

CS221 Section 7

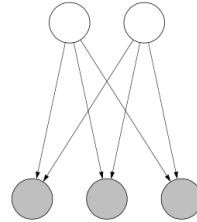
Bayesian Networks

Nov 9th 2018

Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence
- Gibbs Sampling

Bayesian Networks



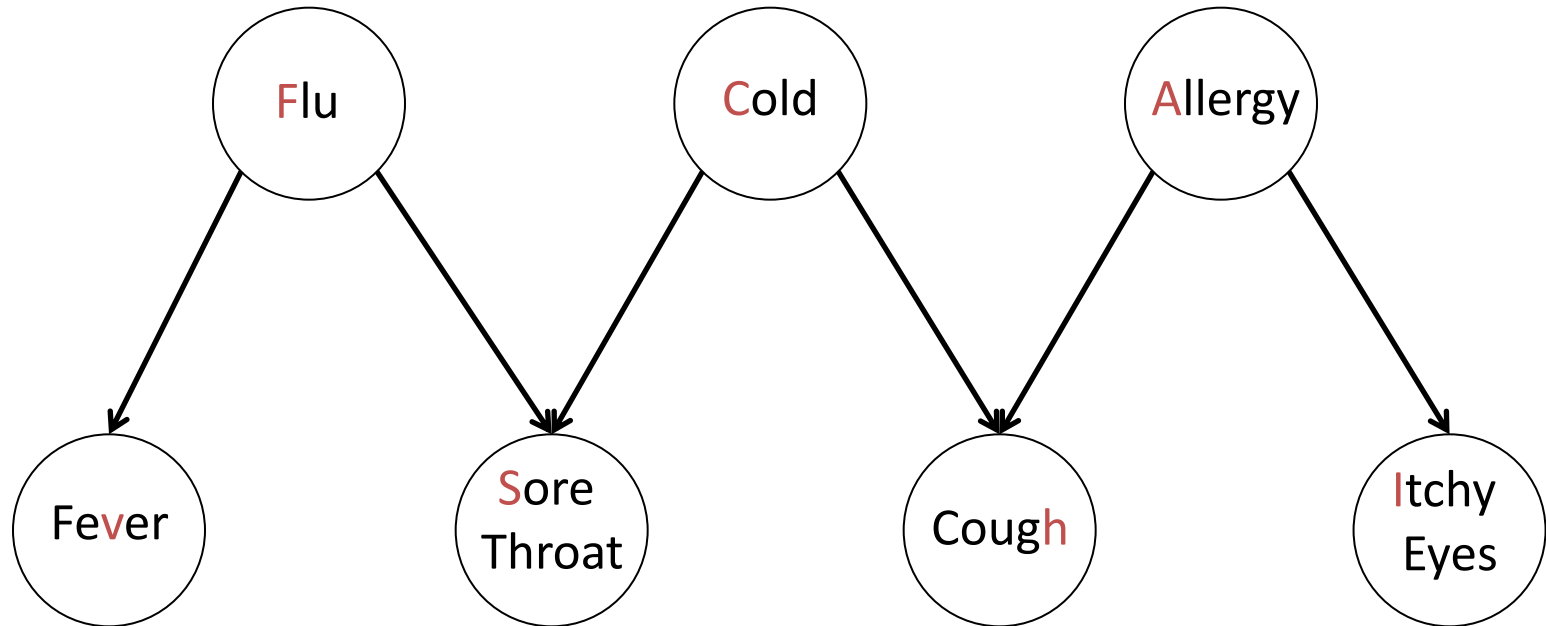
Definition: Bayesian network

Let $X = (X_1, \dots, X_n)$ be random variables.

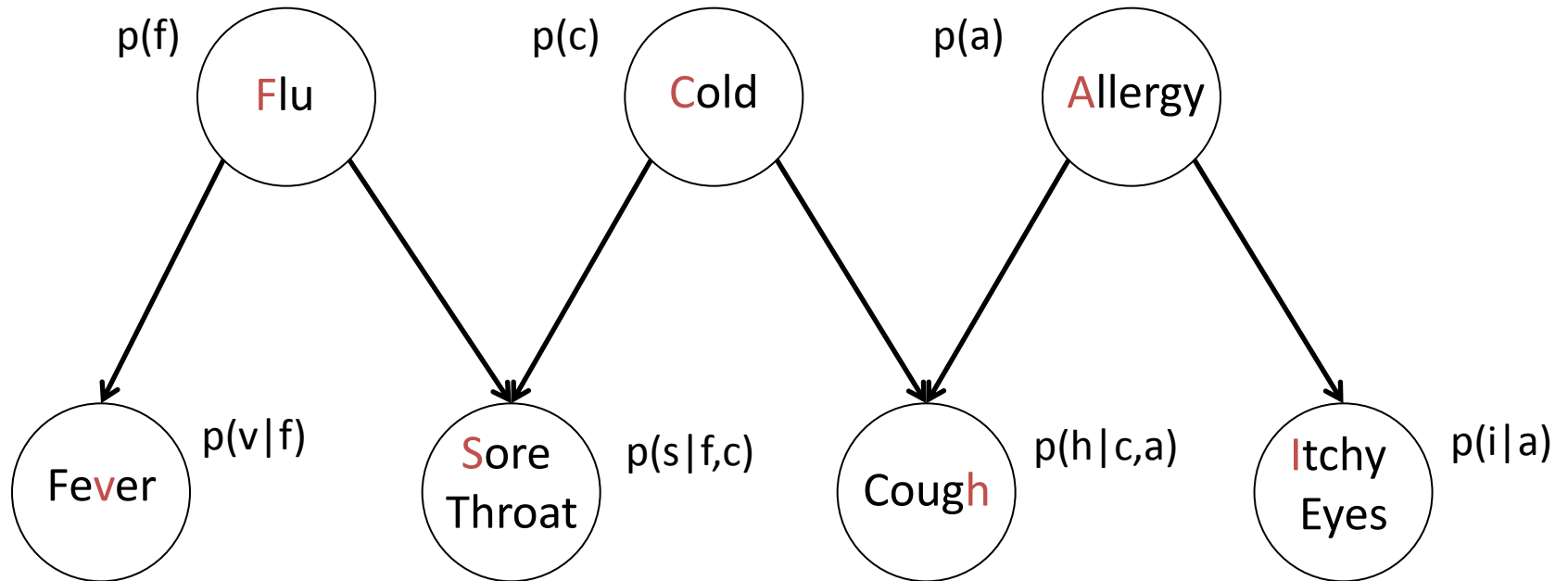
A **Bayesian network** is a directed acyclic graph (DAG) that specifies a **joint distribution** over X as a product of **local conditional distributions**, one for each node:

$$\mathbb{P}(X_1 = x_1, \dots, X_n = x_n) = \prod_{i=1}^n p(x_i \mid x_{\text{Parents}(i)})$$

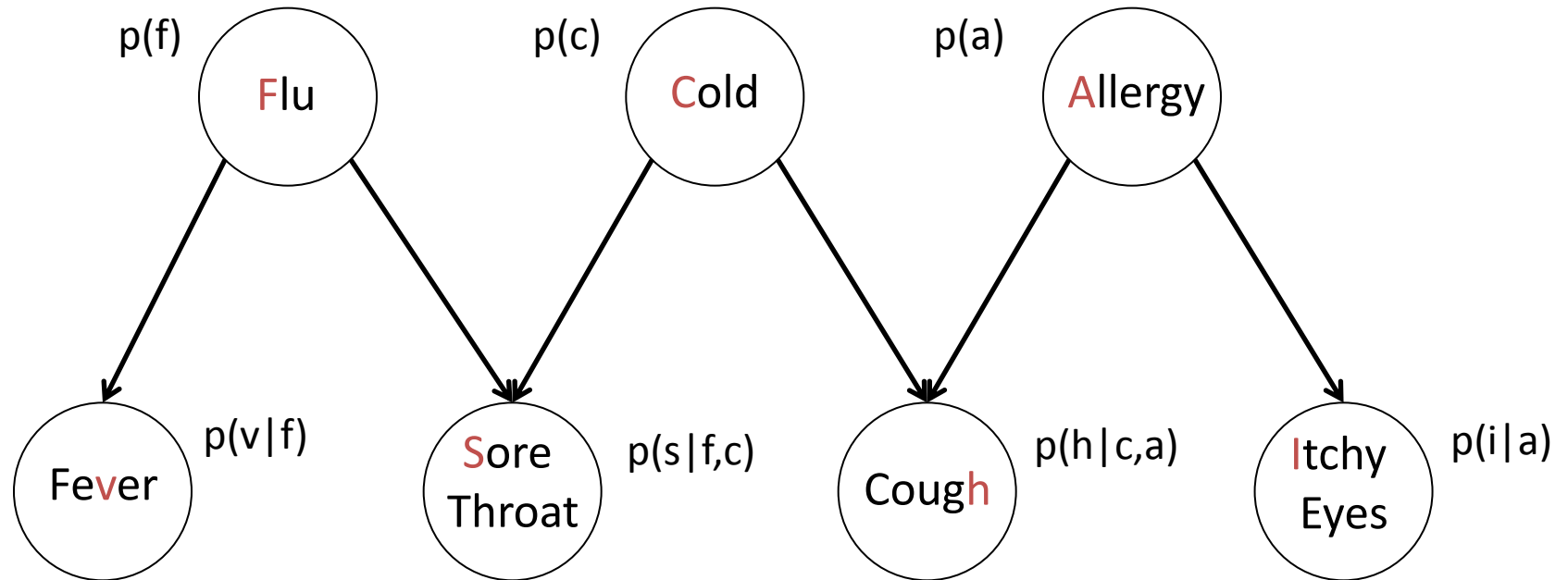
Bayesian Networks



A Bayesian network represents a joint probability distribution.



A Bayesian network represents a joint probability distribution.



$$P(F=f, C=c, A=a, V=v, S=s, C=c, I=i) = p(f)p(c)p(a)p(v|a)p(s|f, c)p(h|c,a)p(i|a)$$

Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence
- Gibbs Sampling

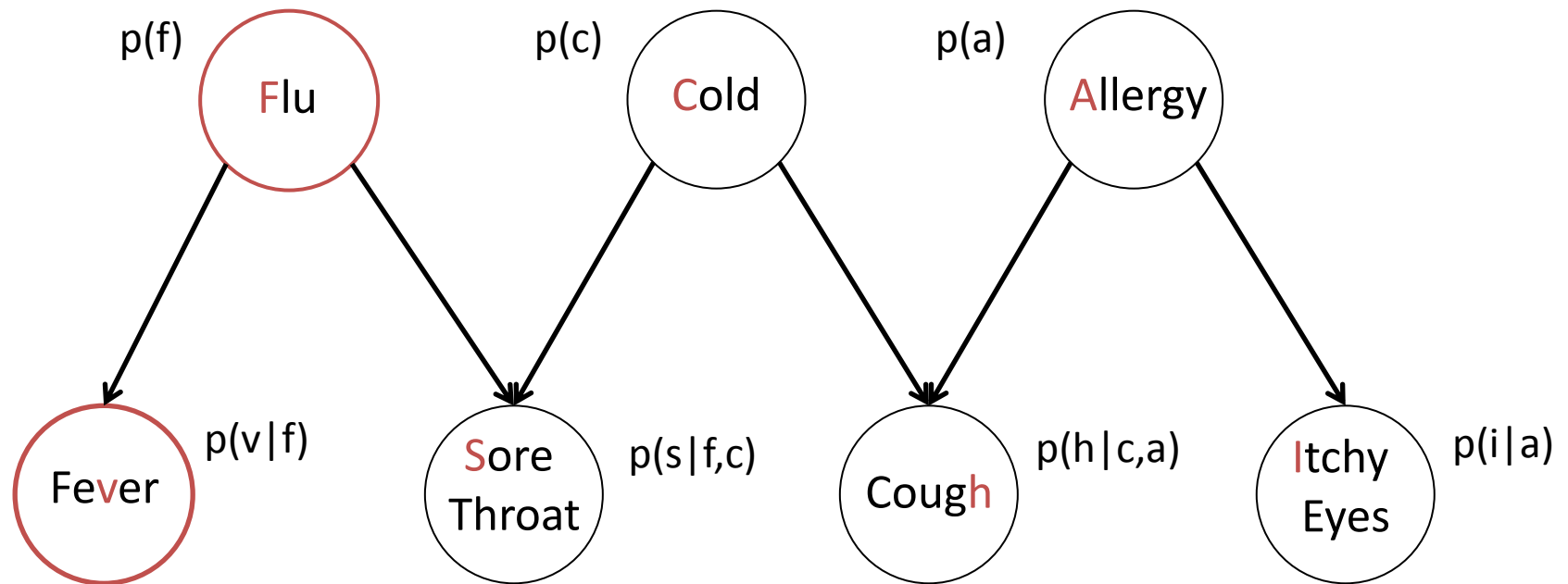
Probabilistic Queries – Cookbook

Given a query $P(Q|E=e)$

1. Remove (marginalize) variables not ancestors of Q or E .
2. Convert Bayesian network to factor graph.
3. Condition (shade nodes / disconnect) on $E = e$.
4. Remove (marginalize) nodes disconnected from Q .
5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

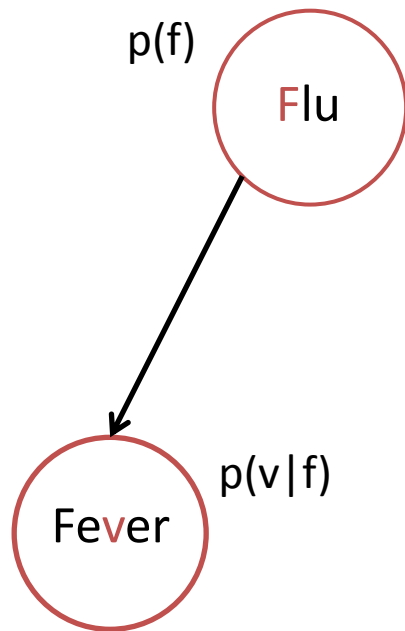
Probabilistic Queries - Examples

$$P(F=1 | V=1) = ?$$



Probabilistic Queries - Examples

$$P(F=1 \mid V=1) = ?$$

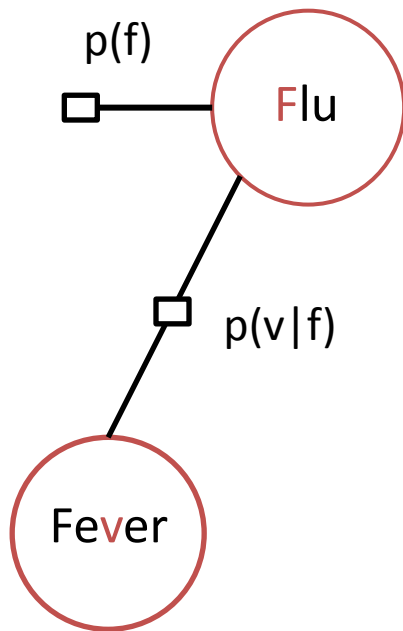


1. Remove (marginalize) variables not ancestors of Q or E.

Probabilistic Queries - Examples

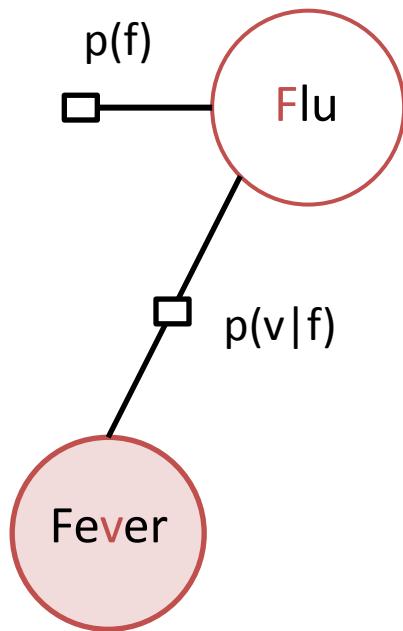
$$P(F=1 \mid V=1) = ?$$

2. Convert Bayesian network to factor graph.



Probabilistic Queries - Examples

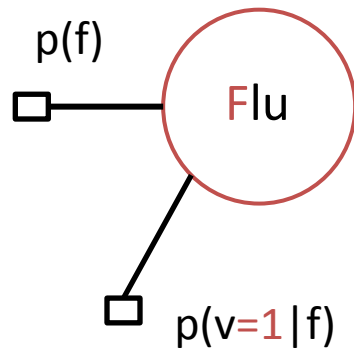
$$P(F=1 | V=1) = ?$$



3. Condition on $E = e$.
3.1 shade nodes

Probabilistic Queries - Examples

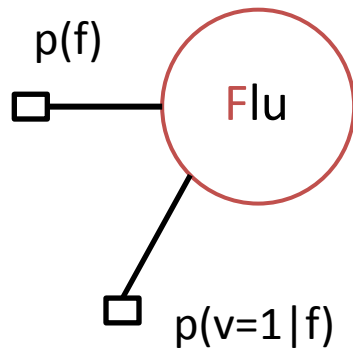
$$P(F=1 \mid V=1) = ?$$



3. Condition on $E = e$.
3.2 disconnect

Probabilistic Queries - Examples

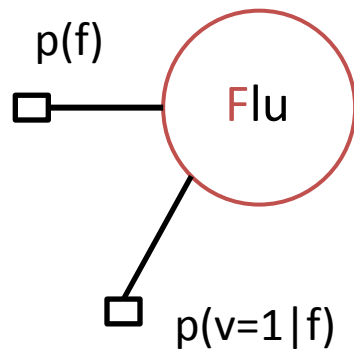
$$P(F=1 \mid V=1) = ?$$



4. Remove (marginalize) nodes disconnected from Q.

Probabilistic Queries - Examples

$$P(F=1 | V=1) = ?$$



5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

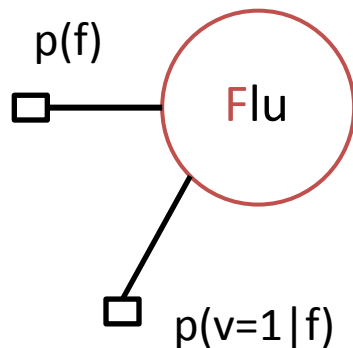
f	p(f)
0	1- α
1	α

f	v	p(v f)
0	0	0.70
0	1	0.30
1	0	0.20
1	1	0.80

$$P(F=f | V=1) \propto p(f) p(v=1|f)$$

Probabilistic Queries - Examples

$$P(F=1 | V=1) = ?$$



5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

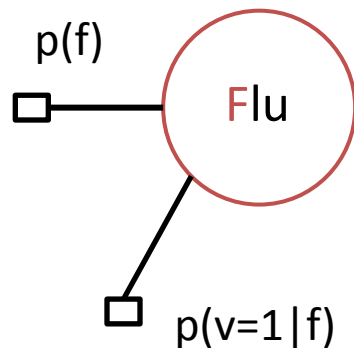
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1	α

f	v	p(v f)
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0	1	0.30
1	0	0.20
1	1	0.80

$$P(F=f|V=1) \propto p(f) p(v=1|f) = (1 - \alpha) * 0.30, \quad f = 0$$

Probabilistic Queries - Examples

$$P(F=1 | V=1) = ?$$



5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

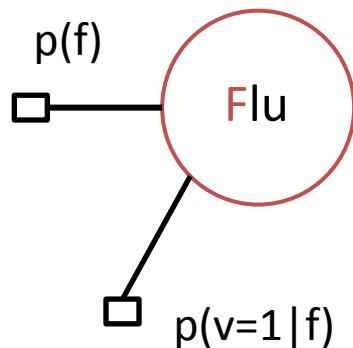
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$$P(F=f|V=1) \propto p(f) p(v=1|f) = \begin{cases} (1-\alpha) * 0.30, & f=0 \\ \alpha * 0.80, & f=1 \end{cases}$$

Probabilistic Queries - Examples

$$P(F=1 | V=1) = ?$$



5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

f	p(f)
0	1- α
1	α

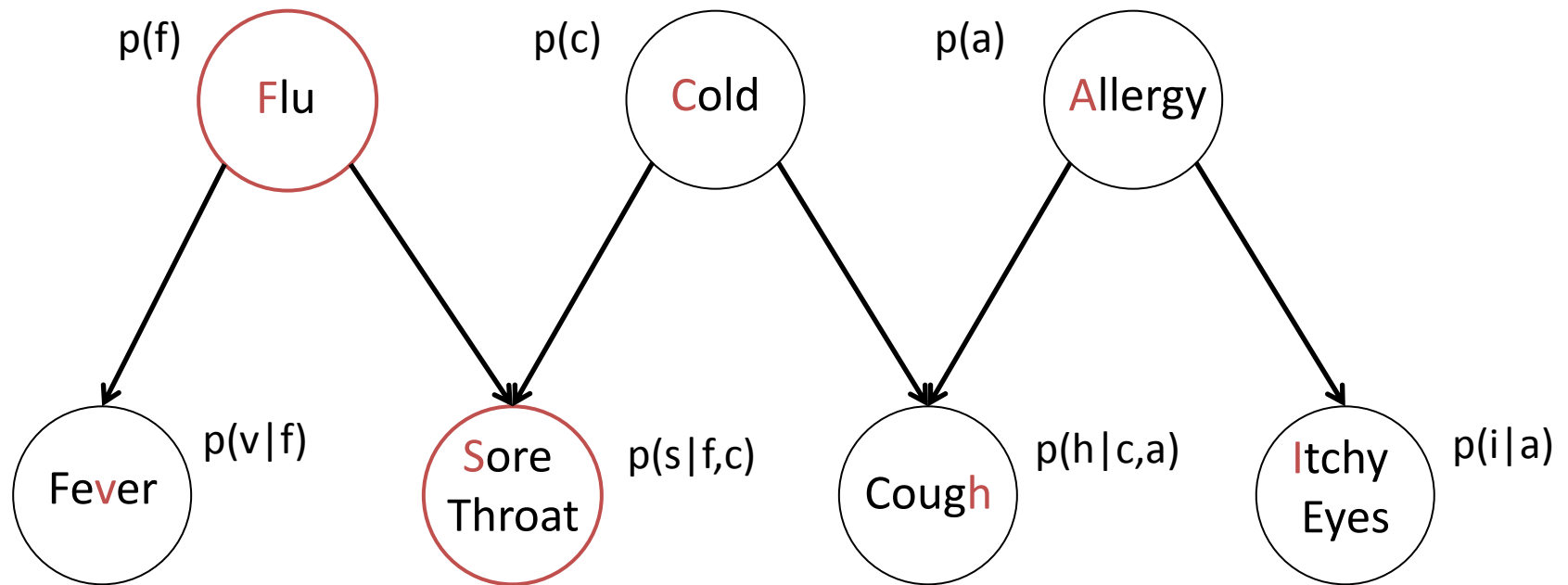
f	v	p(v f)
0	0	0.70
0	1	0.30
1	0	0.20
1	1	0.80

$$P(F=f|V=1) \propto p(f) p(v=1|f) = \begin{aligned} & (1 - \alpha) * 0.30, & f = 0 \\ & \alpha * 0.80, & f = 1 \end{aligned}$$

$$P(F=1|V=1) = \frac{\alpha * 0.80}{\alpha * 0.80 + (1 - \alpha) * 0.30}$$

Probabilistic Queries - Examples

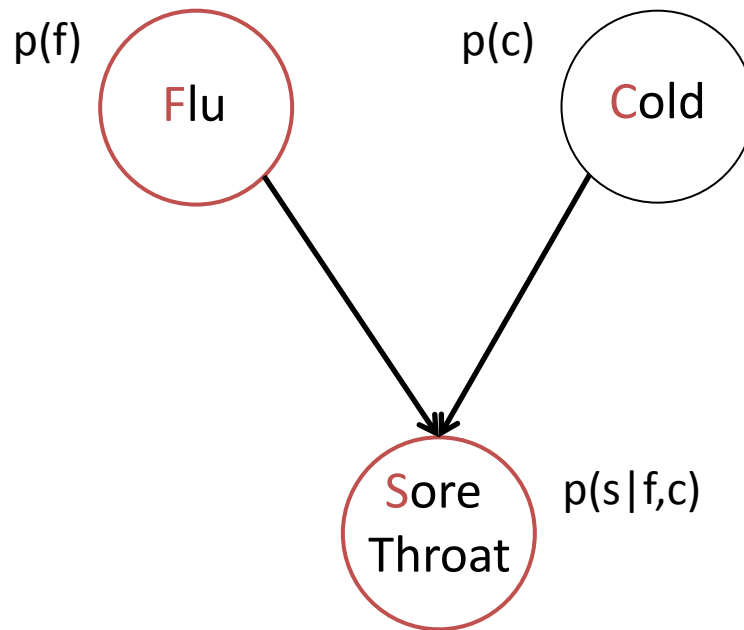
$$P(F=1 | S=1) = ?$$



Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$

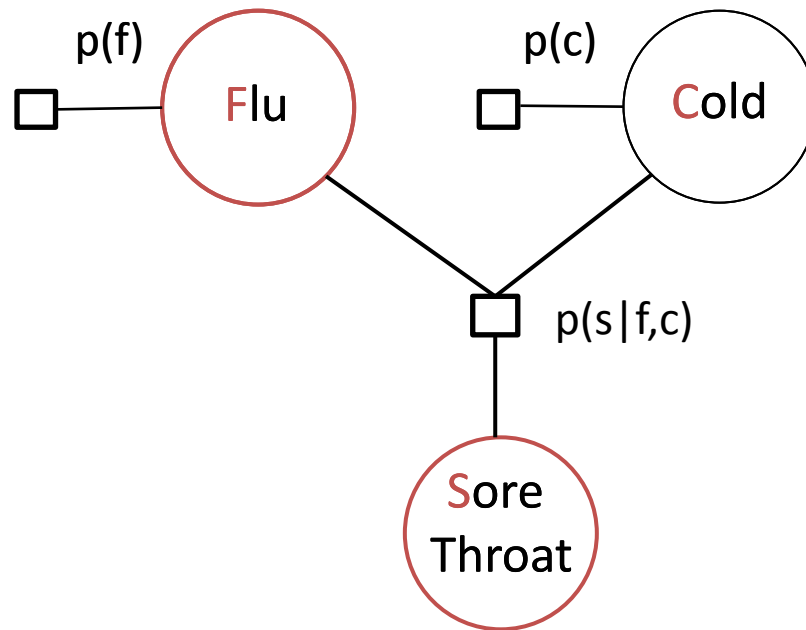
1. Remove (marginalize) variables not ancestors of Q or E.



Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$

2. Convert Bayesian network to factor graph.

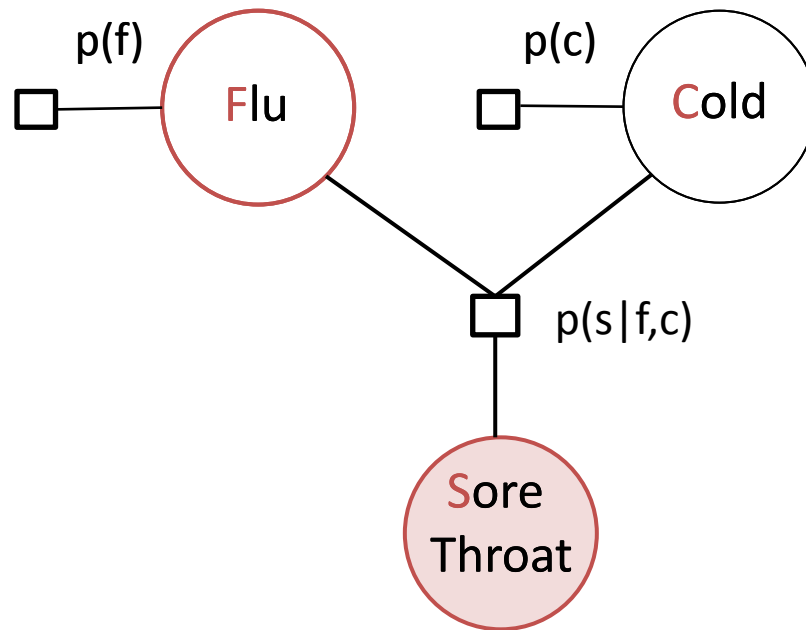


★ One factor per variable!

Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$

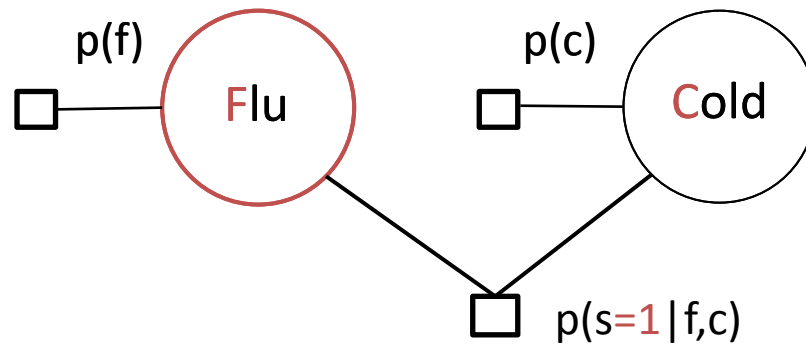
3. Condition on $E = e$.
3.1 shade nodes



Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$

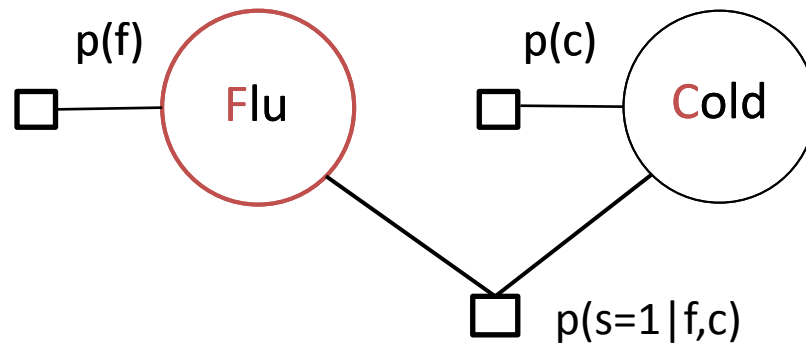
3. Condition on $E = e$.
3.2 disconnect



Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$

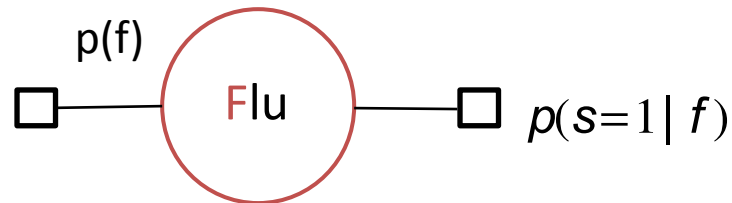
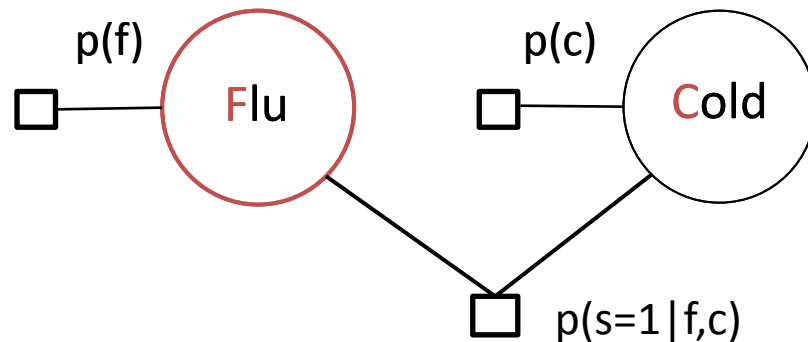
4. Remove (marginalize) nodes disconnected from Q.



Probabilistic Queries - Examples

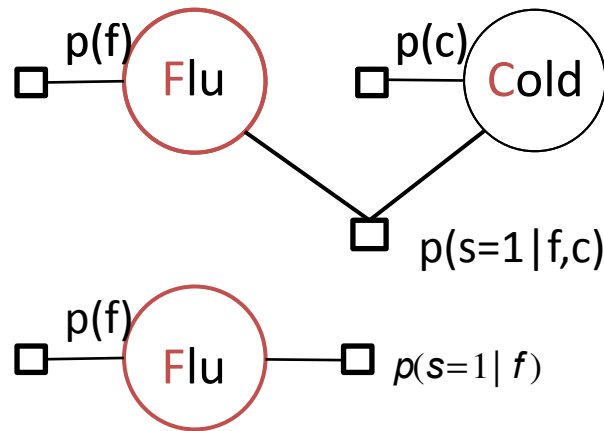
$$P(F=1 | S=1) = ?$$

5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).



Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).

$$p(s=1 | f)$$

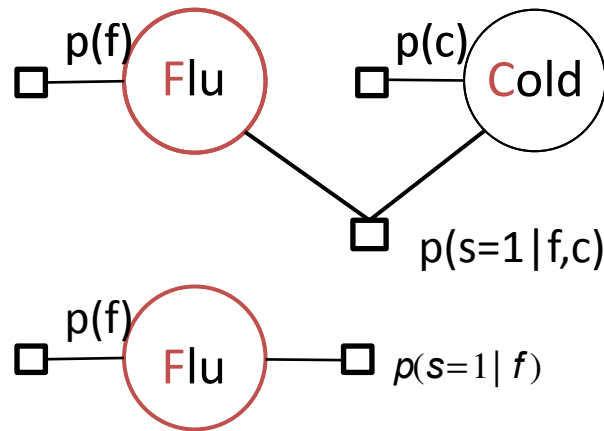
$$= \sum_c p(c) p(s=1 | f, c)$$

$$= p(c=0) p(s=1 | f, c=0) + p(c=1) p(s=1 | f, c=1)$$

f	p(s=1, f)
0	?
1	?

Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



$$p(s=1 | f)$$

$$= \sum_c p(c) p(s=1 | f, c)$$

$$= p(c=0) p(s=1 | f, c=0) + p(c=1) p(s=1 | f, c=1)$$

$$= (1 - \beta) * 0 + \beta * 0.75, \quad f = 0$$

5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).

f	p(f)
0	$1-\alpha$
1	α

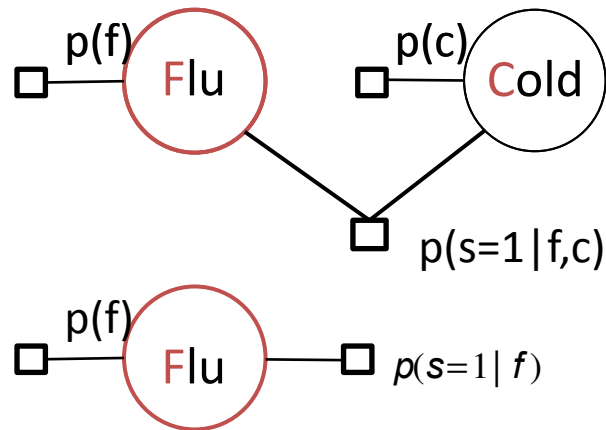
c	p(c)
0	$1-\beta$
1	β

s	f	c	p(s f,c)
0	0	0	1.00
1	0	0	0
0	1	0	0.30
1	1	0	0.70
0	0	1	0.25
1	0	1	0.75
0	1	1	0.10
1	1	1	0.90

f	p(s=1,f)
0	$\beta * 0.75$
1	?

Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



$$p(s=1 | f)$$

$$= \sum_c p(c) p(s=1 | f, c)$$

$$= p(c=0) p(s=1 | f, c=0) + p(c=1) p(s=1 | f, c=1)$$

$$= (1 - \beta) * 0 + \beta * 0.75, \quad f = 0$$

$$= (1 - \beta) * 0.70 + \beta * 0.9, \quad f = 1$$

5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).

f	p(f)
0	1- α
1	α

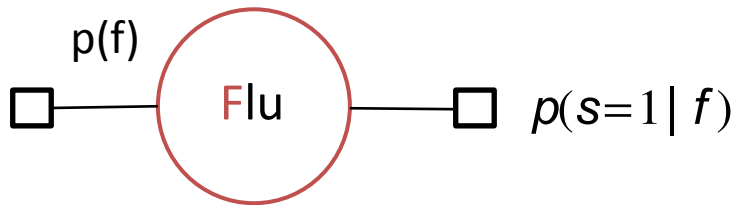
c	p(c)
0	1- β
1	β

s	f	c	p(s f,c)
0	0	0	1.00
1	0	0	0
0	1	0	0.30
1	1	0	0.70
0	0	1	0.25
1	0	1	0.75
0	1	1	0.10
1	1	1	0.90

f	p(s=1,f)
0	$\beta * 0.75$
1	$((1-\beta) * 0.7 + \beta * 0.9)$

Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



$$P(F = f | S=1)$$

$$\propto p(f)p(s=1 | f)$$

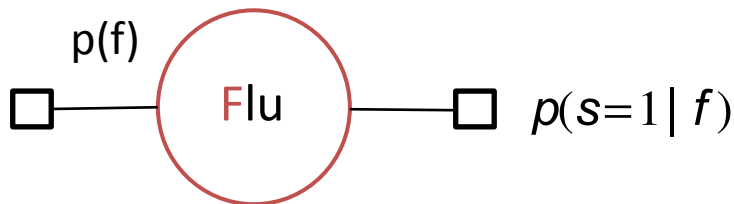
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f	p(f)
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Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



$$P(F = f | S=1)$$

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$$= (1 - \alpha) * 0.75, \quad f = 0$$

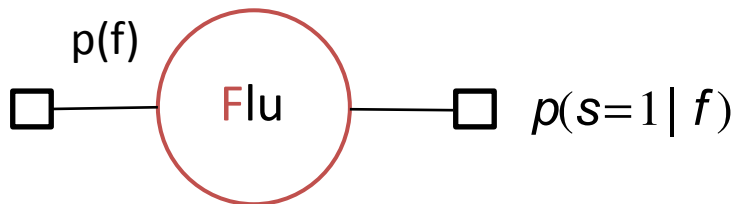
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Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



$$P(F = f | S=1)$$

$$\propto p(f)p(s=1 | f)$$

$$= \begin{cases} (1 - \alpha) * 0.75, & f = 0 \\ ((1 - \alpha) * 0.70 + \alpha * 0.9), & f = 1 \end{cases}$$

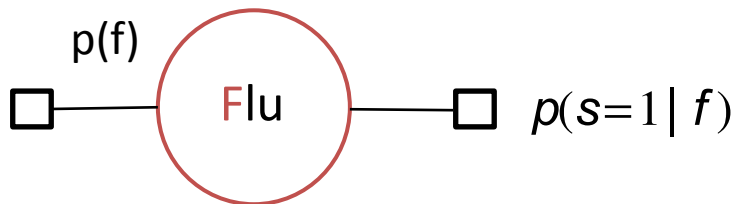
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Probabilistic Queries - Examples

$$P(F=1 | S=1) = ?$$



5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).

f	p(f)
0	$1-\alpha$
1	α

f	p(s=1 f)
0	$\beta * 0.75$
1	$(1-\beta) * 0.7 + \beta * 0.9$

$$P(F = f | S=1)$$

$$\propto p(f)p(s=1 | f)$$

$$= \begin{matrix} (1-\alpha) * 0.75, & f=0 \\ ((1-\alpha) * 0.70 + \alpha * 0.9), & f=1 \end{matrix}$$

$$\begin{aligned} P(F=1 | S=1) &= \frac{p(f=1)p(s=1 | f=1)}{p(f=1)p(s=1 | f=1) + p(f=0)p(s=1 | f=0)} \\ &= \frac{\alpha * 0.9}{\alpha * 0.9 + (1-\alpha) * 0.75} \end{aligned}$$

Probabilistic Queries – Cookbook

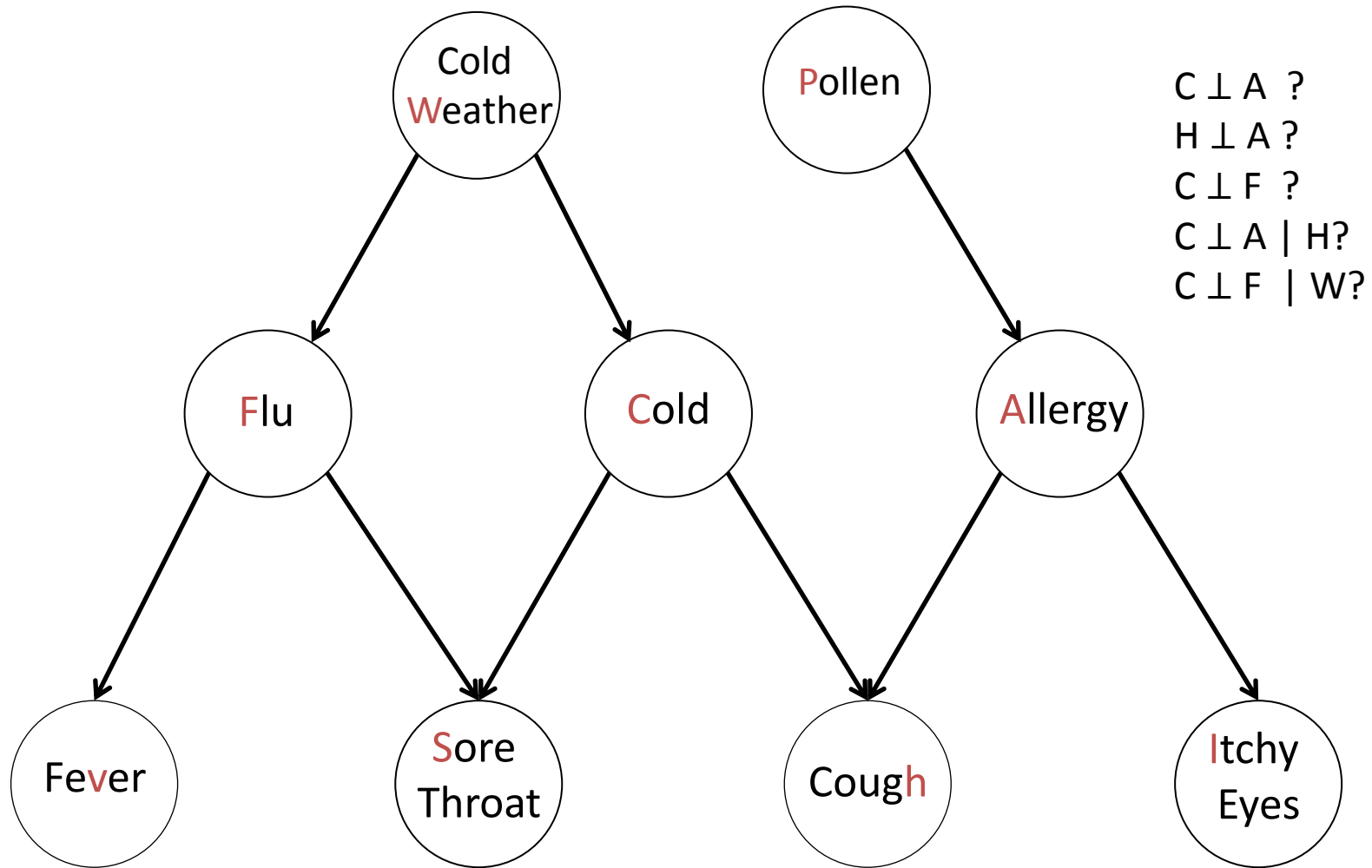
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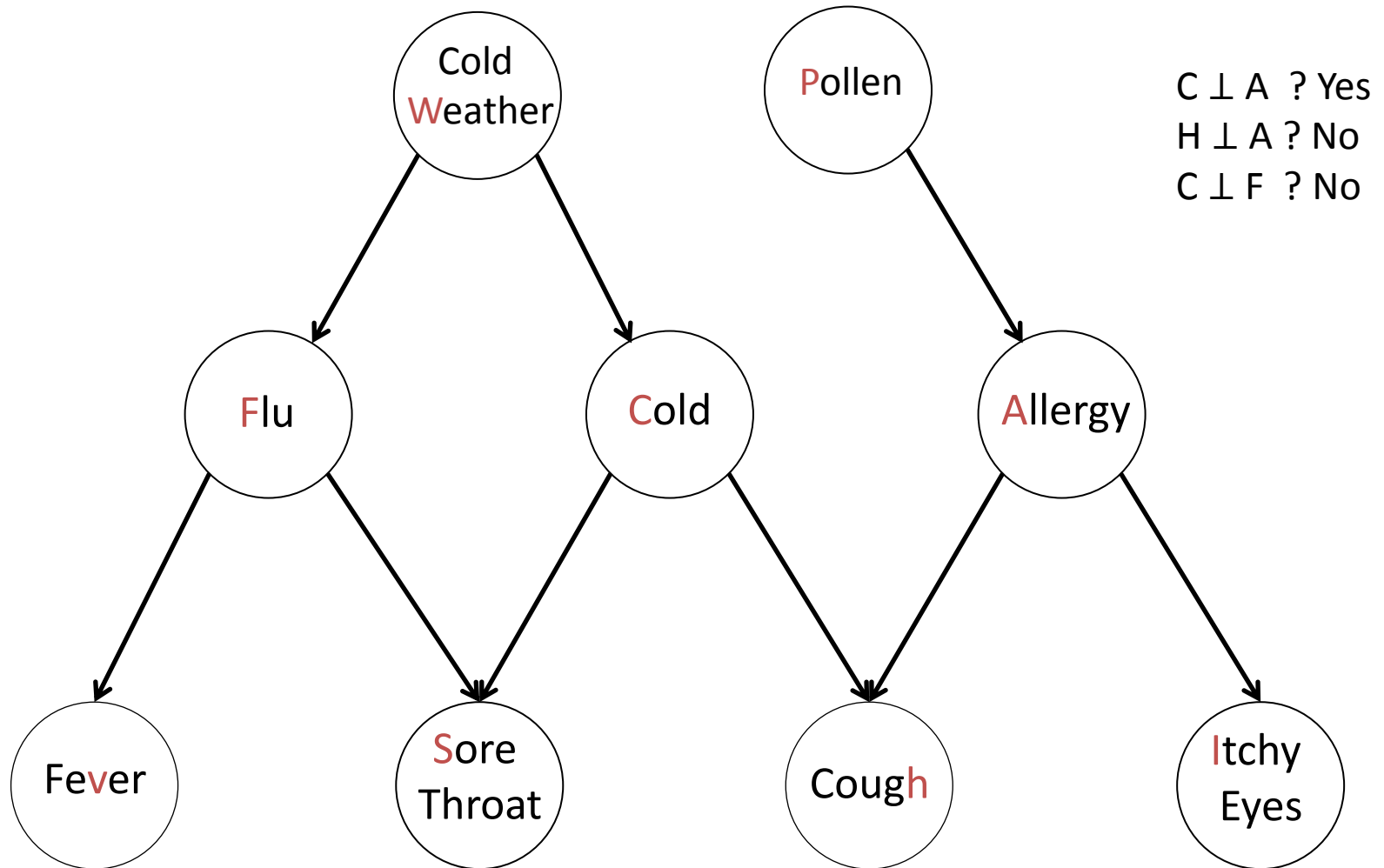
Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence
- Gibbs Sampling

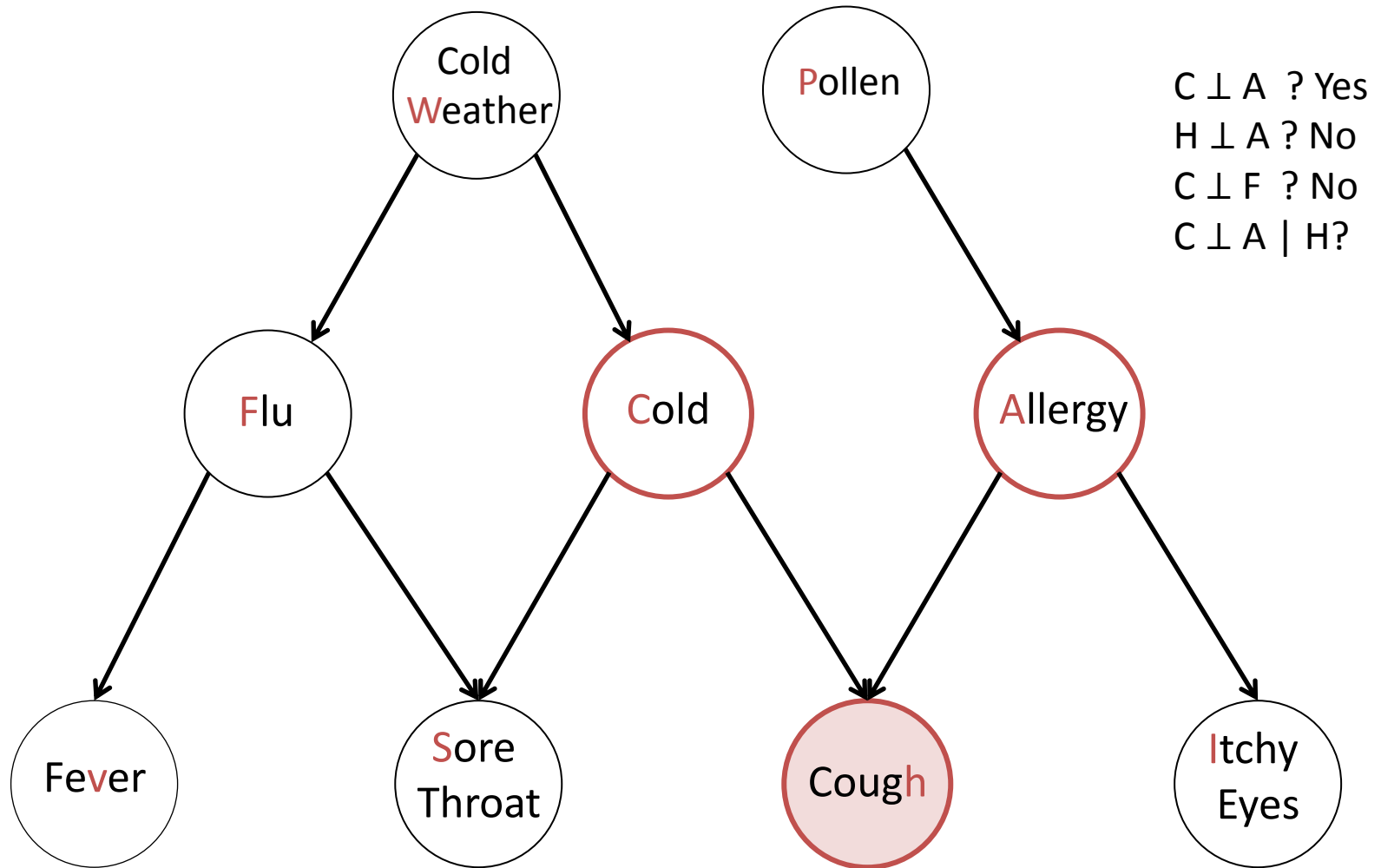
Conditional Independence



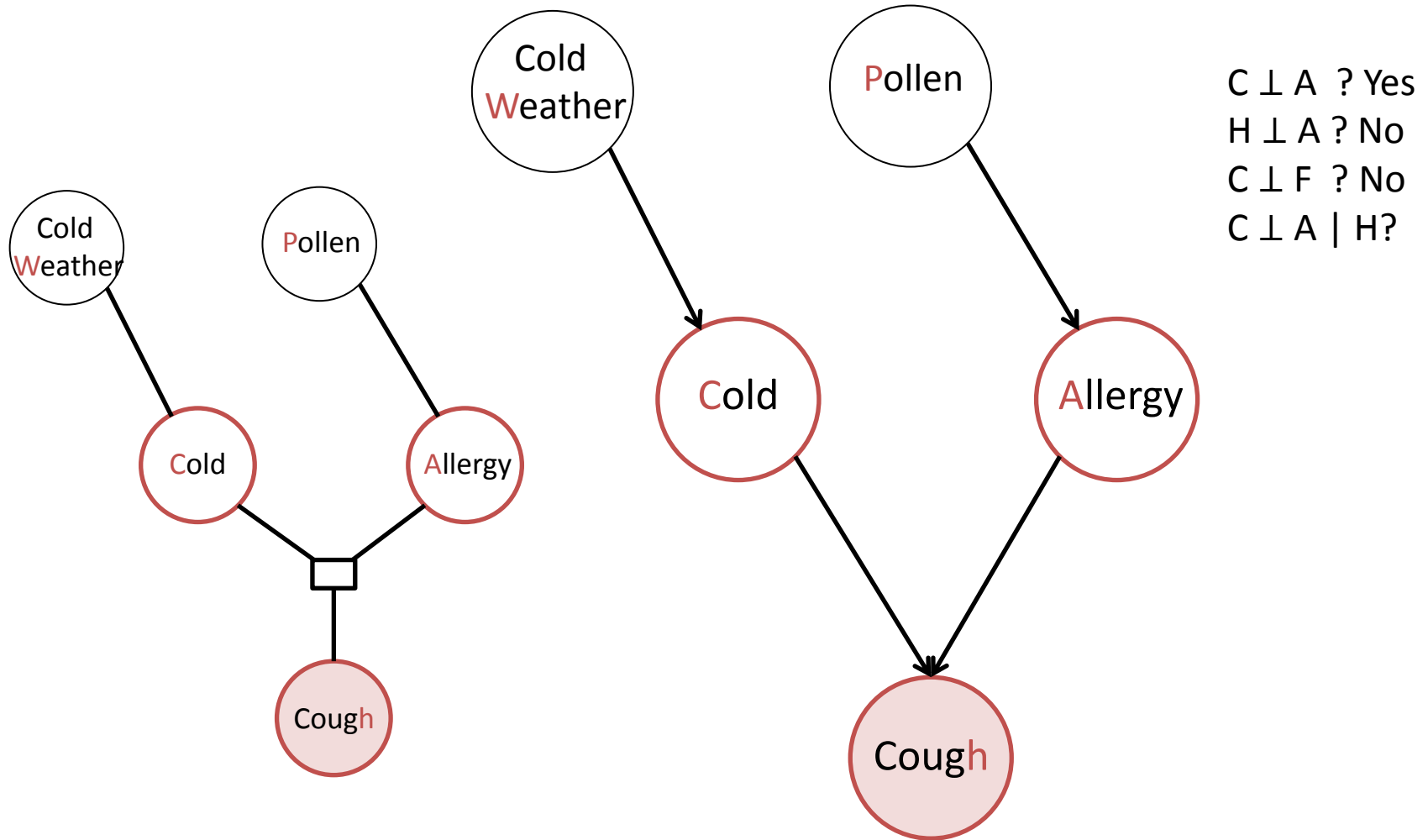
Conditional Independence



Conditional Independence

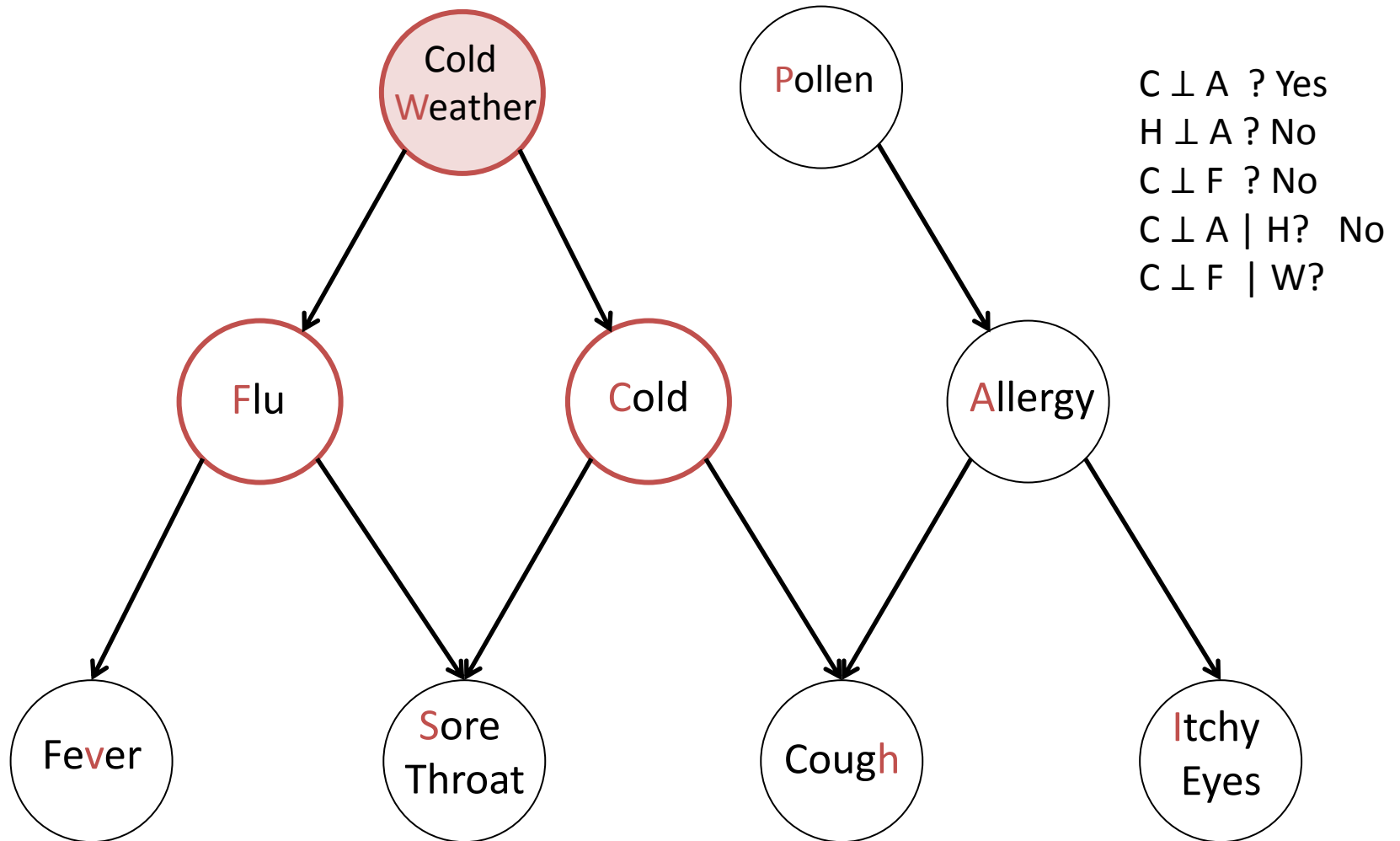


Conditional Independence

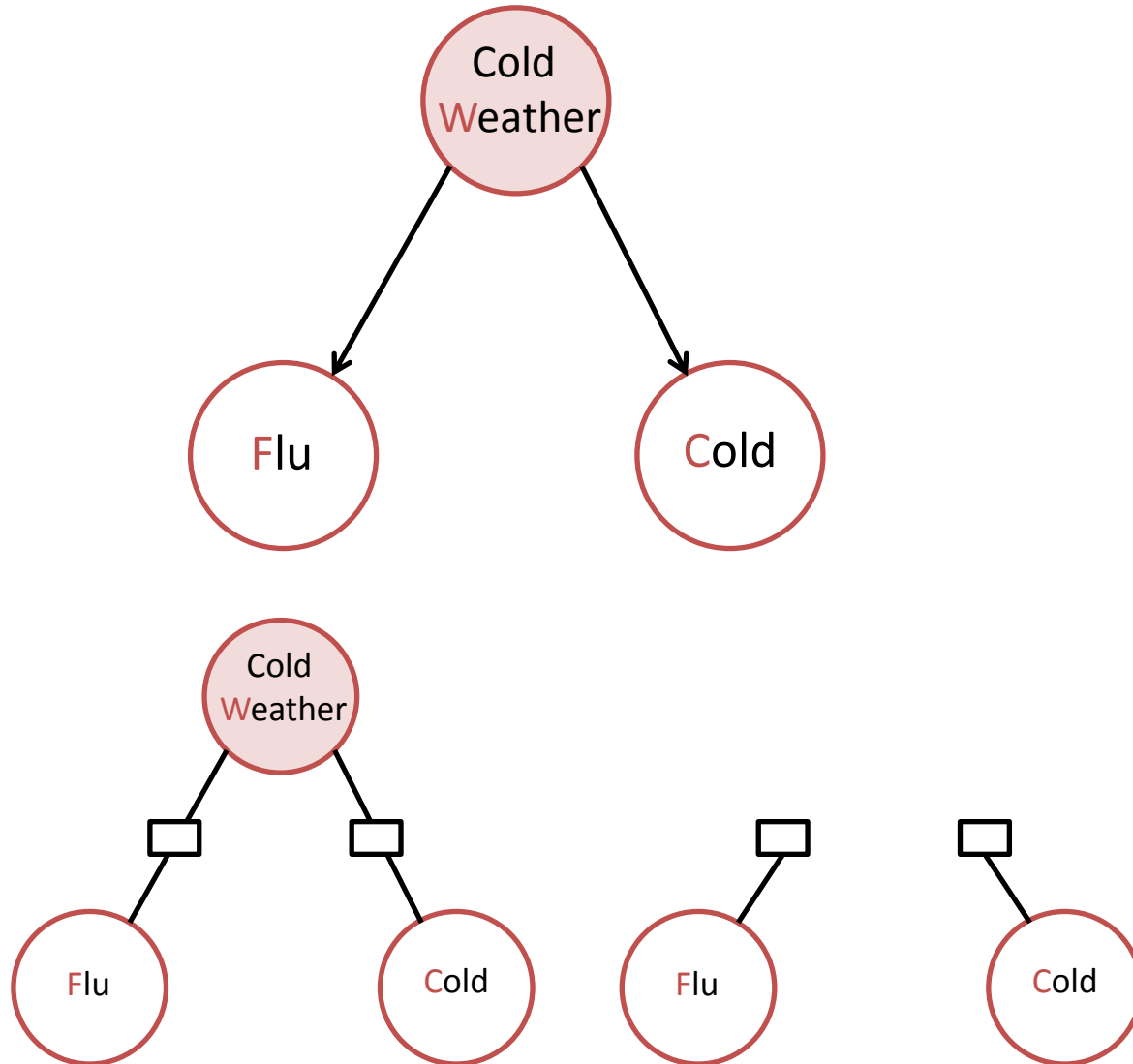


Explaining Away!

Conditional Independence

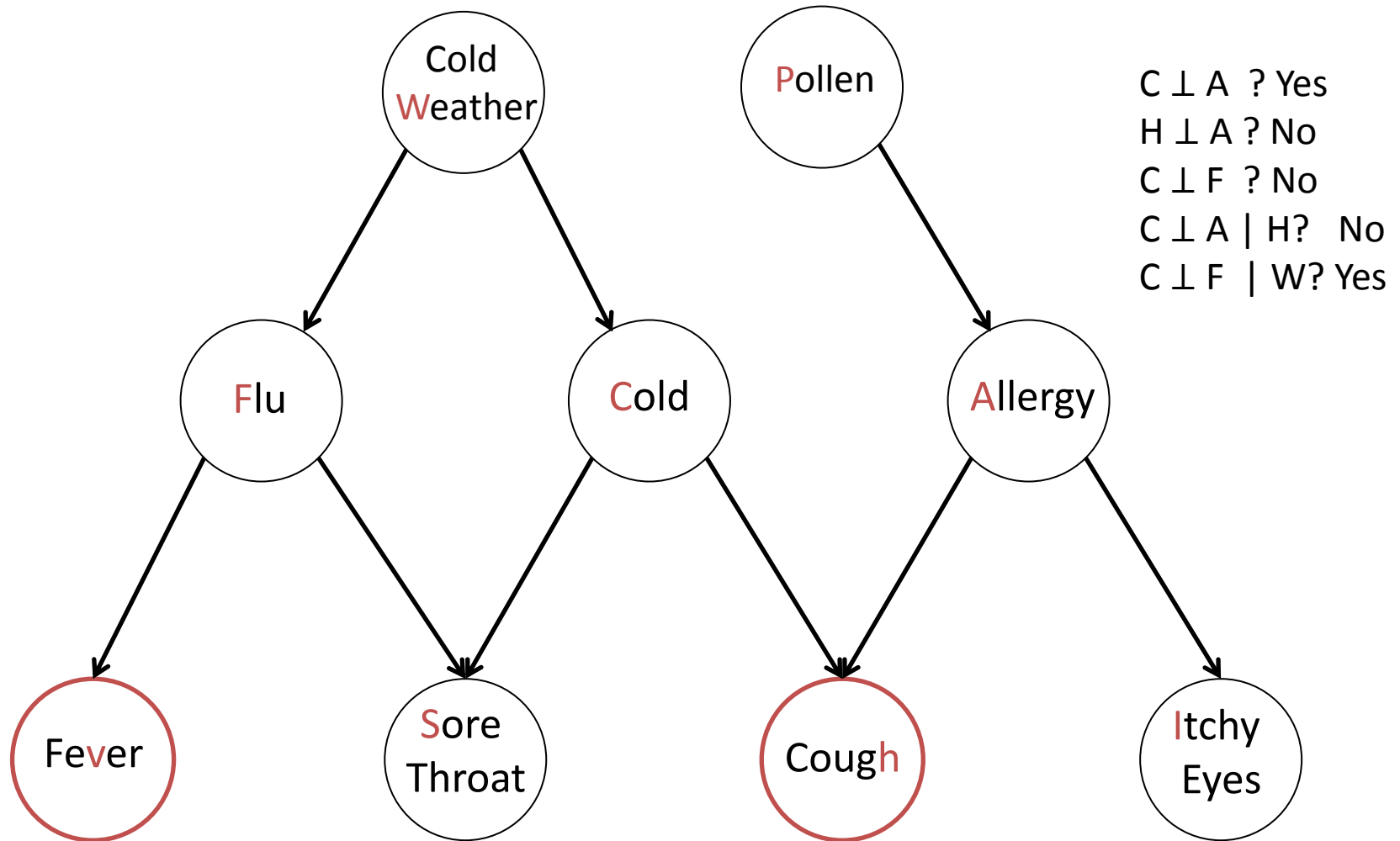


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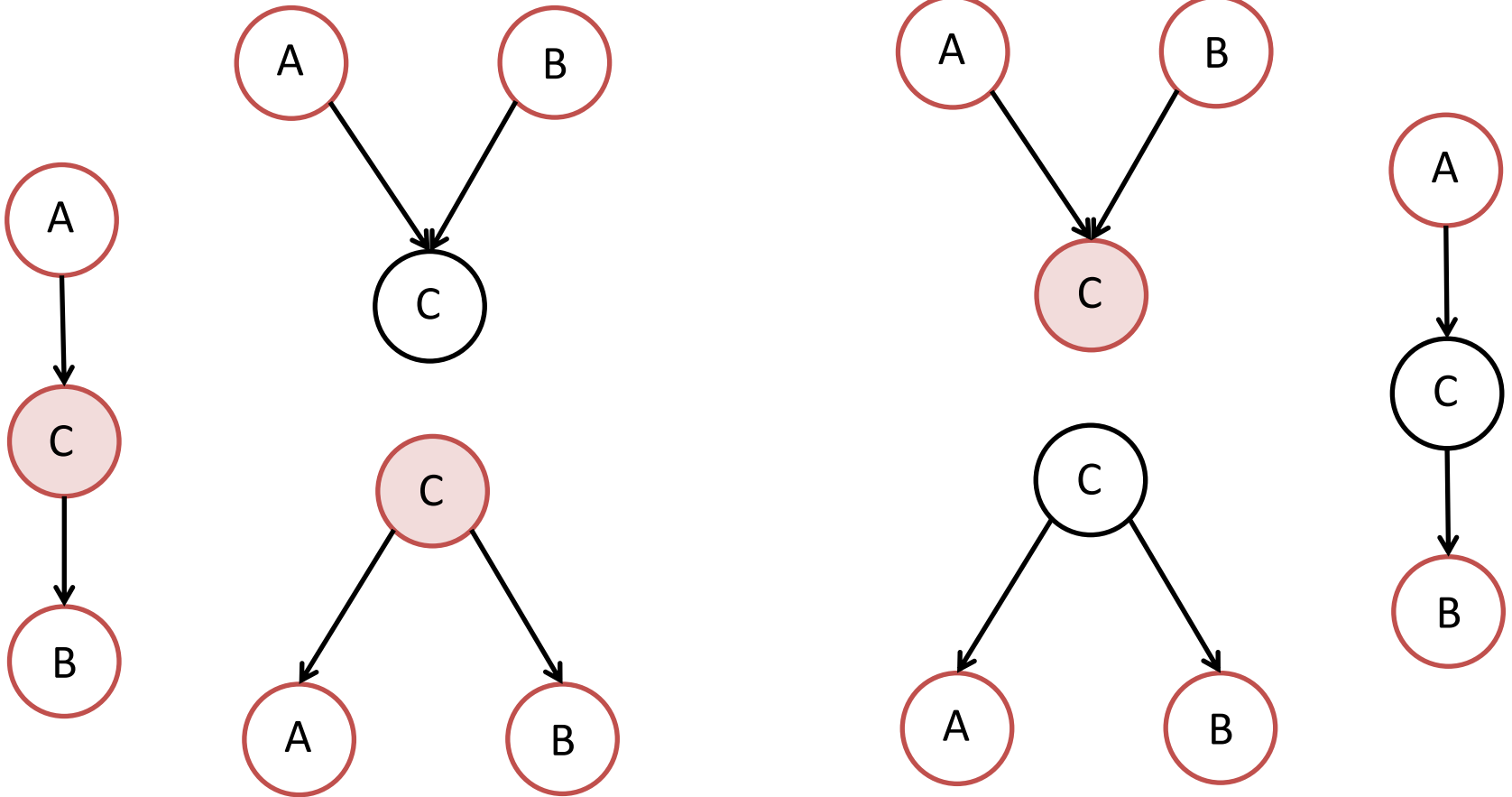


$C \perp A$? Yes
 $H \perp A$? No
 $C \perp F$? No
 $C \perp A \mid H$? No
 $C \perp F \mid W$?

Conditional Independence



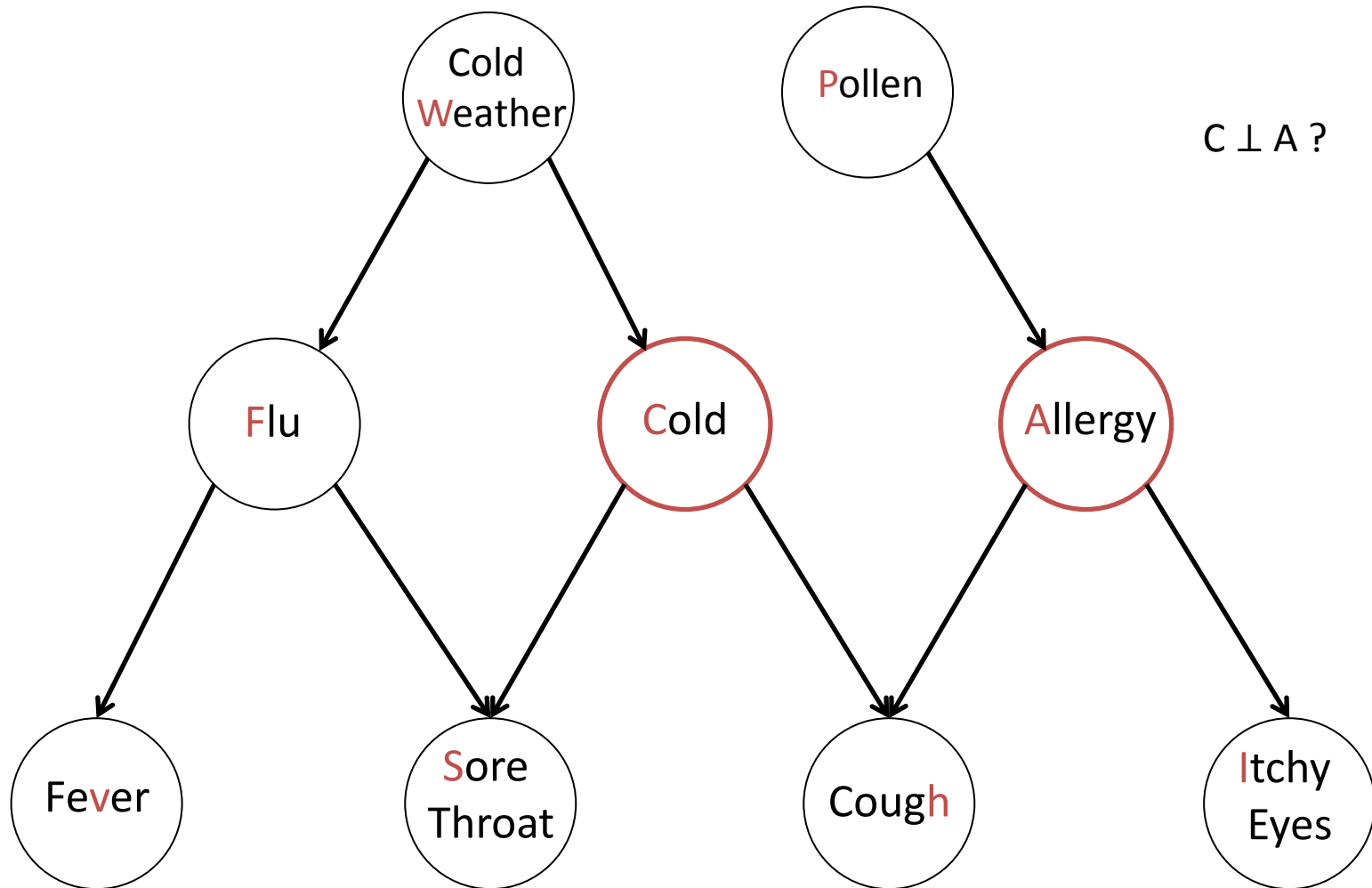
Patterns



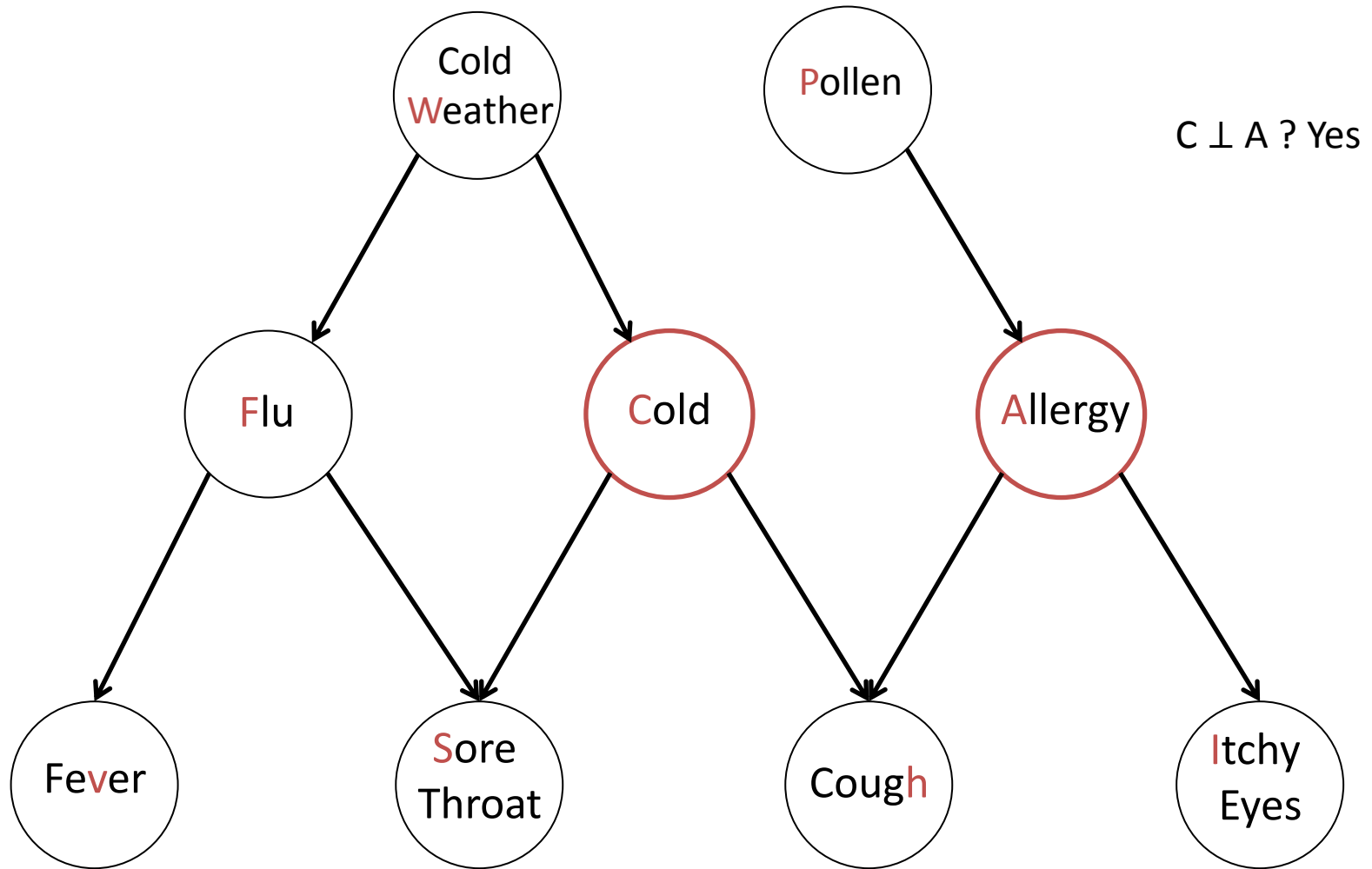
Independent

Dependent

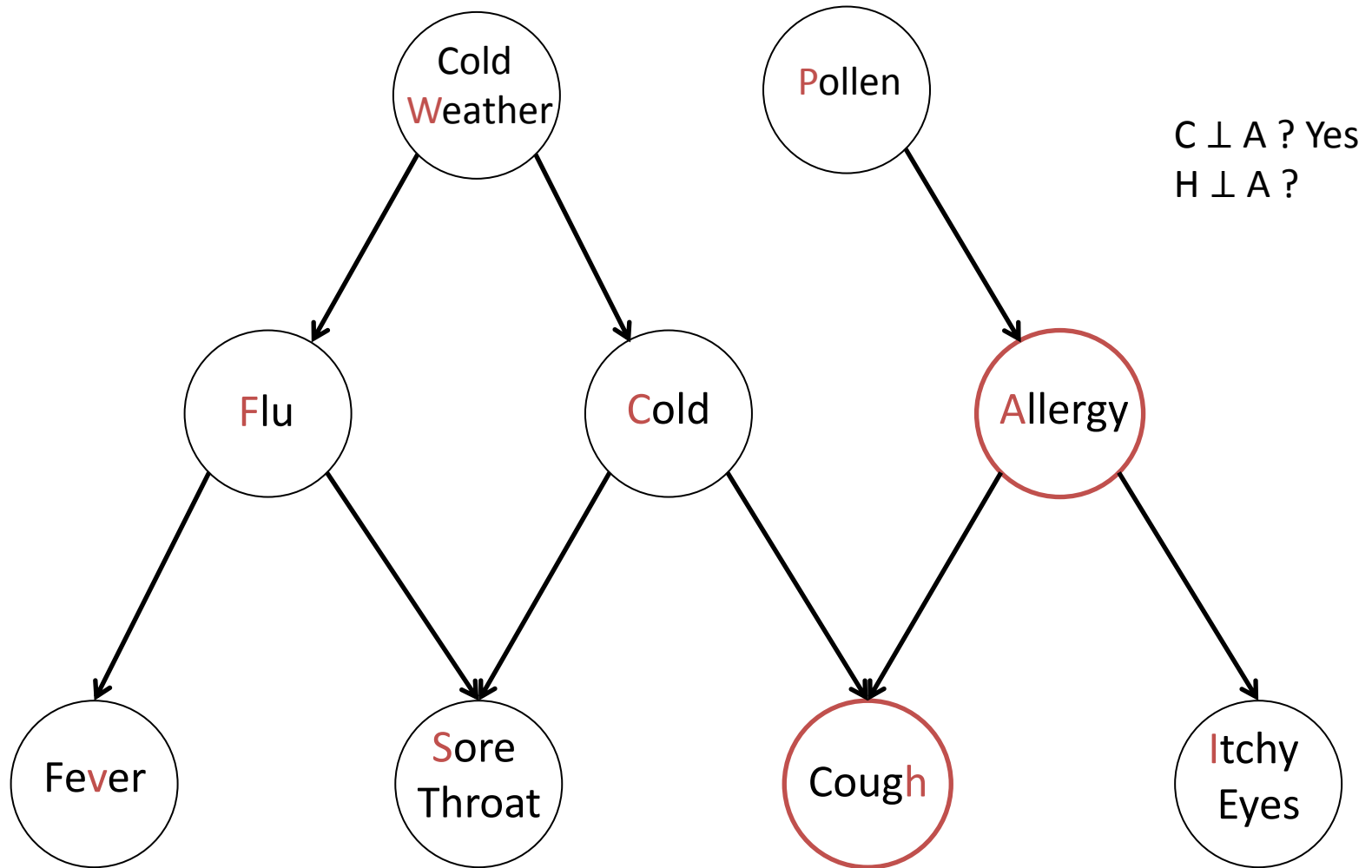
Conditional Independence



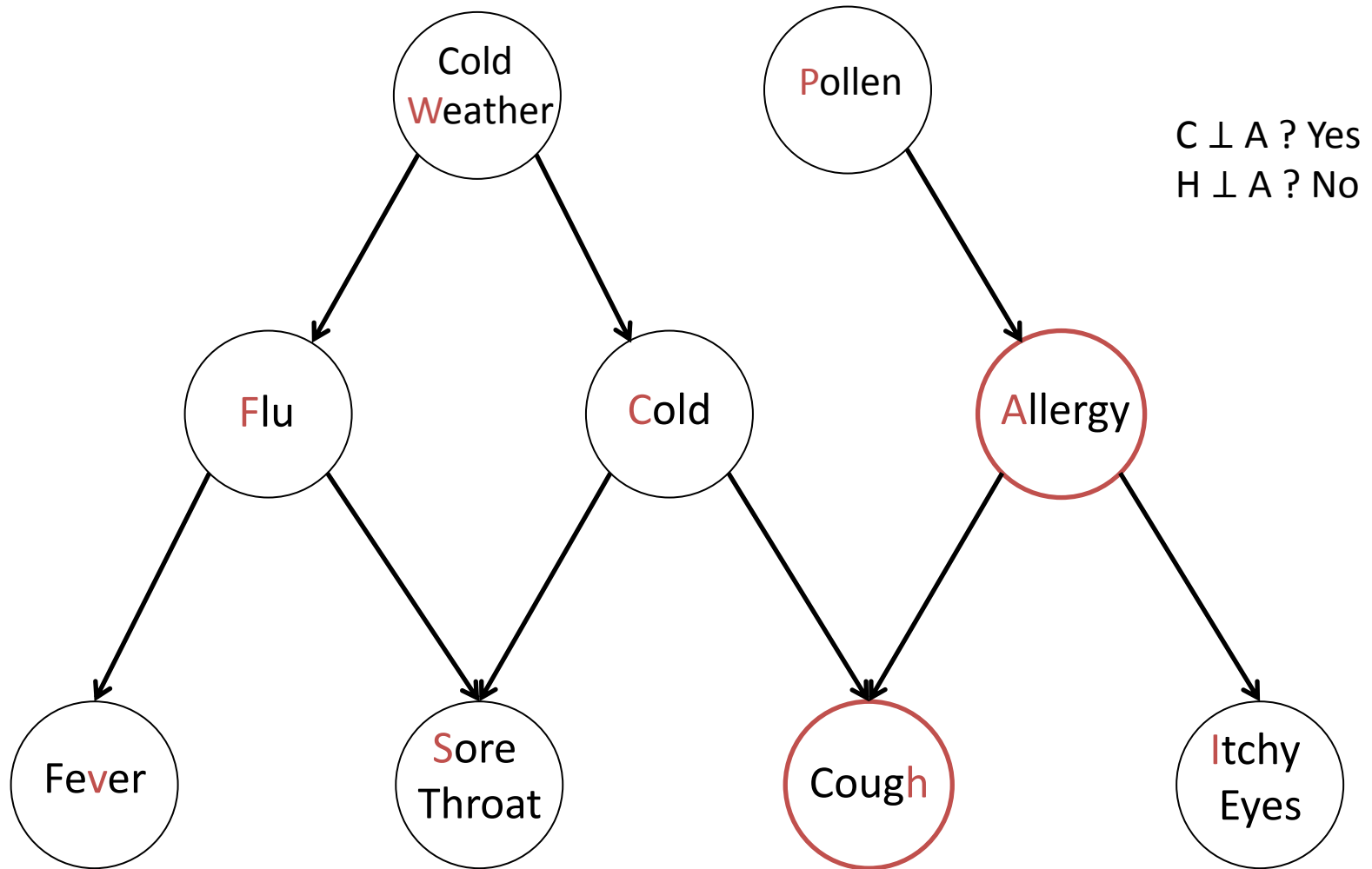
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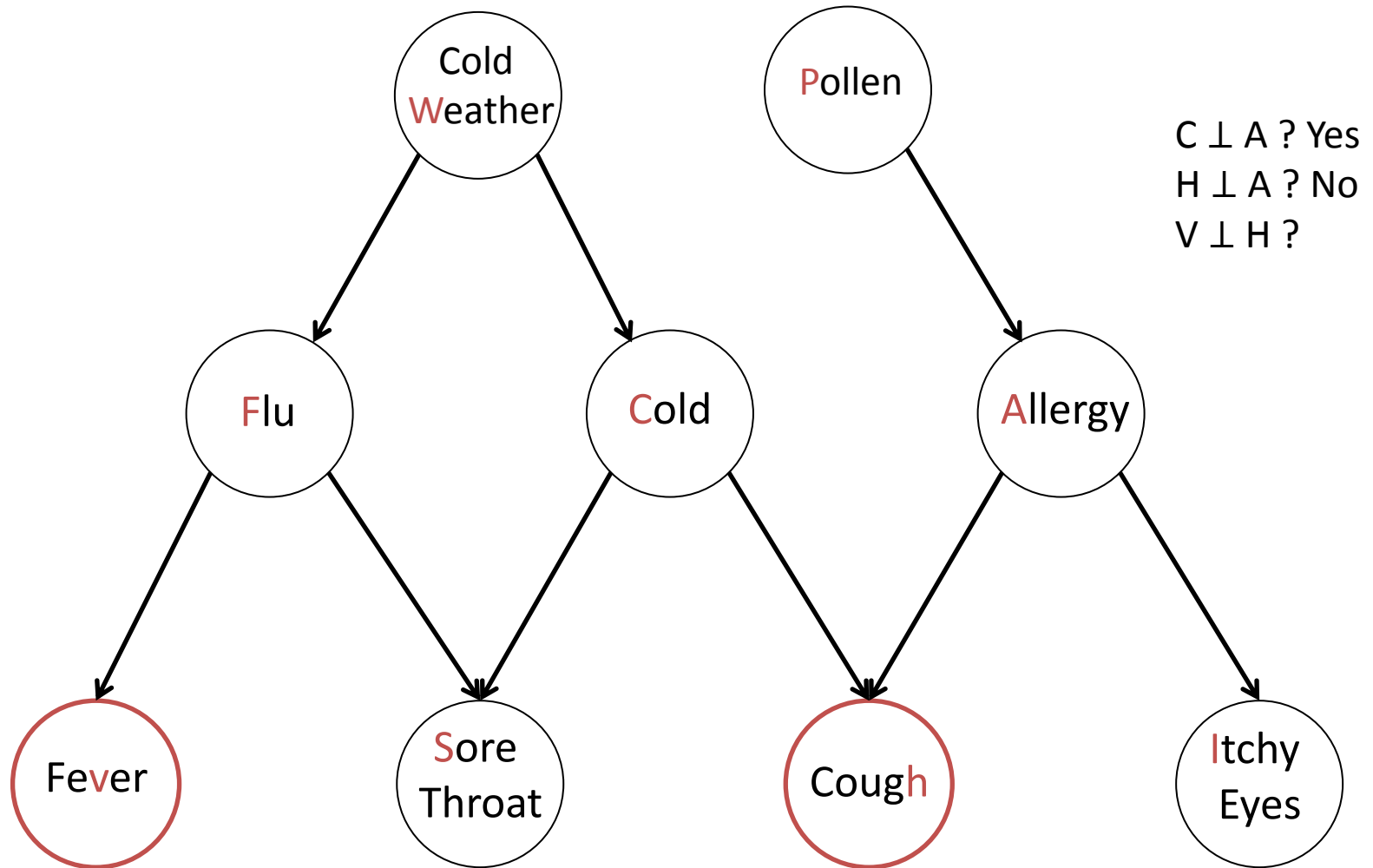
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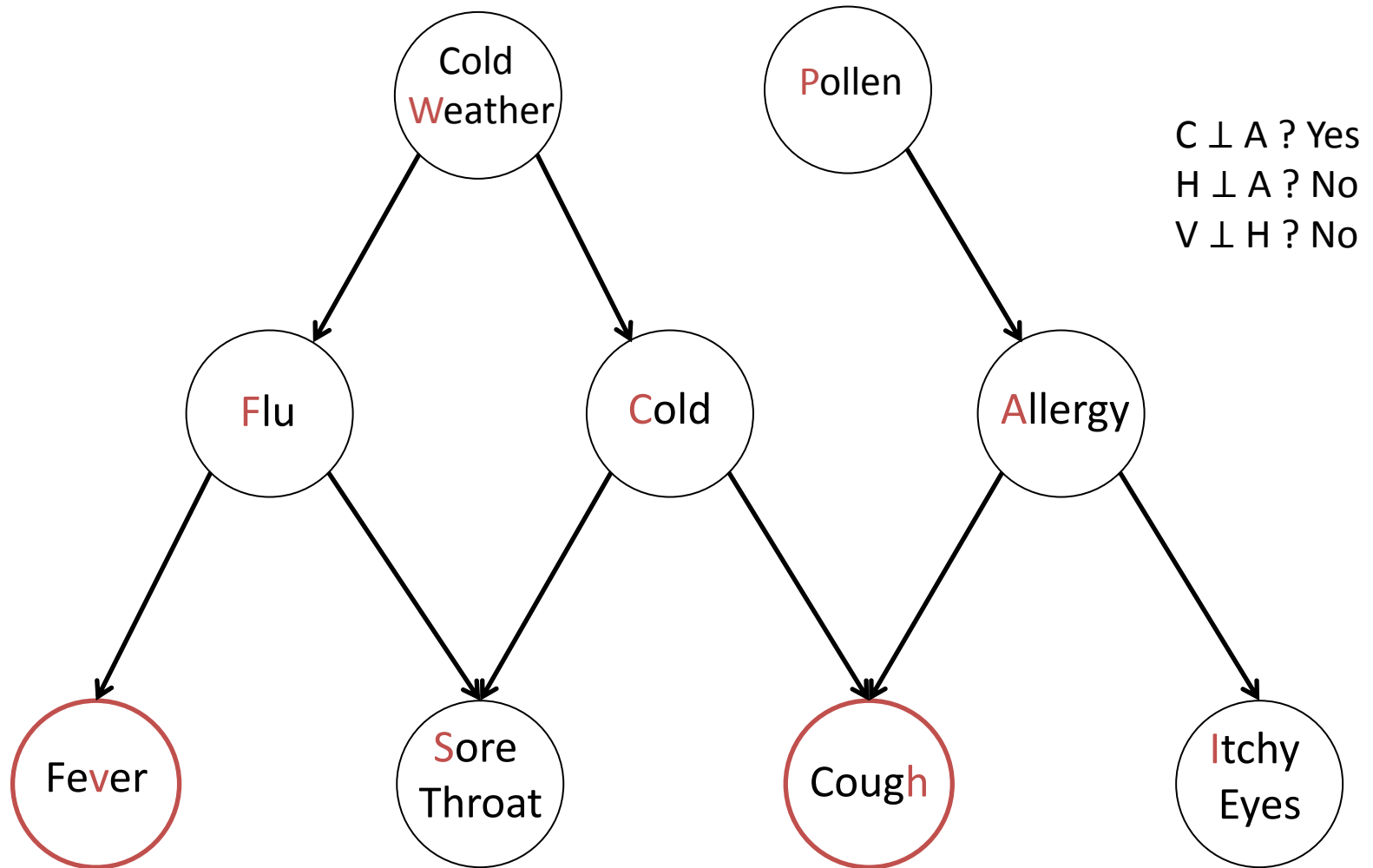
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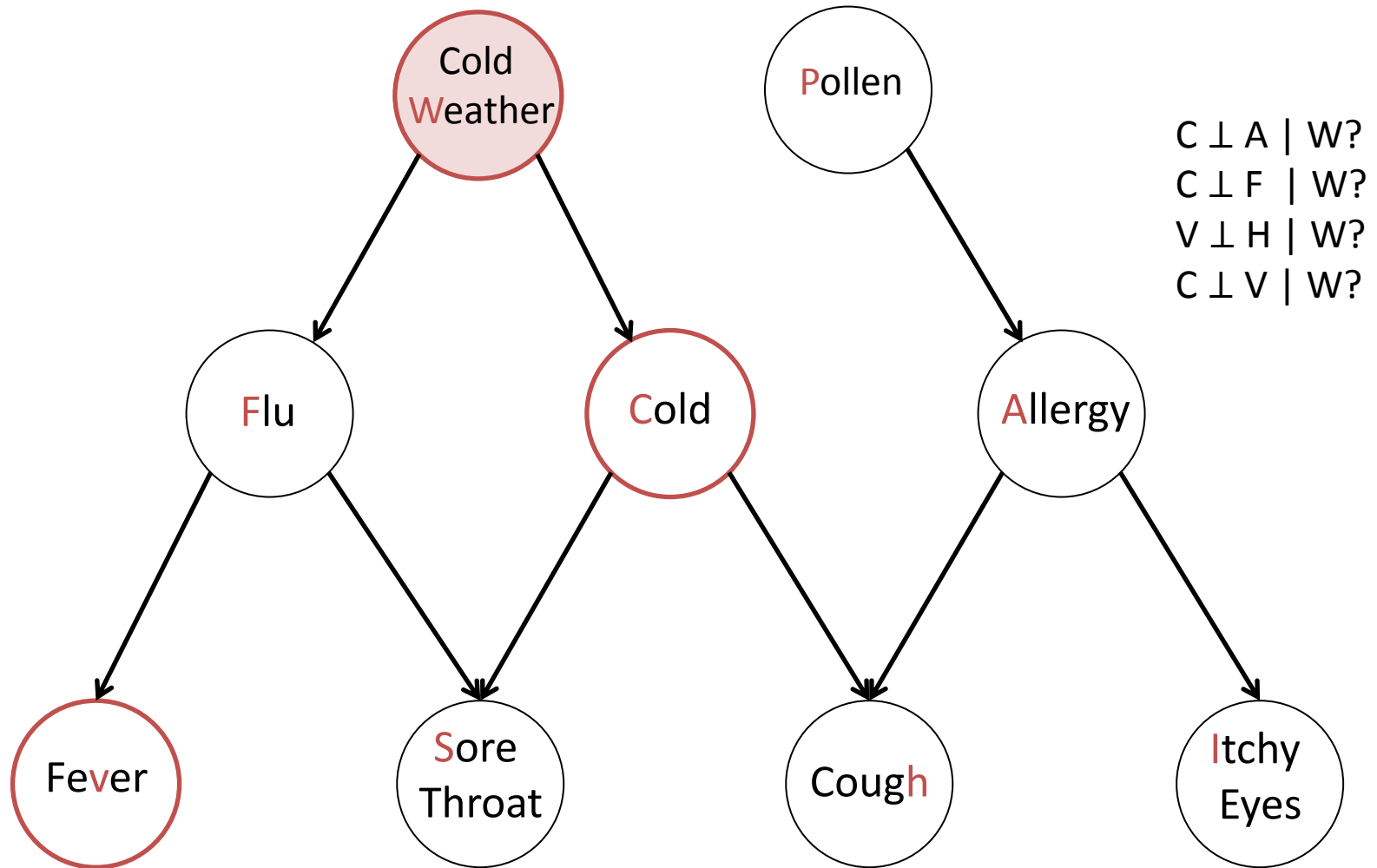
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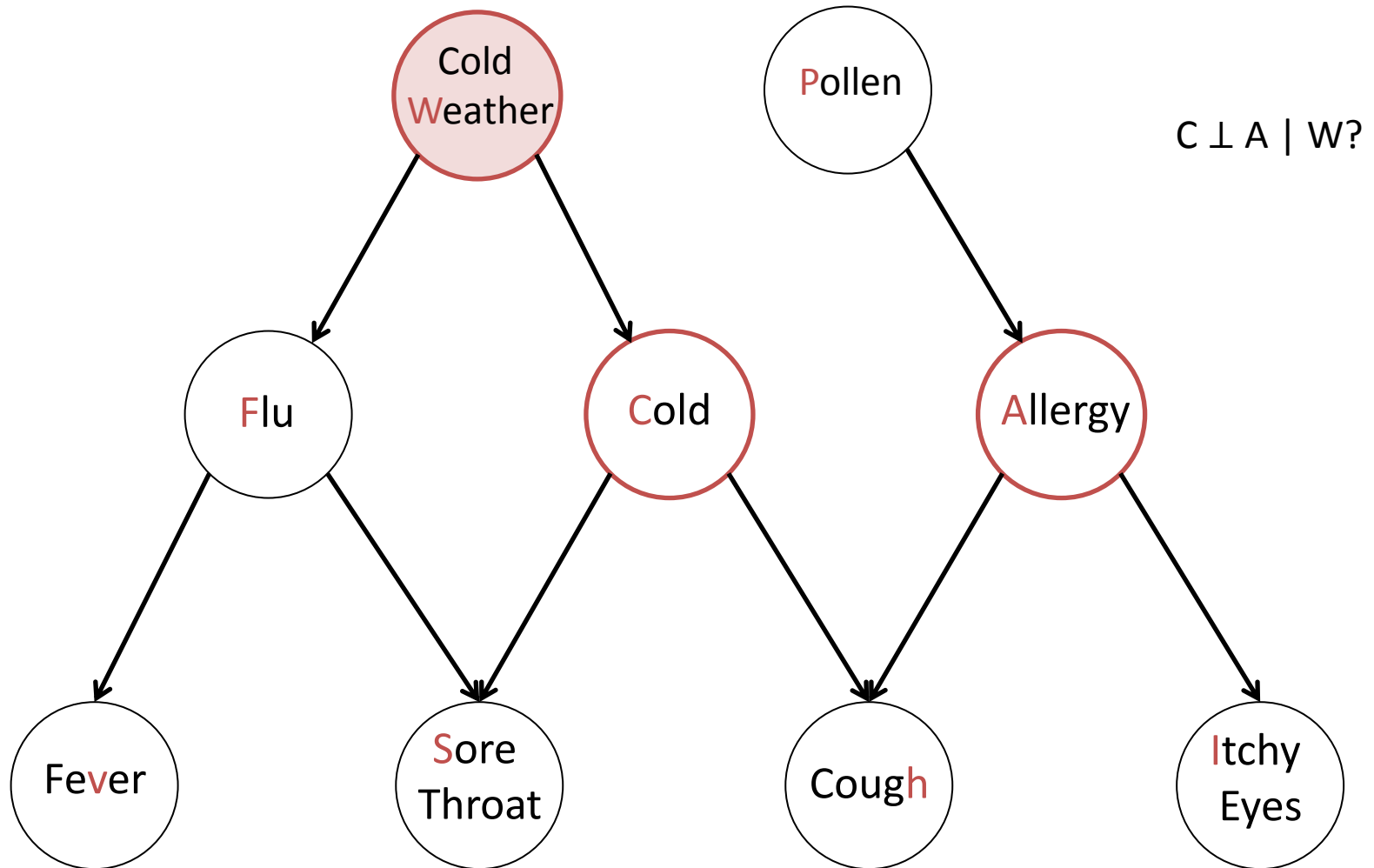
Conditional Independence



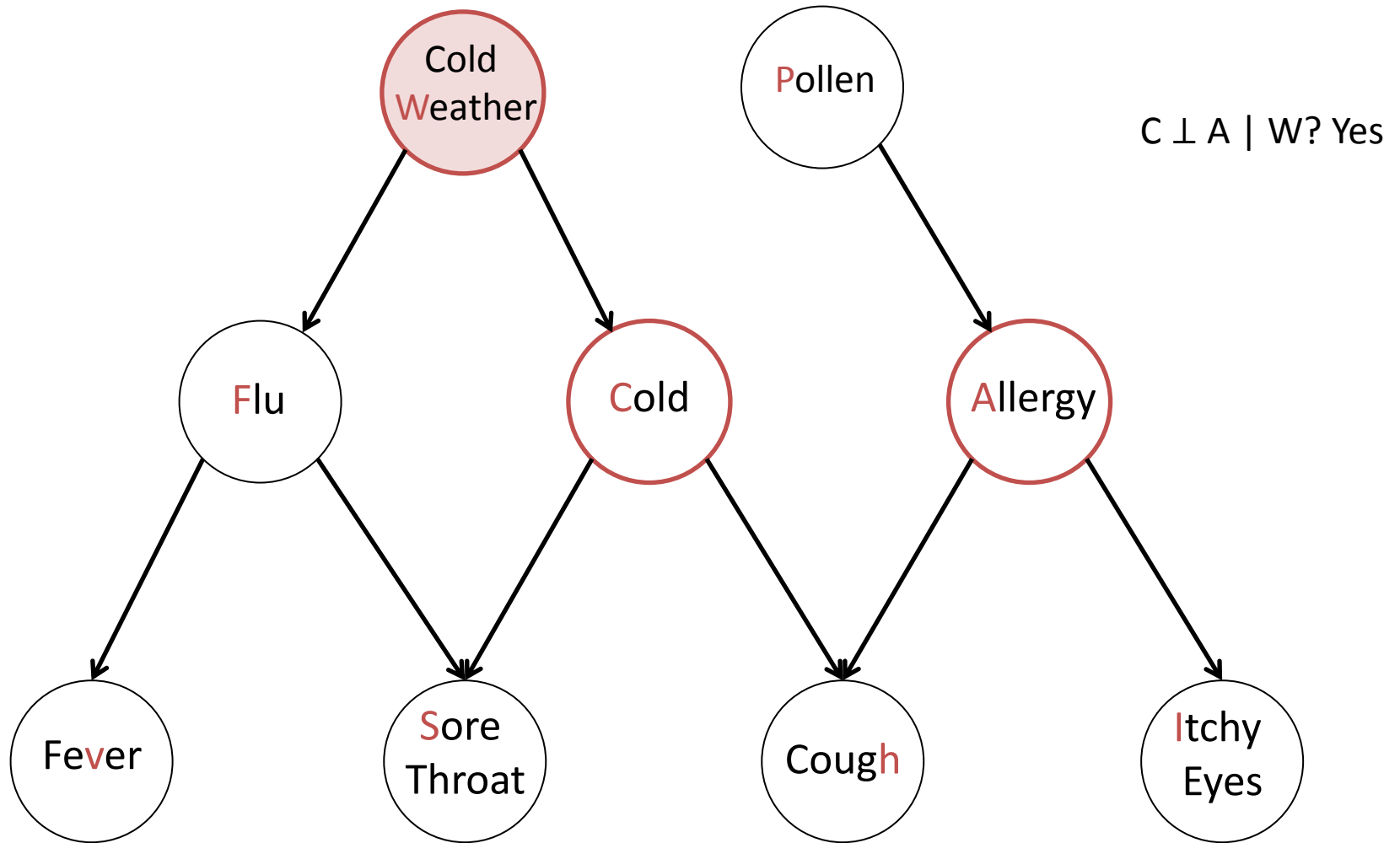
Conditional Independence



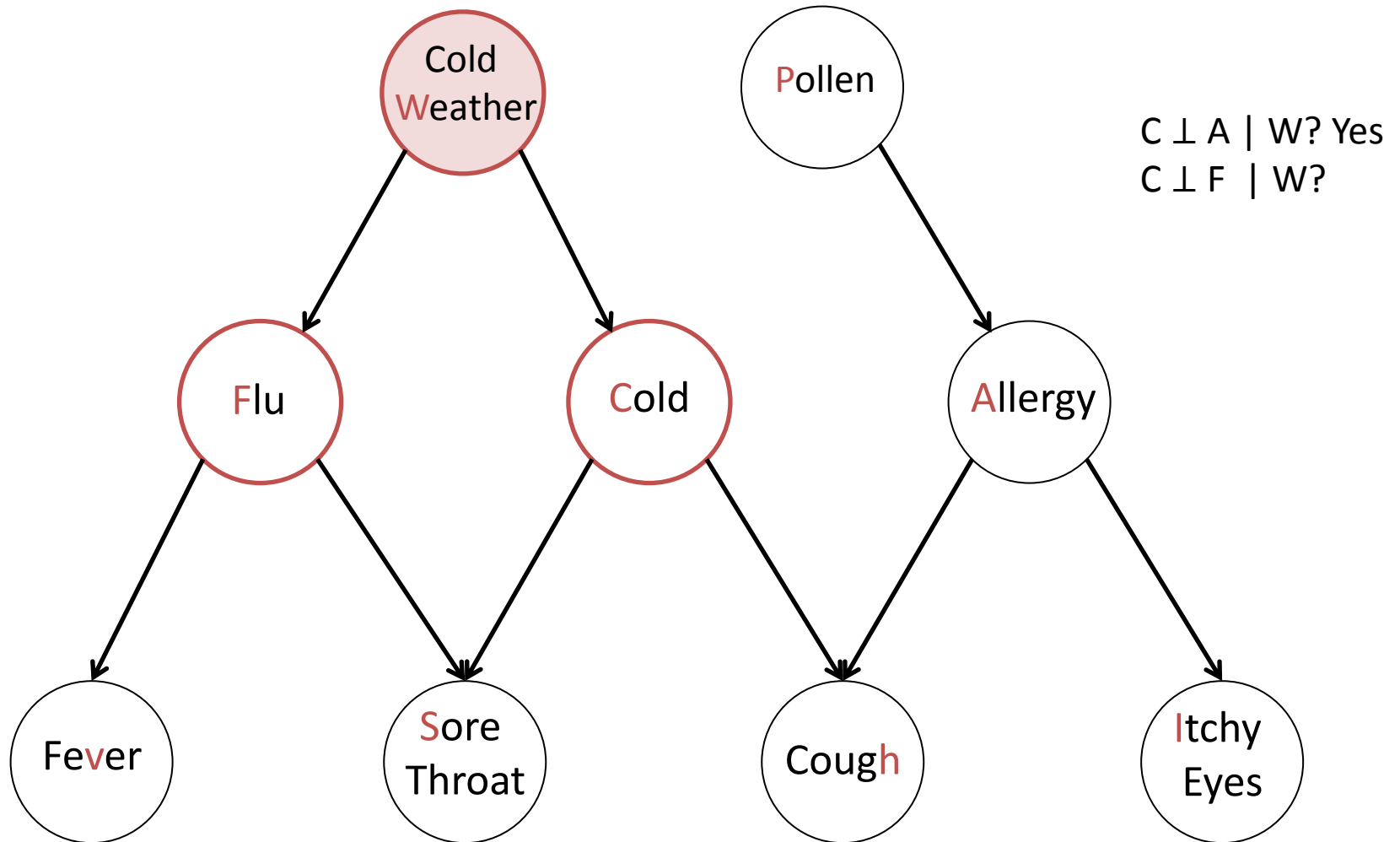
Conditional Independence



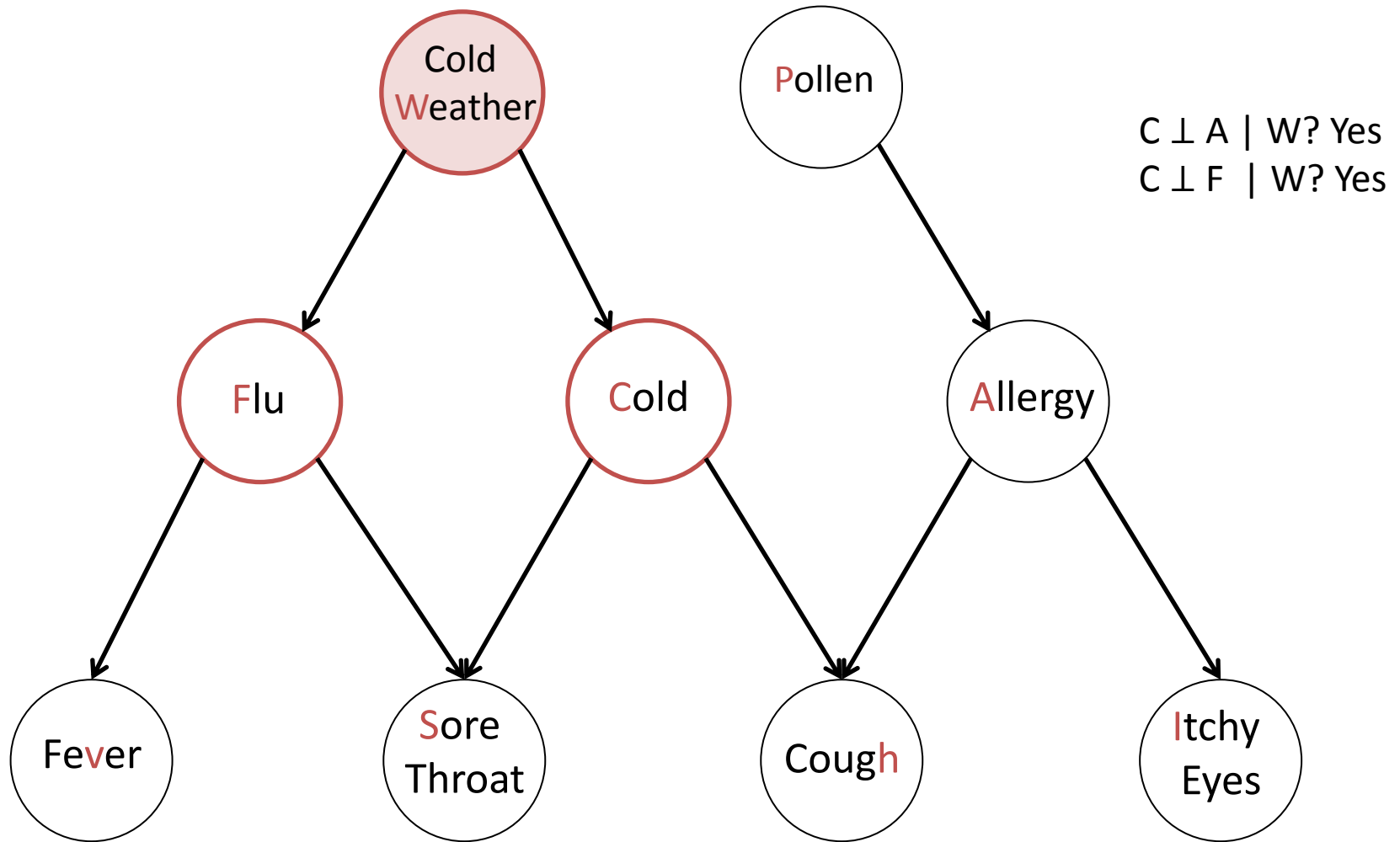
Conditional Independence



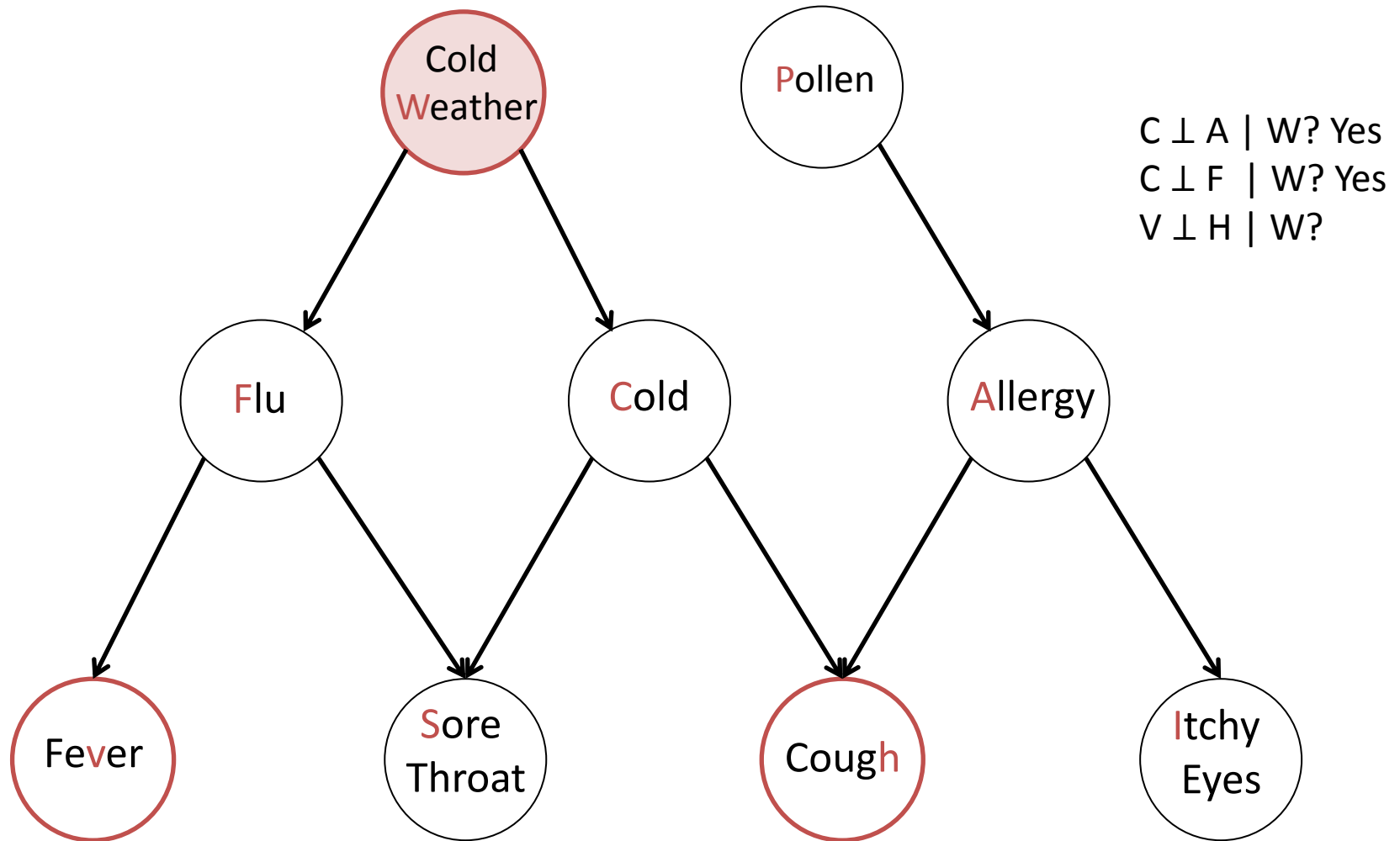
Conditional Independence



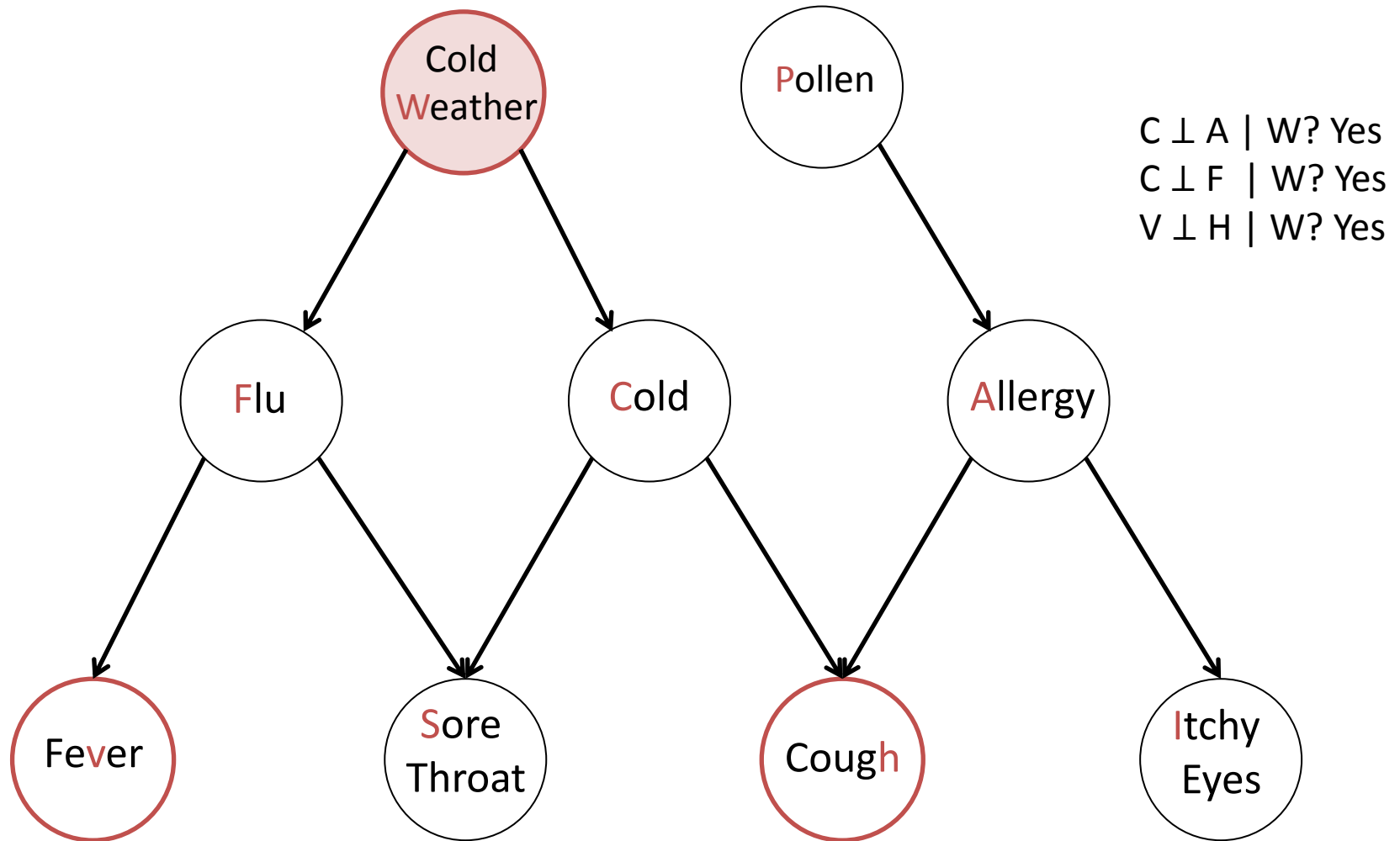
Conditional Independence



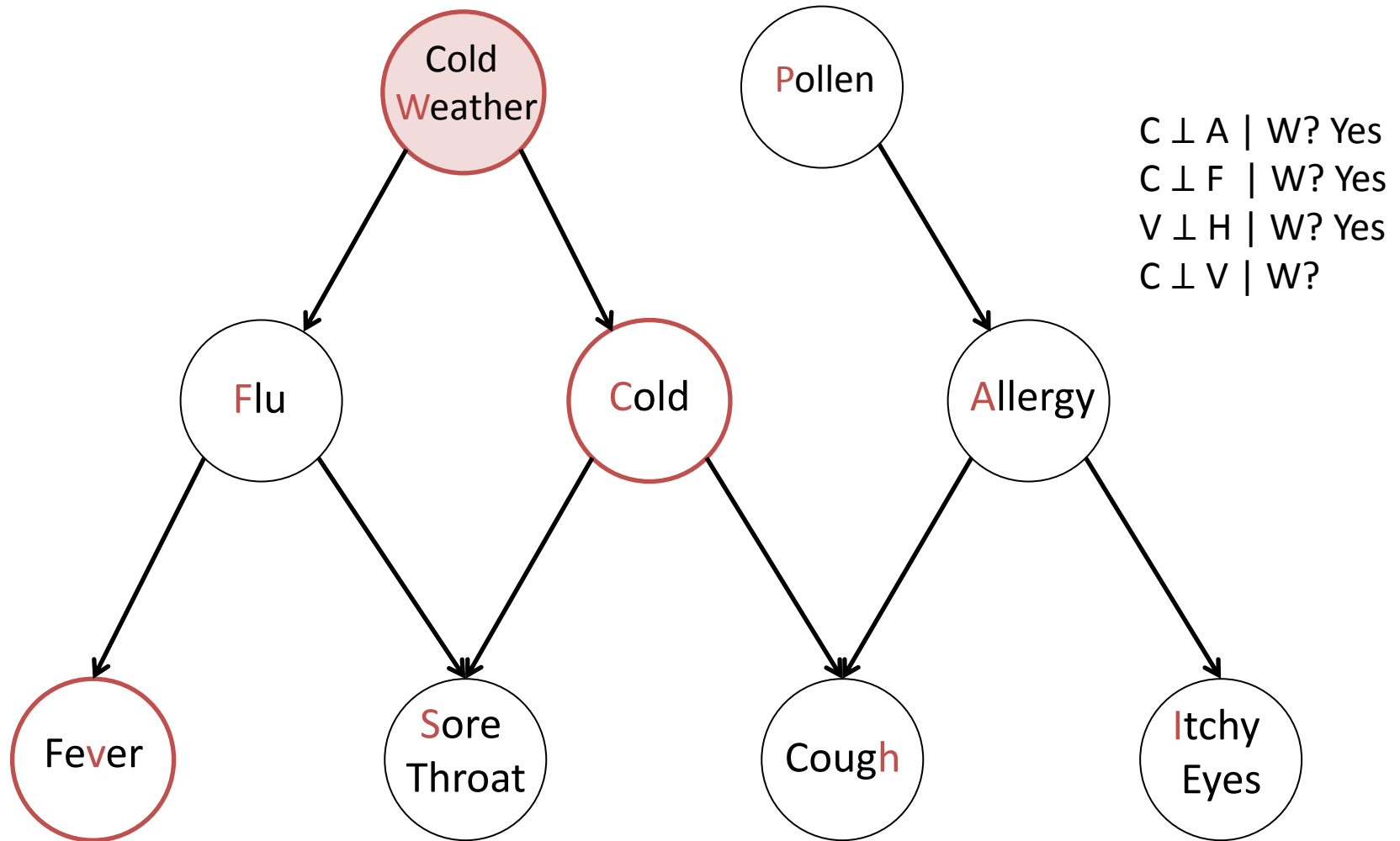
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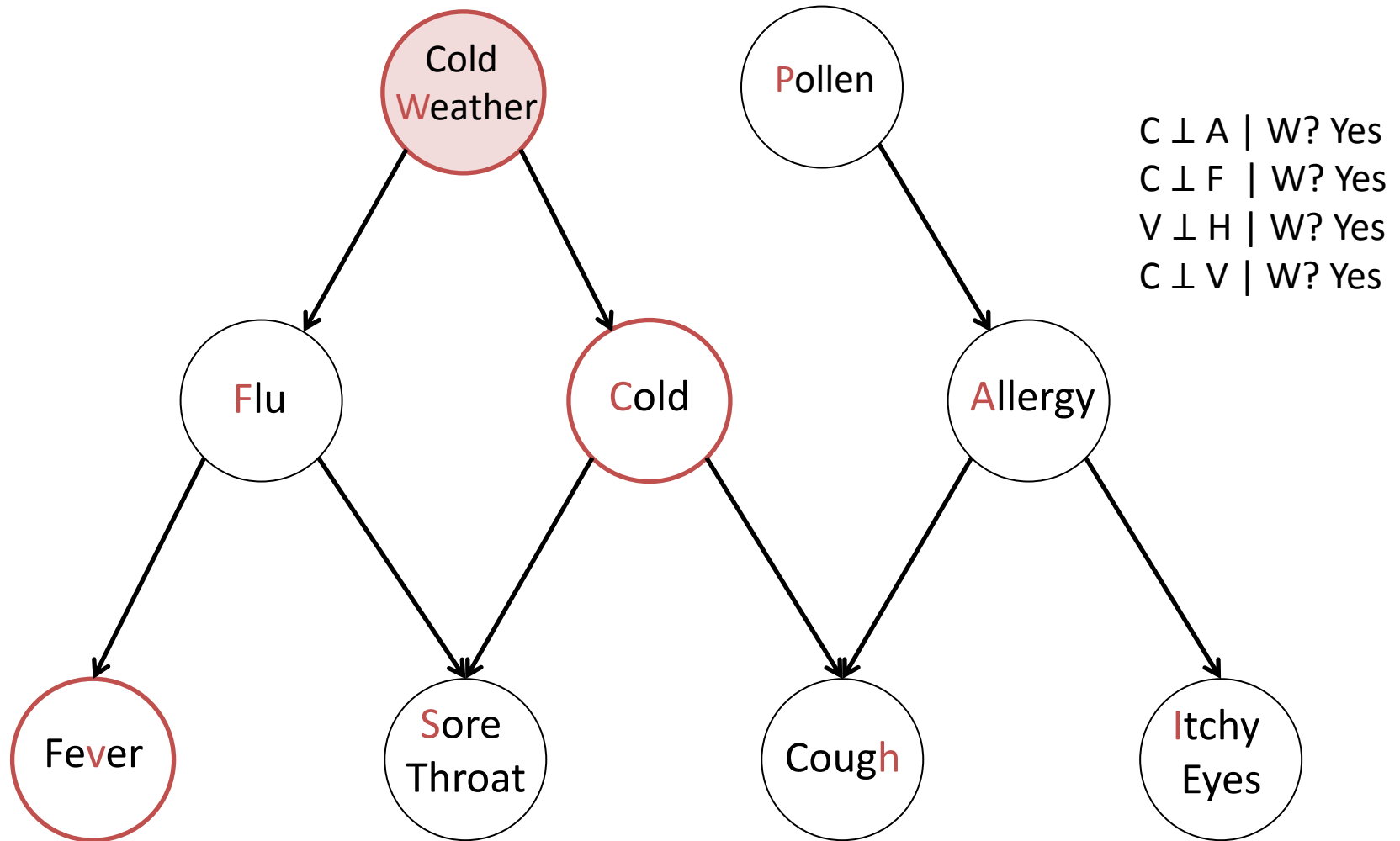
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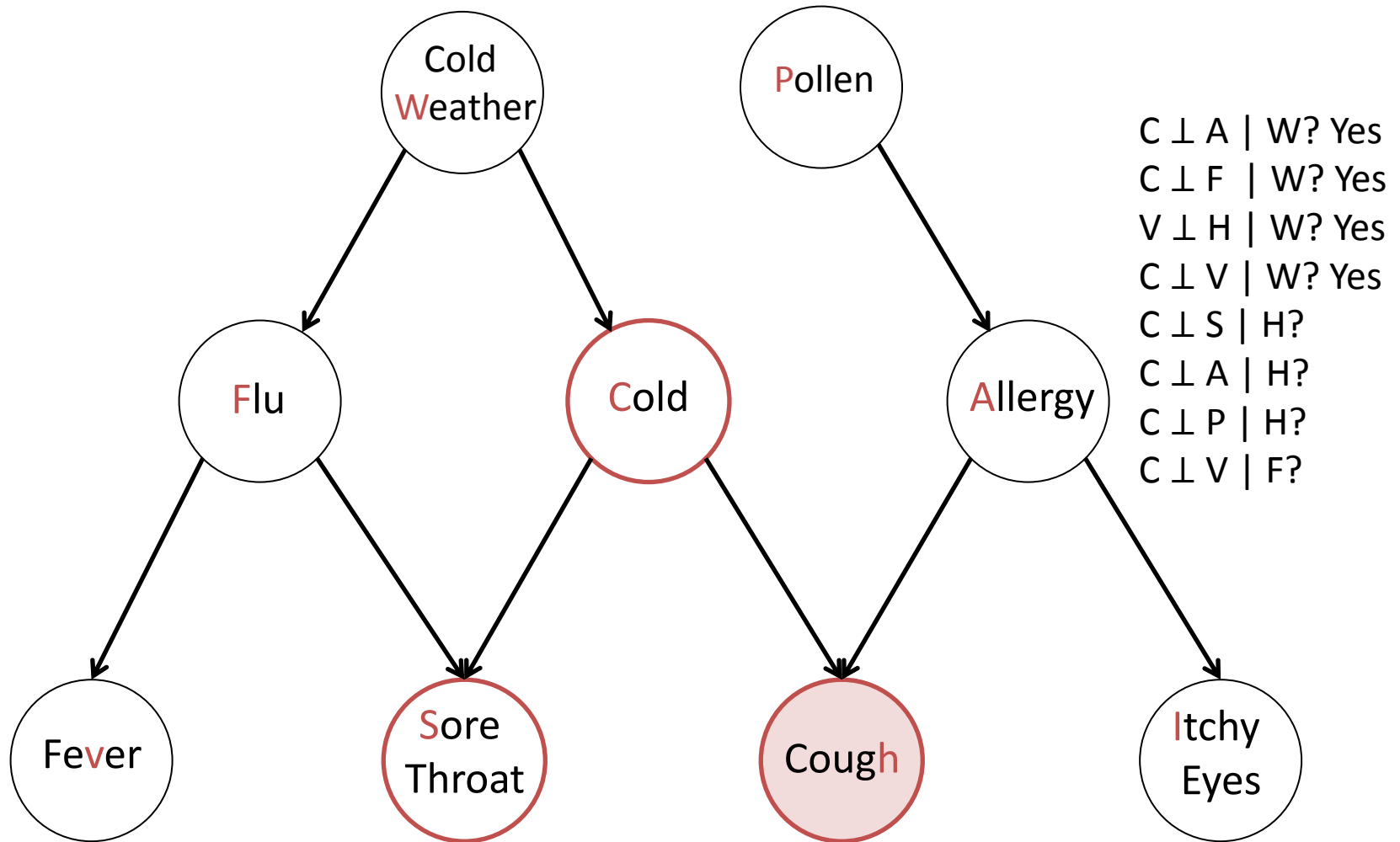
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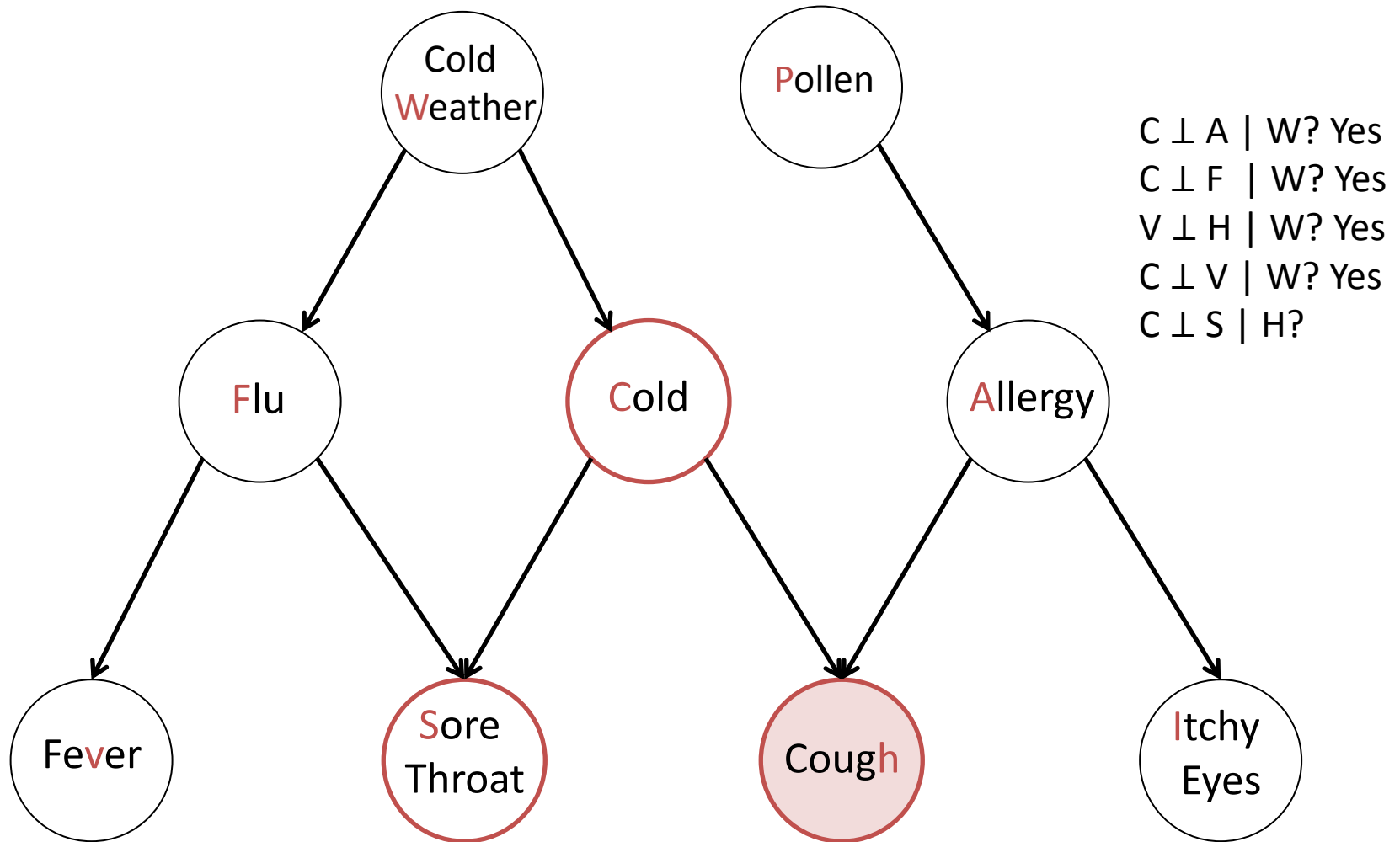
Conditional Independence



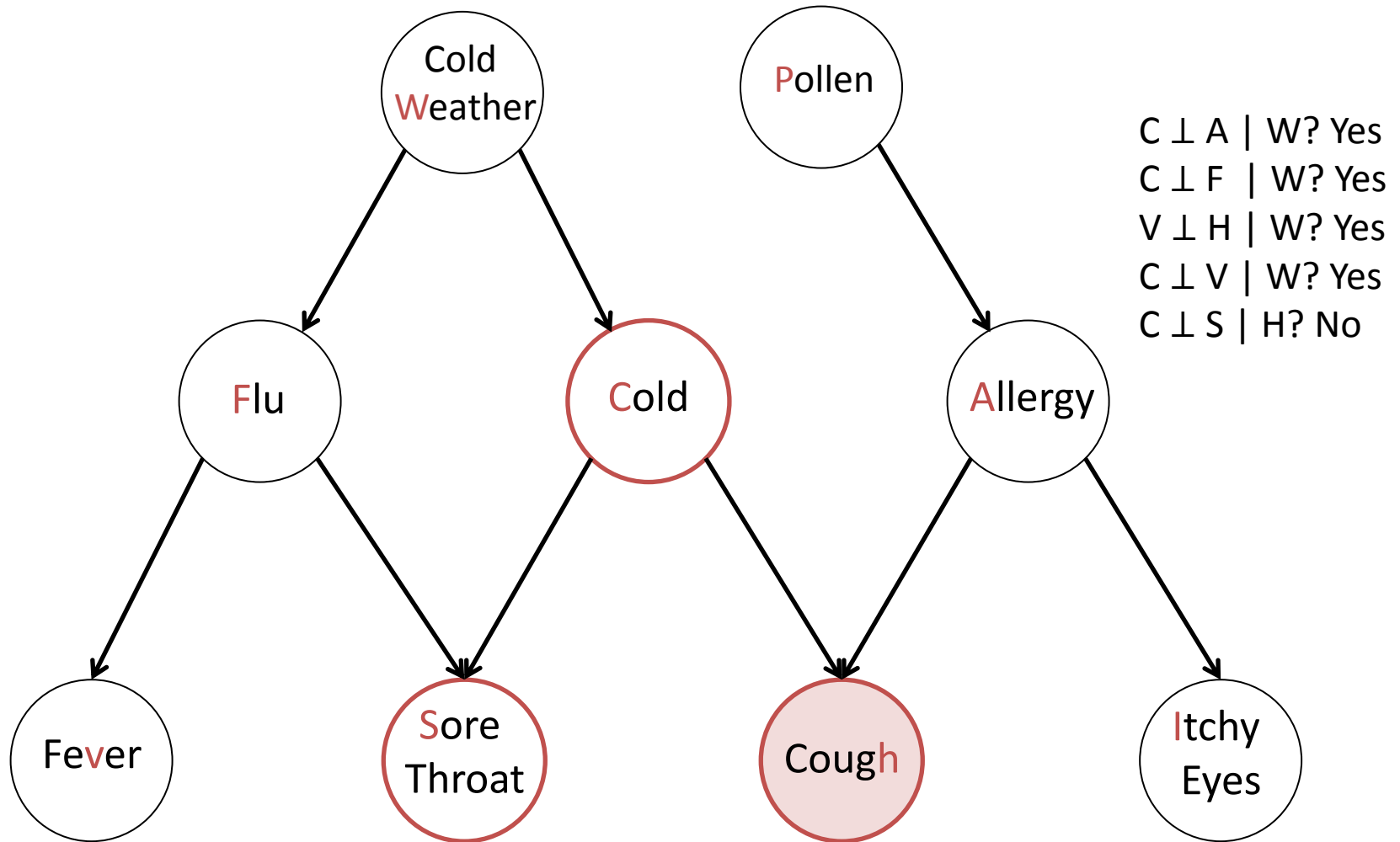
Conditional Independence



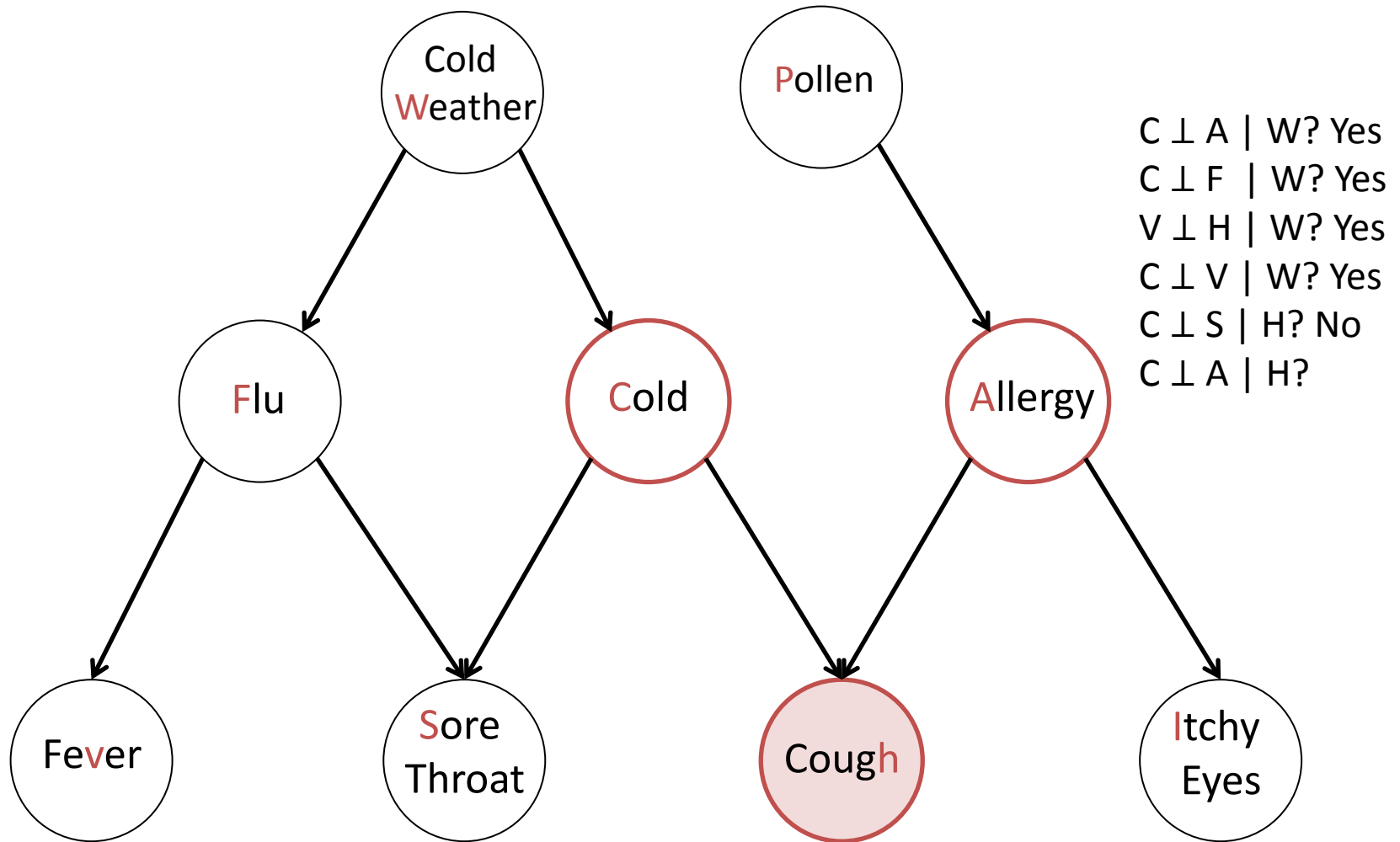
Conditional Independence



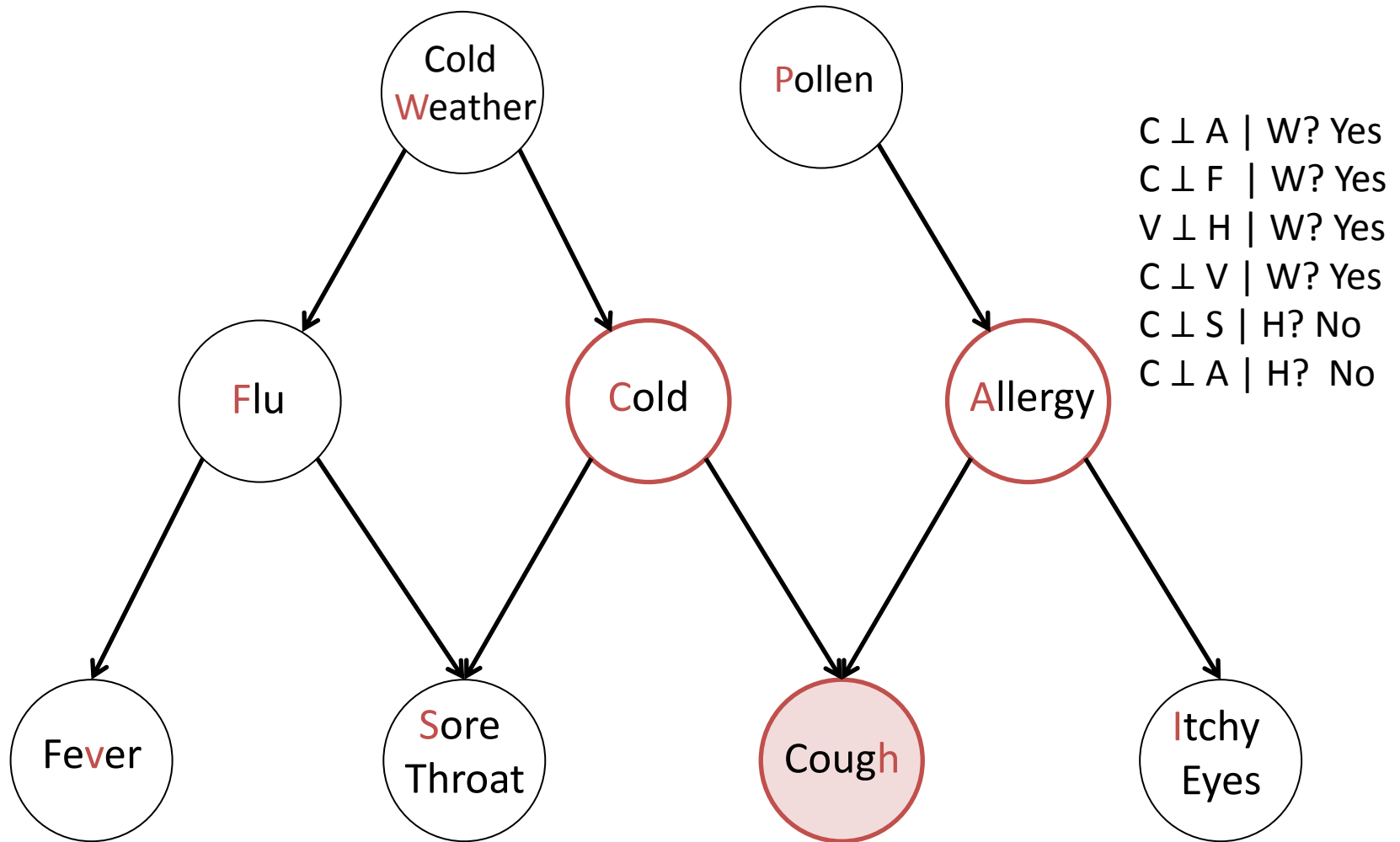
Conditional Independence



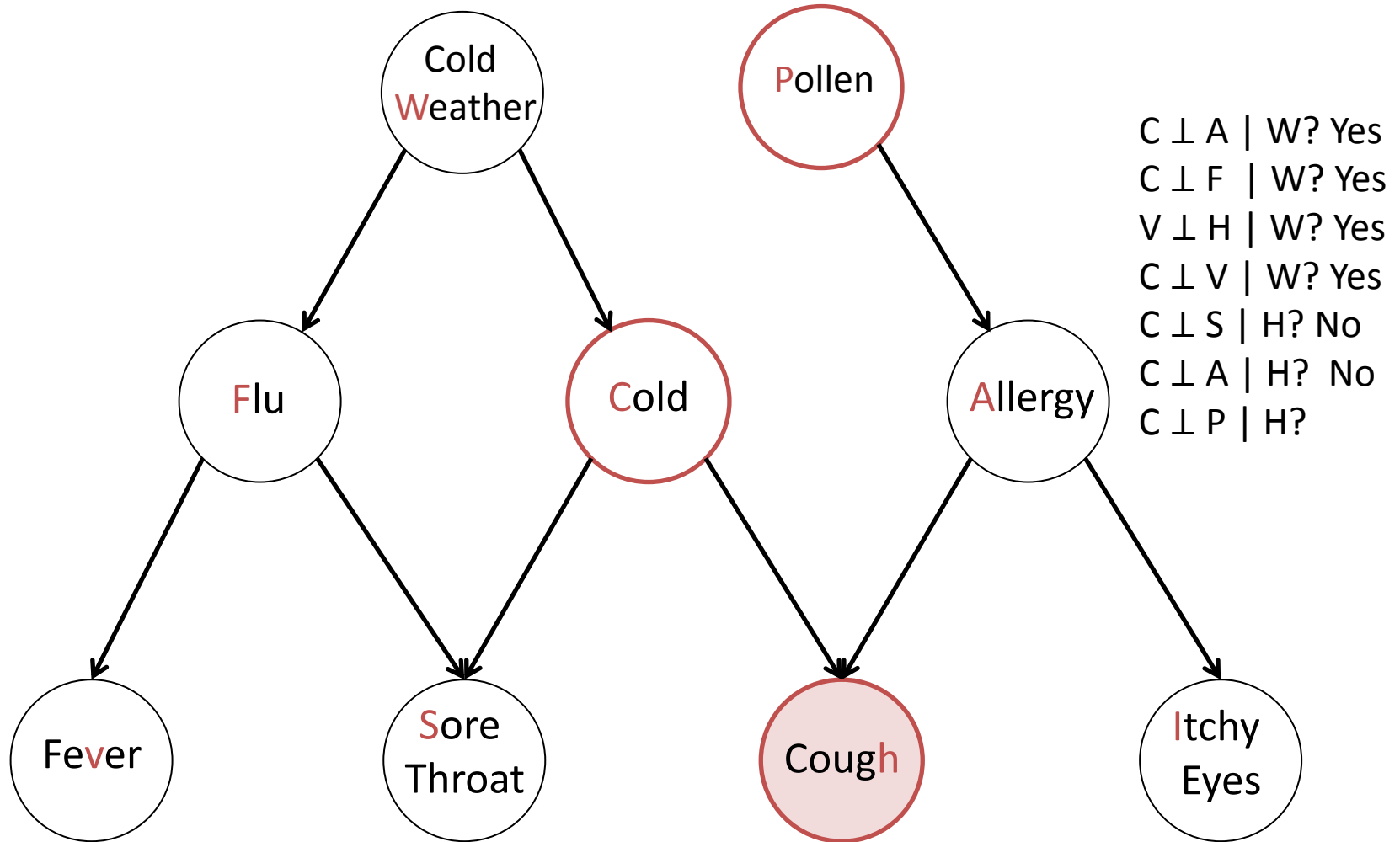
Conditional Independence



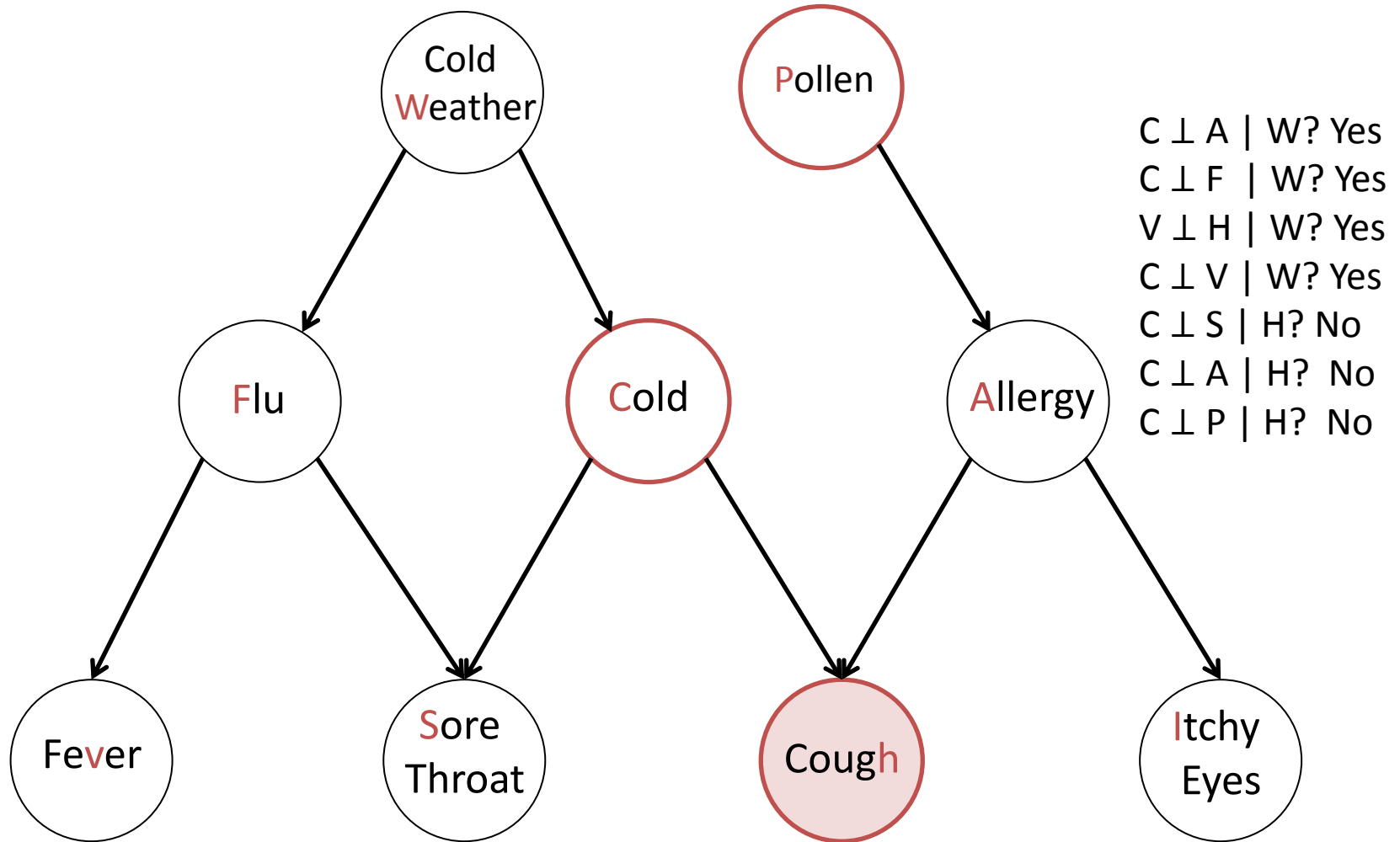
Conditional Independence



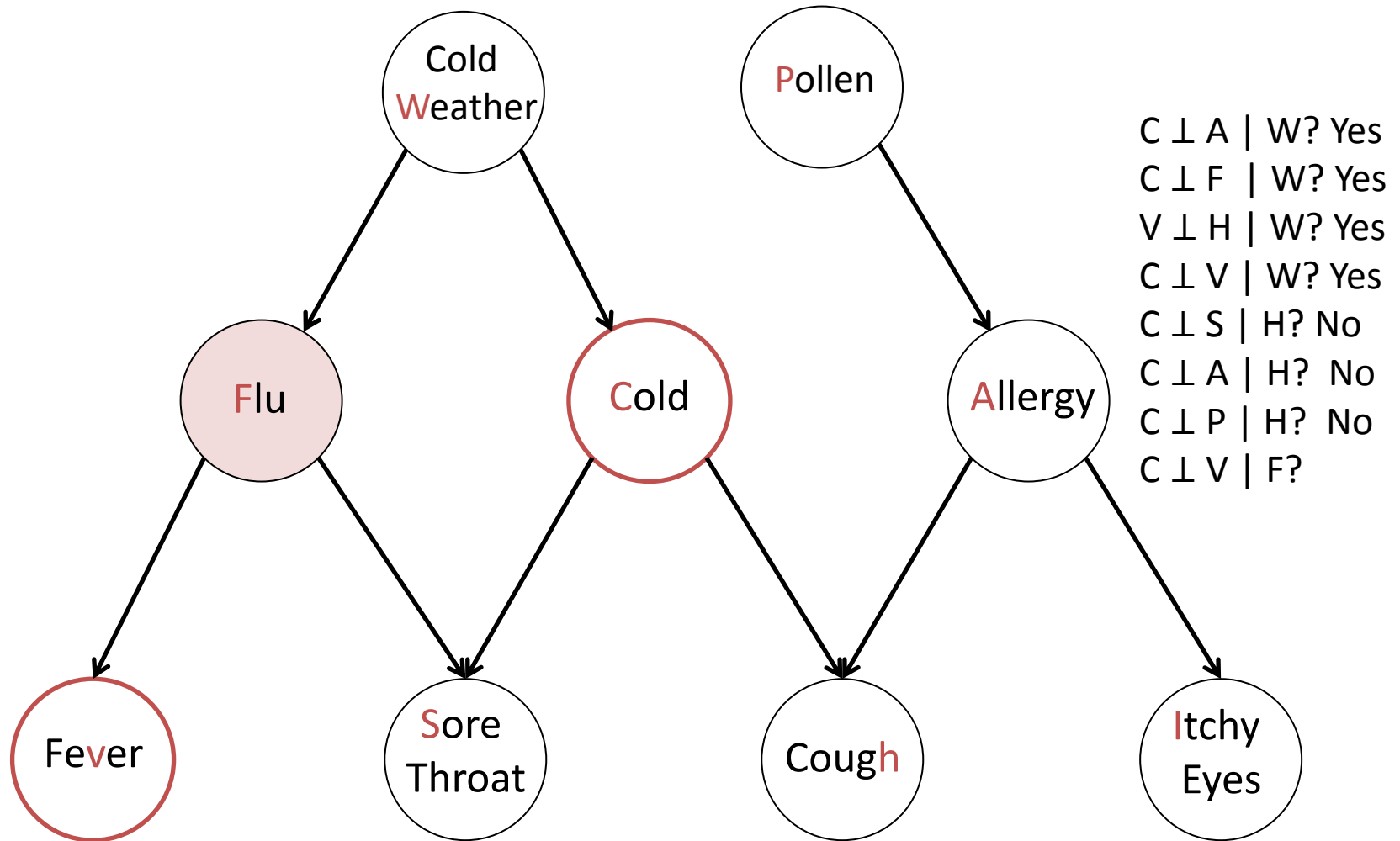
Conditional Independence



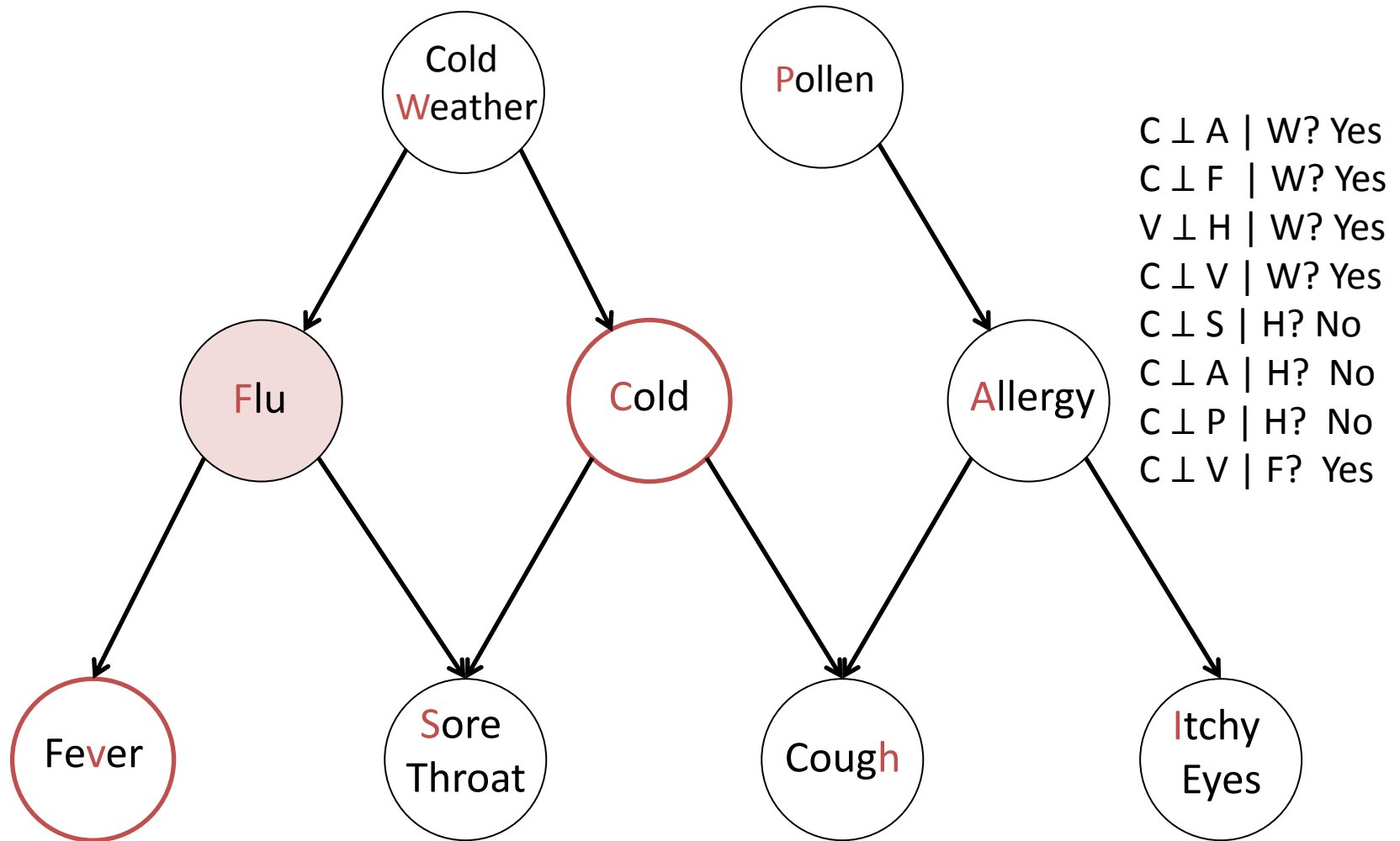
Conditional Independence



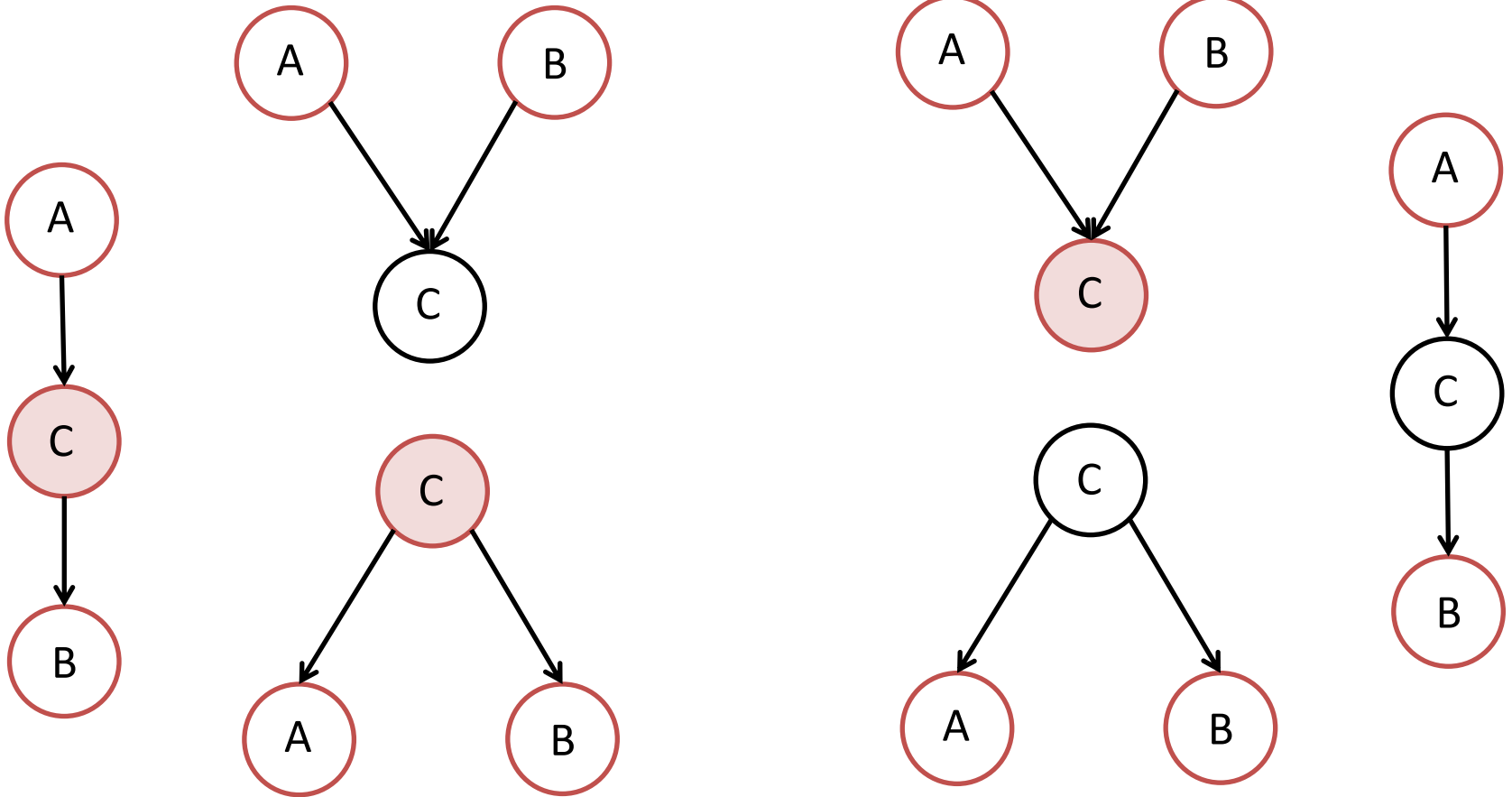
Conditional Independence



Conditional Independence



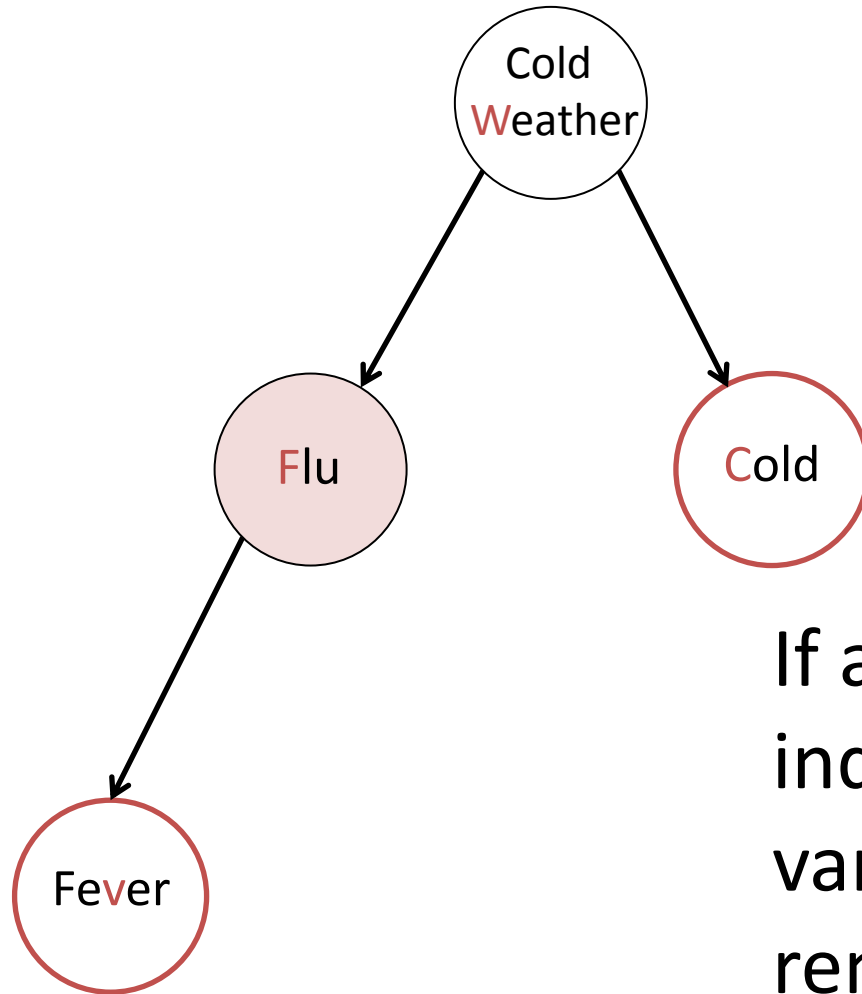
Patterns



Independent

Dependent

Conditional Independence



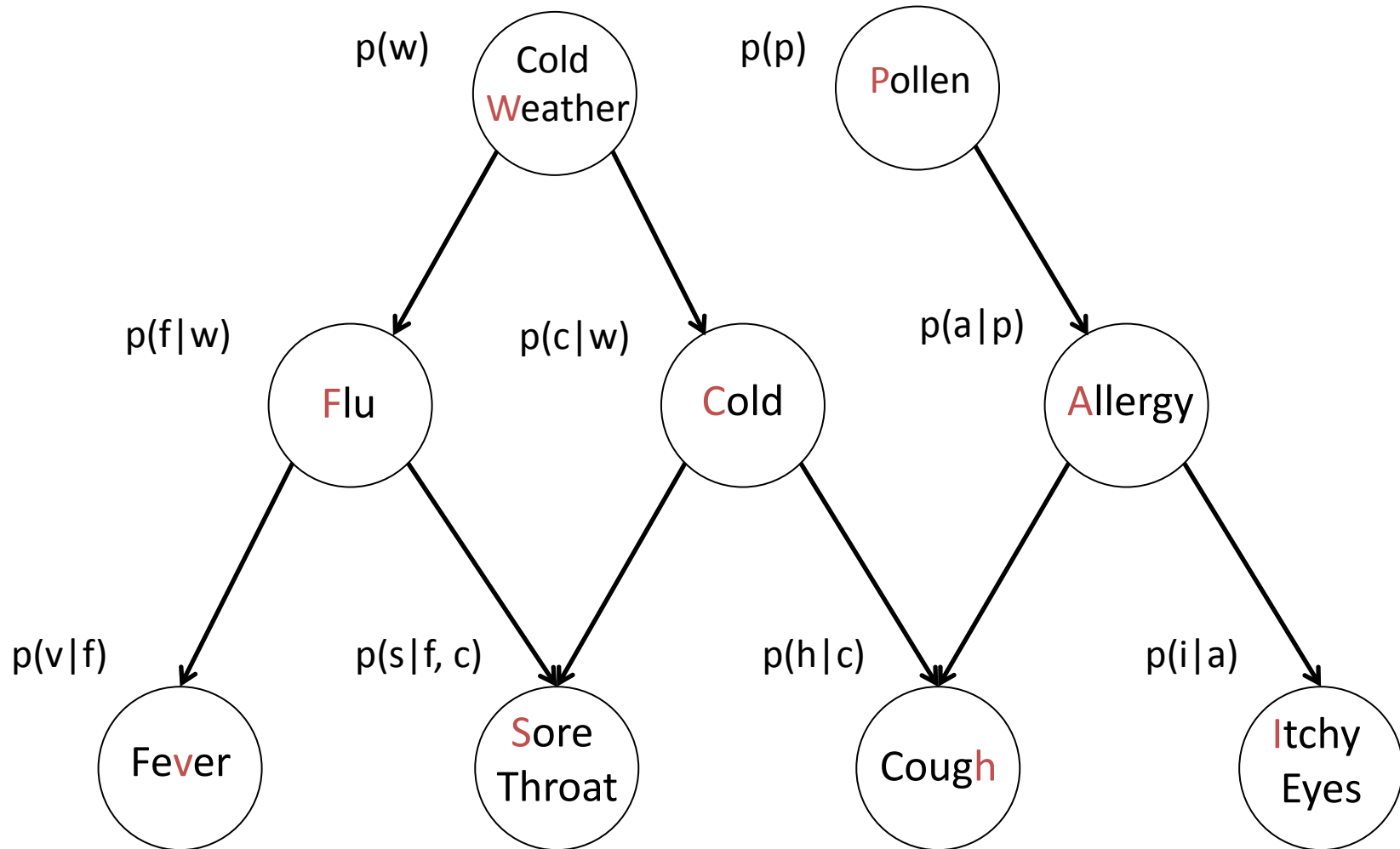
$$P(C=c | F=f) = ?$$

If a variable (Fever) is independent of the Query variable Q (Cold), we can remove(marginalize) it.

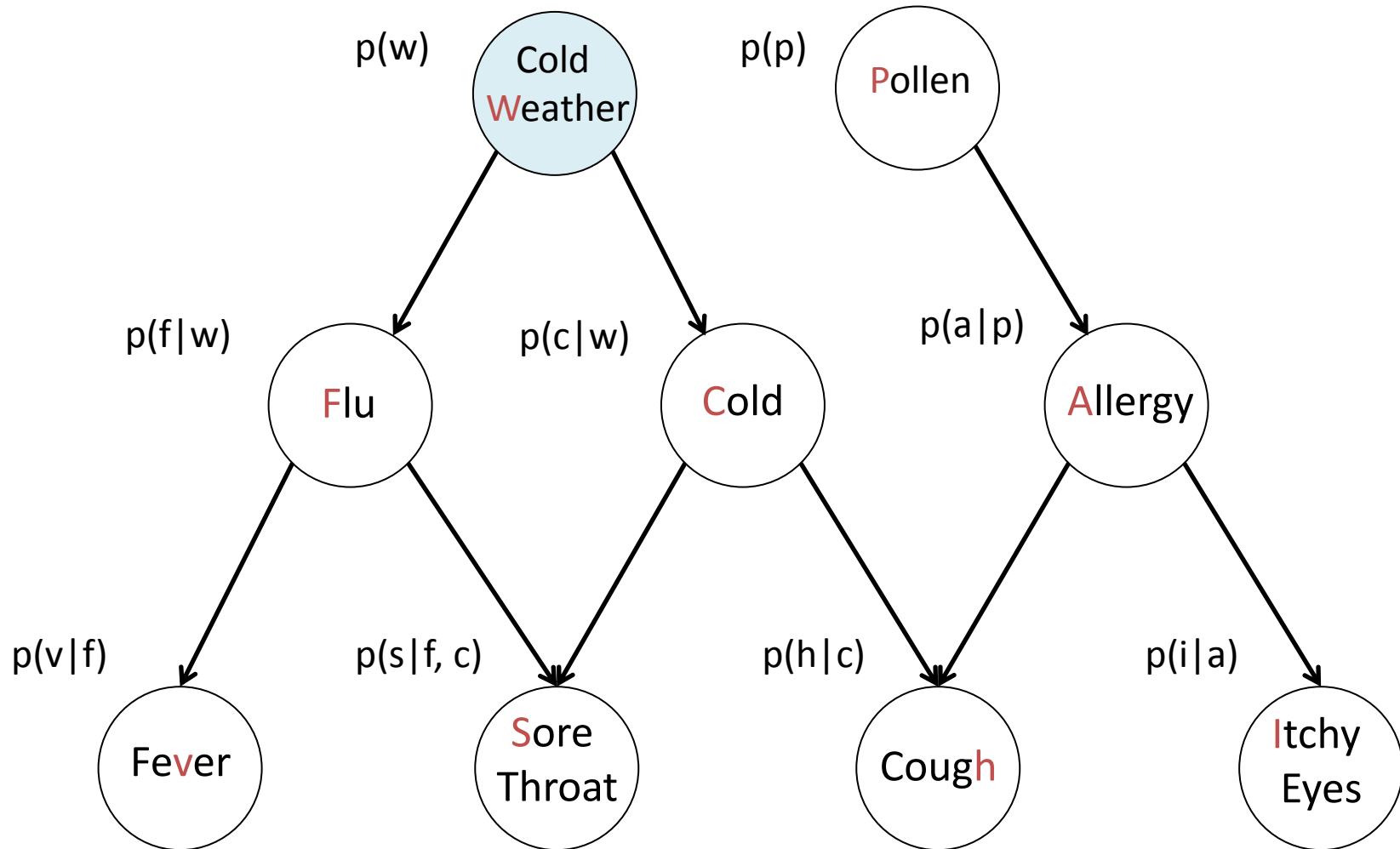
Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence
- Gibbs Sampling

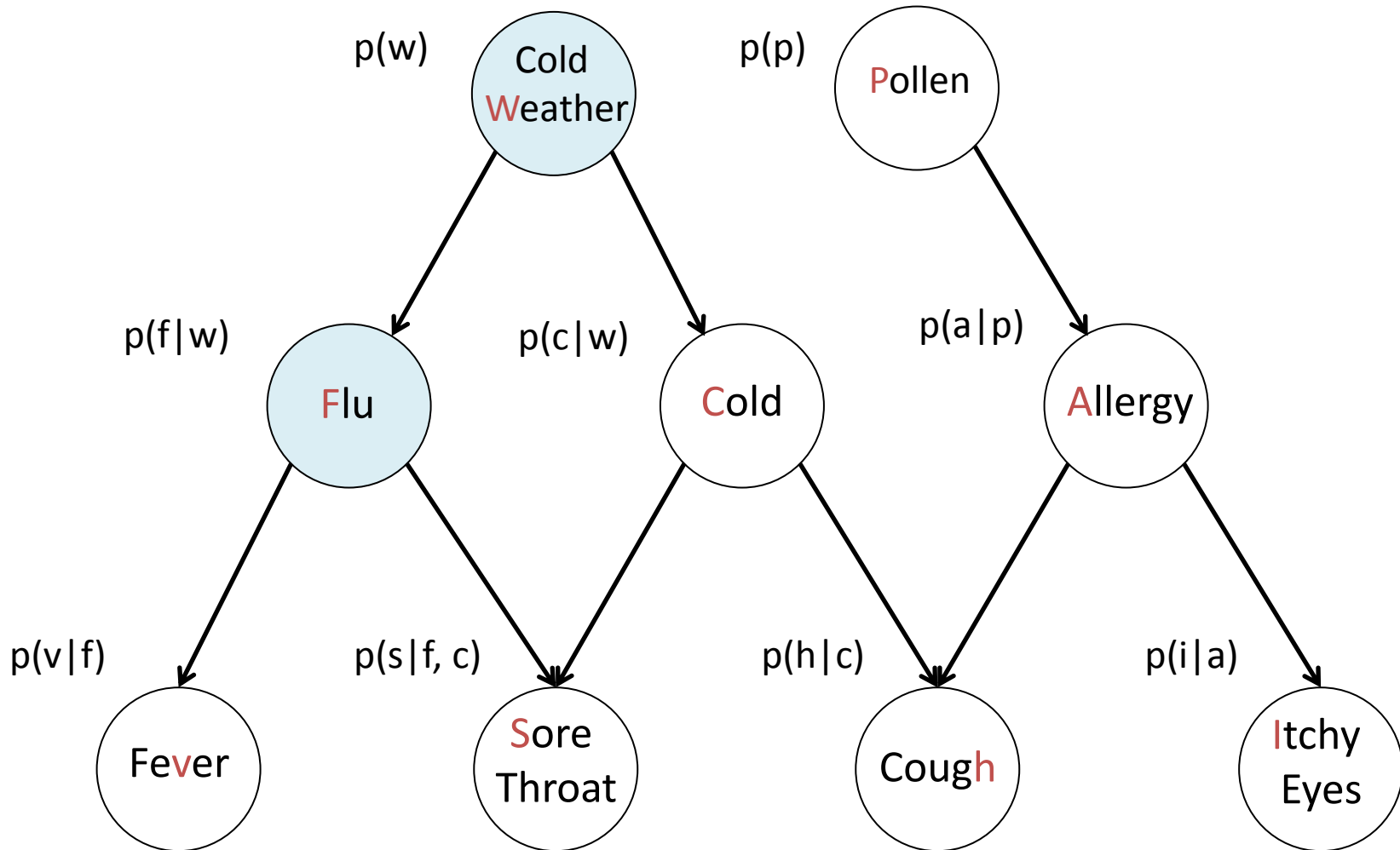
Sample 1M samples from joint distribution



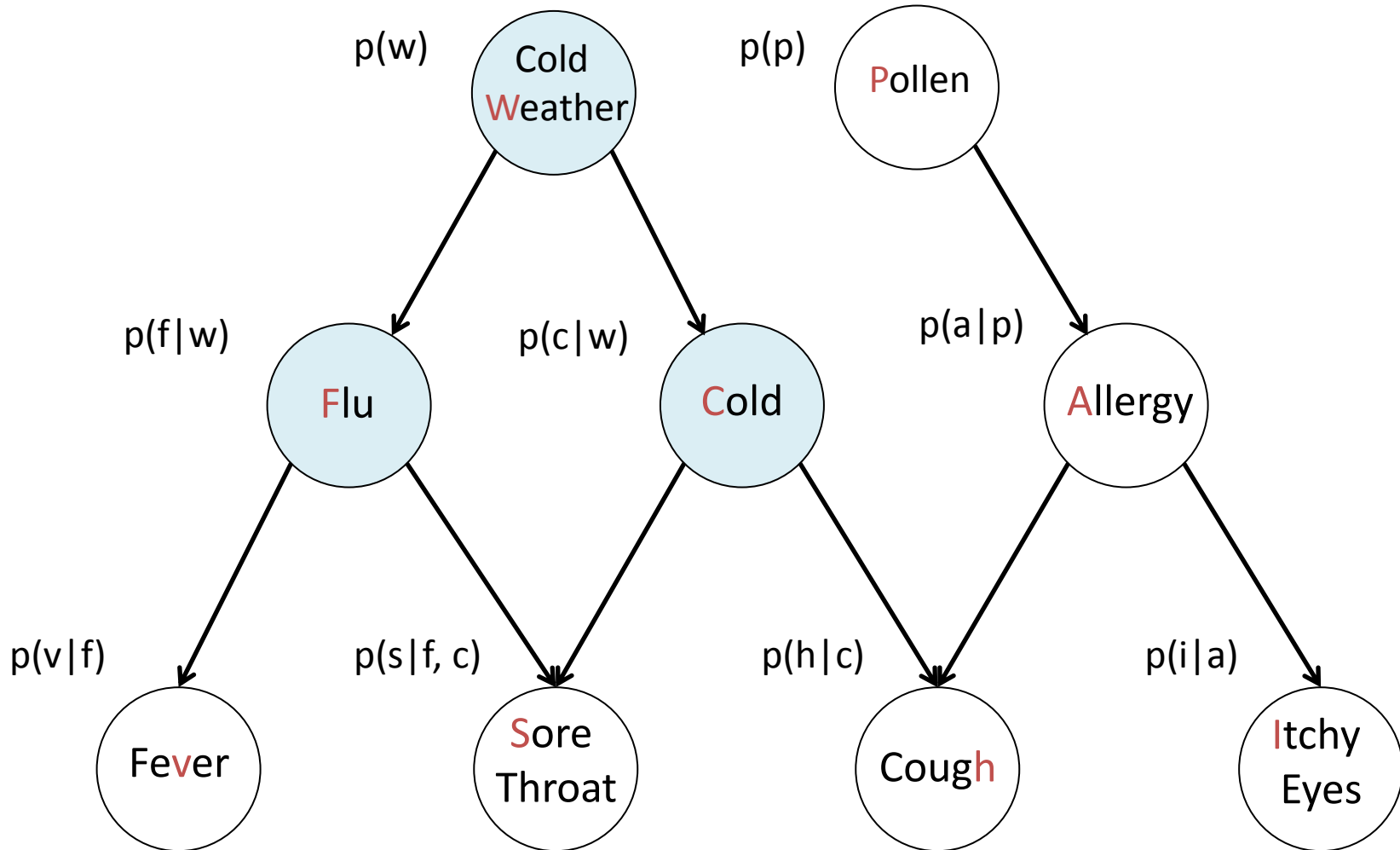
Forward Sampling



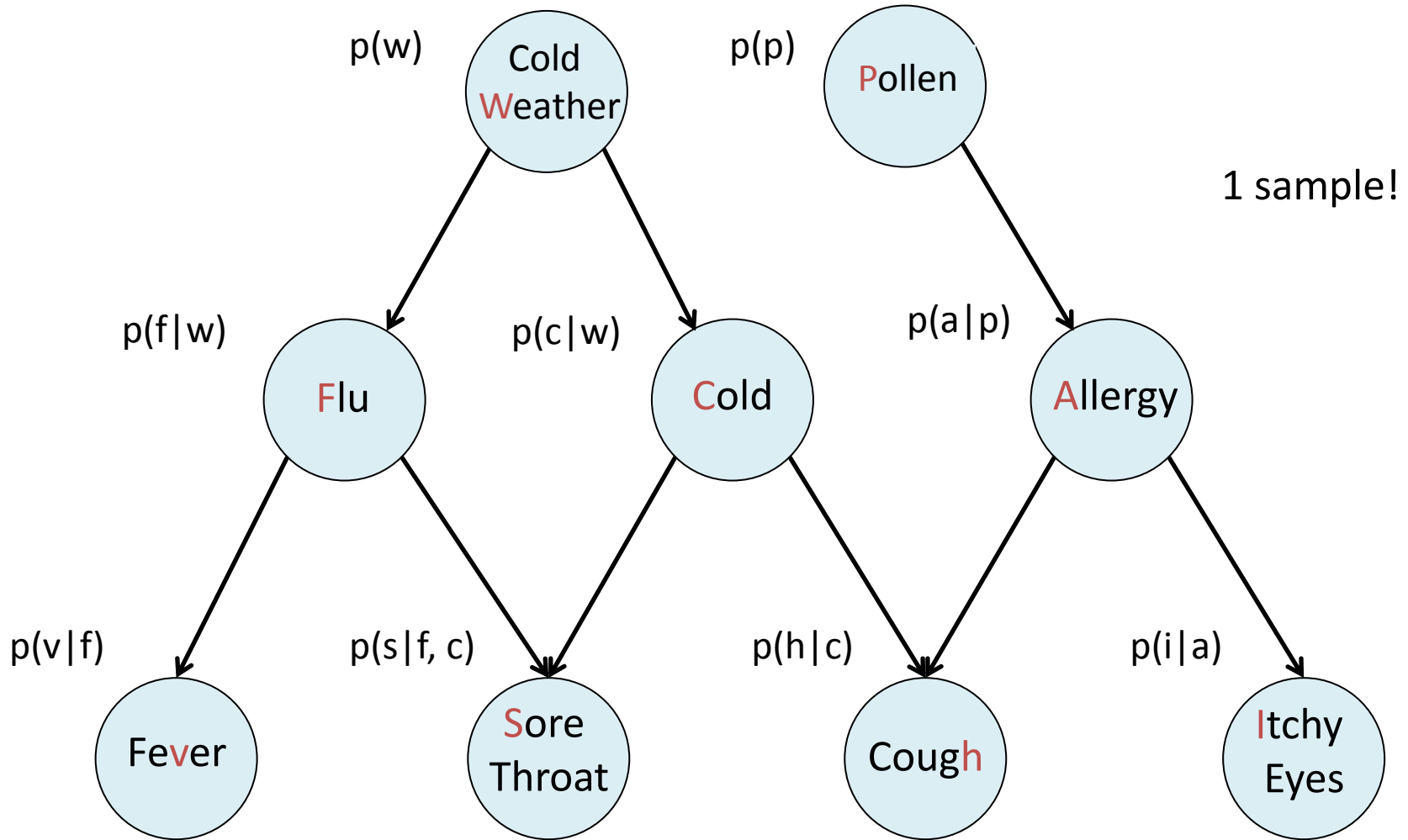
Forward Sampling



Forward Sampling



Forward Sampling



Gibbs Sampling



Algorithm: Gibbs sampling

Initialize x to a random complete assignment

Loop through $i = 1, \dots, n$ until convergence:

for each v , compute weight of $\{X_i : v\} \cup x \setminus \{x_i\}$

Choose $\{X_i : v\} \cup x \setminus \{x_i\}$ with prob prop. to weight

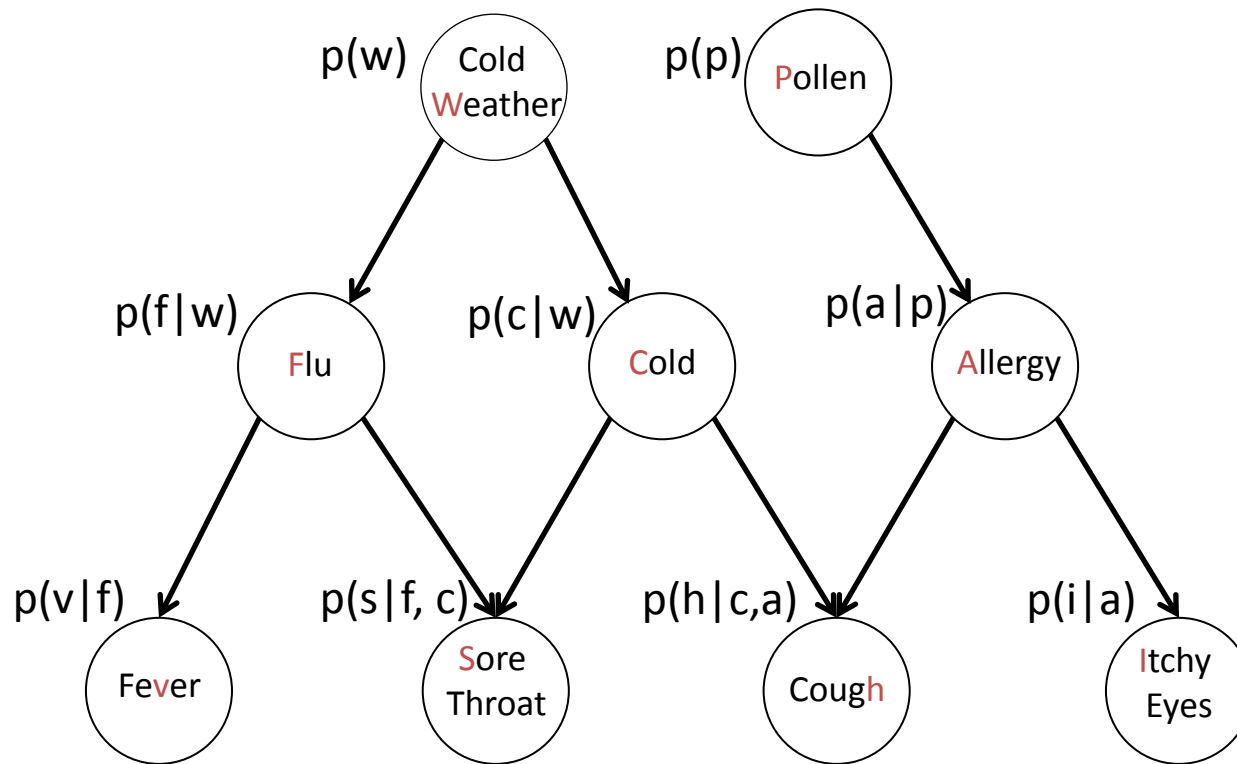
Gibbs sampling (probabilistic interpretation)

Loop through $i = 1, \dots, n$ until convergence:

Set $X_i = v$ with prob. $\mathbb{P}(X_i = v \mid X_{-i} = x_{-i})$

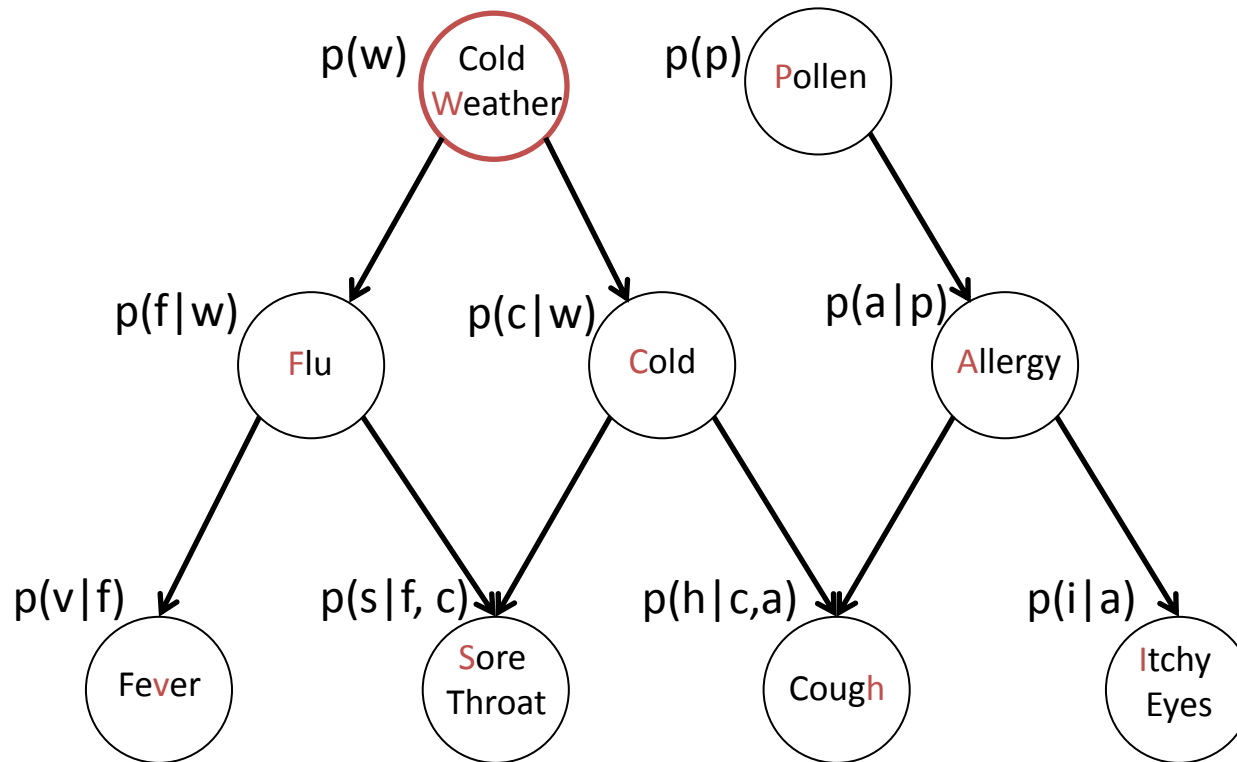
(notation: $X_{-i} = X \setminus \{X_i\}$)

Gibbs Sampling



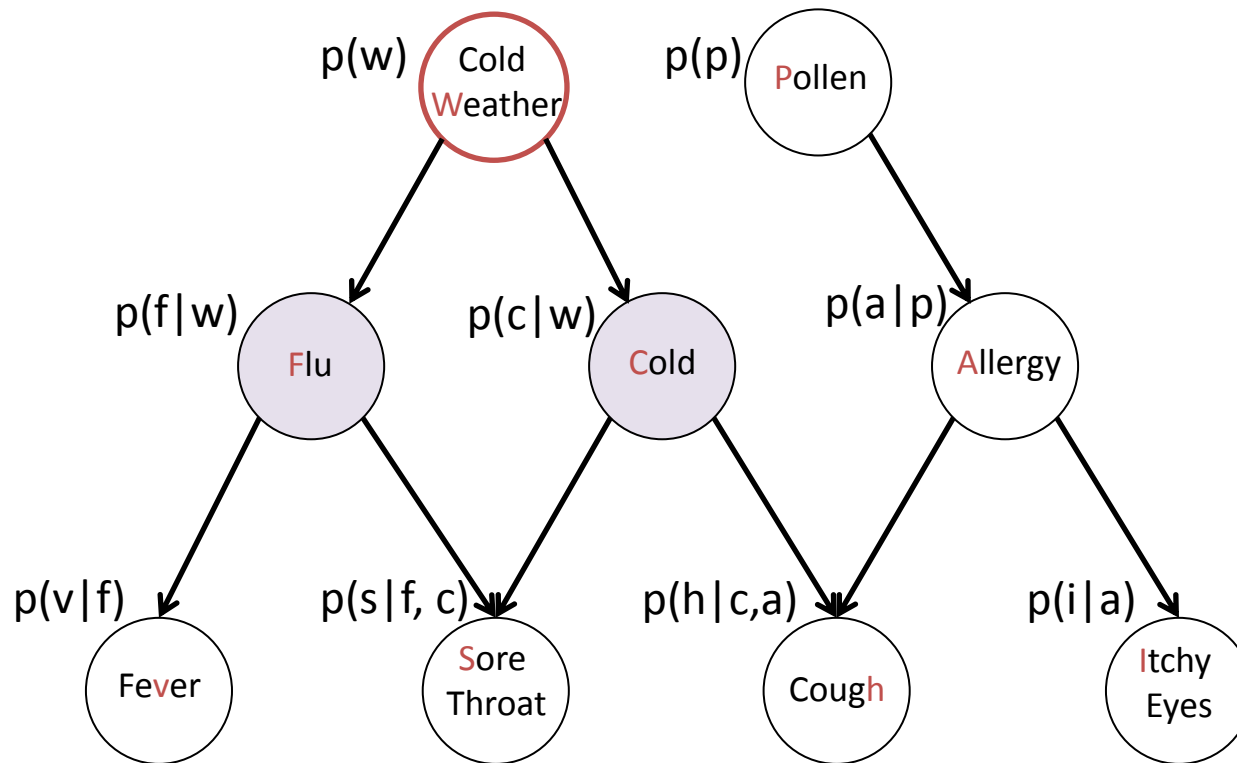
Gibbs Sampling

How do we sample a new value for W?



Gibbs Sampling

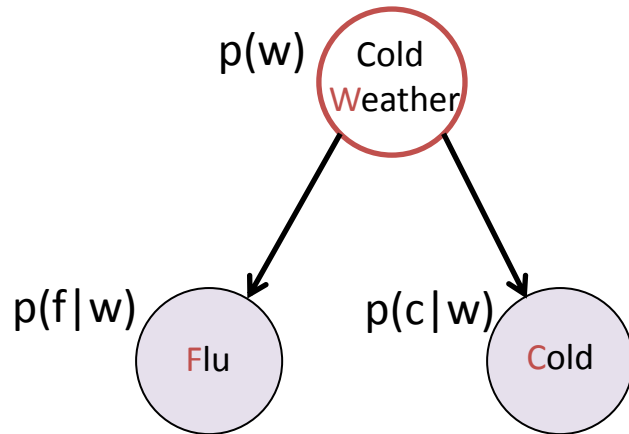
How do we sample a new value for W?



$$P(W=w|F=1, P=1, C=0, \dots, I=0) \\ = P(W=w|F=1, C=0)$$

Markov Blanket!

Gibbs Sampling

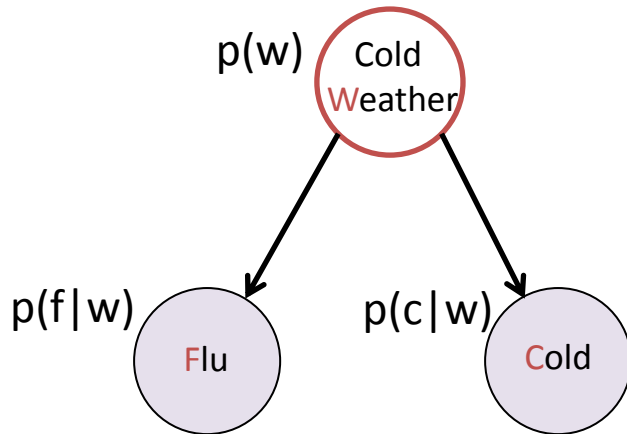


w	p(w)
0	0.4
1	0.6

w	f	p(f w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

w	c	p(f w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

Gibbs Sampling



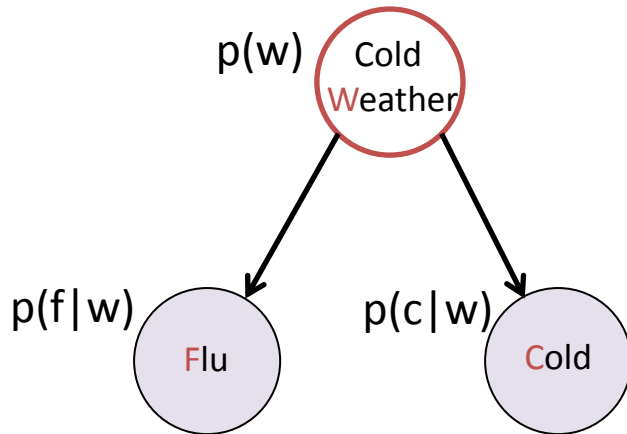
w	p(w)
0	0.4
1	0.6

w	f	p(f w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

w	c	p(c w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

$$\begin{aligned}
 &P(W=w|F=1, P=1, C=0, \dots, I=0) \\
 &= P(W=w|F=1, C=0) \\
 &\propto P(F=1|W=w) * P(C=0|W=w) * P(W=w)
 \end{aligned}$$

Gibbs Sampling



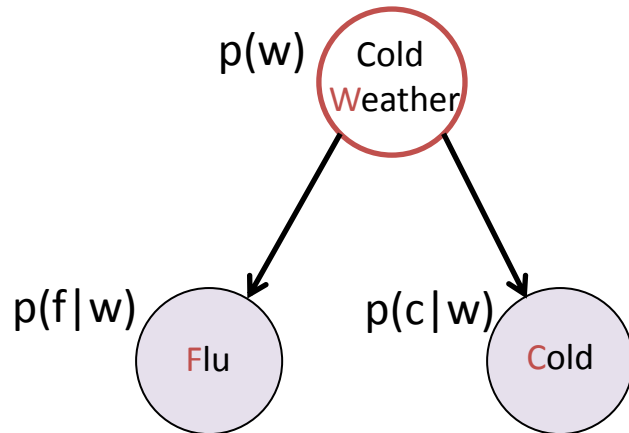
w	p(w)
0	0.40
1	0.60

w	f	p(f w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

w	c	p(c w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

$$\begin{aligned}
 & P(W=w|F=1, P=1, C=0, \dots, I=0) \\
 &= P(W=w|F=1, C=0) \\
 &\propto P(F=1|W=w) * P(C=0|W=w) * P(W=w) \\
 &= 0.05 * 0.88 * 0.40, \quad W=0
 \end{aligned}$$

Gibbs Sampling



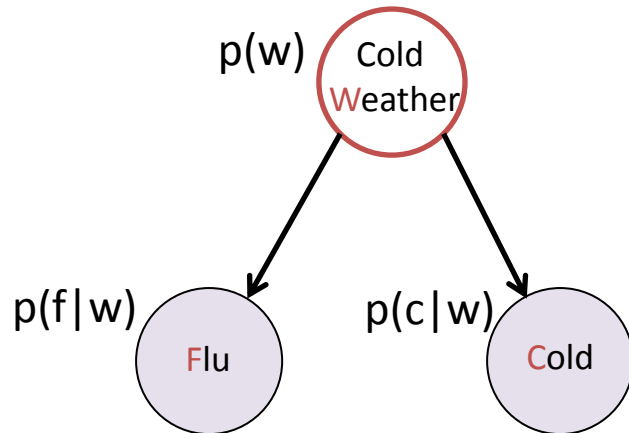
w	p(w)
0	0.40
1	0.60

w	f	p(f w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

w	c	p(c w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

$$\begin{aligned}
 & P(W=w|F=1, P=1, C=0, \dots, I=0) \\
 &= P(W=w|F=1, C=0) \\
 &\propto P(F=1|W=w) * P(C=0|W=w) * P(W=w) \\
 &= \begin{aligned} & 0.05 * 0.88 * 0.40, & W=0 \\ & 0.20 * 0.70 * 0.60, & W=1 \end{aligned}
 \end{aligned}$$

Gibbs Sampling



w	p(w)
0	0.40
1	0.60

w	f	p(f w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

w	c	p(c w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

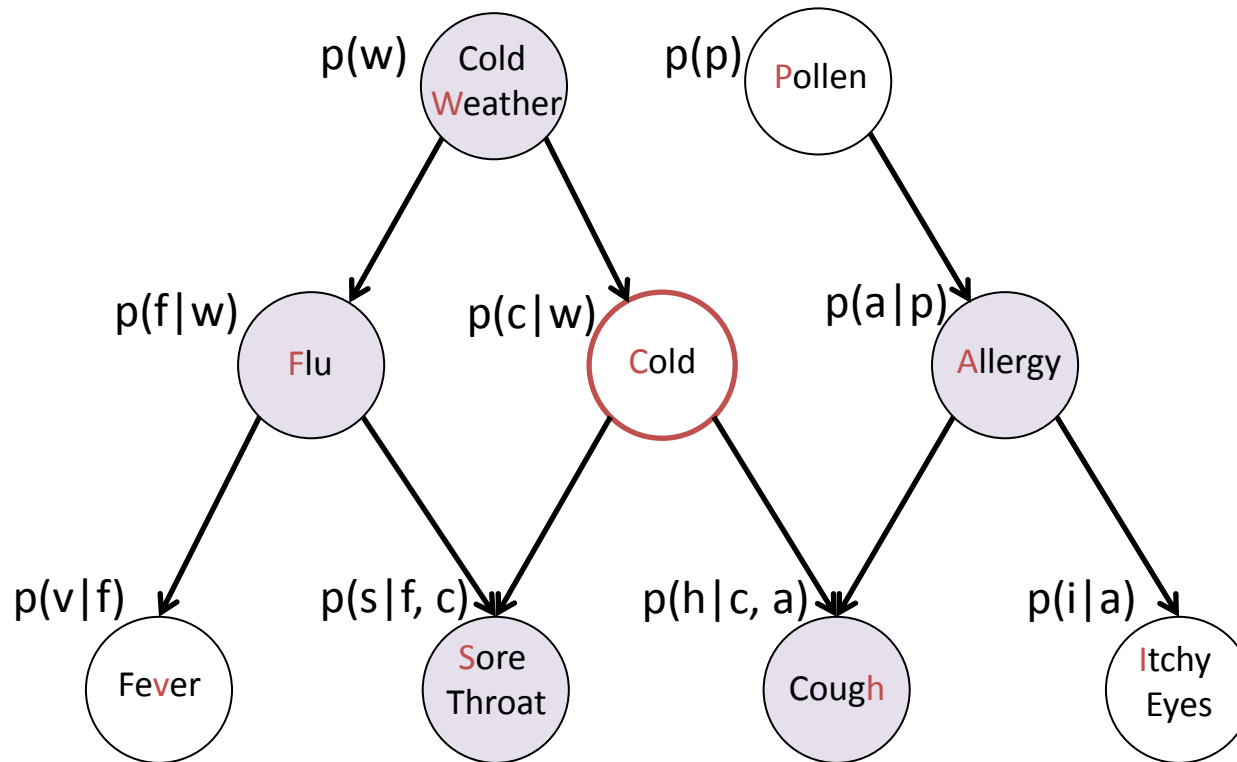
$$\begin{aligned}
 & P(W=w|F=1, C=0, \dots, I=0) \\
 &= P(W=w|F=1, C=0) \\
 &\propto P(F=1|W=w) * P(C=0|W=w) * P(W=w) \\
 &= \begin{aligned} & 0.05 * 0.88 * 0.40, & W=0 \\ & 0.20 * 0.70 * 0.60, & W=1 \end{aligned}
 \end{aligned}$$

$$\begin{aligned}
 & P(W=w|F=1, C=0) \\
 &= \begin{aligned} & 0.0176 / (0.0176 + 0.084), & w=0 \\ & 0.084 / (0.0176 + 0.084), & w=1 \end{aligned} \\
 &= \begin{aligned} & 0.173, & w=0 \\ & 0.827, & w=1 \end{aligned}
 \end{aligned}$$

Sample a new w!

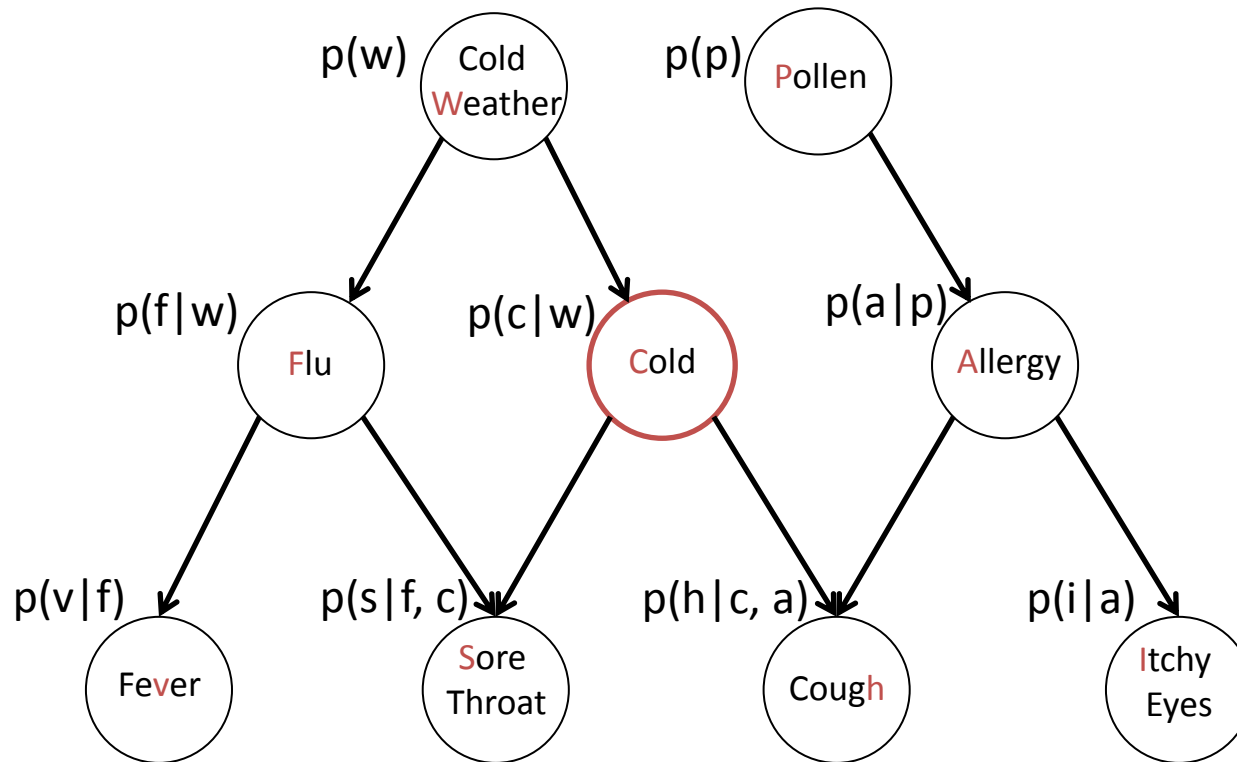
Gibbs Sampling

How do we sample a new value for C?



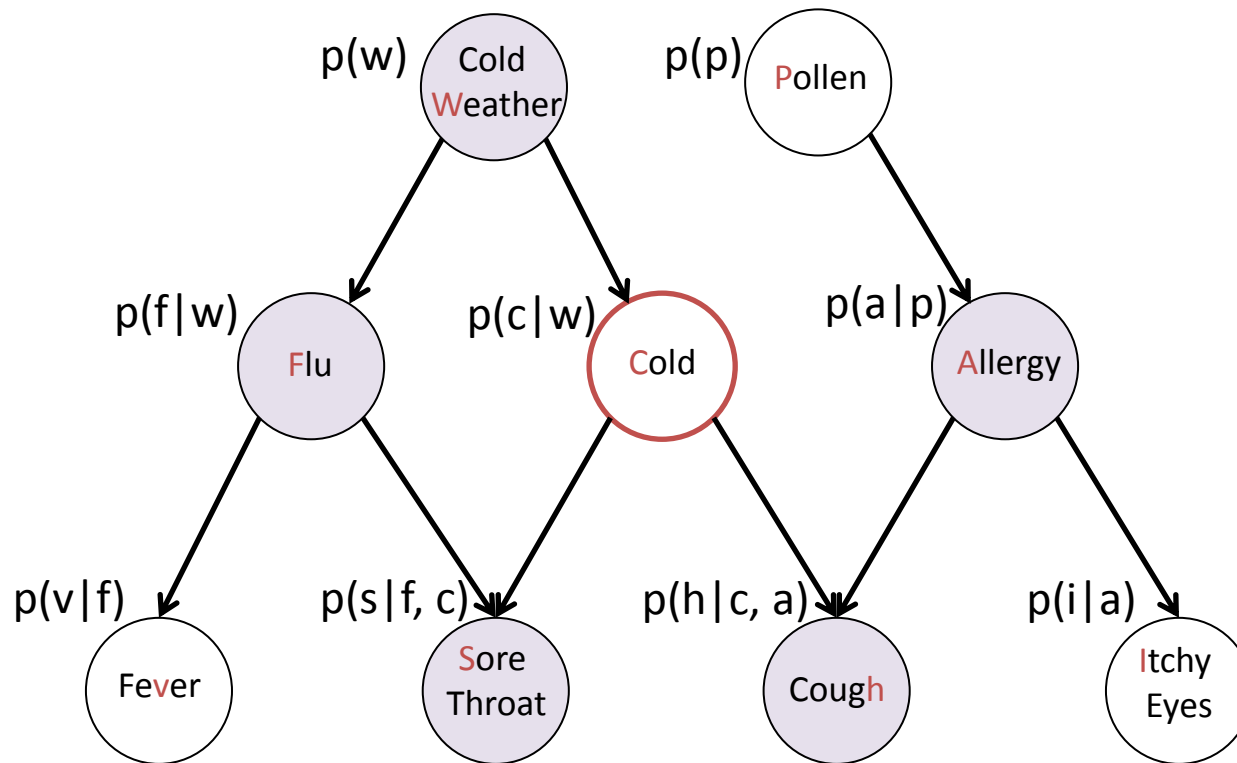
Gibbs Sampling

How do we sample a new value for C?



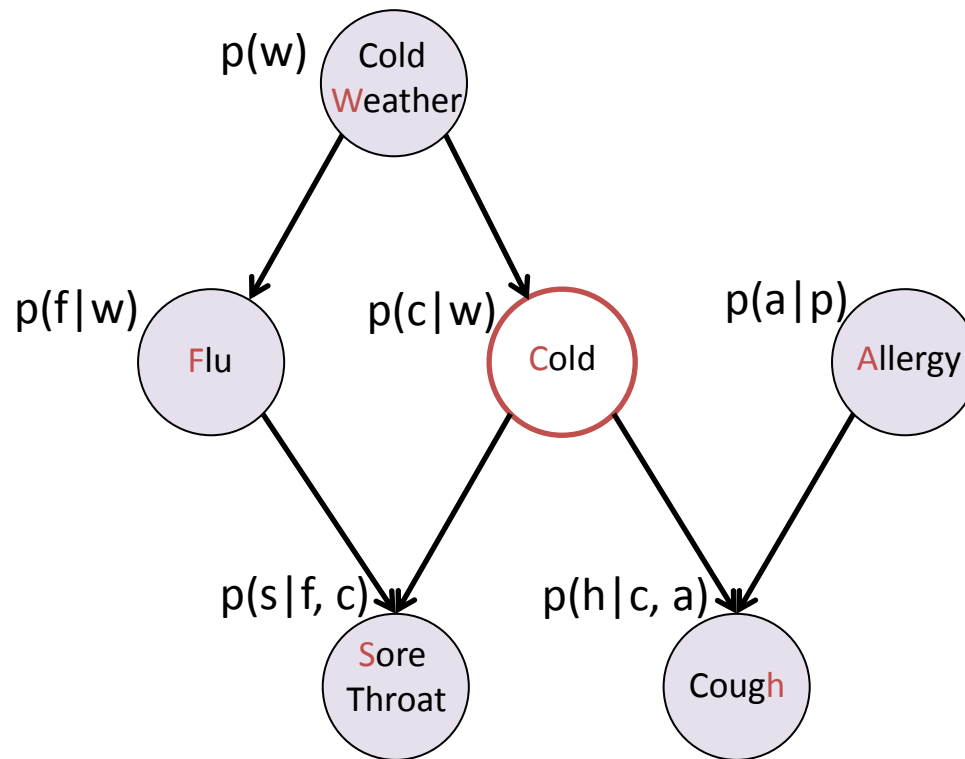
Gibbs Sampling

How do we sample a new value for C?



$$\begin{aligned} & P(C=c \mid W=1, F=1, P=1, \dots, I=0) \\ &= P(C=c \mid W=1, F=1, S=0, H=1, A=1) \quad \text{Markov Blanket!} \end{aligned}$$

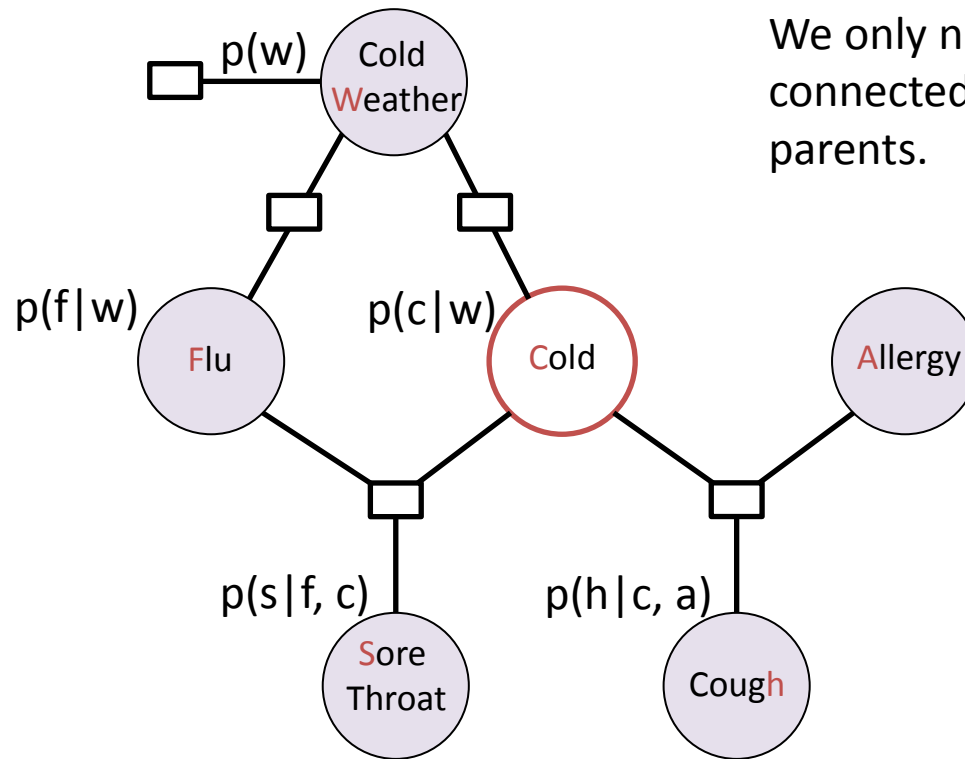
Gibbs Sampling



$$\begin{aligned} &P(C=c \mid W=1, F=1, P=1, \dots, I=0) \\ &= P(C=c \mid W=1, F=1, S=0, H=1, A=1) \end{aligned}$$

Gibbs Sampling

From a Factor Graph Perspective



We only need look at the factors connected to the children and the parents.

$$\begin{aligned} &P(C=c \mid W=1, F=1, P=1, \dots, I=0) \\ &= P(C=c \mid W=1, F=1, S=0, H=1, A=1) \\ &= p(w) p(f \mid w) p(c \mid w) p(s \mid f, c) p(h \mid c, a) \end{aligned}$$

Questions?