COMP 341 Intro to AI
Bayesian Networks – Exact Inference

How certain are we that the butler did it?

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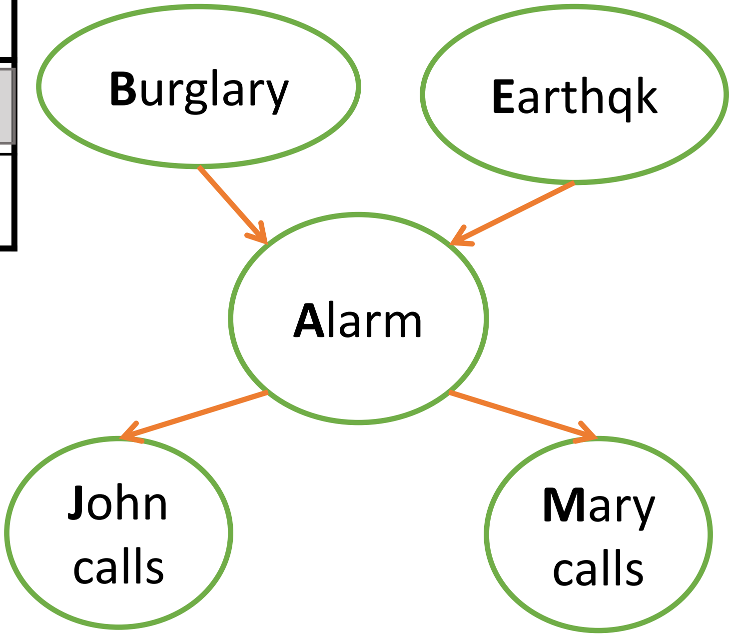
Example: Alarm Network

B	P(B)
+b	0.001
-b	0.999



E	P(E)
+e	0.002
-e	0.998

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

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

$$P(+b, -e, +a, -j, +m) =$$
$$P(+b)P(-e)P(+a|+b,-e)P(-j|+a)P(+m|+a) =$$
$$0.001 \times 0.998 \times 0.94 \times 0.1 \times 0.7$$

Probabilistic Inference

- Inference: Calculating a useful quantity from a joint probability distribution
- We have seen "inference by enumeration"

- Posterior Probability: $\mathrm{P}(Q|E_1 = e_1, \ldots, E_k = e_k)$
- Most Likely Explanation: $\mathrm{argmax_q}\ \mathrm{P}(Q = q|E_1 = e_1, \ldots, E_k = e_k)$

- Mary called me to tell me that my house alarm was ringing. How likely is it that there is a burglar?
- Why did Mehmet get a medical report for the exam?

Probabilistic Inference Methods

- Enumeration (exact, exponential complexity)
- Variable elimination (exact, worst-case exponential complexity, often better)

- Exact Inference is NP-Hard

- Sampling (approximate)

Inference by Enumeration given the Joint Dist.

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

$\left.\begin{matrix} E_1 \ldots E_k = e_1 \ldots e_k \\ Q \\ H_1 \ldots H_r \end{matrix}\right\} X_1, X_2, \ldots X_n$

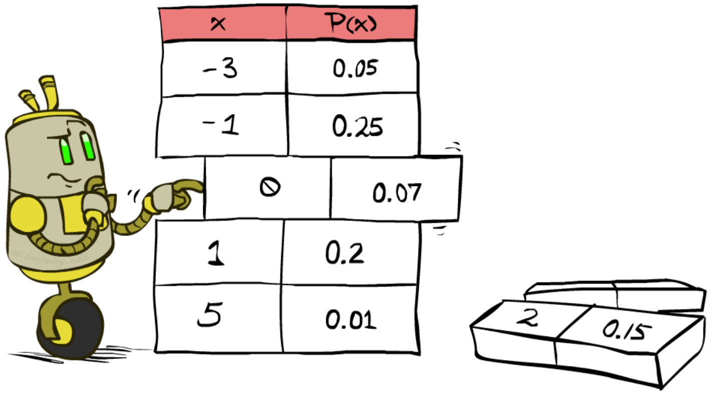
All variables

- We want:

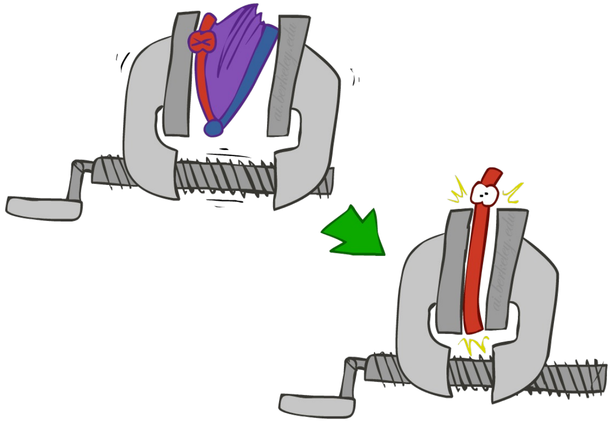
** Works fine with multiple query variables, too*

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

- Step 1: Select the entries consistent with the evidence



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



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

- Step 3: Normalize

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

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

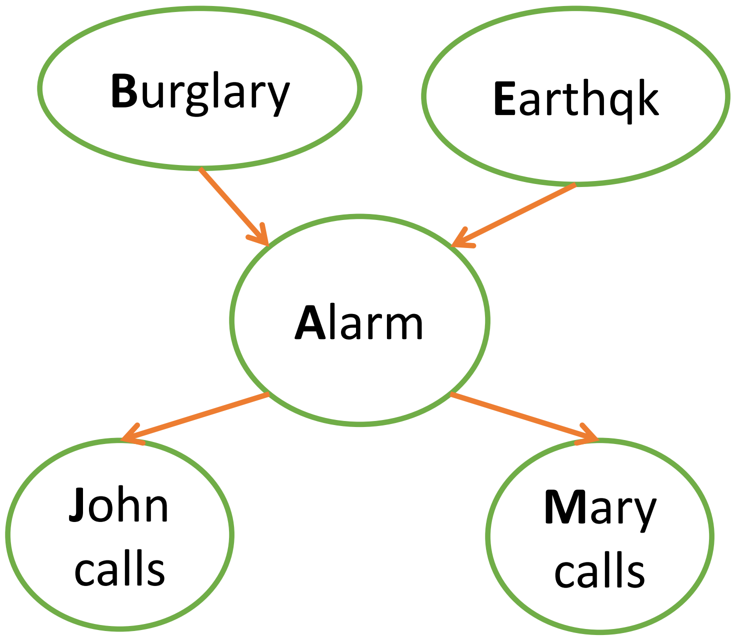
$$P(Q|e_1 \cdots e_k) = \frac{1}{Z} P(Q, e_1 \cdots e_k)$$

Inference by Enumeration in BNs

- Easy! Just need lots of time
  - State all conditional probabilities needed
  - Figure out all atomic probabilities needed
  - Combine, marginalize and normalize

- E.g.

$\mathrm{P}(B, E, A, J, M) = P(B)P(E)P(A|B, E)P(J|A)P(M|A)$
$\mathrm{P}(B| +j, +m) = ?$



Inference Example

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

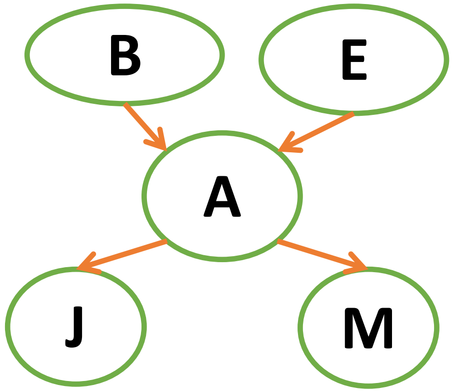
$$=\alpha\sum_{e,a}\mathrm{P}\,(B)\mathrm{P}(e)\mathrm{P}(a|B,e)\mathrm{P}(+j|a)\mathrm{P}(+m|a)$$

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

$$+\quad \mathrm{P}(B)P(-e)\mathrm{P}(+a|B,-e)P(+j|+a)P(+m|+a)$$

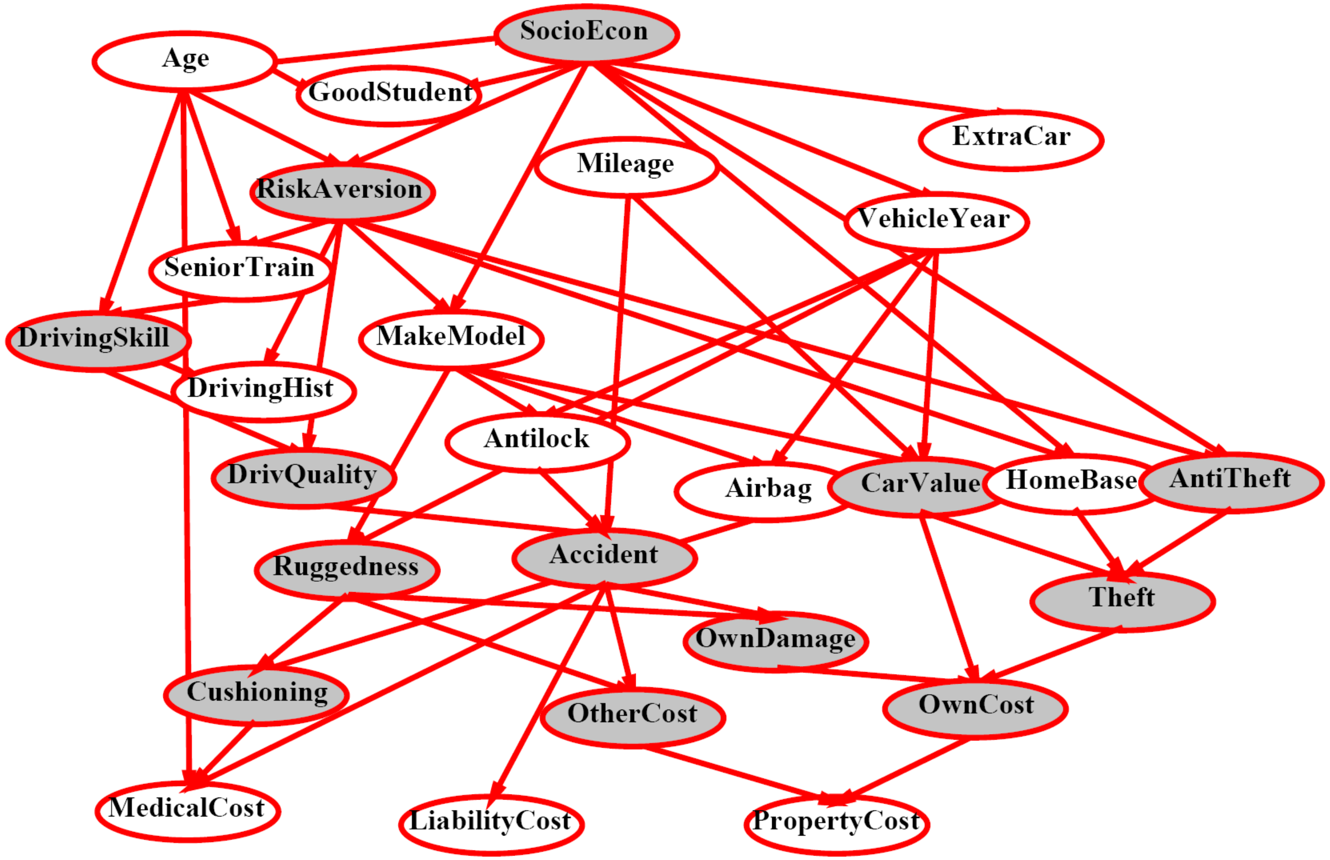
$$+\quad \mathrm{P}(B)P(+e)\mathrm{P}(-a|B,+e)P(+j|-a)P(+m|-a)$$

$$+\quad \mathrm{P}(B)P(-e)\mathrm{P}(-a|B,-e)P(+j|-a)P(+m|-a))$$



Calculate for both +b and –b. Then normalize to get rid of α

Another Example

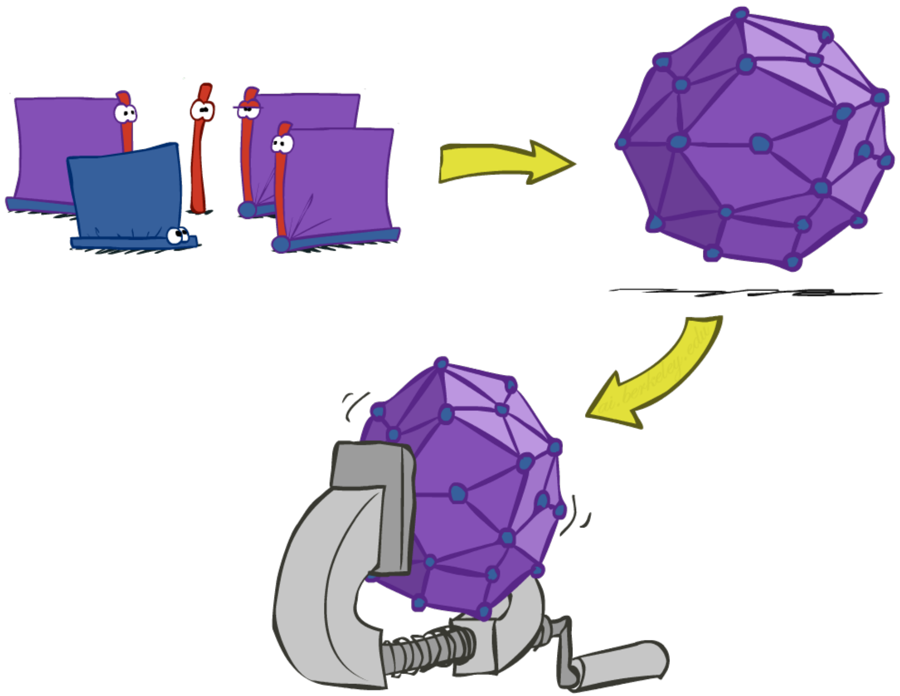


$$P(LiabilityCost|ShadedVariables) = ?$$

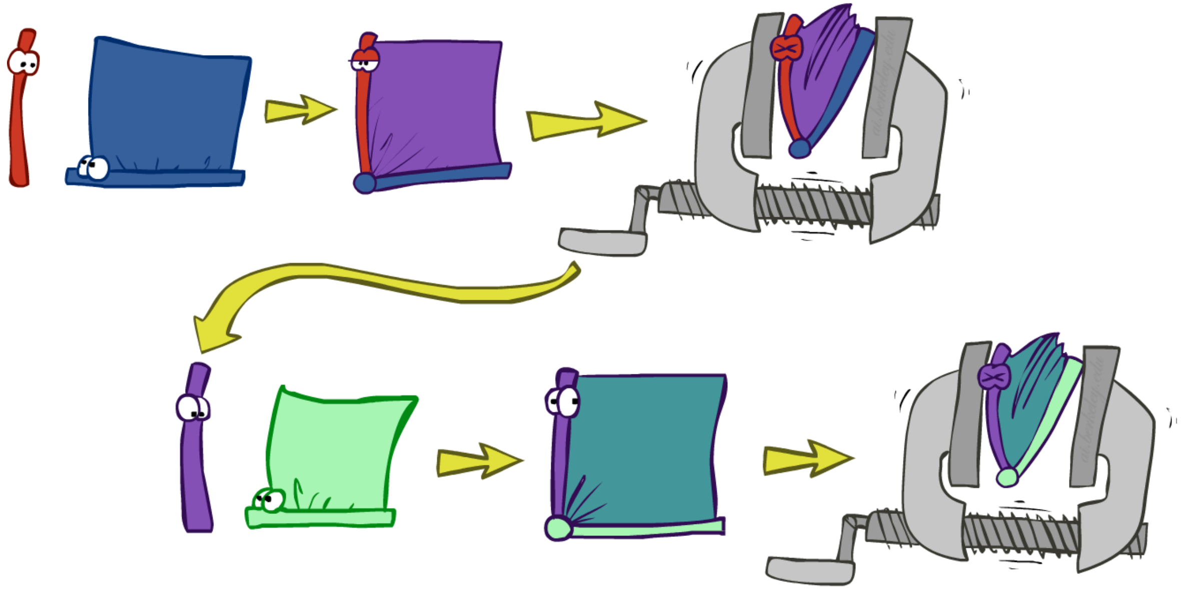
Would be cumbersome with enumeration (aka brute force), but there is a much easier way for this example

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 marginalizing!
  - Called “Variable Elimination”
  - Still NP-hard, but usually faster than inference by enumeration



- First we’ll need some new notation: factors

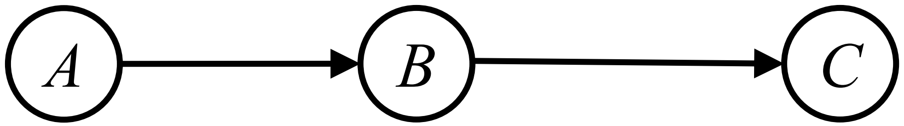
Factors

- **Factorization**: "Decomposition of an object into product of other objects or *factors*"

- Pointwise product of two factors:
  $$f_1(x_1, \dots, x_n, \underline{y_1, \dots, y_k}) \cdot f_2(\underline{y_1, \dots, y_k}, z_1, \dots, z_l) = f(x_1, \dots, x_n, \underline{y_1, \dots, y_k}, z_1, \dots, z_l)$$

- "Multiplying the tables"

Simple Example



$$\mathrm{P}(A)\mathrm{P}(B|A)\mathrm{P}(C|B) = \mathrm{P}(A, B, C)$$

$$\mathrm{P}(A) = f_1(A),\ \mathrm{P}(B|A) = f_2(A, B),\ \mathrm{P}(C|B) = f_3(B, C)$$
$$\rightarrow P(A, B, C) = f(A, B, C)$$

$\mathrm{P}(A)$

+a	0.1
-a	0.9

$\mathrm{P}(B|A)$

+a	+b	0.8
+a	-b	0.2
-a	+b	0.1
-a	-b	0.9

$\mathrm{P}(C|B)$

+b	+c	0.3
+b	-c	0.7
-b	+c	0.1
-b	-c	0.9

Optional: Go Over At Home

A	B	C	$\mathrm{P}(A,B,C)$
+a	+b	+c	$\mathrm{P}(A=+a)\mathrm{P}(B=+b \mid A=+a)\mathrm{P}(C=+c \mid B=+b) = P(A=+a, B=+b, C=+c)$ $= 0.1 \cdot 0.8 \cdot$0.3=**0.024**
+a	+b	-c	$\mathrm{P}(A=+a)\mathrm{P}(B=+b \mid A=+a)\mathrm{P}(C=-c \mid B=+b) = P(A=+a, B=+b, C=-c)$ $= 0.1 \cdot 0.8 \cdot$0.7=0.056
+a	-b	+c	$\mathrm{P}(A=+a)\mathrm{P}(B=-b \mid A=+a)\mathrm{P}(C=+c \mid B=-b) = P(A=+a, B=-b, C=+c)$ $= 0.1 \cdot 0.2 \cdot$0.1=**0.002**
+a	-b	-c	$\mathrm{P}(A=+a)\mathrm{P}(B=-b \mid A=+a)\mathrm{P}(C=-c \mid B=-b) = P(A=+a, B=-b, C=-c)$ $= 0.1 \cdot 0.2 \cdot$0.9=**0.018**
-a	+b	+c	$\mathrm{P}(A=-a)\mathrm{P}(B=+b \mid A=-a)\mathrm{P}(C=+c \mid B=+b) = P(A=-a, B=+b, C=+c)$ $= 0.9 \cdot 0.1 \cdot$0.3=**0.027**
-a	+b	-c	$\mathrm{P}(A=-a)\mathrm{P}(B=+b \mid A=-a)\mathrm{P}(C=-c \mid B=+b) = P(A=-a, B=+b, C=-c)$ $= 0.9 \cdot 0.1 \cdot$0.7=**0.063**
-a	-b	+c	$\mathrm{P}(A=-a)\mathrm{P}(B=-b \mid A=-a)\mathrm{P}(C=+c \mid B=-b) = P(A=-a, B=-b, C=+c)$ $= 0.9 \cdot 0.9 \cdot$0.1=**0.081**
-a	-b	-c	$\mathrm{P}(A=-a)\mathrm{P}(B=-b \mid A=-a)\mathrm{P}(C=-c \mid B=-b) = P(A=-a, B=-b, C=-c)$ $= 0.9 \cdot 0.9 \cdot$0.9=**0.729**

Factors

- **Factorization**: "Decomposition of an object into product of other objects or *factors*"

- Pointwise product of two factors:
$$f_1(x_1, \dots, x_n, \underline{y_1, \dots, y_k}) \cdot f_2(\underline{y_1, \dots, y_k}, z_1, \dots, z_l) = f(x_1, \dots, x_n, \underline{y_1, \dots, y_k}, z_1, \dots, z_l)$$

- "Multiplying the tables"

- What are some factors that we can use in BNs?

Factors I

- 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

- Number of capitals (unobserved variables) affect dimensionality of the table

Factors II

- 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 III

- Specified family: P(y | X)
  - Entries P(y | x) for fixed y, but for all x
  - Sums to … who knows!

$$P(rain|T)$$

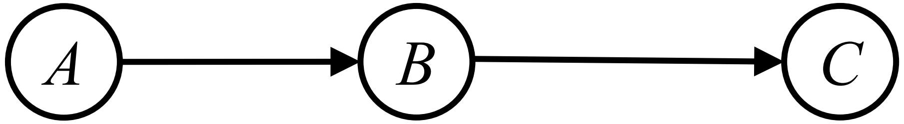
T	W	P
hot	rain	0.2
cold	rain	0.6

$P(rain|hot)$

$P(rain|cold)$

- In general, a factor is $P(Y_1, \ldots, Y_N | X_1, \ldots, X_M)$
  - Multi-dimensional array
  - Its values are $P(y_1 \ldots y_N \mid x_1 \ldots x_M)$
  - Any assigned (=lower-case) X or Y is a dimension missing (selected) from the array

Simple Example Revisited



$\mathrm{P}(A)$ $\mathrm{P}(B|A)$ $\mathrm{P}(C|B)$

$$\mathrm{P}(A) = f_1(A),\ \mathrm{P}(B|A) = f_2(A,B),\ \mathrm{P}(C|B) = f_3(B,C)$$

- Let's get the joint step by step

$\mathrm{P}(A)\mathrm{P}(B|A) = \mathrm{P}(A,B)$ or $f_4(A,B) = f_1(A)f_2(A,B)$

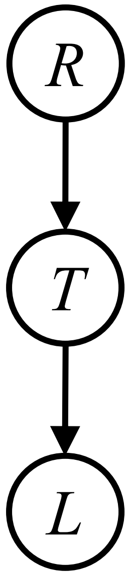
$$f_5(A,B,C) = f_3(B,C)f_4(A,B)$$

Enumeration and Factors

- Inference: Given the query (Q) and evidence variables (E), find P(Q|E)
- Inference by Enumeration:
  - Join the individual distributions with the instantiated evidence variables
  - Marginalize (sum out) the hidden variables
  - Normalize
- Thinking with factors simplify the process since we do not track the corresponding probabilities
- We are going to see a different version where we interleave joining and marginalization where factors will be more useful

Example: Traffic Domain

- Random Variables
  - R: Raining
  - T: Traffic
  - L: Late for class!



$P(R)$

+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

$$P(L) = ?$$

$$= \sum_{r,t} P(r, t, L)$$

$$= \sum_{r,t} P(r)P(t|r)P(L|t)$$

Inference by Enumeration: Procedural Outline

- Track objects called factors
- 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

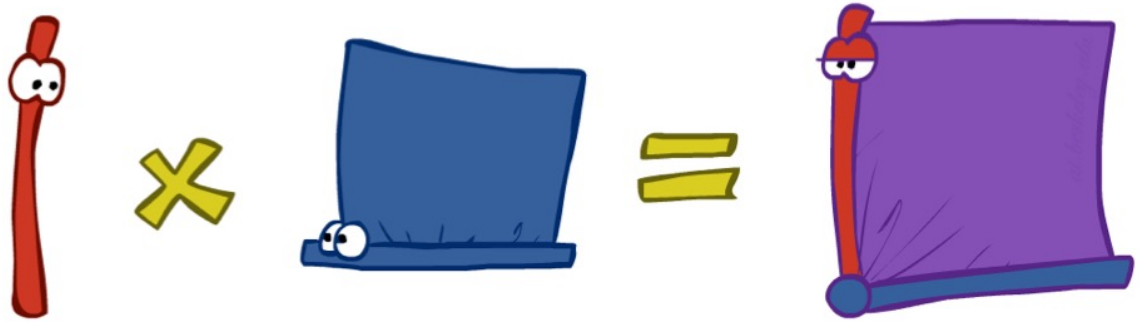
$P(+\ell|T)$

+t	+l	0.3
-t	+l	0.1

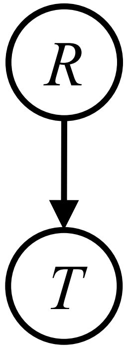
- Procedure: Join all factors, then eliminate all hidden variables

Operation 1: Join Factors

- First basic operation: joining factors
- Combining factors:
  - Get all factors over the joining variable
  - Build a new factor over the union of the variables involved



- Example: Join on R



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

$P(R)$

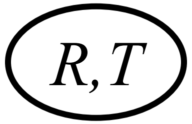
+r	0.1
-r	0.9

$P(T|R)$

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

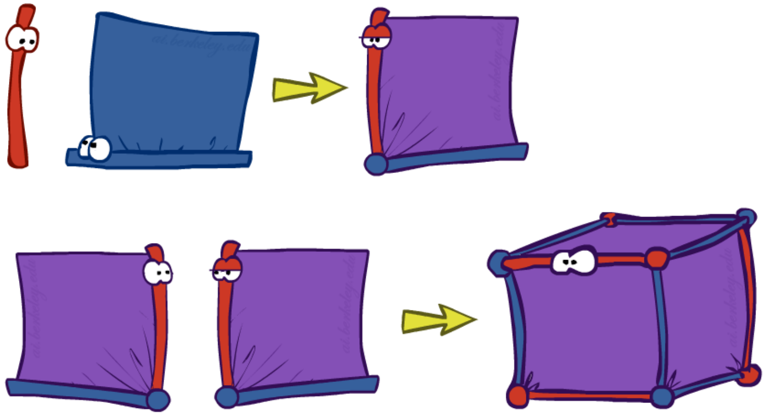
$P(R,T)$

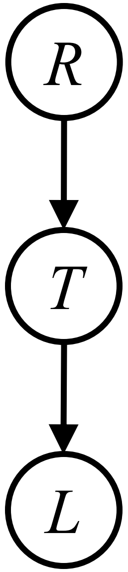
+r	+t	0.08
+r	-t	0.02
-r	+t	0.09
-r	-t	0.81



- Computation for each entry: pointwise products $\forall r, t: \quad P(r,t) = P(r) \cdot P(t|r)$

Example: Multiple Joins





$P(R)$

+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

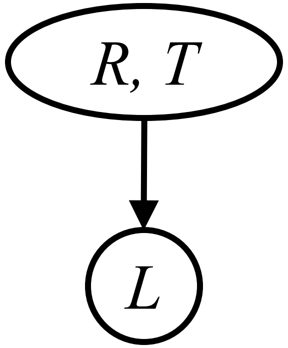
Join R

$P(R,T)$

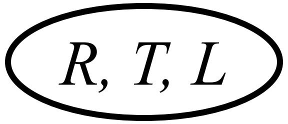
+r	+t	0.08
+r	-t	0.02
-r	+t	0.09
-r	-t	0.81

$P(L|T)$

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



Join T

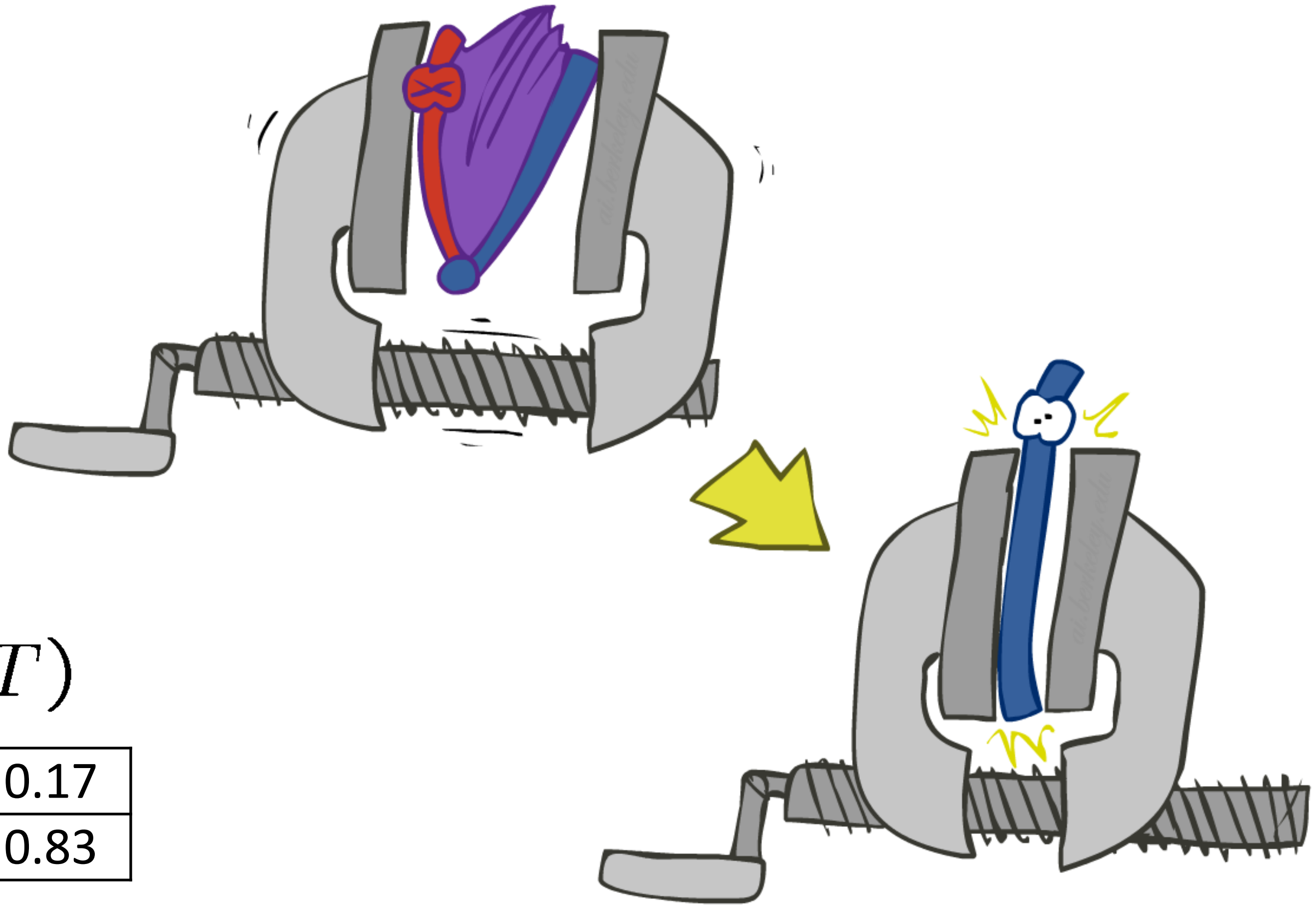


$P(R,T,L)$

+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

Operation 2: Eliminate

- Second basic operation: marginalization
- Take a factor and sum out a variable
  - Shrinks a factor to a smaller one
  - A projection operation



- 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

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

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

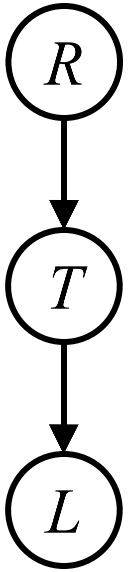
L

$P(L)$

+l	0.134
-l	0.886

Thus far, we have seen multiple-join and multiple-eliminate which is inference by enumeration!
Variable elimination is when we marginalize early

Traffic Domain



$$P(L) = ?$$

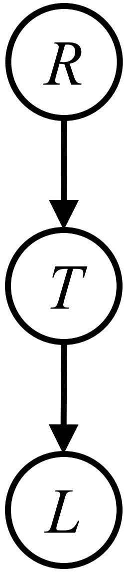
- Inference by Enumeration

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

- Variable Elimination (VE)

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

Marginalizing Early! (aka VE)



$P(R)$

+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

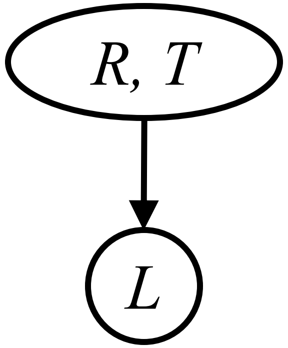
$P(L|T)$

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

Join R

$P(R,T)$

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



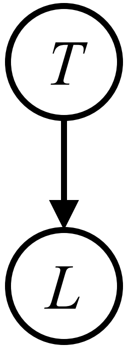
$P(L|T)$

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

Sum out R

$P(T)$

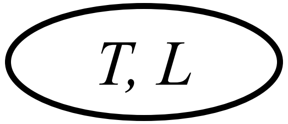
+t	0.17
-t	0.83



$P(L|T)$

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

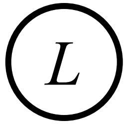
Join T



$P(T,L)$

+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

Evidence

- If you have evidence, start with factors that select that evidence
  - No evidence uses these initial factors:

$P(R)$

+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

  - Computing $P(L| +r)$ the initial factors become:

$P(+r)$

+r	0.1

$P(T| +r)$

+r	+t	0.8
+r	-t	0.2

$P(L|T)$

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

- We eliminate all vars other than query + evidence

Evidence II

- Result will be a selected joint of query and evidence
  - E.g. for P(L | +r), we would end up with:

$P(+r, L)$

+r	+l	0.026
+r	-l	0.074

Normalize

$P(L| + r)$

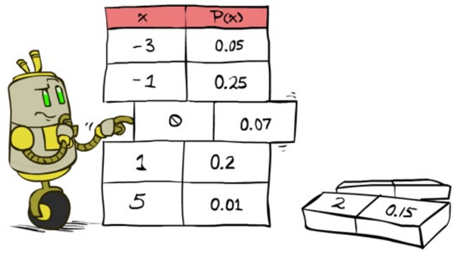
+l	0.26
-l	0.74

- To get our answer, just normalize this!

- That ’s it!

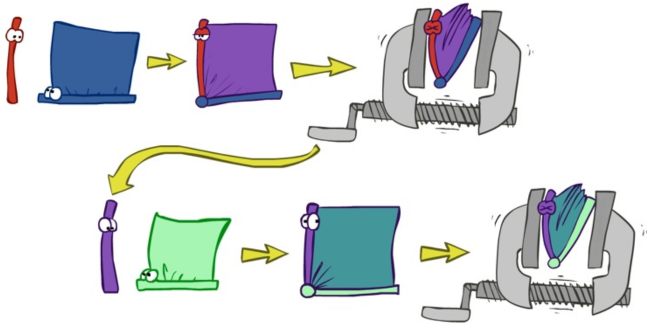
General Variable Elimination

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

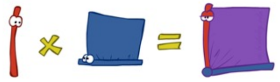


- Start with initial factors:
  - Local CPTs (but instantiated by evidence)

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



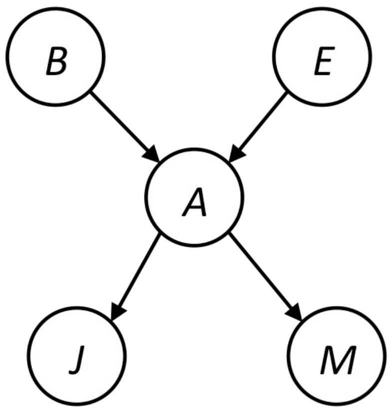
- Join all remaining factors and normalize



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

Example

- What is the probability of a burglar being in my house if both John and Marry calls? OR $P(B|+j,+m)=?$



Query Variables: B

Evidence Variables: $+j,+m$

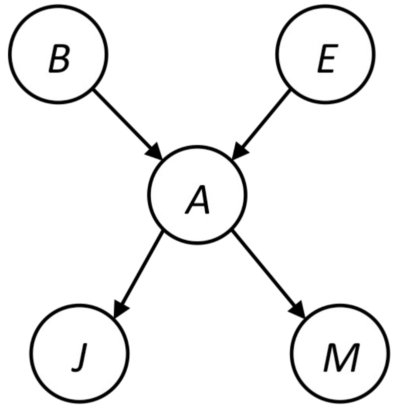
Hidden Variables: A, E

Example

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

Current factors

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



Choose A

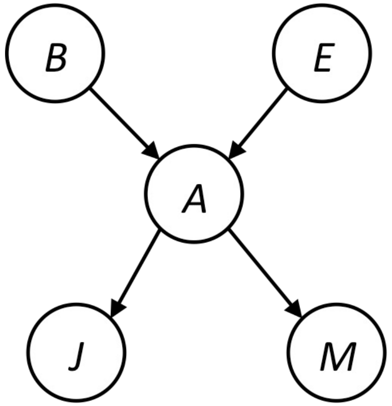
$$\left.\begin{array}{l} P(A|B,E) \\ P(j|A) \\ P(m|A) \end{array}\right. \xrightarrow{\times} P(j,m,A|B,E) \xrightarrow{\sum} P(j,m|B,E)$$

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

Factors after eliminating A

Example

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



Choose E

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

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

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

No more hidden vars, now what?
"Join all remaining and normalize"

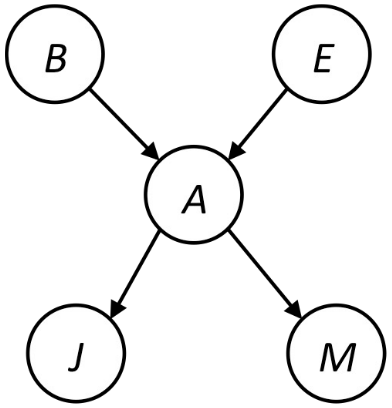
Finish with B

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

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

Same Example in Equations

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



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

$$\begin{aligned}
P(B|j,m) &\propto P(B,j,m) \\
&= \sum_{e,a} P(B,j,m,e,a) \\
&= \sum_{e,a} P(B)P(e)P(a|B,e)P(j|a)P(m|a) \\
&= \sum_{e} P(B)P(e)\sum_{a} P(a|B,e)P(j|a)P(m|a) \\
&= \sum_{e} P(B)P(e)f_1(B,e,j,m) \\
&= P(B)\sum_{e} P(e)f_1(B,e,j,m) \\
&= P(B)f_2(B,j,m)
\end{aligned}$$

marginal can be obtained from joint by summing out

use Bayes' net joint distribution expression

use x*(y+z) = xy + xz

joining on a, and then summing out gives f_1

use x*(y+z) = xy + xz

joining on e, and then summing out gives f_2

All we are doing is exploiting uwy + uwz + uxy + uxz + vwy + vwz + vxy +vxz = (u+v)(w+x)(y+z) to improve computational efficiency!

Another Variable Elimination Example

Query: $P(X_3|Y_1 = y_1, Y_2 = y_2, Y_3 = y_3)$

Start by inserting evidence, which gives the following initial factors:

$$p(Z)p(X_1|Z)p(X_2|Z)p(X_3|Z)p(y_1|X_1)p(y_2|X_2)p(y_3|X_3)$$

Eliminate X_1, this introduces the factor $f_1(Z, y_1) = \sum_{x_1} p(x_1|Z)p(y_1|x_1)$, and we are left with:

$$p(Z)f_1(Z, y_1)p(X_2|Z)p(X_3|Z)p(y_2|X_2)p(y_3|X_3)$$

Eliminate X_2, this introduces the factor $f_2(Z, y_2) = \sum_{x_2} p(x_2|Z)p(y_2|x_2)$, and we are left with:

$$p(Z)f_1(Z, y_1)f_2(Z, y_2)p(X_3|Z)p(y_3|X_3)$$

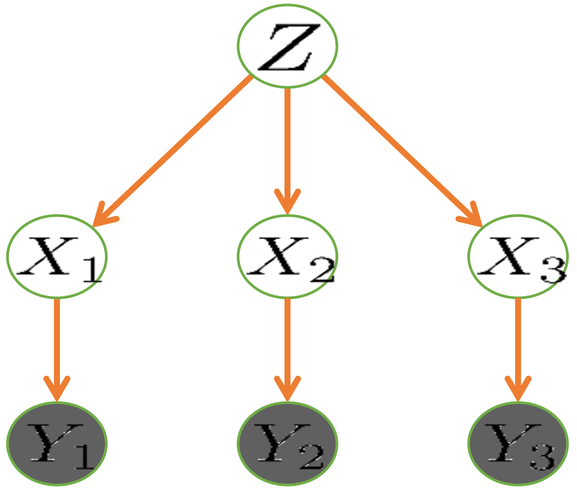
Eliminate Z, this introduces the factor $f_3(y_1, y_2, X_3) = \sum_z p(z)f_1(z, y_1)f_2(z, y_2)p(X_3|z)$, and we are left:

$$p(y_3|X_3), f_3(y_1, y_2, X_3)$$

No hidden variables left. Join the remaining factors to get:

$$f_4(y_1, y_2, y_3, X_3) = P(y_3|X_3)f_3(y_1, y_2, X_3).$$

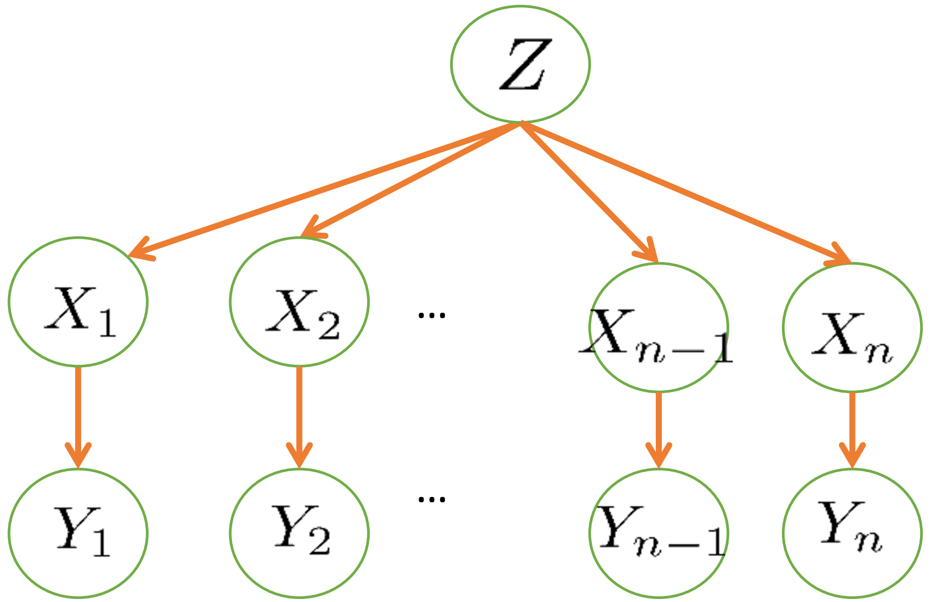
Normalizing over X_3 gives $P(X_3|y_1, y_2, y_3)$.



Computational complexity critically depends on the largest factor being generated in this process. Size of factor = number of entries in table. In example above (assuming binary) all factors generated are of size 2 --- as they all only have one parent.

Variable Elimination Ordering

- For the query $P(X_n|y_1,\ldots,y_n)$ work through the following two different orderings as done in previous slide: $Z, X_1, \ldots, X_{n-1}$ and $X_1, \ldots, X_{n-1}, Z$. What is the size of the maximum factor generated for each of the orderings?



- Answer: 2^{n+1} versus 2^2 (assuming binary)
- In general: the ordering can greatly affect efficiency.

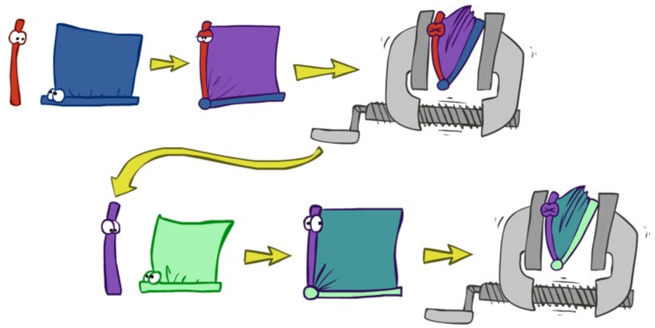
VE: Computational and Space Complexity

- The computational and space complexity of variable elimination is determined by the largest factor

- The elimination ordering can greatly affect the size of the largest factor.
  - E.g., previous slide’s example 2^n vs. 2^2

- Does there always exist an ordering that only results in small factors?
  - No!

Variable Elimination Summary



- Interleave joining and marginalizing
- d^k entries computed for a factor over k variables with domain sizes d
- Ordering of elimination of hidden variables can affect size of factors generated
- Worst case: running time exponential in the size of the Bayes' net
- Better than enumeration in practice, saves time by marginalizing variables as soon as possible rather than at the end

- Not efficient enough for big BNs, so next we'll talk about *Approximate Inference* techniques