(A|\neg w)$

- Query variables:  $A$
- Evidence variables:  $W$
- Hidden variables:  $B$

# Define the Factors

---

Define factor  $f_1(B)$

$b$	0.5
$\neg b$	0.5

Define factor  $f_2(B, A)$

$b$	$a$	0.3
$b$	$\neg a$	0.7
$\neg b$	$a$	0.4
$\neg b$	$\neg a$	0.6

Define factor  $f_3(A, W)$

$a$	$w$	0.1
$a$	$\neg w$	0.9
$\neg a$	$w$	0.2
$\neg a$	$\neg w$	0.8

# Restrict the Factors

Restrict factor  $f_3(A, W)$  to  $\neg w$  produce factor  $f_4(A)$

$a$	$w$	0.1
$a$	$\neg w$	0.9
$\neg a$	$w$	0.2
$\neg a$	$\neg w$	0.8



$a$	0.9
$\neg a$	0.8

The remaining factors are  $f_1(B)$ ,  $f_2(B, A)$ ,  $f_4(A)$ .

$b$	0.5
$\neg b$	0.5

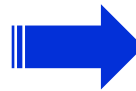
$b$	$a$	0.3
$b$	$\neg a$	0.7
$\neg b$	$a$	0.4
$\neg b$	$\neg a$	0.6

$a$	0.9
$\neg a$	0.8

# Eliminate the Hidden Variable $B$

Multiply  $f_1(B)$  and  $f_2(B, A)$  to produce factor  $f_5(B, A)$ .

$b$	0.5
$\neg b$	0.5



$b$	$a$	0.3
$b$	$\neg a$	0.7
$\neg b$	$a$	0.4
$\neg b$	$\neg a$	0.6

$b$	$a$	0.15
$b$	$\neg a$	0.35
$\neg b$	$a$	0.2
$\neg b$	$\neg a$	0.3

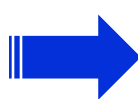
The remaining factors are  $f_4(A)$ ,  $f_5(B, A)$ .

# Eliminate the Hidden Variable $B$

---

Sum out  $B$  from  $f_5(B, A)$  to produce factor  $f_6(A)$ .

$b$	$a$	0.15
$b$	$\neg a$	0.35
$\neg b$	$a$	0.2
$\neg b$	$\neg a$	0.3



$a$	0.35
$\neg a$	0.65

The remaining factors are  $f_4(A)$ ,  $f_6(A)$ .

$a$	0.9
$\neg a$	0.8

$a$	0.35
$\neg a$	0.65

# Multiply the Remaining Factors

---

Multiply  $f_4(A)$  and  $f_6(A)$  to produce factor  $f_7(A)$ .

$a$	0.9
$\neg a$	0.8



$a$	0.315
$\neg a$	0.52

$a$	0.35
$\neg a$	0.65

The remaining factor is  $f_7(A)$ .

# Normalize the Factor

---

Normalize  $f_7(A)$  to produce factor  $f_8(A)$  .

$a$	0.315
$\neg a$	0.52



$a$	0.377
$\neg a$	0.623



# What Did VEA Really Do?

---

① Restrict      ② Multiply      ③ Sum out

$$P(A|\neg w) = P(\neg w|A) \left( \sum_B P(B)P(A|B) \right)$$

④ Multiply      ⑤ Normalize.

# Revisiting the Learning Goals

---

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

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

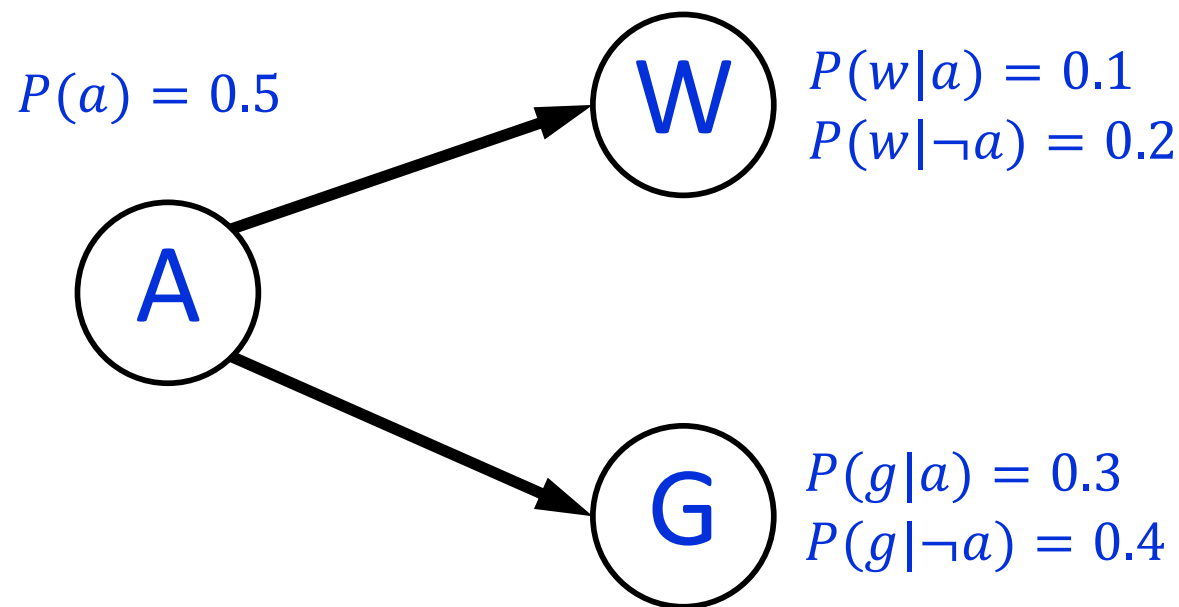
---

# **AN EXTRA EXAMPLE ON VEA**

# A VEA Example

---

Calculate  $P(W|\neg g)$  using the variable elimination algorithm.



# Categorize the Variables

---

Calculate  $P(W|\neg g)$

- Query variables:  $W$
- Evidence variables:  $G$
- Hidden variables:  $A$

# Define the Factors

---

Define factor  $f_1(A)$

$a$	0.5
$\neg a$	0.5

Define factor  $f_2(A, W)$

$a$	$w$	0.1
$a$	$\neg w$	0.9
$\neg a$	$w$	0.2
$\neg a$	$\neg w$	0.8

Define factor  $f_3(A, G)$

$a$	$g$	0.3
$a$	$\neg g$	0.7
$\neg a$	$g$	0.4
$\neg a$	$\neg g$	0.6

# Restrict the Factors

---

Restrict factor  $f_3(A, G)$  to  $\neg g$  produce factor  $f_4(A)$

$a$	0.7
$\neg a$	0.6

The remaining factors are  $f_1(A)$ ,  $f_2(A, W)$ ,  $f_4(A)$ .

# Eliminate the Hidden Variable A

---

Multiply  $f_1(A)$ ,  $f_2(A, W)$ , and  $f_4(A)$  to produce factor  $f_5(A, W)$ .

$a$	$w$	0.035
$a$	$\neg w$	0.315
$\neg a$	$w$	0.06
$\neg a$	$\neg w$	0.24

Sum out  $A$  from  $f_5(A, W)$  to produce factor  $f_6(W)$ .

$w$	0.095
$\neg w$	0.555

The remaining factor is  $f_6(W)$ .



# Multiply and Normalize

---

No need to multiply since there is one factor remaining.

Normalize factor  $f_6(W)$  to get factor  $f_7(W)$ .

$w$	0.146
$\neg w$	0.854

That is,  $P(w|\neg g) = 0.146$  and  $P(\neg w|\neg g) = 0.854$ .