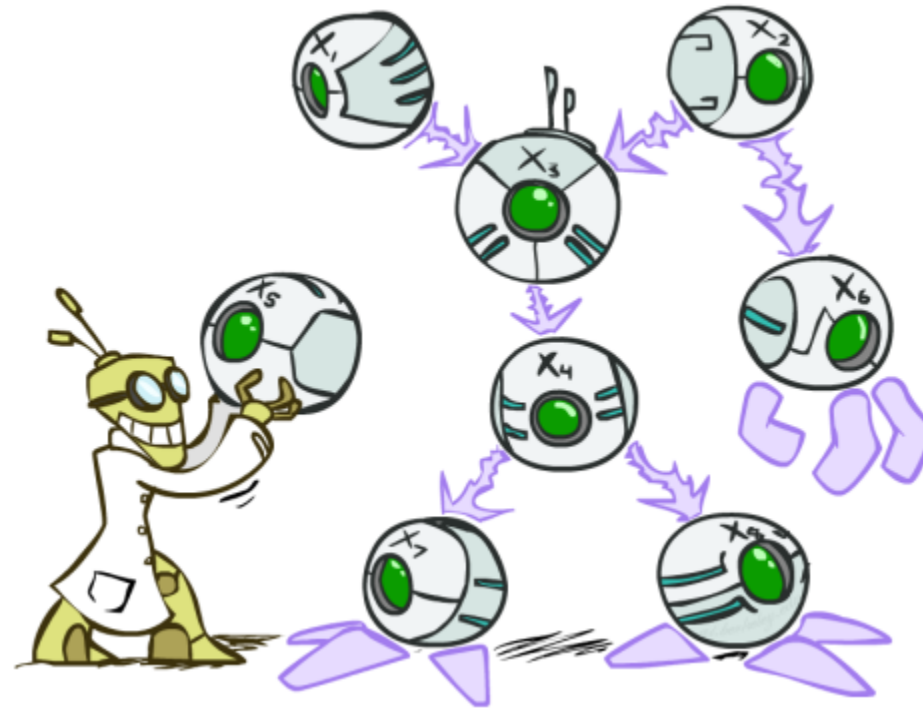


AI: Representation and Problem Solving

Bayes Nets Inference



Instructors: Tuomas Sandholm and Vincent Conitzer

Slide credits: CMU AI and <http://ai.berkeley.edu>

Announcements

- HW8 (online) due tomorrow Thursday April 3
- HW9 (online, written) released tomorrow Thursday April 3, due next Thursday April 10
- No TA office hours during carnival EXCEPT Saturday April 5 12-2pm

Bayes Nets

✓ Part I: Representation and Independence

Part II: Exact inference

- Enumeration (always exponential complexity)
- Variable elimination (worst-case exponential complexity, often better)
- Inference is NP-hard in general

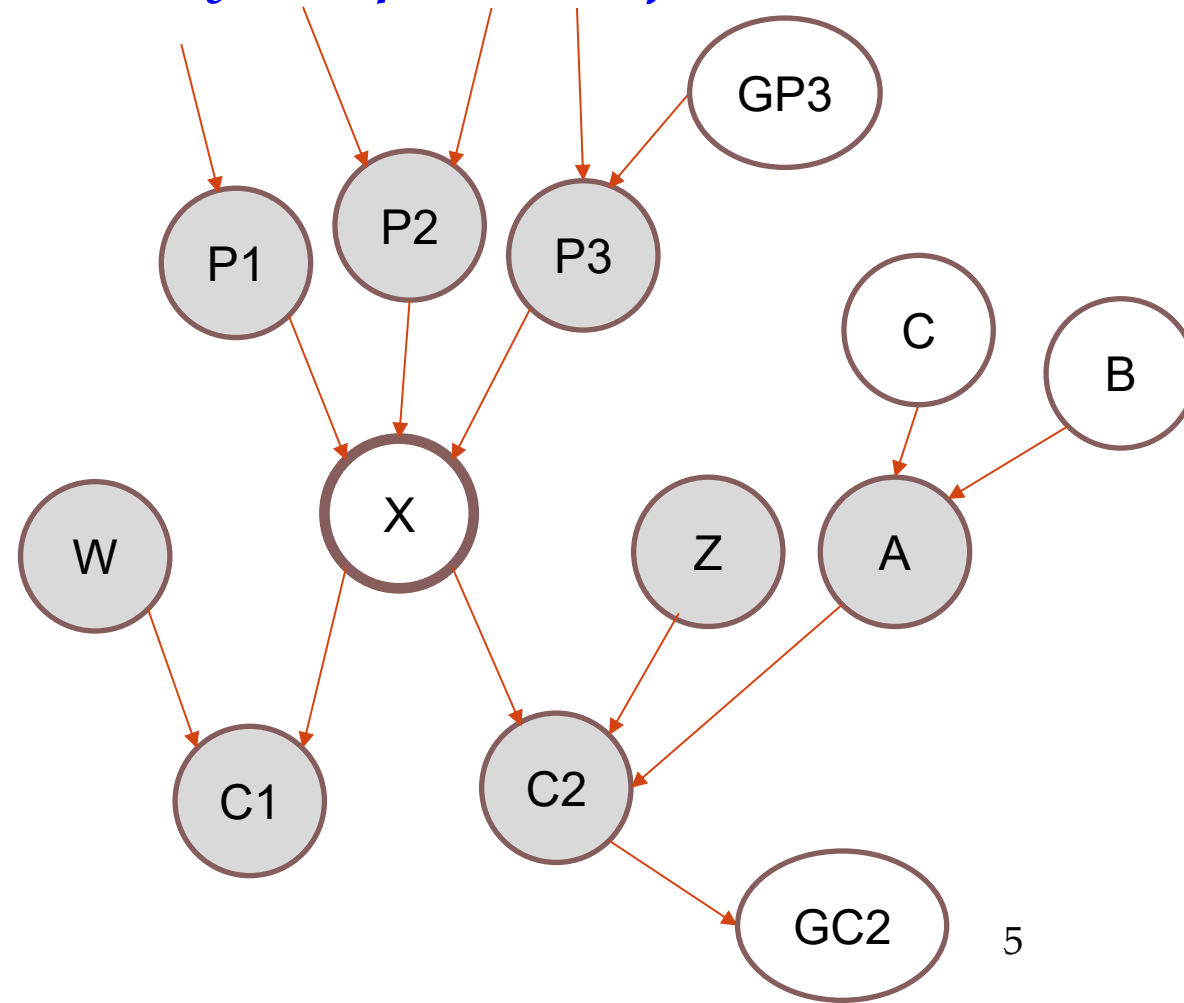
Part III: Approximate Inference

Markov blanket

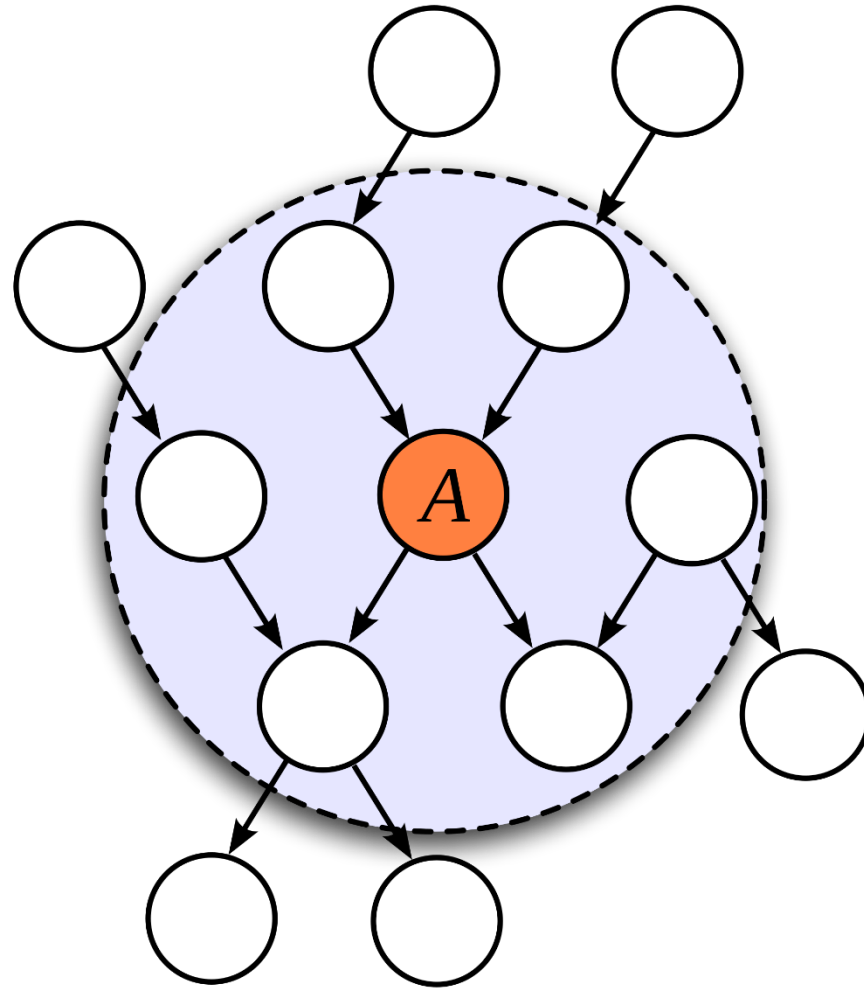
- Markov blanket of X - subset of variables such that all other variables are independent of X conditioned on the blanket

Markov blanket

- A variable's Markov blanket consists of parents, children, children's other parents
- *Every variable is conditionally independent of all other variables given its Markov blanket*



Markov blanket



Bayes Nets

Part I: Representation and Independence

→ Part II: Exact inference

- Enumeration (always exponential complexity)
- Variable elimination (worst-case exponential complexity, often better)
- Inference is NP-hard in general

Part III: Approximate Inference

Queries

- What is the probability of *this* given what I know? $P(q | e)$
- What are the probabilities of all the possible outcomes (given what I know)? $P(Q | e)$
- Which outcome is the most likely outcome (given what I know)?
 $\operatorname{argmax}_{q \in Q} P(q | e)$

Queries

- What is the probability of *this* given what I know?

$$P(q | e) = \frac{P(q, e)}{P(e)}$$

- What are the probabilities of all the possible outcomes (given what I know)?

$$P(Q | e) = \frac{P(Q, e)}{P(e)}$$

- Which outcome is the most likely outcome (given what I know)?

$$\operatorname{argmax}_{q \in Q} P(q | e) = \operatorname{argmax}_{q \in Q} \frac{P(q, e)}{P(e)}$$

Queries

- What is the probability of *this* given what I know?

$$P(q | e) = \frac{P(q, e)}{P(e)} = \frac{\sum_{h_1} \sum_{h_2} P(q, h_1, h_2, e)}{P(e)}$$

- What are the probabilities of all the possible outcomes (given what I know)?

$$P(Q | e) = \frac{P(Q, e)}{P(e)} = \frac{\sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)}{P(e)}$$

- Which outcome is the most likely outcome (given what I know)?

$$\operatorname{argmax}_{q \in Q} P(q | e) = \operatorname{argmax}_{q \in Q} \frac{P(q, e)}{P(e)} = \operatorname{argmax}_{q \in Q} \frac{\sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)}{P(e)}$$

Poll 1

- If we only have the joint table $P(Q, H_1, H_2, E)$, what is the **minimum number of times** we need to compute $P(e)$ to build $P(Q | e)$?

$$P(Q | e) = \frac{P(Q, e)}{P(e)} = \frac{\sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)}{P(e)}$$

- A) 0
- B) 1
- C) 10
- D) 30
- E) 200
- F) 600

- Q can take on 10 different values
- H_1 can take on 4 different values
- H_2 can take on 5 different values
- E can take on 3 different values

Poll 2

- If we only have the joint table $P(Q, H_1, H_2, E)$, what is the **minimum** number of times we need to compute $P(e)$ to compute the following?

$$\operatorname{argmax}_{q \in Q} P(q | e) = \frac{P(q, e)}{P(e)} = \frac{\sum_{h_1} \sum_{h_2} P(q, h_1, h_2, e)}{P(e)}$$

- A) 0
- B) 1
- C) 10
- D) 30
- E) 200
- F) 600

- Q can take on 10 different values
- H_1 can take on 4 different values
- H_2 can take on 5 different values
- E can take on 3 different values

Normalization

- Sometimes we don't care about exact probability and we skip $P(e)$

$$P(Q | e) = \frac{\sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)}{P(e)}$$

$$P(Q | e) = \frac{1}{Z} \sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)$$

$$P(Q | e) = \alpha \sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)$$

$$P(Q | e) \propto \sum_{h_1} \sum_{h_2} P(Q, h_1, h_2, e)$$

Bayes Nets in the Wild

Example: Speech Recognition

“artificial

Find most probable next word given “artificial” and the audio for second word.

Bayes Nets in the Wild

Example: Speech Recognition

“artificial

Find most probable next word given “artificial” and the audio for second word.

Which second word gives the highest probability?

Break down problem

n-gram probability * audio probability

$$P(\mathbf{limb} \mid \text{artificial}, [\text{audio}])$$

$$P(\mathbf{limb} \mid \text{artificial}) * P([\text{audio}] \mid \mathbf{limb})$$

$$P(\mathbf{intelligence} \mid \text{artificial}, [\text{audio}])$$

$$P(\mathbf{intelligence} \mid \text{artificial}) * P([\text{audio}] \mid \mathbf{intelligence})$$

$$P(\mathbf{flavoring} \mid \text{artificial}, [\text{audio}])$$

$$P(\mathbf{flavoring} \mid \text{artificial}) * P([\text{audio}] \mid \mathbf{flavoring})$$

Bayes Nets in the Wild

$$\begin{aligned} \text{second}^* &= \operatorname{argmax}_{\text{second}} P(\mathbf{second} \mid \text{artificial}, [\text{audio}]) \\ &= \operatorname{argmax}_{\text{second}} \frac{P(\mathbf{second}, \text{artificial}, [\text{audio}])}{P(\text{artificial}, [\text{audio}])} \\ &= \operatorname{argmax}_{\text{second}} P(\mathbf{second}, \text{artificial}, [\text{audio}]) \\ &= \operatorname{argmax}_{\text{second}} P(\text{artificial}) P(\mathbf{second} \mid \text{artificial}) P([\text{audio}] \mid \text{artificial}, \mathbf{second}) \\ &= \operatorname{argmax}_{\text{second}} P(\text{artificial}) P(\mathbf{second} \mid \text{artificial}) P([\text{audio}] \mid \mathbf{second}) \\ &= \operatorname{argmax}_{\text{second}} P(\mathbf{second} \mid \text{artificial}) P([\text{audio}] \mid \mathbf{second}) \\ &\quad \text{n-gram probability} * [\text{audio}] \text{ probability} \end{aligned}$$

Inference

○ **Inference:** calculating some useful quantity from a probability model (joint probability distribution)

▪ **Examples:**

▪ Posterior marginal probability

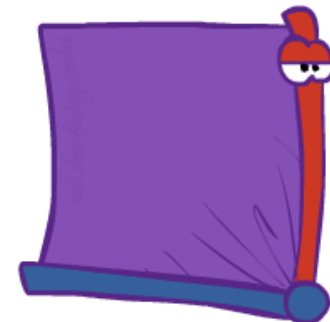
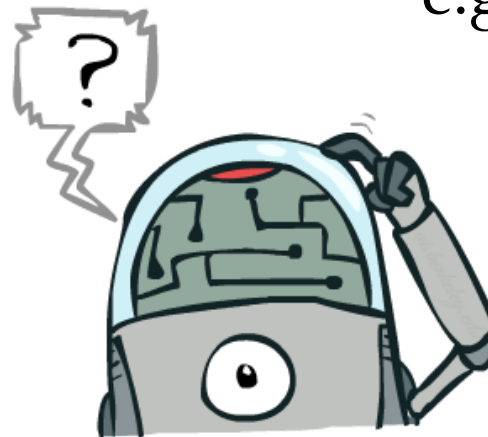
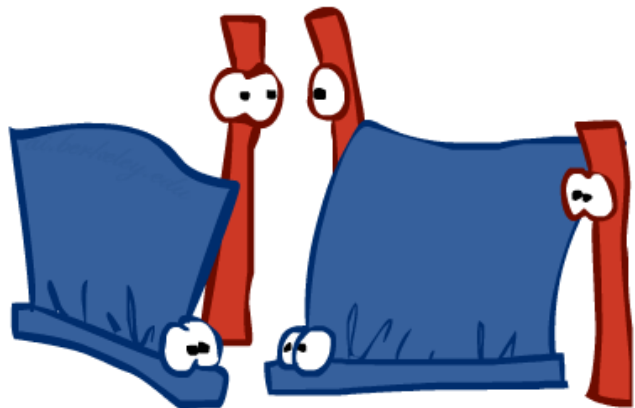
▪ $P(Q | e_1, \dots, e_k)$

▪ e.g., what disease might I have?

▪ Most likely explanation:

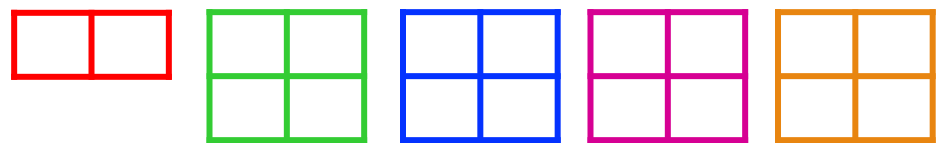
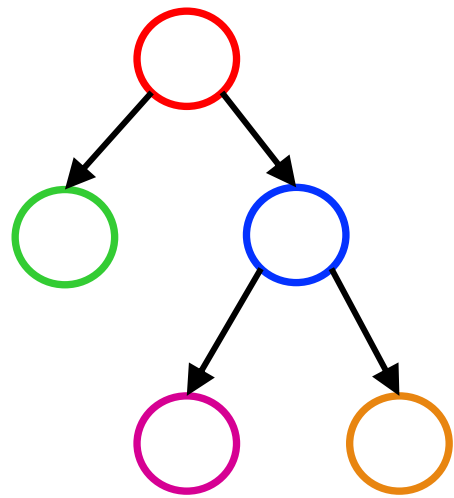
▪ $\operatorname{argmax}_{q,r,s} P(Q=q, R=r, S=s | e_1, \dots, e_k)$

▪ e.g., what was just said?



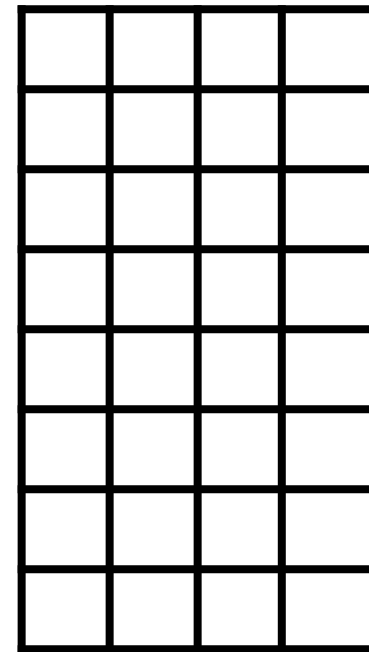
Answer Any Query from Bayes Net

Bayes Net



$P(A)$ $P(B|A)$ $P(C|A)$ $P(D|C)$ $P(E|C)$

Joint

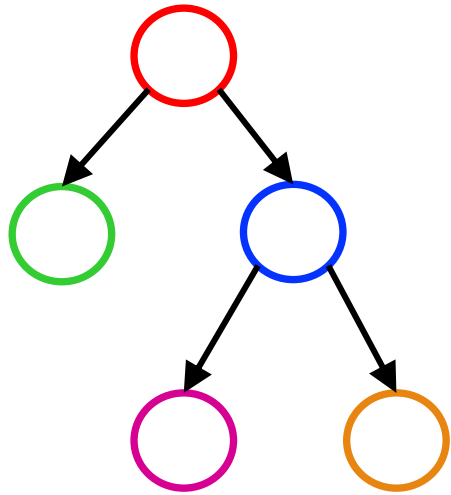


Query

$P(a | e)$

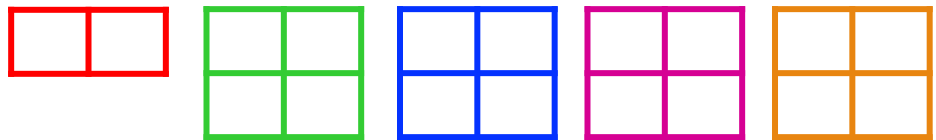
Next: Answer Any Query from Bayes Net

Bayes Net



Query

$$P(a | e)$$

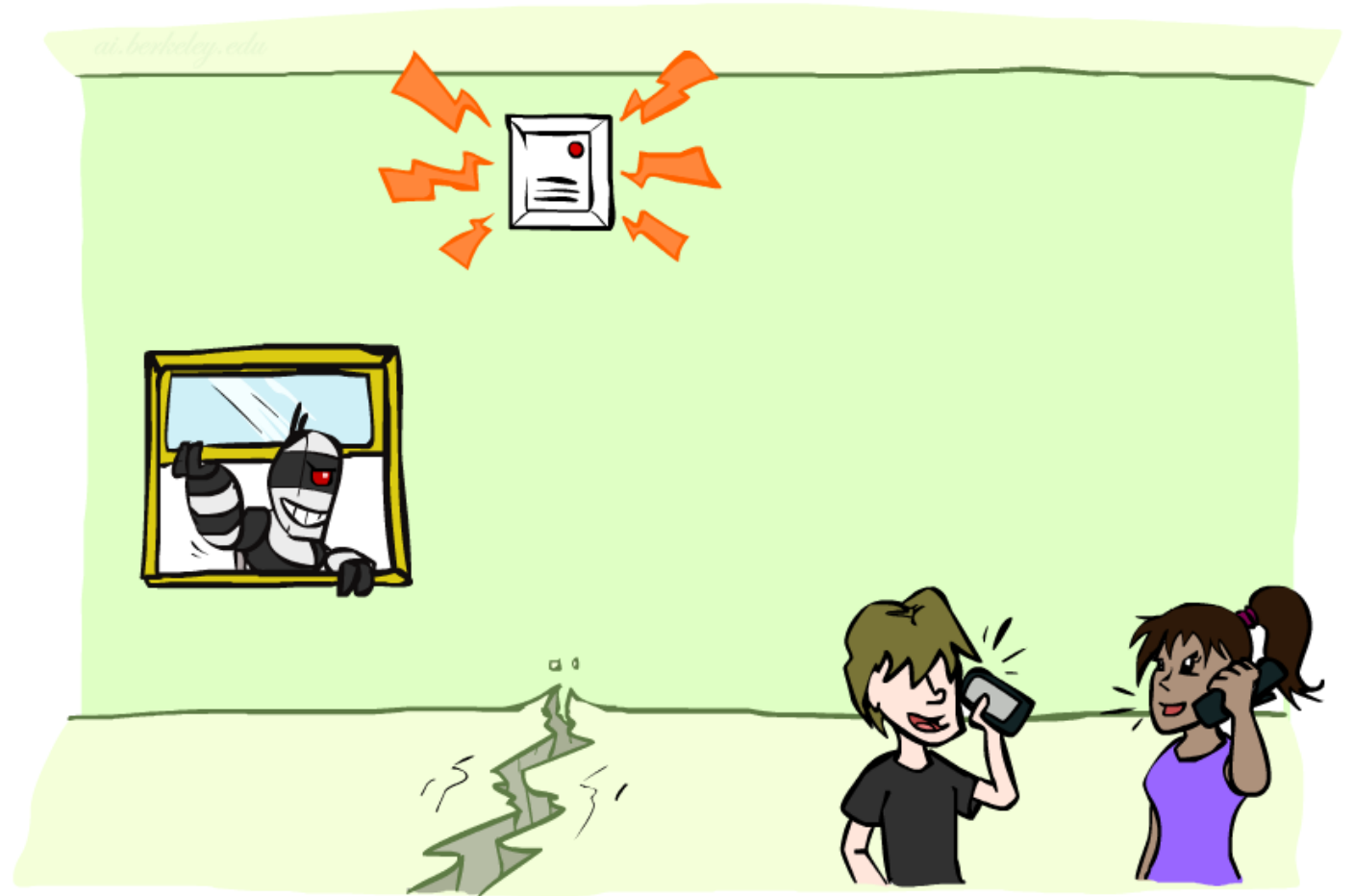


$$P(A) \quad P(B|A) \quad P(C|A) \quad P(D|C) \quad P(E|C)$$

Example: Alarm Network

- Variables

- B: Burglary
- A: Alarm goes off
- M: Mary calls
- J: John calls
- E: Earthquake!



Example: Alarm Network



- Joint distribution factorization example

- Generic chain rule

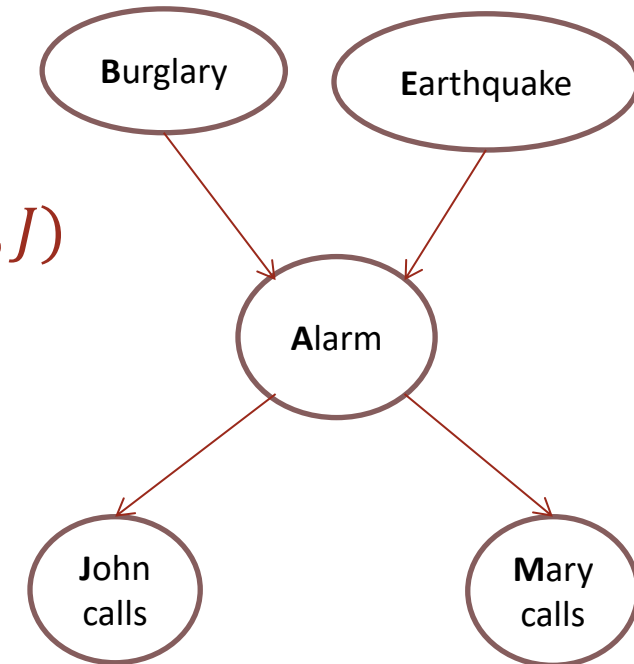
- $P(X_1 \dots X_n) = \prod_i P(X_i | X_1 \dots X_{i-1})$

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

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

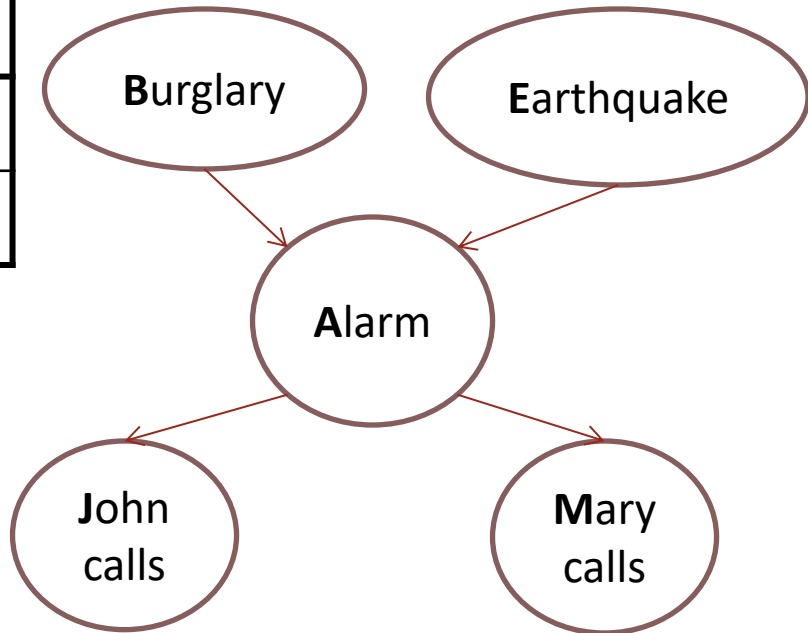
- Bayes nets

- $P(X_1 \dots X_n) = \prod_i P(X_i | Parents(X_i))$



Example: Alarm Network

B	P(B)
+b	0.001
-b	0.999



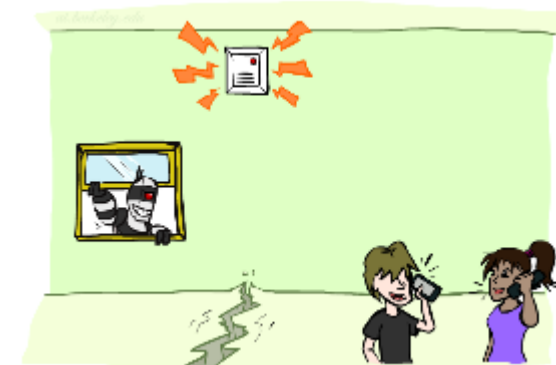
E	P(E)
+e	0.002
-e	0.998

$$P(+b, -e, -a, -j, -m) =$$

A	J	P(J A)
+a	+j	0.9
+a	-j	0.1
-a	+j	0.05
-a	-j	0.95

A	M	P(M A)
+a	+m	0.7
+a	-m	0.3
-a	+m	0.01
-a	-m	0.99

B	E	A	P(A B,E)
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999



Example: Alarm Network

$$\begin{aligned} P(+b, -e, -a, -j, -m) &= P(+b) * P(-e) * P(-a|+b, -e) * P(-j|-a) * P(-m|-a) \\ &= 0.001 * 0.998 * 0.06 * 0.95 * 0.99 \end{aligned}$$

$$\begin{aligned} P(+b, -e, -a, -j, -m) &= P(-e) * P(-a|+b, -e) * P(+b) * P(-j|-a) * P(-m|-a) \\ &= 0.998 * 0.06 * 0.001 * 0.95 * 0.99 \end{aligned}$$

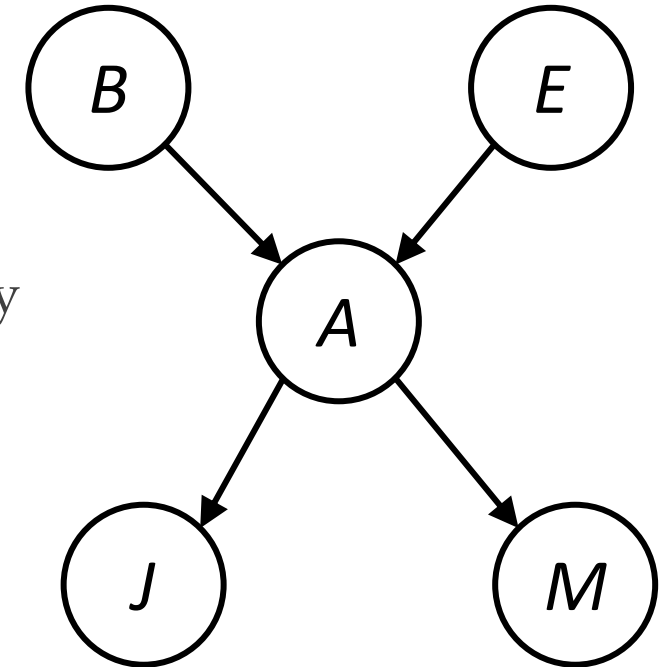
$$\begin{aligned} P(+b, -e, -a, -j, -m) &= P(-e) * P(-a|+b, -e) * P(+b) P(-j|-a) * P(-m|-a) \\ &= 0.998 * 0.06 * 0.0095 * 0.99 \end{aligned}$$

- Multiplication order can change (commutativity)
- Multiplication pairs don't have to make sense (associativity)

Inference by Enumeration in Bayes Net

- Inference by enumeration:
 - Any probability of interest can be computed by summing entries from the joint distribution
 - Entries from the joint distribution can be obtained from a BN by multiplying the corresponding conditional probabilities

$$\begin{aligned}P(B \mid j, m) &= \alpha P(B, j, m) \\ &= \alpha \sum_{e,a} P(B, e, a, j, m) \\ &= \alpha \sum_{e,a} P(B) P(e) P(a \mid B, e) P(j \mid a) P(m \mid a)\end{aligned}$$



- So inference in Bayes nets means computing sums of products of numbers: sounds easy!!
- Problem: sums of *exponentially many* products!

Can we do better?

- $P(B | j, m) = \sum_e \sum_a P(B) P(e) P(a | B, e) P(j | a) P(m | a)$

$$\begin{aligned} &= P(B) P(+e) P(+a | B, +e) P(j | +a) P(m | +a) \\ &+ P(B) P(-e) P(+a | B, -e) P(j | +a) P(m | +a) \\ &+ P(B) P(+e) P(-a | B, +e) P(j | -a) P(m | -a) \\ &+ P(B) P(-e) P(-a | B, -e) P(j | -a) P(m | -a) \end{aligned}$$

- **Lots of repeated subexpressions!**

Can we do better?

- $P(B | j, m) = \sum_e \sum_a P(B) P(e) P(a | B, e) P(j | a) P(m | a)$

$$\begin{aligned} &= P(B) P(+e) P(+a | B, +e) P(j | +a) P(m | +a) \\ &+ P(B) P(-e) P(+a | B, -e) P(j | +a) P(m | +a) \\ &+ P(B) P(+e) P(-a | B, +e) P(j | -a) P(m | -a) \\ &+ P(B) P(-e) P(-a | B, -e) P(j | -a) P(m | -a) \end{aligned}$$

- **Lots of repeated subexpressions!**

Inference Overview

- Given random variables Q, H, E (query, hidden, evidence)
- We know how to do inference on a joint distribution

$$\begin{aligned} P(q|e) &= \alpha P(q, e) \\ &= \alpha \sum_{h \in \{h_1, h_2\}} P(q, h, e) \end{aligned}$$

- Bayes nets break down joint distribution into CPT factors

$$\begin{aligned} P(q|e) &= \alpha \sum_{h \in \{h_1, h_2\}} P(h) P(q|h) P(e|q) \\ &= \alpha [P(h_1) P(q|h_1) P(e|q) + P(h_2) P(q|h_2) P(e|q)] \end{aligned}$$



- But we can be more efficient

$$\begin{aligned} P(q|e) &= \alpha P(e|q) \sum_{h \in \{h_1, h_2\}} P(h) P(q|h) \\ &= \alpha P(e|q) [P(h_1) P(q|h_1) + P(h_2) P(q|h_2)] \\ &= \alpha P(e|q) P(q) \end{aligned}$$

- Now just extend to larger Bayes nets and a variety of queries

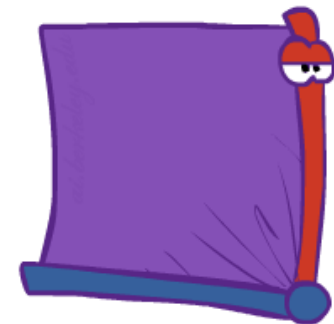
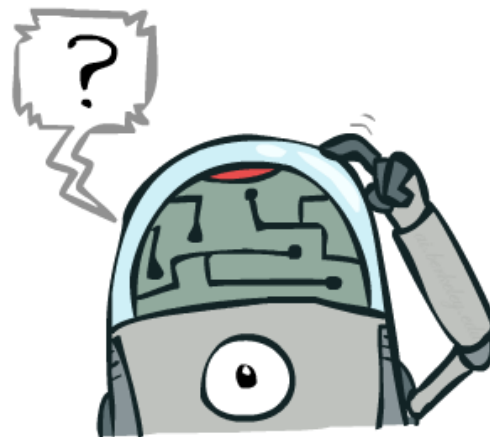
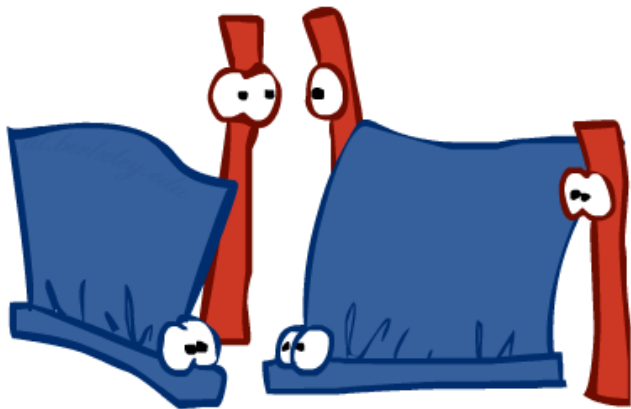
Enumeration

Elimination

Factor Tables

$$\begin{aligned} P(+b, -e, -a, -j, -m) &= P(+b) * P(-e) * P(-a|+b, -e) * P(-j|-a) * P(-m|-a) \\ &= 0.001 * 0.998 * 0.06 * 0.95 * 0.99 \end{aligned}$$

$$\begin{aligned} P(+b, -e, -a, -j, -m) &= P(-e) * P(-a|+b, -e) * P(+b) * P(-j|-a) * P(-m|-a) \\ &= 0.998 * 0.06 * 0.001 * 0.95 * 0.99 \end{aligned}$$



Variable elimination: The basic ideas

- Move summations inwards as far as possible

$$\begin{aligned} P(B \mid j, m) &= \alpha \sum_e \sum_a P(B, e, a, j, m) \\ &= \alpha \sum_e \sum_a P(j|a) P(e) P(m|a) P(a|B, e) P(B) \end{aligned}$$

Variable elimination: The basic ideas

- Move summations inwards as far as possible, inner sum is easier to compute

$$P(B \mid j, m) = \alpha \sum_e \sum_a P(B, e, a, j, m)$$

$$= \alpha \sum_e \sum_a P(j|a) P(e) P(m|a) P(a|B, e) P(B)$$

$$= \alpha P(B) \sum_e P(e) \sum_a P(j|a) P(m|a) P(a|B, e)$$

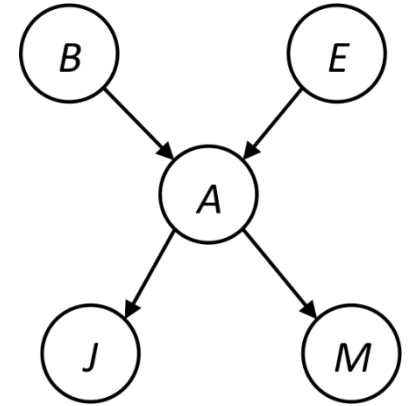
Variable Elimination

- Query: $P(Q_1, \dots, Q_m \mid E_1=e_1, \dots, E_k=e_k)$
- Start with initial factors:
 - Local CPTs (but instantiated by evidence)
- While there are still **hidden** variables (not Q_i or evidence):
 - Pick a hidden variable H
 - **Join** all factors mentioning H
 - **Eliminate** (sum out) H
- Join all remaining factors and normalize

Example

Query $P(B \mid j, m)$

$$= \alpha \sum_e \sum_a P(j|a) P(e) P(m|a) P(a|B, e) P(B)$$



Push summations inwards such that products that do not depend on the variable are pulled out of the sum.

$$= \alpha P(B) \sum_e P(e) \sum_a P(j|a) P(m|a) P(a|B, e)$$

Example

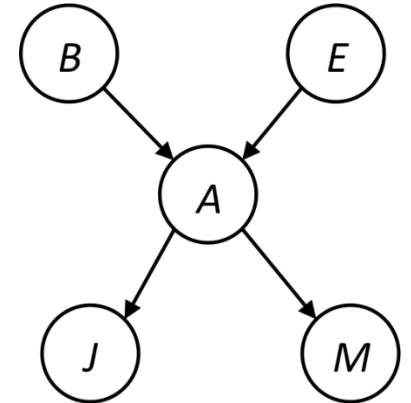
Query $P(B \mid j, m)$

$$= \alpha P(B) \sum_e P(e) \sum_a P(j \mid a) P(m \mid a) P(a \mid B, e)$$

Choose A (innermost sum)

Create a table $t_1 = P(A \mid B, E)P(j \mid A)P(m \mid A)$
How many entries does this table have?

$$= \alpha P(B) \sum_e P(e) \sum_a t_1(a, B, e, j, m)$$



Example

Query $P(B \mid j, m)$

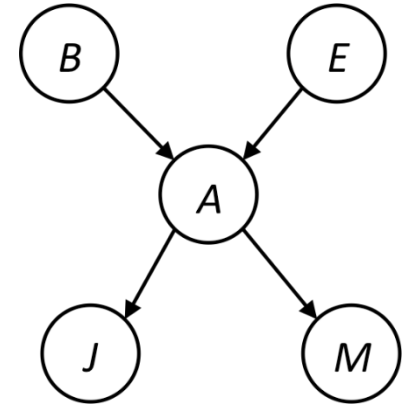
$$= \alpha P(B) \sum_e P(e) \sum_a t(a, B, e, j, m)$$

Choose A (inner most sum)

Sum over A in the table to create a factor $f_1 = \sum_a t(a, B, e, j, m)$

How many entries does this new factor table have?

$$= \alpha P(B) \sum_e P(e) f_1(B, e, j, m)$$



Example

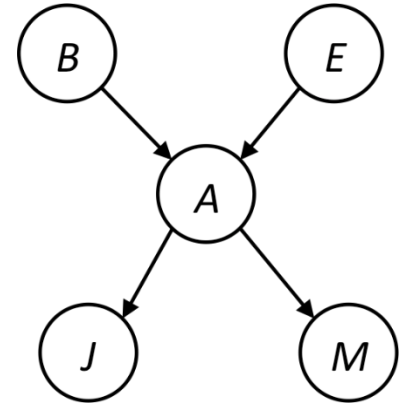
$$= \alpha P(B) \sum_e P(e) f_1(B, e, j, m)$$

Choose E (innermost sum)

Create a table $t_2 = P(E) f_1(B, E, j, m)$

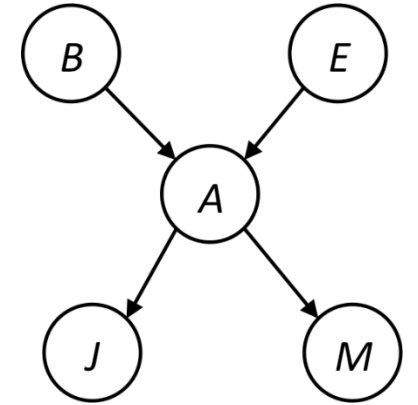
How many entries does this table have?

$$= \alpha P(B) \sum_e t_2(B, e, j, m)$$



Example

$$= \alpha P(B) \sum_e t_2(B, e, j, m)$$



Choose E (innermost sum)

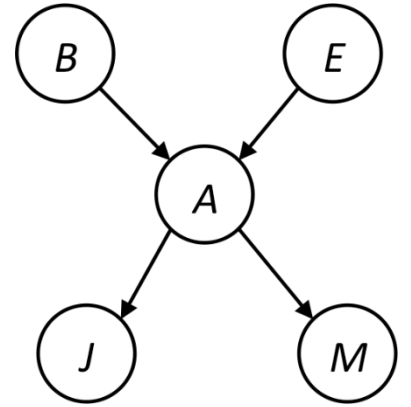
*Sum over E in the table to create a factor $f_2 = \sum_e t_2(B, e, j, m)$
How many entries does this new factor table have?*

$$= \alpha P(B) f_2(B, j, m)$$

Example

$$= \alpha P(B) f_2(B, j, m)$$

Multiply remaining probability to create joint probability $P(B, j, m)$



How many entries does this probability table have?

Don't forget the normalization to compute the conditional probability!

$$\alpha = \frac{1}{Z} = \frac{1}{P(j, m)} =$$

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

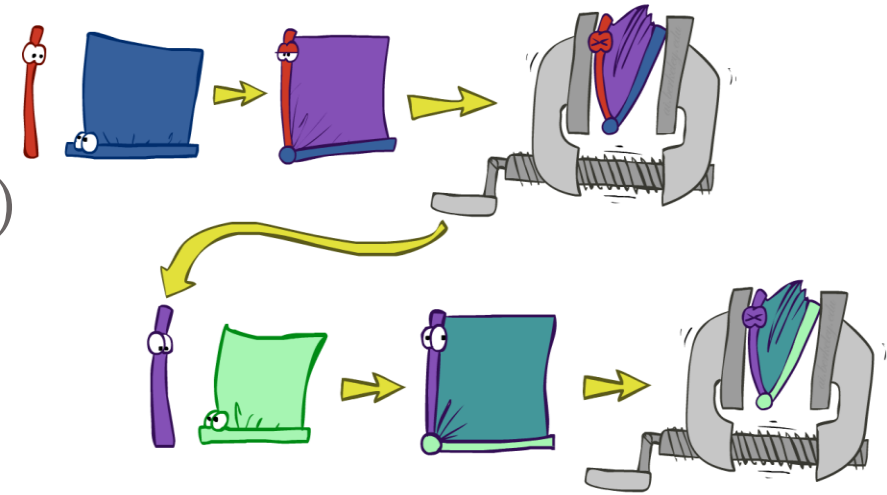
Example summary

- Query $P(B \mid j, m) \propto \sum_e \sum_a P(j \mid a) P(e) P(m \mid a) P(a \mid B, e) P(B)$
- Join **A** to get table $P(A \mid B, E) P(j \mid A) P(m \mid A)$
- Eliminate **A** to get factor $f_1(B, E, j, m)$
- Join **E** to get table $P(E) f_1(B, E, j, m)$
- Eliminate **E** to get table $P(B) f_2(B, j, m)$
- Join **B** to get $P(B, j, m)$ and then normalize

Variable elimination: The basic ideas

- Move summations inwards as far as possible

$$\begin{aligned} \circ P(B \mid j, m) &= \alpha \sum_e \sum_a P(B) P(e) P(a \mid B, e) P(j \mid a) P(m \mid a) \\ &= \alpha P(B) \sum_e P(e) \sum_a P(a \mid B, e) P(j \mid a) P(m \mid a) \end{aligned}$$



- Do the calculation from the inside out

- I.e., sum over a first, then sum over e
- Problem: $P(a \mid B, e)$ isn't a single number, it's a bunch of different numbers depending on the values of B and e
- Solution: use arrays of numbers (of various dimensions) with appropriate operations on them; these are called **factors**

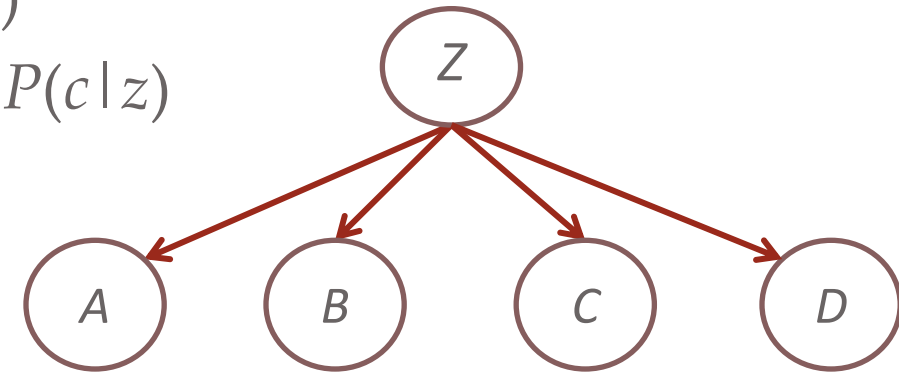
Order matters

- Elimination Order: C, B, A, Z

- $P(D) = \alpha \sum_{z,a,b,c} P(D|z) P(z) P(a|z) P(b|z) P(c|z)$

- $= \alpha \sum_z P(D|z) P(z) \sum_a P(a|z) \sum_b P(b|z) \sum_c P(c|z)$

- Largest factor has 2 variables (D,Z)



- Elimination Order: Z, C, B, A

- $P(D) = \alpha \sum_{a,b,c,z} P(a|z) P(b|z) P(c|z) P(D|z) P(z)$

- $= \alpha \sum_a \sum_b \sum_c \sum_z P(a|z) P(b|z) P(c|z) P(D|z) P(z)$

- Largest factor has 4 variables (A,B,C,D)

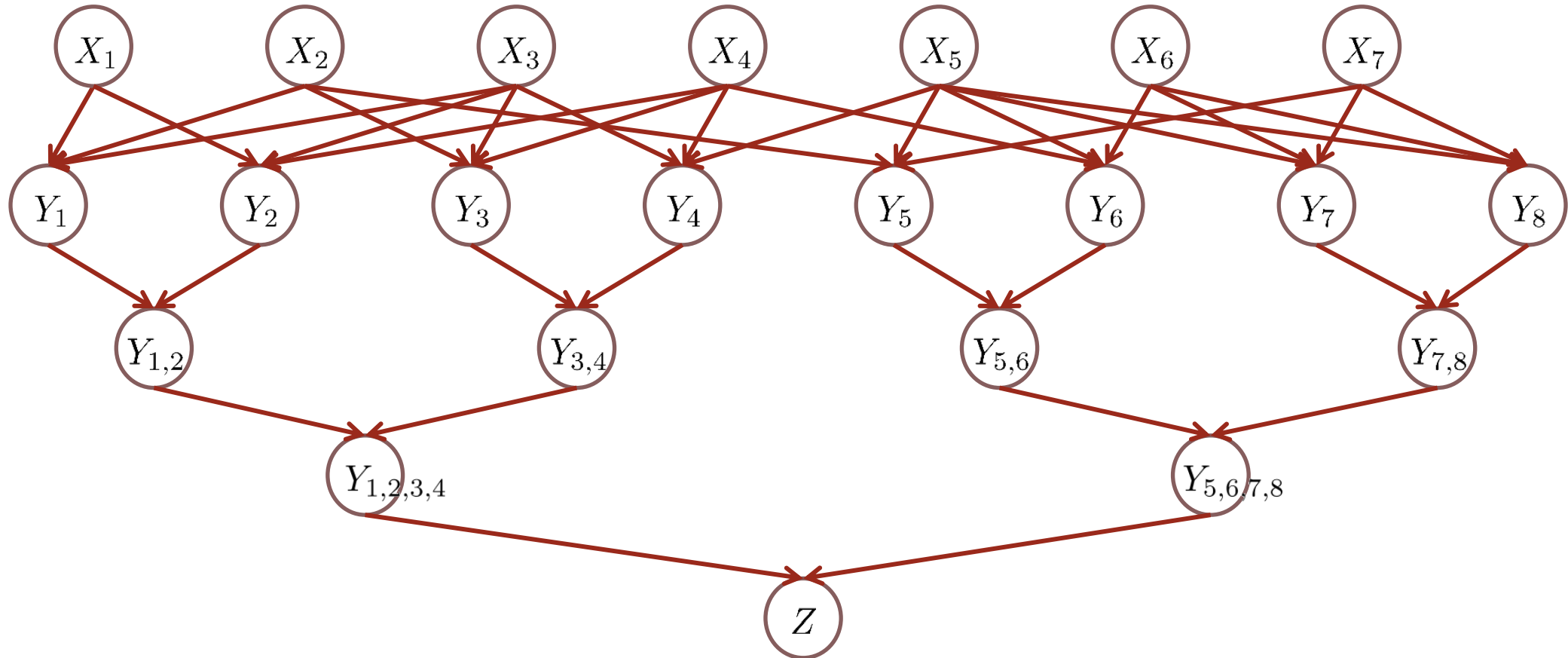
- In general, with n leaves, factor of size 2^n

VE: Computational and Space Complexity

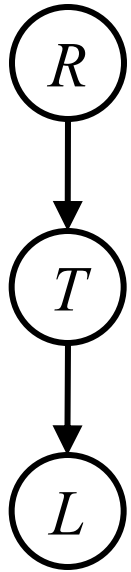
- The computational and space complexity of variable elimination is determined by the largest factor (and it's space that kills you)
- The elimination ordering can greatly affect the size of the largest factor.
 - E.g., previous slide's example 2^n vs. 2
- Does there always exist an ordering that only results in small factors?
 - **No!**

VE: Computational and Space Complexity

- Inference in Bayes' nets is NP-hard.
- No known efficient probabilistic inference in general.



Another example



$$P(L) = ?$$

- Inference by Enumeration

$$= \sum_t \sum_r \underbrace{P(L|t)P(r)P(t|r)}_{\text{Join on } r}$$
$$\underbrace{\hspace{10em}}_{\text{Join on } t}$$
$$\underbrace{\hspace{10em}}_{\text{Eliminate } r}$$
$$\underbrace{\hspace{10em}}_{\text{Eliminate } t}$$

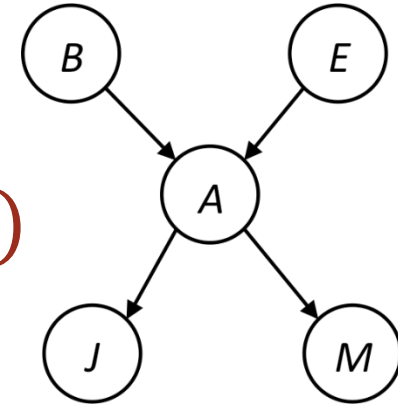
- Variable Elimination

$$= \sum_t P(L|t) \underbrace{\sum_r P(r)P(t|r)}_{\text{Join on } r}$$
$$\underbrace{\hspace{10em}}_{\text{Eliminate } r}$$
$$\underbrace{\hspace{10em}}_{\text{Join on } t}$$
$$\underbrace{\hspace{10em}}_{\text{Eliminate } t}$$

New Example

Query $P(E \mid m)$

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



Push summations inwards such that products that do not depend on the variable are pulled out of the sum.

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

Poll 3

○ How many entries does the factor that results after summing out the second variable (a) on the previous slide have?

A) 0

B) 1

C) 2

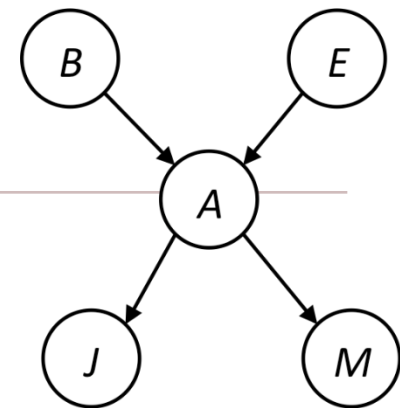
D) 4

E) 6

F) 8

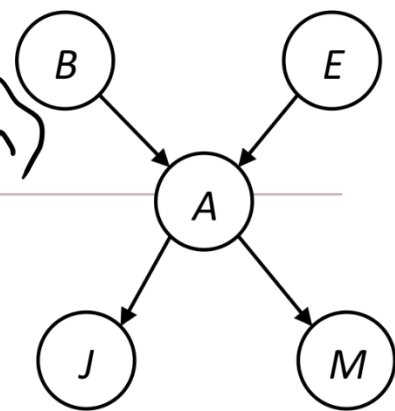
$$P(B \mid j, m)$$

See video: [Math for Variable Elimination](#)



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

$$\alpha = \frac{1}{P(j, m)} = \frac{1}{\sum_b P(b, j, m)}$$



$$= \alpha \sum_a \sum_e P(B, e, a, j, m)$$

$$= \alpha \sum_a \sum_e f_1(B) f_2(e) f_3(a, B, e) f_4(j, a) f_5(m, a)$$

$$= \alpha \sum_e f_1(B) f_2(e) \sum_a f_3(a, B, e) f_4(j, a) f_5(m, a)$$

$$= \alpha \sum_e f_1(B) f_2(e) \sum_a f_6(B, e, a, j, m)$$

$$= \alpha \sum_e f_1(B) f_2(e) f_7(B, e, j, m)$$

$$= \alpha f_1(B) \sum_e f_8(B, e, j, m)$$

$$= \alpha f_1(B) f_9(B, j, m)$$

$$= \alpha f_{10}(B, j, m)$$

$$= P(B | j, m)$$

$$\alpha = \frac{1}{P(j, m)} = \frac{1}{\sum_b f_{10}(b, j, m)}$$



Bayes Nets

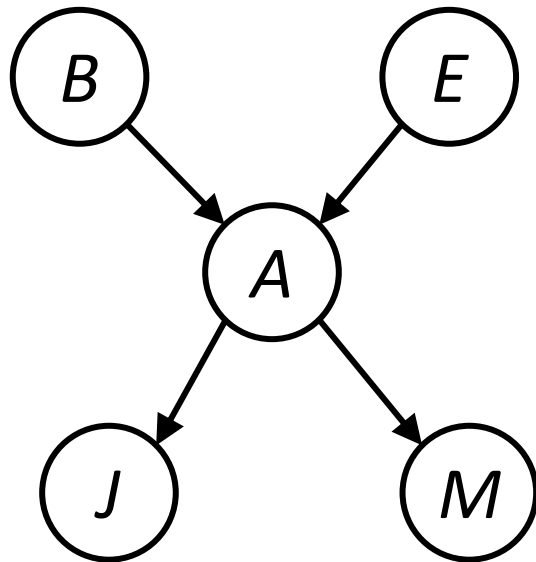
- ✓ Part I: Representation and Independence
- ✓ Part II: Exact inference
 - ✓ ○ Enumeration (always exponential complexity)
 - ✓ ○ Variable elimination (worst-case exponential complexity, often better)
 - ✓ ○ Inference is NP-hard in general

Part III: Approximate Inference

Example (with numbers!)

- Start with a Bayes net, the associated CPTs, and a query, $P(B \mid +j, +m)$

B	P(B)
+b	0.001
-b	0.999



E	P(E)
+e	0.002
-e	0.998

A	J	P(J A)
+a	+j	0.9
+a	-j	0.1
-a	+j	0.05
-a	-j	0.95

A	M	P(M A)
+a	+m	0.7
+a	-m	0.3
-a	+m	0.01
-a	-m	0.99

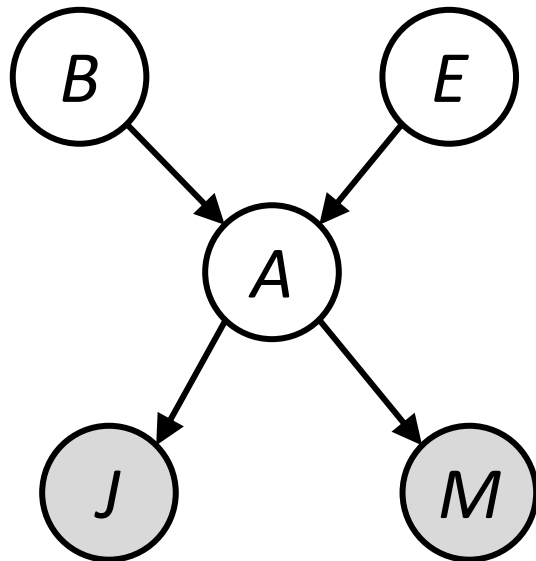
B	E	A	P(A B,E)
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 1: Remove any entries in tables that don't match the evidence, $+j, +m$

B	P(B)
+b	0.001
-b	0.999



E	P(E)
+e	0.002
-e	0.998

A	J	P(J A)
+a	+j	0.9
-a	+j	0.05

A	M	P(M A)
+a	+m	0.7
-a	+m	0.01

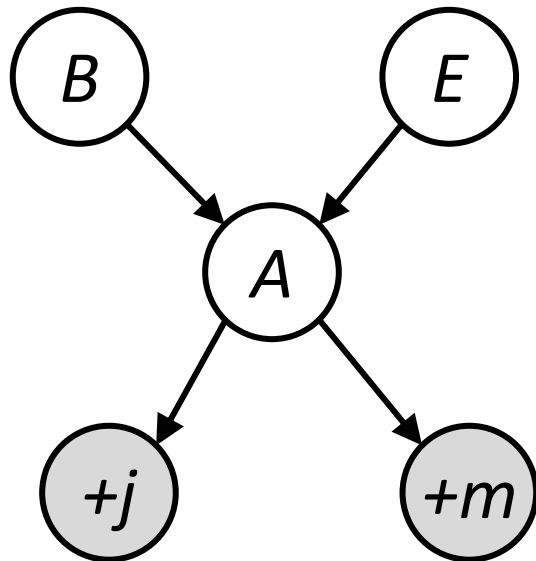
B	E	A	P(A B,E)
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 1: Remove any entries in tables that don't match the evidence, $+j, +m$

B	P(B)
+b	0.001
-b	0.999



E	P(E)
+e	0.002
-e	0.998

A	+j	P(+j A)
+a	+j	0.9
-a	+j	0.05

A	+m	P(+m A)
+a	+m	0.7
-a	+m	0.01

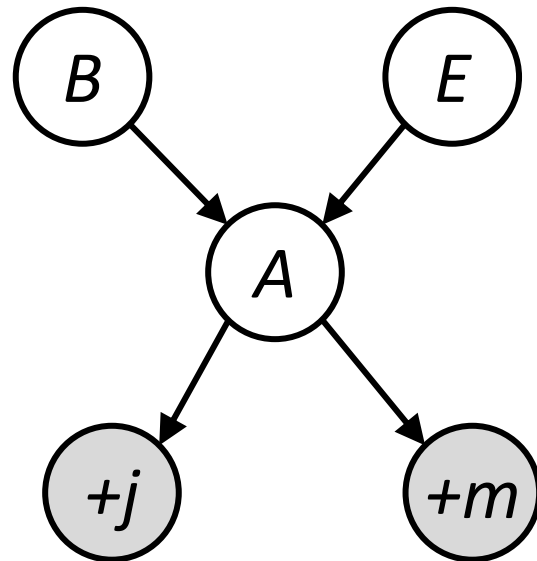
B	E	A	P(A B,E)
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 2: Think each table as just a factor table rather than probabilities

B	$f_1(B)$
+b	0.001
-b	0.999



E	$f_2(E)$
+e	0.002
-e	0.998

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

Example (with numbers!) Query: $P(B \mid +j, +m)$

- Step 2: Think each table as just a factor table rather than probabilities

B	$f_1(B)$
+b	0.001
-b	0.999

E	$f_2(E)$
+e	0.002
-e	0.998

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E (we chose E first this time)
 - i: Collect all factors tables associated with E

B	$f_1(B)$
+b	0.001
-b	0.999

E	$f_2(E)$
+e	0.002
-e	0.998

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together

E	$f_2(E)$
+e	0.002
-e	0.998

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

B	E	A	$f_4(A, B, E)$
+b	+e	+a	
+b	+e	-a	
+b	-e	+a	
+b	-e	-a	
-b	+e	+a	
-b	+e	-a	
-b	-e	+a	
-b	-e	-a	

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together

E	$f_2(E)$
+e	0.002
-e	0.998

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

B	E	A	$f_4(A, B, E)$
+b	+e	+a	$0.002 \cdot 0.95$
+b	+e	-a	$0.002 \cdot 0.05$
+b	-e	+a	$0.998 \cdot 0.94$
+b	-e	-a	$0.998 \cdot 0.06$
-b	+e	+a	$0.002 \cdot 0.29$
-b	+e	-a	$0.002 \cdot 0.71$
-b	-e	+a	$0.998 \cdot 0.001$
-b	-e	-a	$0.998 \cdot 0.999$

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together

E	$f_2(E)$
+e	0.002
-e	0.998

B	E	A	$f_3(A, B, E)$
+b	+e	+a	0.95
+b	+e	-a	0.05
+b	-e	+a	0.94
+b	-e	-a	0.06
-b	+e	+a	0.29
-b	+e	-a	0.71
-b	-e	+a	0.001
-b	-e	-a	0.999

B	E	A	$f_6(A, B, E)$
+b	+e	+a	0.001900
+b	+e	-a	0.000100
+b	-e	+a	0.938120
+b	-e	-a	0.059880
-b	+e	+a	0.000580
-b	+e	-a	0.001420
-b	-e	+a	0.000998
-b	-e	-a	0.997002

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together
 - iii: Create another new factor by summing over E

B	A	$f_7(A, B)$
+b	+a	
+b	-a	
-b	+a	
-b	-a	

B	E	A	$f_6(A, B, E)$
+b	+e	+a	0.001900
+b	+e	-a	0.000100
+b	-e	+a	0.938120
+b	-e	-a	0.059880
-b	+e	+a	0.000580
-b	+e	-a	0.001420
-b	-e	+a	0.000998
-b	-e	-a	0.997002

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together
 - iii: Create another new factor by summing over E

B	A	$f_7(A, B)$
+b	+a	0.001900 + 0.938120
+b	-a	0.000100 + 0.059880
-b	+a	0.000580 + 0.000998
-b	-a	0.001420 + 0.997002

B	E	A	$f_6(A, B, E)$
+b	+e	+a	0.001900
+b	+e	-a	0.000100
+b	-e	+a	0.938120
+b	-e	-a	0.059880
-b	+e	+a	0.000580
-b	+e	-a	0.001420
-b	-e	+a	0.000998
-b	-e	-a	0.997002

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E
 - i: Collect all factors tables associated with E
 - ii: Create new factor table by multiplying them together
 - iii: Create another new factor by summing over E

B	A	$f_7(A, B)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

B	E	A	$f_6(A, B, E)$
+b	+e	+a	0.001900
+b	+e	-a	0.000100
+b	-e	+a	0.938120
+b	-e	-a	0.059880
-b	+e	+a	0.000580
-b	+e	-a	0.001420
-b	-e	+a	0.000998
-b	-e	-a	0.997002

Example (with numbers!) Query: $P(B \mid +j, +m)$

- Step 3(E): Eliminate hidden variable E (and return to list of tables)

B	$f_1(B)$
+b	0.001
-b	0.999

B	A	$f_7(A, B)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A

B	$f_1(B)$
+b	0.001
-b	0.999

B	A	$f_7(A, B)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A

B	$f_1(B)$
+b	0.001
-b	0.999

B	A	$f_7(A, B)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A
 - ii: Create new factor table by multiplying them together

B	A	$f_7(B, A)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

B	A	+j	+m	$f_8(B, A, +j, +m)$
+b	+a	+j	+m	
+b	-a	+j	+m	
-b	+a	+j	+m	
-b	-a	+j	+m	

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A
 - ii: Create new factor table by multiplying them together

B	A	$f_7(B, A)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

B	A	+j	+m	$f_8(B, A, +j, +m)$
+b	+a	+j	+m	$0.940020 \cdot 0.9 \cdot 0.7$
+b	-a	+j	+m	$0.059980 \cdot 0.05 \cdot 0.01$
-b	+a	+j	+m	$0.001578 \cdot 0.9 \cdot 0.7$
-b	-a	+j	+m	$0.998422 \cdot 0.05 \cdot 0.01$

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A
 - ii: Create new factor table by multiplying them together

B	A	$f_7(B, A)$
+b	+a	0.940020
+b	-a	0.059980
-b	+a	0.001578
-b	-a	0.998422

A	+j	$f_4(+j, A)$
+a	+j	0.9
-a	+j	0.05

A	+m	$f_5(+m, A)$
+a	+m	0.7
-a	+m	0.01

B	A	+j	+m	$f_8(B, A, +j, +m)$
+b	+a	+j	+m	0.592213
+b	-a	+j	+m	0.000030
-b	+a	+j	+m	0.000994
-b	-a	+j	+m	0.000499

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A
 - ii: Create new factor table by multiplying them together
 - iii: Create another new factor by summing over A

B	+j	+m	$f_8(B, +j, +m)$
+b	+j	+m	
-b	+j	+m	

B	A	+j	+m	$f_8(B, A, +j, +m)$
+b	+a	+j	+m	0.592213
+b	-a	+j	+m	0.000030
-b	+a	+j	+m	0.000994
-b	-a	+j	+m	0.000499

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A
 - i: Collect all factors tables associated with A
 - ii: Create new factor table by multiplying them together
 - iii: Create another new factor by summing over A

B	+j	+m	$f_g(B, +j, +m)$
+b	+j	+m	0.592243
-b	+j	+m	0.001493

B	A	+j	+m	$f_g(B, A, +j, +m)$
+b	+a	+j	+m	0.592213
+b	-a	+j	+m	0.000030
-b	+a	+j	+m	0.000994
-b	-a	+j	+m	0.000499

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 3(A): Eliminate hidden variable A (and return to list of tables)

B	$f_1(B)$
+b	0.001
-b	0.999

B	+j	+m	$f_8(B, +j, +m)$
+b	+j	+m	0.592243
-b	+j	+m	0.001493

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 4: Multiply remaining factor tables

B	$f_1(B)$
+b	0.001
-b	0.999

B	+j	+m	$f_8(B, +j, +m)$
+b	+j	+m	0.592243
-b	+j	+m	0.001493

B	+j	+m	$f_9(B, +j, +m)$
+b	+j	+m	
-b	+j	+m	

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 4: Multiply remaining factor tables

B	$f_1(B)$
+b	0.001
-b	0.999

B	+j	+m	$f_8(B, +j, +m)$
+b	+j	+m	0.592243
-b	+j	+m	0.001493

B	+j	+m	$f_9(B, +j, +m)$
+b	+j	+m	0.001 · 0.592243
-b	+j	+m	0.999 · 0.001493

Example (with numbers!)

Query: $P(B \mid +j, +m)$

- Step 4: Multiply remaining factor tables

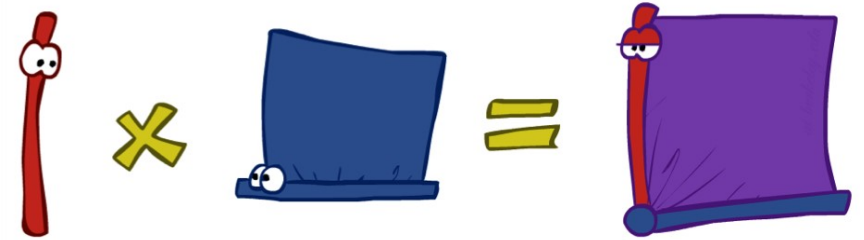
B	$f_1(B)$
+b	0.001
-b	0.999

B	+j	+m	$f_8(B, +j, +m)$
+b	+j	+m	0.592243
-b	+j	+m	0.001493

B	+j	+m	$f_9(B, +j, +m)$
+b	+j	+m	0.000592
-b	+j	+m	0.001492

Operation 1: Pointwise product

- First basic operation: **pointwise product** of factors (similar to a **database join**, *not* matrix multiply!)
 - New factor has **union** of variables of the two original factors
 - Each entry is the product of the corresponding entries from the original factors



- Example: $P(A) \times P(J|A) = P(A,J)$

	$P(A)$	\times	$P(J A)$	$=$	$P(A,J)$																						
	<table border="1"><tr><td>true</td><td>0.1</td></tr><tr><td>false</td><td>0.9</td></tr></table>	true	0.1	false	0.9		<table border="1"><tr><td>A \ J</td><td>true</td><td>false</td></tr><tr><td>true</td><td>0.9</td><td>0.1</td></tr><tr><td>false</td><td>0.05</td><td>0.95</td></tr></table>	A \ J	true	false	true	0.9	0.1	false	0.05	0.95		<table border="1"><tr><td>A \ J</td><td>true</td><td>false</td></tr><tr><td>true</td><td>0.09</td><td>0.01</td></tr><tr><td>false</td><td>0.045</td><td>0.855</td></tr></table>	A \ J	true	false	true	0.09	0.01	false	0.045	0.855
true	0.1																										
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