

# Exact Inference

3007/7059 Artificial Intelligence

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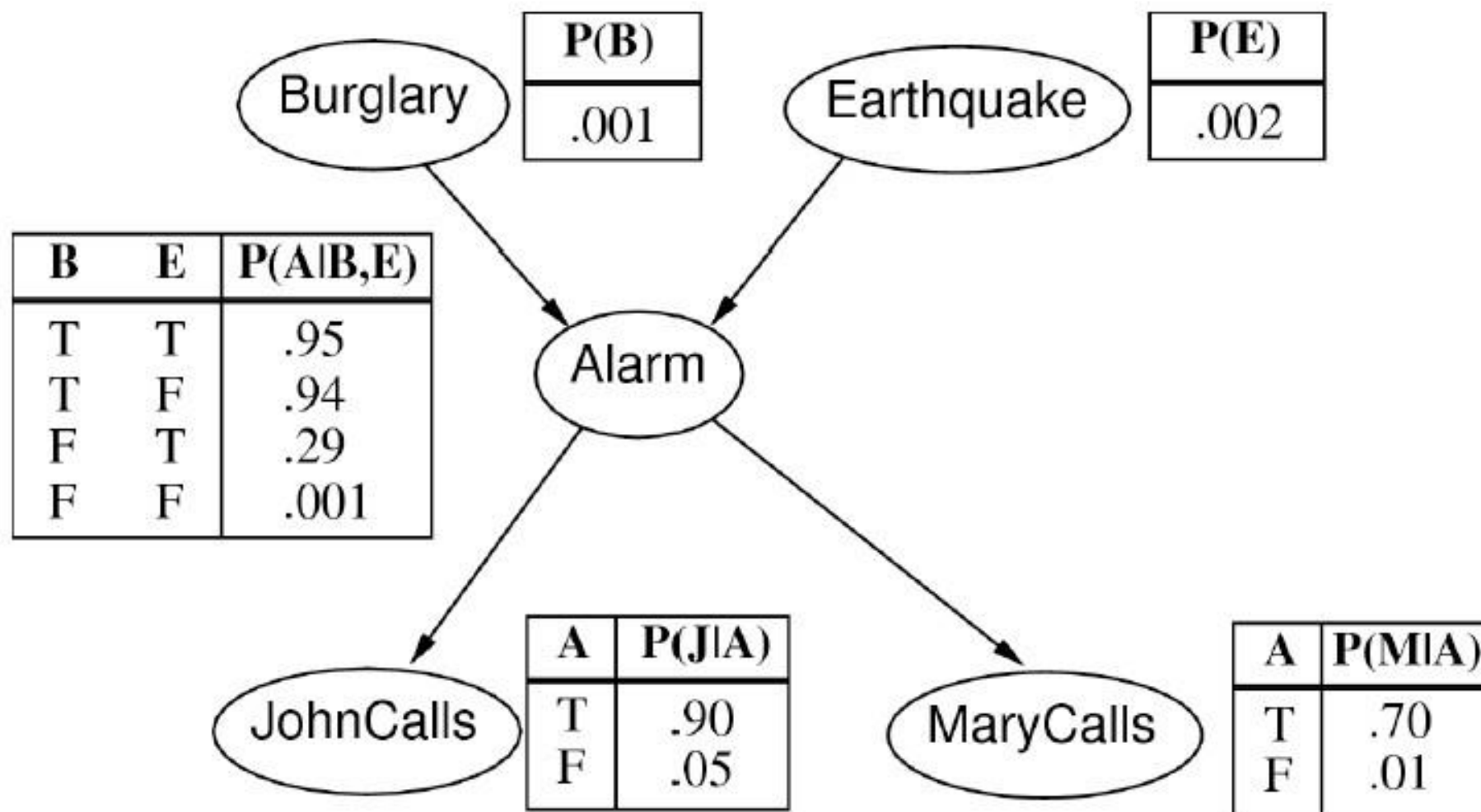
# Outline

- Recap of Bayesian Networks
- Inference by enumeration
- Inference by variable elimination

# Recap: Inference problem

I'm at work, neighbour John called to say my alarm is ringing, but neighbour Mary didn't call. Sometimes it's set off by minor earthquakes. Is there a burglar?

$$P(b|j, \neg m)$$



# Recap: Global semantic of a Bayesian network

A Bayesian Network encodes our knowledge on how the variables interact. This is specified in terms of conditional independence assertions.

The global semantics of a network define a **joint distribution of all variables** as the product of **local conditional distributions**.

The joint distribution defined by a Bayesian Network with variables  $X_1, \dots, X_n$  is:

$$\begin{aligned} P(X_1, \dots, X_n) &= P(X_1 | Parents(X_1)) \times P(X_2 | Parents(X_2)) \\ &\quad \times \dots \times P(X_n | Parents(X_n)) \\ &= \prod_{i=1}^n P(X_i | Parents(X_i)) \end{aligned}$$

where  $Parents(X_i)$  are parents of  $X_i$  as specified by the particular Bayesian Network.

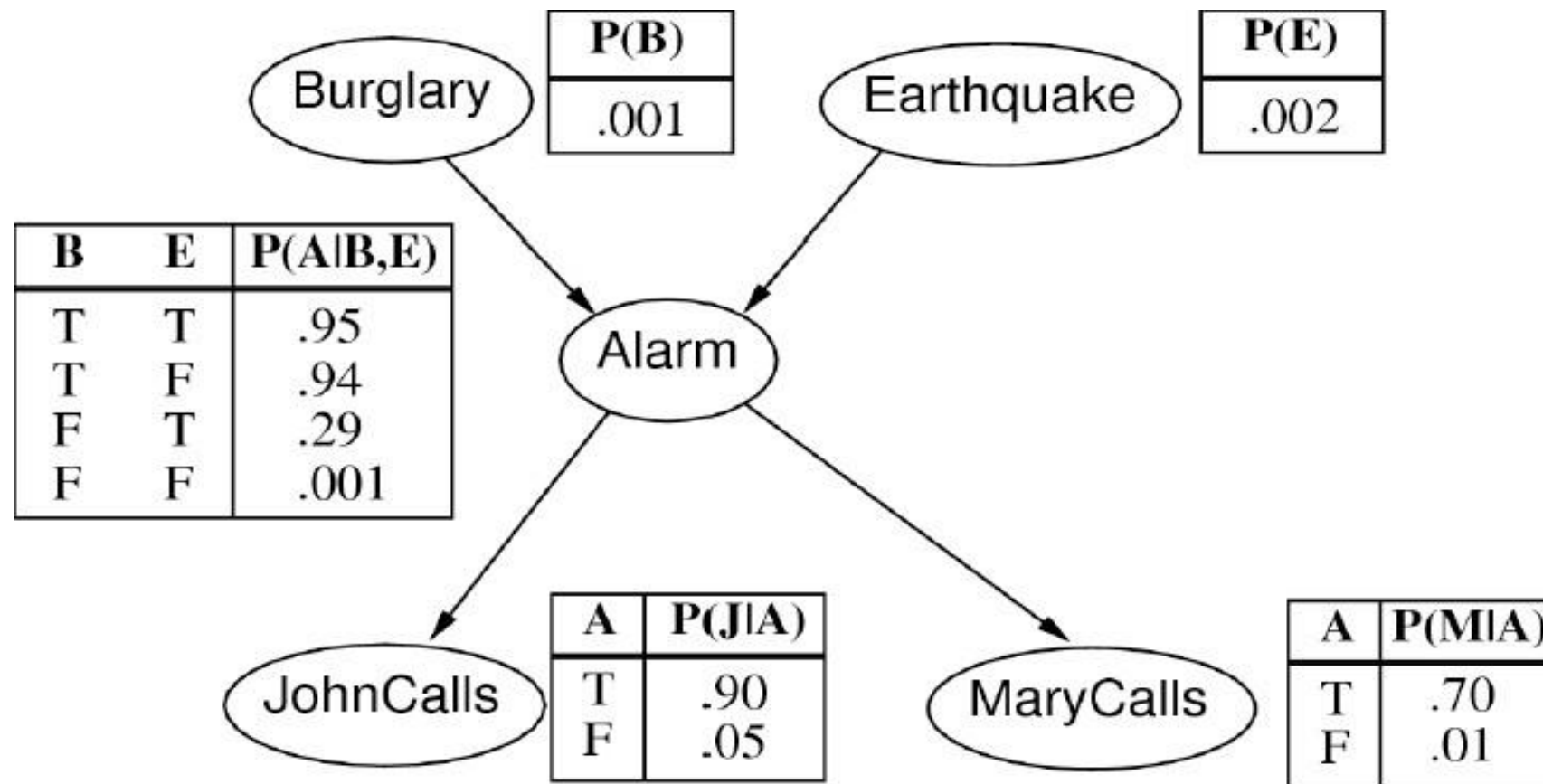
# Recap: Inference

Recall the general rule of statistical inference:

$$P(X|e) = \alpha \sum_{\forall Y} P(X, e, Y)$$

where  $X$  is the query variable,  $e$  the observed values for the evidence variables, and  $Y$  the unobserved variables. As usual  $\alpha$  is a normalisation constant that we solve for at the end.

# Performing inference



$$P(B, E, A, J, M)? \quad P(b|j, \neg m)?$$

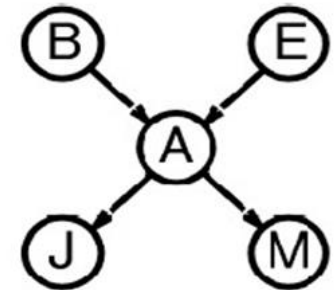
$$P(J, M, A, B, E) = P(J|A)P(M|A)P(A|B, E)P(B)P(E)$$



# Performing inference on Bayesian networks

A direct application of the general rule yields

$$P(b|j, \neg m) = \alpha \sum_E \sum_A P(b, j, \neg m, E, A)$$



Observe that the summands are joint probabilities of all the variables. Hence, we introduce the **global semantics** of the network:

$$P(b|j, \neg m) = \alpha \sum_E \sum_A P(b)P(E)P(A|b, E)P(j|A)P(\neg m|A)$$

# Inference by enumeration

Expanding by **enumerating the summands** we obtain

$$\begin{aligned}P(b|j, \neg m) &= \alpha \sum_E \sum_A P(b)P(E)P(A|b, E)P(j|A)P(\neg m|A) \\&= \alpha [P(b)P(e)P(a|b, e)P(j|a)P(\neg m|a) && e, a \\&\quad + P(b)P(e)P(\neg a|b, e)P(j|\neg a)P(\neg m|\neg a) && e, -a \\&\quad + P(b)P(\neg e)P(a|b, \neg e)P(j|a)P(\neg m|a) && -e, a \\&\quad + P(b)P(\neg e)P(\neg a|b, \neg e)P(j|\neg a)P(\neg m|\neg a)] && -e, -a\end{aligned}$$

For each of the components on the RHS, we read its value from the appropriate CPT, yielding  $P(b|j, \neg m) = \alpha 0.00025677$ .

Note that the result does not yet amount to a probability value as we haven't solved for  $\alpha$ .



# Inference by enumeration

Calculate the scaling factor

To compute  $\alpha = \frac{1}{P(j, \neg m)}$  we obtain the marginal probability

$$P(j, \neg m) = \sum_B \sum_E \sum_A P(B, E, A, j, \neg m)$$

# Inference by enumeration

An alternative is to realise that  $\langle P(b|j, \neg m), P(\neg b|j, \neg m) \rangle$  is a probability distribution and that  $\alpha$  is a normalisation constant that ensures that the probability distribution sums to 1.

Hence, compute  $P(\neg b|j, \neg m) = \alpha 0.0498$ , using the global semantics and enumerating the summands as before, yielding

$$\langle P(b|j, \neg m), P(\neg b|j, \neg m) \rangle = \alpha \langle 0.00025677, 0.0498 \rangle = \langle 0.0051, 0.9949 \rangle$$

where  $\alpha$  is solved as  $\frac{1}{0.00025677+0.0498}$ .

# Complexity of inference by enumeration

In the burglar-alarm example, we evaluate the expression

$$\begin{aligned}P(b|j, \neg m) &= \alpha \sum_E \sum_A P(b)P(E)P(A|b, E)P(j|A)P(\neg m|A) \\&= \alpha [P(b)P(e)P(a|b, e)P(j|a)P(\neg m|a) \\&\quad + P(b)P(e)P(\neg a|b, e)P(j|\neg a)P(\neg m|\neg a) \\&\quad + P(b)P(\neg e)P(a|b, \neg e)P(j|a)P(\neg m|a) \\&\quad + P(b)P(\neg e)P(\neg a|b, \neg e)P(j|\neg a)P(\neg m|\neg a)]\end{aligned}$$

by adding up 4 terms, each obtained by multiplying 5 numbers—  
In total we need 16 multiplications and 3 additions (excludes the contribution due to term  $\alpha$ ).

# Complexity of inference by enumeration

In the burglar-alarm example, we evaluate the expression

$$P(b|j, \neg m) = \alpha \sum_E \sum_A P(b)P(E)P(A|b, E)P(j|A)P(\neg m|A)$$

In the worst case, where we have to sum out almost all of the  $n$  variables (where we assume they are all Boolean), the complexity of inference by enumeration is  $\mathcal{O}(n2^n)$ .

This means we will not be able to perform inference by enumeration except for the smallest networks!



# Depth-first Evaluation

An improvement can be achieved by observing that  $P(b)$  is a constant that can be moved outside the summations over  $E$  and  $A$ , while  $P(e)$  can be moved outside the summation over  $A$ :

$$P(b|j, \neg m) = \alpha P(b) \sum_E P(E) \sum_A P(A|b, E) P(j|A) P(\neg m|A)$$

Thus we evaluate by looping through the variables in order, multiplying CPT entries as we go.

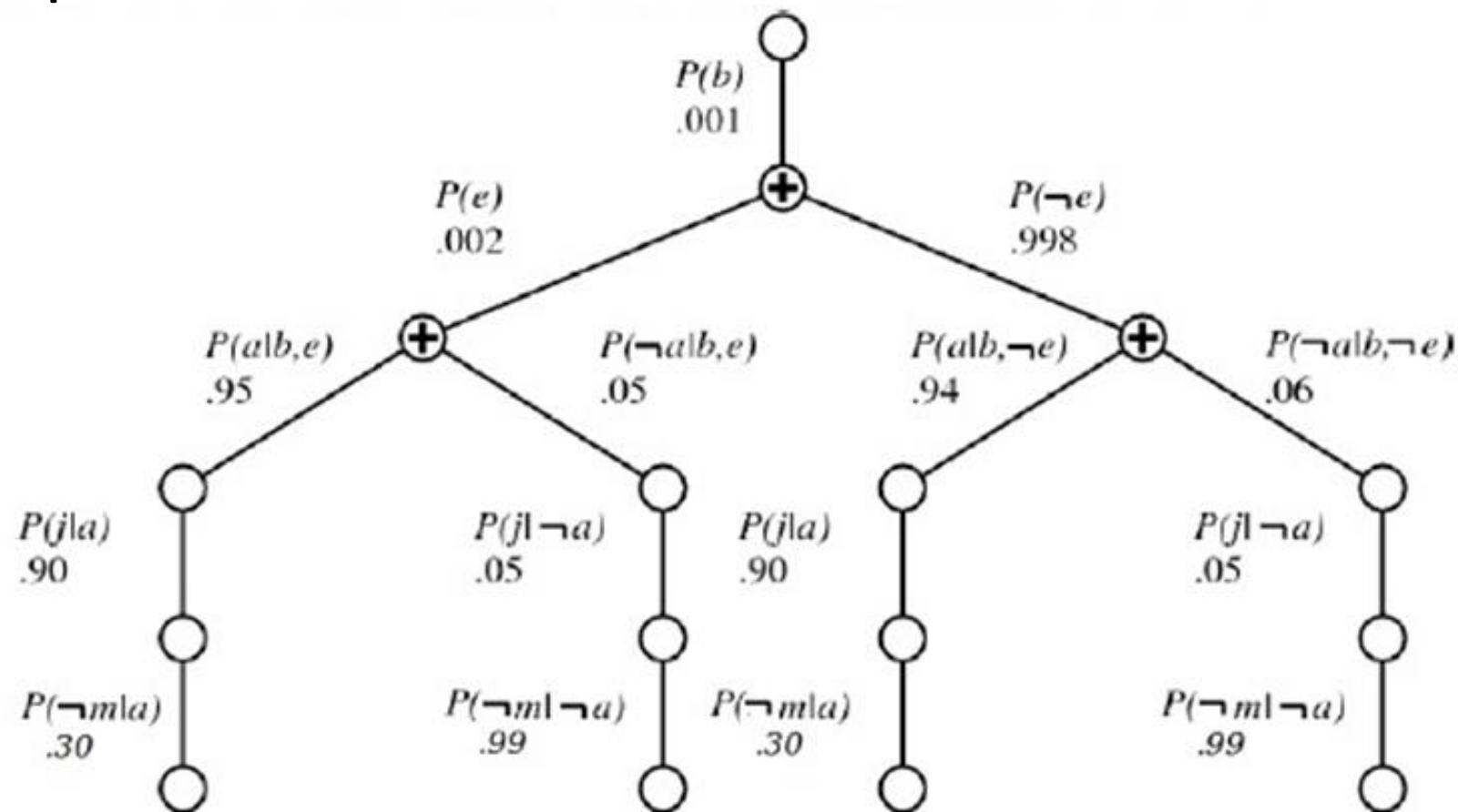
Now evaluating the expression involves 11 multiplications and 3 additions (again excluding the contribution due to term  $\alpha$ ).

$$= \alpha P(b) \sum_E P(E) [P(a|b, E) P(j|a) P(\neg m|a) + P(\neg a|b, E) P(j|\neg a) P(\neg m|\neg a)]$$

# Depth-first Evaluation

$$P(b|j, \neg m) = \alpha P(b) \sum_E P(E) \sum_A P(A|b, E) P(j|A) P(\neg m|A)$$

The process can be illustrated as an evaluation tree.



The evaluation proceeds top-down, multiplying values along each path and summing at the “+” nodes



# Complexity of Depth-first Evaluation

$$\begin{aligned}
 P(b|j, \neg m) &= \alpha \sum_E \sum_A P(b)P(E)P(A|b, E)P(j|A)P(\neg m|A) \\
 &= \alpha [P(b)P(e)P(a|b, e)P(j|a)P(\neg m|a) \\
 &\quad + P(b)P(e)P(\neg a|b, e)P(j|\neg a)P(\neg m|\neg a) \\
 &\quad + P(b)P(\neg e)P(a|b, \neg e)P(j|a)P(\neg m|a) \\
 &\quad + P(b)P(\neg e)P(\neg a|b, \neg e)P(j|\neg a)P(\neg m|\neg a)]
 \end{aligned}$$

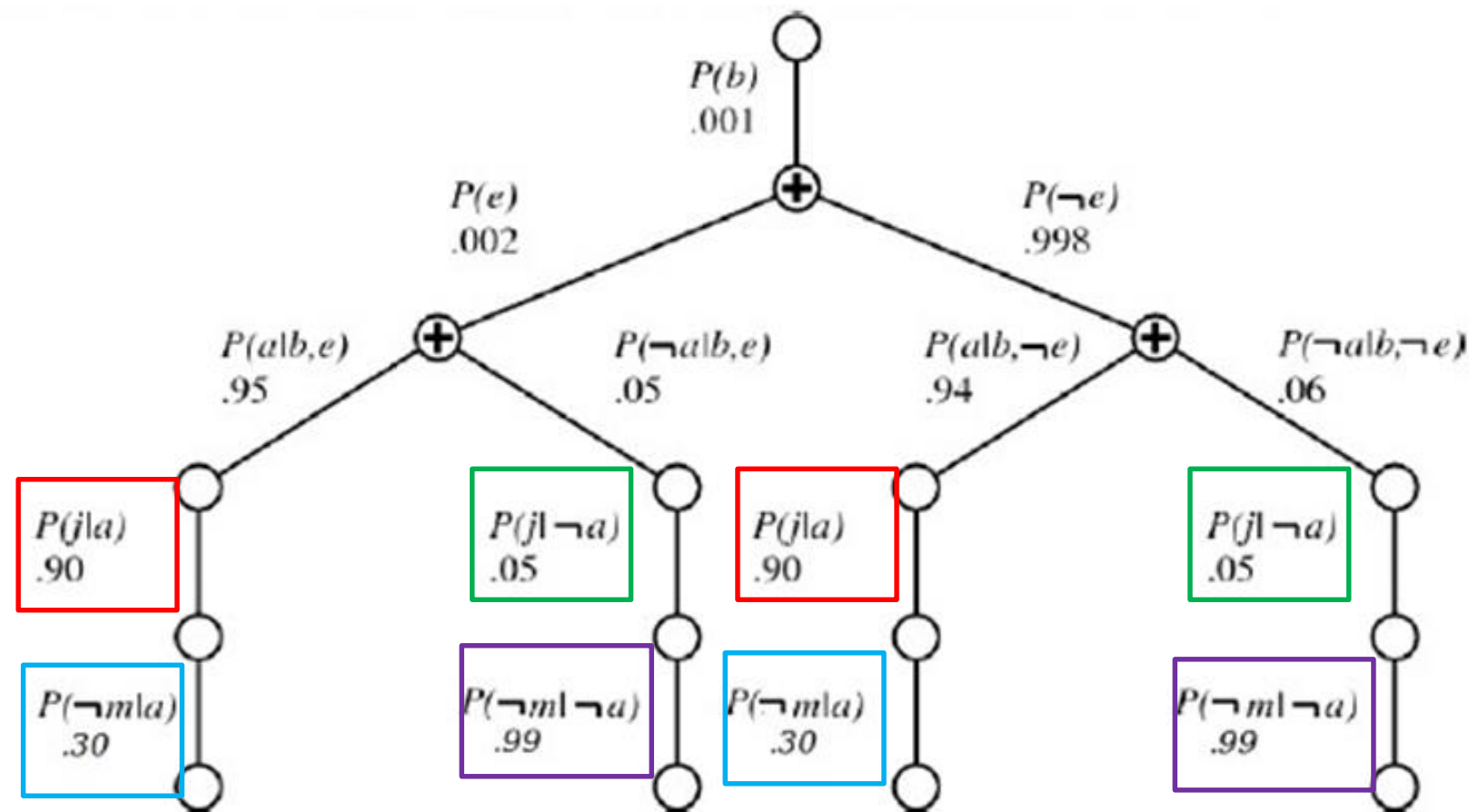
$O(n 2^n)$

$$P(b|j, \neg m) = \alpha P(b) \sum_E P(E) \sum_A P(A|b, E)P(j|A)P(\neg m|A)$$

$O(2^n)$

# Problem of DF Evaluation

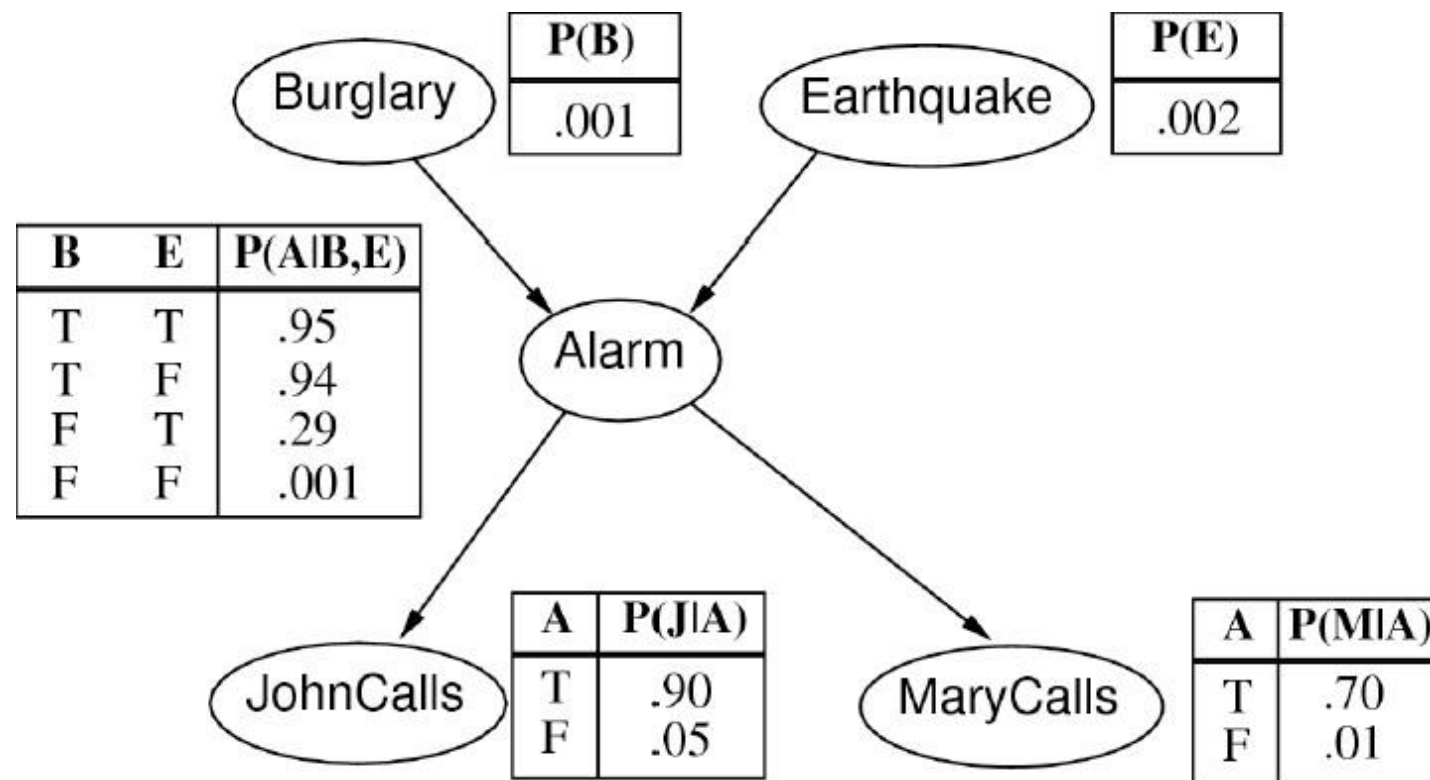
$$P(b|j, \neg m) = \alpha P(b) \sum_E P(E) \sum_A P(A|b, E) P(j|A) P(\neg m|A)$$



Repeat computation!

# Problem with DF evaluation

$$P(E|j, m) = \alpha P(E, j, m)$$



# Problem with DF evaluation

We need to do this sum both for  $E = true$  and  $E = false$ . For the first case:

$$P(e) \left( \begin{array}{l} P(b) (P(a|b, e)P(j|a)P(m|a) + P(\neg a|b, e)P(j|\neg a)P(m|\neg a)) + \\ P(\neg b) (P(a|\neg b, e)P(j|a)P(m|a) + P(\neg a|\neg b, e)P(j|\neg a)P(m|\neg a)) \end{array} \right)$$

# Problem with DF evaluation

We need to do this sum both for  $E = true$  and  $E = false$ . For the first case:

$$P(e) \left( \begin{array}{l} P(b) (P(a|b, e) \boxed{P(j|a)P(m|a)} + P(\neg a|b, e) \boxed{P(j|\neg a)P(m|\neg a)}) + \\ P(\neg b) (P(a|\neg b, e) \boxed{P(j|a)P(m|a)} + P(\neg a|\neg b, e) \boxed{P(j|\neg a)P(m|\neg a)}) \end{array} \right)$$

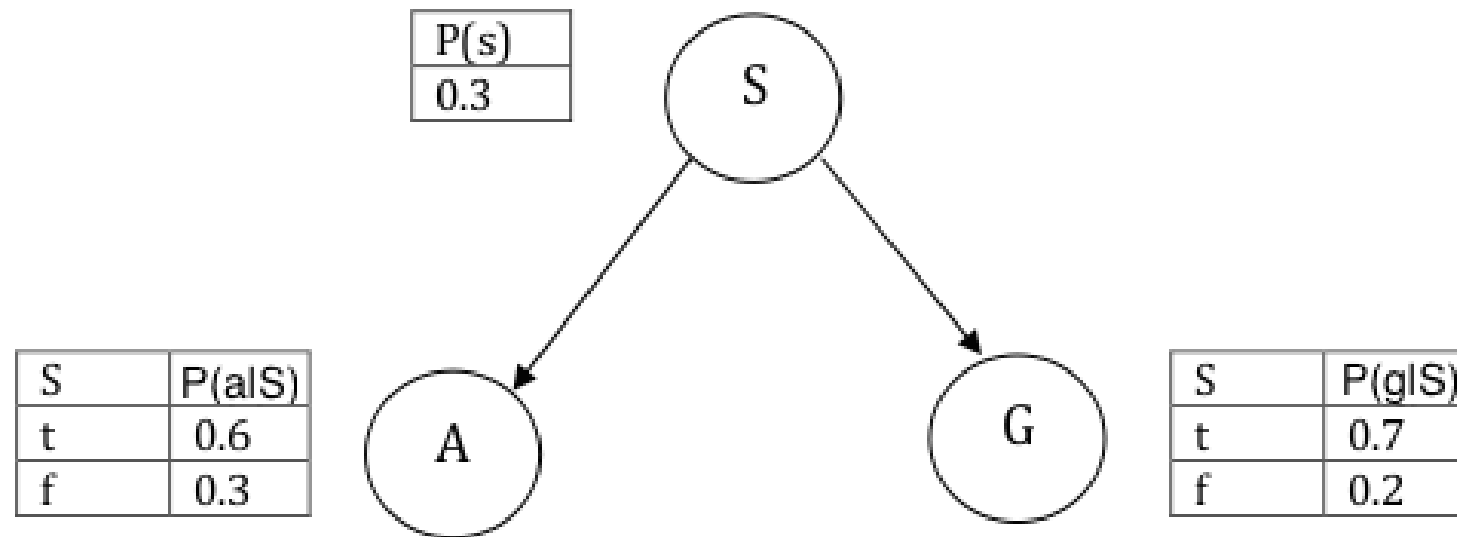
Repeat computation!

# Variable Elimination

- Recursively eliminate variables and merge terms into factors
- Store factors to avoid repeating computations



# Variable Elimination



$$P(A) = \sum_S \sum_G P(A, S, G)$$

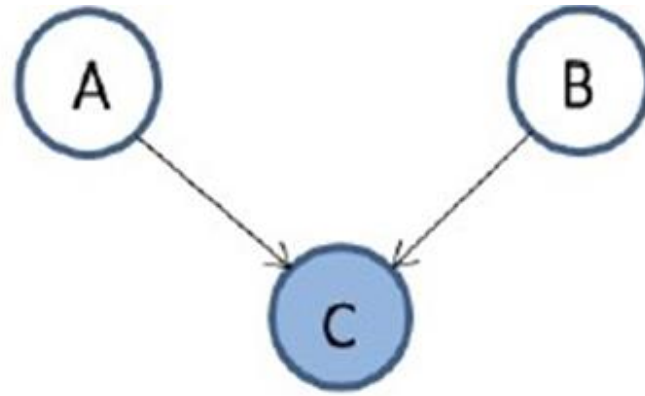
$$= \sum_S \sum_G P(S) P(A|S) P(G|S)$$

$$= \sum_S \left( P(S) P(A|S) \sum_G P(G|S) \right)$$

$$= \sum_S P(S) P(A|S)$$

Eliminate G

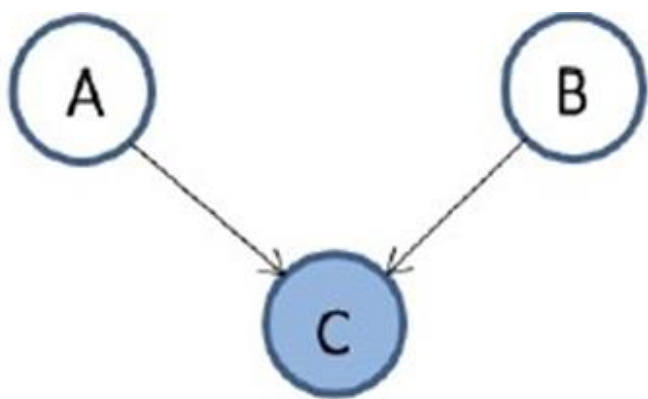
# Variable Elimination



$$\begin{aligned} P(C) &= \sum_A \sum_B P(A, B, C) \\ &= \sum_A \sum_B P(A)P(B)P(C|A, B) \\ &= \sum_B P(B) \sum_A P(A)P(C|A, B) && \text{Eliminate A} \\ &= \sum_B P(B)f_1(B, C) \\ &= f_2(C) && \text{Eliminate B} \end{aligned}$$

# Variable Elimination-Factor

- Factor associate a real value for each setting of its arguments.
- Factor in BN is corresponding to conditional probability distributions.
- The joint distribution is a product of factors.



$$P(A, B, C) = P(A)P(B)P(C|A, B)$$

# Variable Elimination

## -Factor Operation

- Let  $X$ ,  $Y$  and  $Z$  are three random variables, and  $\phi_1(X, Y)$  and  $\phi_2(Y, Z)$  are two factors, their product is a new factor:

$$\psi(X, Y, Z) = \phi_1(X, Y)\phi_2(Y, Z)$$

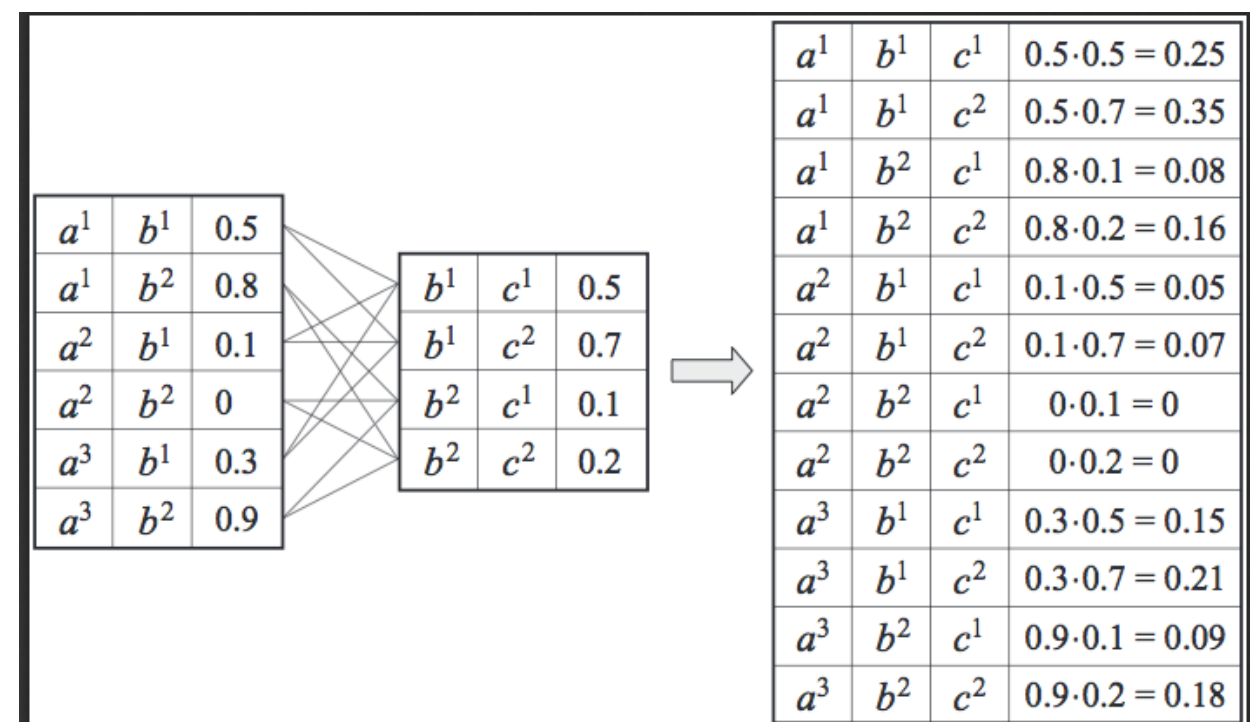
- An Example:

$\phi_1$  has  $3 \times 2 = 6$  entries

$\phi_2$  has  $2 \times 2 = 4$  entries

yields:

$\psi$  has  $3 \times 2 \times 2 = 12$  entries



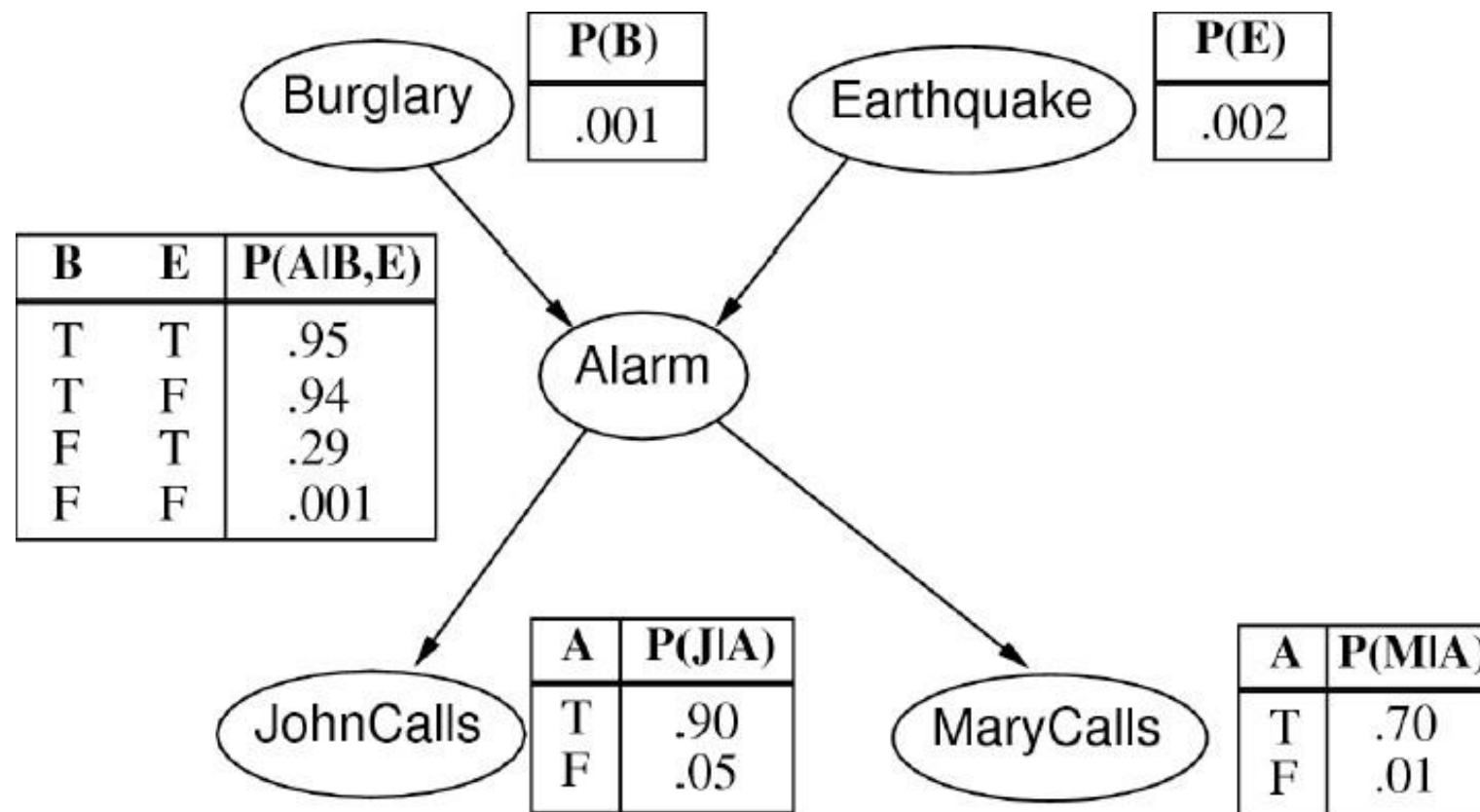
$a^1$	$b^1$	0.5
$a^1$	$b^2$	0.8
$a^2$	$b^1$	0.1
$a^2$	$b^2$	0
$a^3$	$b^1$	0.3
$a^3$	$b^2$	0.9

$b^1$	$c^1$	0.5
$b^1$	$c^2$	0.7
$b^2$	$c^1$	0.1
$b^2$	$c^2$	0.2

$a^1$	$b^1$	$c^1$	$0.5 \cdot 0.5 = 0.25$
$a^1$	$b^1$	$c^2$	$0.5 \cdot 0.7 = 0.35$
$a^1$	$b^2$	$c^1$	$0.8 \cdot 0.1 = 0.08$
$a^1$	$b^2$	$c^2$	$0.8 \cdot 0.2 = 0.16$
$a^2$	$b^1$	$c^1$	$0.1 \cdot 0.5 = 0.05$
$a^2$	$b^1$	$c^2$	$0.1 \cdot 0.7 = 0.07$
$a^2$	$b^2$	$c^1$	$0 \cdot 0.1 = 0$
$a^2$	$b^2$	$c^2$	$0 \cdot 0.2 = 0$
$a^3$	$b^1$	$c^1$	$0.3 \cdot 0.5 = 0.15$
$a^3$	$b^1$	$c^2$	$0.3 \cdot 0.7 = 0.21$
$a^3$	$b^2$	$c^1$	$0.9 \cdot 0.1 = 0.09$
$a^3$	$b^2$	$c^2$	$0.9 \cdot 0.2 = 0.18$

# Variable Elimination

$$\begin{aligned}
 P(E|j, m) &= \alpha P(E, j, m) \\
 &= \alpha \underbrace{P(E)}_E \sum_b \underbrace{P(b)}_B \sum_a \underbrace{P(a|b, E)}_A \underbrace{P(j|a)}_J \underbrace{P(m|a)}_M \\
 &\quad f_E(E) \quad f_B(B) \quad f_A(A, B, E) \quad f_J(A) \quad f_M(A)
 \end{aligned}$$



# Variable Elimination

$$P(E|j, m) = \alpha P(E, j, m)$$

$$\alpha \underbrace{P(E)}_E \sum_b \underbrace{P(b)}_B \sum_a \underbrace{P(a|b, E)}_A \underbrace{P(j|a)}_J \underbrace{P(m|a)}_M$$

$$f_E(E) \quad f_B(B) \quad f_A(A, B, E) \quad f_J(A) \quad f_M(A)$$

E	$f_E(E)$
T	.002
F	.998

B	$f_B(B)$
T	.001
F	.999

A	B	E	$f_A(A, B, E)$
T	T	T	.95
T	T	F	.94
T	F	T	.29
T	F	F	.001
F	T	T	.05
F	T	F	.06
F	F	T	.71
F	F	F	.999

A	$f_J(A)$
T	.9
F	.05

A	$f_M(A)$
T	.7
F	.01



# Variable Elimination

$$\begin{aligned}P(E|j, m) &= \alpha P(E, j, m) \\&= \alpha P(E) \sum_b P(b) \sum_a P(a|b, E) P(j|a) P(m|a) \\&= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_J(A) f_M(A) \quad \text{factorize}\end{aligned}$$

$$\mathbf{P}(E \mid j, m) = \alpha \mathbf{f}_E(E) \times \sum_b (\mathbf{f}_B(B) \times \sum_a (\mathbf{f}_A(A, B, E) \times \mathbf{f}_J(A) \times \mathbf{f}_M(A)))$$

# Variable Elimination

$$P(E|j, m) = \alpha P(E, j, m)$$

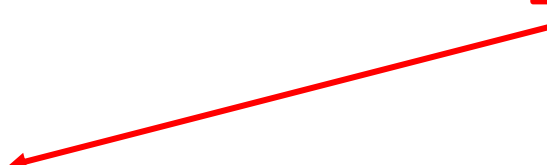
$$= \alpha P(E) \sum_b P(b) \sum_a P(a|b, E) P(j|a) P(m|a)$$

$$= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_J(A) f_M(A)$$

factorize

$$= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_{JM}(A)$$

factor product



A	$f_{JM}(A)$
T	.9 * .7
F	.05 * .01

=

A	$f_J(A)$
T	.9
F	.05

A	$f_M(A)$
T	.7
F	.01

$$f_{JM}(A) = f_J(A) f_M(A)$$

# Variable Elimination

$$\begin{aligned}
 P(E|j, m) &= \alpha P(E, j, m) \\
 &= \alpha P(E) \sum_b P(b) \sum_a P(a|b, E) P(j|a) P(m|a) \\
 &= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_J(A) f_M(A) && \text{factorize} \\
 &= \alpha f_E(E) \sum_b f_B(B) \sum_a \boxed{f_A(A, B, E) f_{JM}(A)} && \text{factor product} \\
 &= \alpha f_E(E) \sum_b f_B(B) \sum_a \boxed{f_{AJM}(A, B, E)} && \text{factor product}
 \end{aligned}$$

A	B	E	$f_{AJM}(A, B, E)$
T	T	T	.95 * .63
T	T	F	.94 * .63
T	F	T	.29 * .63
T	F	F	.001 * .63
F	T	T	.05 * .0005
F	T	F	.06 * .0005
F	F	T	.71 * .0005
F	F	F	.999 * .0005

=

A	B	E	$f_A(A, B, E)$
T	T	T	.95
T	T	F	.94
T	F	T	.29
T	F	F	.001
F	T	T	.05
F	T	F	.06
F	F	T	.71
F	F	F	.999

A	$f_{JM}(A)$
T	.63
F	.0005

$$f_{AJM}(A, B, E) = f_A(A, B, E) f_{JM}(A)$$

# Variable Elimination

$$P(E|j, m) = \alpha P(E, j, m)$$

$$= \alpha P(E) \sum_b P(b) \sum_a P(a|b, E) P(j|a) P(m|a)$$

$$= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_J(A) f_M(A) \quad \text{factorize}$$

$$= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_{JM}(A) \quad \text{factor product}$$

$$= \alpha f_E(E) \sum_b f_B(B) \sum_a f_{AJM}(A, B, E) \quad \text{factor product}$$

$$= \alpha f_E(E) \sum_b f_B(B) f_{\bar{A}JM}(B, E) \quad \text{factor marginalization, and eliminate A}$$

A	B	E	$f_{AJM}(A, B, E)$
T	T	T	.95 * .63
T	T	F	.94 * .63
T	F	T	.29 * .63
T	F	F	.001 * .63
F	T	T	.05 * .0005
F	T	F	.06 * .0005
F	F	T	.71 * .0005
F	F	F	.999 * .0005

B	E	$f_{\bar{A}JM}(B, E)$
T	T	.95 * .63 + .05 * .0005 = .5985
T	F	.94 * .63 + .06 * .0005 = .5922
F	T	.29 * .63 + .71 * .0005 = .1830
F	F	.001 * .63 + .999 * .0005 = .001129

$$f_{\bar{A}JM}(B, E) = \sum_a f_{AJM}(A, B, E)$$

# Variable Elimination

$$\begin{aligned}P(E|j, m) &= \alpha P(E, j, m) \\&= \alpha P(E) \sum_b P(b) \sum_a P(a|b, E) P(j|a) P(m|a) \\&= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_J(A) f_M(A) && \text{factorize} \\&= \alpha f_E(E) \sum_b f_B(B) \sum_a f_A(A, B, E) f_{JM}(A) \\&= \alpha f_E(E) \sum_b f_B(B) \sum_a f_{AJM}(A, B, E) \\&= \alpha f_E(E) \sum_b f_B(B) f_{\bar{A}JM}(B, E) && \text{Eliminate A} \\&= \alpha f_E(E) \sum_b f_{B\bar{A}JM}(B, E) \\&= \alpha f_E(E) f_{\bar{B}\bar{A}JM}(E) && \text{Eliminate B} \\&= \alpha f_{E\bar{B}\bar{A}JM}(E)\end{aligned}$$

The process of evaluation is a process of summing out variables (right to left) from pointwise products of factors to produce new factors, eventually yielding a factor that is the solution, i.e., the posterior distribution over the query variable.

It is bottom-up in the evaluation tree.



# Variable elimination

Also useful for doing inference multiple times

e.g.

$$P(B|J, M) = \alpha P(B, J, M)$$

$$P(B|J) = \alpha P(B, J)$$

$$P(B|M) = \alpha P(B, M)$$



# Variable elimination

$$\begin{aligned}P(B|J, M) &= \alpha P(B, J, M) \\&= \sum_a \sum_e P(B)P(e)P(a|B, e)P(J|A)P(M|a) \\&= \alpha P(B) \sum_e P(e) \sum_a P(a|B, e)P(J|a)P(M|a) \\&= \alpha P(B)f(J, M)\end{aligned}$$

$$\begin{aligned}P(B|J) &= \alpha P(B, J) \\&= \sum_m \sum_a \sum_e P(B)P(e)P(a|B, e)P(J|A)P(m|a) \\&= \alpha P(B) \sum_m \sum_e P(e) \sum_a P(a|B, e)P(J|a)P(m|a) \\&= \alpha P(B) \sum_m f(J, m)\end{aligned}$$

We only need to calculate  $f$  once

$$\begin{aligned}P(B|M) &= \alpha P(B, M) \\&= \sum_j \sum_a \sum_e P(B)P(e)P(a|B, e)P(j|A)P(M|a) \\&= \alpha P(B) \sum_j \sum_e P(e) \sum_a P(a|B, e)P(j|a)P(M|a) \\&= \alpha P(B) \sum_j f(j, M)\end{aligned}$$