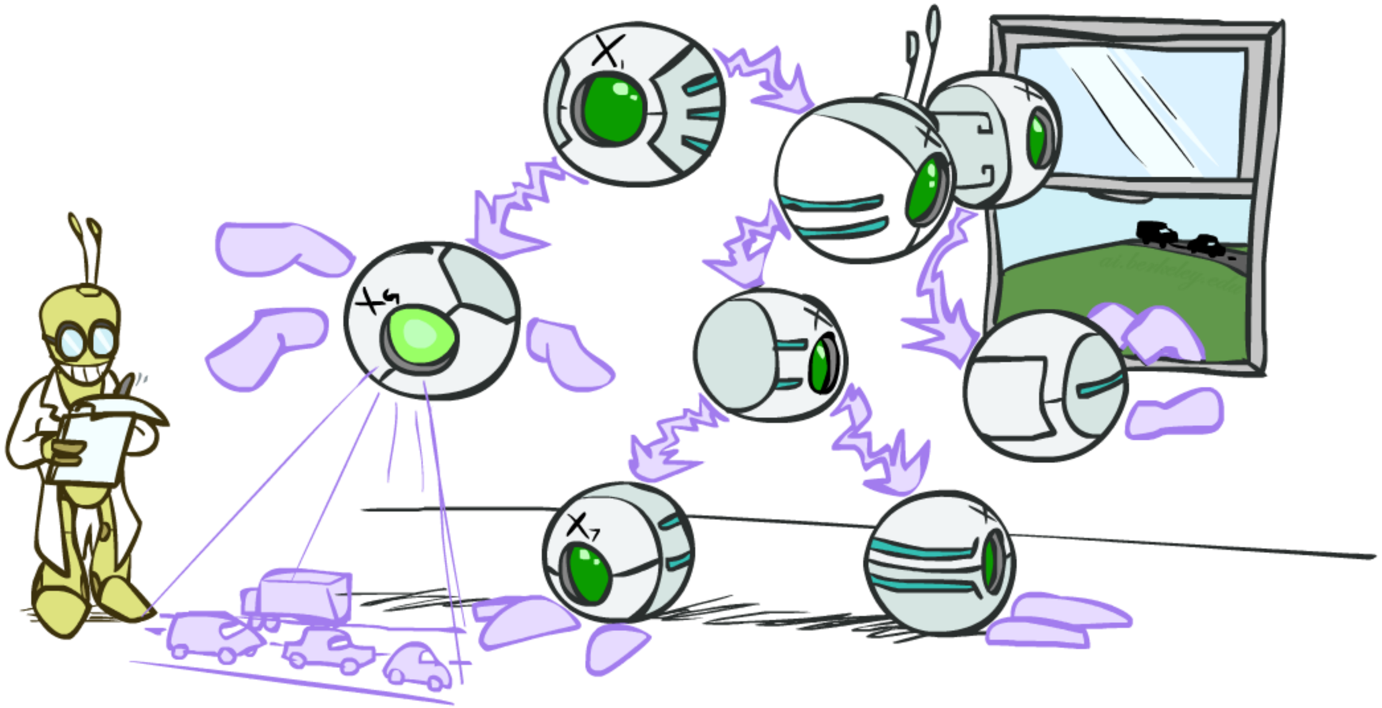
Bayes Nets: Exact Inference



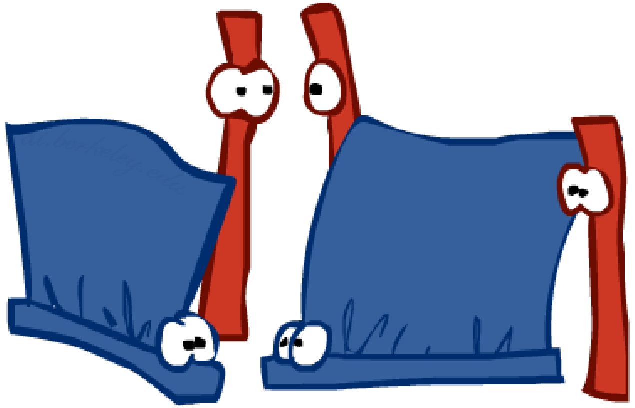
AIMA Chapter 14.4, PRML Chapter 8.4

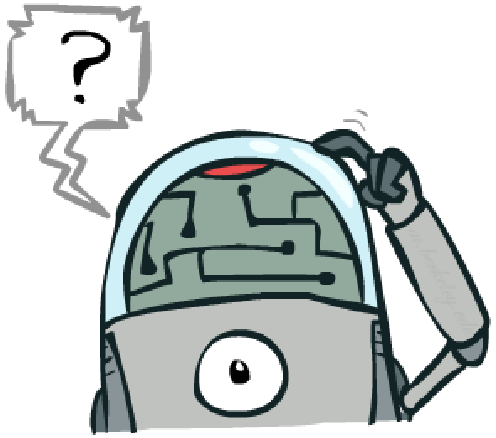
[Adapted from slides by Dan Klein and Pieter Abbeel at UC Berkeley]

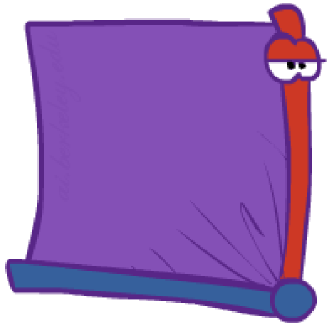
Inference

- Inference: calculating some useful quantity from a probabilistic model (joint probability distribution)

- Examples:
  - Posterior marginal probability
    - $P(Q|e_1,..,e_k)$
    - E.g., what disease might I have?
  - Most likely explanation:
    - $\text{argmax}_q\ P(Q=q|e_1,..,e_k)$
    - E.g., what did he say?







Inference by Enumeration

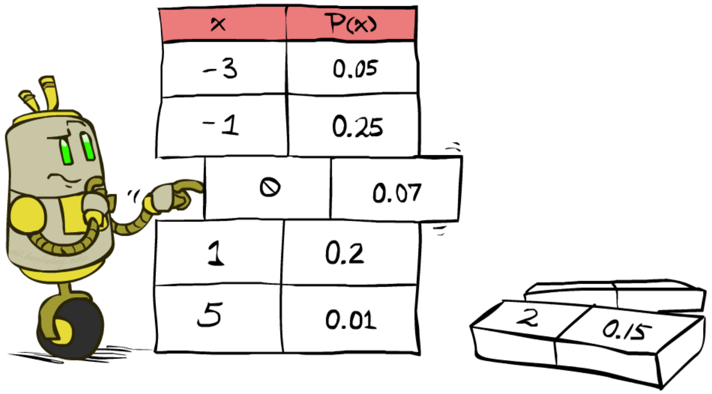
- General case:
  - Evidence variables: $E_1 \dots E_k = e_1 \dots e_k$
  - Query variable: Q
  - Hidden variables: $H_1 \dots H_r$

  $\left.\begin{array}{l} E_1 \dots E_k = e_1 \dots e_k \\ Q \\ H_1 \dots H_r \end{array}\right\} \begin{array}{c} X_1, X_2, \dots X_n \\ \textit{All variables} \end{array}$

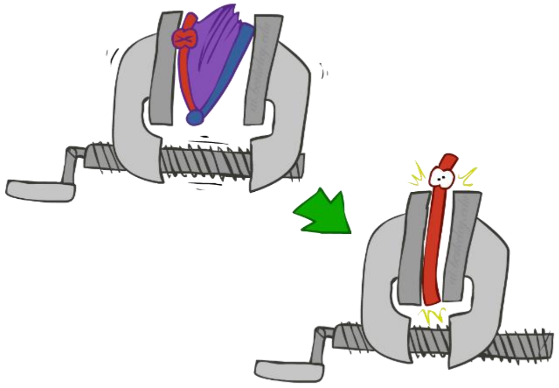
- We want:

$$P(Q|e_1 \dots e_k)$$

- Step 1: Select the entries consistent with the evidence



- Step 2: Sum out H to get joint of Query and evidence



$$P(Q, e_1 \dots e_k) = \sum_{h_1 \dots h_r} \underbrace{P(Q, h_1 \dots h_r, e_1 \dots e_k)}_{X_1, X_2, \dots X_n}$$

- Step 3: Normalize

$$\times \frac{1}{Z}$$

$$Z = \sum_q P(Q, e_1 \cdots e_k)$$

$$P(Q|e_1 \cdots e_k) = \frac{1}{Z} P(Q, e_1 \cdots e_k)$$

Inference by Enumeration in Bayes Net

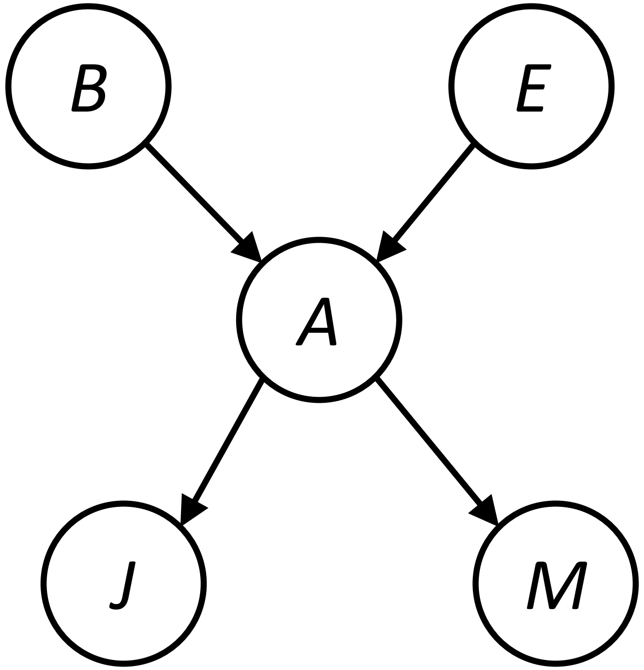
- The joint distribution can be computed from a BN by multiplying the conditional distributions
- Then we can do inference by enumeration

$$P(B \mid +j, +m) \;\; \propto_B P(B, +j, +m)$$

$$= \sum_{e,a} P(B, e, a, +j, +m)$$

$$= \sum_{e,a} P(B)P(e)P(a|B,e)P(+j|a)P(+m|a)$$

- Problem: sums of ***exponentially many*** products!

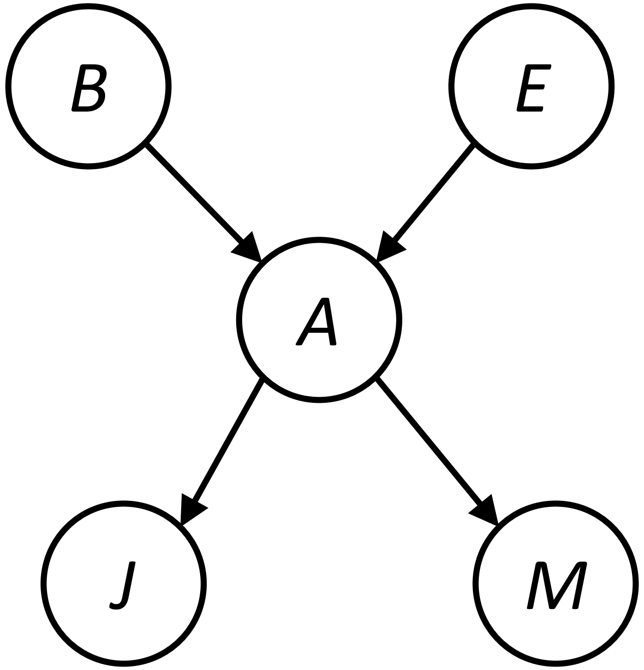


Inference by Enumeration in Bayes Net

$$P(B \mid +j, +m) \;\; \propto_B P(B, +j, +m)$$

$$= \sum_{e,a} P(B, e, a, +j, +m)$$

$$= \sum_{e,a} P(B)P(e)P(a|B,e)P(+j|a)P(+m|a)$$



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

Lots of repeated subexpressions!

Can we do better?

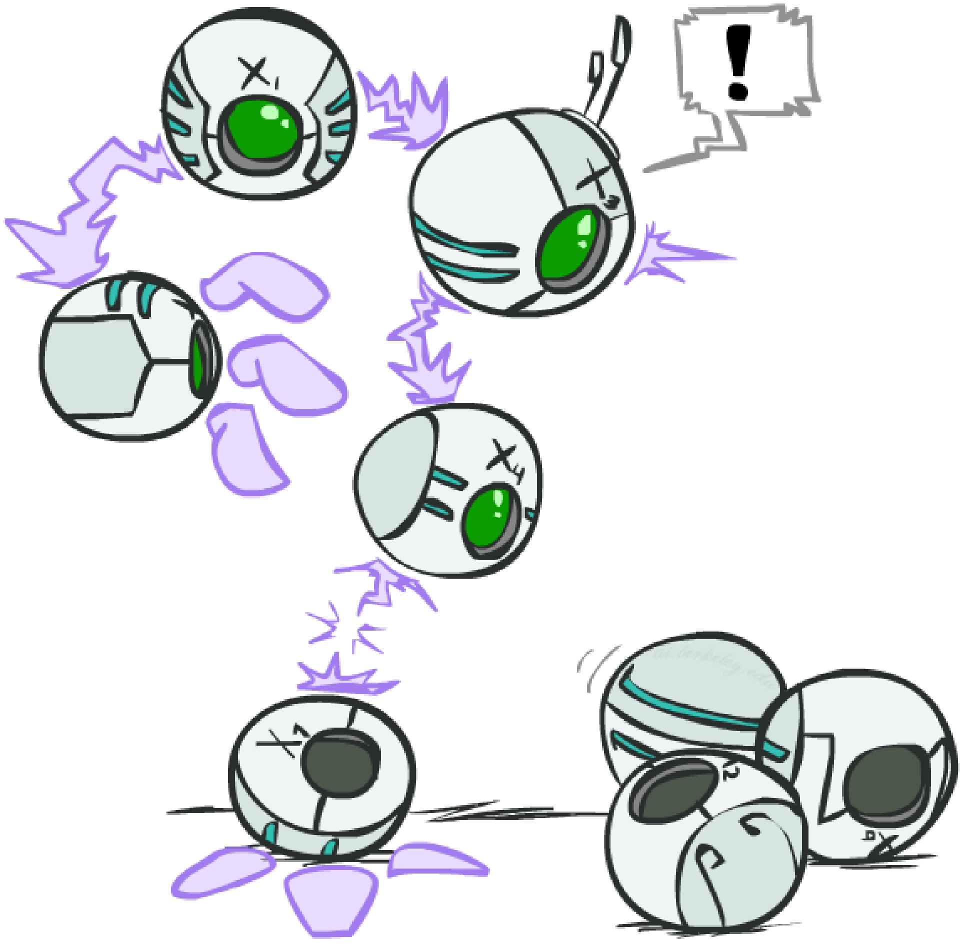
- Consider **uwy + uwz + uxy + uxz + vwy + vwz + vxy +vxz**
  - 16 multiplies, 7 adds
  - Lots of repeated subexpressions!
- Rewrite as **(u+v)(w+x)(y+z)**
  - 2 multiplies, 3 adds

Variable elimination: The basic ideas

- Move summations inwards as far as possible
  - $P(B \mid j, m) = \alpha \sum_{e,a} P(B)\, P(e)\, P(a|B,e)\, P(j|a)\, P(m|a)$
  - $\qquad\qquad\quad = \alpha\, P(B) \sum_{\boldsymbol{e}} P(e) \sum_{\boldsymbol{a}} P(a|B,e)\, P(j|a)\, P(m|a)$

  - Problem: $P(a|B,e)$ isn't a single number, it's a bunch of different numbers depending on the values of B and e
  - Solution: operate on ***factors*** (arrays of numbers)

Operations on Factors



Factors

- A factor is a multi-dimensional array to represent $P(Y_1 \ldots Y_N \mid X_1 \ldots X_M)$
  - If a variable is assigned (represented with lower-case), its dimension is missing from the array

- Joint distribution: P(X,Y)
  - Entries P(x,y) for all x, y
  - Sums to 1

$$P(T, W)$$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

- Selected joint: P(x,Y)
  - A slice of the joint distribution
  - Entries P(x,y) for fixed x, all y
  - Sums to P(x)

$$P(cold, W)$$

T	W	P
cold	sun	0.2
cold	rain	0.3

Factors

- A factor is a multi-dimensional array to represent $P(Y_1 \dots Y_N \mid X_1 \dots X_M)$
  - If a variable is assigned (represented with lower-case), its dimension is missing from the array

- Single conditional: P(Y | x)
  - Entries P(y | x) for fixed x, all y
  - Sums to 1

$$P(W|cold)$$

T	W	P
cold	sun	0.4
cold	rain	0.6

- Family of conditionals: P(X |Y)
  - Multiple conditionals
  - Entries P(x | y) for all x, y
  - Sums to |Y|

$$P(W|T)$$

T	W	P
hot	sun	0.8
hot	rain	0.2
cold	sun	0.4
cold	rain	0.6

$P(W|hot)$

$P(W|cold)$

Factors

- A factor is a multi-dimensional array to represent $P(Y_1 \ldots Y_N \mid X_1 \ldots X_M)$
  - If a variable is assigned (represented with lower-case), its dimension is missing from the array
    - Specified family: P(y | X)
      - Entries P(y | x) for fixed y, but for all x
      - Sums to … who knows!

$P(rain|T)$

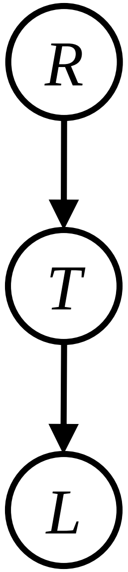
T	W	P
hot	rain	0.2
cold	rain	0.6

$\}\ P(rain|hot)$

$\}\ P(rain|cold)$

Running Example: Traffic Domain

- Random Variables
  - R: Raining
  - T: Traffic
  - L: Late



$P(R)$

+r	0.1
-r	0.9

$P(T|R)$

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

$P(L|T)$

+t	+l	0.3
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9

Running Example: Traffic Domain

- Initial factors are local CPTs (one per node)

$P(R)$

+r	0.1
-r	0.9

$P(T|R)$

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

$P(L|T)$

+t	+l	0.3
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9

- Any known values are selected
  - E.g. if we know $L = +\ell$, the initial factors are

$P(R)$

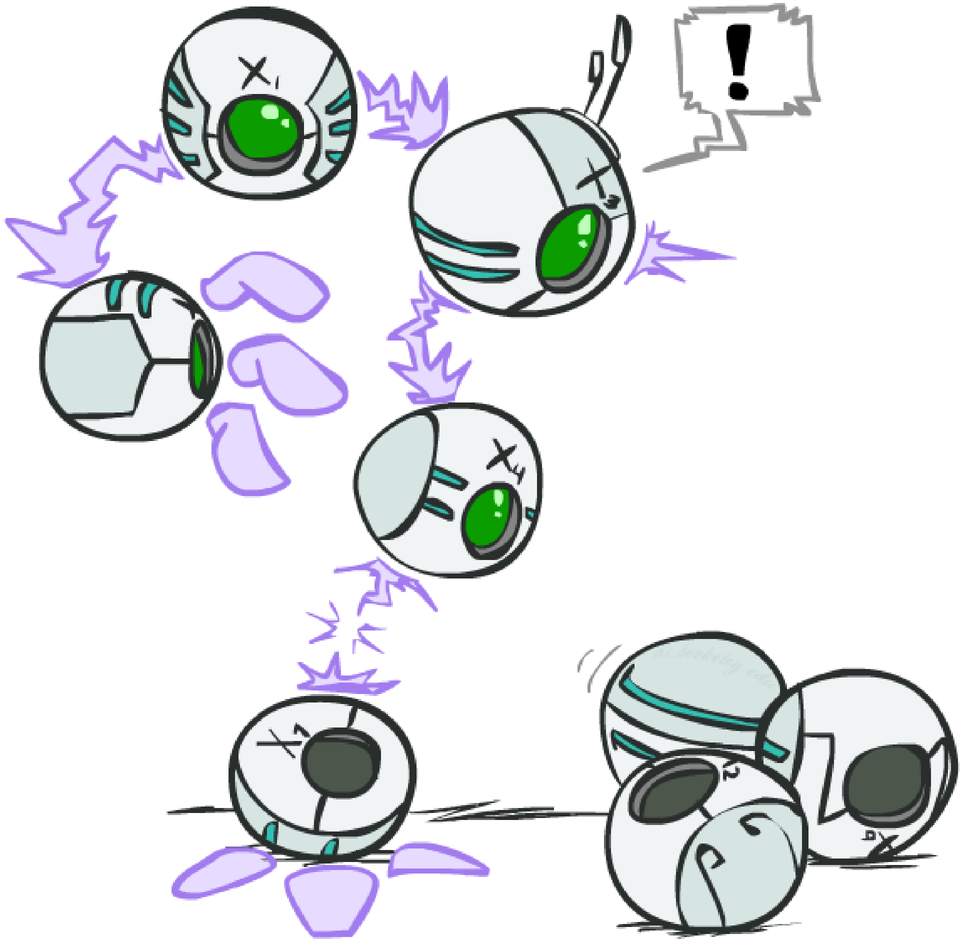
+r	0.1
-r	0.9

$P(T|R)$

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

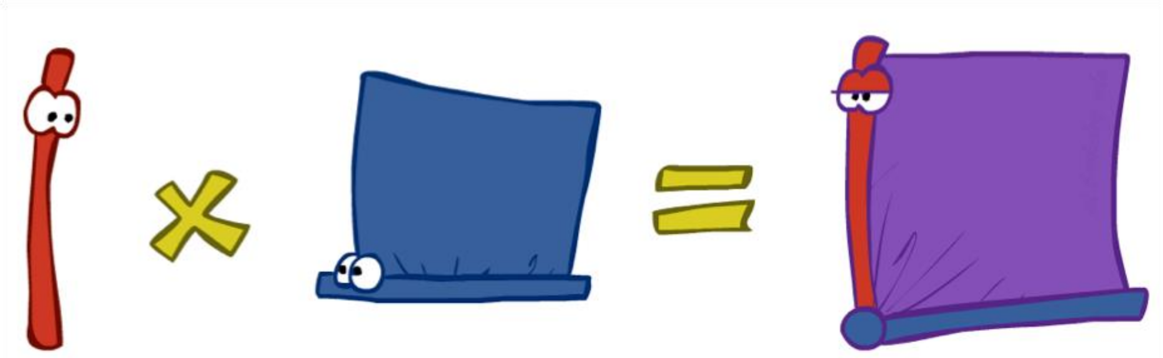
$P(+\ell|T)$

+t	+l	0.3
-t	+l	0.1

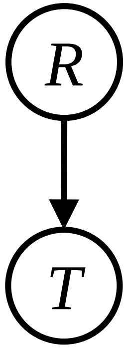


Operation 1: Join Factors

- First basic operation: joining factors
  - Just like a database join
  - Given multiple factors, build a new factor over the union of the variables involved
  - Each entry is computed by pointwise products



- Example:



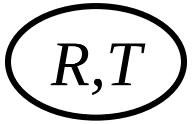
$$P(R) \times P(T|R)$$

+r	0.1
-r	0.9

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

$$P(R,T)$$

+r	+t	0.08
+r	-t	0.02
-r	+t	0.09
-r	-t	0.81



$$\forall r,t : \quad P(r,t) = P(r) \cdot P(t|r)$$

Operation 2: Eliminate

- Second basic operation: eliminating a variable
  - Take a factor and sum out (marginalize) a variable

- Example:

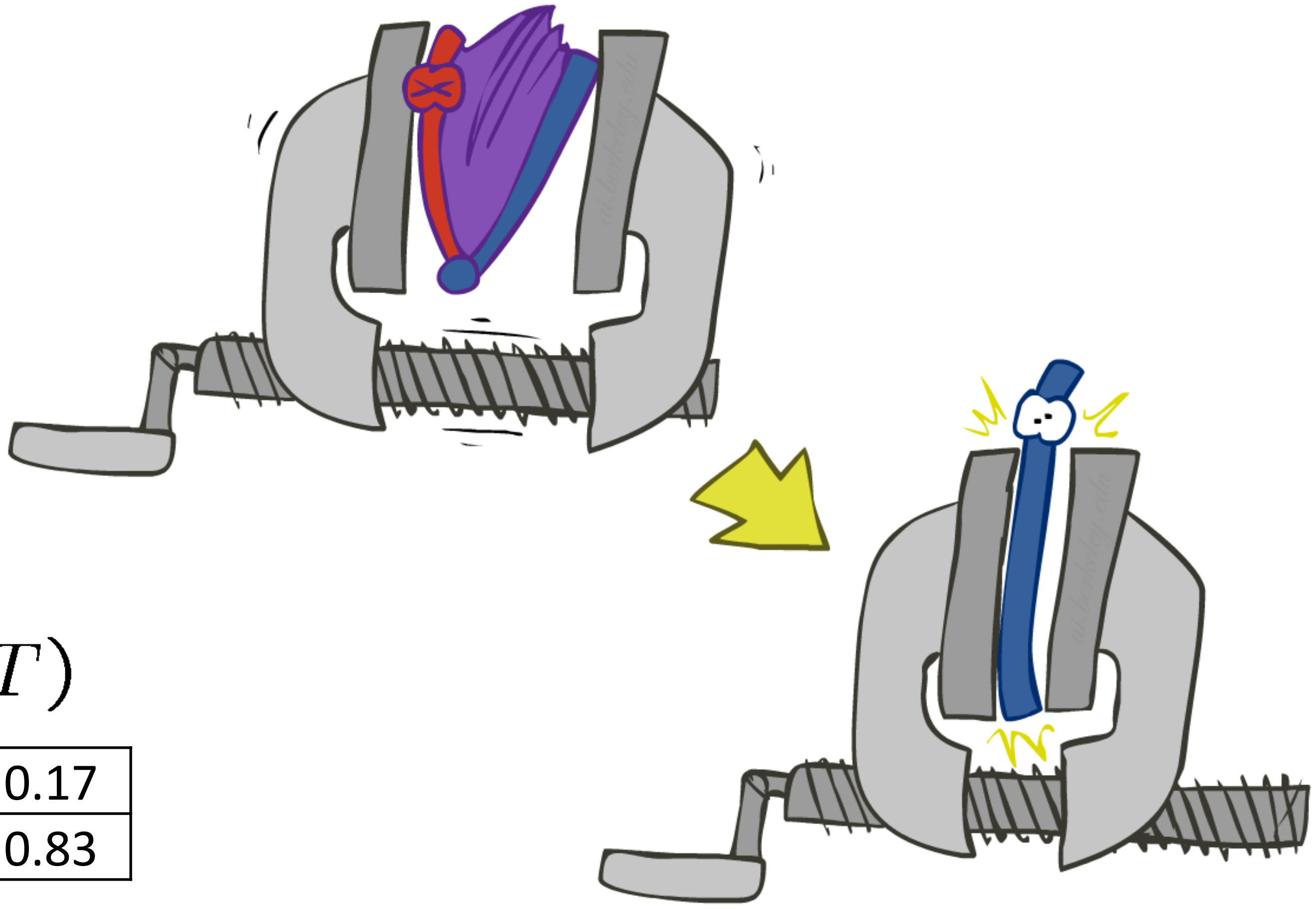
$P(R,T)$

+r	+t	0.08
+r	-t	0.02
-r	+t	0.09
-r	-t	0.81

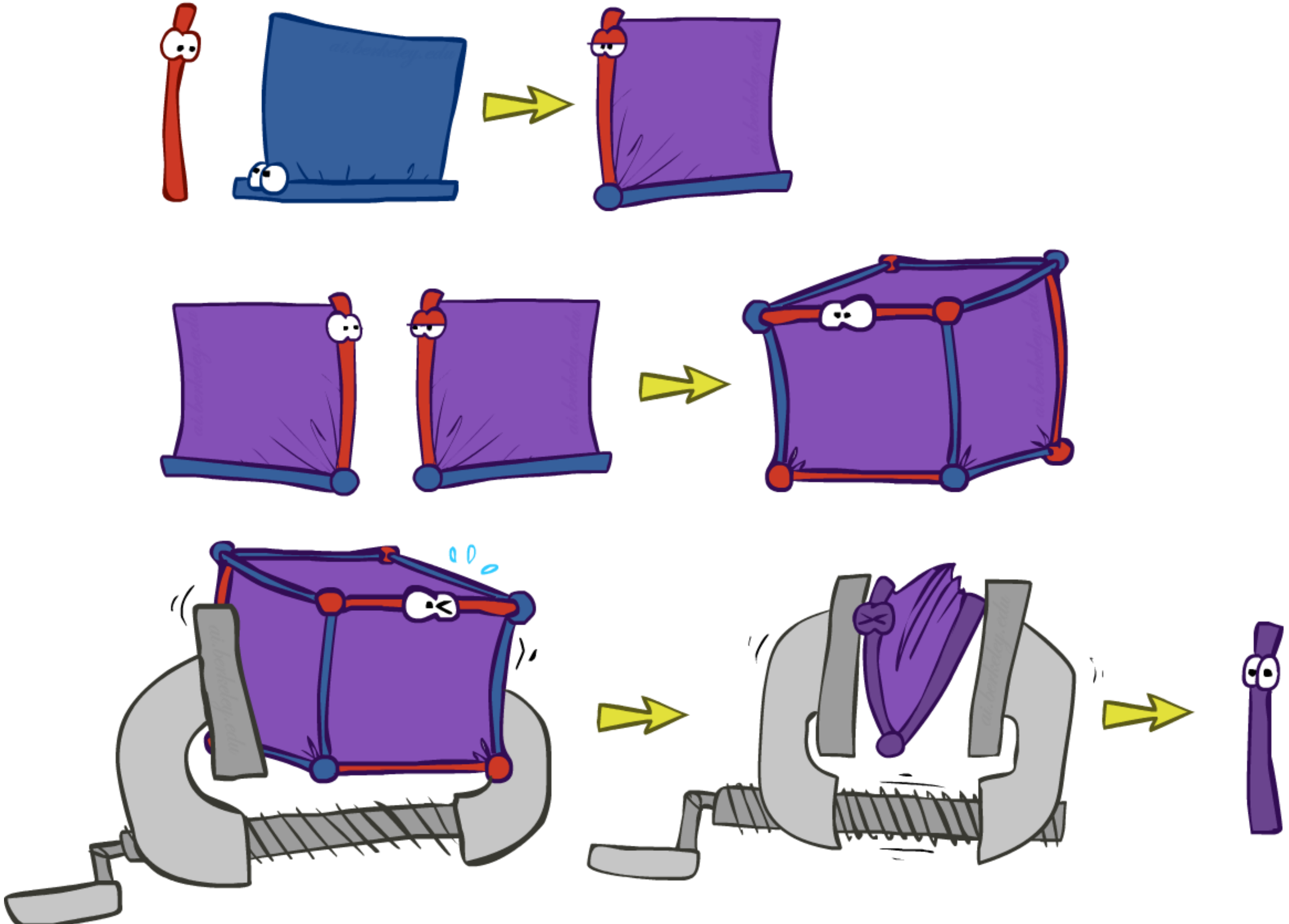
sum R →

$P(T)$

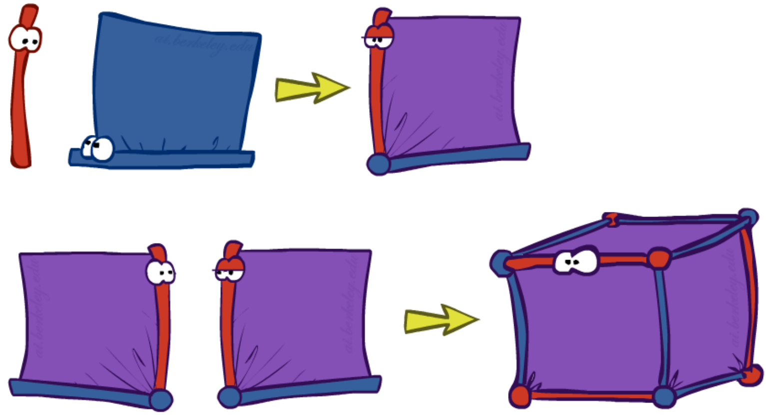
+t	0.17
-t	0.83

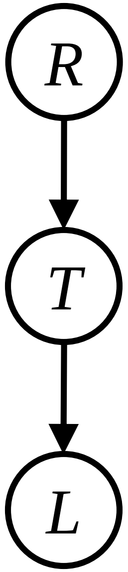


Inference by Enumeration in BN = Multiple Join + Multiple Eliminate



Computing $P(L)$: Multiple Joins





$P(R)$

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-r	0.9

$P(T|R)$

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

$P(L|T)$

+t	+l	0.3
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9

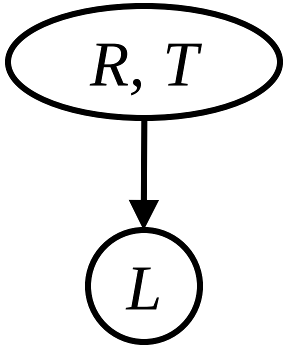
Join

$P(R,T)$

+r	+t	0.08
+r	-t	0.02
-r	+t	0.09
-r	-t	0.81

$P(L|T)$

+t	+l	0.3
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9



Join

$P(R,T,L)$

+r	+t	+l	0.024
+r	+t	-l	0.056
+r	-t	+l	0.002
+r	-t	-l	0.018
-r	+t	+l	0.027
-r	+t	-l	0.063
-r	-t	+l	0.081
-r	-t	-l	0.729

Computing $P(L)$: Multiple Elimination

R, T, L

$P(R,T,L)$

+r	+t	+l	0.024
+r	+t	-l	0.056
+r	-t	+l	0.002
+r	-t	-l	0.018
-r	+t	+l	0.027
-r	+t	-l	0.063
-r	-t	+l	0.081
-r	-t	-l	0.729

A factor of exponential size!

Sum out R

T, L

$P(T,L)$

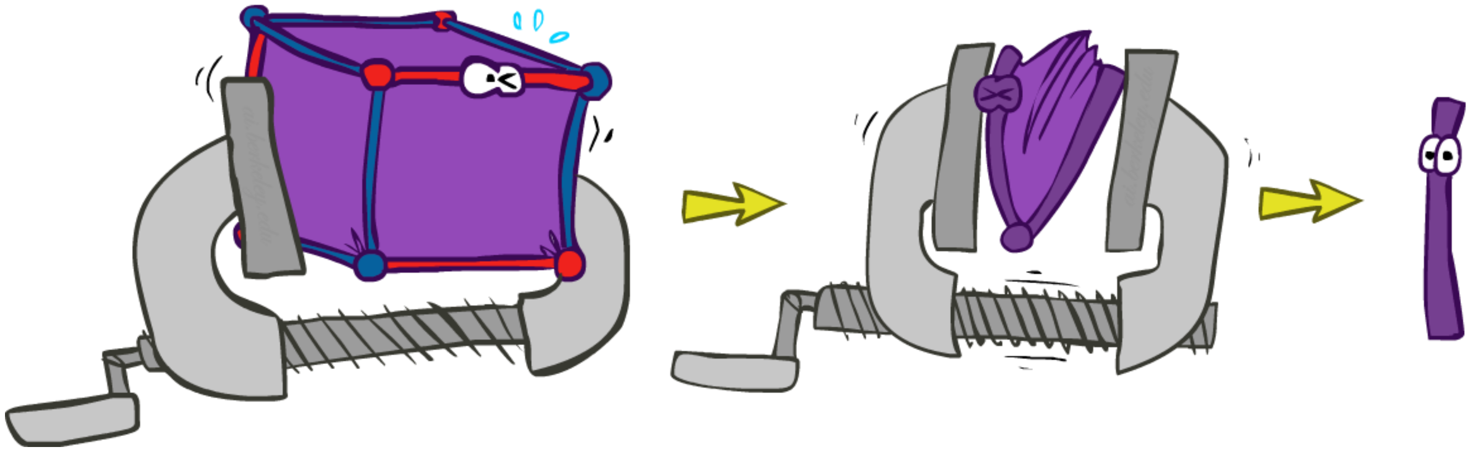
+t	+l	0.051
+t	-l	0.119
-t	+l	0.083
-t	-l	0.747

Sum out T

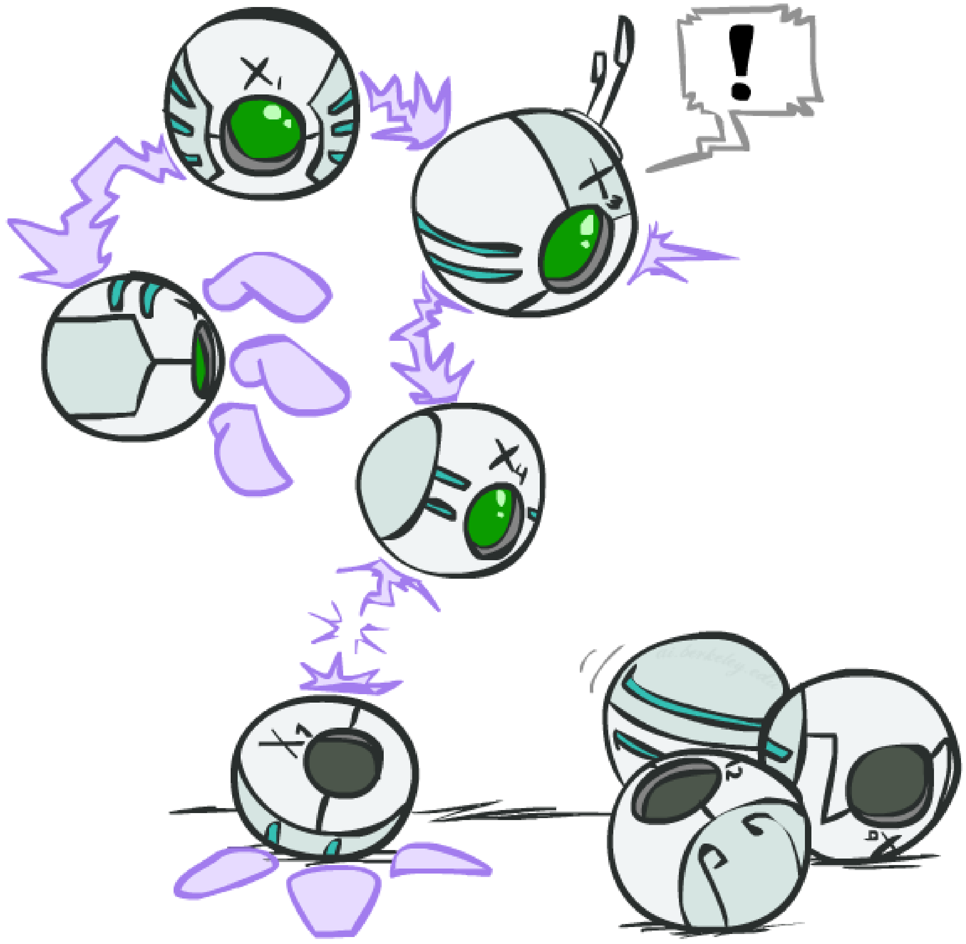
L

$P(L)$

+l	0.134
-l	0.866

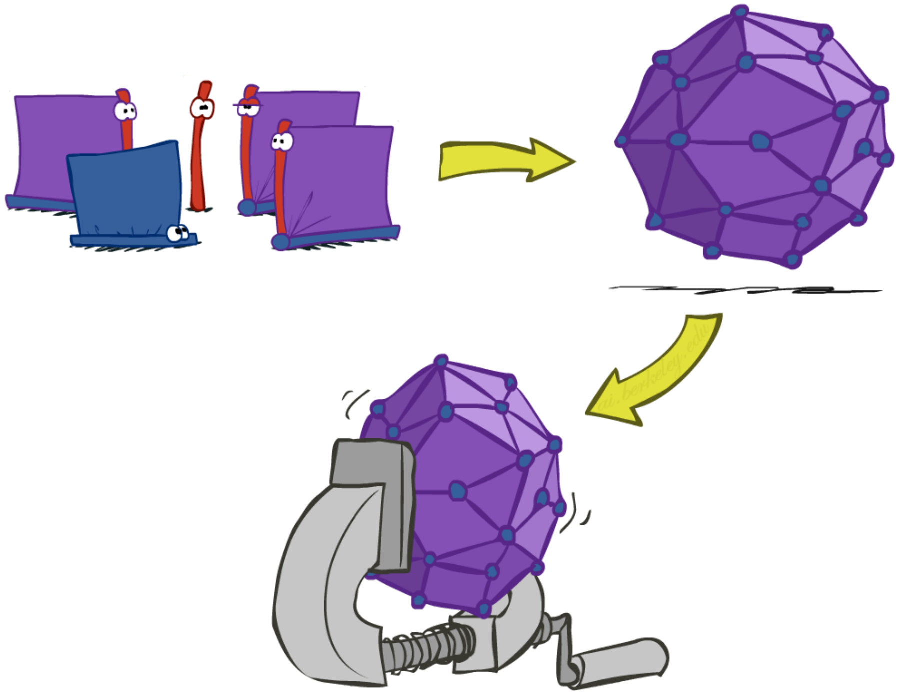


Variable Elimination

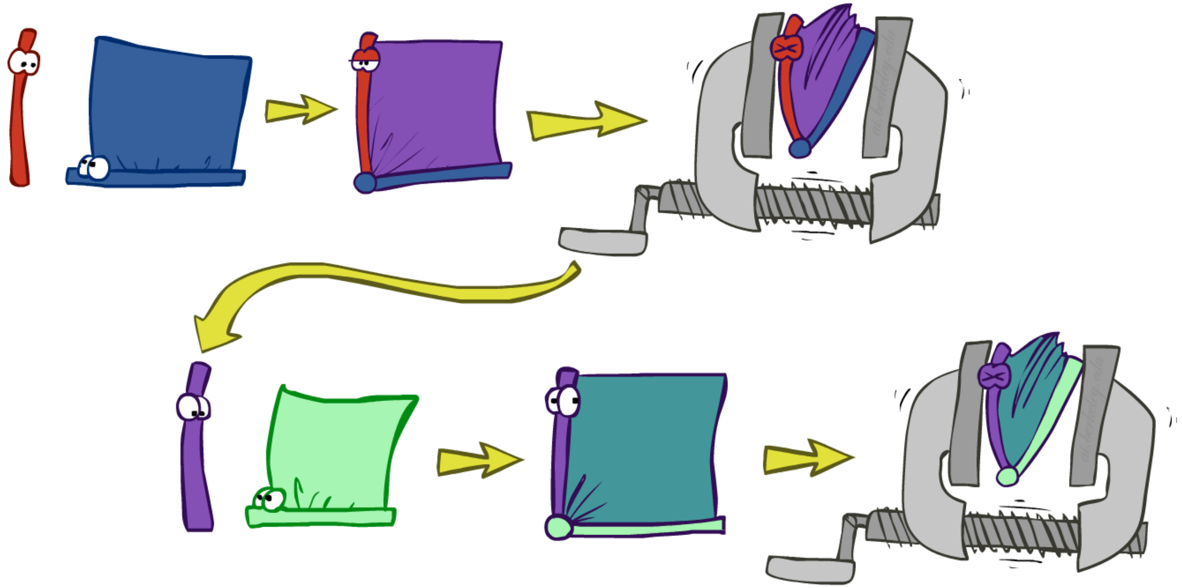


Inference by Enumeration vs. Variable Elimination

- Why is inference by enumeration so slow?
  - You join up the whole joint distribution before you sum out the hidden variables



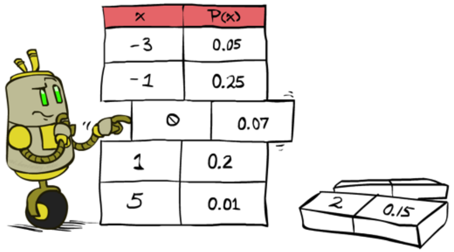
- Idea: interleave joining and elimination!
  - Called “Variable Elimination”
  - Still NP-hard, but usually much faster than inference by enumeration



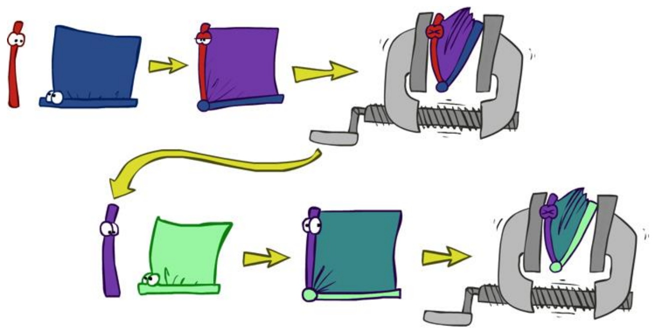
Variable Elimination

- Query: $P(Q|E_1 = e_1, \ldots E_k = e_k)$

- Start with initial factors:
  - Local CPTs (but instantiated by evidence)



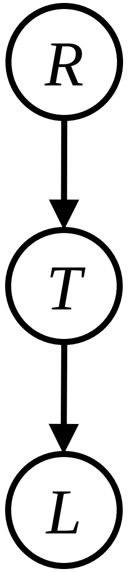
- While there are still hidden variables (not Q or evidence):
  - Pick a hidden variable H
  - Join all factors mentioning H
  - Eliminate (sum out) H



- Join all remaining factors and normalize

$\times \frac{1}{Z}$

Traffic Domain



$$P(L) = ?$$

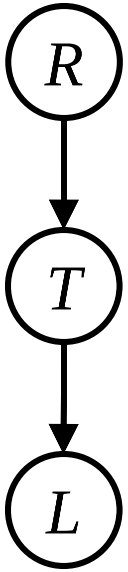
- Inference by Enumeration

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

- Variable Elimination

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

Variable Elimination



$P(R)$

+r	0.1
-r	0.9

$P(T|R)$

+r	+t	0.8
+r	-t	0.2
-r	+t	0.1
-r	-t	0.9

$P(L|T)$

+t	+l	0.3
+t	-l	0.7
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Join R

$P(R,T)$

+r	+t	0.08
+r	-t	0.02
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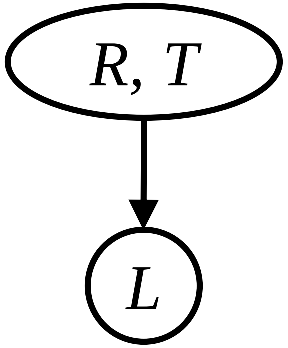

$P(L|T)$

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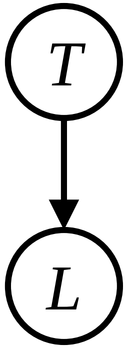
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9

Sum out R

$P(T)$

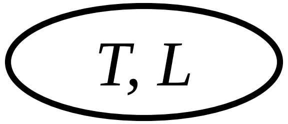
+t	0.17
-t	0.83



$P(L|T)$

+t	+l	0.3
+t	-l	0.7
-t	+l	0.1
-t	-l	0.9

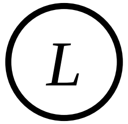
Join T



$P(T,L)$

+t	+l	0.051
+t	-l	0.119
-t	+l	0.083
-t	-l	0.747

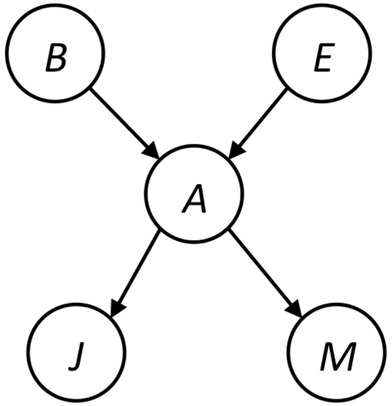
Sum out T



$P(L)$

+l	0.134
-l	0.866

Example



$$P(B|j,m) \propto P(B,j,m)$$

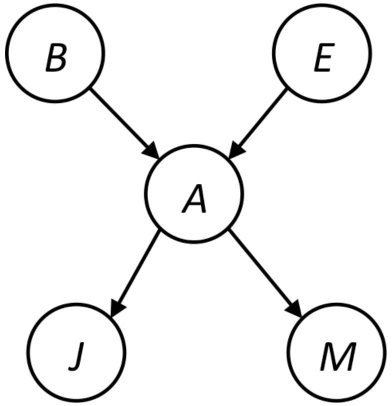
$$\boxed{P(B) \qquad P(E) \qquad P(A|B,E) \qquad P(j|A) \qquad P(m|A)}$$

Choose A

$$\begin{matrix} P(A|B,E) \\ P(j|A) \\ P(m|A) \end{matrix} \xrightarrow{\times} \xrightarrow{\Sigma} P(j,m|B,E)$$

$$\boxed{P(B) \qquad P(E) \qquad P(j,m|B,E)}$$

Example



$$P(B) \qquad P(E) \qquad P(j,m|B,E)$$

Choose E

$$P(E), \; P(j,m|B,E) \xrightarrow{\times} \xrightarrow{\Sigma} P(j,m|B)$$

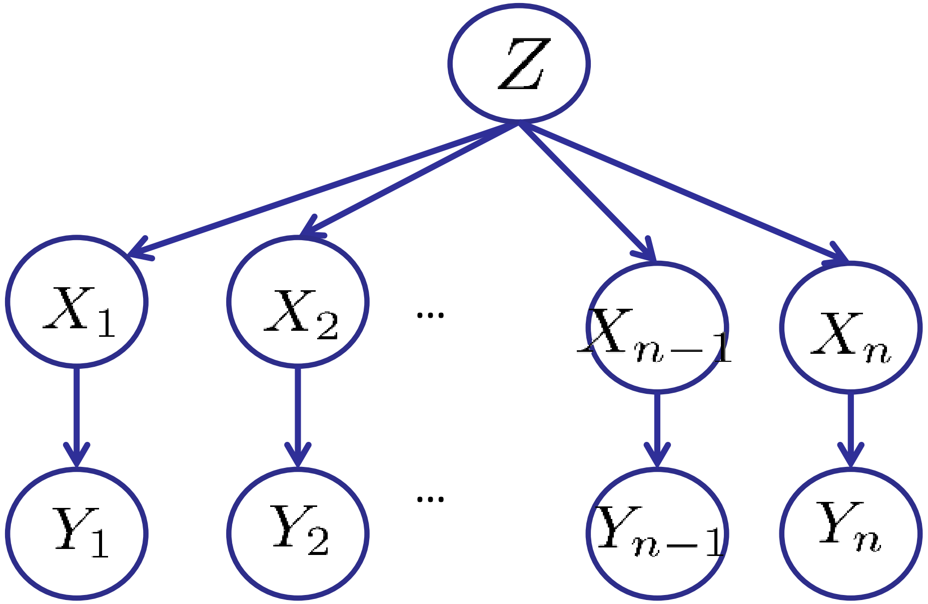
$$P(B) \qquad P(j,m|B)$$

Finish with B

$$P(B), \; P(j,m|B) \xrightarrow{\times} P(j,m,B) \xrightarrow{\text{Normalize}} P(B|j,m)$$

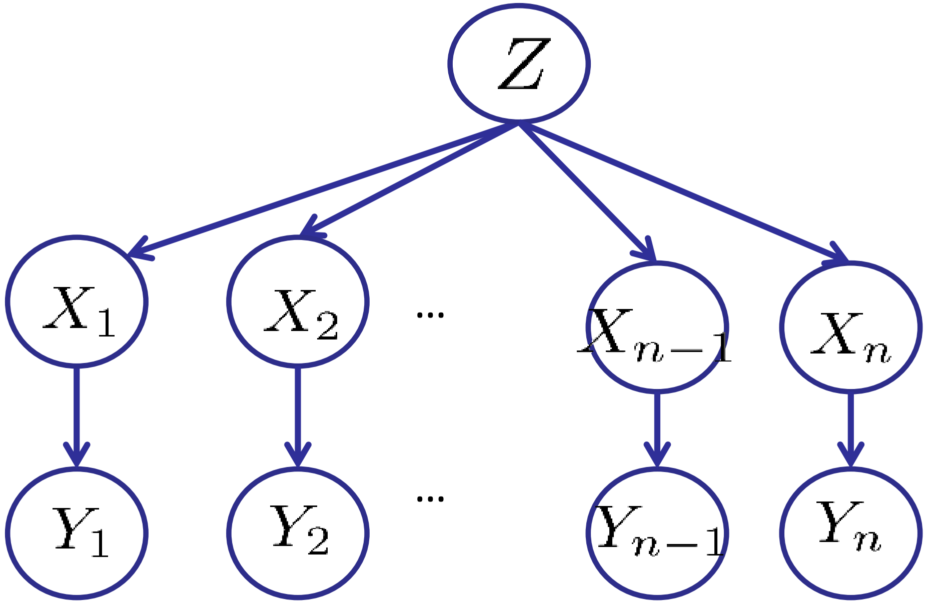
Variable Elimination Ordering

- Query: $P(X_n | y_1,\ldots,y_n)$
- Two different orderings: Z, X_1, …, X_{n-1} and X_1, …, X_{n-1}, Z.
- What is the size of the maximum factor generated for each of the orderings?



Variable Elimination Ordering

- Z, X_1, …, X_{n-1}



$$P(Z)P(X_1|Z)P(X_2|Z), \ldots, P(X_n|Z)$$

$$\Downarrow$$

$$f_1(X_1, X_2, \ldots, X_n)$$

$$\Downarrow$$

$$f_2(y_1, X_2, \ldots, X_n)$$

$$\Downarrow$$

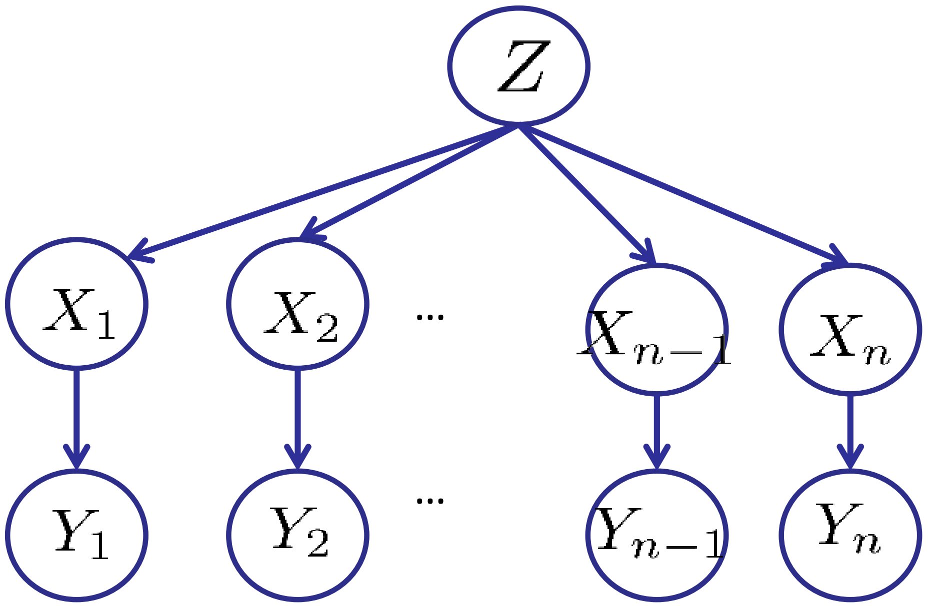
$$f_3(y_1, y_2, \ldots, X_n)$$

$$\vdots$$

$$2^{n+1}$$

Variable Elimination Ordering

- $X_1, \ldots, X_{n-1}, Z$



$$P(X_1|Z)P(y_1|X_1)$$

$$\Downarrow$$

$$f_1(Z, y_1)$$

$$\vdots$$

$$f_1(Z, y_1), f_2(Z, y_2), \ldots, f_{n-1}(Z, y_{n-1}), P(Z), P(X_n|Z)$$

$$\Downarrow$$

$$f_n(X_n, y_1, \ldots, y_{n-1})$$

$$\vdots$$

$$2^2$$

VE: Computational Complexity

- The size of the largest factor determines the time and space complexity of VE
- The elimination ordering can greatly affect the size of the largest factor.
  - E.g., previous slide's example 2^{n+1} vs. 2^2
- Does there always exist an ordering that only results in small factors?
  - No!

Reduction from 3SAT

$$(x_1 \vee x_2 \vee \neg x_3) \wedge (\neg x_1 \vee x_3 \vee \neg x_4) \wedge (x_2 \vee \neg x_2 \vee x_4) \wedge (\neg x_3 \vee \neg x_4 \vee \neg x_5) \wedge (x_2 \vee x_5 \vee x_7) \wedge (x_4 \vee x_5 \vee x_6) \wedge (\neg x_5 \vee x_6 \vee \neg x_7) \wedge (\neg x_5 \vee \neg x_6 \vee x_7)$$

$P(X_i = 0) = P(X_i = 1) = 0.5$

$Y_1 = X_1 \vee X_2 \vee \neg X_3$

...

$Y_8 = \neg X_5 \vee X_6 \vee X_7$

$Y_{1,2} = Y_1 \wedge Y_2$

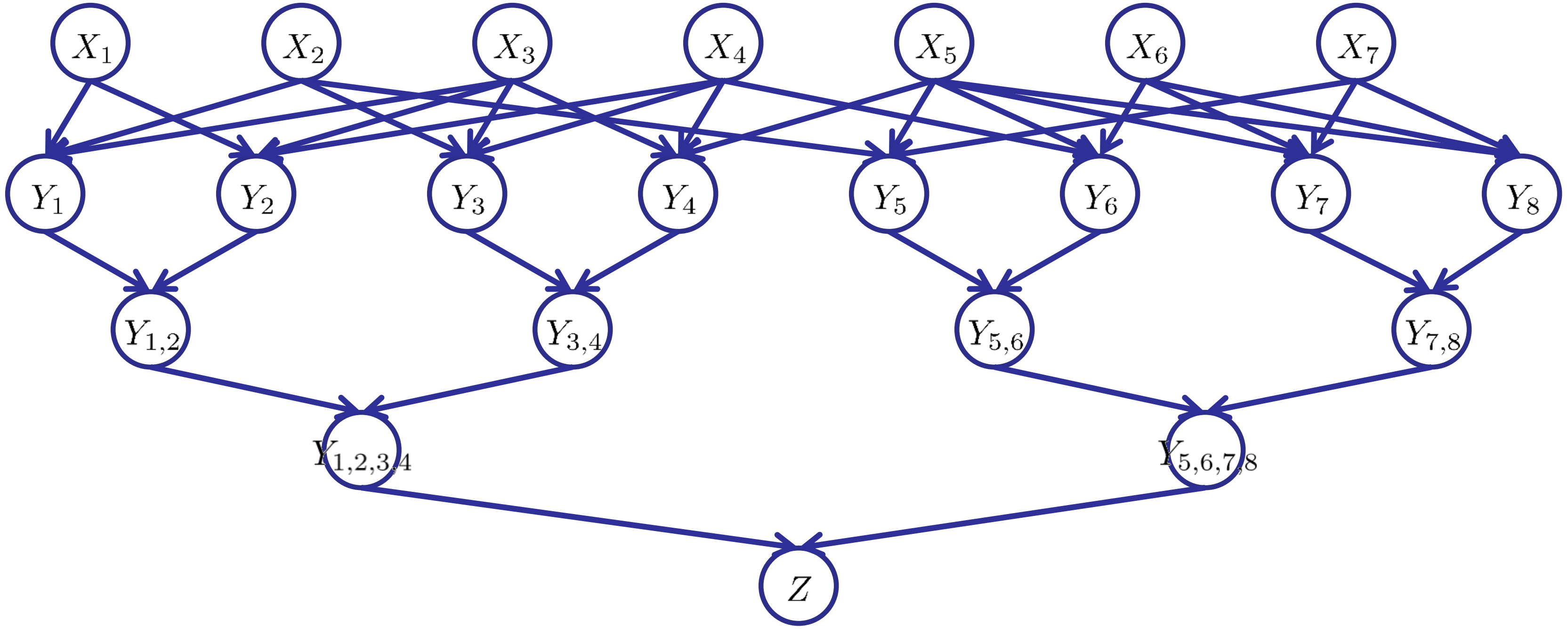
...

$Y_{7,8} = Y_7 \wedge Y_8$

$Y_{1,2,3,4} = Y_{1,2} \wedge Y_{3,4}$

$Y_{5,6,7,8} = Y_{5,6} \wedge Y_{7,8}$

$Z = Y_{1,2,3,4} \wedge Y_{5,6,7,8}$

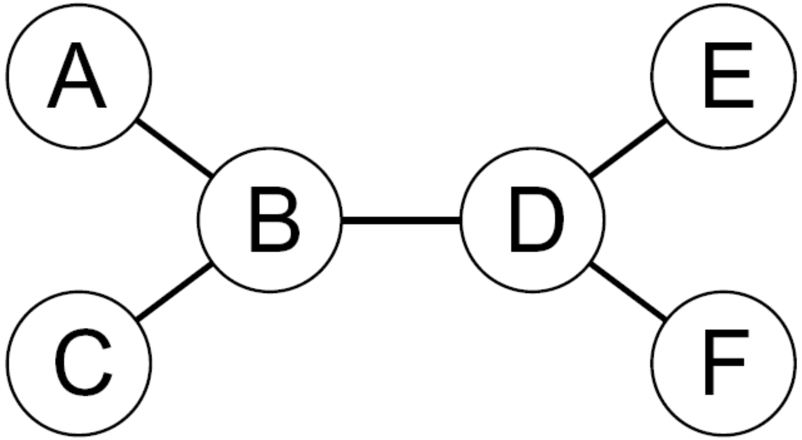


$$P(+z) = \sum_{\mathbf{x},\mathbf{y}} P(\mathbf{x}, \mathbf{y}, +z) = \sum_{\mathbf{x} \text{ s.t. } z=T} P(\mathbf{x})$$

- P(z) > 0 iff the sentence is satisfiable ➔ NP-hard
- P(z) = S×0.5^7 where S is the number of satisfying assignments ➔ #P-hard

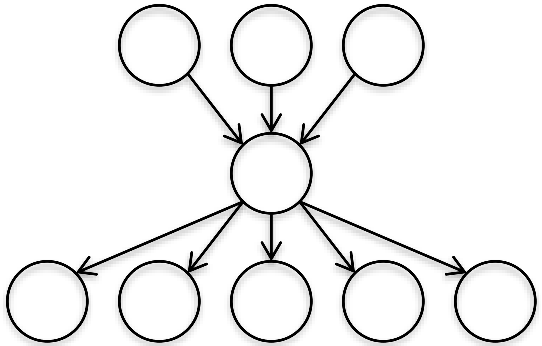
When do we have tractable inference?

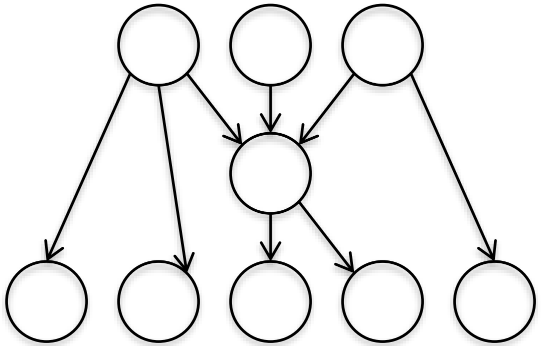
- Recall: Tree-Structured CSPs
  - CSP is NP-hard in general
  - If the constraint graph has no loops (i.e., tree), the CSP can be solved in linear time!

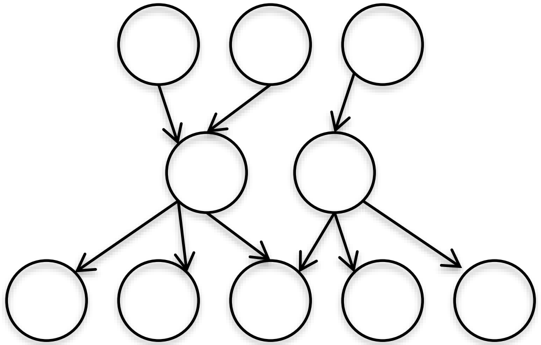


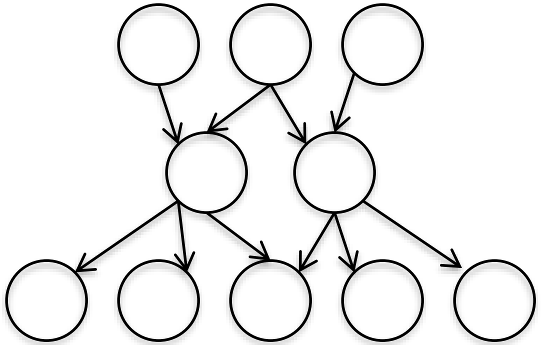
Polytrees

- A polytree is a directed graph with no undirected cycles



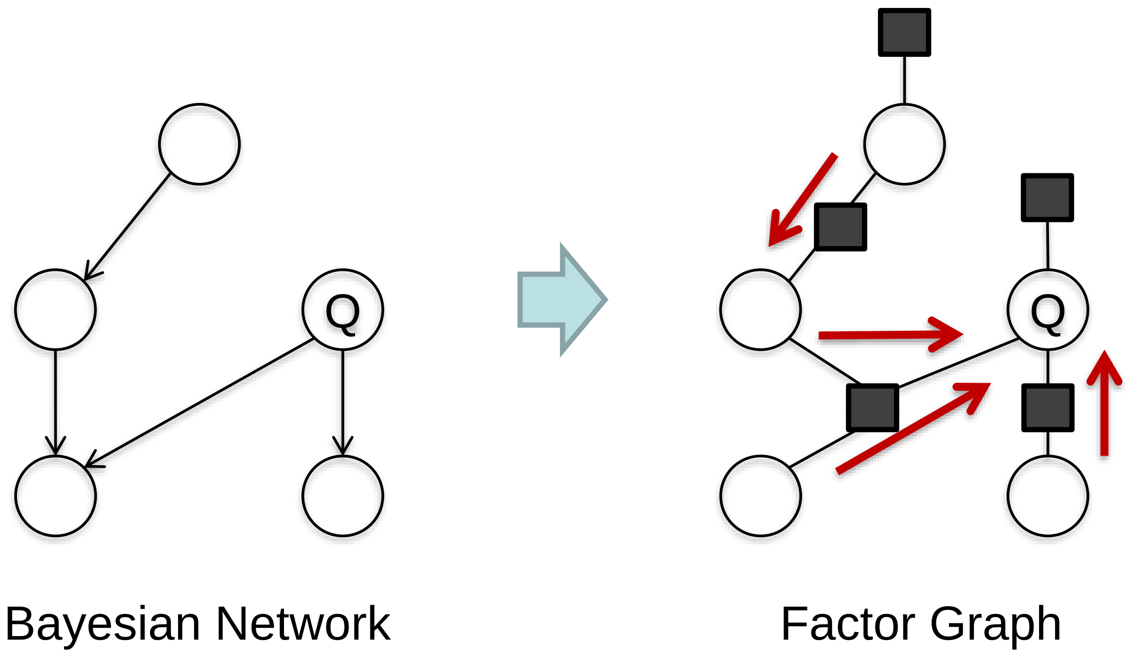






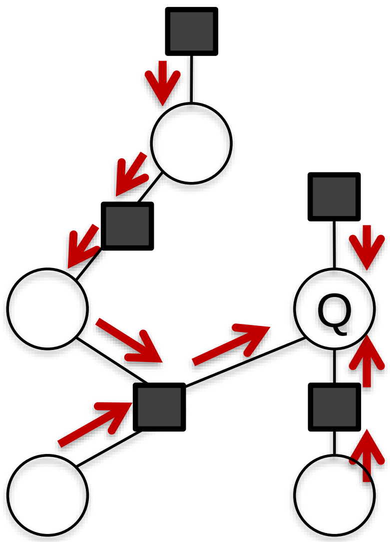
Variable Elimination on Polytrees

- For poly-tree BNs, the complexity of VE is ***linear in the BN size*** (number of CPT entries) with the following elimination ordering:
  - Convert to a factor graph
  - Take Q as the root
  - Eliminate from the leaves towards the root



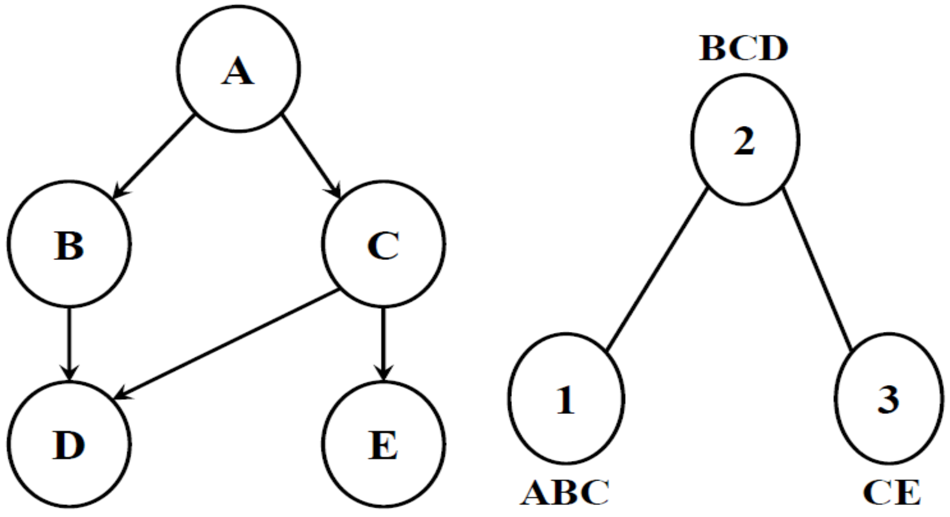
Variable Elimination on Polytrees

- VE for poly-tree BNs is equivalent to
  - Sum-product message passing algorithm or belief propagation algorithm (i.e., passing messages/beliefs from leaf nodes to the root node)
  - "Messages" are just 1d factors resulted from joining/elimination



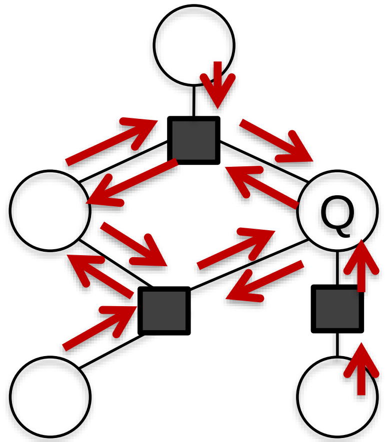
Message Passing on General Graphs

- Exact inference: Junction Tree Algorithm
  - Group individual nodes to form cluster nodes in such a way that the resulting network is a polytree (called a junction tree or join tree)
  - Run a sum-product-like algorithm on the junction tree.
  - *Intractable* on graphs with large cluster nodes (i.e., large tree-width).



Message Passing on General Graphs

- Approximate inference: Loopy Belief Propagation
  - Simply pass the messages on the general graph
    - Will not terminate with loops
    - Run until convergence (not guaranteed!)
  - *Approximate* but *tractable* for large graphs.
  - Sometime works well, sometimes not at all.



Summary

- Exact inference of Bayesian networks
  - Enumeration
    - exponential complexity
  - Variable Eliminating
    - worst-case exponential complexity, often better
  - VE on polytrees
    - linear complexity
    - = message passing
  - Message passing on general graphs
    - Junction Tree Algorithm
    - Loopy Belief Propagation: no longer exact