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# BN: INFERENCE

## ① Setup:

→ Random Vars:  $\vec{X} = \{X_1, \dots, X_n\}$  (all categorical for now)

→ Given BN Structure: DAG  $G = (V, E)$

→ Given BN Parameters CPTs  $P(X_i | Pa_{X_i})$

→ Some "evidence" variables  $\vec{E} \subseteq \vec{X} = \{X_1, \dots, X_n\}$   
& their states  $\vec{E} = \vec{e}$  or  $E_1 = e_1, E_2 = e_2, \dots$

→ Some <sup>Query</sup> variables of interest  $\vec{Y} \subseteq \vec{X}$   
 $\{Y_1, Y_2, \dots\}$

→ CONDITIONAL PROB. / MARGINAL Inference  
Find  $P(\vec{Y} = \vec{y} | \vec{E} = \vec{e})$

→ MAP Inference [Also called MPE]  
Find  $\text{argmax}_{\vec{X} \setminus \vec{E}} P(\vec{X} \setminus \vec{E} | \vec{E} = \vec{e})$

"Find the best setting of everything else"

→ MARGINAL-MAP Inference [Also called MAP]  
Find  $\text{argmax}_{\vec{Y}} P(\vec{Y} = \vec{y} | \vec{E} = \vec{e})$

$$= \text{argmax}_{\vec{Y}} \sum_{\vec{X}} P(\vec{Y} = \vec{y}, \vec{X} \setminus \{\vec{Y} \cup \vec{E}\} = \vec{x} | \vec{E} = \vec{e})$$

"Marginalize out things I don't care about, then tell me best setting of variables I do care about"

② Is MAP "consistent" with Marginals?

Consider  $(S) \rightarrow (N)$

$$P(S) = \begin{bmatrix} 0.6 & 0 \\ 0.4 & 1 \end{bmatrix}$$

$$P(N|S) = \begin{array}{c|cc} & S=0 & S=1 \\ \hline 0 & 0.5 & 0 \\ 1 & 0.5 & 1 \end{array}$$

$P(S, N) =$

S	N	Prob
0	0	0.3
0	1	0.3
1	0	0
1	1	0.4

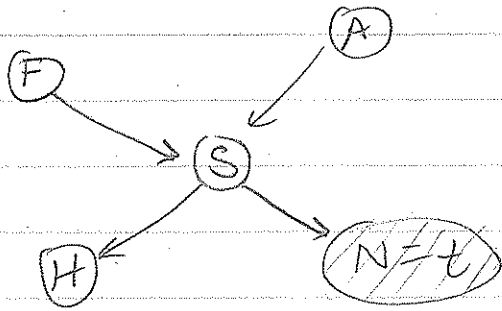
$$\text{MAP} = \underset{S, N}{\text{argmax}} P(S, N) = (1, 1)$$

Marginal  $P(S) = \begin{bmatrix} 0.6 \\ 0.4 \end{bmatrix}$

$$\text{So } \underset{S}{\text{argmax}} P(S=s) \neq \underset{S, N}{\text{argmax}} P(S=S, N=N)$$



### ③ Marginal Inference Example



Compute:  $P(F | N=t)$

First Notice that  $P(F=f | N=t) = \frac{P(F=f, N=t)}{P(N=t)}$

$$= \frac{P(F=f, N=t)}{\underbrace{\sum_{f'} P(F=f', N=t)}_{\text{Normalization constant}}}$$

So lets do this; let's compute

$$\begin{bmatrix} P(F=f, N=t) \\ P(F=t, N=t) \end{bmatrix}$$

Then lets "normalize" this vector to get  $P(F | N=t)$

In general  $P(Y | \vec{E} = \vec{e}) \propto P(Y, \vec{E} = \vec{e})$

↑

So need to compute  $P(\vec{Y} = \vec{y}, \vec{E} = \vec{e}) \forall \vec{y}$

Now,

$$P(CF=f, N=t) = \underbrace{\sum_a \sum_s \sum_h}_{2^8 \text{ sums}} P(CF=f, A=a, S=s, H=s, N=t)$$

Naively:  $2^8$  sums  
In general  $n$  vars  $\Rightarrow 2^n$  sums  
 $\Rightarrow$  Exponential!

Can we do better?

In worst case, no. #P-hardness.

But sometime ( $\equiv$  special cases), Yes!

For example, notice:

$$\sum_a \sum_s \sum_h P(f) P(a) P(s|f, a) P(h|s) P(N=t|s)$$

# terms that depend on A: 2

S: 3

H: 1 } Interesting

Let's "Eliminate" H first  $\Rightarrow$  push in  $\sum_h$

$$\sum_a \sum_s P(f) P(a) P(s|f, a) P(N=t|s) \sum_h P(h|s) \xrightarrow{1}$$

Very Nice!

Let's "Eliminate" S next

$$\sum_a P(f) P(a) \underbrace{\sum_s P(s|f, a) P(N=t|s)}_{\text{New "Factor" } g(CF, A)}$$

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$$g(F=f, A=a) = \begin{array}{c|cc} F \backslash A & 0 & 1 \\ \hline 0 & g(0,0) & g(0,1) \\ \hline 1 & g(1,0) & g(1,1) \end{array}$$

$$g(f,a) = \sum_s P(s|f,a) P(N=t|s)$$

2<sup>2</sup> entries. (1 sum per entry)

Now, let's Eliminate A

$$P(f) \sum_a P(a) g(f,a)$$

New factor  $h(f)$

$$\begin{bmatrix} h(0) \\ h(1) \end{bmatrix} \quad \begin{array}{l} 2 \text{ entries} \\ (1 \text{ sum per entry}) \end{array}$$

Finally,

$$P(F=f, N=t) = P(f) \cdot h(f) \quad \left. \vphantom{P(F=f, N=t)} \right\} \begin{array}{l} \text{Normalize to get} \\ P(F=N=t) \end{array}$$

# Recap: Variable Elimination Algorithm in BNs

Elim Ordering: H, S, A

time/iteration	List of Factors	Operation/ Elimination	New Factor
1	$P(F)P(A)P(S F,A)P(H S)P(N H,S)$	$\sum_h P(H S)$	$\emptyset$
2	$P(F)P(A)P(S F,A)P(N=H S)$	$\sum_s P(S F,A)P(N=H S)$	$g(F,A)$ size $2^2$
3	$P(F)P(A)g(F,A)$	$\sum_a P(A)g(F,A)$	$h(F)$ size $2^1$

Thus  $P(F|N=t) \propto P(F)h(F)$

left-over factors  
Normalize to get answer