

# CS221 Section 7

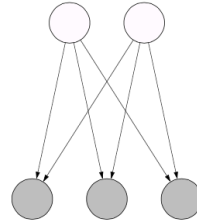
## Bayesian Networks

Spring 2018

# Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence

# Bayesian Networks



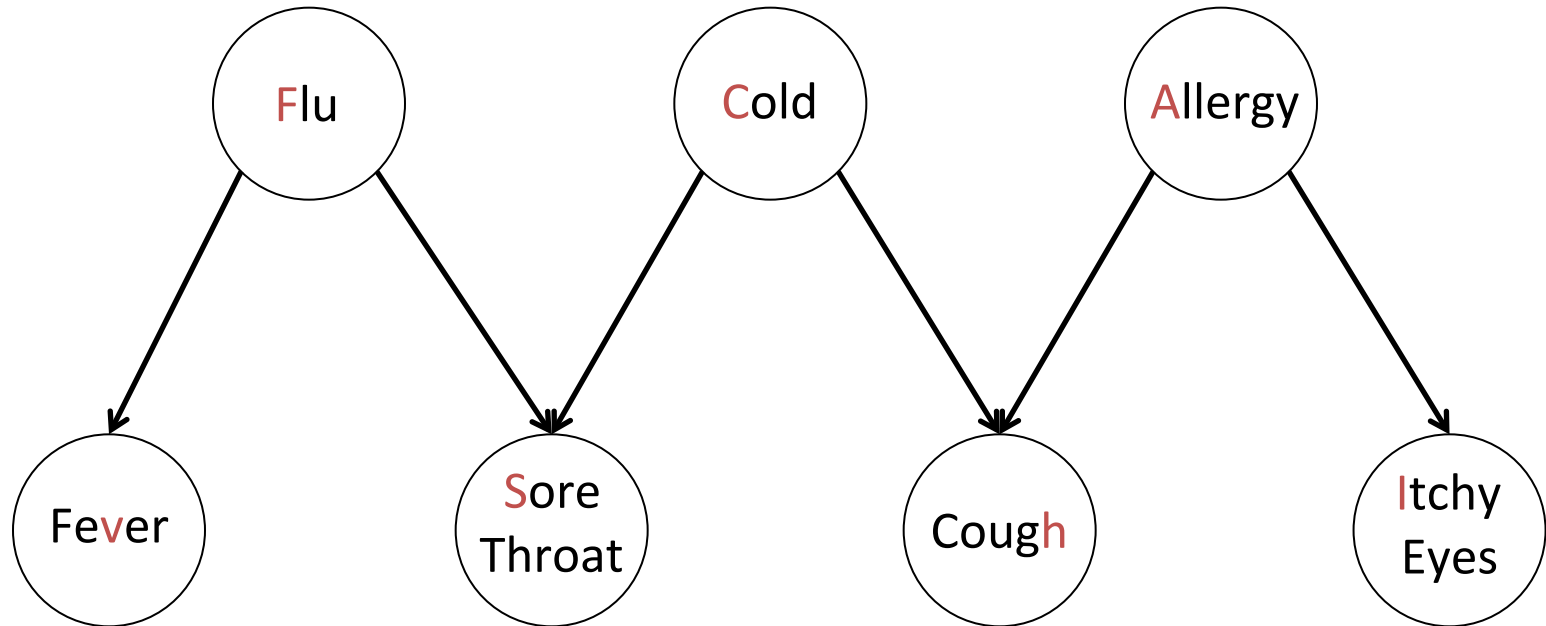
## Definition: Bayesian network

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

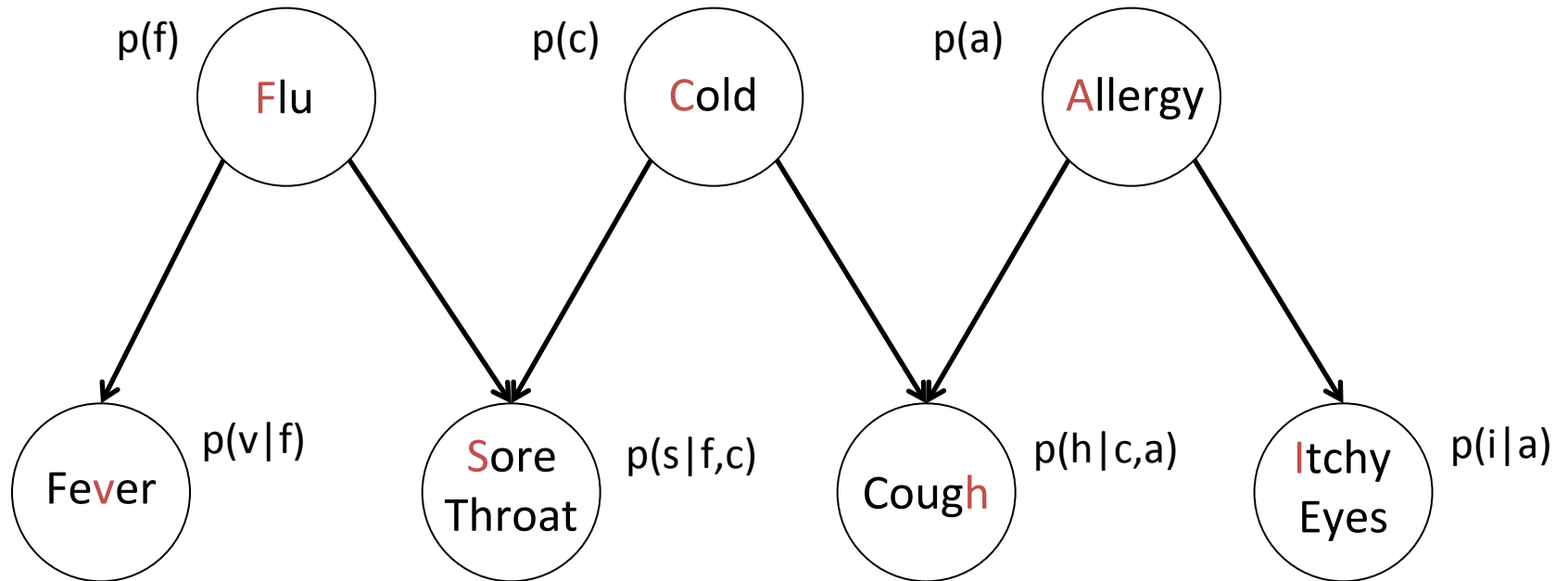
A **Bayesian network** is a directed acyclic graph (DAG) that specifies a **joint distribution** over  $X$  as a product of **local conditional distributions**, one for each node:

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

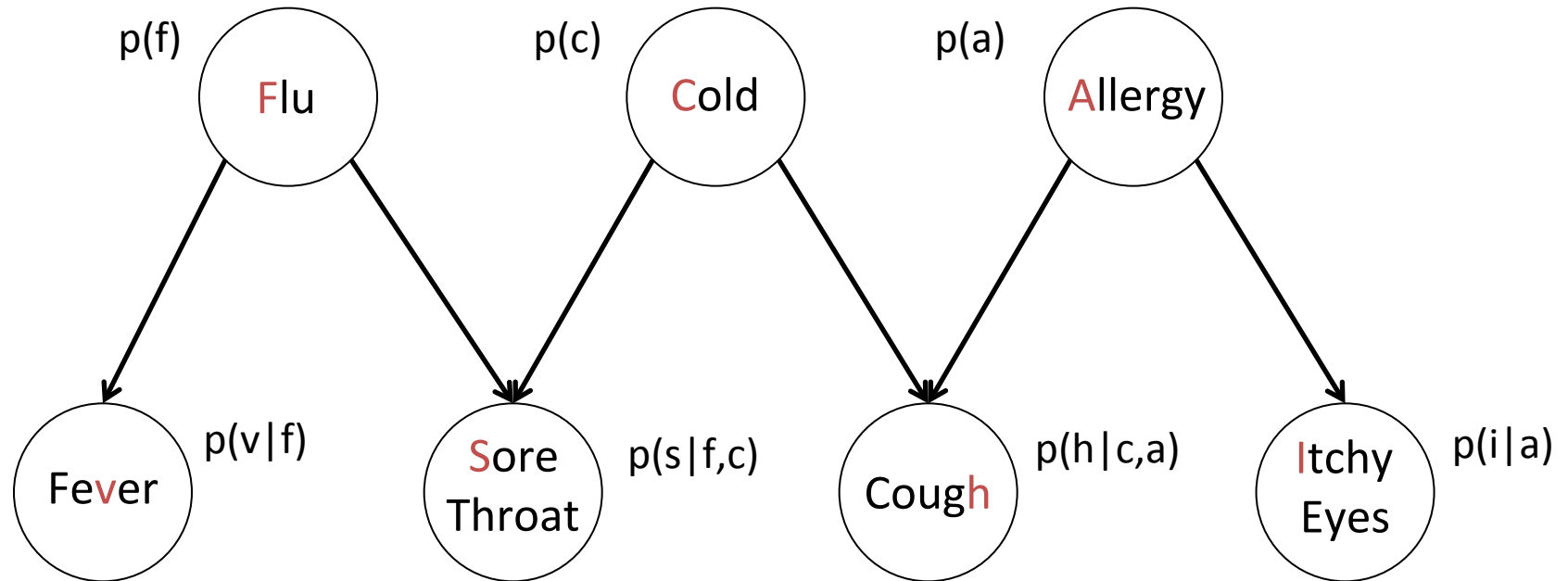
# Bayesian Networks



# A Bayesian network represents a joint probability distribution.



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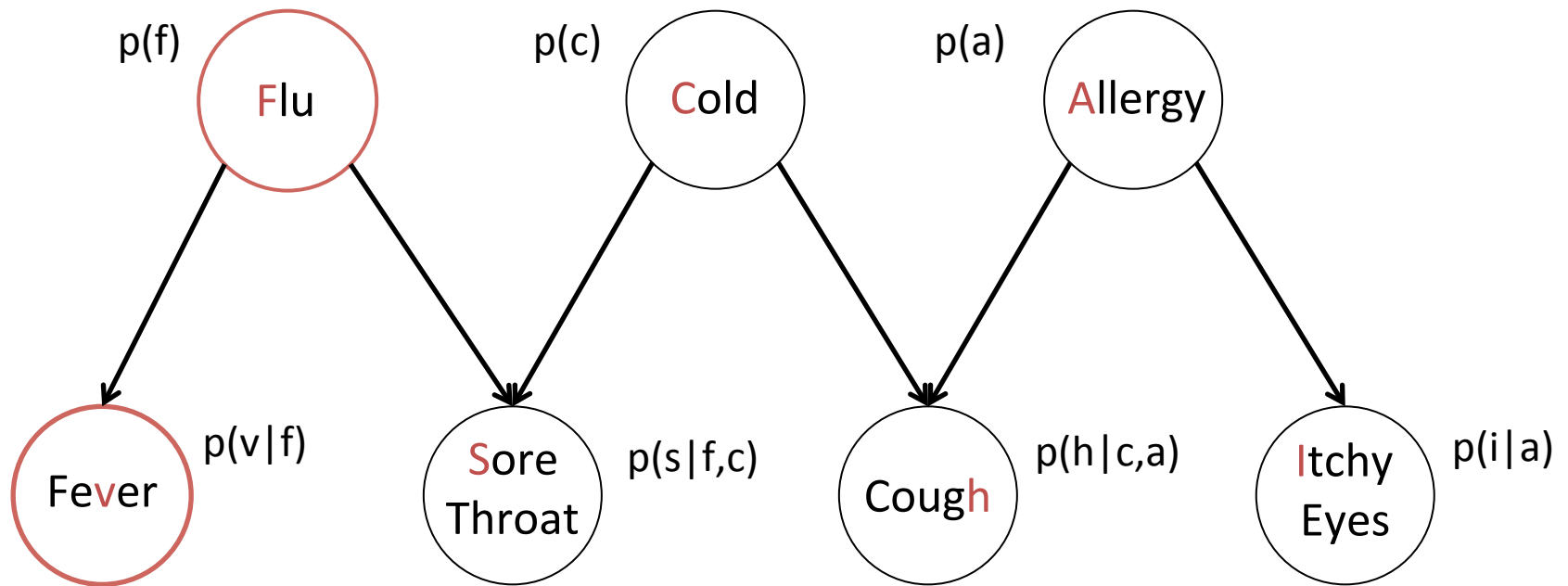
$$P(F=f, C=c, A=a, V=v, S=s, C=c, I=i) = p(f)p(c)p(a)p(v|a)p(s|f, c)p(h|c,a)p(i|a)$$

# Roadmap

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence

# Probabilistic Queries - Examples

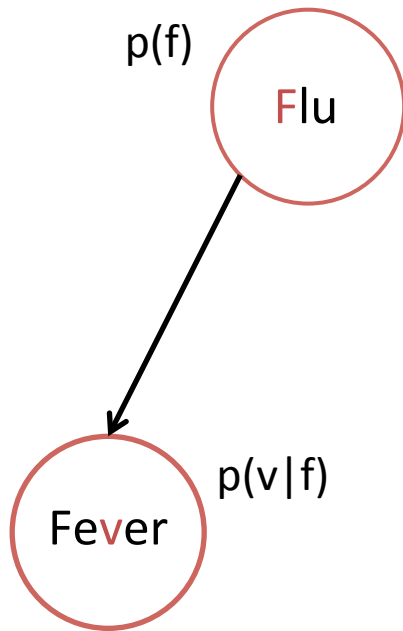
$$P(F=1 | V=1) = ?$$





# Probabilistic Queries - Examples

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

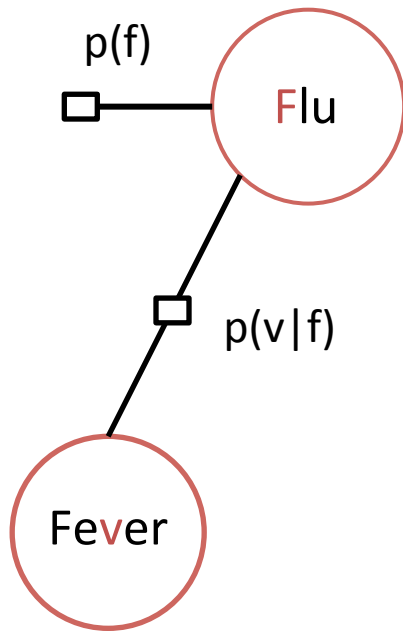


1. Remove (marginalize) variables not ancestors of Q or E.

# Probabilistic Queries - Examples

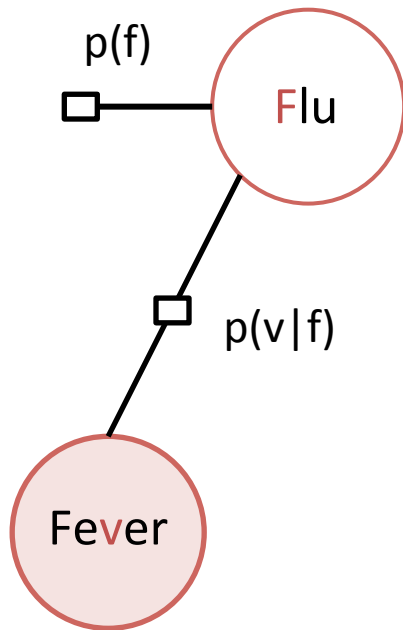
$$P(F=1 | V=1) = ?$$

2. Convert Bayesian network to factor graph.



# Probabilistic Queries - Examples

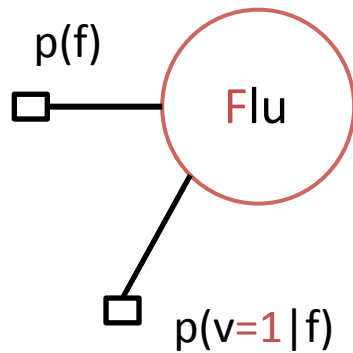
$$P(F=1 | V=1) = ?$$



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

# Probabilistic Queries - Examples

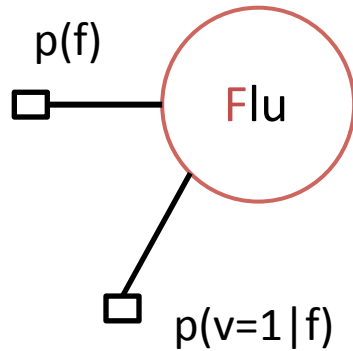
$$P(F=1 | V=1) = ?$$



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

# Probabilistic Queries - Examples

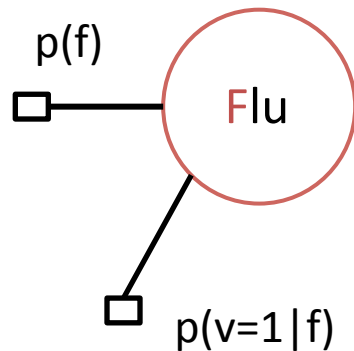
$$P(F=1 | V=1) = ?$$



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).

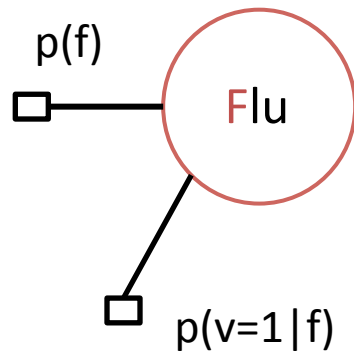
f	p(f)
0	1- $\alpha$
1	$\alpha$

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).

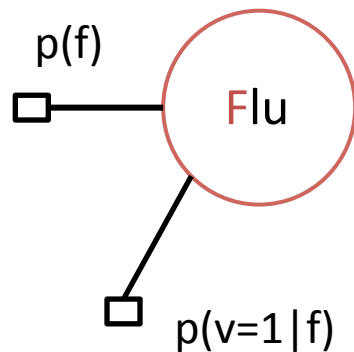
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$$P(F=f|V=1) \propto p(f) p(v=1|f) = \begin{cases} (1-\alpha) * 0.30, & f = 0 \\ \alpha * 0.80, & f = 1 \end{cases}$$

# 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- $\alpha$
1	$\alpha$

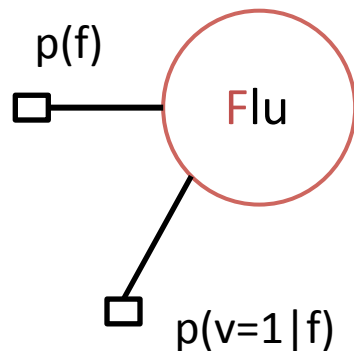
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$$P(F=1 | V=1) = ?$$



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

f	p(f)
0	1- $\alpha$
1	$\alpha$

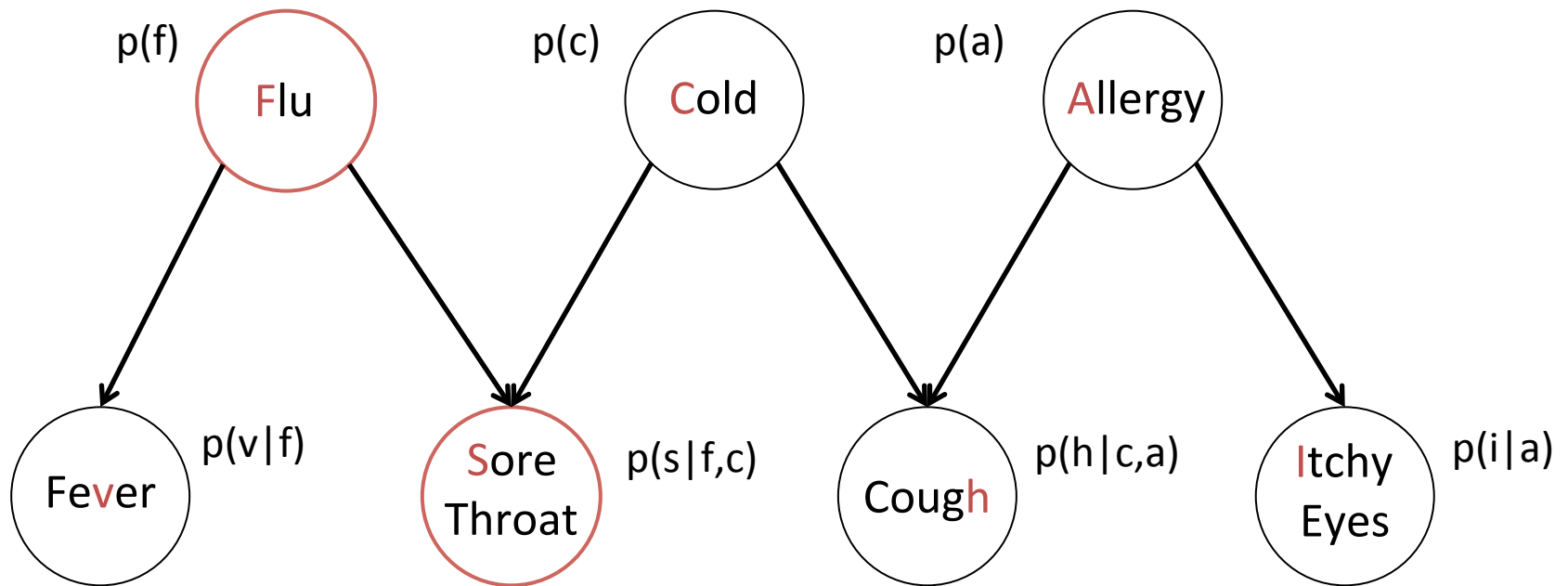
f	v	p(v   f)
0	0	0.70
0	1	0.30
1	0	0.20
1	1	0.80

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

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

# Probabilistic Queries - Examples

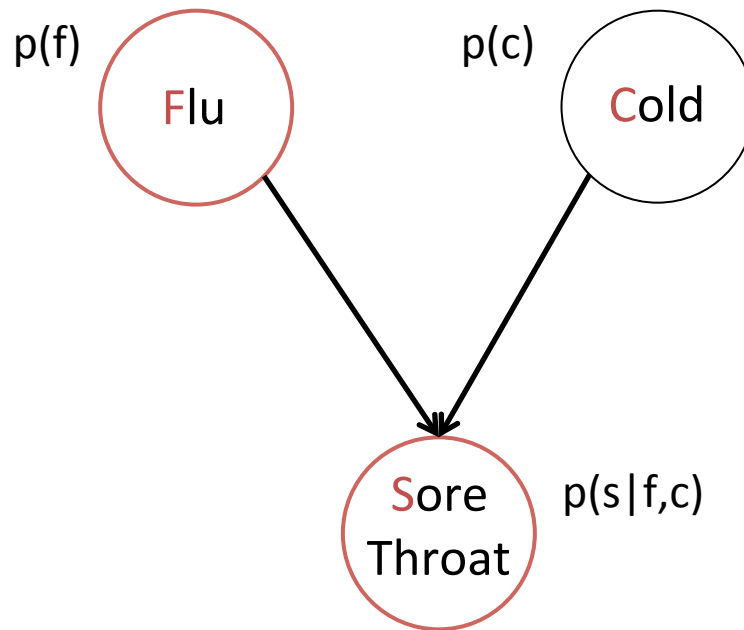
$$P(F=1 | S=1) = ?$$



# Probabilistic Queries - Examples

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

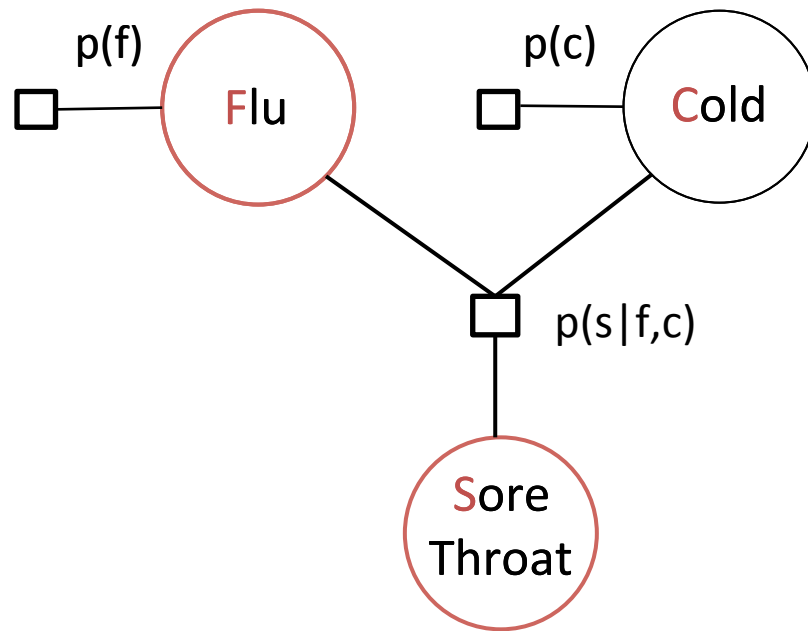
1. Remove (marginalize) variables not ancestors of Q or E.



# Probabilistic Queries - Examples

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

2. Convert Bayesian network to factor graph.

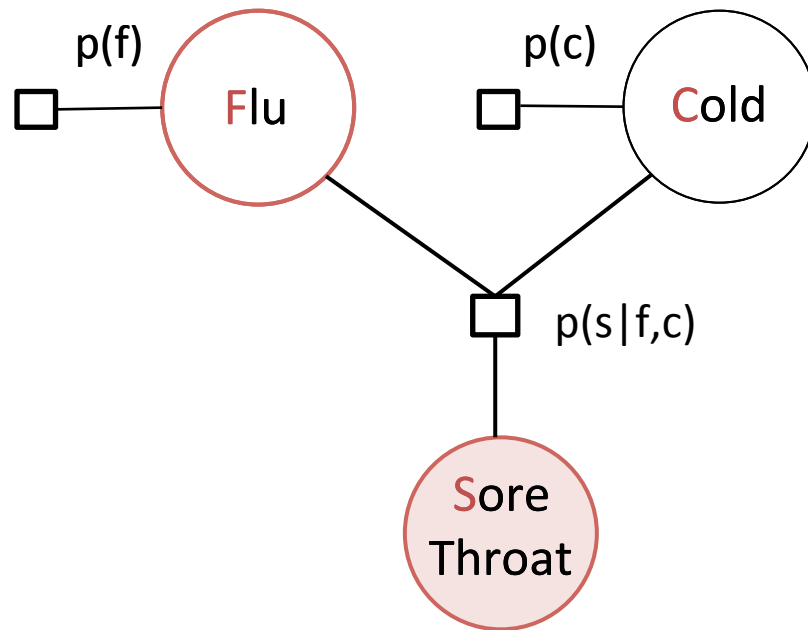


★ One factor per variable!

# Probabilistic Queries - Examples

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

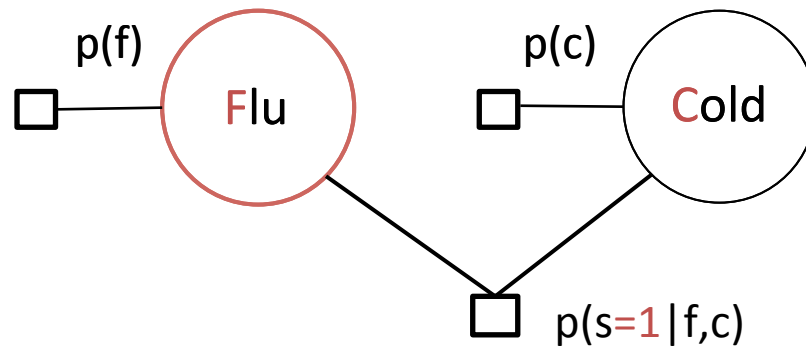
3. Condition on  $E = e$ .  
3.1 shade nodes



# Probabilistic Queries - Examples

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

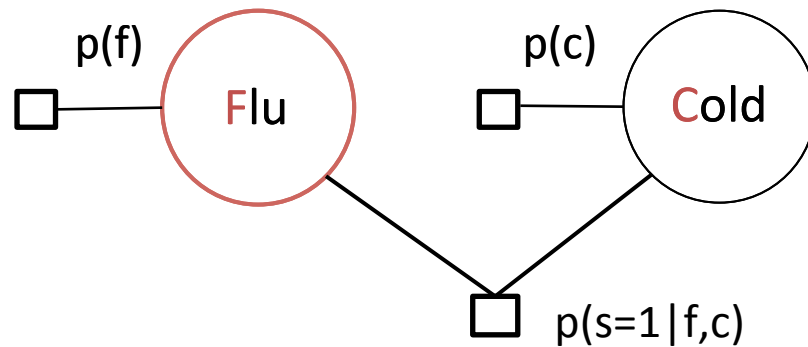
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3.2 disconnect



# Probabilistic Queries - Examples

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

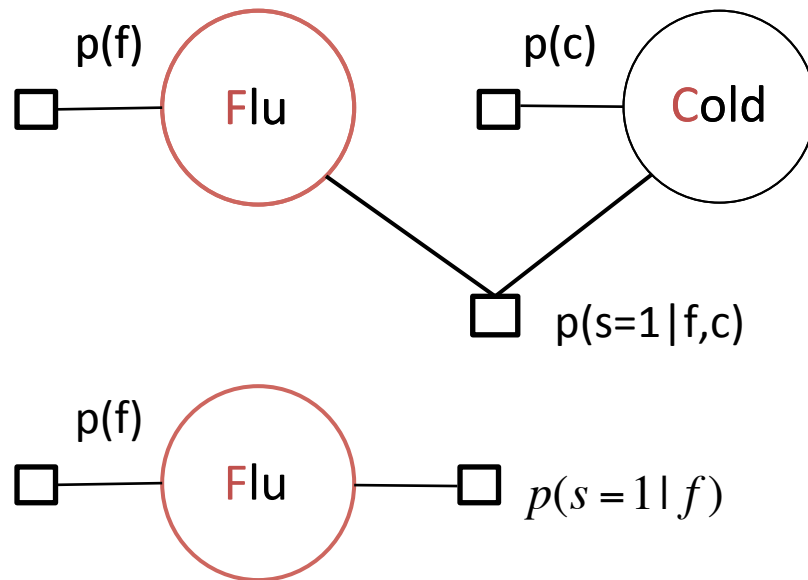
4. Remove (marginalize) nodes disconnected from Q.



# Probabilistic Queries - Examples

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

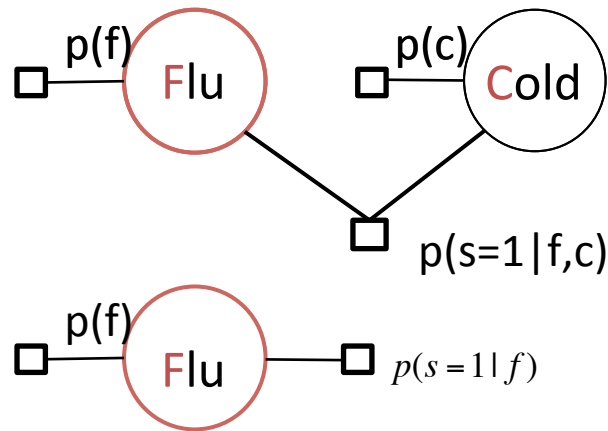
5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).





# Probabilistic Queries - Examples

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



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

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

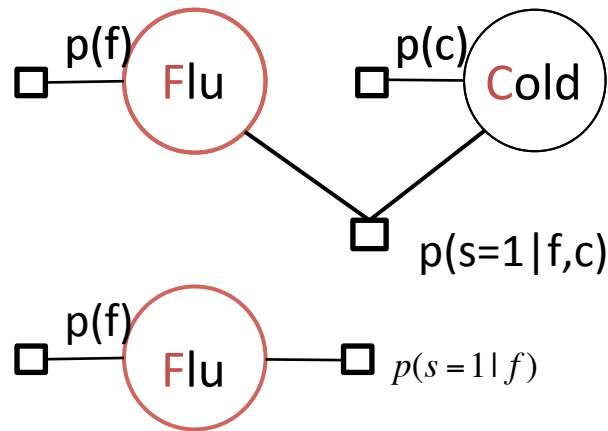
$$= \sum_c p(c) p(s=1 | f, c)$$

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

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

# Probabilistic Queries - Examples

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



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

f	$p(f)$
0	$1-\alpha$
1	$\alpha$

c	$p(c)$
0	$1-\beta$
1	$\beta$

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

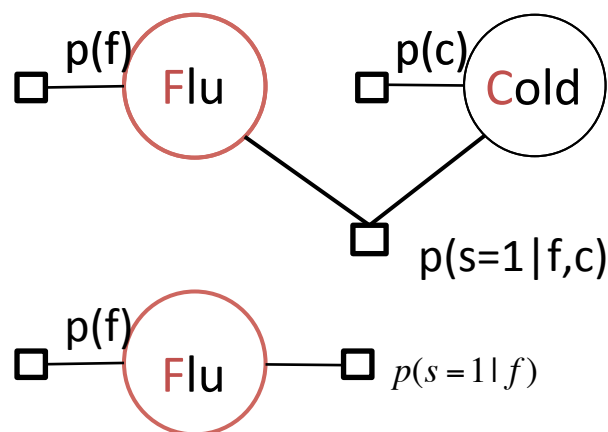
f	$p(s=1, f)$
0	$\beta * 0.75$
1	?



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# 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	$1-\alpha$
1	$\alpha$

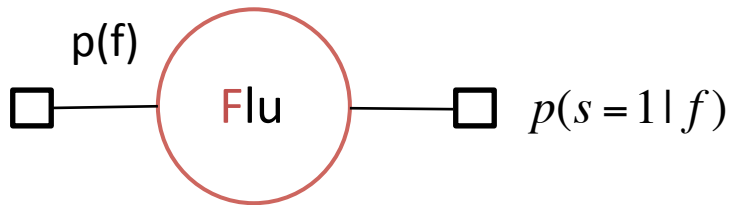
c	p(c)
0	$1-\beta$
1	$\beta$

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

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



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

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

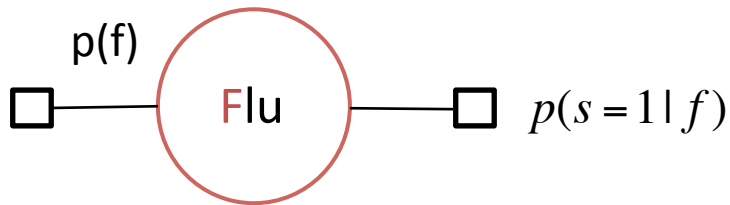
5. Run probabilistic inference algorithm (manual, **variable elimination**, Gibbs sampling, particle filtering).

f	p(f)
0	$1-\alpha$
1	$\alpha$

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

# Probabilistic Queries - Examples

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



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

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

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

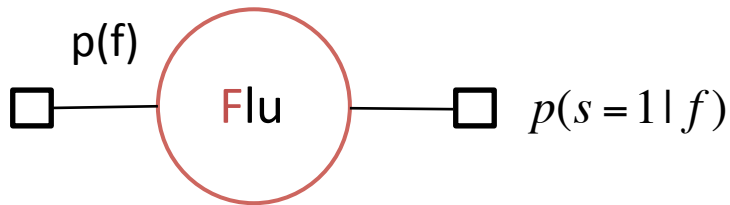
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0	$1 - \alpha$
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# Probabilistic Queries - Examples

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



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

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

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

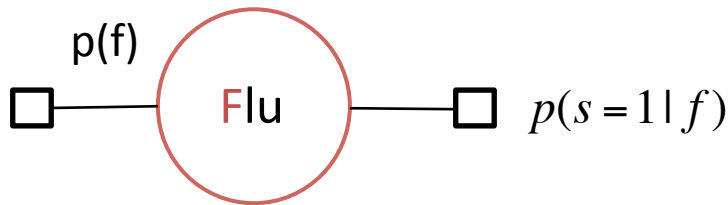
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f	p(s=1   f)
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# Probabilistic Queries - Examples

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



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

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

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

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

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

$$P(F = 1 | S = 1) = \frac{p(f = 1)p(s = 1 | f = 1)}{p(f = 1)p(s = 1 | f = 1) + p(f = 0)p(s = 1 | f = 0)}$$

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

# 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

- Bayesian Networks Introduction
- Probabilistic Queries
- Conditional Independence

# Conditional Independence



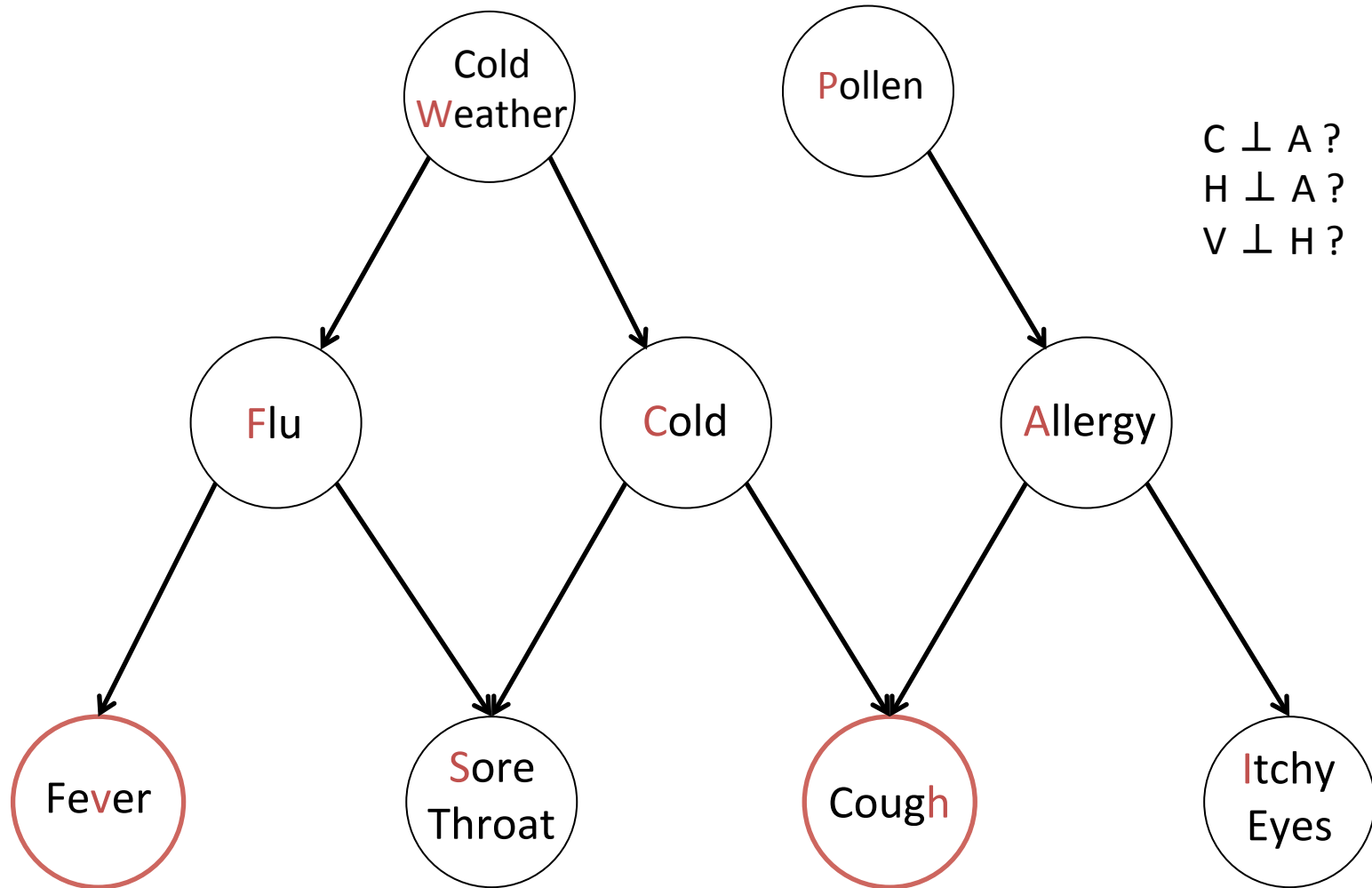
## Definition: conditional independence

- Let  $A, B, C$  be a partitioning of the variables.
- We say  $A$  and  $B$  are **conditionally independent** given  $C$  if conditioning on  $C$  produces a graph in which  $A$  and  $B$  are independent.
- In symbols:  $A \perp\!\!\!\perp B \mid C$ .

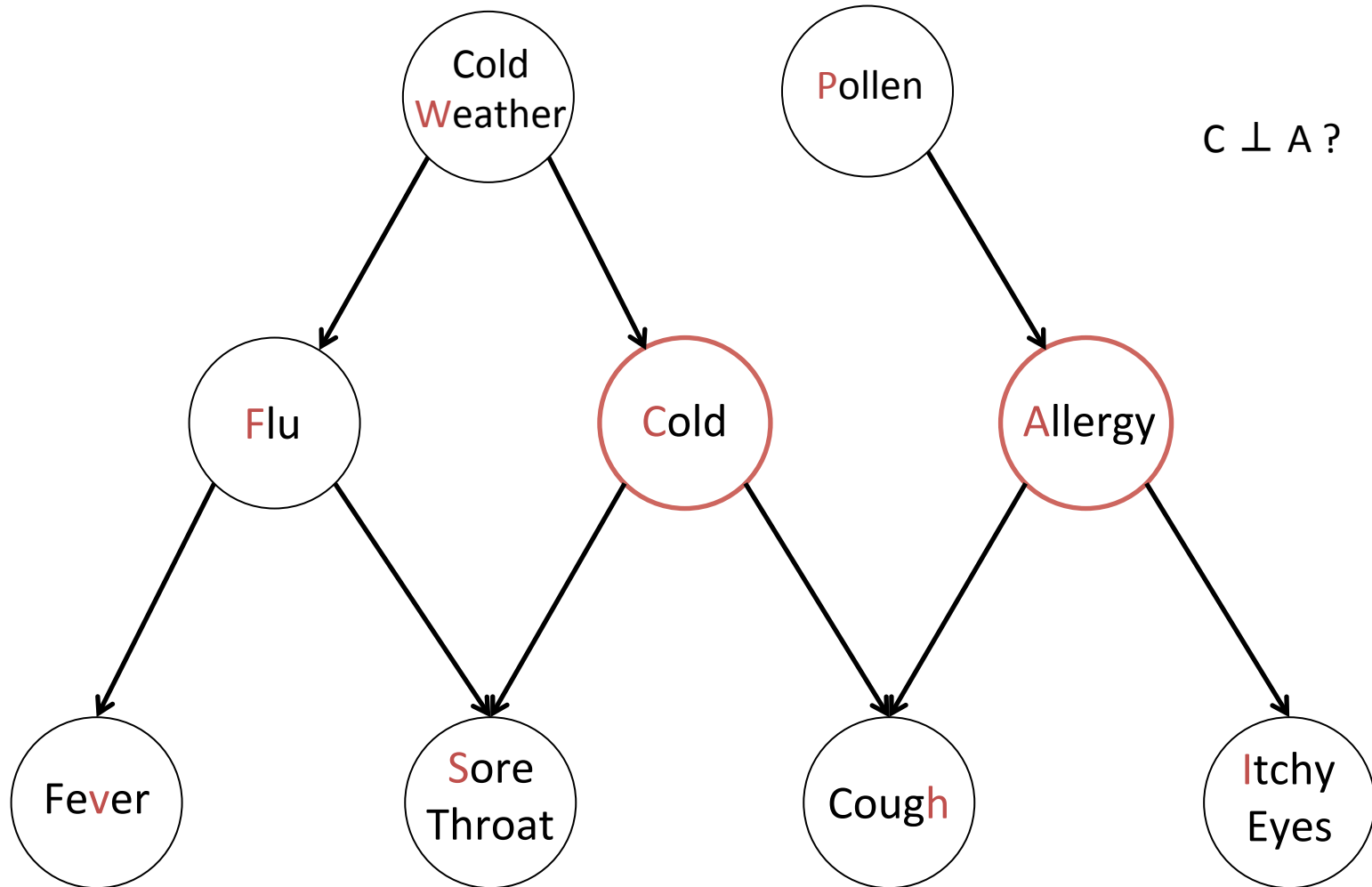
# How to determine if A and B are independent, given C?

- If every undirected path from X to Y is **blocked** by C, then X and Y are conditional independent given C
- Paths between X and Y are blocked if:
  - $X \rightarrow C \rightarrow Y$
  - $X \leftarrow C \rightarrow Y$

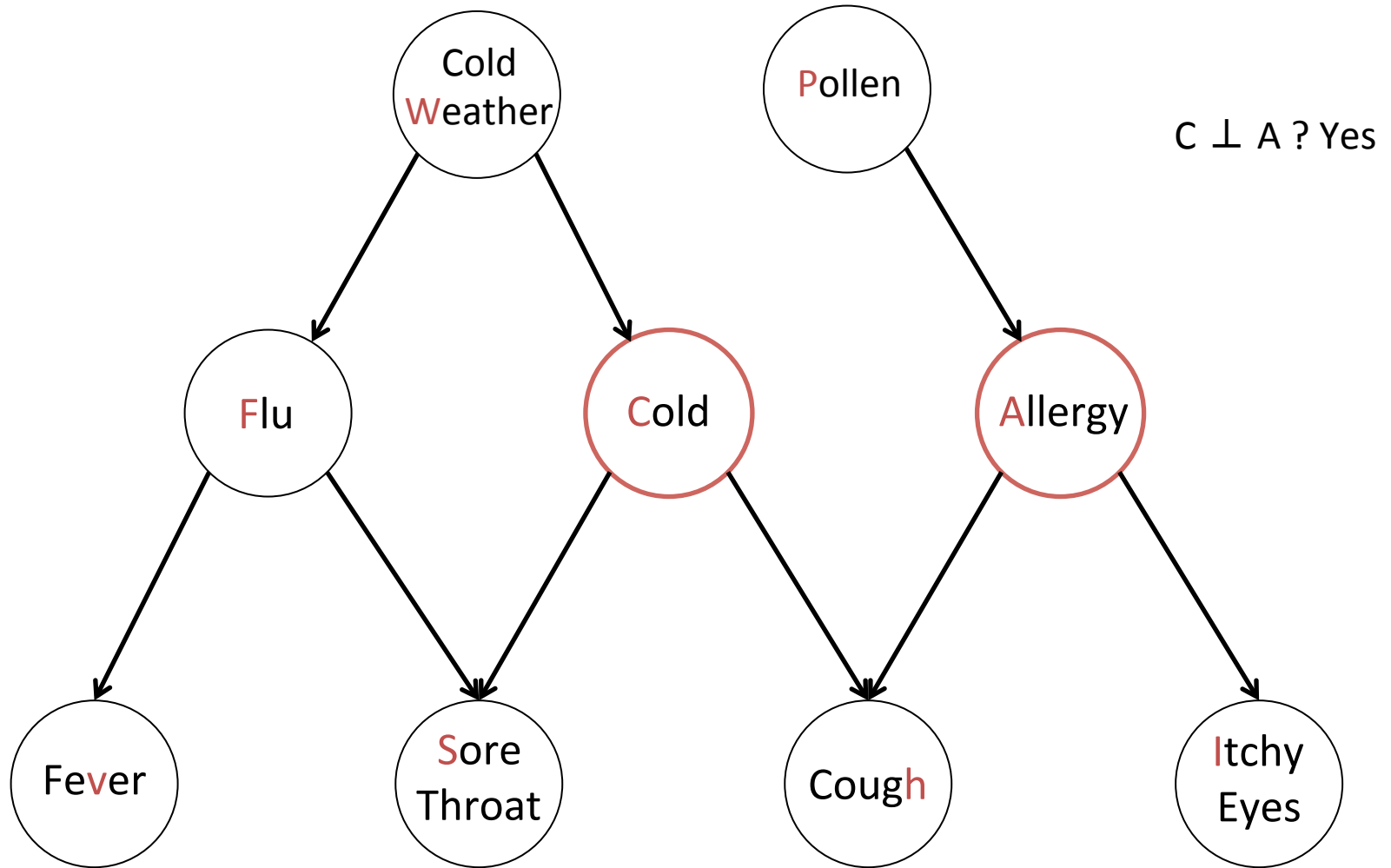
# Conditional Independence



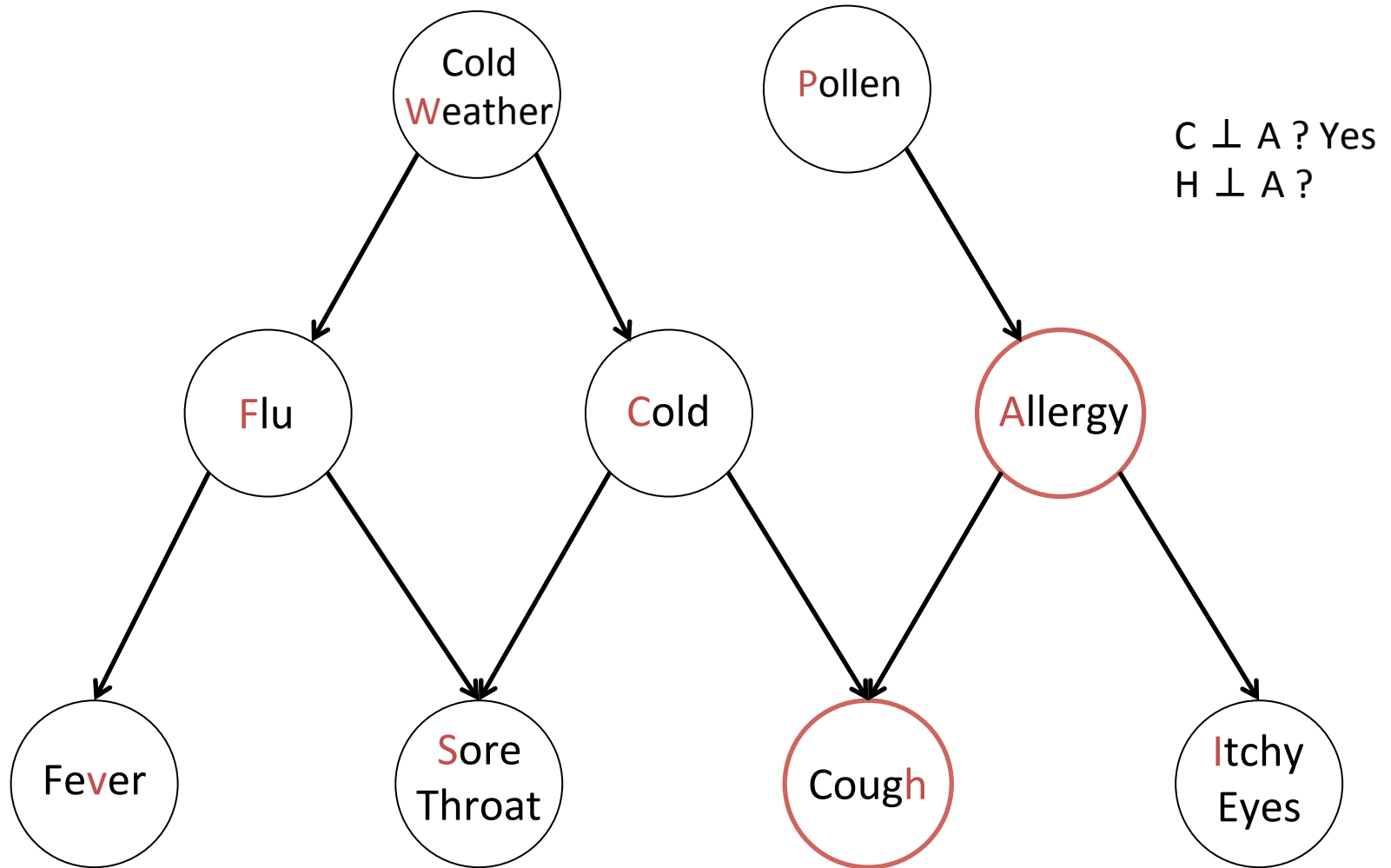
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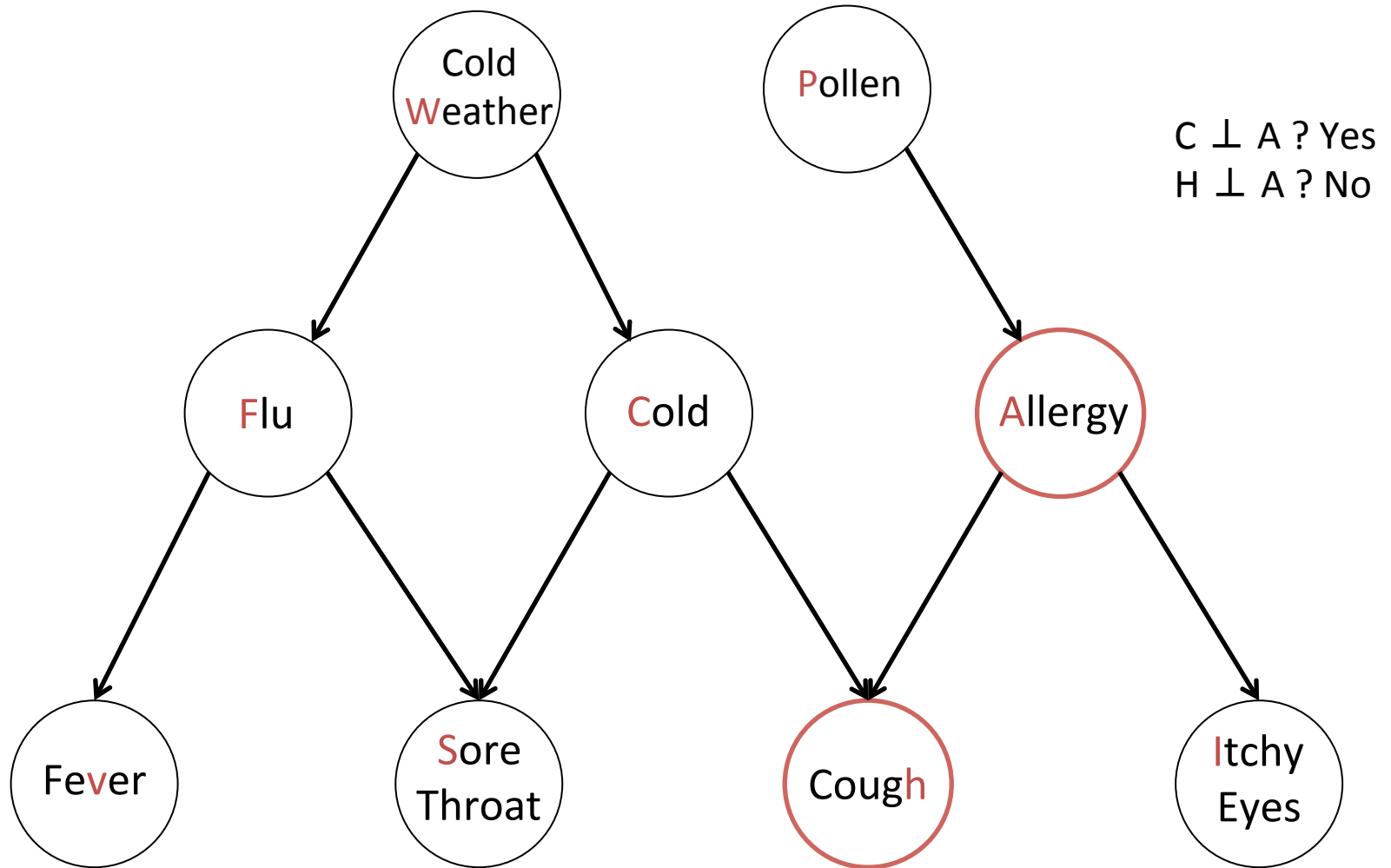
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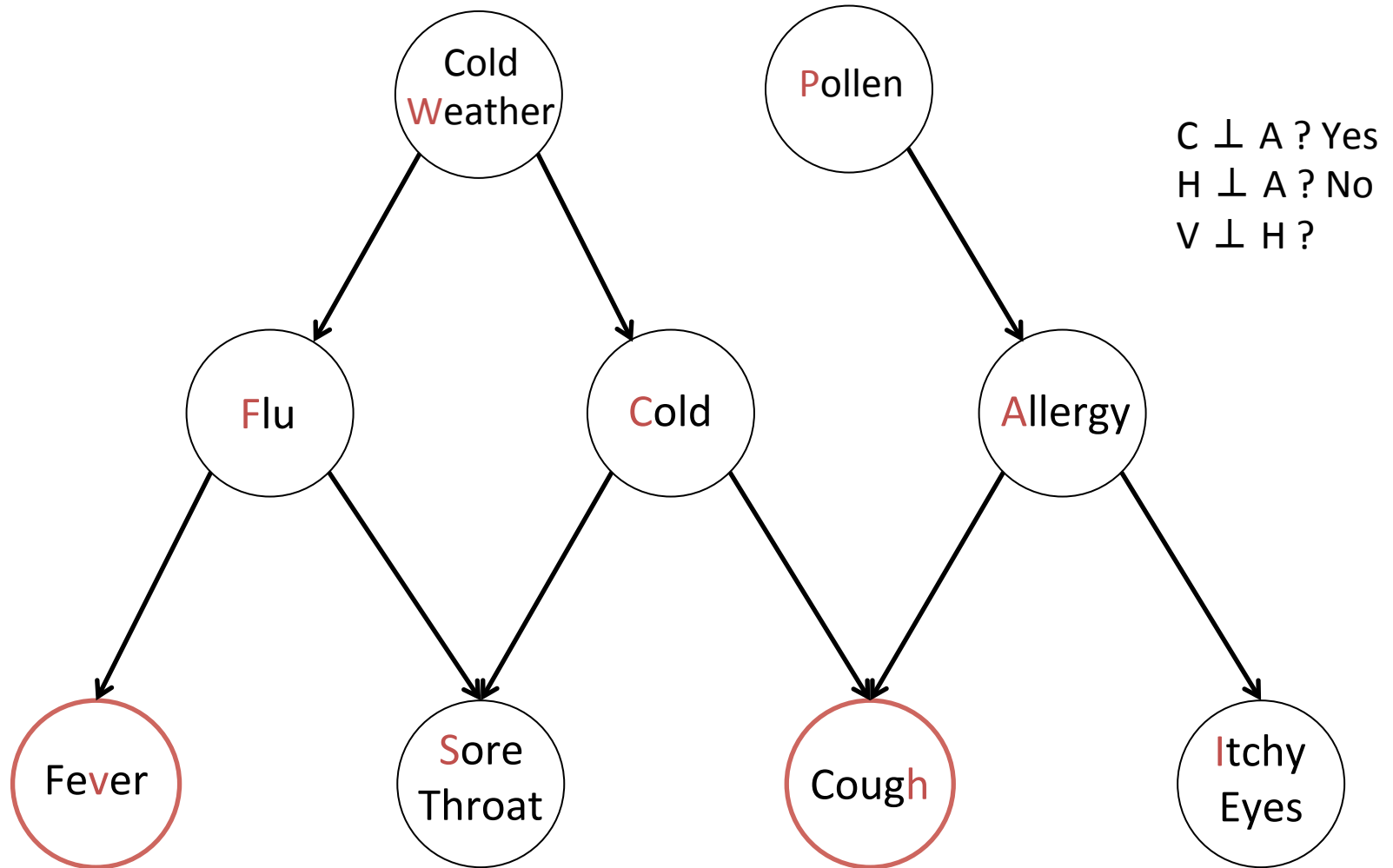


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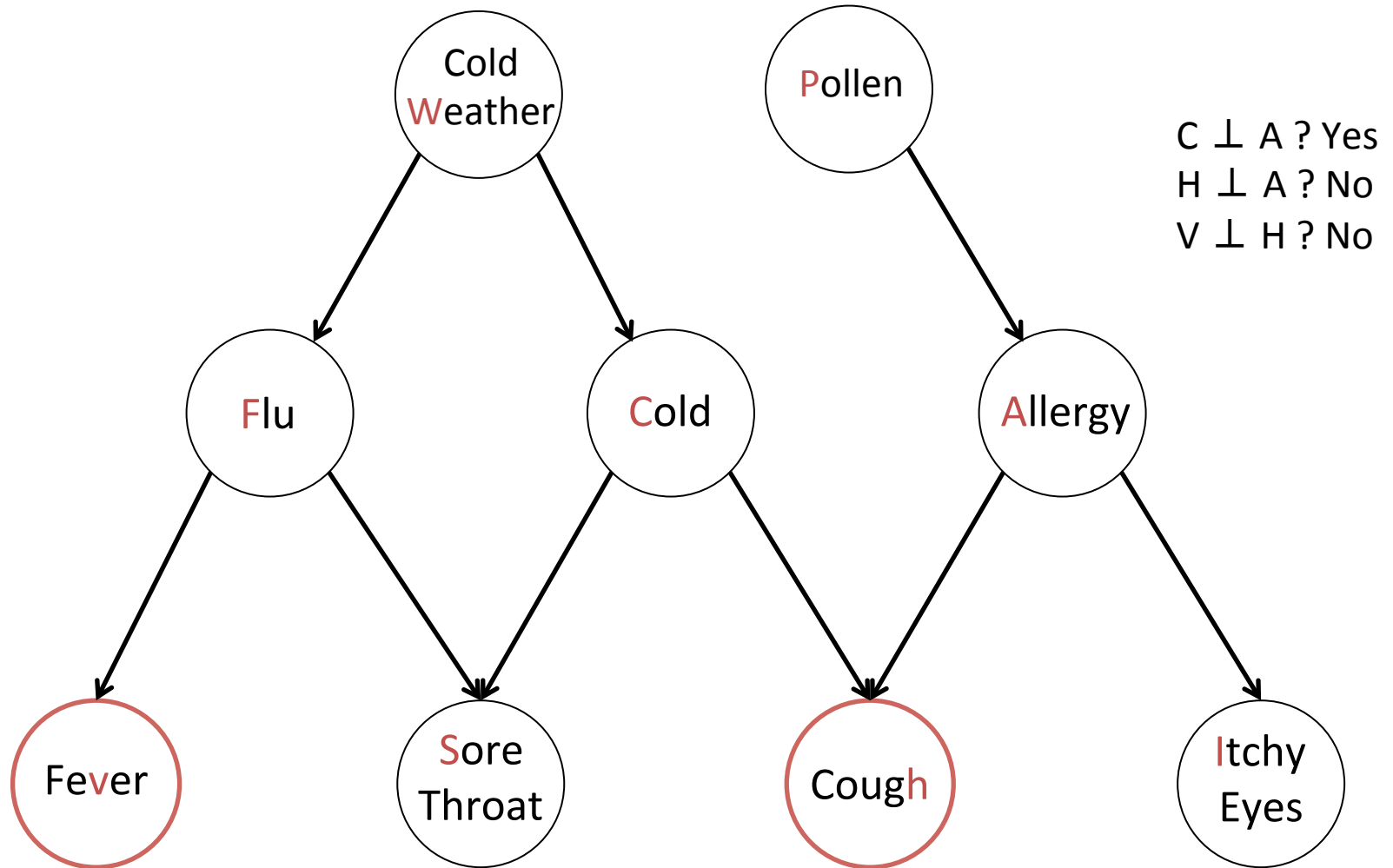




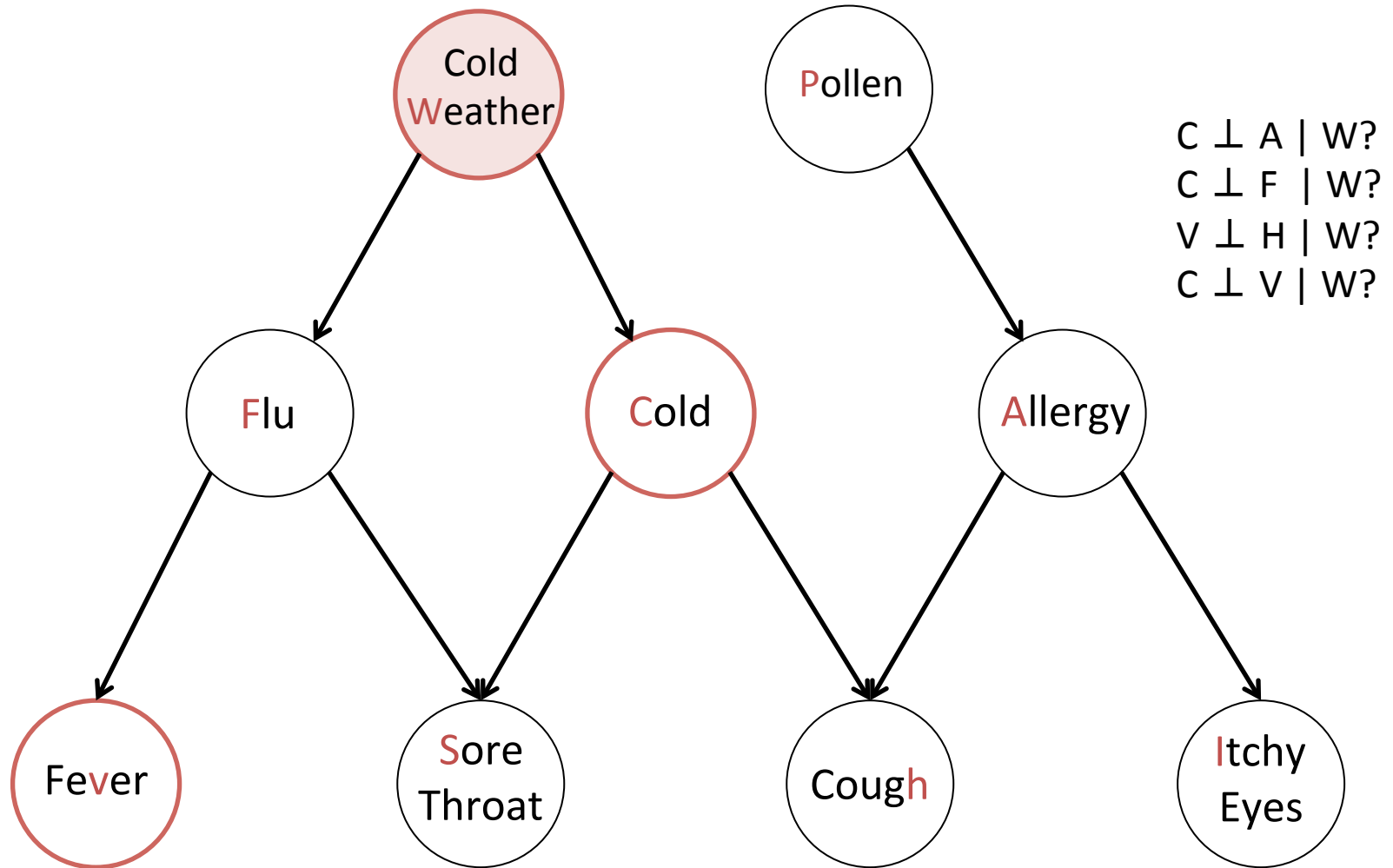
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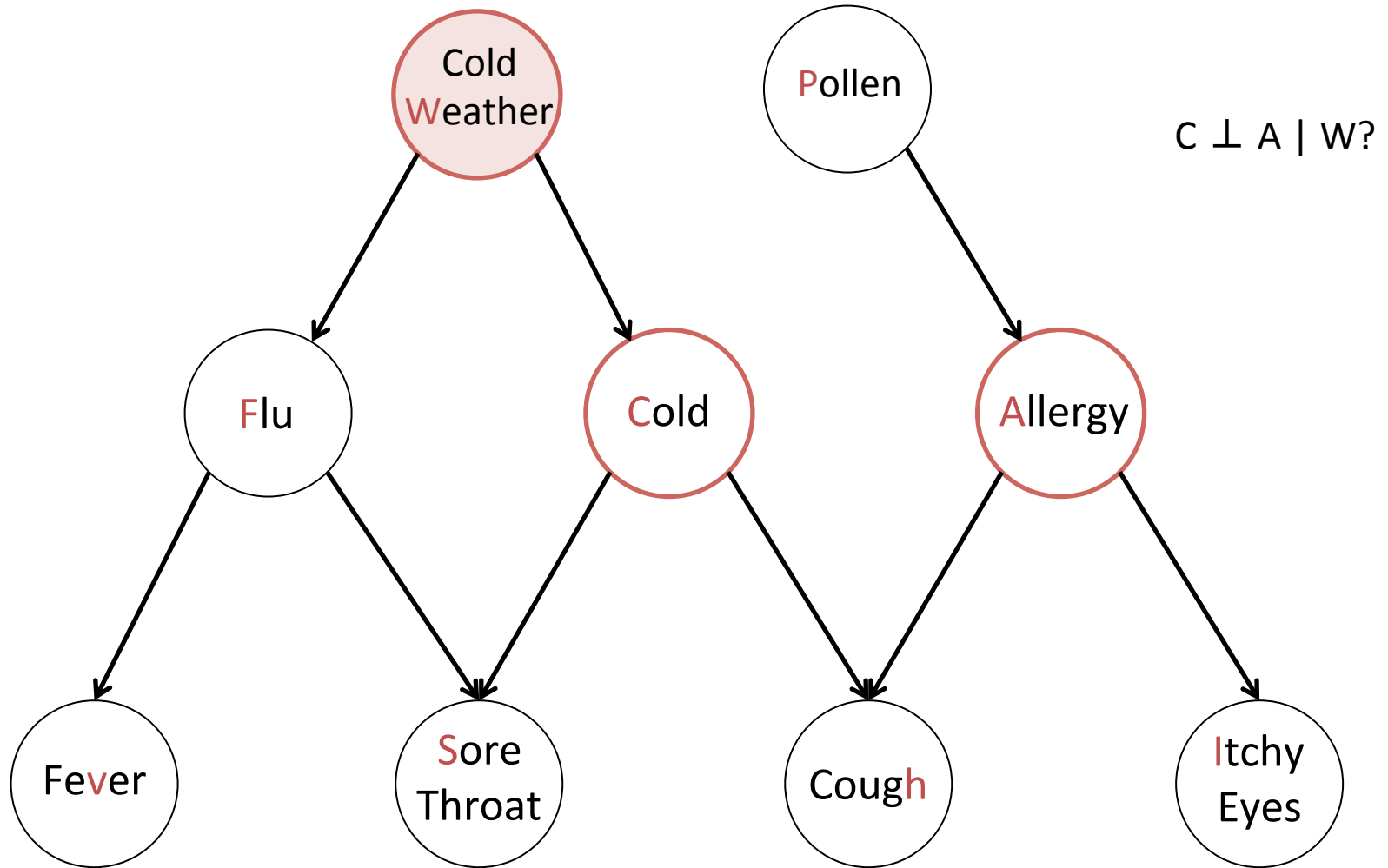
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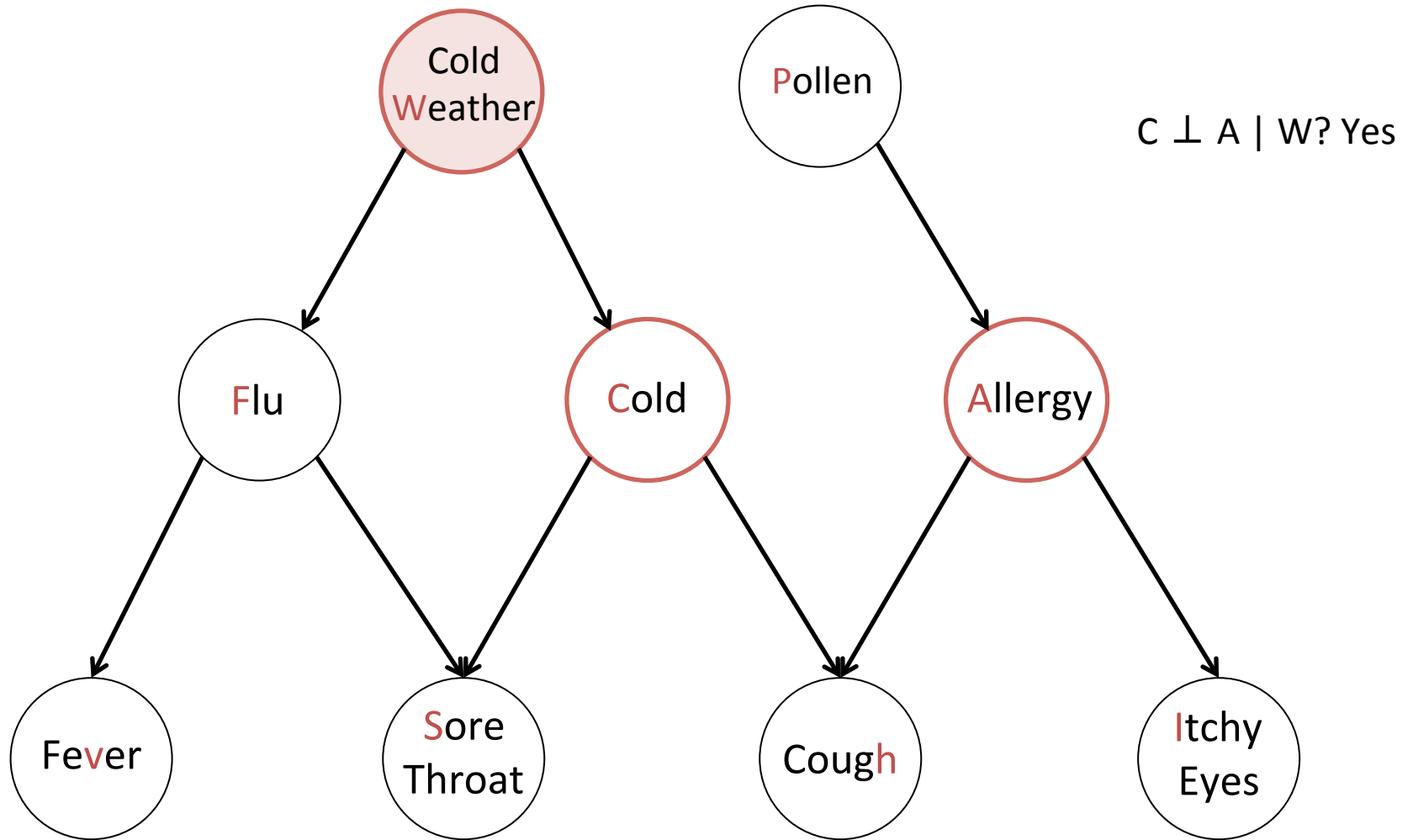
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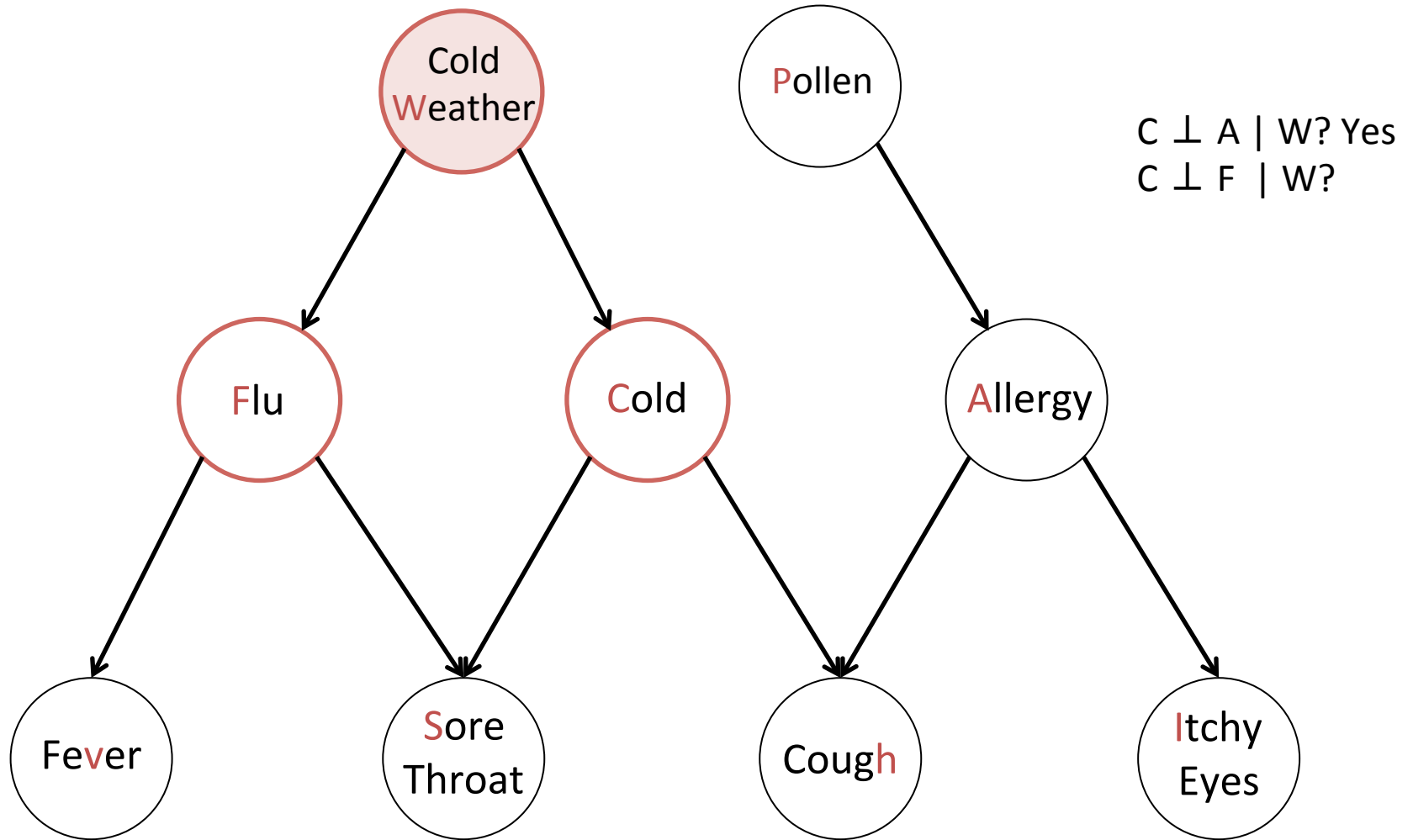
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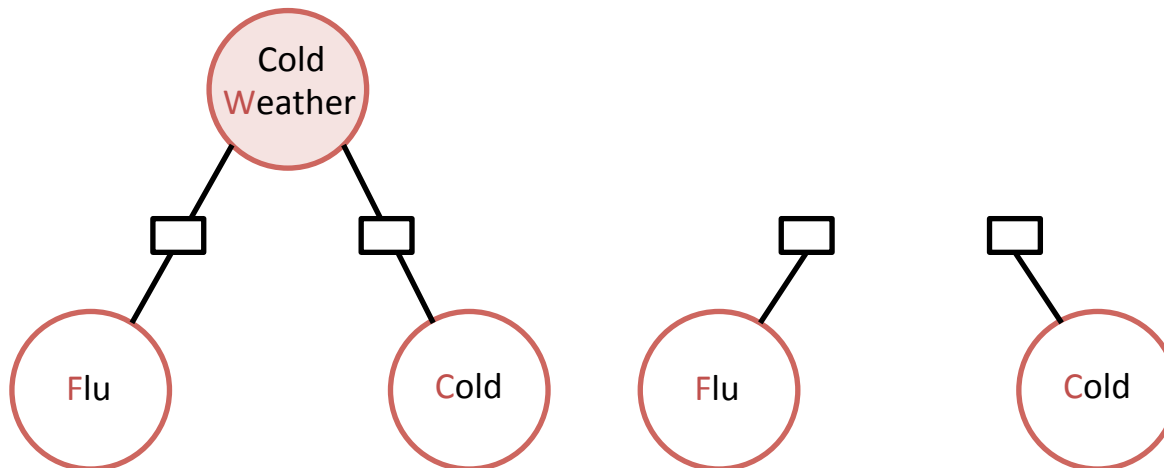
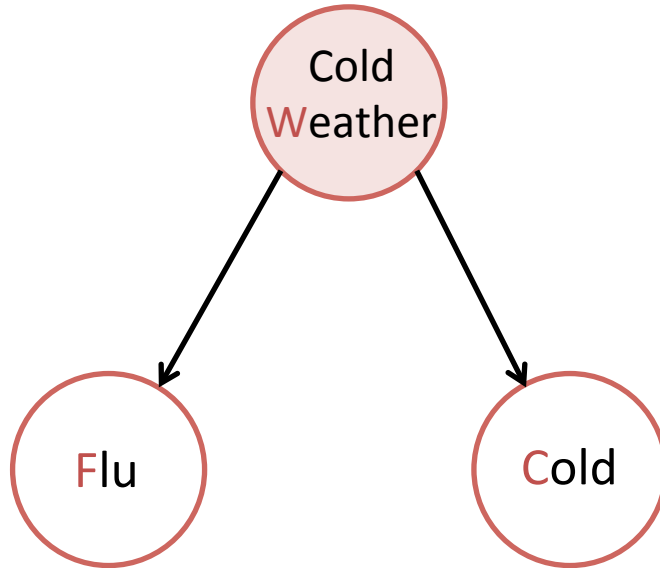


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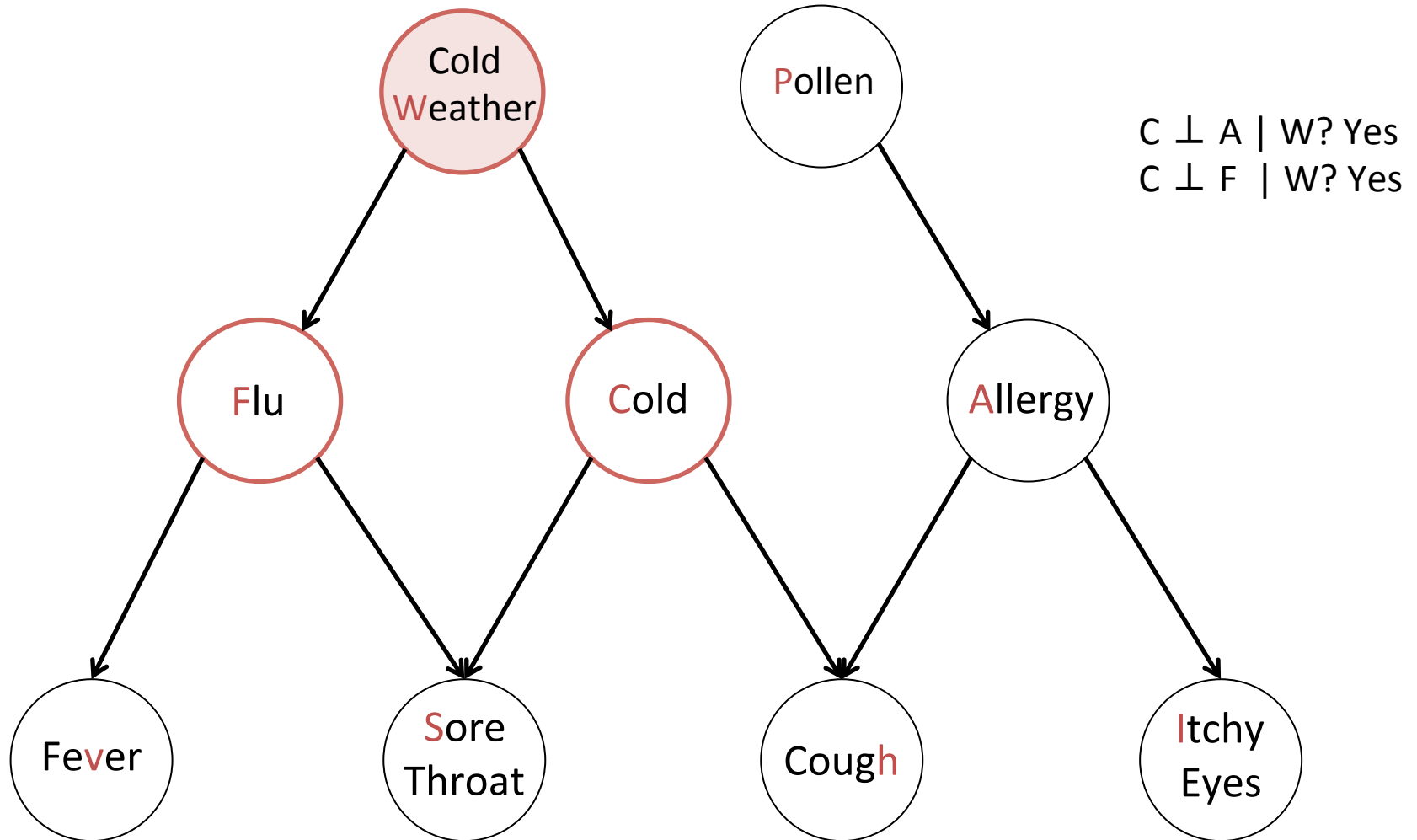


# Conditional Independence

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

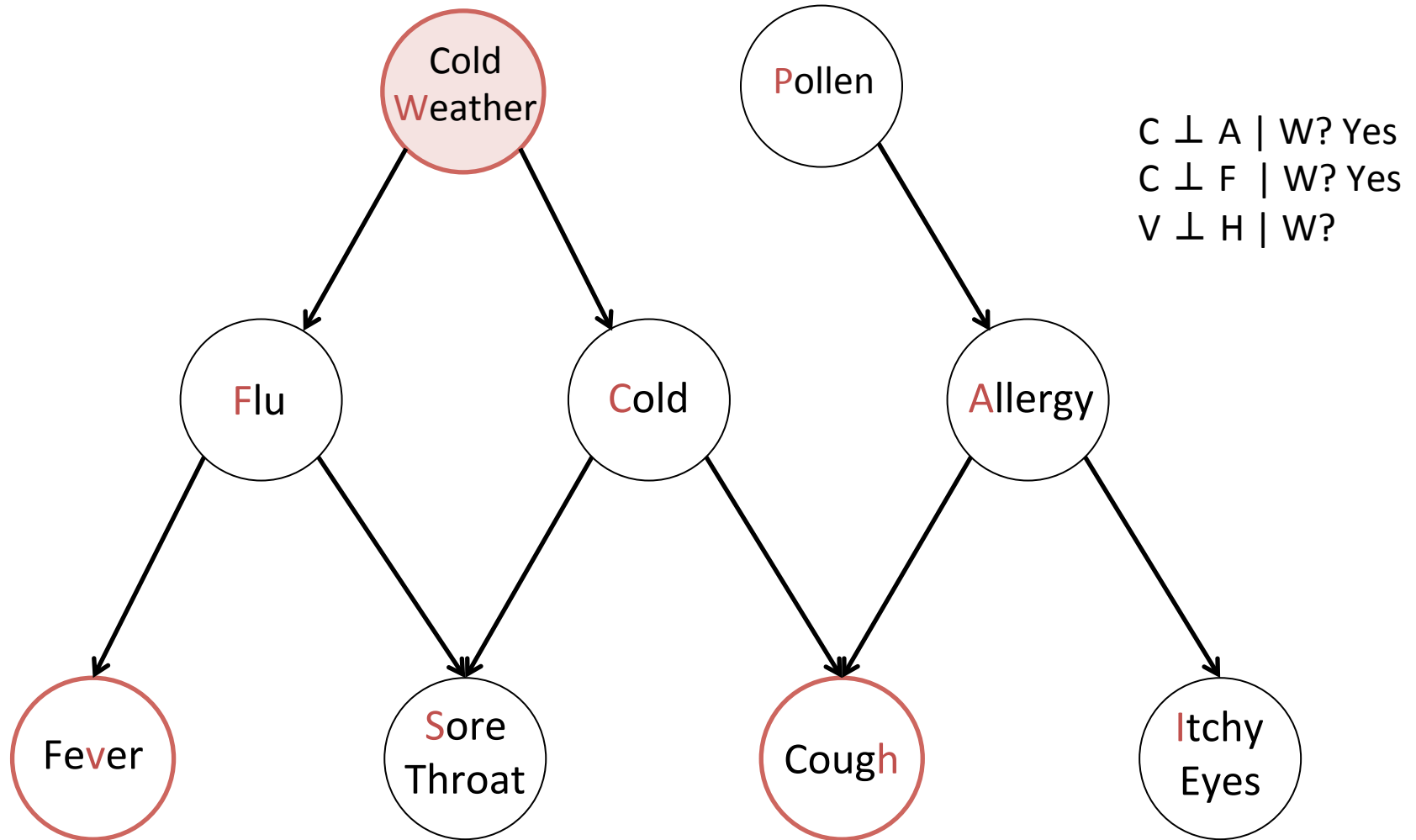


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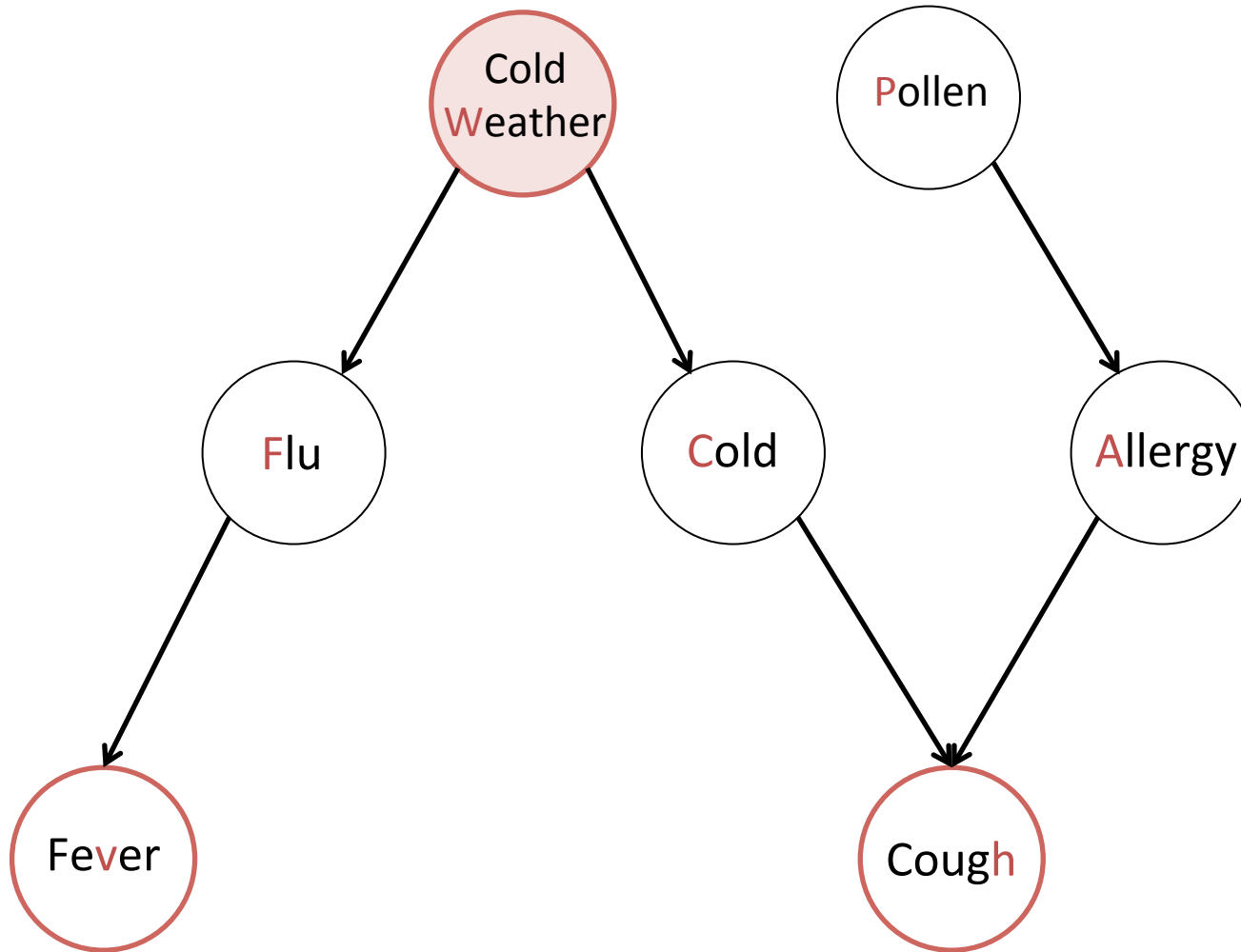




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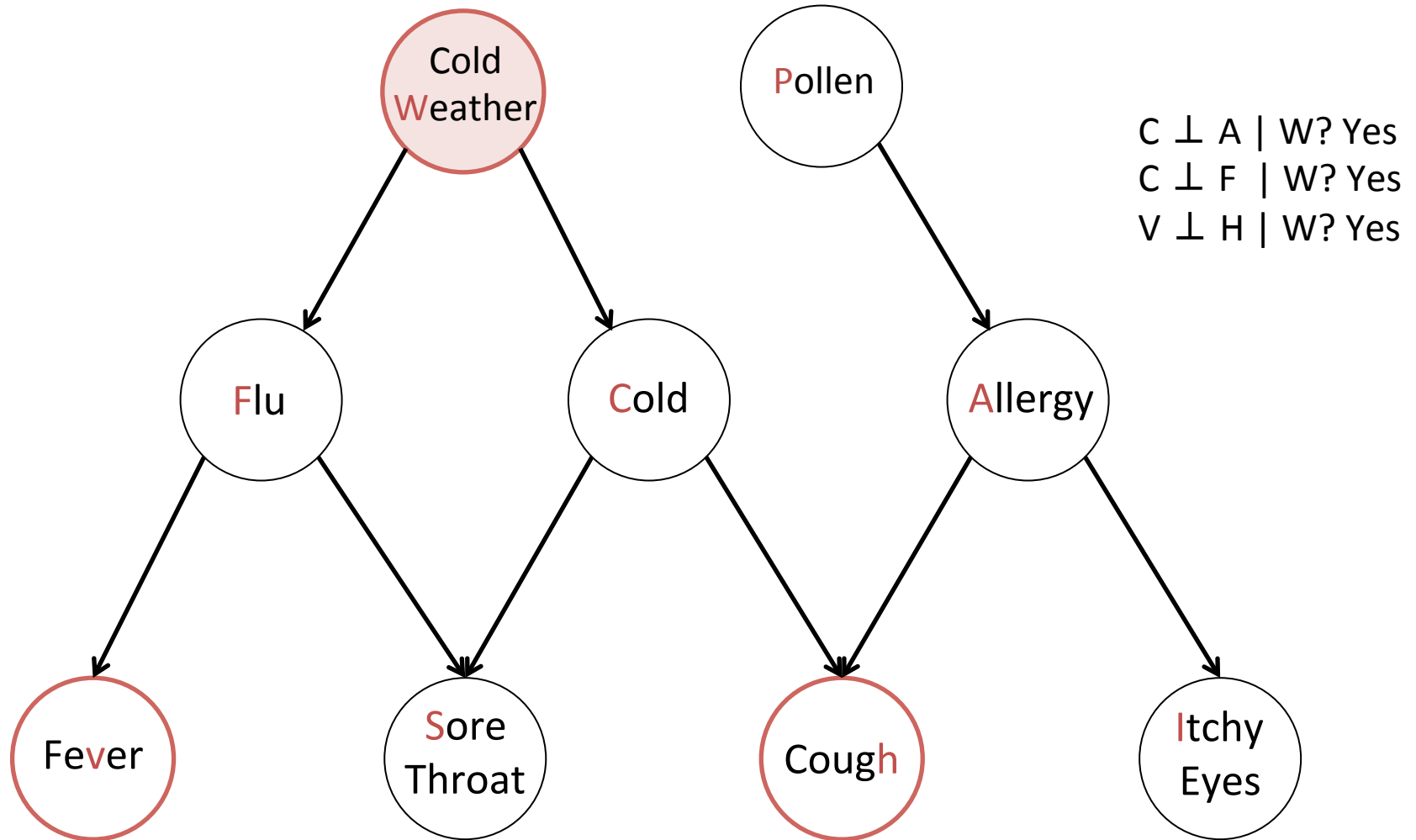


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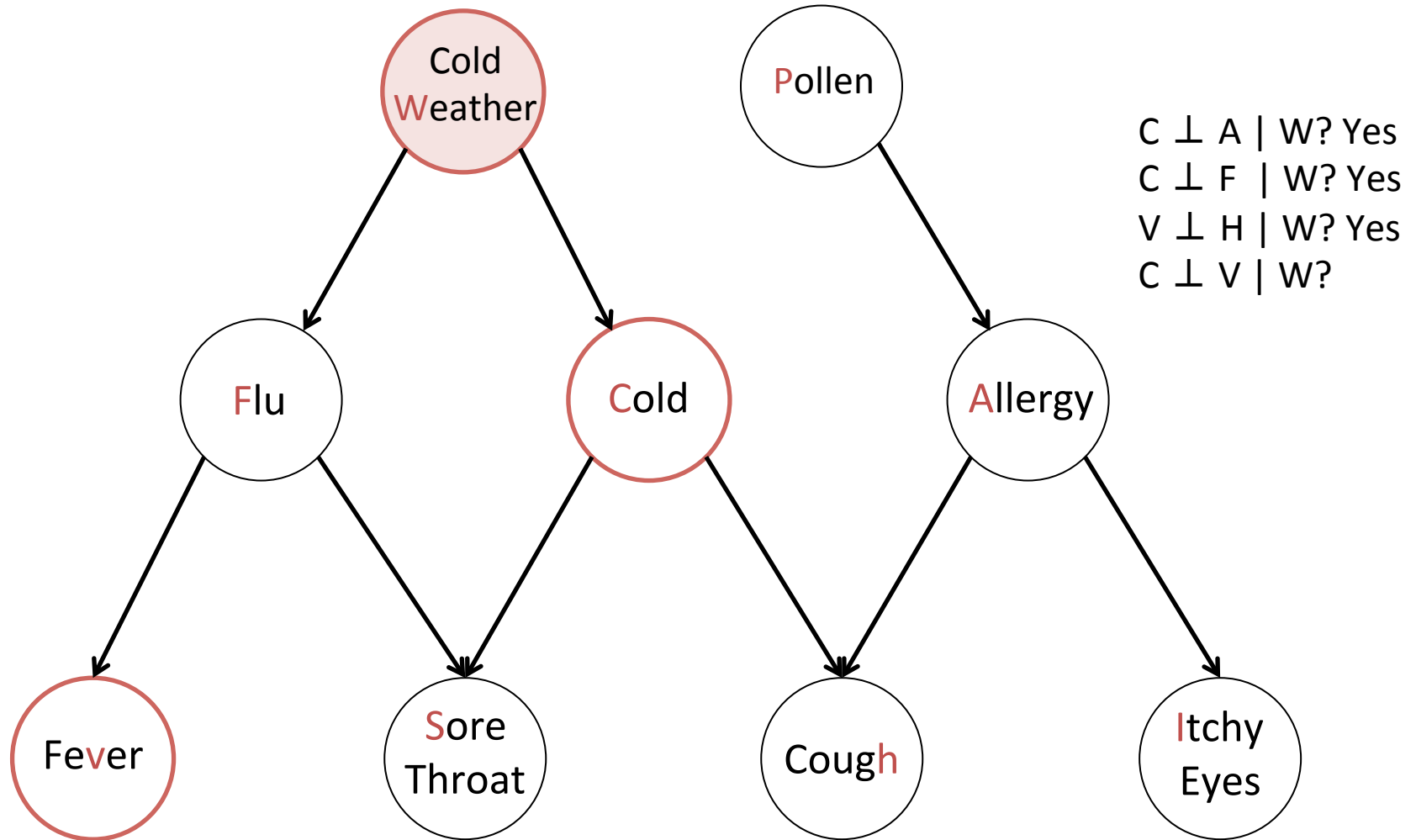


$C \perp A \mid W$ ? Yes  
 $C \perp F \mid W$ ? Yes  
 $V \perp H \mid W$ ?

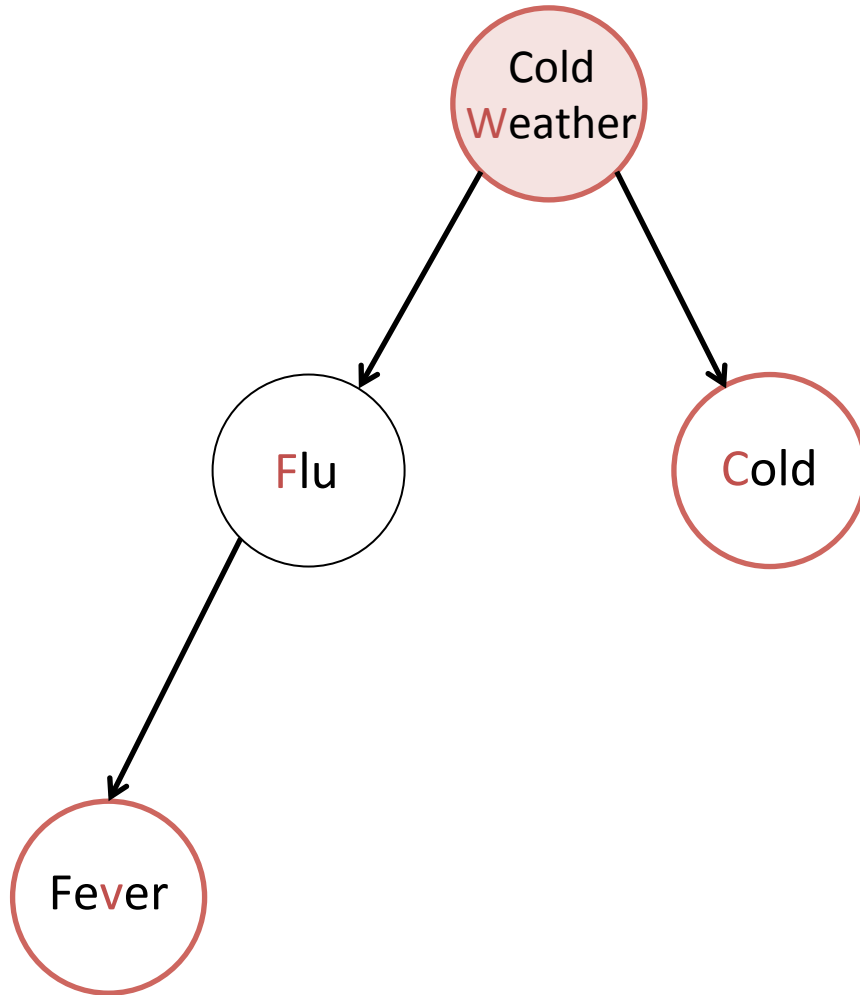
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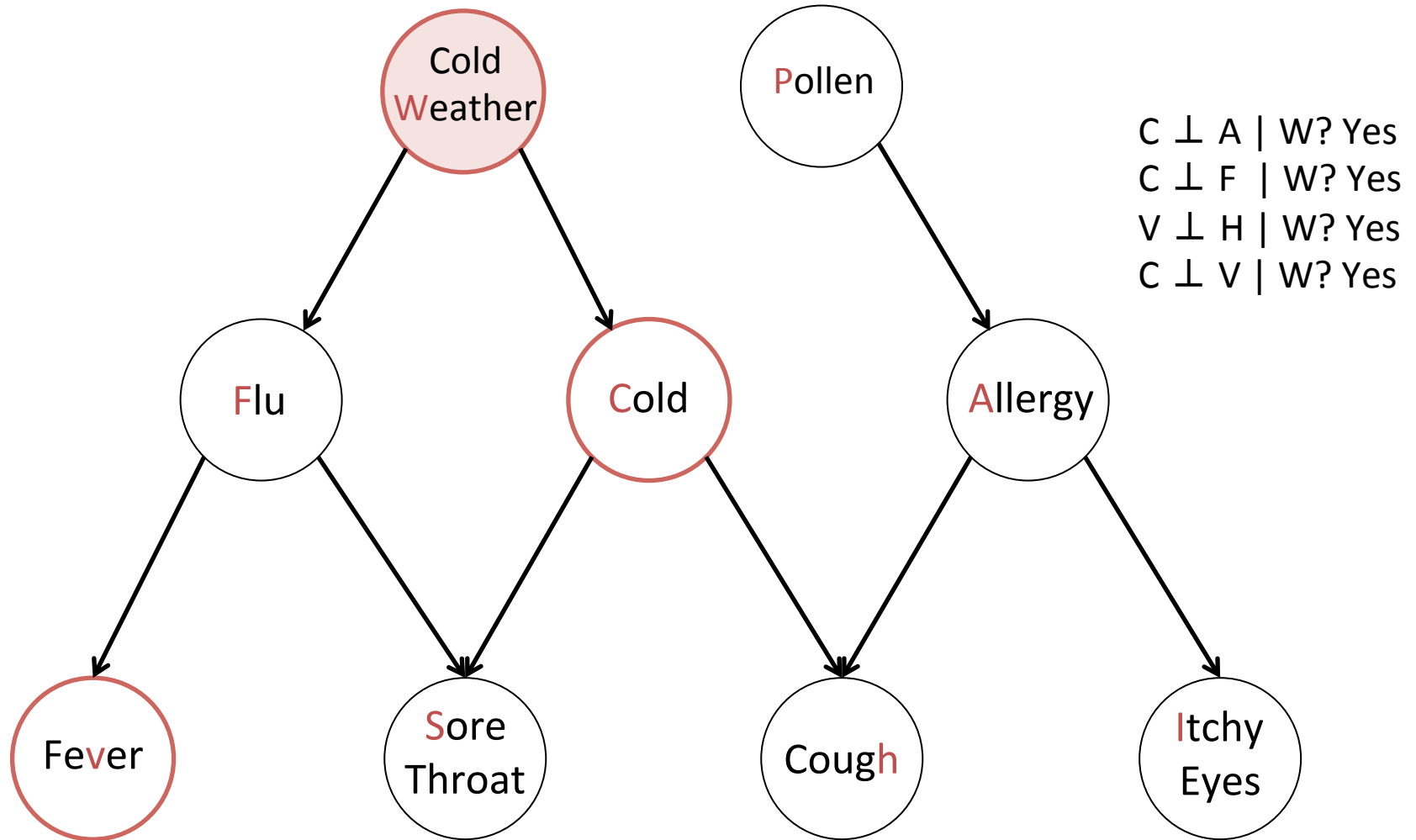


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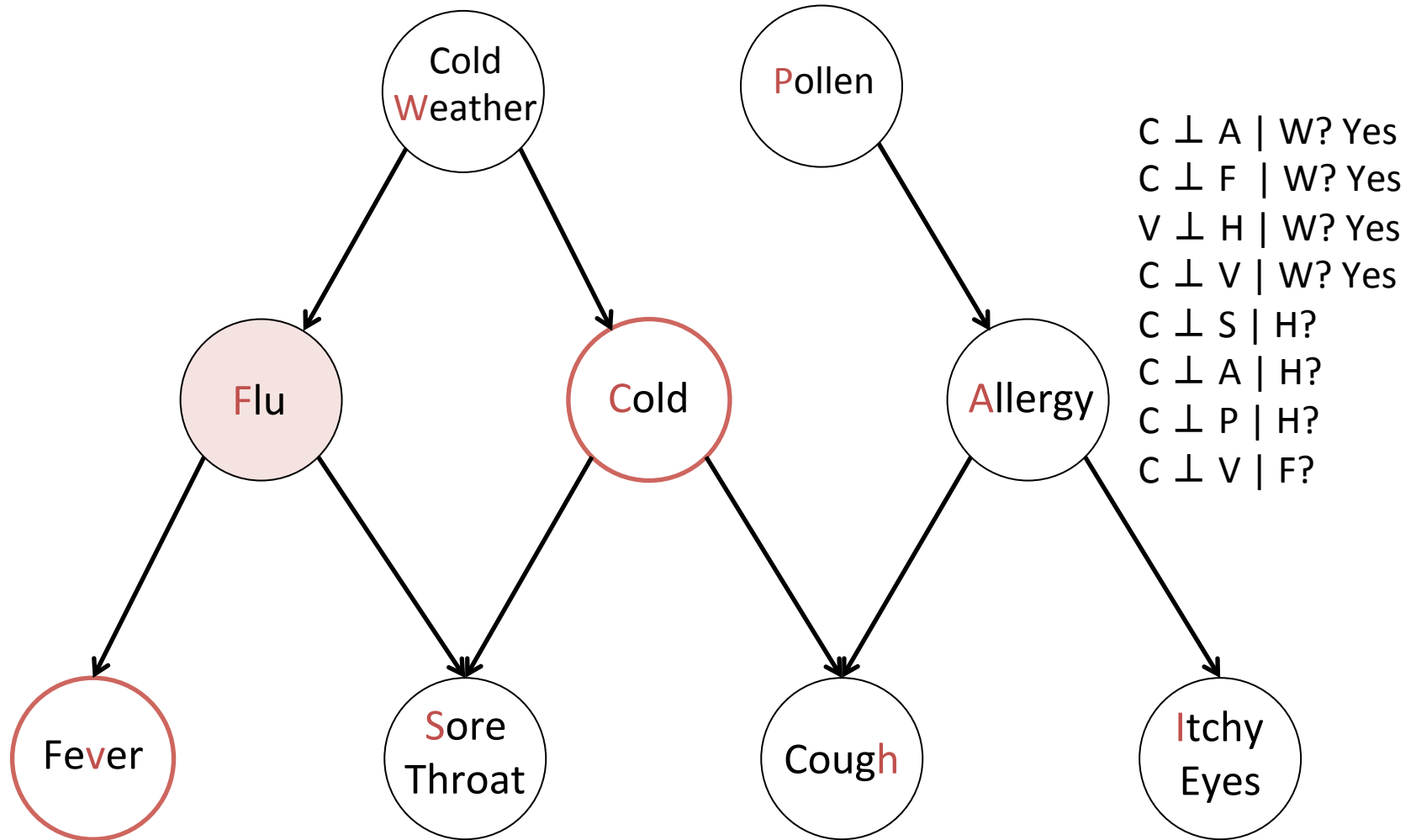


$C \perp A \mid W?$  Yes  
 $C \perp F \mid W?$  Yes  
 $V \perp H \mid W?$  Yes  
 $C \perp V \mid W?$

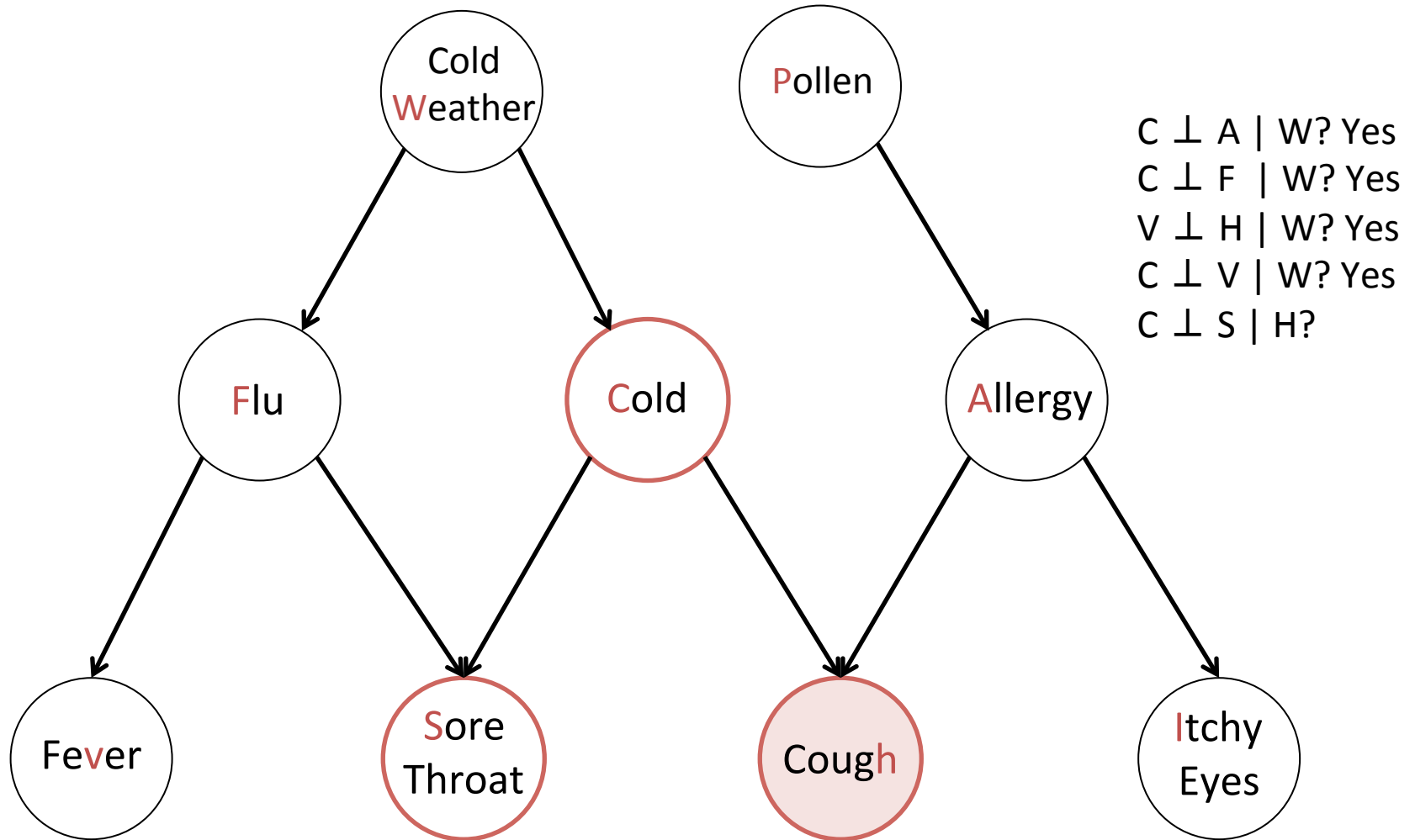
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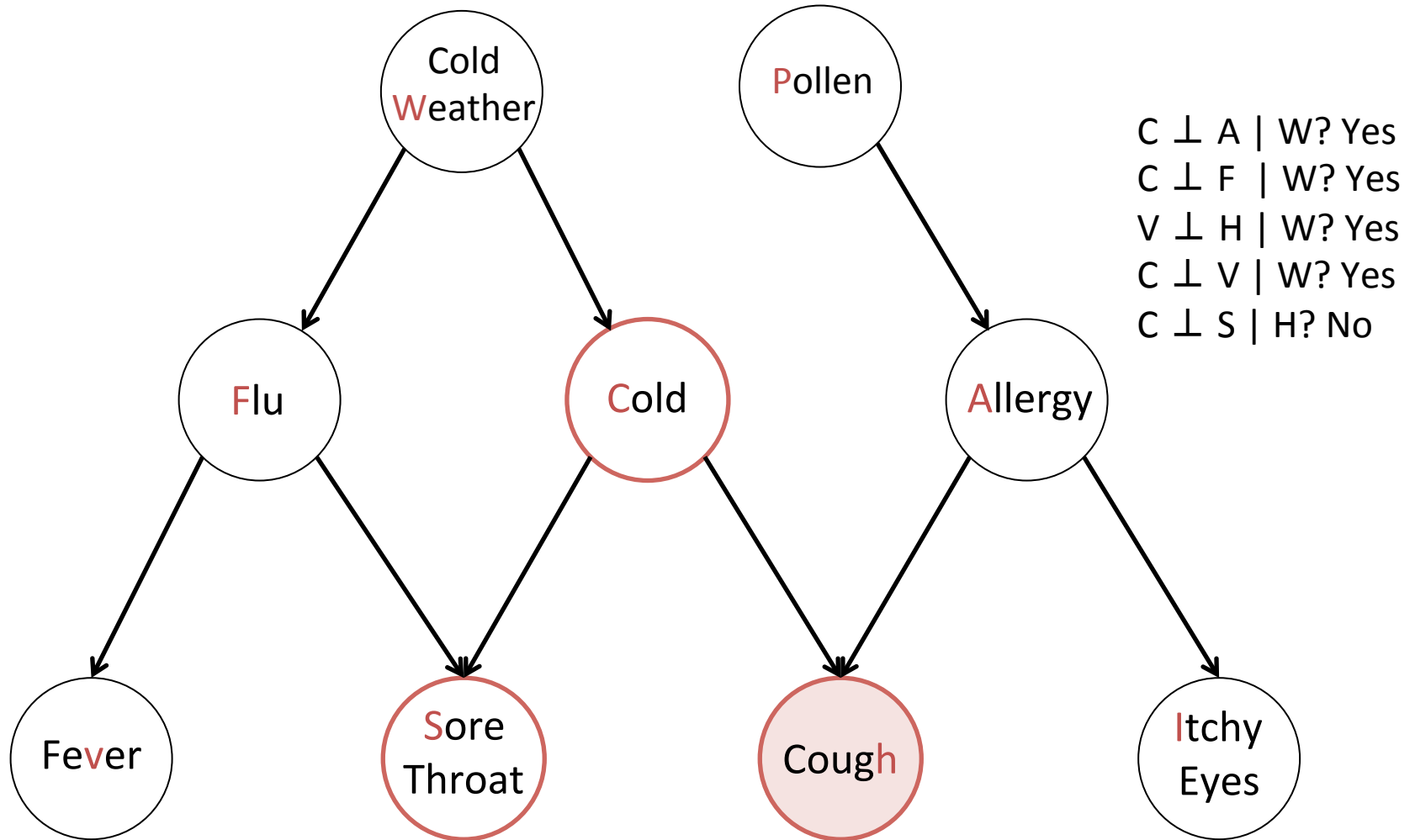


# Conditional Independence

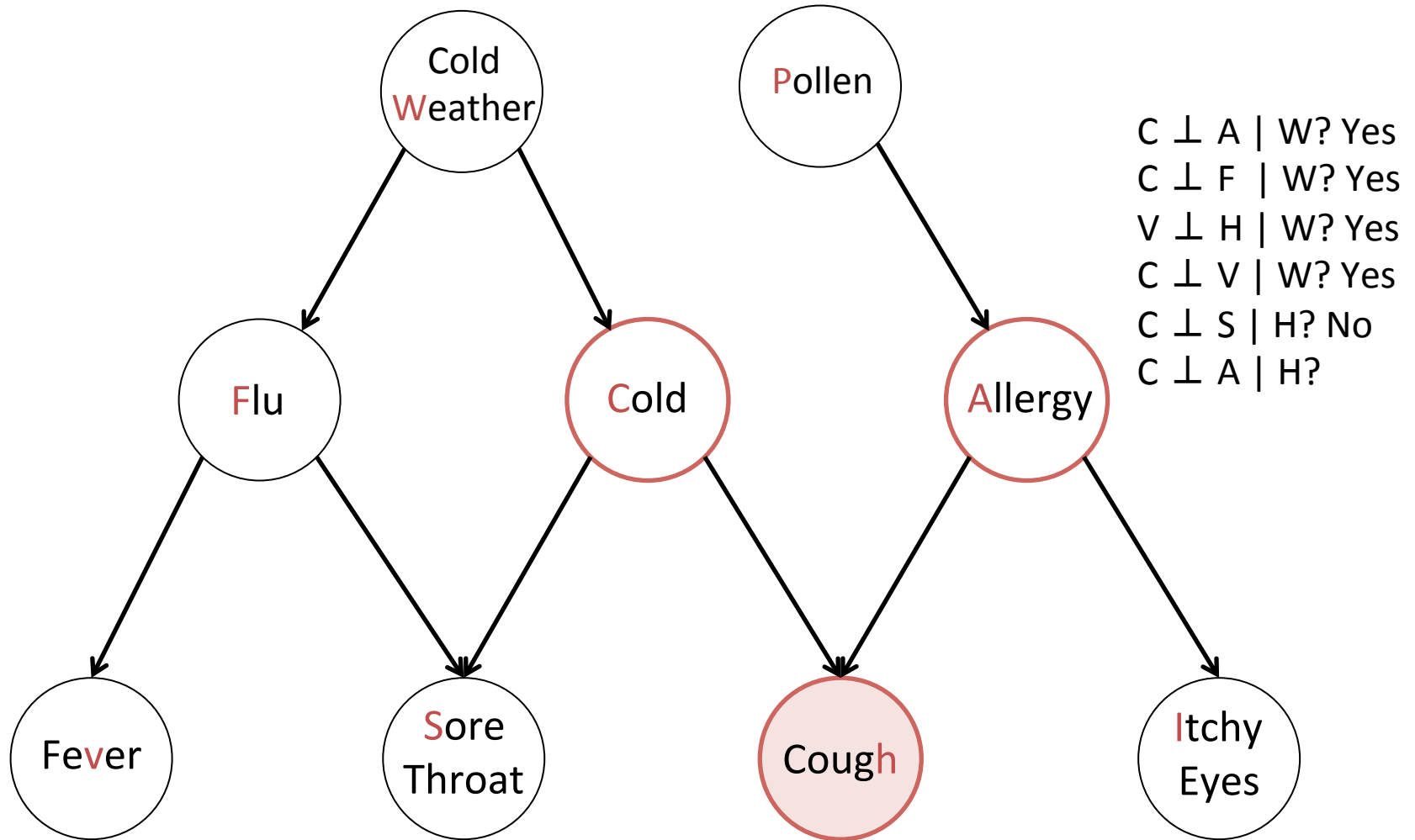




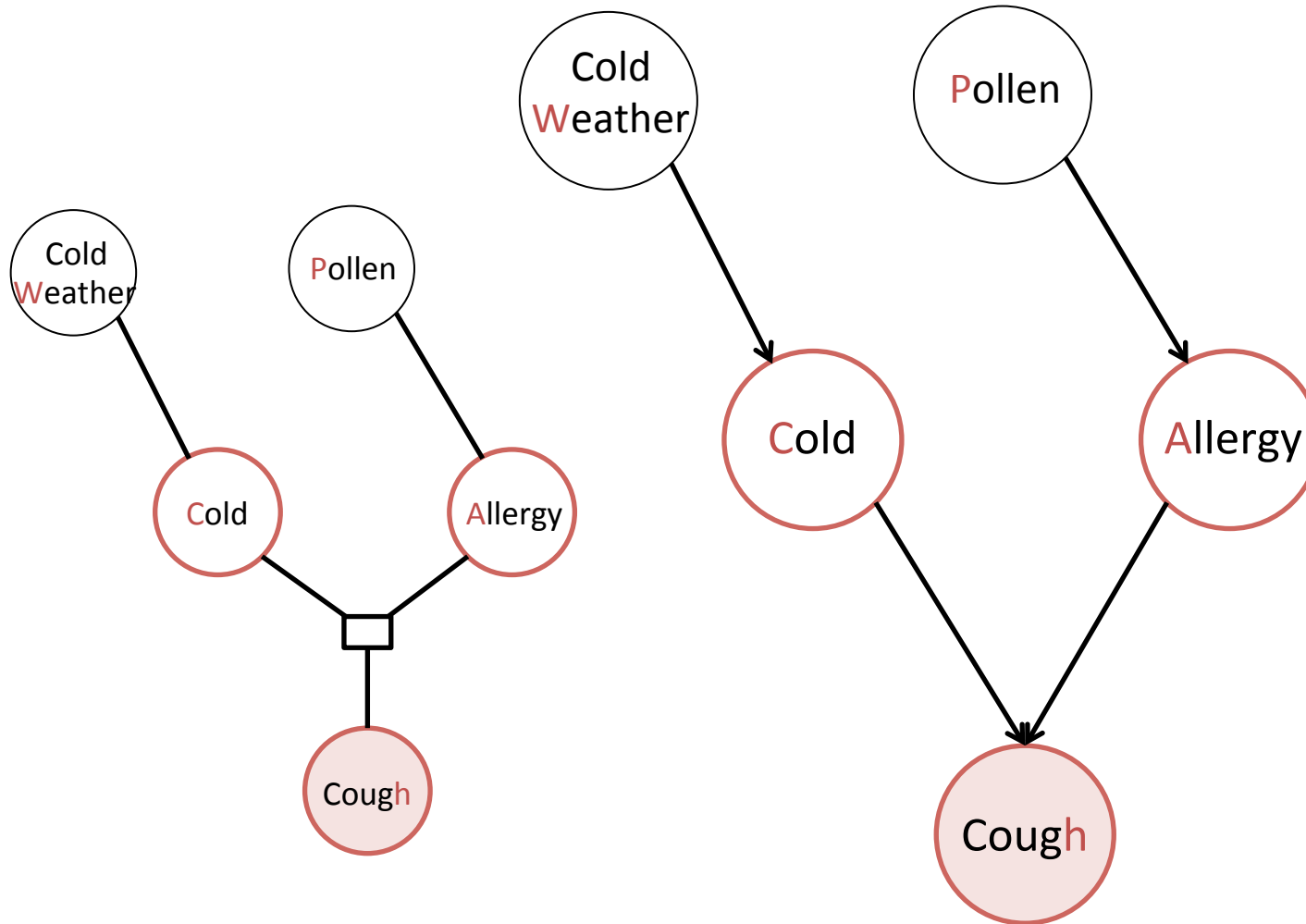
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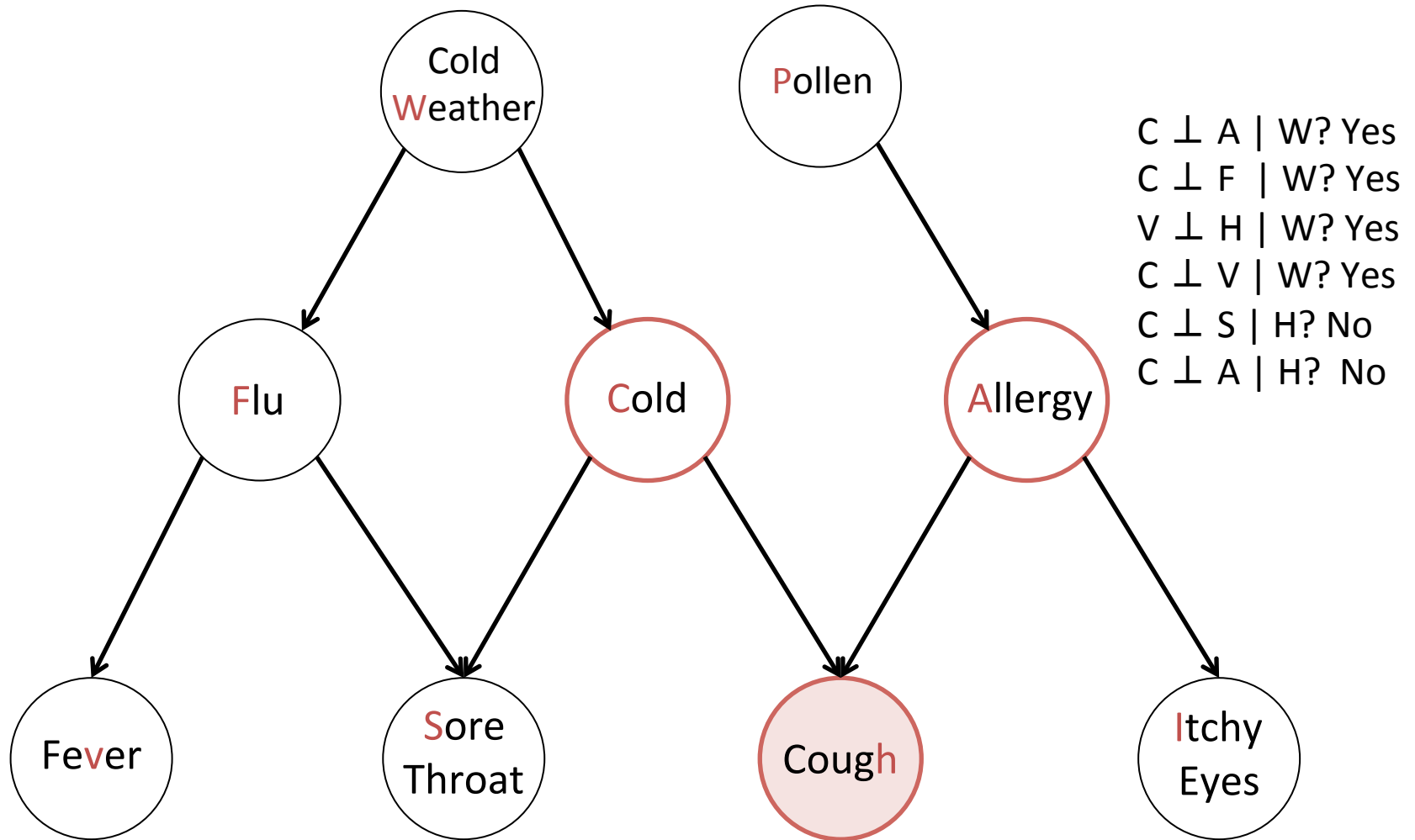
# Conditional Independence



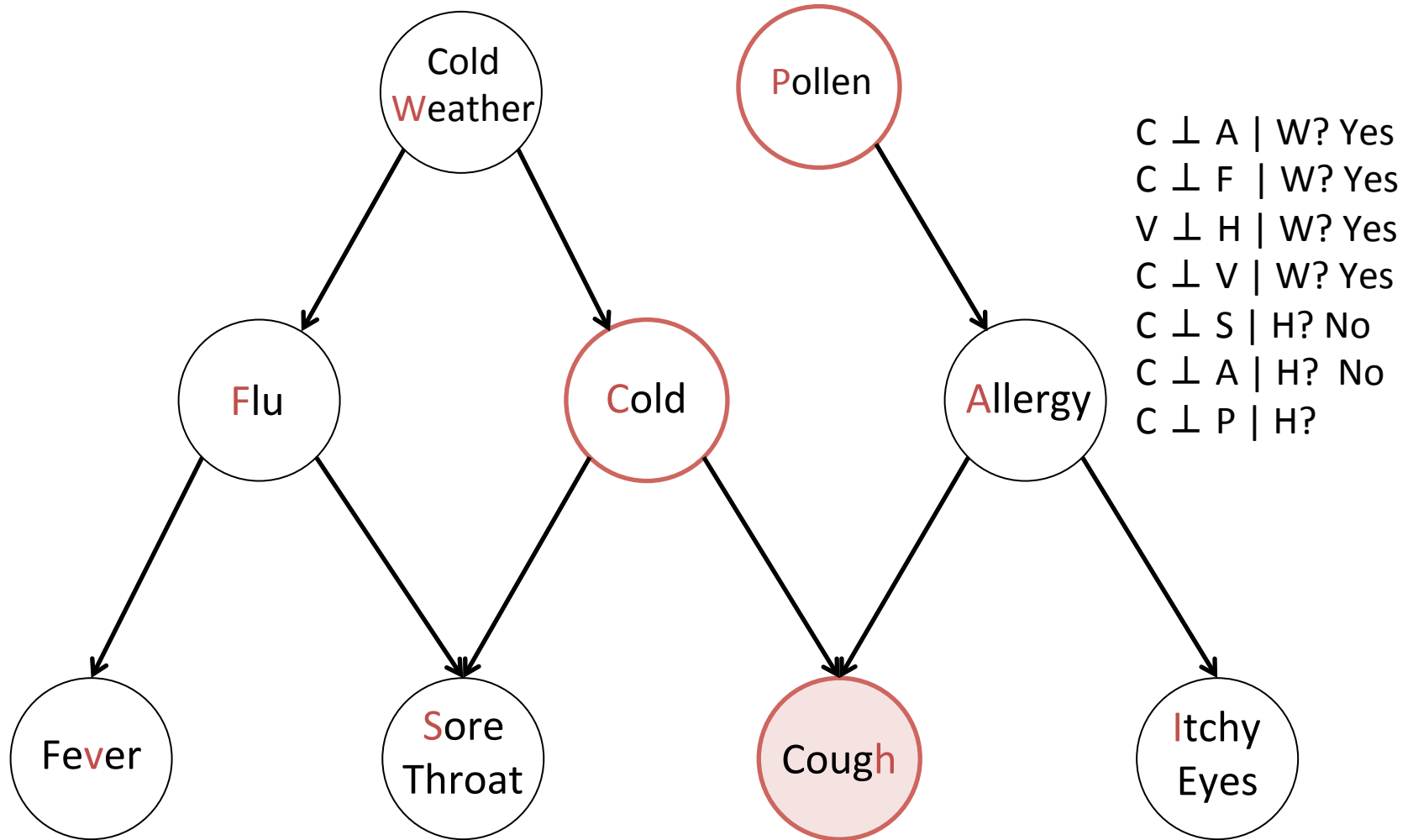
$C \perp A \mid W$ ? Yes  
 $C \perp F \mid W$ ? Yes  
 $V \perp H \mid W$ ? Yes  
 $C \perp V \mid W$ ? Yes  
 $C \perp S \mid H$ ? No  
 $C \perp A \mid H$ ?

Explaining Away!

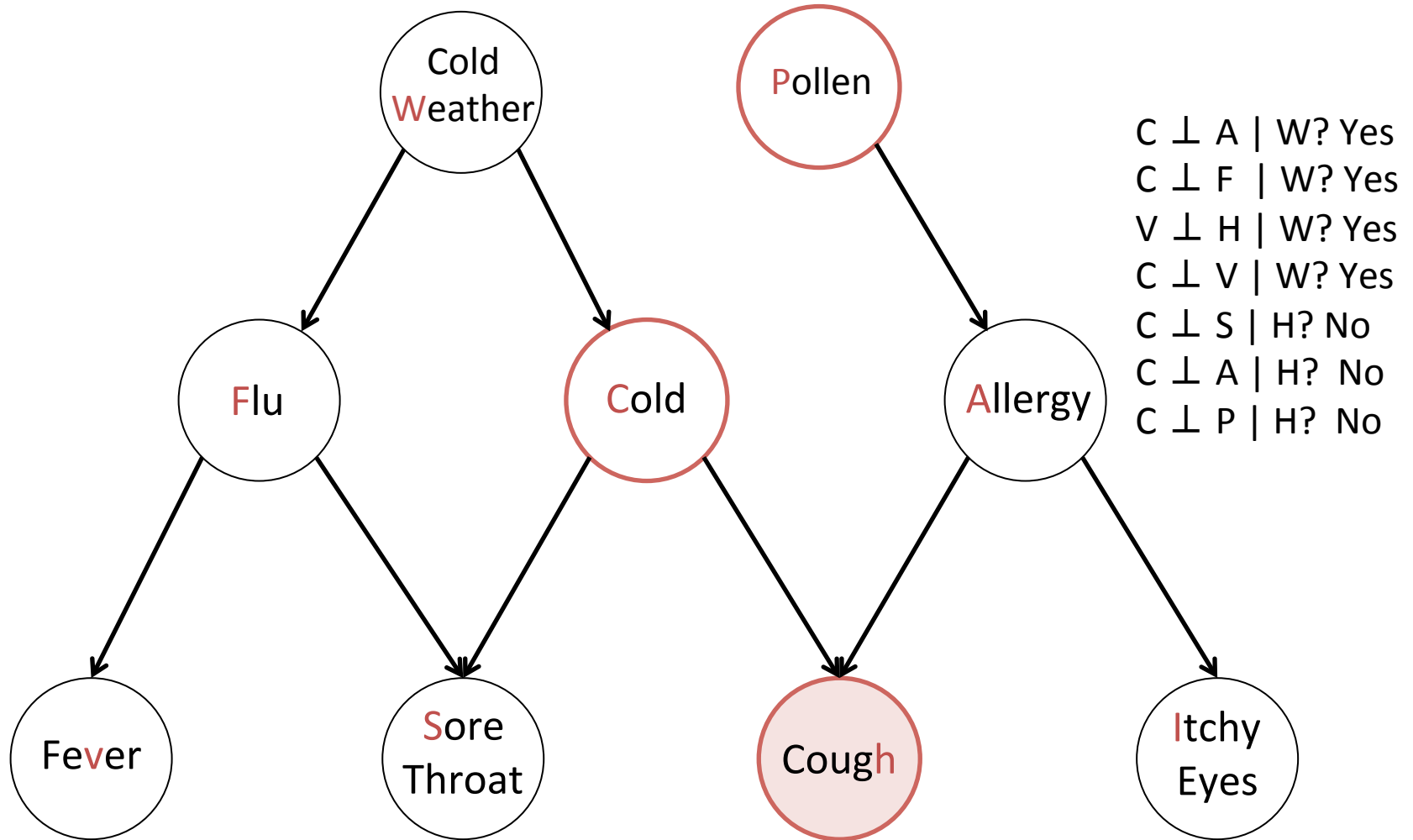
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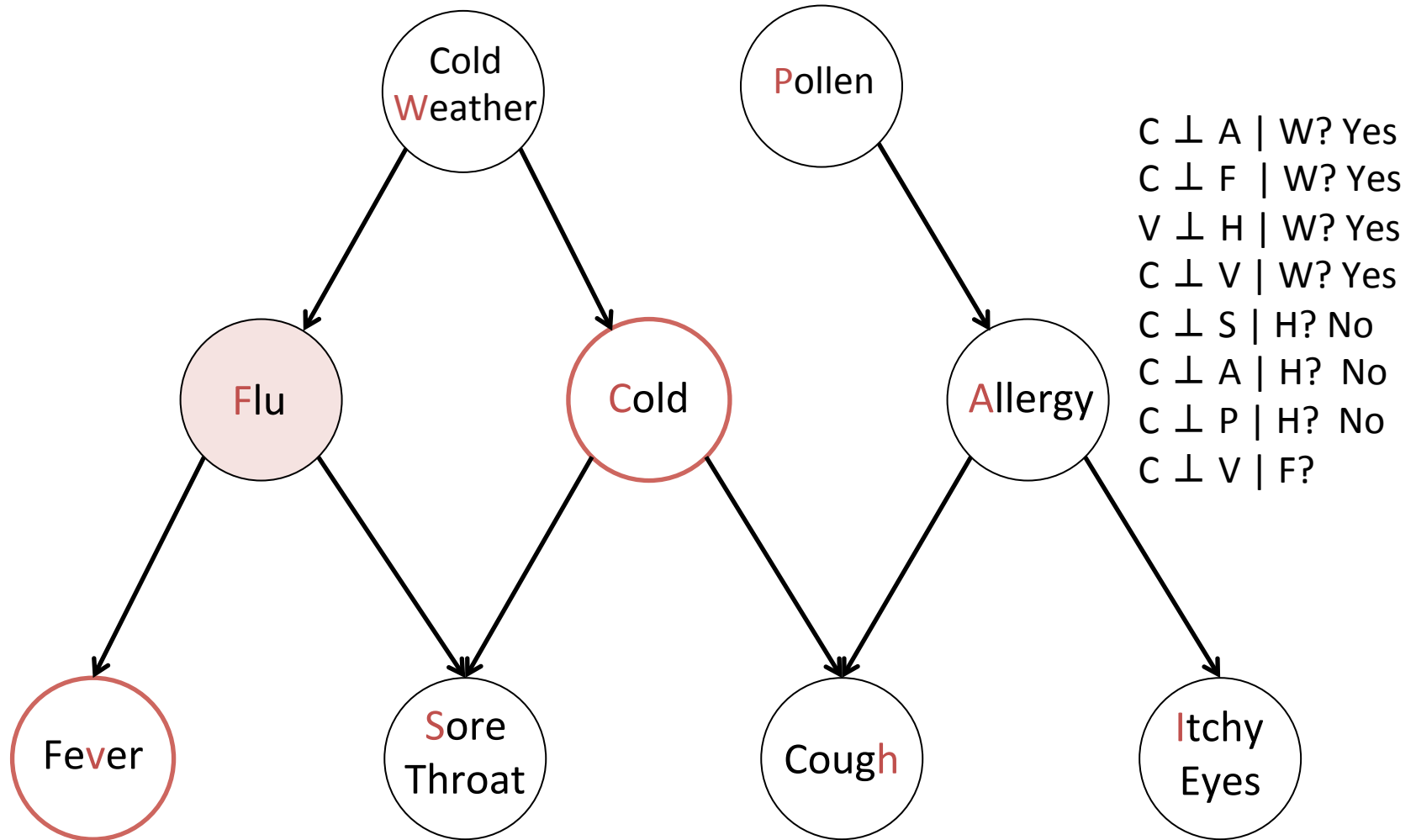
# Conditional Independence



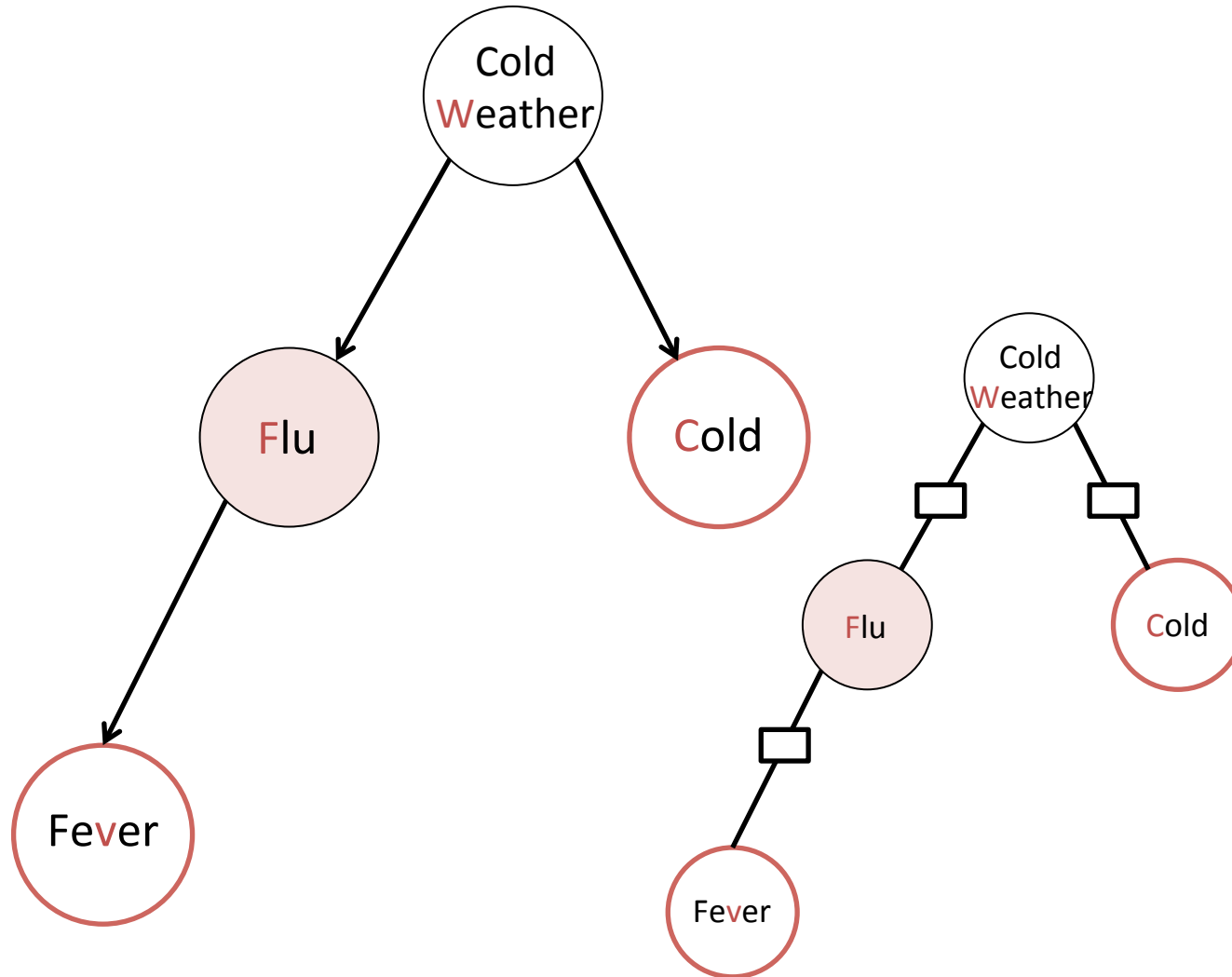
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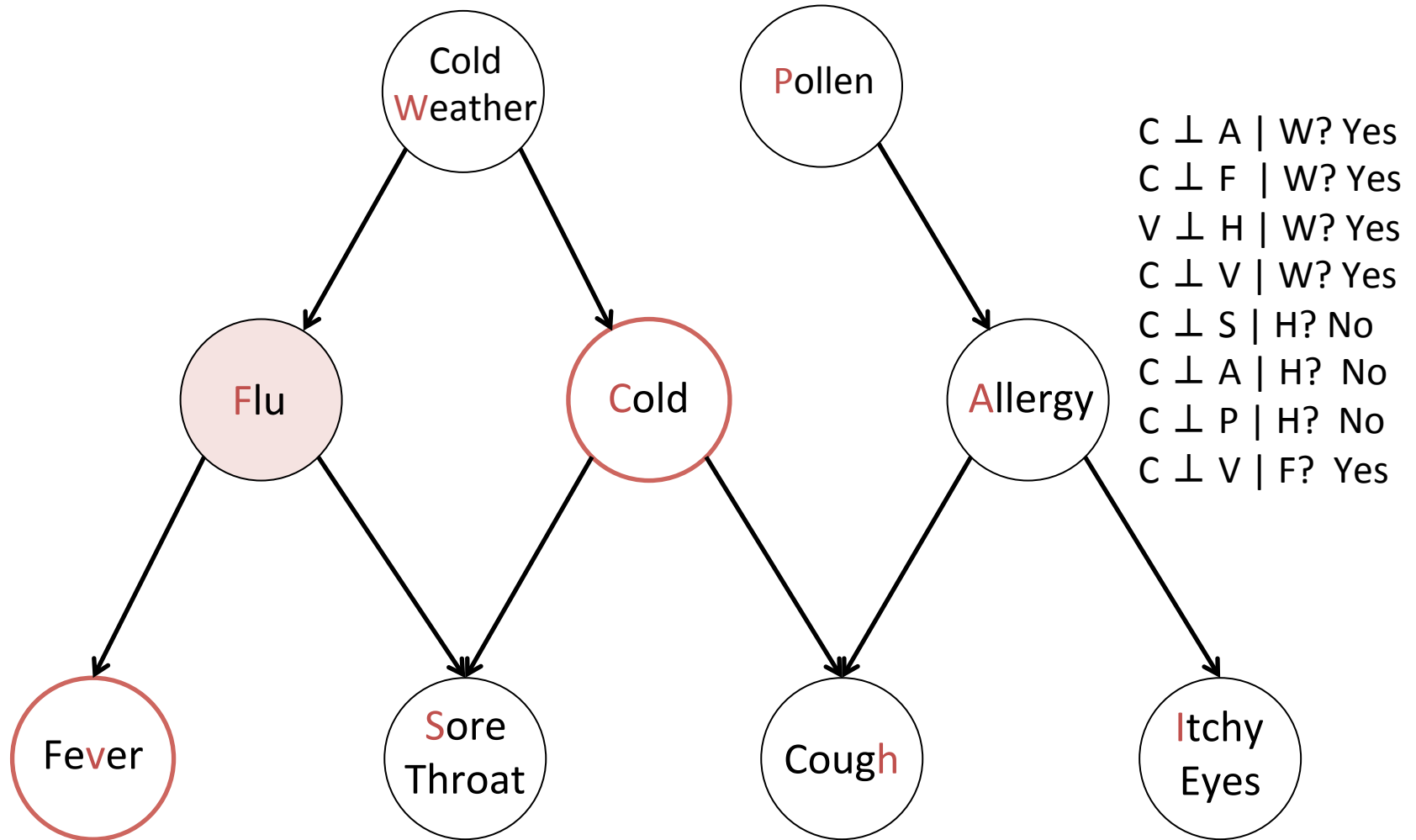
# Conditional Independence



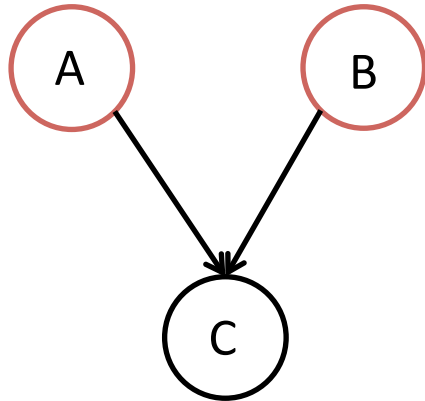
$C \perp A \mid W?$  Yes  
 $C \perp F \mid W?$  Yes  
 $V \perp H \mid W?$  Yes  
 $C \perp V \mid W?$  Yes  
 $C \perp S \mid H?$  No  
 $C \perp A \mid H?$  No  
 $C \perp P \mid H?$  No  
 $C \perp V \mid F?$



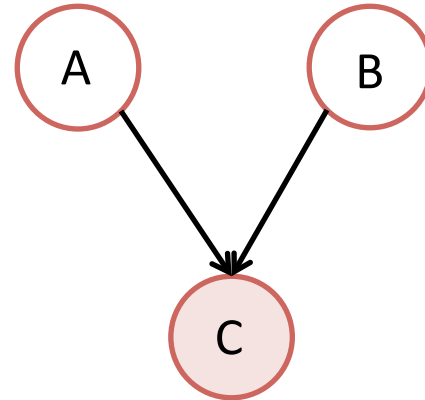
# Conditional Independence



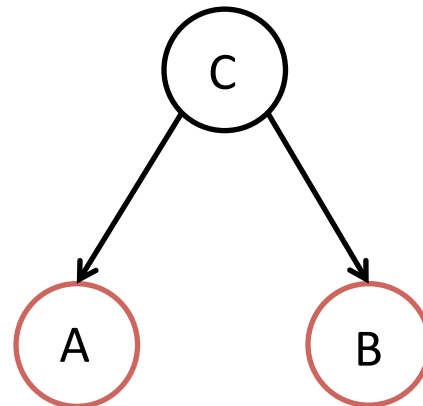
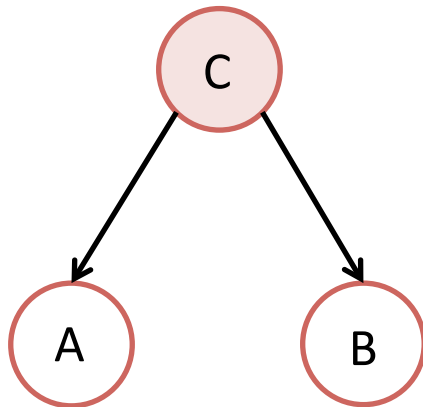
# Patterns



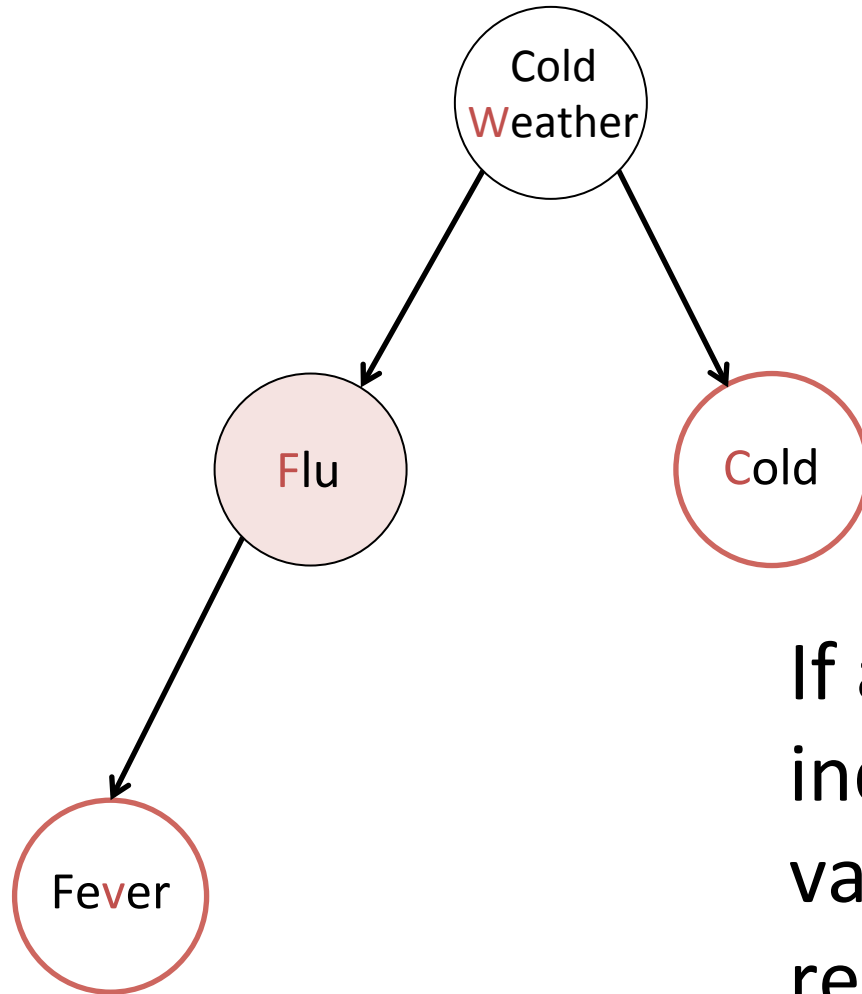
Independent



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.

# Questions?