

# Belief network inference

Four main approaches to determine posterior distributions in belief networks:

- Variable Elimination: exploit the structure of the network to eliminate (sum out) the non-observed, non-query variables one at a time.
- Search-based approaches: enumerate some of the possible worlds, and estimate posterior probabilities from the worlds generated.
- Stochastic simulation: random cases are generated according to the probability distributions.
- Variational methods: find the closest tractable distribution to the (posterior) distribution we are interested in.

# 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  $f(X_1, \dots, X_j)$ .

We can assign some or all of the variables of a 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  $v_i$ .

The former is also written as  $f(X_1, X_2, \dots, X_j)_{X_1 = v_1}$ , etc.

# Example factors

$r(X, Y, Z)$ :

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

$r(X=t, Y, Z)$ :

Y	Z	val
t	t	0.1
t	f	
f	t	
f	f	

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$r(X=t, Y=f, Z=f) =$

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$r(X=t, Y, Z=f)$ :

Y	val
t	0.9
f	0.8

$r(X=t, Y=f, Z=f) = 0.8$

# Multiplying factors

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

$$(f_1 \times f_2)(\bar{X}, \bar{Y}, \bar{Z}) = f_1(\bar{X}, \bar{Y})f_2(\bar{Y}, \bar{Z}).$$

# Multiplying factors example

$f_1$ :

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

$f_2$ :

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

$f_1 \times f_2$ :

A	B	C	val
t	t	t	0.03
t	t	f	
t	f	t	
t	f	f	
f	t	t	
f	t	f	
f	f	t	
f	f	f	

# Multiplying factors example

$f_1$ :

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t	t	0.1
t	f	0.9
f	t	0.2
f	f	0.8

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

$f_1 \times f_2$ :

A	B	C	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

# Summing out variables

We can **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:

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

# Summing out a variable example

$f_3$ :

A	B	C	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

$\sum_B f_3$ :

A	C	val
t	t	0.57
t	f	
f	t	
f	f	

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t	t	f	0.07
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f	t	f	0.14
f	f	t	0.48
f	f	f	0.32

$\sum_B f_3$ :

A	C	val
t	t	0.57
t	f	0.43
f	t	0.54
f	f	0.46

# Exercise

Given factors:

s:

A	val
t	0.75
f	0.25

t:

A	B	val
t	t	0.6
t	f	0.4
f	t	0.2
f	f	0.8

o:

A	val
t	0.3
f	0.1

What is?

(a)  $s \times t$

(b)  $\sum_A s \times t$

(c)  $\sum_B s \times t$

(d)  $s \times t \times o$

(e)  $\sum_A s \times t \times o$

(f)  $\sum_b s \times t \times o$

If we want to compute the posterior probability of  $Z$  given evidence  $Y_1 = v_1 \wedge \dots \wedge Y_j = v_j$ :

$$P(Z|Y_1 = v_1, \dots, Y_j = v_j)$$

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$$\begin{aligned} &P(Z|Y_1 = v_1, \dots, Y_j = v_j) \\ &= \frac{P(Z, Y_1 = v_1, \dots, Y_j = v_j)}{P(Y_1 = v_1, \dots, Y_j = v_j)} \\ &= \end{aligned}$$

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So the computation reduces to the probability of  $P(Z, Y_1 = v_1, \dots, Y_j = v_j)$ .

We normalize at the end.

# Probability of a conjunction

Suppose the variables of the belief network are  $X_1, \dots, X_n$ .  
To compute  $P(Z, Y_1 = v_1, \dots, Y_j = v_j)$ , we sum out the other variables,  $Z_1, \dots, Z_k = \{X_1, \dots, X_n\} - \{Z\} - \{Y_1, \dots, Y_j\}$ .  
We order the  $Z_i$  into an **elimination ordering**.

$$P(Z, Y_1 = v_1, \dots, Y_j = v_j)$$

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$$\begin{aligned} &P(Z, Y_1 = v_1, \dots, Y_j = v_j) \\ &= \sum_{Z_k} \cdots \sum_{Z_1} P(X_1, \dots, X_n)_{Y_1 = v_1, \dots, Y_j = v_j} \\ &= \end{aligned}$$

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$$\begin{aligned} & P(Z, Y_1 = v_1, \dots, Y_j = v_j) \\ &= \sum_{Z_k} \cdots \sum_{Z_1} P(X_1, \dots, X_n)_{Y_1 = v_1, \dots, Y_j = v_j} \\ &= \sum_{Z_k} \cdots \sum_{Z_1} \prod_{i=1}^n P(X_i | \text{parents}(X_i))_{Y_1 = v_1, \dots, Y_j = v_j} \end{aligned}$$

# Computing sums of products

Computation in belief networks reduces to computing the sums of products.

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- How can we compute  $\sum_{Z_1} \prod_{i=1}^n P(X_i | \text{parents}(X_i))$  efficiently?
- Distribute out those factors that don't involve  $Z_1$ .

# Variable elimination algorithm

To compute  $P(Z|Y_1 = v_1 \wedge \dots \wedge Y_j = v_j)$ :

- Construct a factor for each conditional probability.
- Set the observed variables to their observed values.
- Sum out each of the other variables (the  $\{Z_1, \dots, Z_k\}$ ) according to some elimination ordering.
- Multiply the remaining factors. Normalize by dividing the resulting factor  $f(Z)$  by  $\sum_Z f(Z)$ .

# Summing out a variable

To sum out a variable  $Z_j$  from a product  $f_1, \dots, f_k$  of factors:

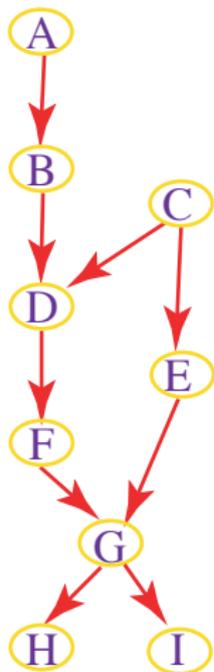
- Partition the factors into
  - ▶ those that don't contain  $Z_j$ , say  $f_1, \dots, f_i$ ,
  - ▶ those that contain  $Z_j$ , say  $f_{i+1}, \dots, f_k$

We know:

$$\sum_{Z_j} f_1 \times \dots \times f_k = f_1 \times \dots \times f_i \times \left( \sum_{Z_j} f_{i+1} \times \dots \times f_k \right).$$

- Explicitly construct a representation of the rightmost factor. Replace the factors  $f_{i+1}, \dots, f_k$  by the new factor.

# Variable elimination example



$$\left. \begin{array}{l} P(A) \\ P(B|A) \end{array} \right\} \xrightarrow{\text{elim } A} f_1(B)$$

$$\left. \begin{array}{l} P(C) \\ P(D|BC) \\ P(E|C) \end{array} \right\} \xrightarrow{\text{elim } C} f_2(BDE)$$

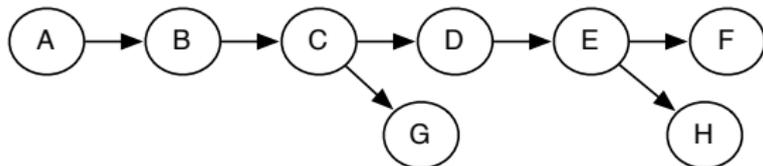
$$\begin{array}{l} P(F|D) \\ P(G|FE) \end{array}$$

$$P(H|G) \left. \right\} \xrightarrow{\text{obs } H} f_3(G)$$

$$P(I|G) \left. \right\} \xrightarrow{\text{elim } I} f_4(G)$$

$$P(D, h) = \dots (\sum_A P(A)P(B|A)) (\sum_I P(I|G))$$

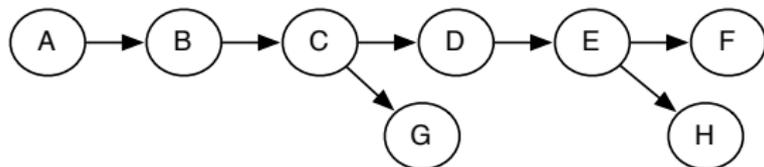
# Variable Elimination example



Query:  $P(G|f)$ ; elimination ordering:  $A, H, E, D, B, C$

$$P(G|f) \propto$$

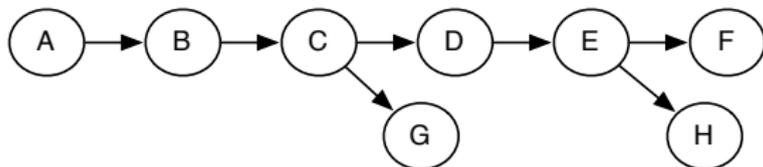
# Variable Elimination example



Query:  $P(G|f)$ ; elimination ordering:  $A, H, E, D, B, C$

$$P(G|f) \propto \sum_C \sum_B \sum_D \sum_E \sum_H \sum_A P(A)P(B|A)P(C|B) \\ P(D|C)P(E|D)P(f|E)P(G|C)P(H|E)$$

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$$P(G|f) \propto \sum_C \sum_B \sum_D \sum_E \sum_H \sum_A P(A)P(B|A)P(C|B) \\ P(D|C)P(E|D)P(f|E)P(G|C)P(H|E)$$

$$= \sum_C \left( \sum_B \left( \sum_A P(A)P(B|A) \right) P(C|B) \right) P(G|C) \\ \left( \sum_D P(D|C) \left( \sum_E P(E|D)P(f|E) \sum_H P(H|E) \right) \right)$$