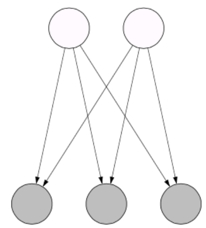
CS221 Section 7
Bayesian Networks

Nov 6th 2015

Roadmap

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

Bayesian Networks



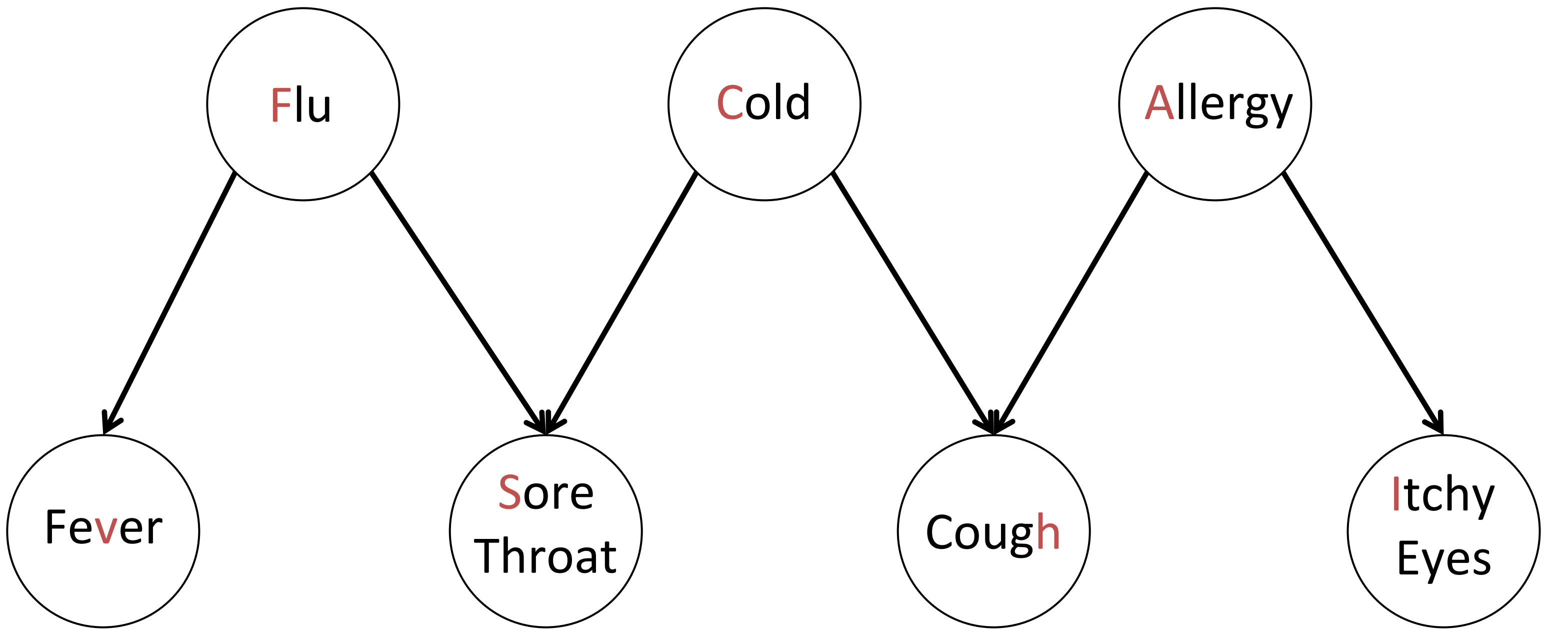
Definition: Bayesian network

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

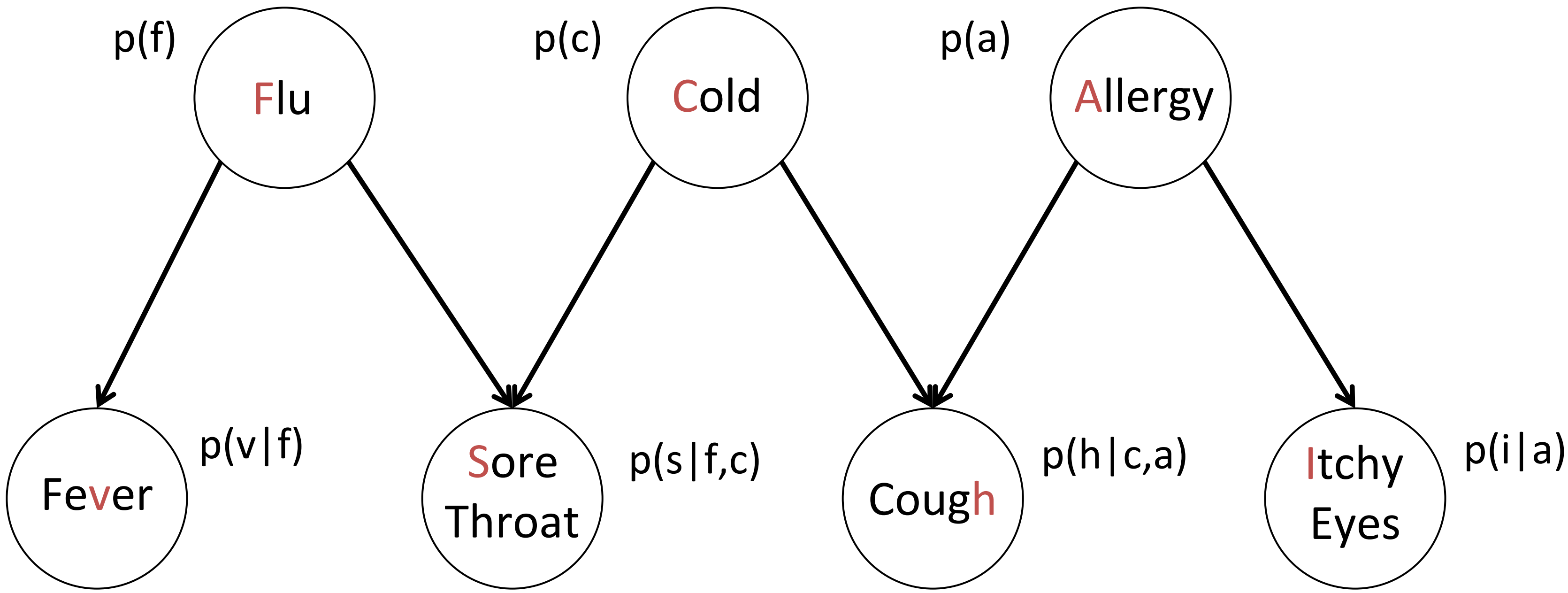
A **Bayesian network** is a directed acyclic graph (DAG) that specifies a joint distribution over X as a product of local conditional distributions, one for each node:

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

Bayesian Networks



A Bayesian network represents a joint probability distribution.



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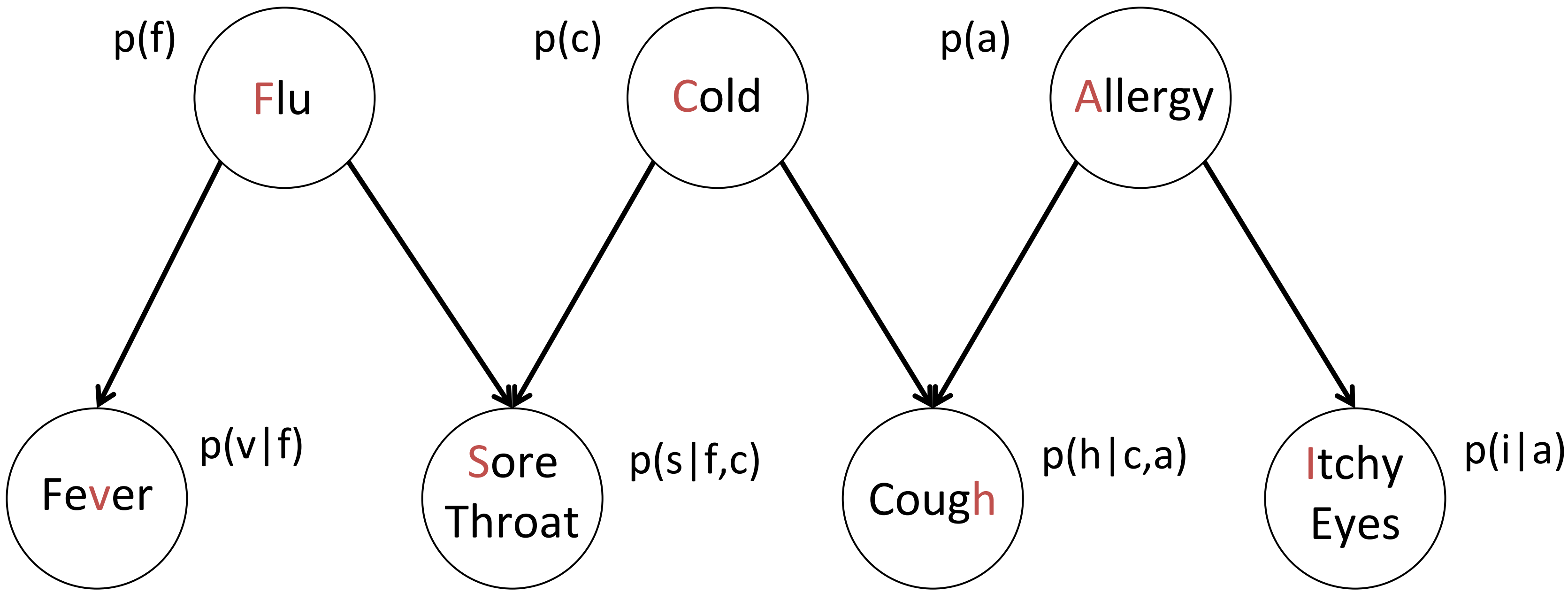


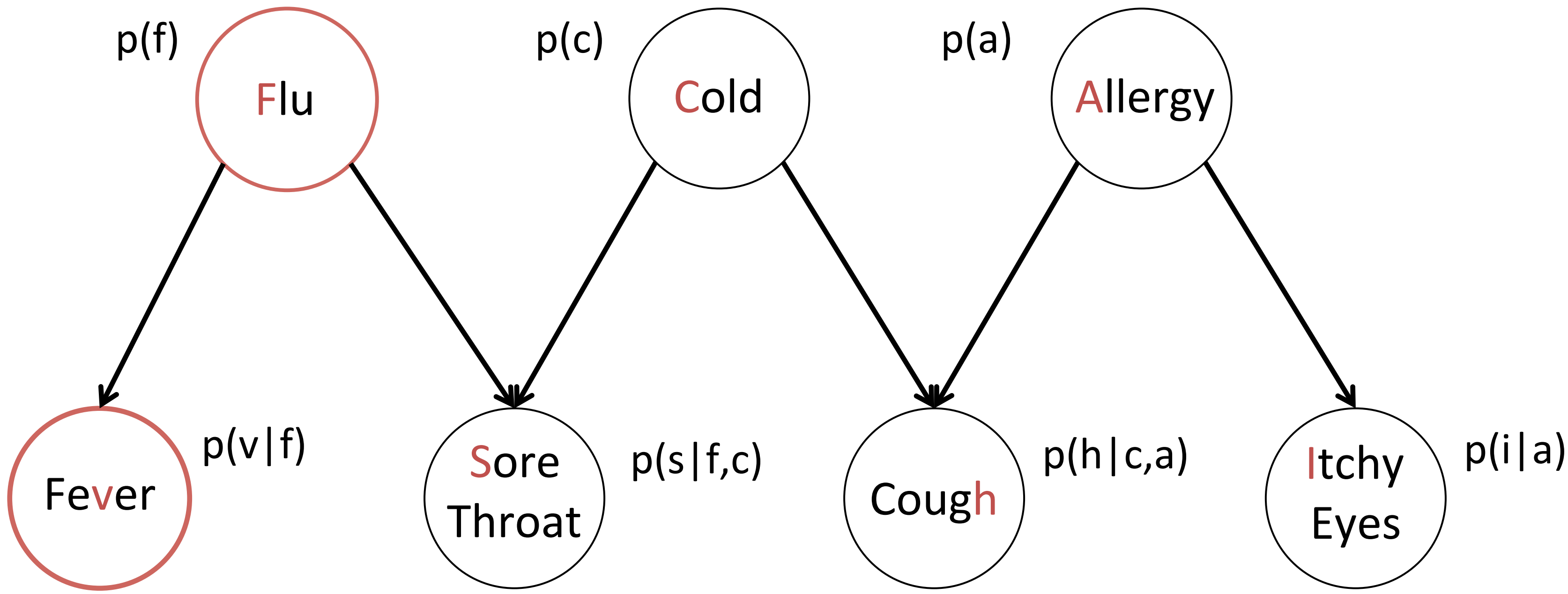
P(F=f, C=c, A=a, V=v, S=s, C=c, I=i) = p(f)p(c)p(a)p(v|a)p(s|f, c)p(h|c,a)p(i|a)

Roadmap

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

Probabilistic Queries - Examples

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



Probabilistic Queries - Examples

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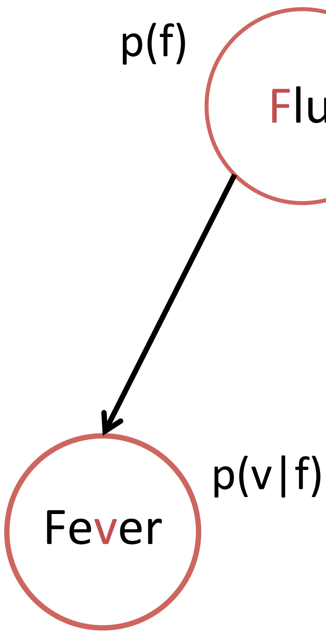
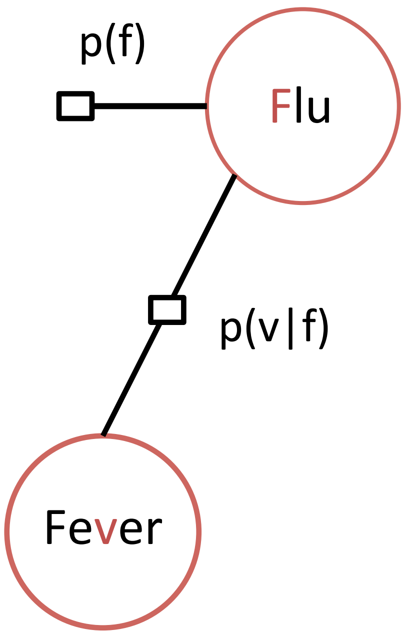


1. Remove (marginalize) variables not ancestors of Q or E.

Probabilistic Queries - Examples

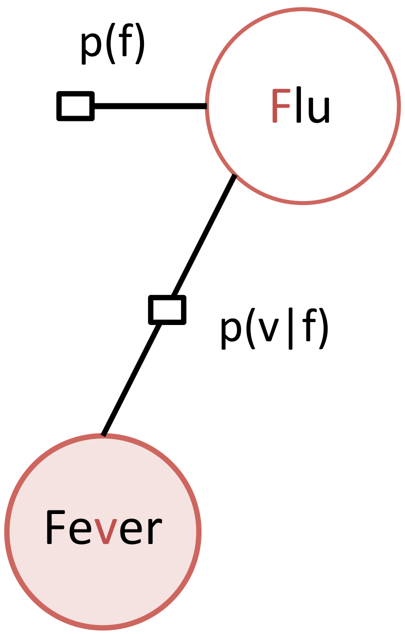
$P(F=1|V=1) = ?$



2. Convert Bayesian network to factor graph.

Probabilistic Queries - Examples

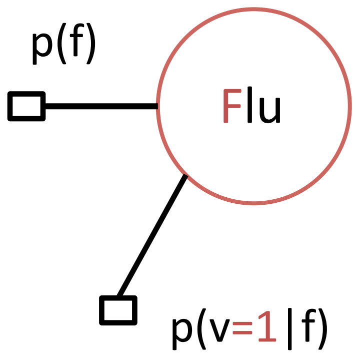
$P(F{=}1|V{=}1) = ?$



3. Condition on E = e.
   3.1 shade nodes

Probabilistic Queries - Examples

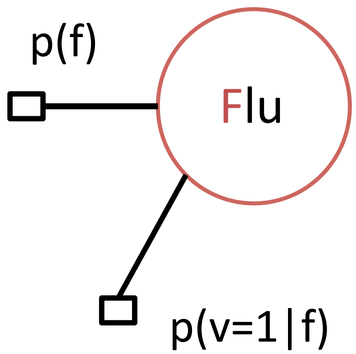
P(F=1|V=1) = ?



3. Condition on E = e.
   3.2 disconnect

Probabilistic Queries - Examples

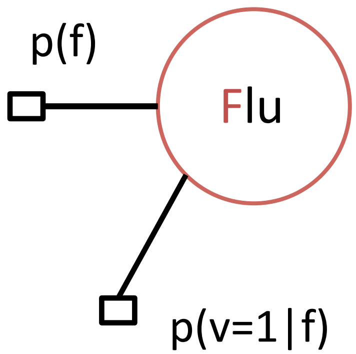
P(F=1|V=1) = ?



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).

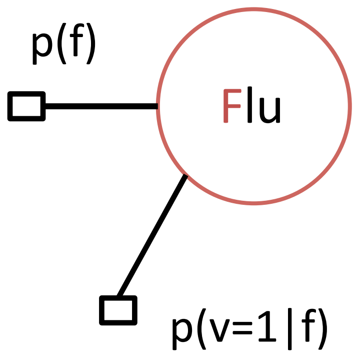
f	p(f)
0	1-α
1	α

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) = ?



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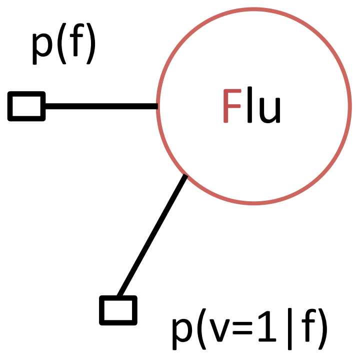
$$P(F=f|V=1) \propto p(f)\, p(v=1|f) = \begin{cases} (1-\alpha) * 0.30, & f = 0 \\ \end{cases}$$

Probabilistic Queries - Examples

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



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Probabilistic Queries - Examples

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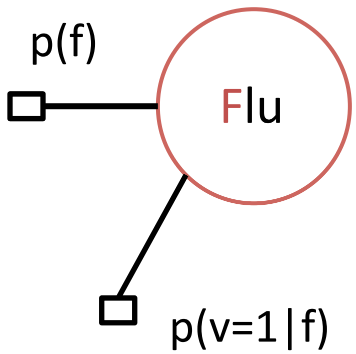

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f	v	p(v|f)
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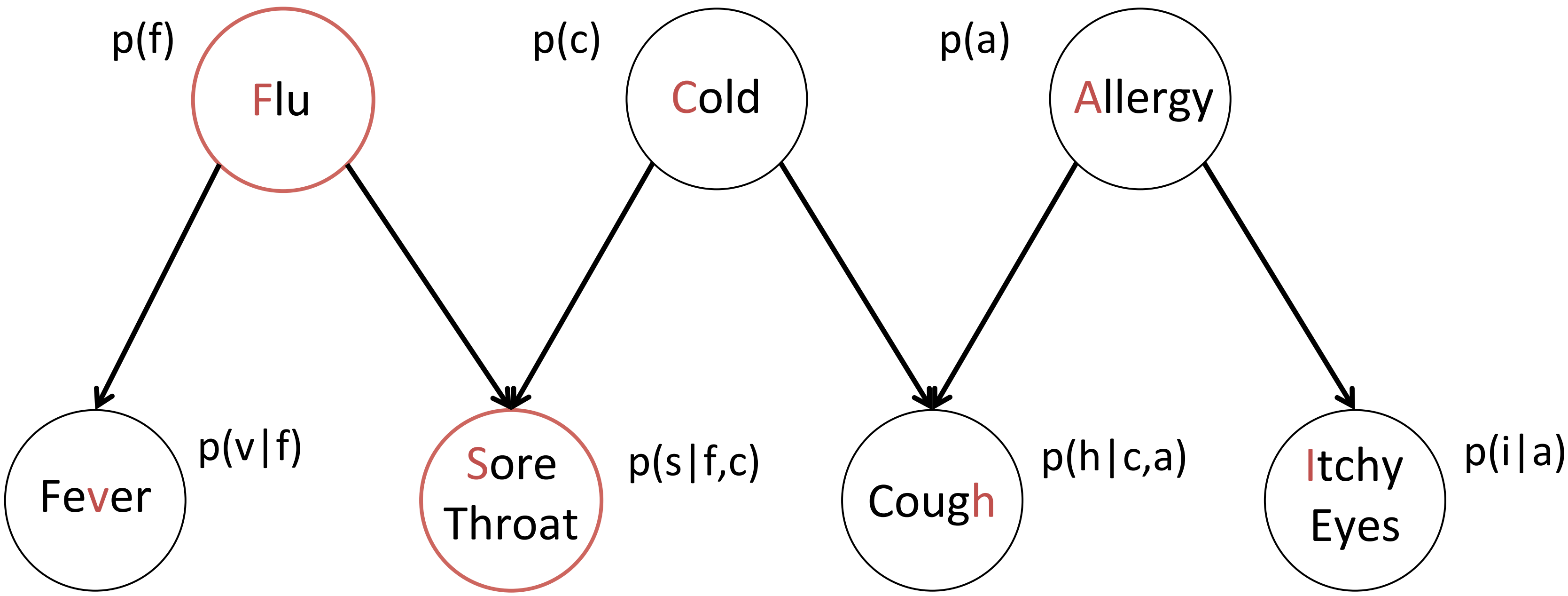
1	1	0.80

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

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

Probabilistic Queries - Examples

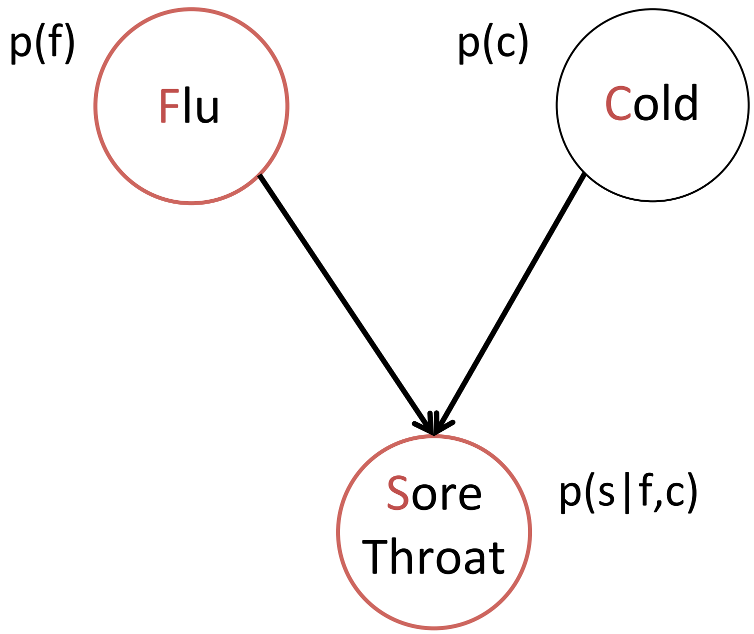
$P(F=1|S=1) = ?$



Probabilistic Queries - Examples

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

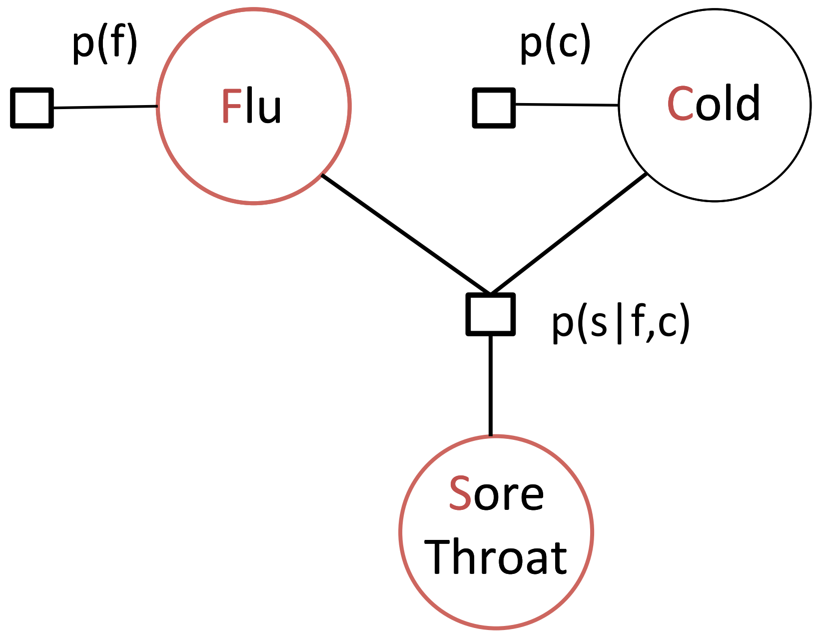
1. Remove (marginalize) variables not ancestors of Q or E.



Probabilistic Queries - Examples

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

2. Convert Bayesian network to factor graph.

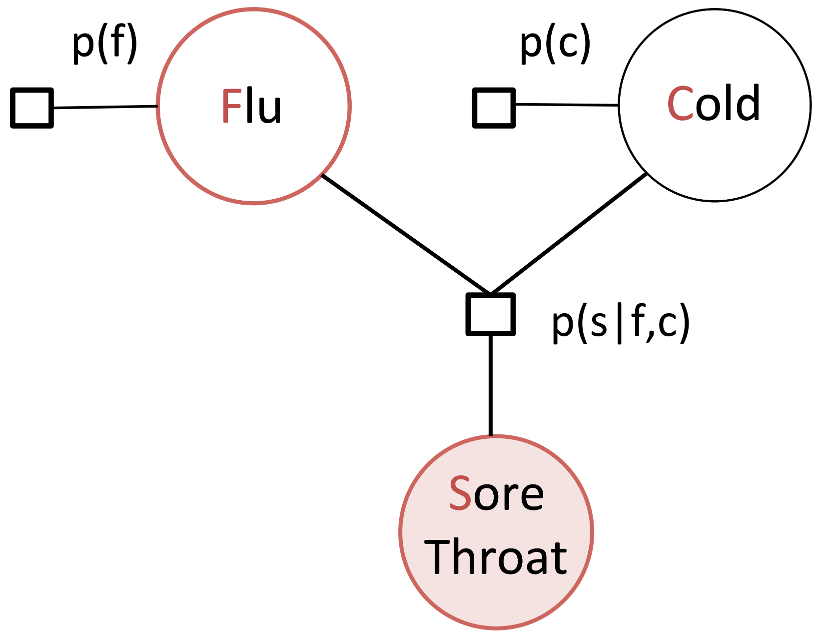


★ One factor per variable!

Probabilistic Queries - Examples

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

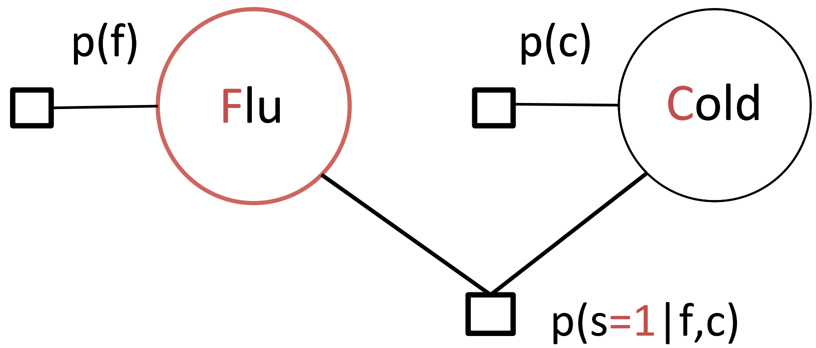
3. Condition on E = e.
   3.1 shade nodes



Probabilistic Queries - Examples

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

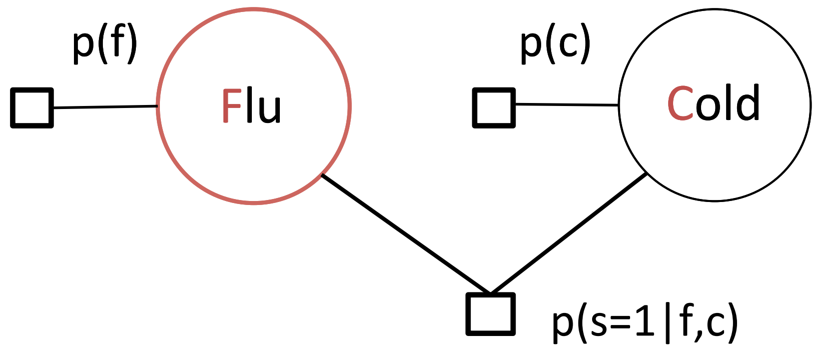
3. Condition on E = e.
    3.2 disconnect



Probabilistic Queries - Examples

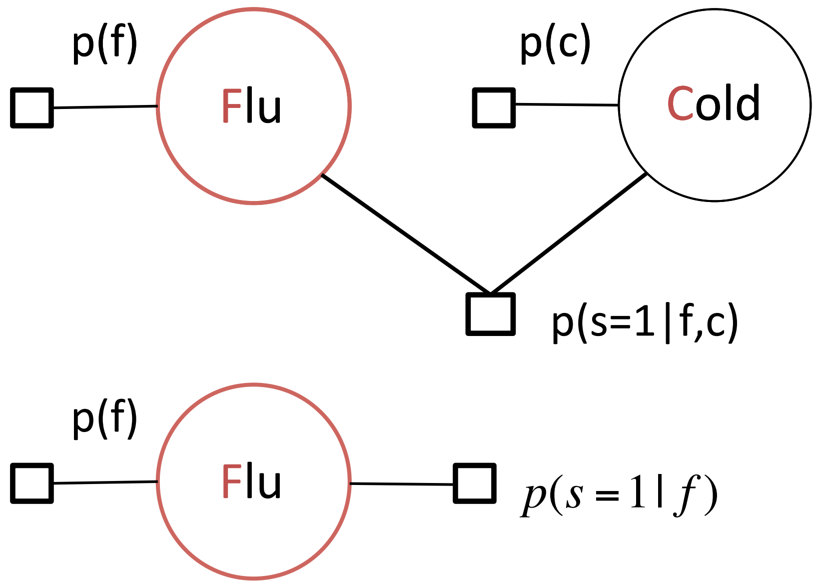
P(F=1|S=1) = ?

4. Remove (marginalize) nodes disconnected from Q.



Probabilistic Queries - Examples

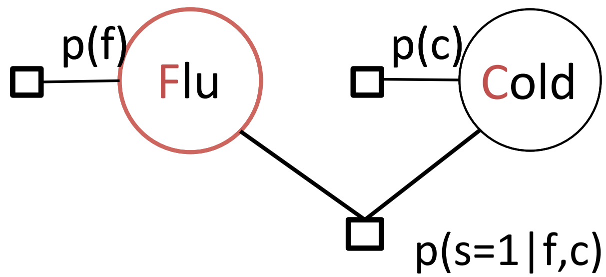
$P(F=1|S=1) = ?$

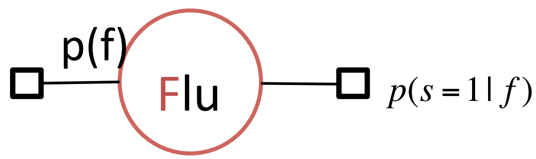


5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

Probabilistic Queries - Examples

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





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

$$p(s=1 \mid f)$$

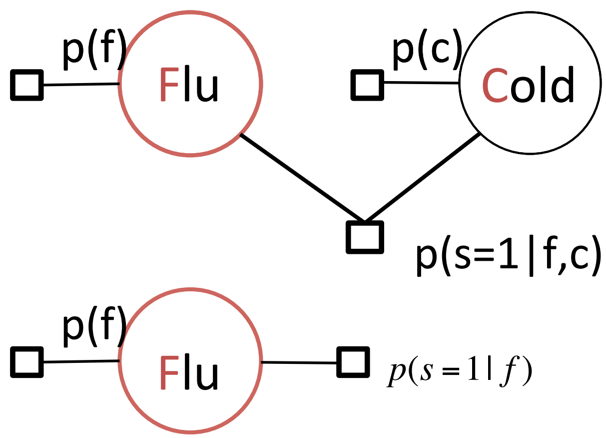
$$= \sum_c p(c) p(s=1 \mid f, c)$$

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

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

Probabilistic Queries - Examples

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



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

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

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

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

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

f	p(f)
0	1-α
1	α

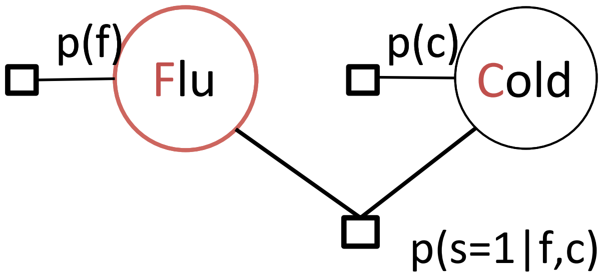
c	p(c)
0	1-β
1	β

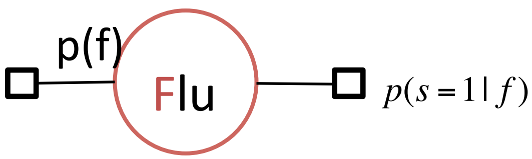
s	f	c	p(s|f,c)
0	0	0	1.00
1	0	0	0
0	1	0	0.30
1	1	0	0.70
0	0	1	0.25
1	0	1	0.75
0	1	1	0.10
1	1	1	0.90

f	p(s=1,f)
0	β*0.75
1	?

Probabilistic Queries - Examples

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





$$p(s=1|f)$$
$$=\sum_c p(c)p(s=1|f,c)$$
$$=p(c=0)p(s=1|f,c=0)+p(c=1)p(s=1|f,c=1)$$
$$=\begin{cases}(1-\beta)*0+\beta*0.75, & f=0\\(1-\beta)*0.70+\beta*0.9, & f=1\end{cases}$$

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

f	p(f)
0	1-α
1	α

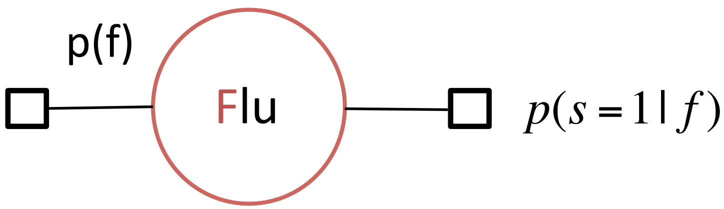
c	p(c)
0	1-β
1	β

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	β*0.75
1	((1-β)*0.7+β*0.9)

Probabilistic Queries - Examples

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



$$P(F=f \mid S=1)$$
$$\propto p(f)p(s=1 \mid f)$$

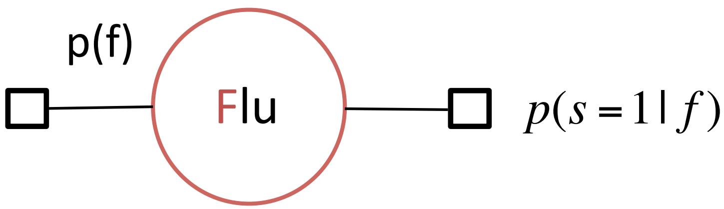
5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

f	p(f)
0	1-α
1	α

f	p(s=1|f)
0	β*0.75
1	((1-β)*0.7+β*0.9)

Probabilistic Queries - Examples

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



$$P(F=f \mid S=1)$$

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

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

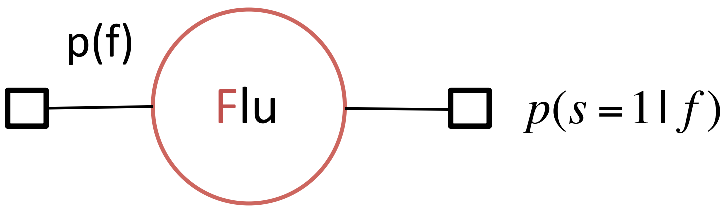
5. Run probabilistic inference algorithm (manual, variable elimination, Gibbs sampling, particle filtering).

f	p(f)
0	1-α
1	α

f	p(s=1|f)
0	β*0.75
1	((1-β)*0.7+β*0.9)

Probabilistic Queries - Examples

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



$$P(F=f \mid S=1)$$

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

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

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

f	p(f)
0	1-α
1	α

f	p(s=1|f)
0	β*0.75
1	(1-β)*0.7+β*0.9

Probabilistic Queries - Examples

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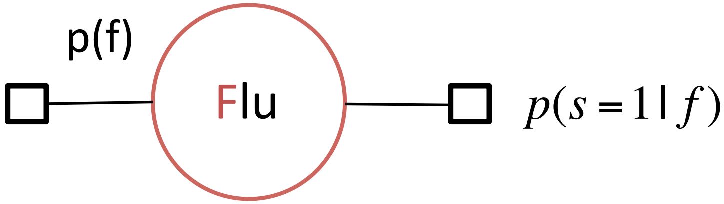

$$P(F=f \mid S=1)$$

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

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

$$P(F=1 \mid S=1)=\frac{p(f=1)p(s=1 \mid f=1)}{p(f=1)p(s=1 \mid f=1)+p(f=1)p(s=1 \mid f=1)}$$

$$=\frac{\alpha((1-\beta)*0.70+\beta*0.9)}{(1-\alpha)\beta*0.75+\alpha((1-\beta)*0.70+\beta*0.9),}$$

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

f	p(f)
0	1-α
1	α

f	p(s=1|f)
0	β*0.75
1	(1-β)*0.7+β*0.9

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).

Roadmap

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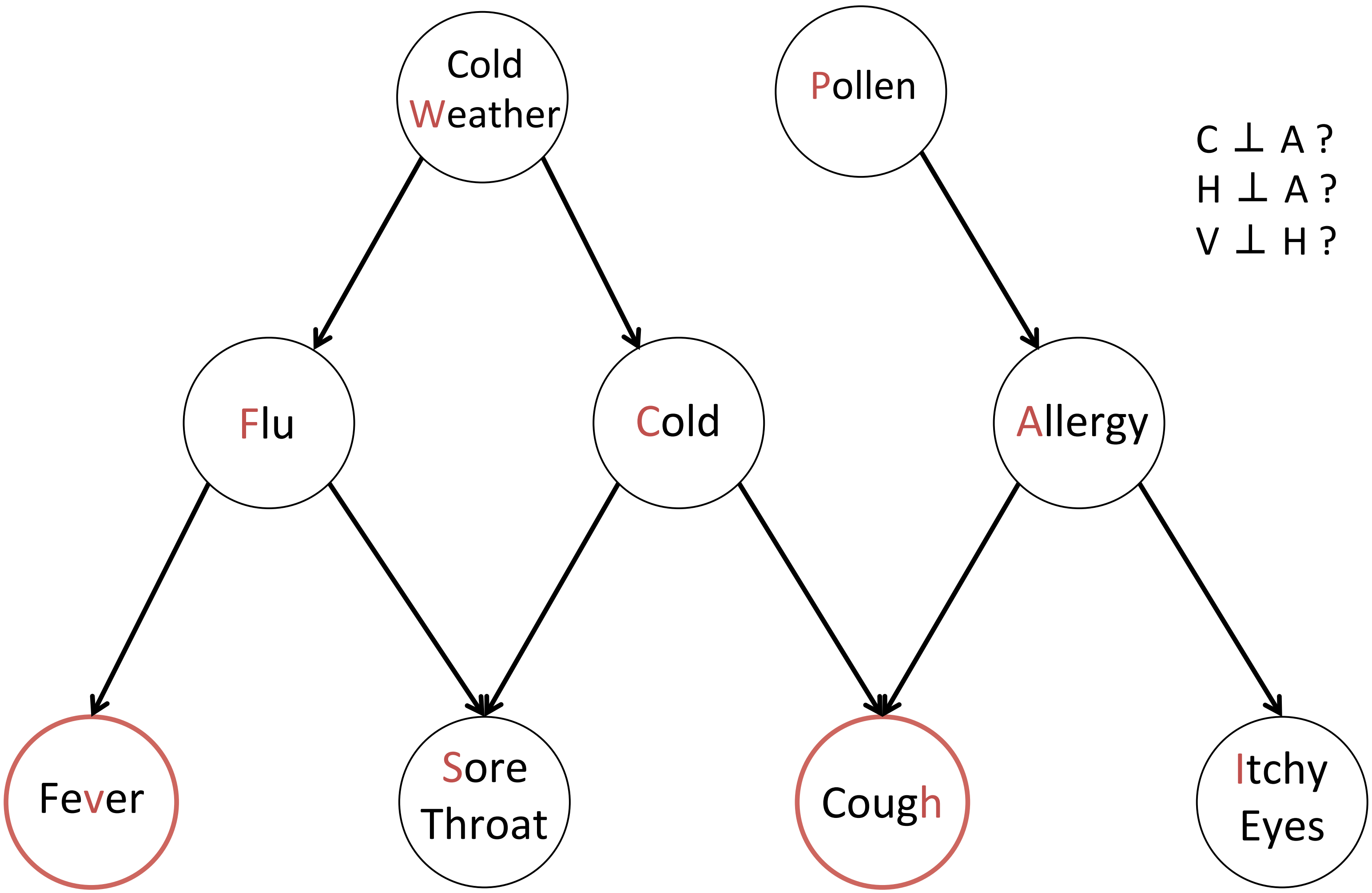
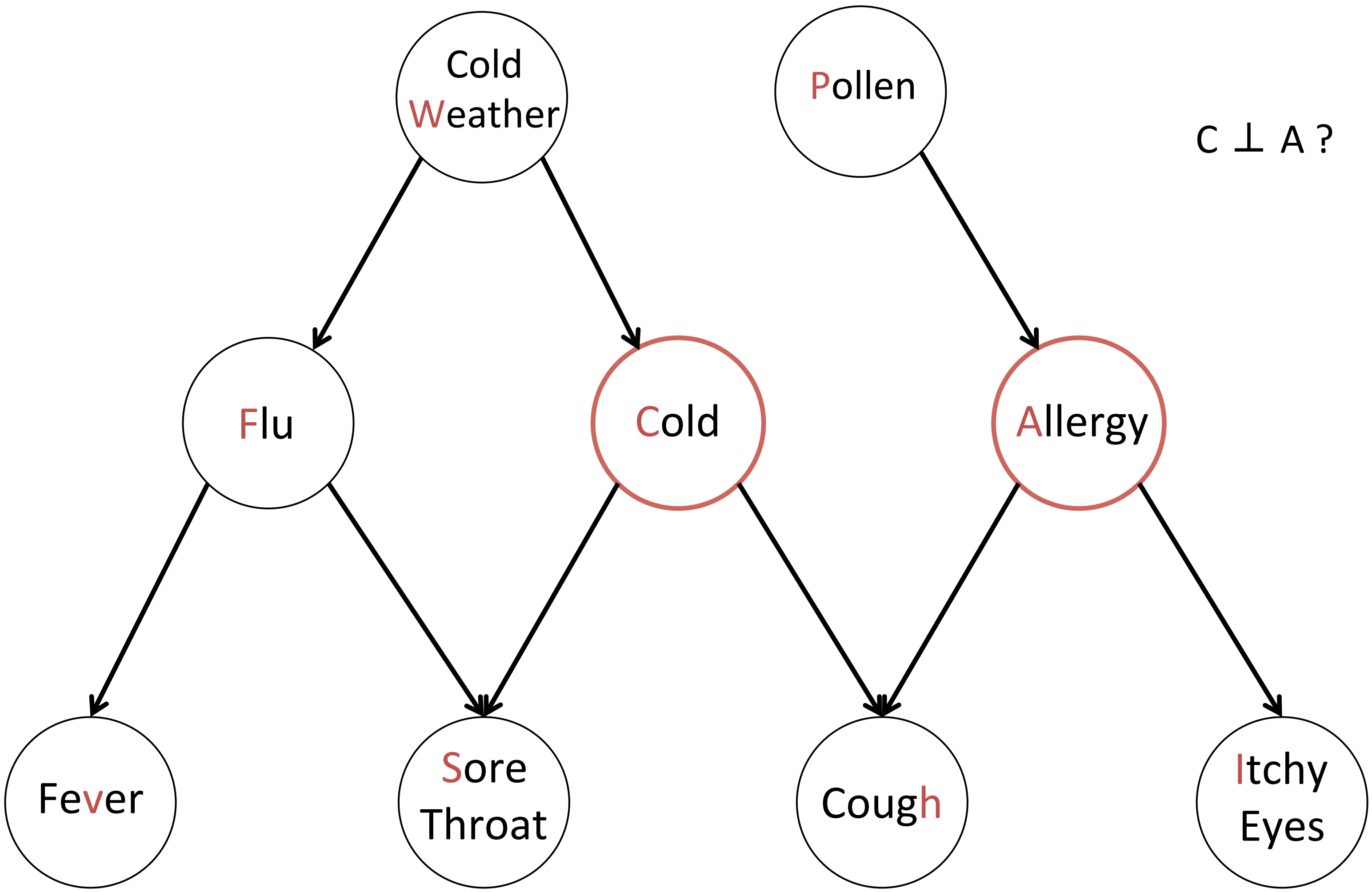
- Probabilistic Queries
- Conditional Independence
- Gibbs Sampling

Conditional Independence

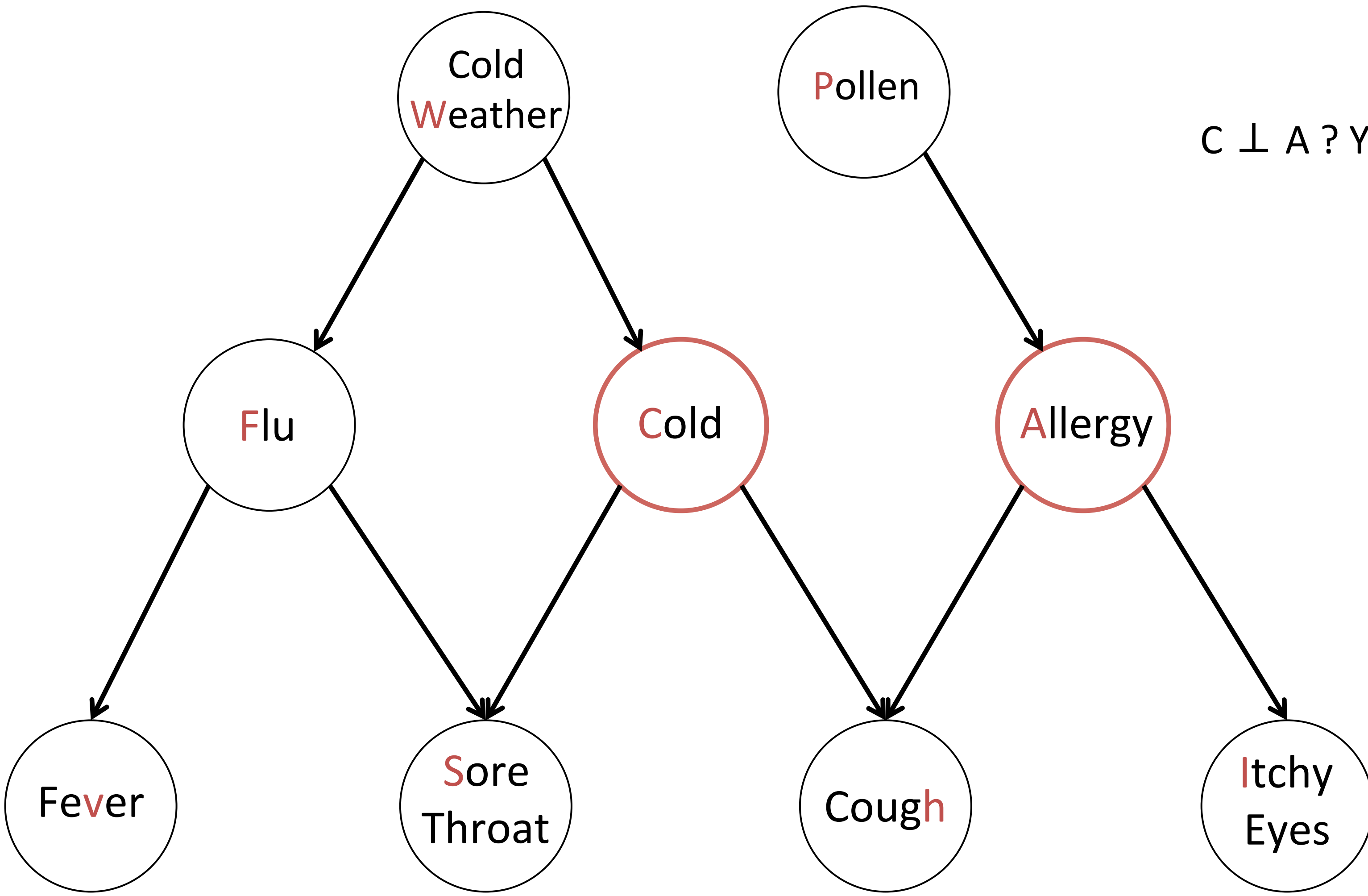


C ⊥ A ?
H ⊥ A ?
V ⊥ H ?

Conditional Independence

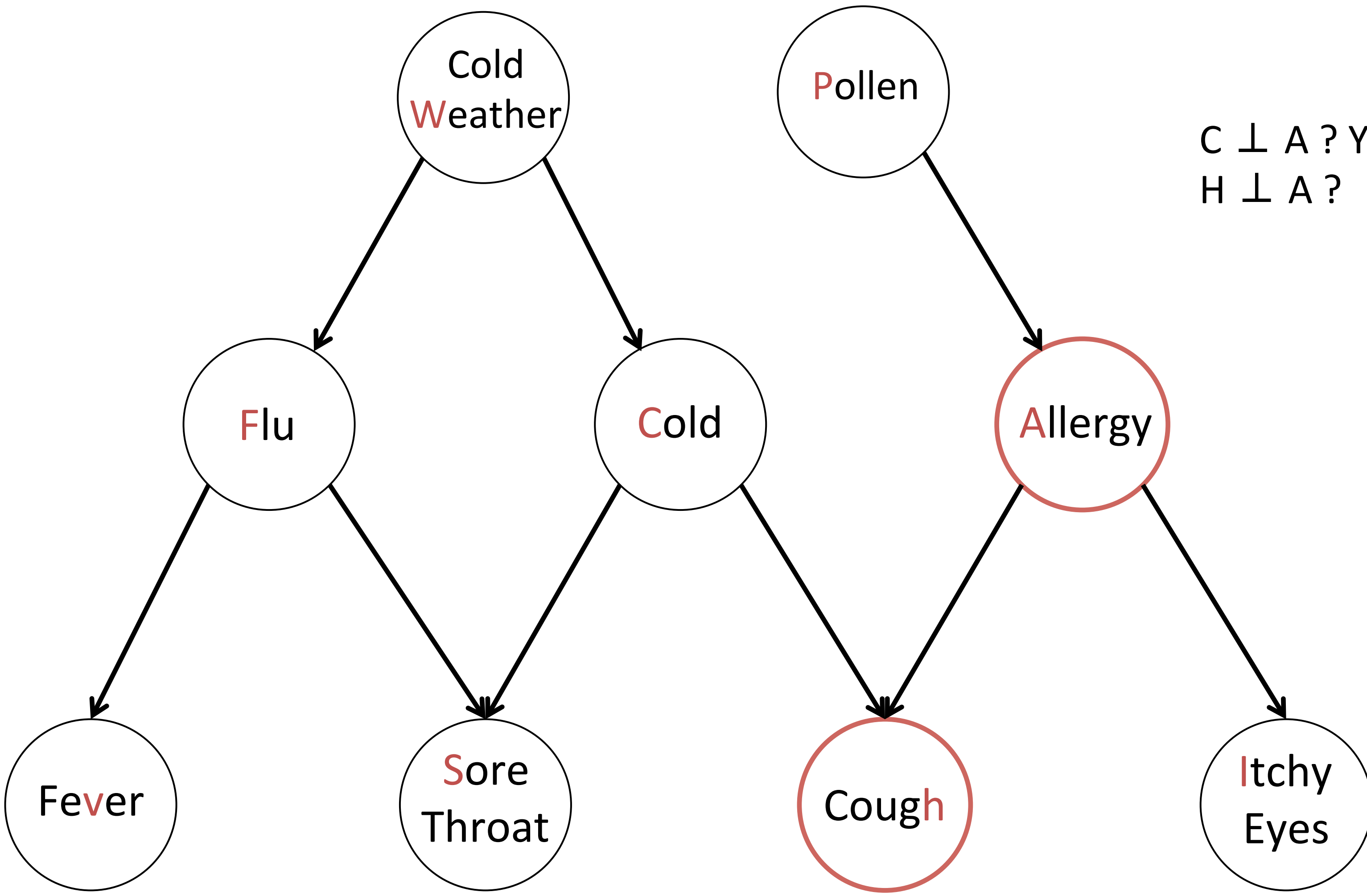


Conditional Independence



C ⊥ A ? Yes

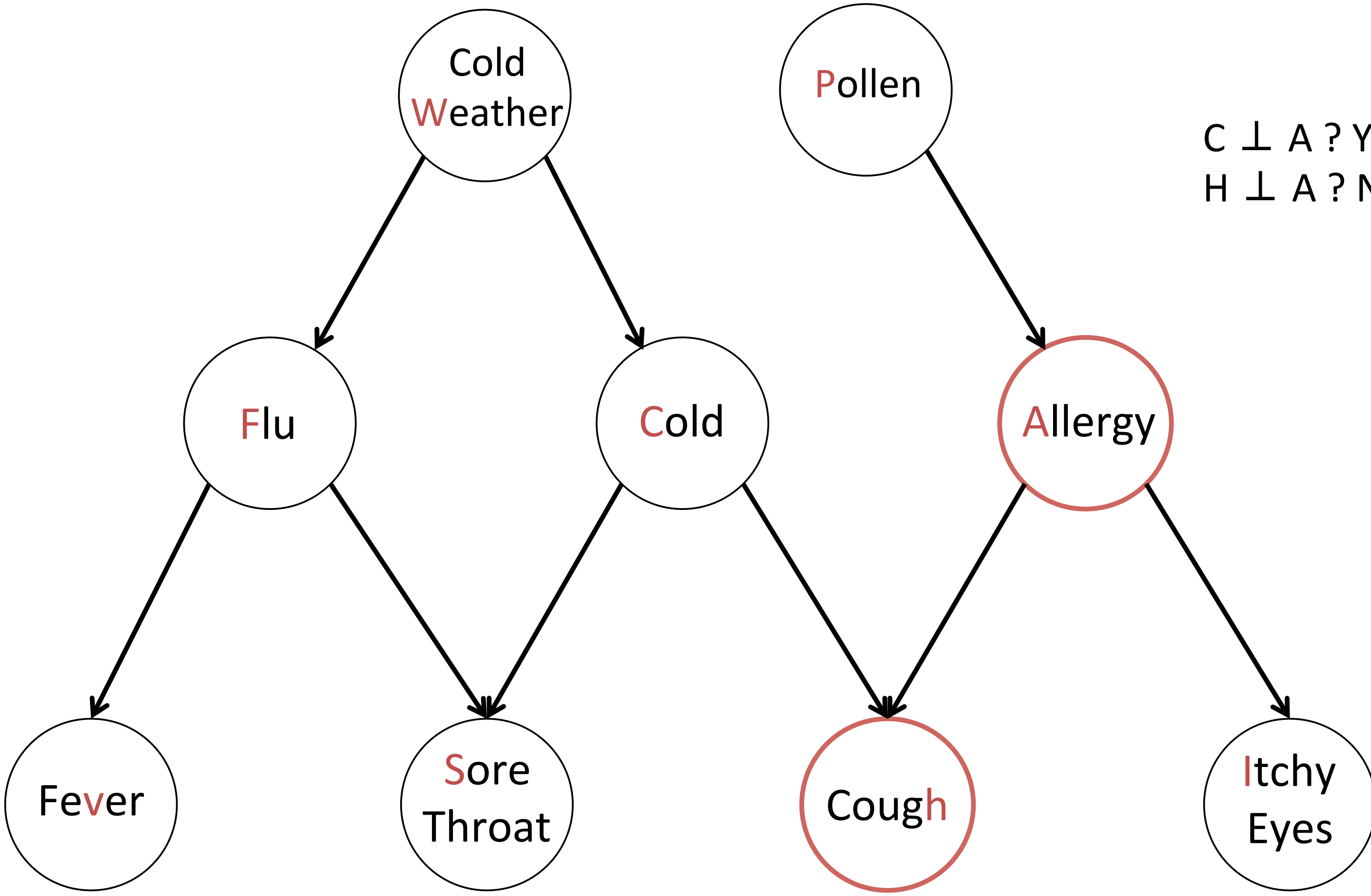
Conditional Independence



$C \perp A$? Yes

$H \perp A$?

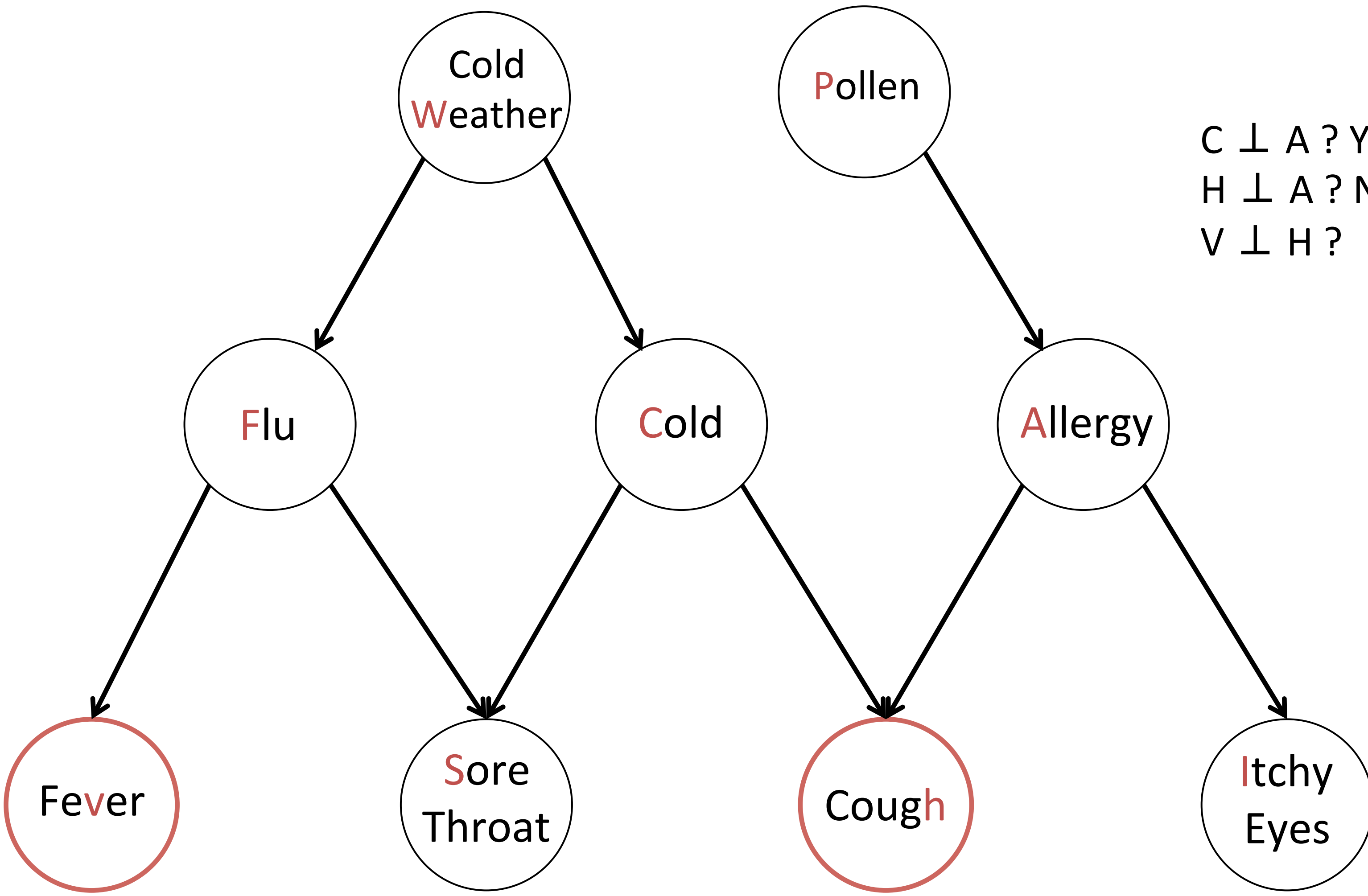
Conditional Independence



$C \perp A$? Yes

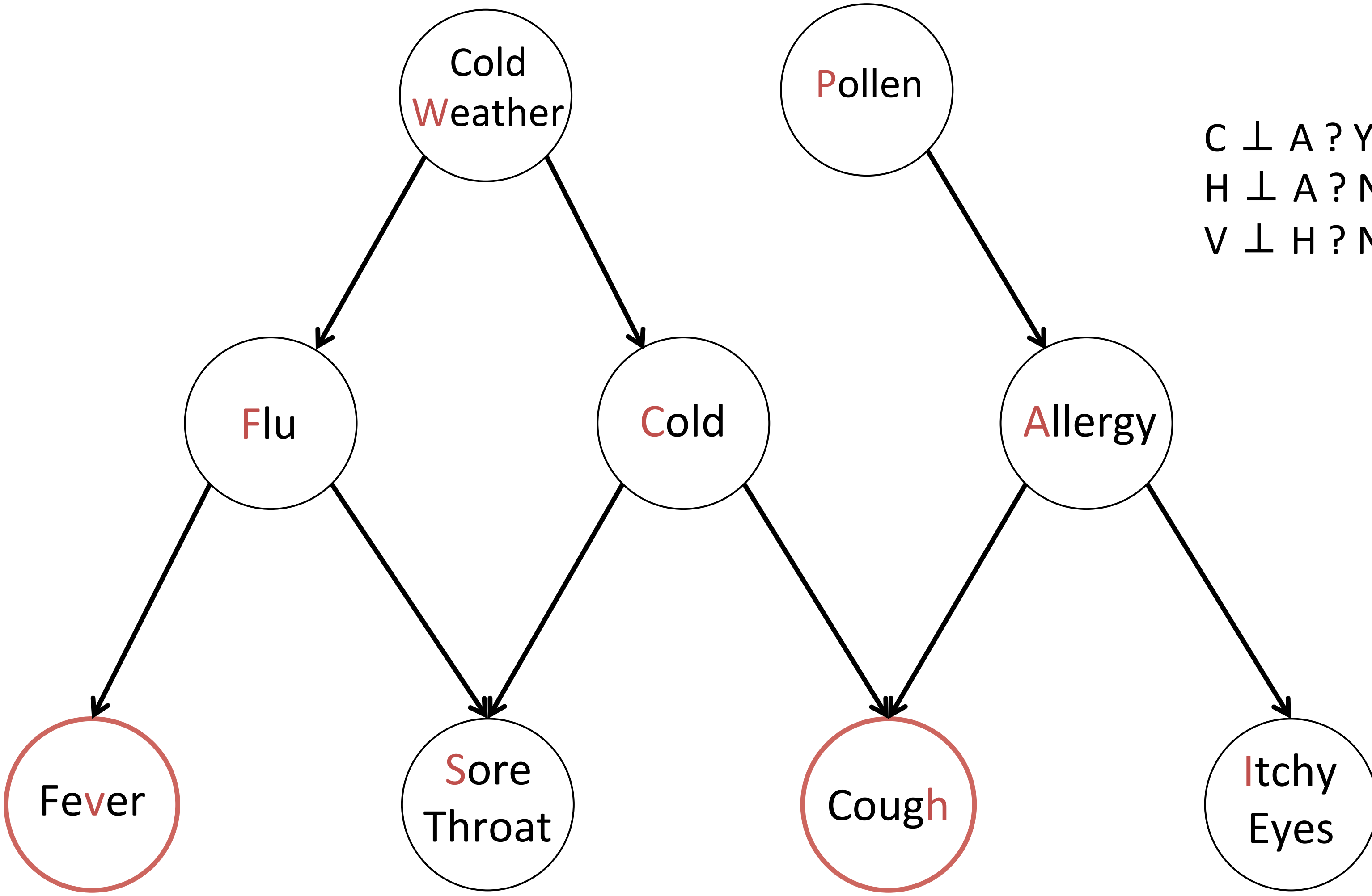
$H \perp A$? No

Conditional Independence



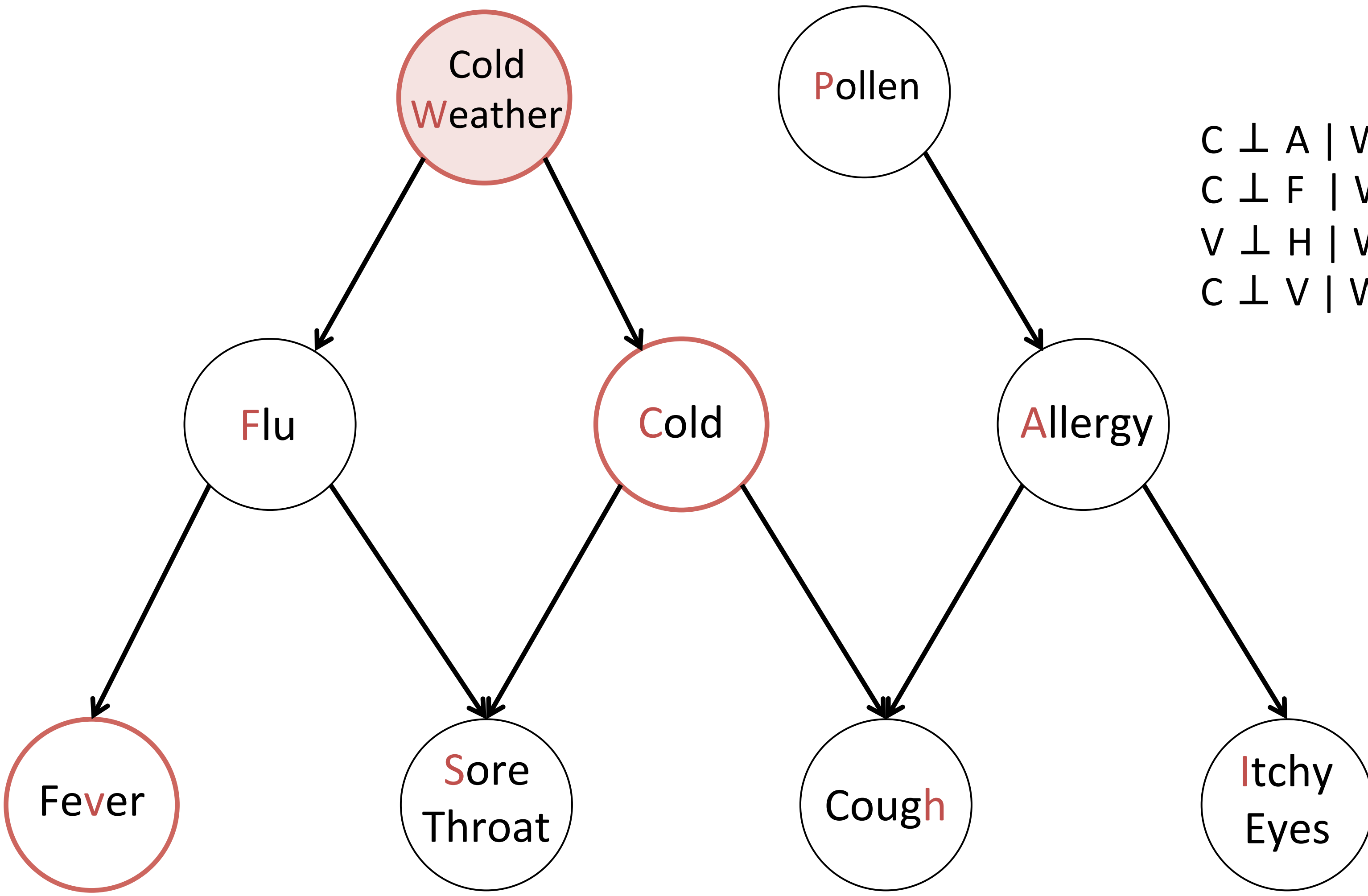
$C \perp A$? Yes
$H \perp A$? No
$V \perp H$?

Conditional Independence



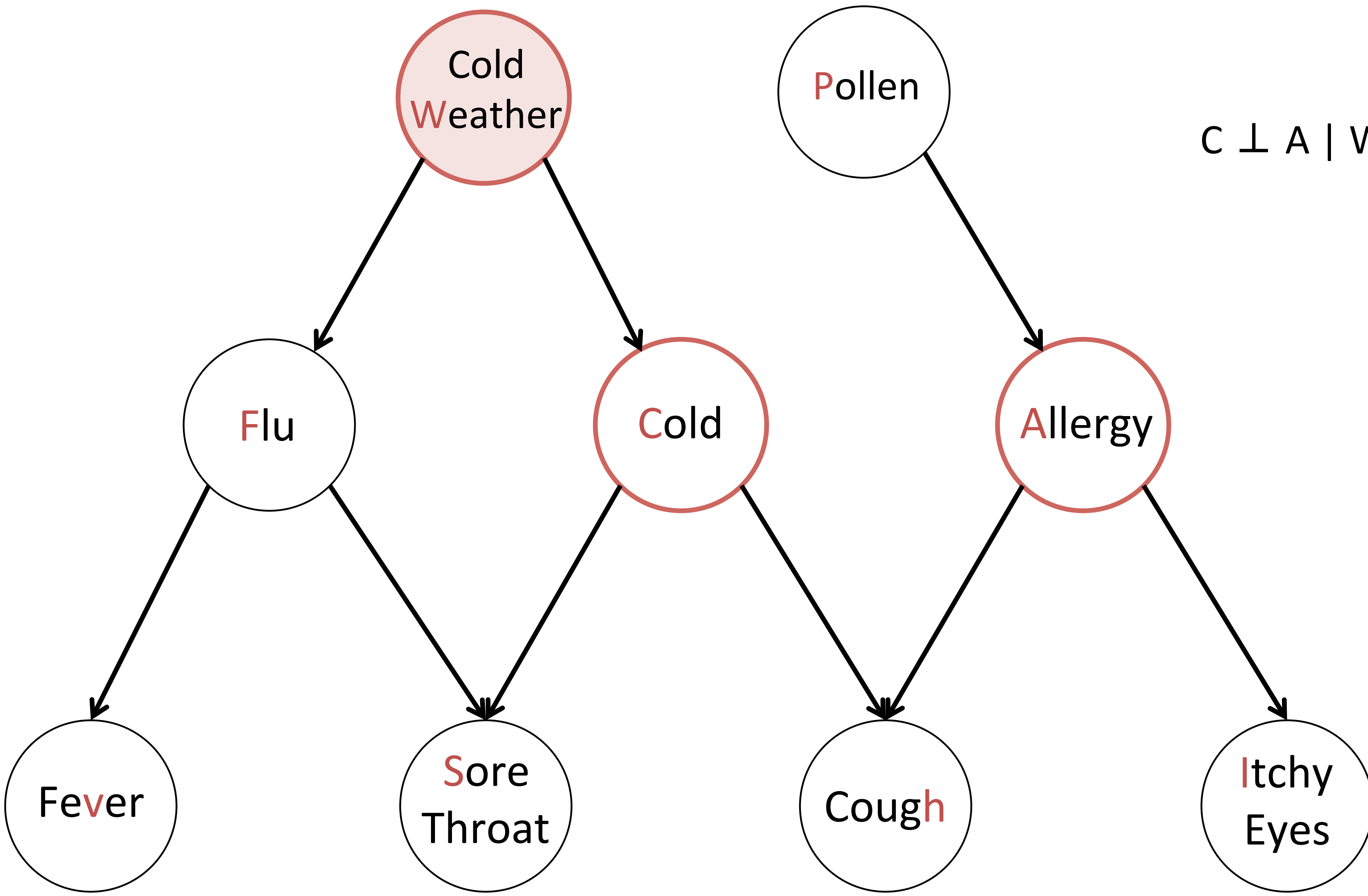
C ⊥ A ? Yes
H ⊥ A ? No
V ⊥ H ? No

Conditional Independence



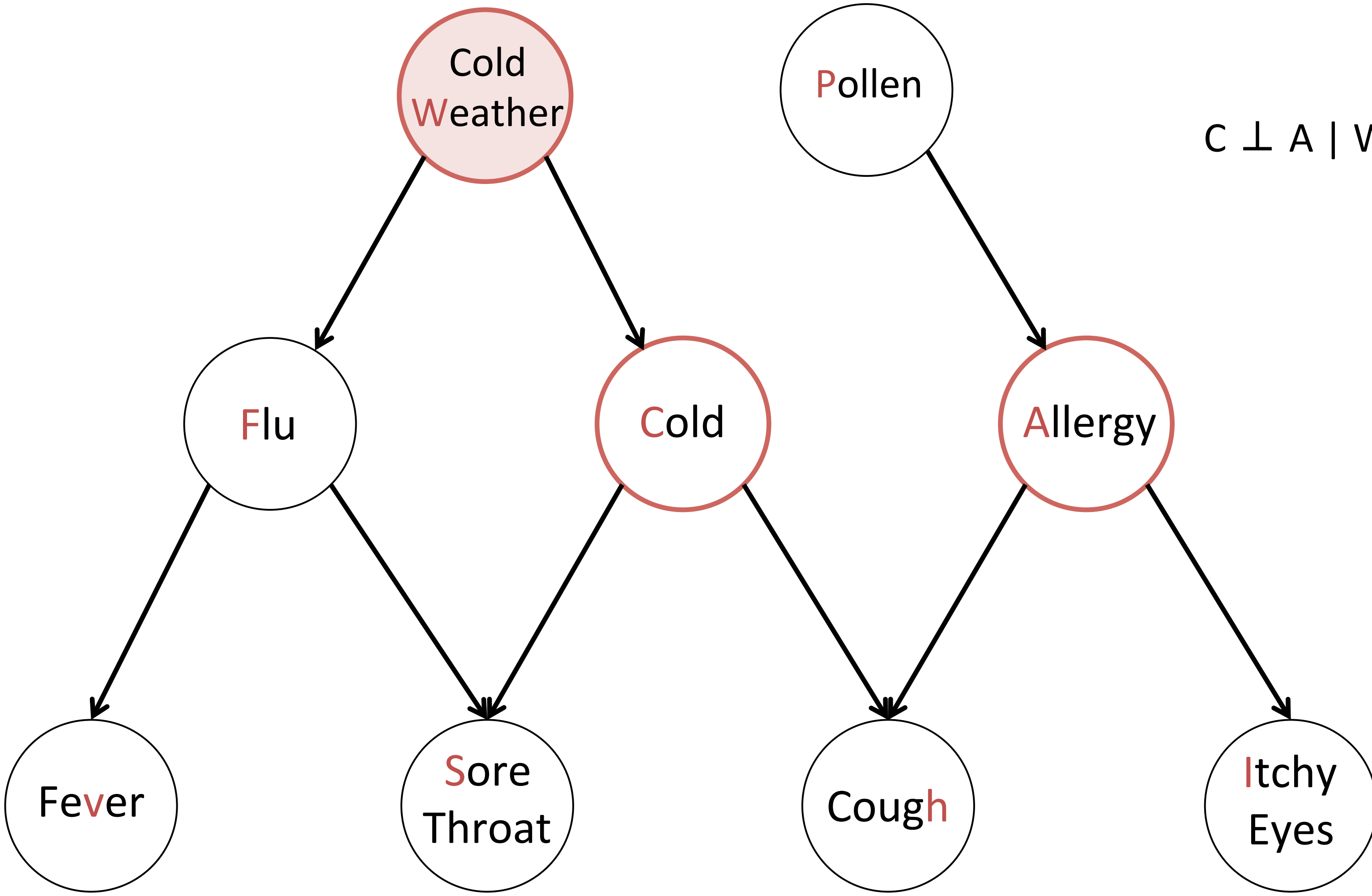
$C \perp A \mid W?$
$C \perp F \mid W?$
$V \perp H \mid W?$
$C \perp V \mid W?$

Conditional Independence



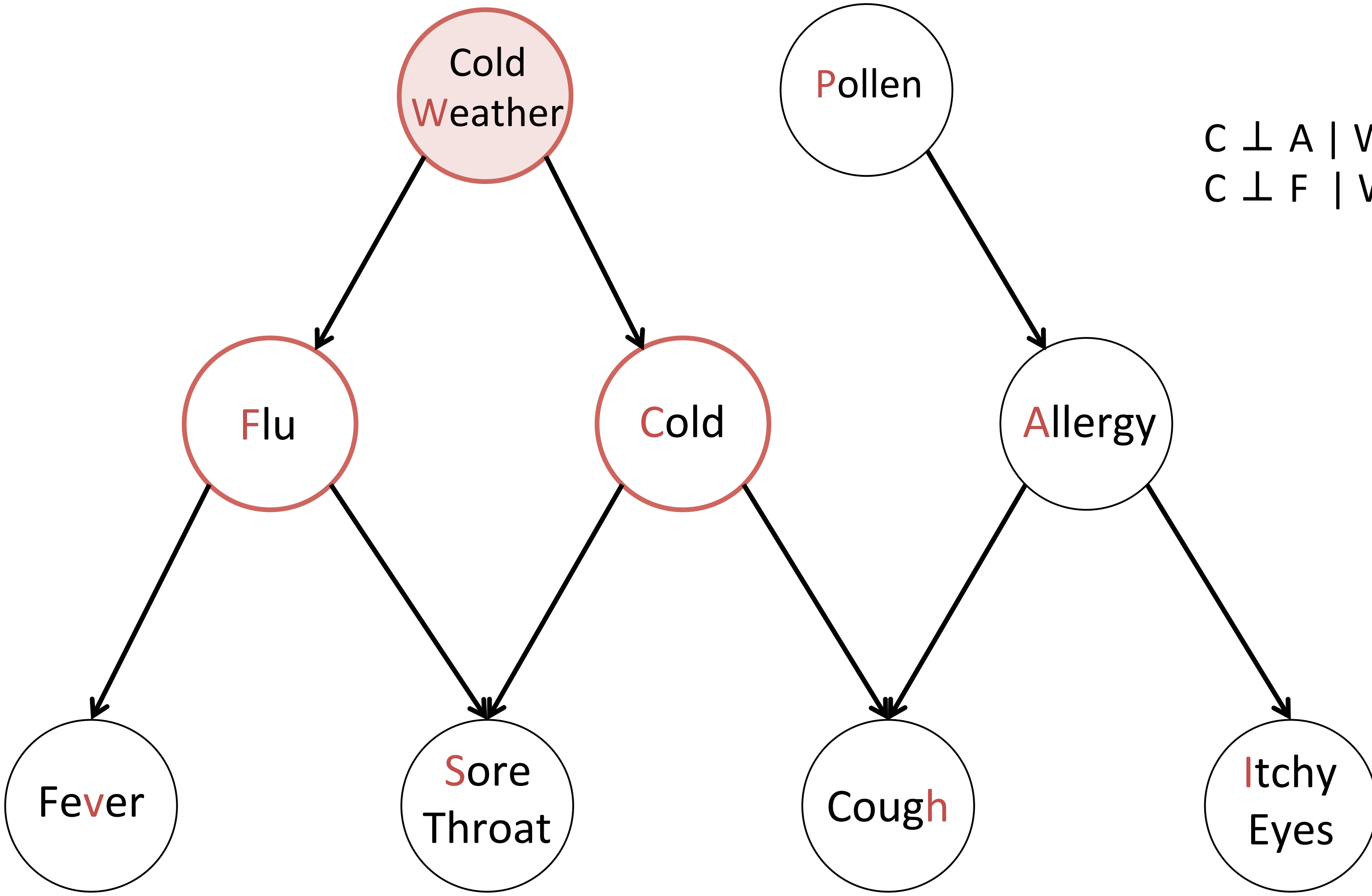
C ⊥ A | W?

Conditional Independence



C ⊥ A | W? Yes

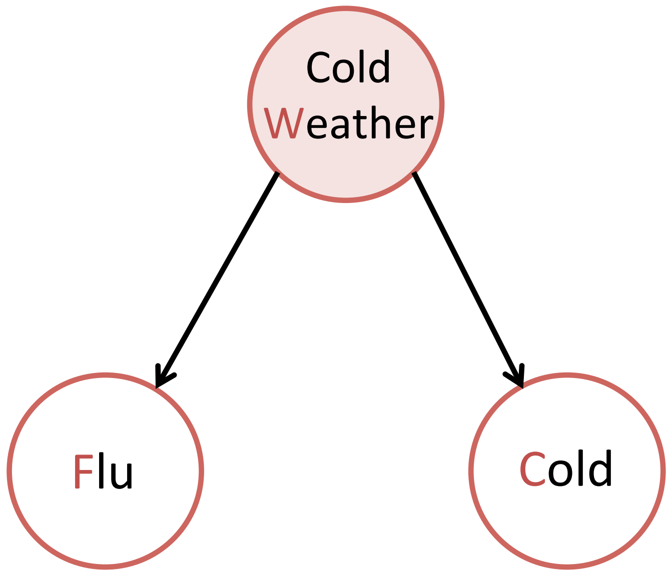
Conditional Independence



$C \perp A \mid W$? Yes

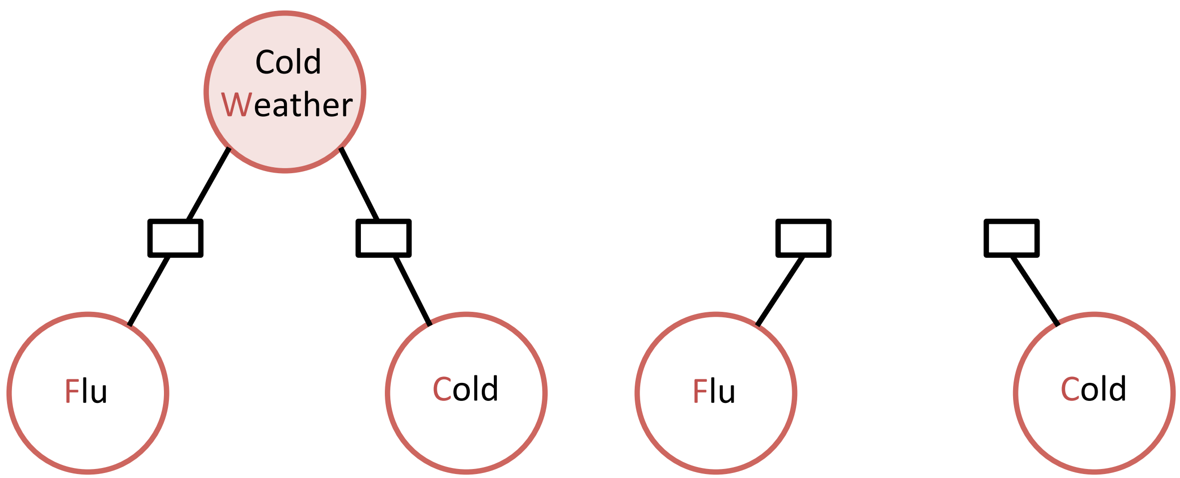
$C \perp F \mid W$?

Conditional Independence

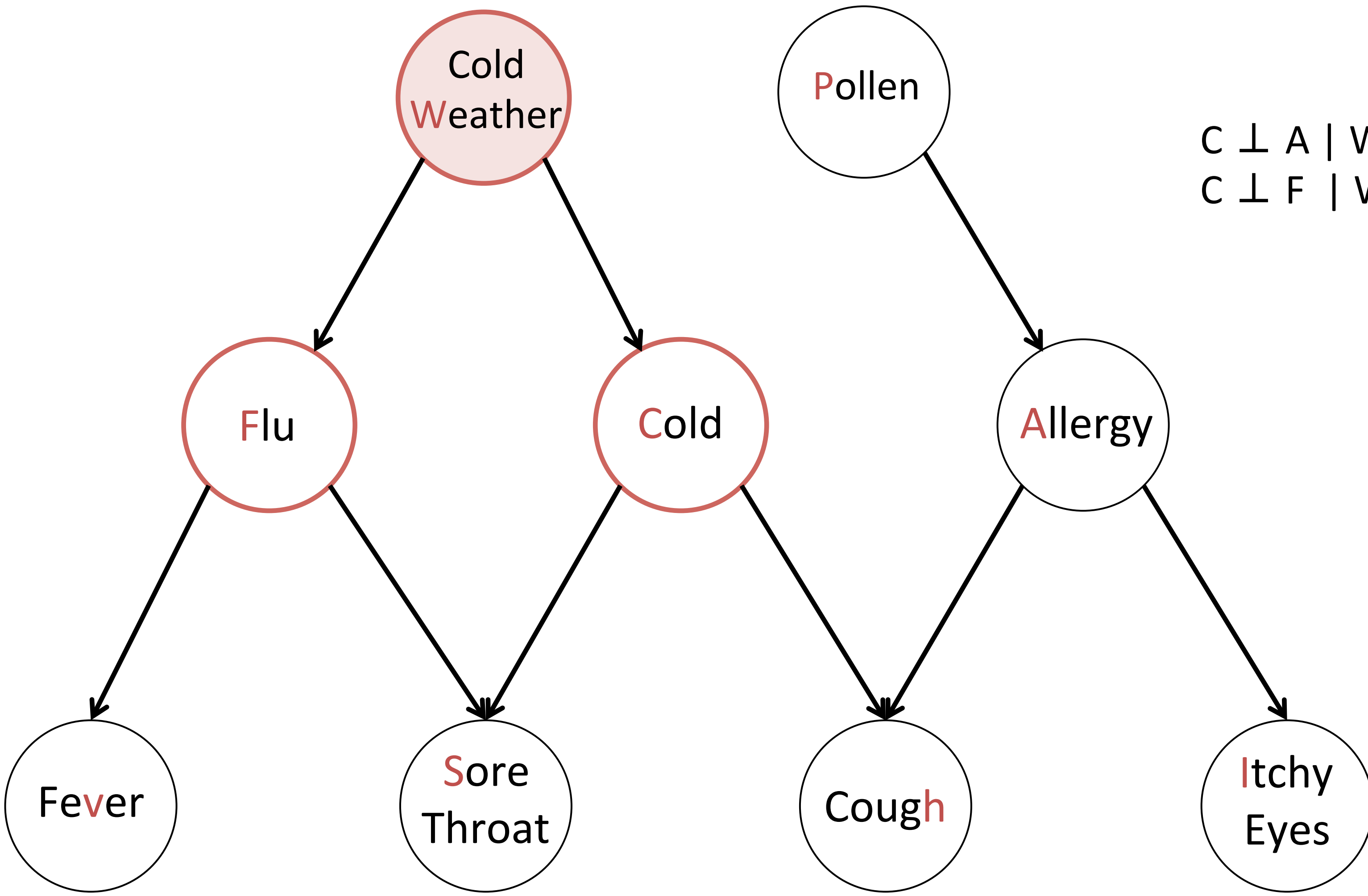


C ⊥ A | W? Yes

C ⊥ F | W?

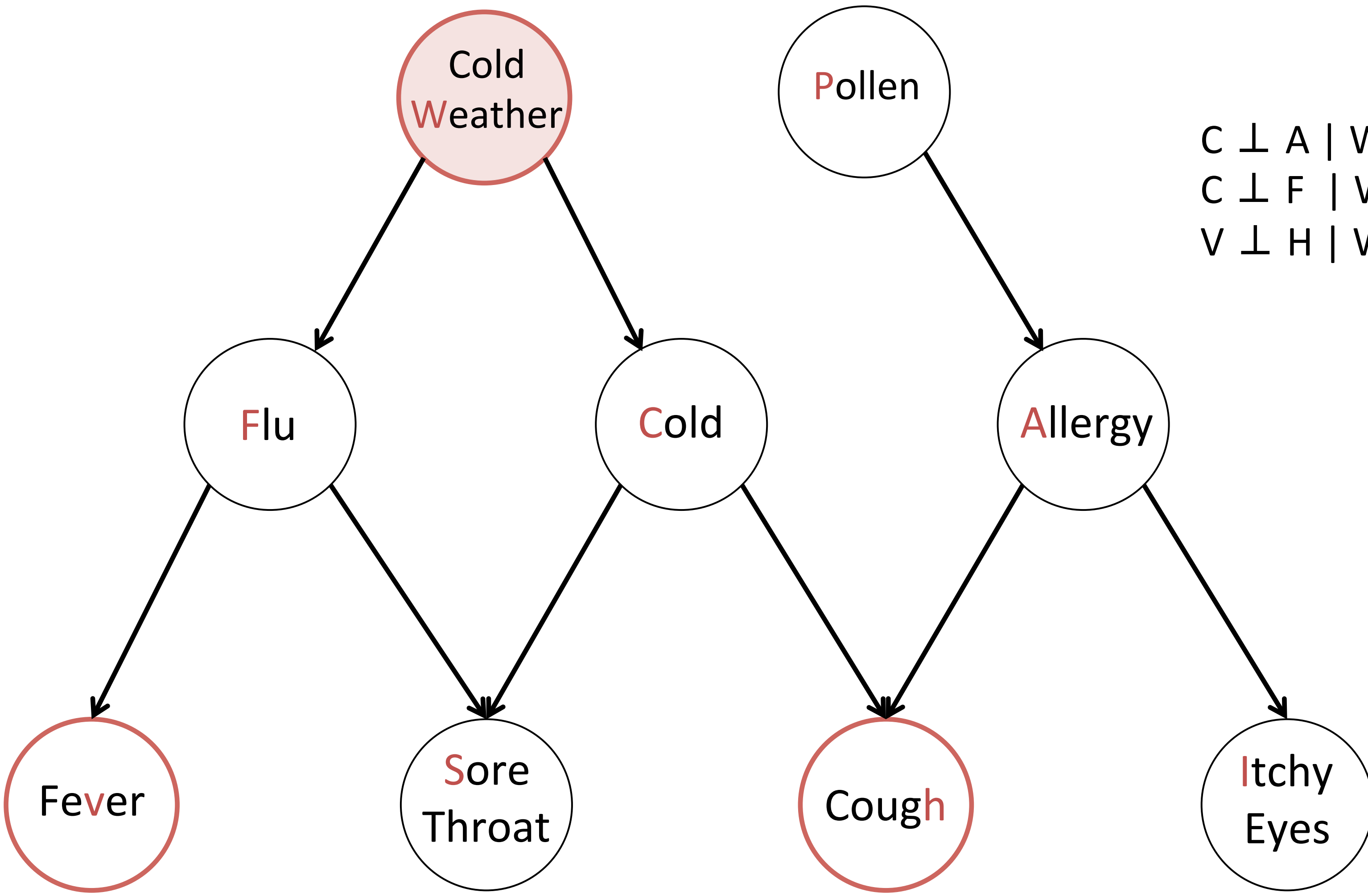


Conditional Independence



$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes

Conditional Independence

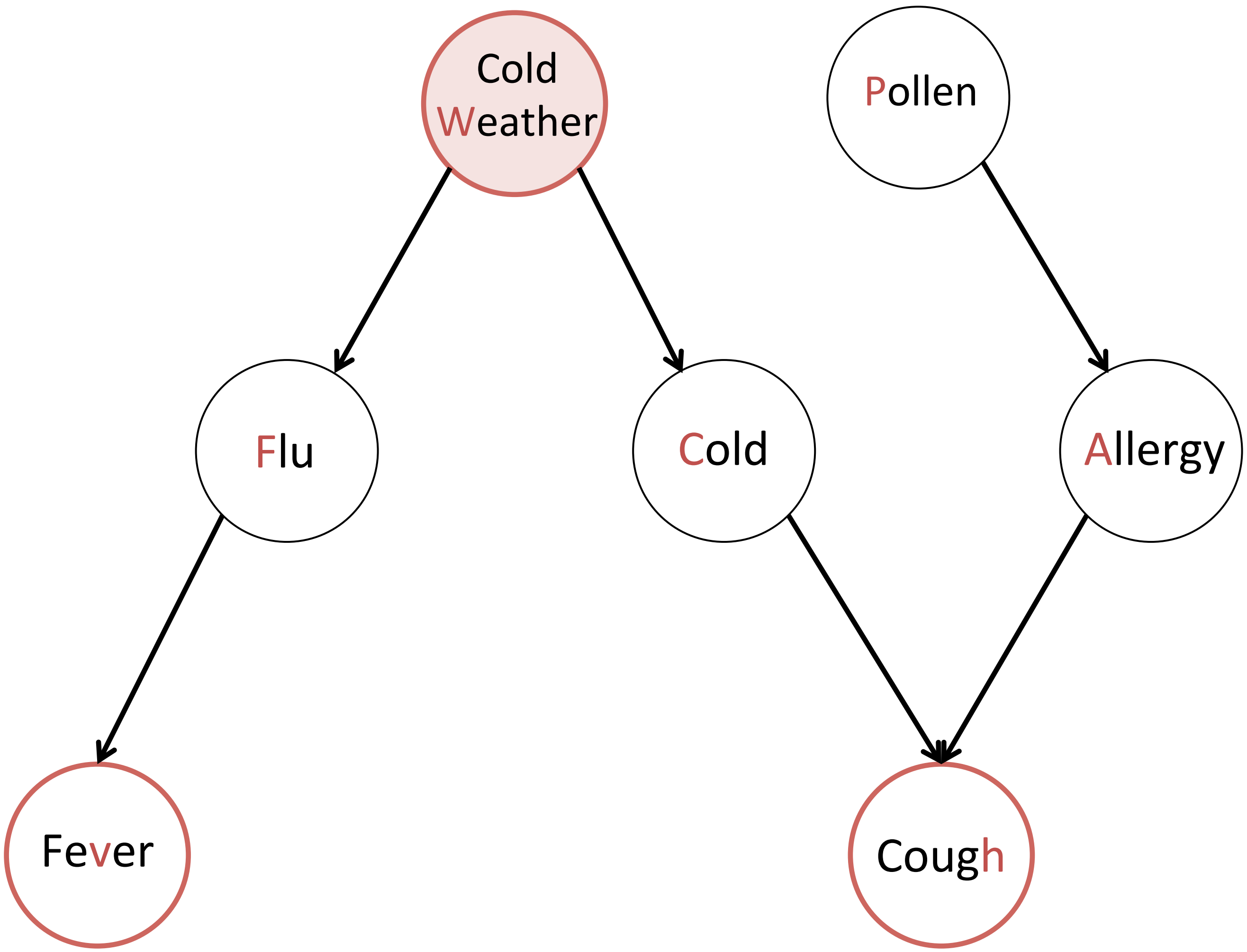


$C \perp A \mid W$? Yes

$C \perp F \mid W$? Yes

$V \perp H \mid W$?

Conditional Independence

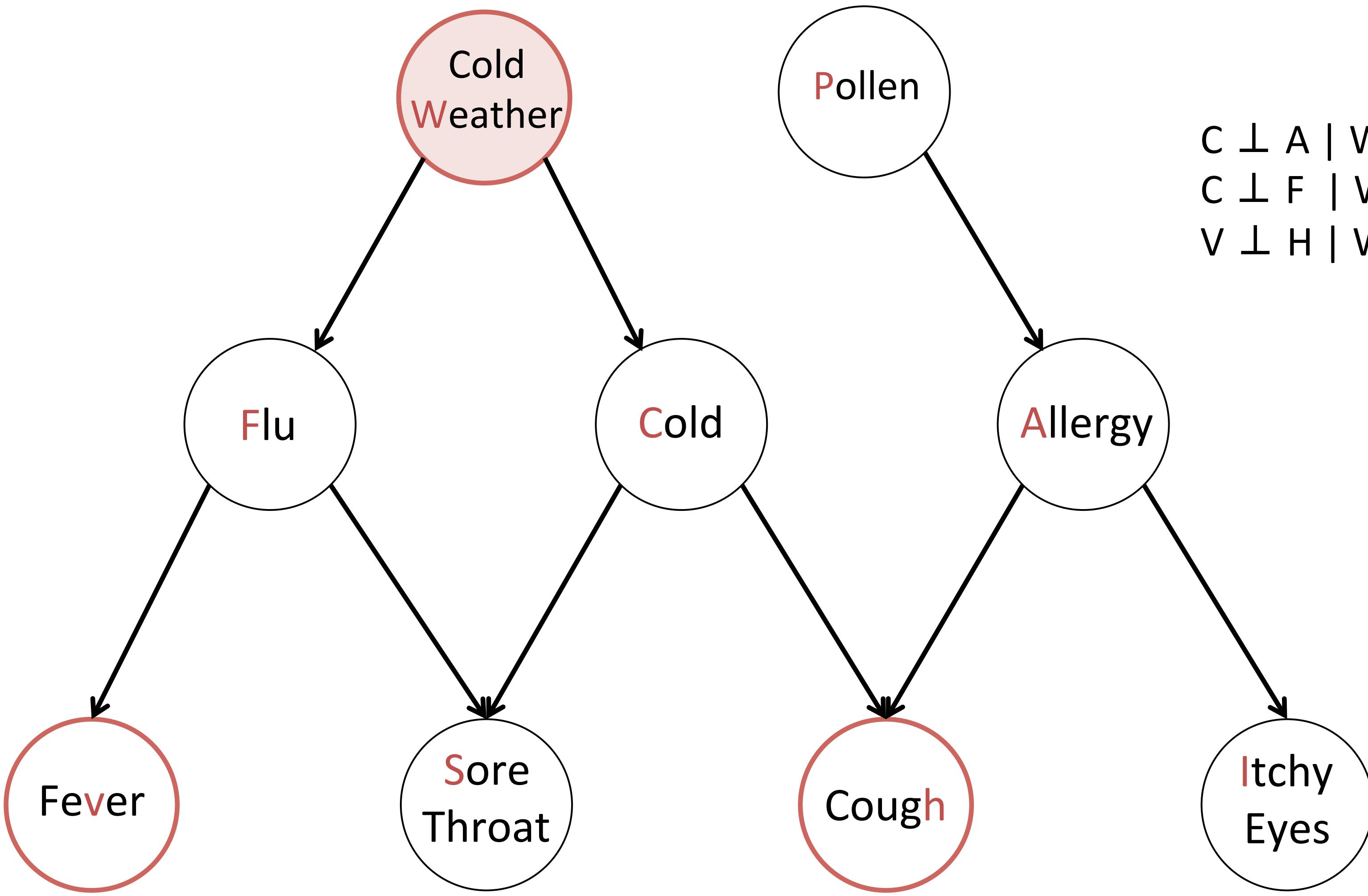


$C \perp A \mid W$? Yes

$C \perp F \mid W$? Yes

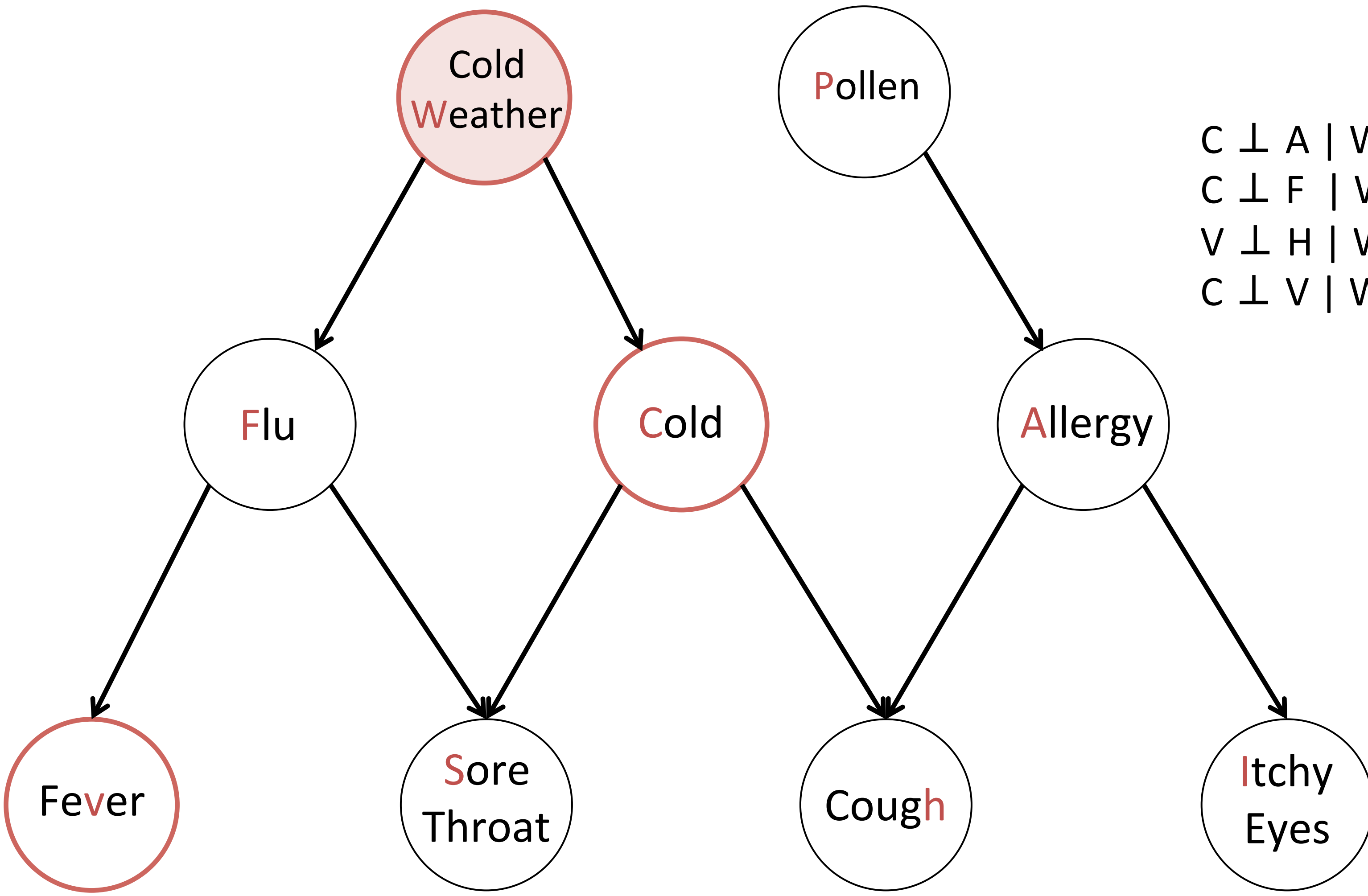
$V \perp H \mid W$?

Conditional Independence



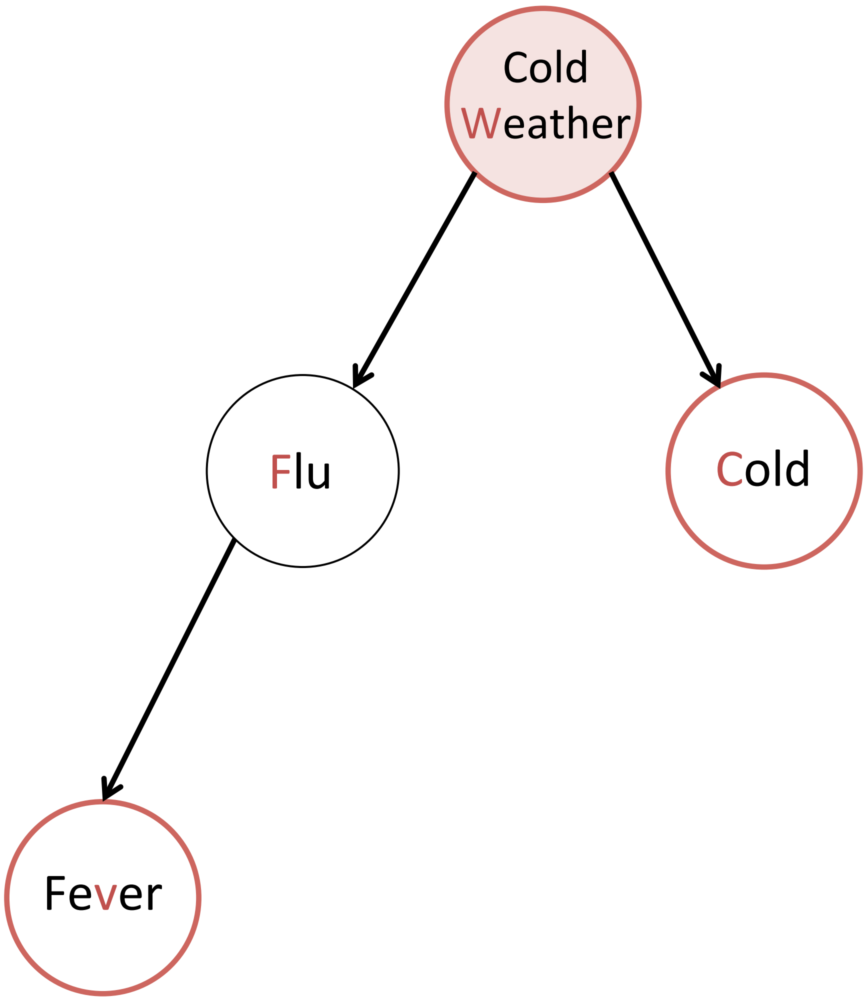
C ⊥ A | W? Yes
C ⊥ F | W? Yes
V ⊥ H | W? Yes

Conditional Independence



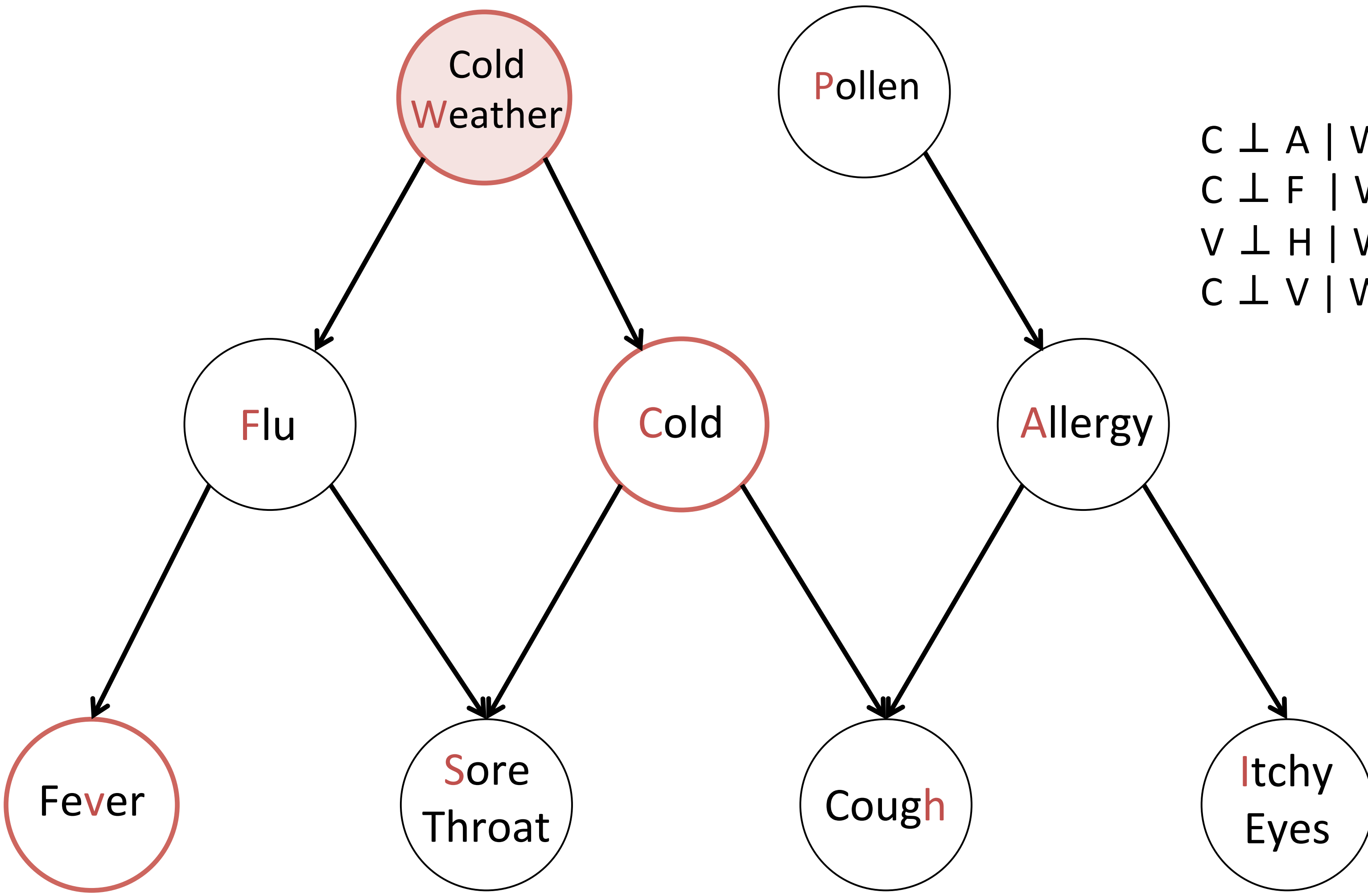
$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$?

Conditional Independence



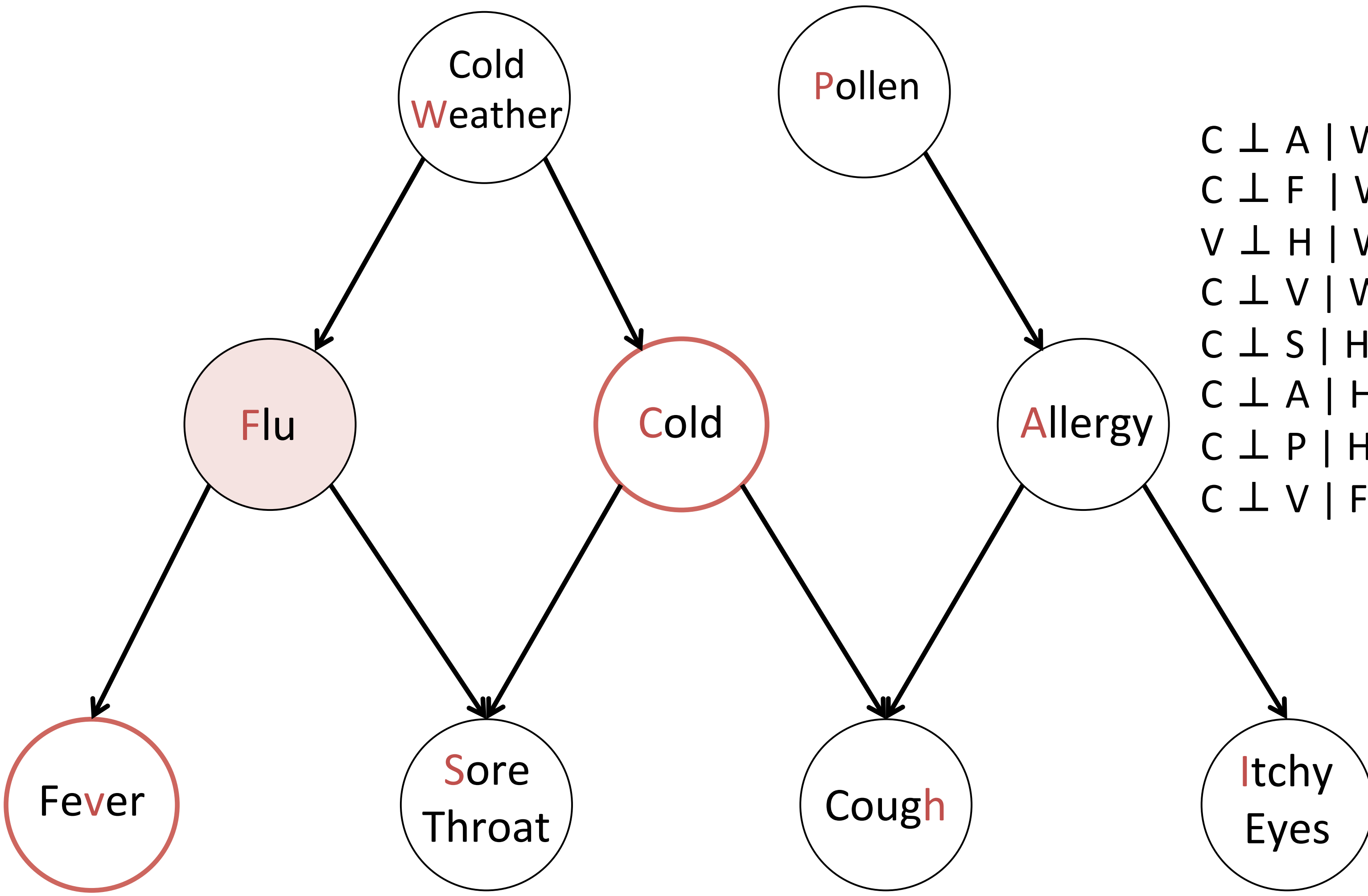
C ⊥ A | W? Yes
C ⊥ F | W? Yes
V ⊥ H | W? Yes
C ⊥ V | W?

Conditional Independence



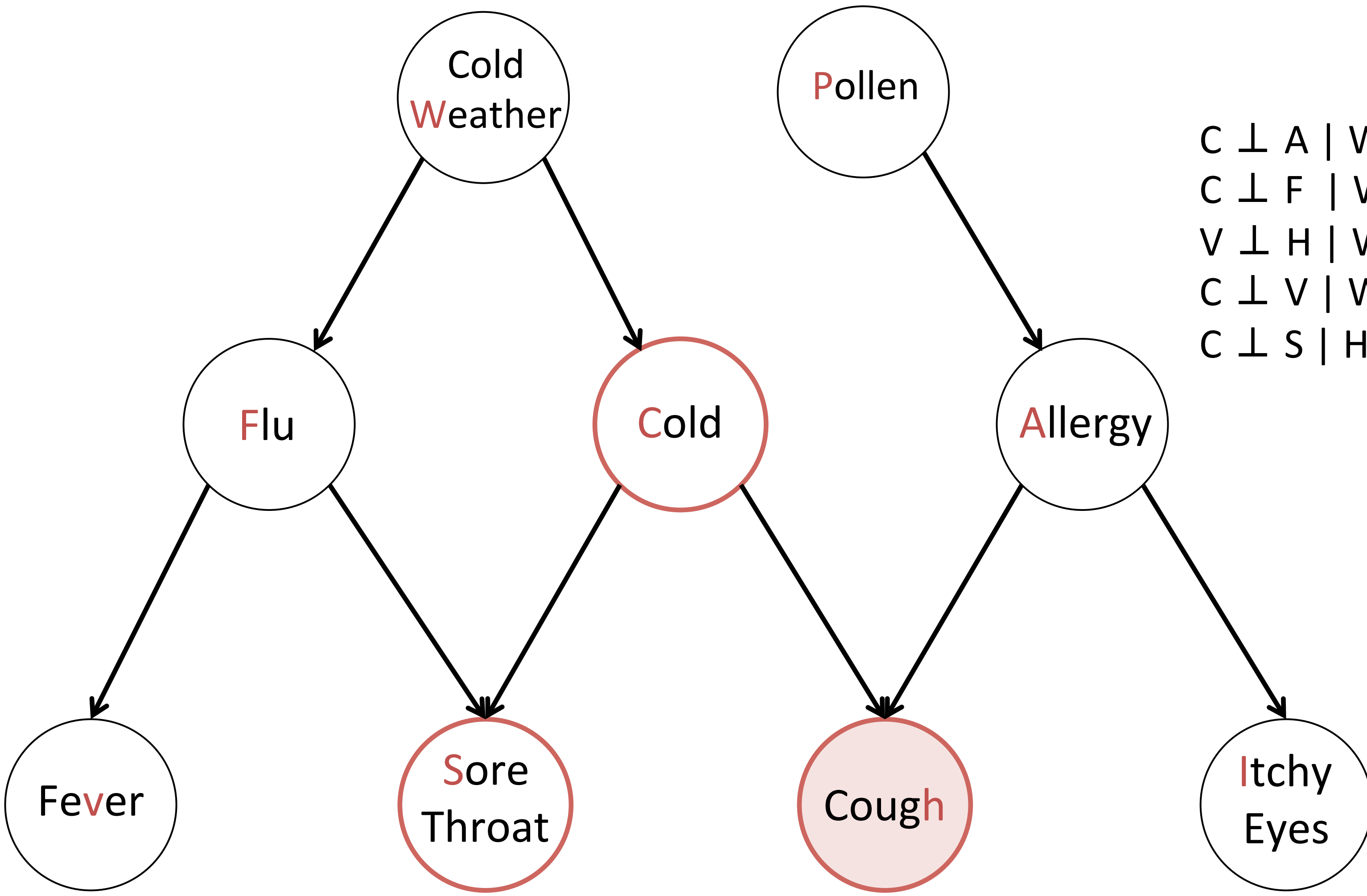
C ⊥ A | W? Yes
C ⊥ F | W? Yes
V ⊥ H | W? Yes
C ⊥ V | W? Yes

Conditional Independence



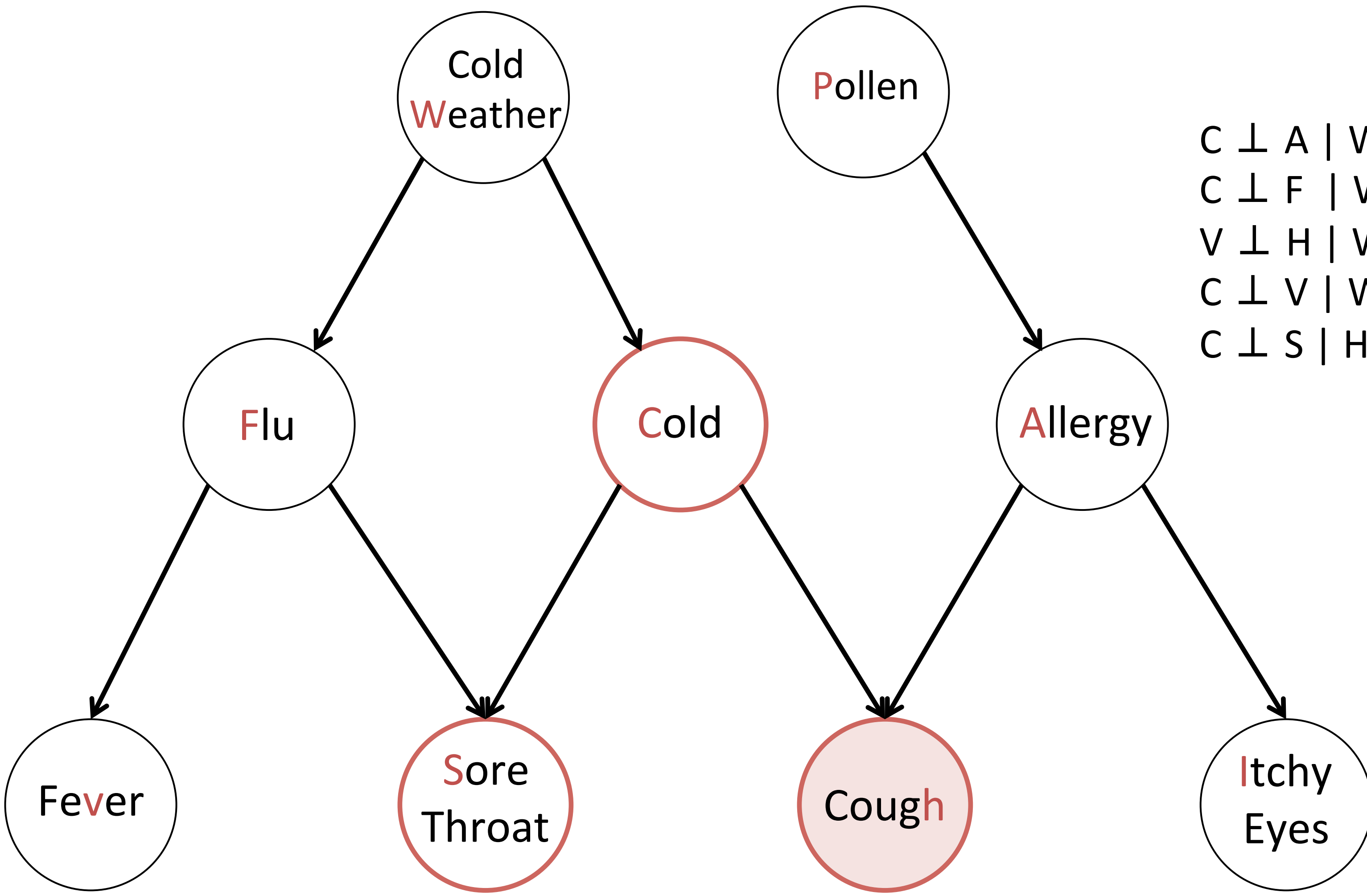
$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$?
$C \perp A \mid H$?
$C \perp P \mid H$?
$C \perp V \mid F$?

Conditional Independence



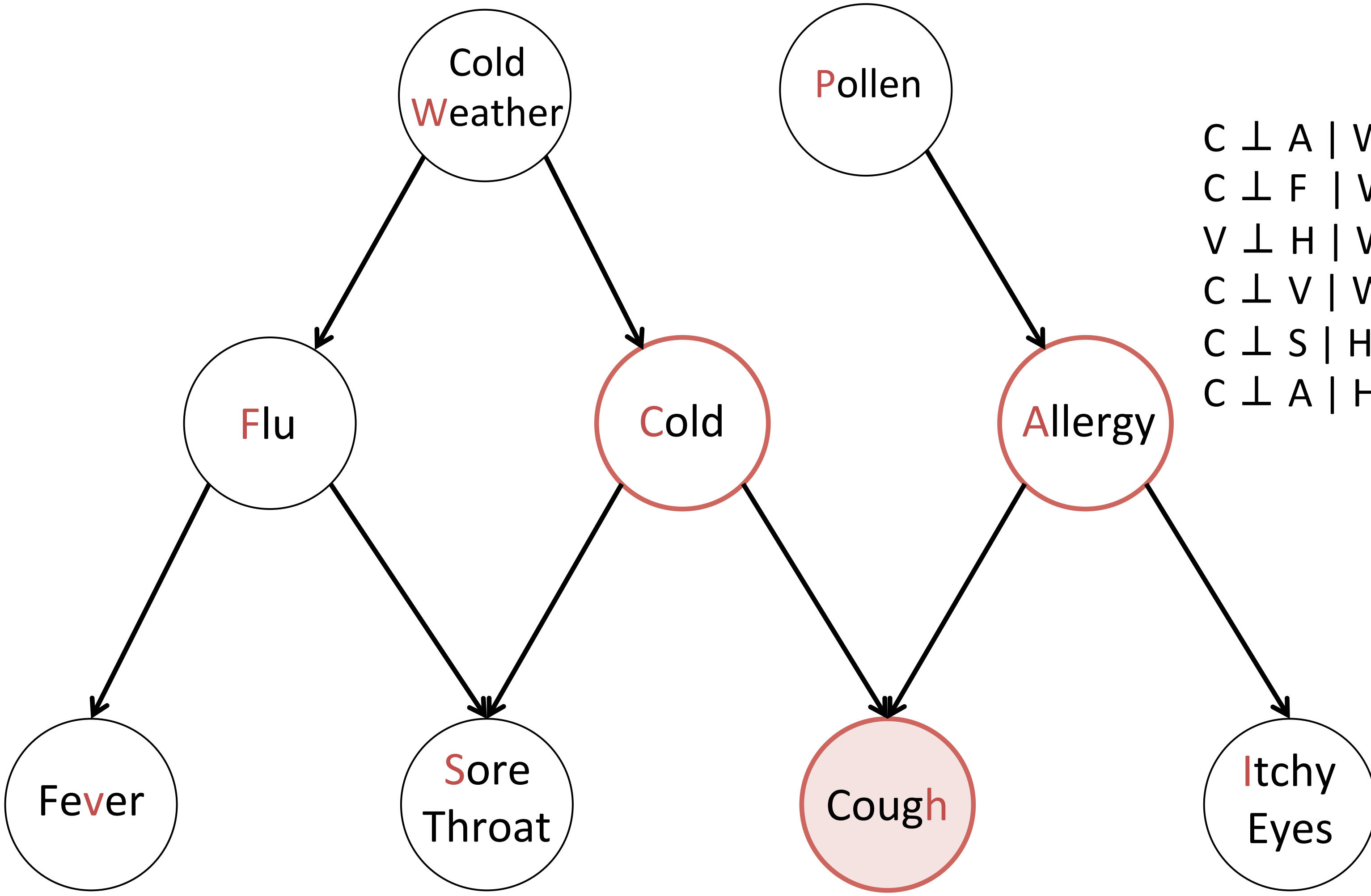
$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$?

Conditional Independence



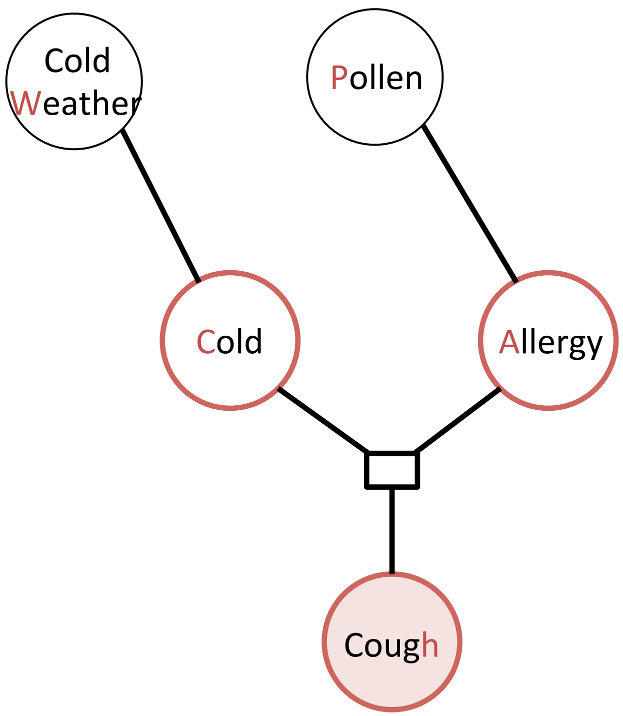
C ⊥ A | W? Yes
C ⊥ F | W? Yes
V ⊥ H | W? Yes
C ⊥ V | W? Yes
C ⊥ S | H? No

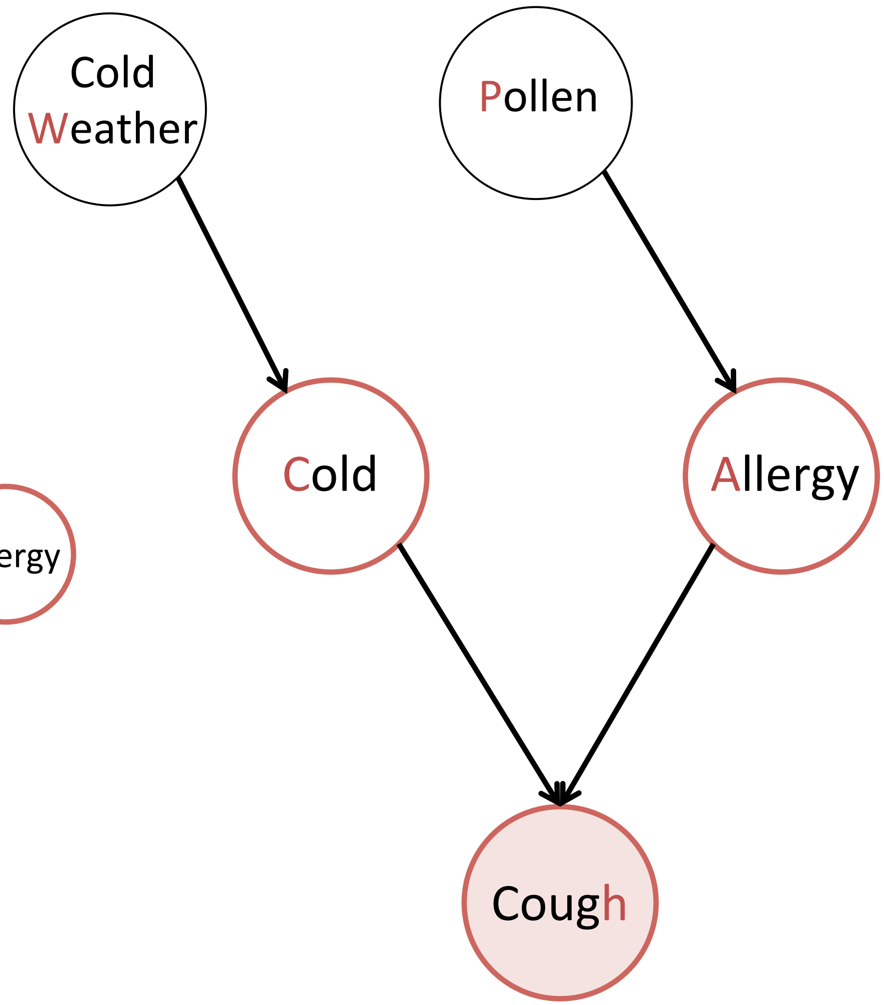
Conditional Independence



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

Conditional Independence

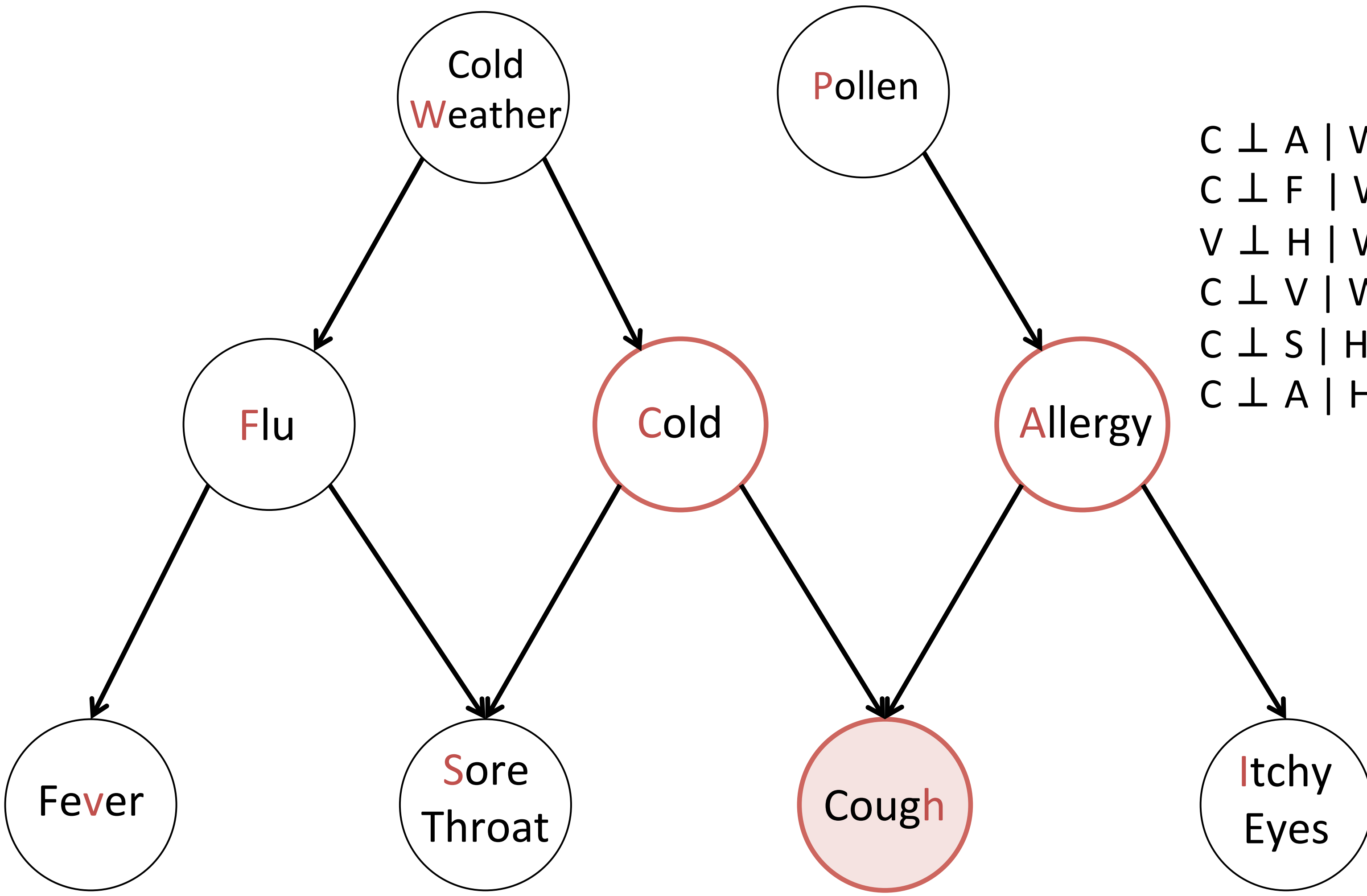




$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$? No
$C \perp A \mid H$?

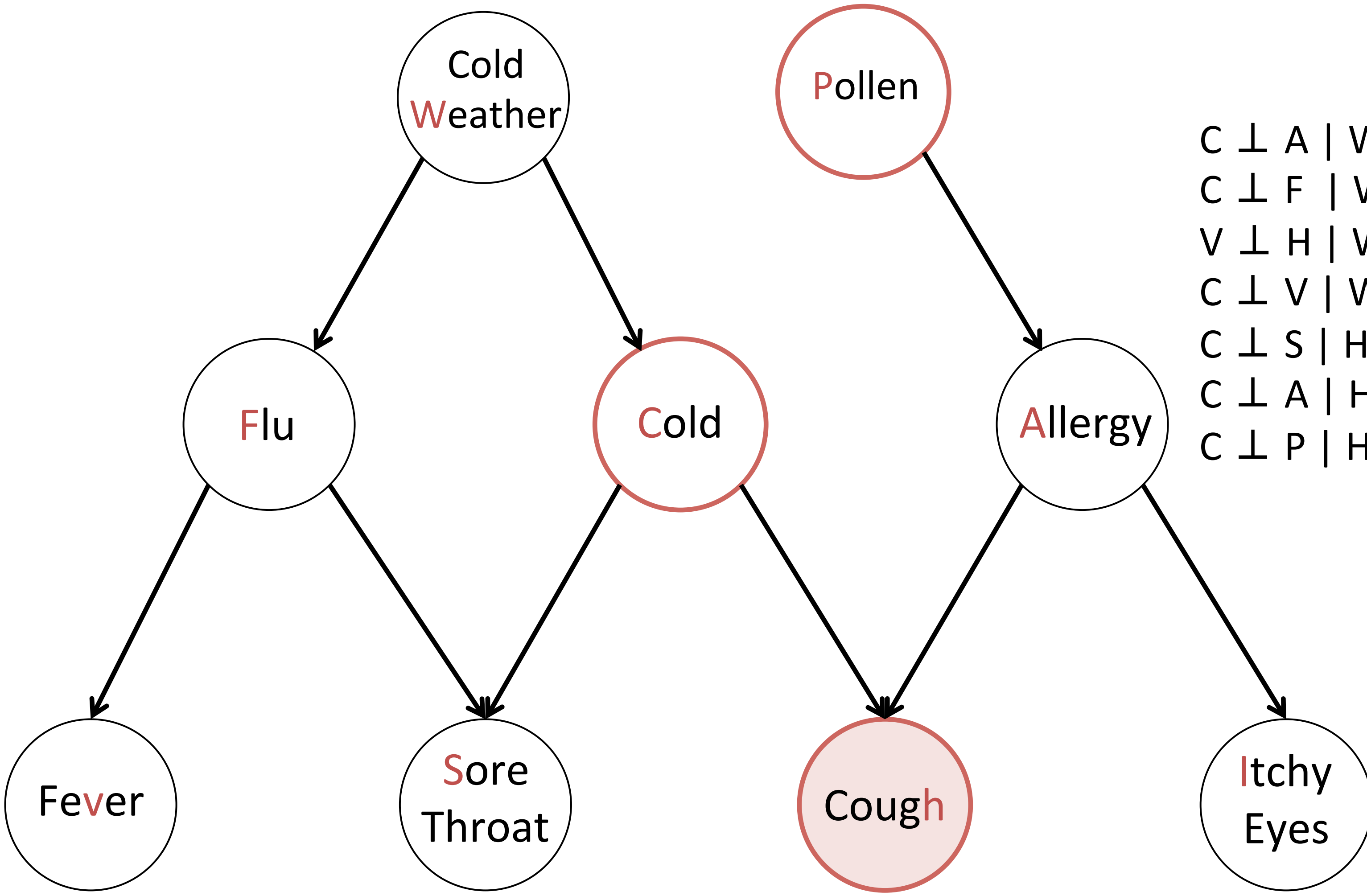
Explaining Away!

Conditional Independence



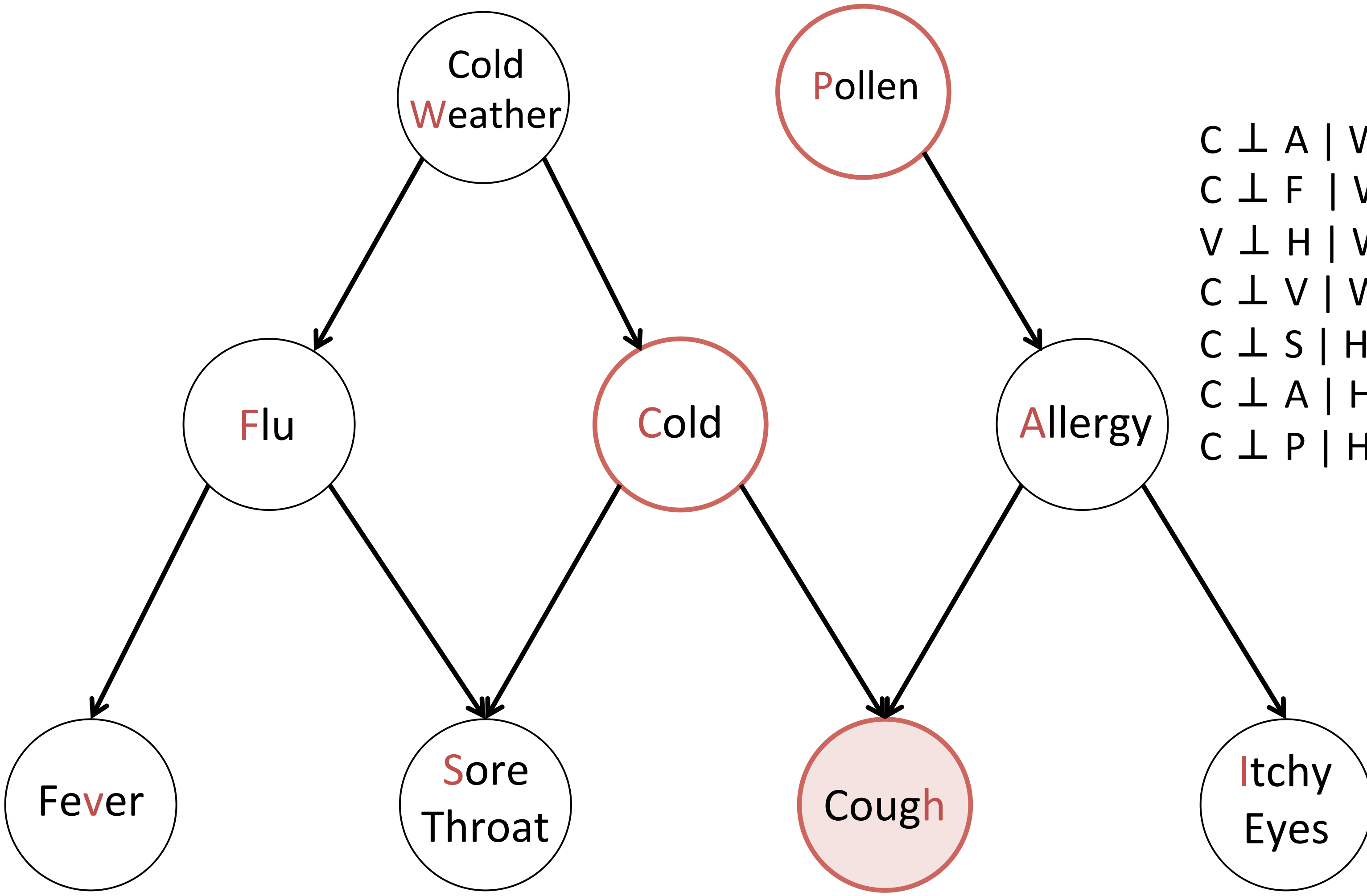
$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$? No
$C \perp A \mid H$? No

Conditional Independence



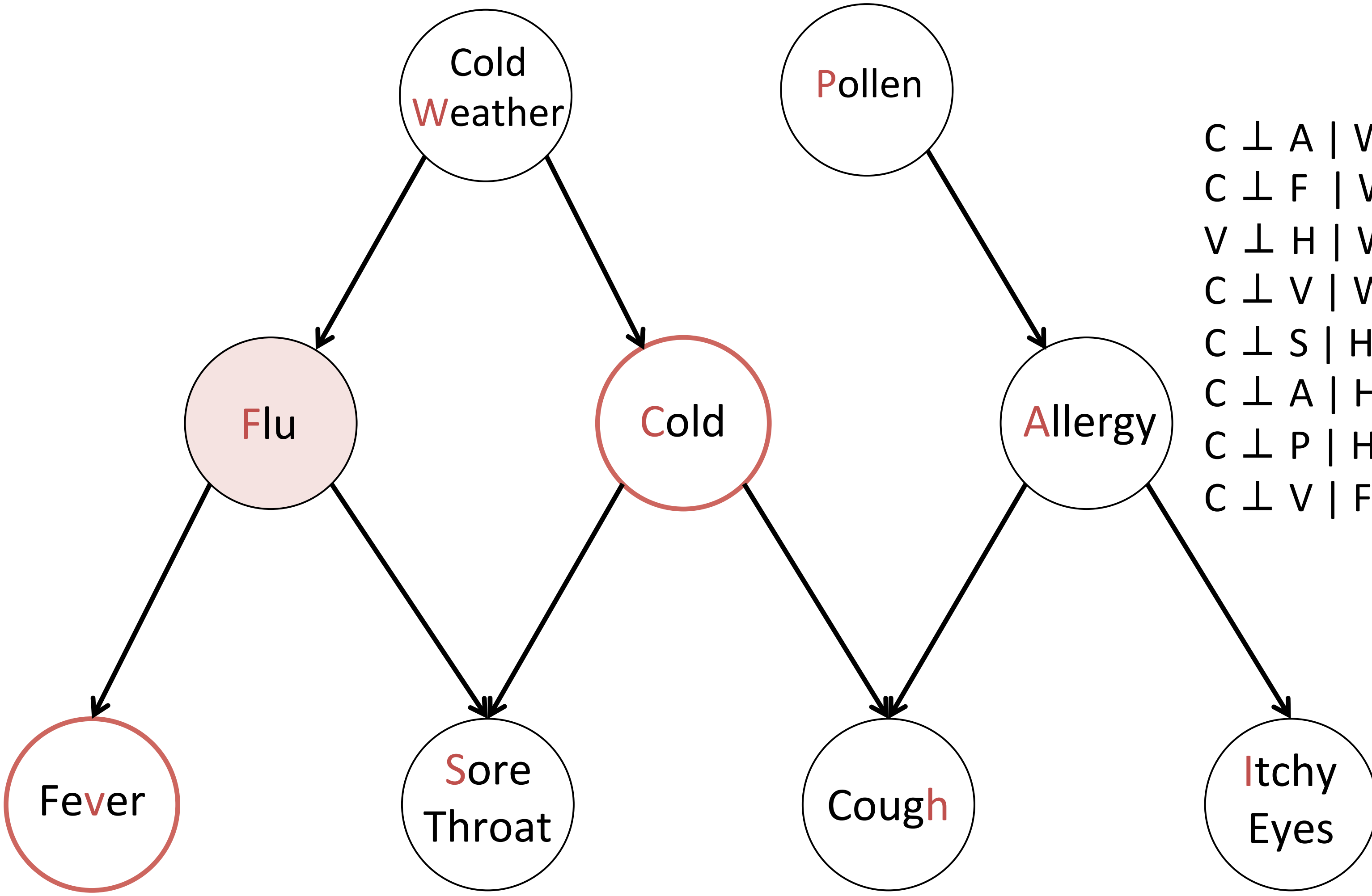
$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$? No
$C \perp A \mid H$? No
$C \perp P \mid H$?

Conditional Independence



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

Conditional Independence



$C \perp A \mid W$? Yes

$C \perp F \mid W$? Yes

$V \perp H \mid W$? Yes

$C \perp V \mid W$? Yes

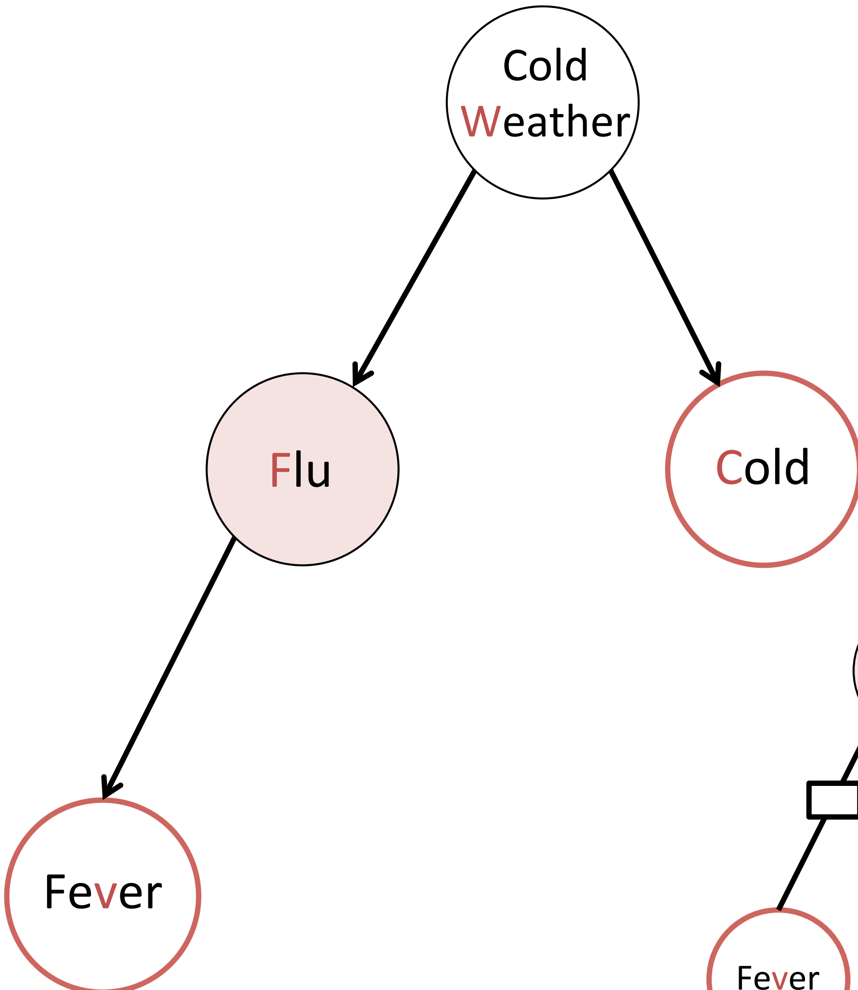
$C \perp S \mid H$? No

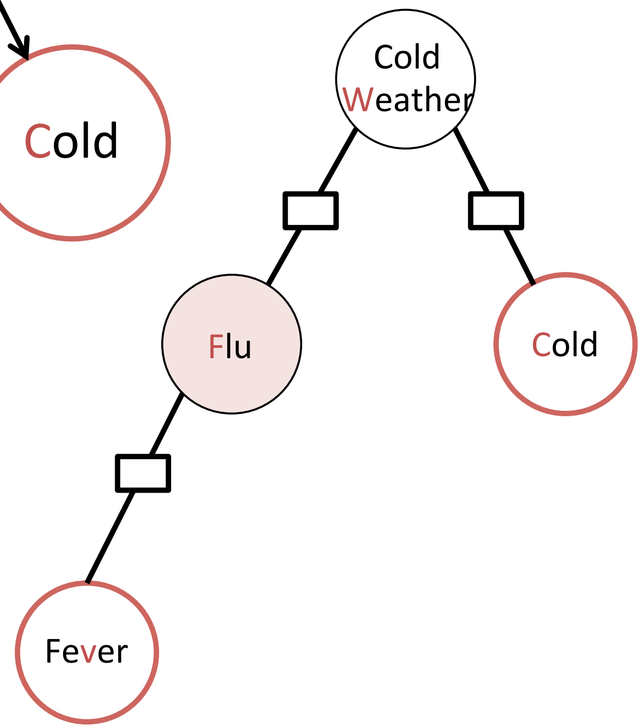
$C \perp A \mid H$? No

$C \perp P \mid H$? No

$C \perp V \mid F$?

Conditional Independence





$C \perp A \mid W$? Yes

$C \perp F \mid W$? Yes

$V \perp H \mid W$? Yes

$C \perp V \mid W$? Yes

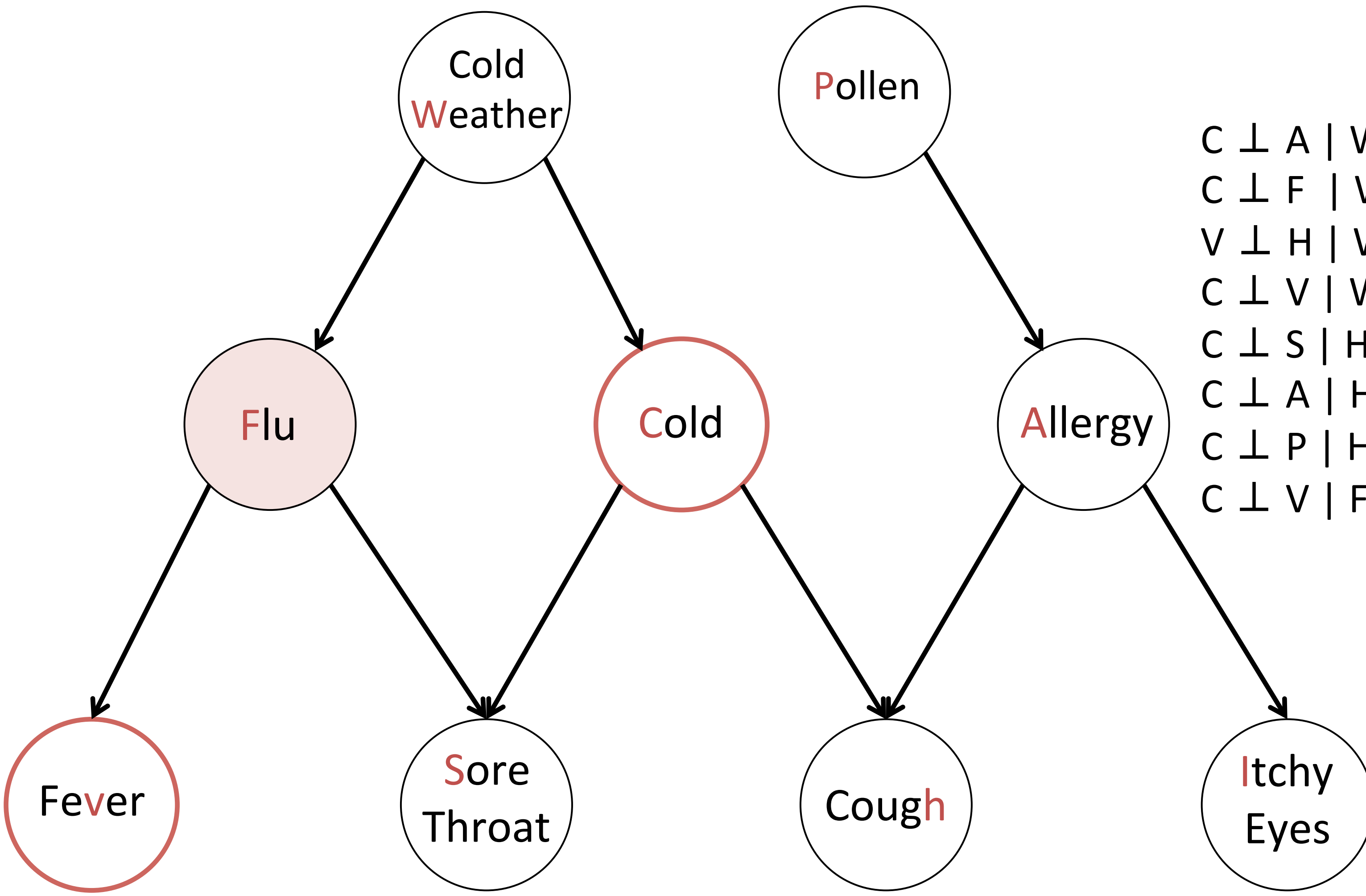
$C \perp S \mid H$? No

$C \perp A \mid H$? No

$C \perp P \mid H$? No

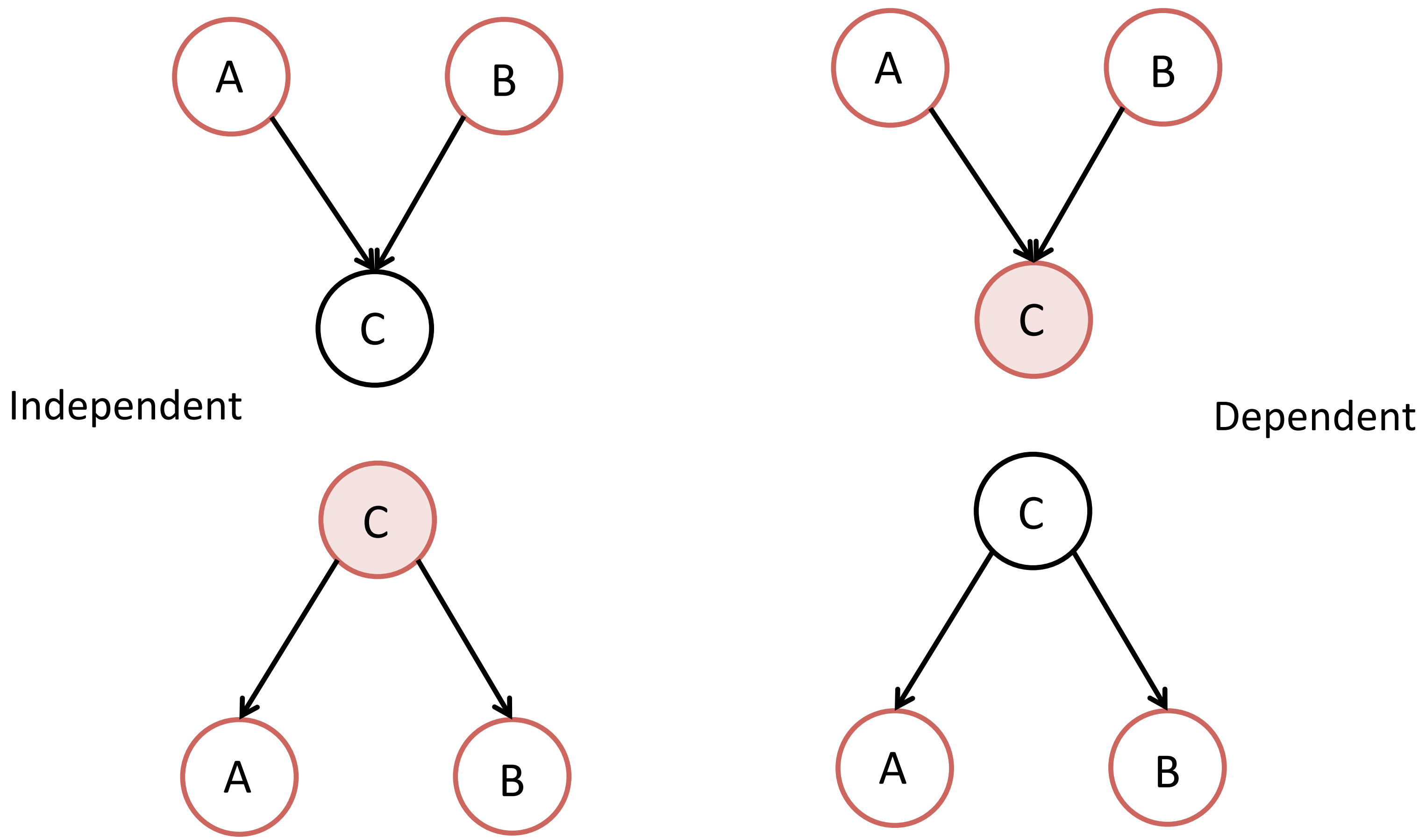
$C \perp V \mid F$?

Conditional Independence

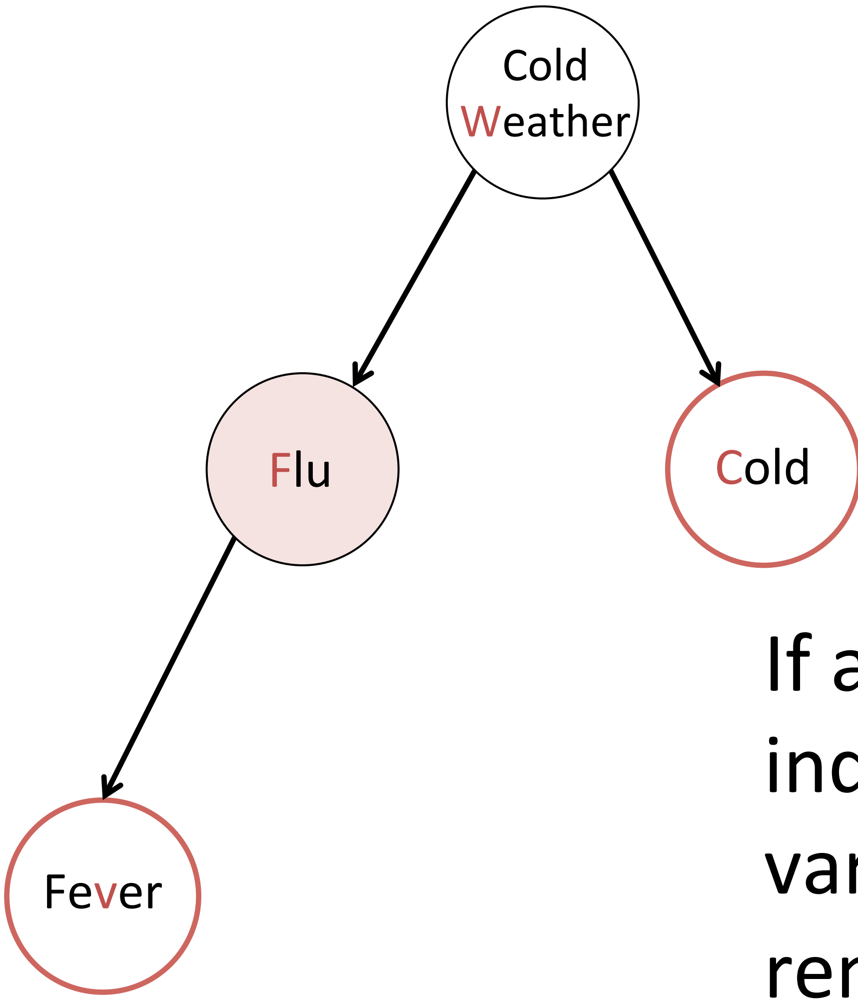


$C \perp A \mid W$? Yes
$C \perp F \mid W$? Yes
$V \perp H \mid W$? Yes
$C \perp V \mid W$? Yes
$C \perp S \mid H$? No
$C \perp A \mid H$? No
$C \perp P \mid H$? No
$C \perp V \mid F$? Yes

Patterns



Conditional Independence



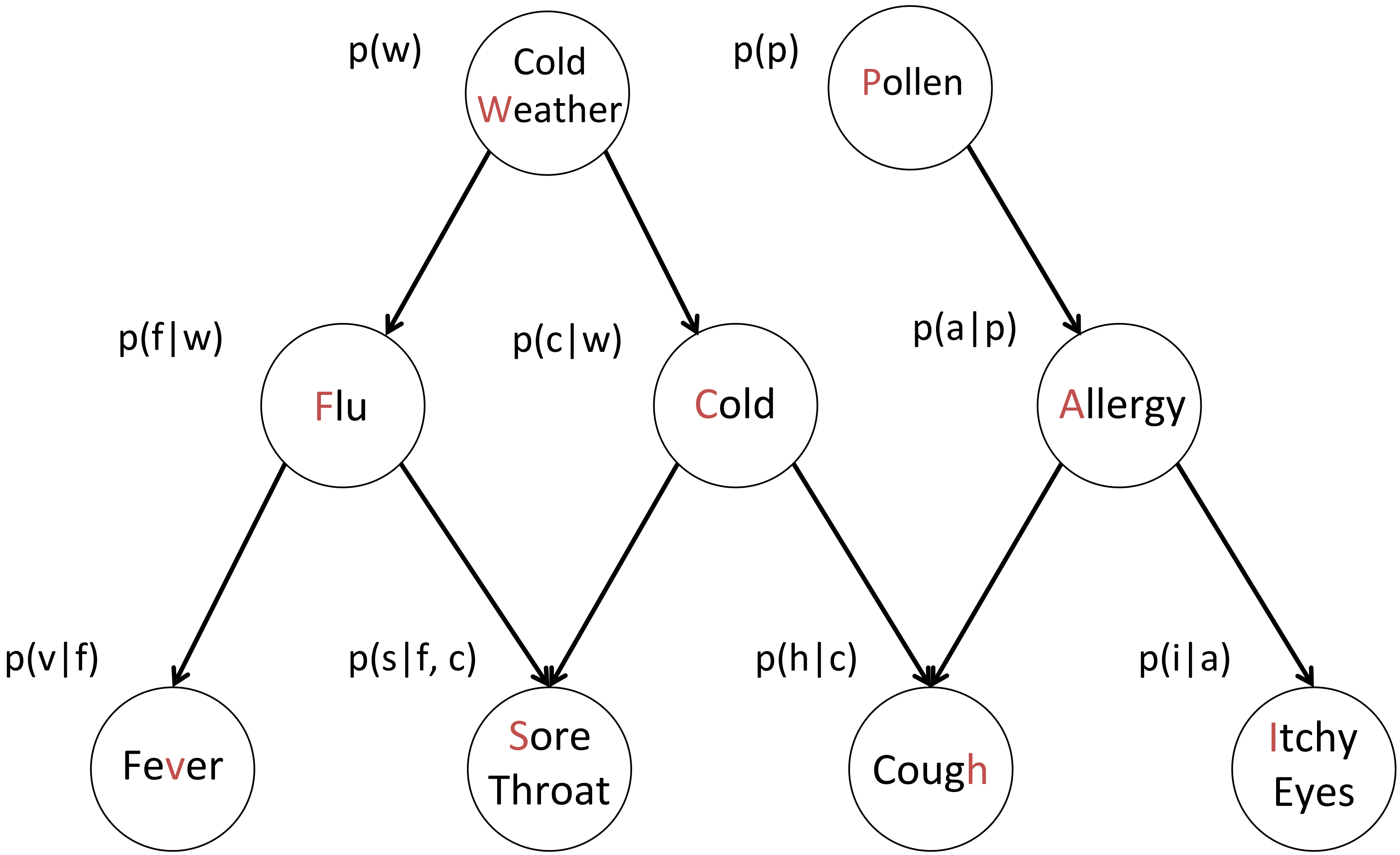
P(C=c|F=f) = ?

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

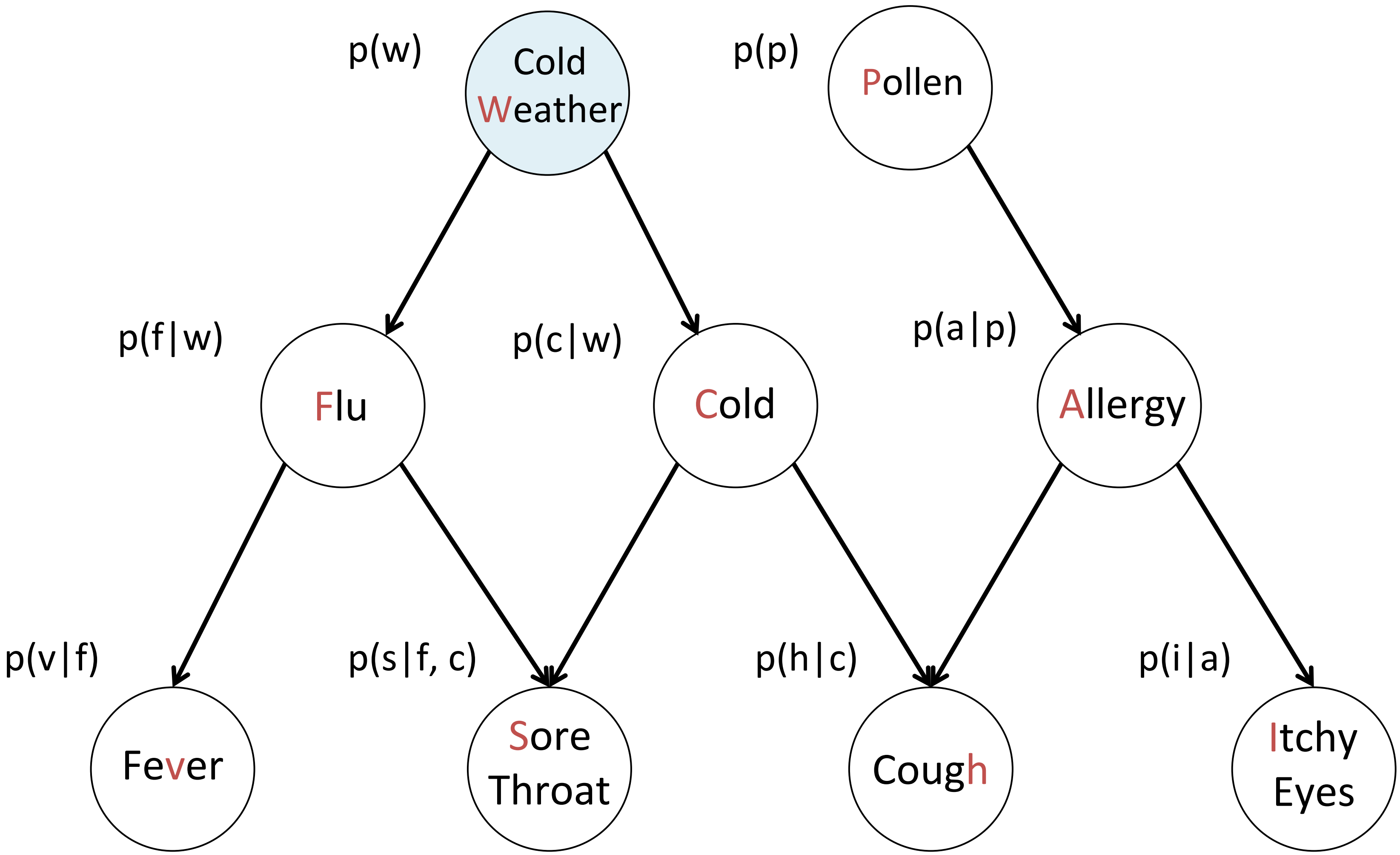
Roadmap

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

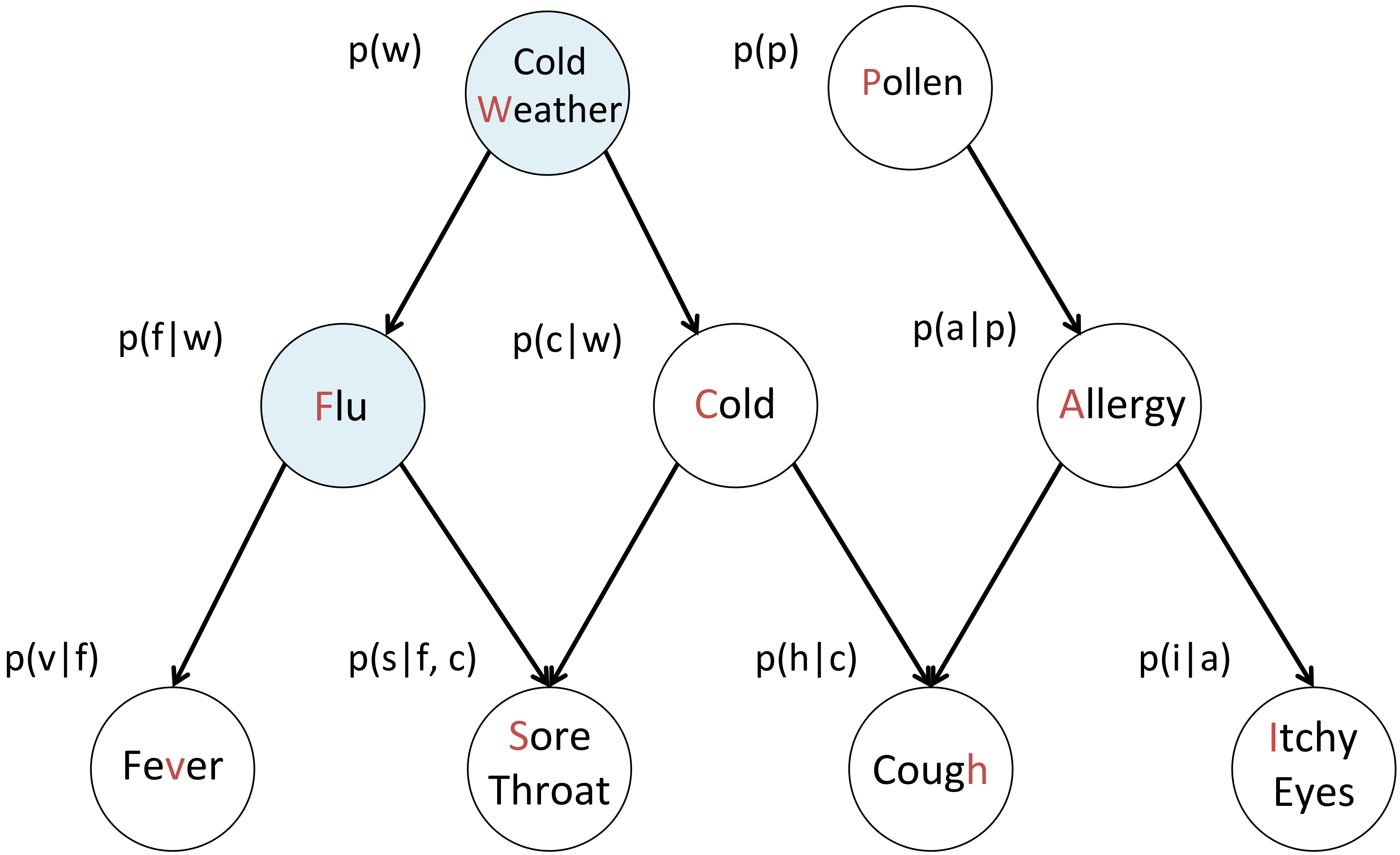
Sample 1M samples from joint distribution



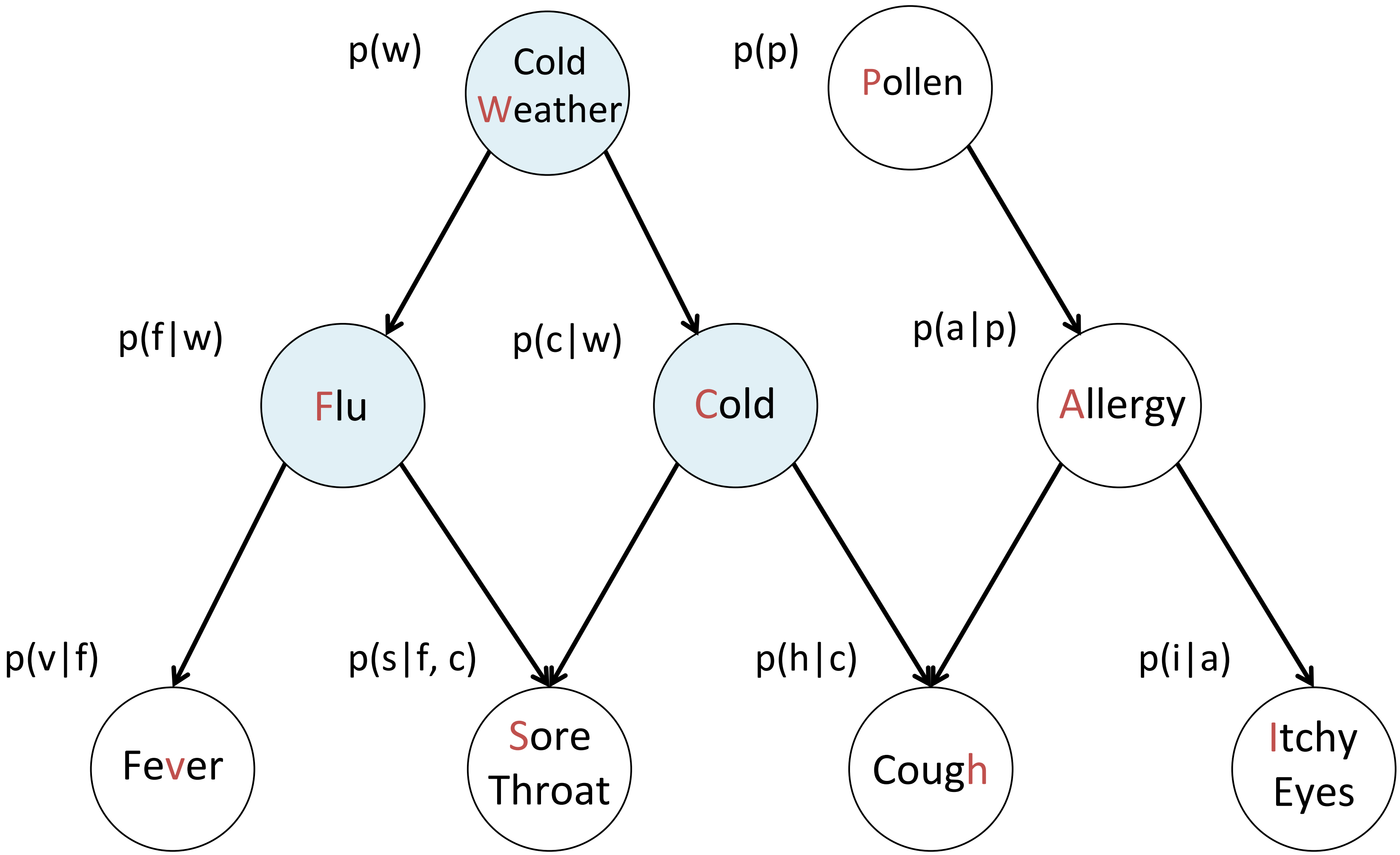
Forward Sampling



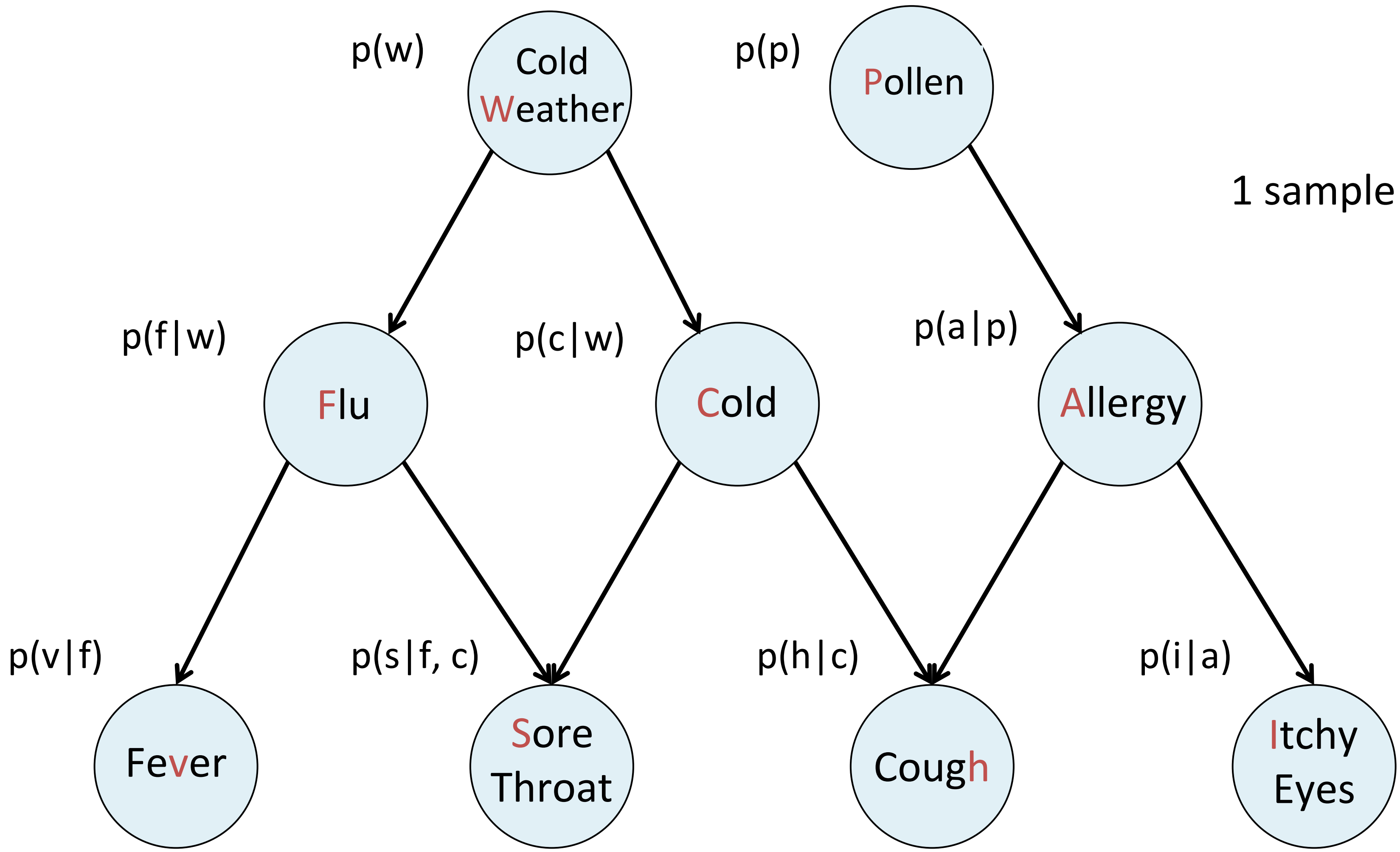
Forward Sampling



Forward Sampling



Forward Sampling



Gibbs Sampling

Algorithm: Gibbs sampling

Initialize x to a random complete assignment

Loop through $i = 1, \ldots, n$ 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)

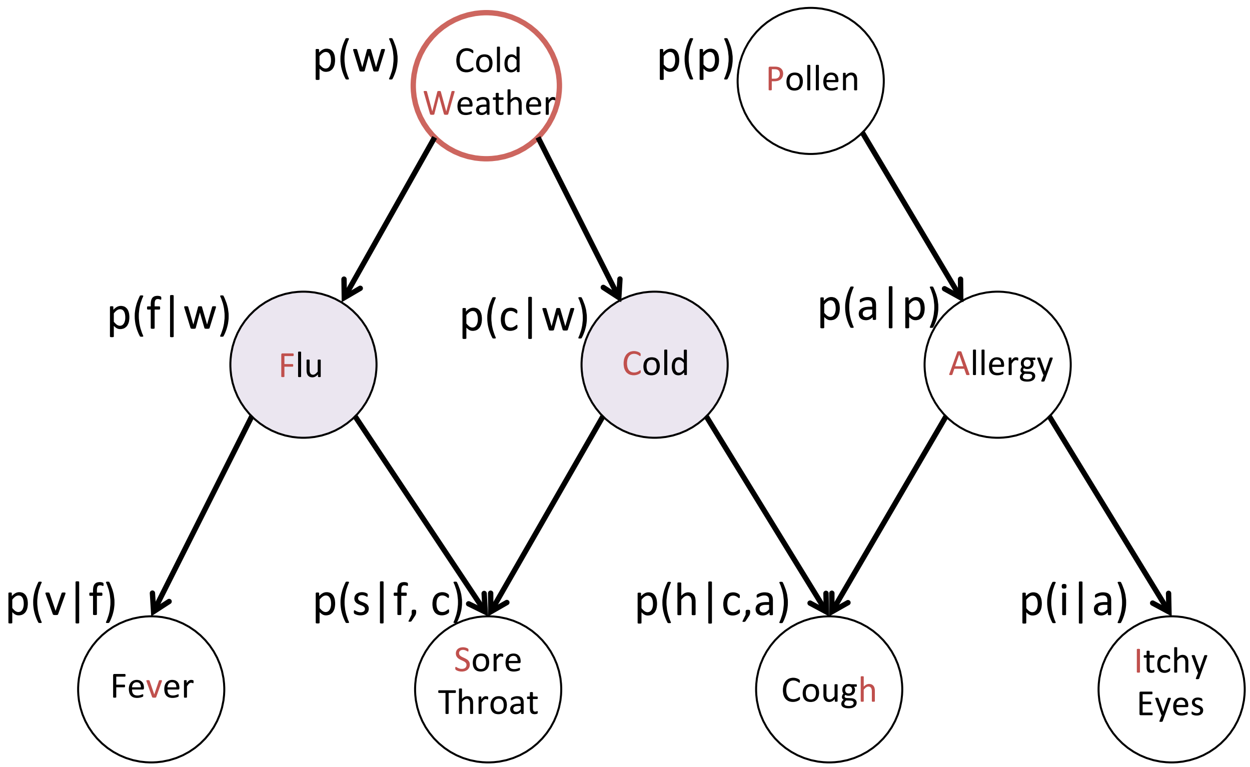
Loop through $i = 1, \ldots, n$ until convergence:

  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

How do we sample a new value for W?

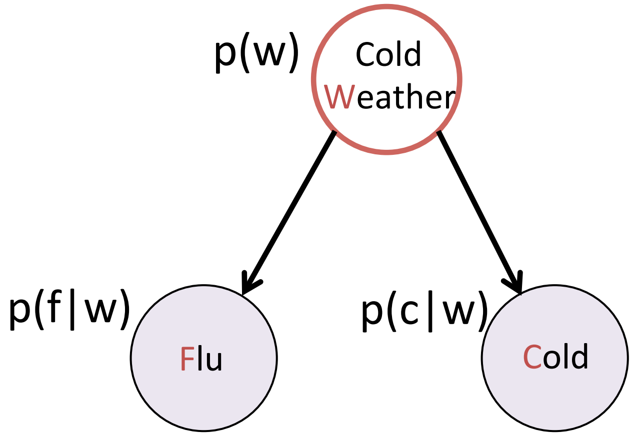


$$P(W=w|F=1, P=1, C=0, \ldots, I=0)$$

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

Markov Blanket!

Gibbs Sampling

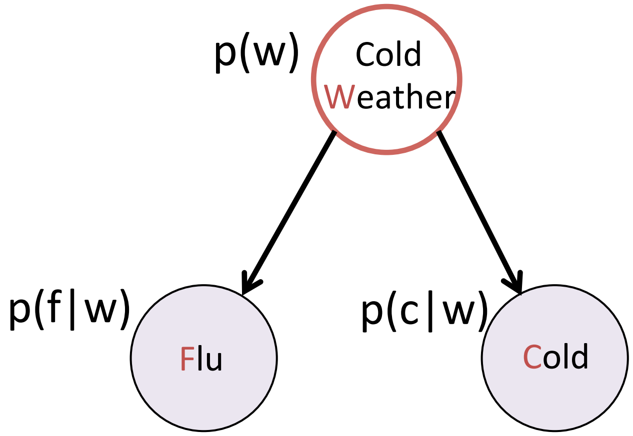


w	p(w)
0	0.4
1	0.6

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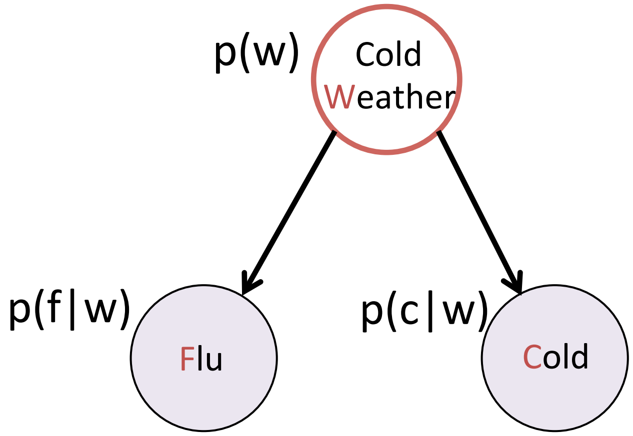
w	f	p(f|w)
0	0	0.95
0	1	0.05
1	0	0.80
1	1	0.20

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

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

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(f|w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

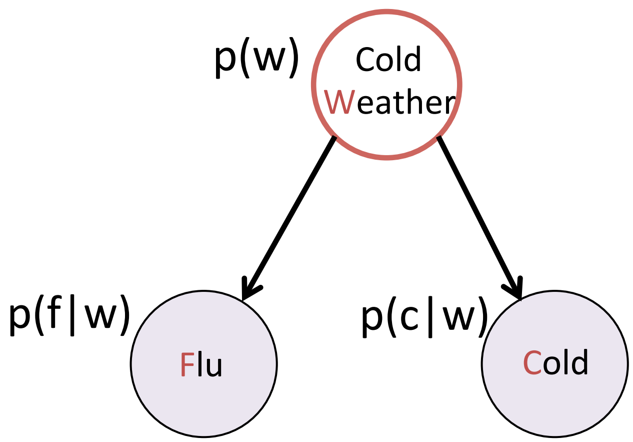
$$P(W=w|F=1, P=1, C=0, \ldots, I=0)$$

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

$$\propto P(F=1|W=w)*P(C=0|W=w)*P(W=w)$$

$$= \begin{cases} 0.05 * 0.88 * 0.40, & W = 0 \\ & \end{cases}$$

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(f|w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

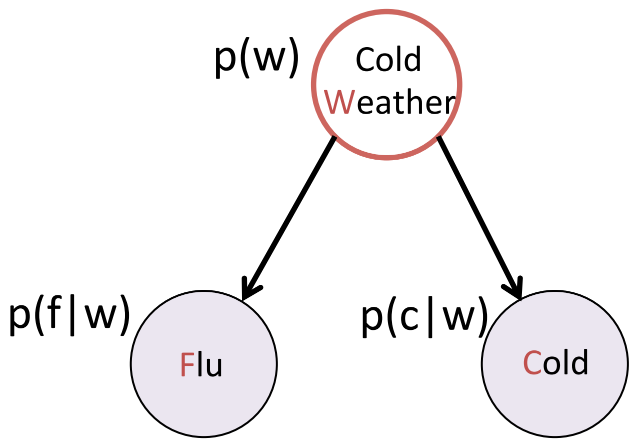
$$P(W=w|F=1, P=1, C=0, \ldots, I=0)$$

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

$$\propto P(F=1|W=w)*P(C=0|W=w)*P(W=w)$$

$$= \begin{cases} 0.05*0.88*0.40, & W=0 \\ 0.20*0.70*0.60, & W=1 \end{cases}$$

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(f|w)
0	0	0.88
0	1	0.12
1	0	0.70
1	1	0.30

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

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

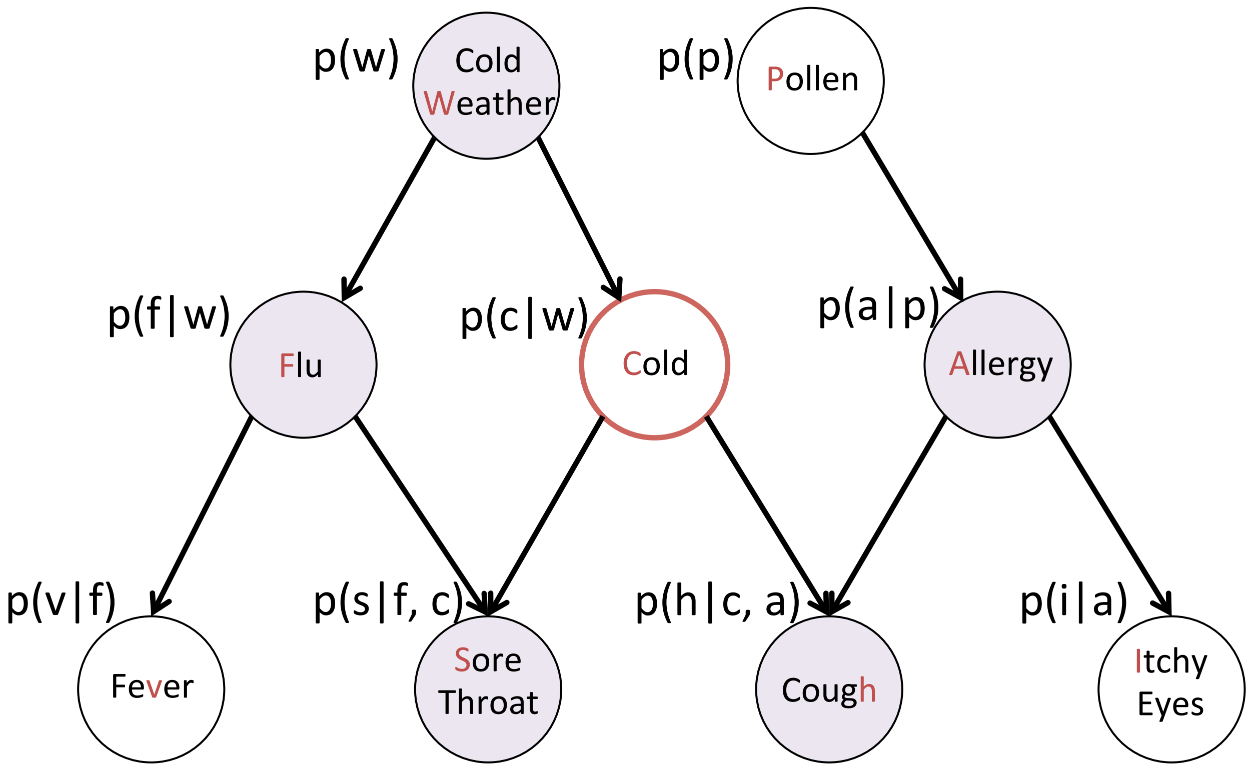
$$= \begin{cases} 0.0176/(0.0176+0.084), & w=0 \\ 0.084\,/\,(0.0176+0.084), & w=1 \end{cases}$$

$$= \begin{cases} 0.173, & w=0 \\ 0.827, & w=1 \end{cases}$$

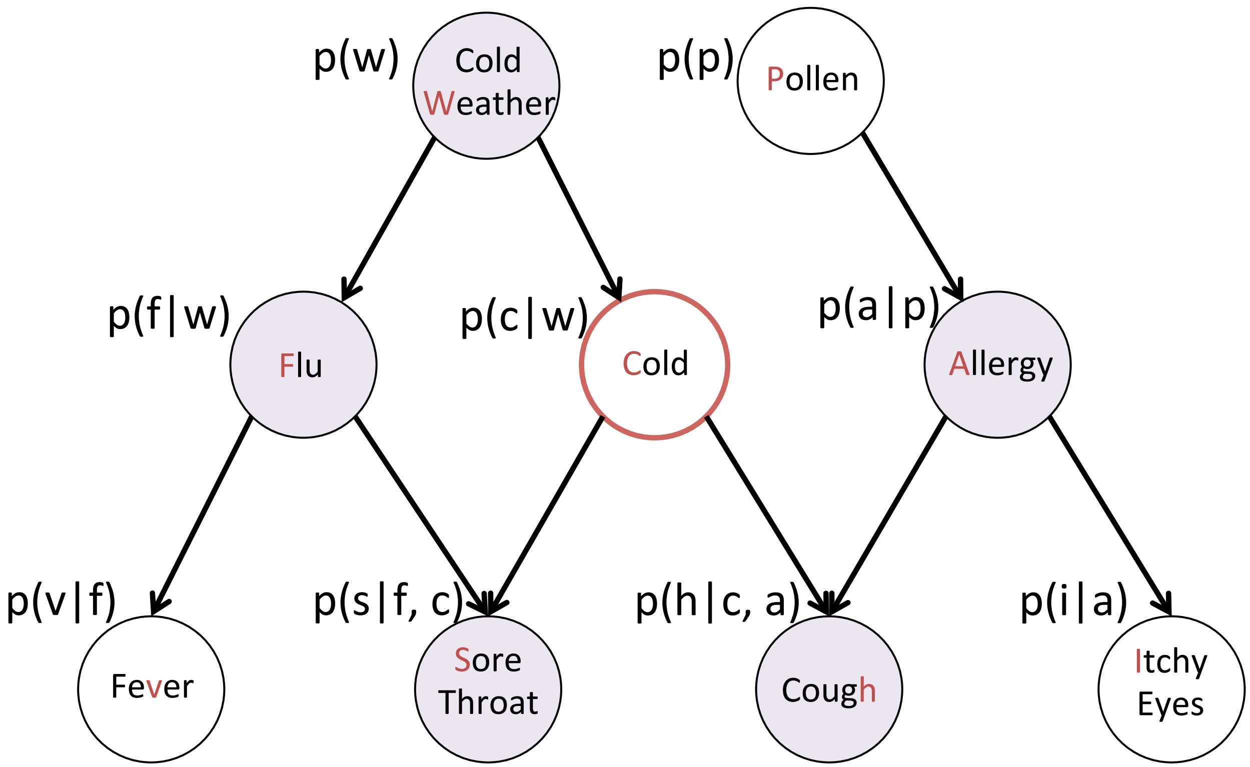
Sample a new w!

Gibbs Sampling

How do we sample a new value for C?



Gibbs Sampling

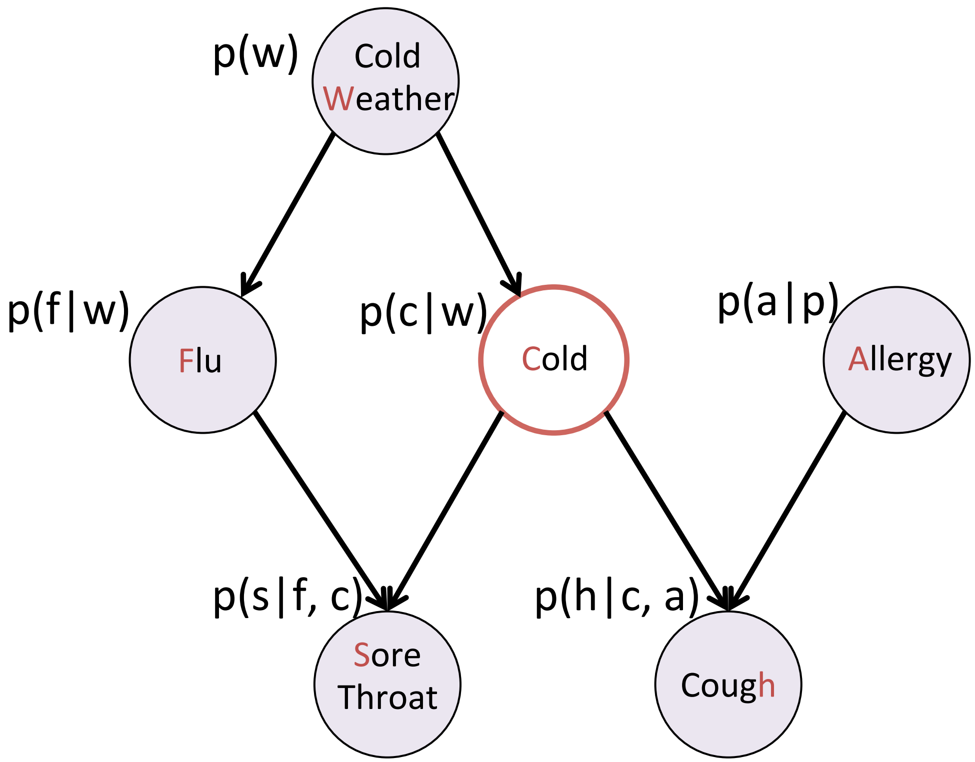


$$P(C=c \mid W=1, F=1, P=1, \ldots, I=0)$$

$$= P(C=c \mid W=1, F=1, S=0, H=1, A=1)$$

Markov Blanket!

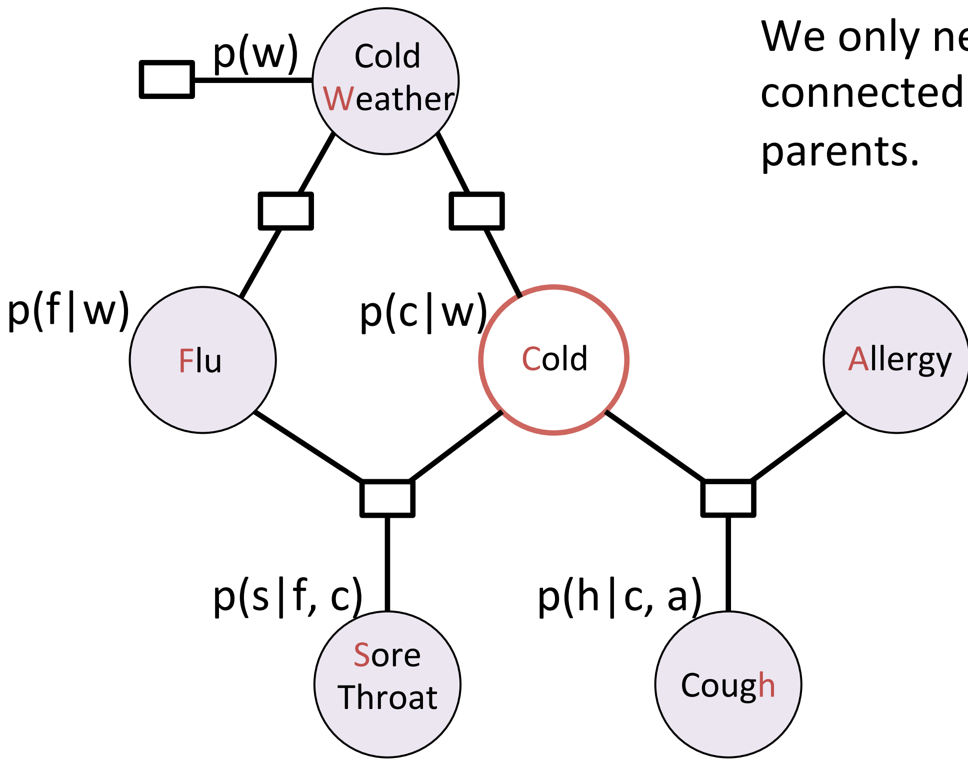
Gibbs Sampling



$$P(C{=}c \mid W{=}1, F{=}1, P{=}1, \ldots, I{=}0$$

$$= P(C{=}c \mid W{=}1, F{=}1, S{=}0, H{=}1, A{=}1)$$

Gibbs Sampling
From a Factor Graph Perspective



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

P(C=c | W=1, F=1, P=1, …, I=0

= P(C=c | W=1, F=1, S=0, H=1, A=1)

= p(w) p(f | w) p(c | w) p(s | f, c) p(h | c, a)

Questions?