

# CPS 270: Artificial Intelligence

<http://www.cs.duke.edu/courses/fall08/cps270/>

## Bayesian networks

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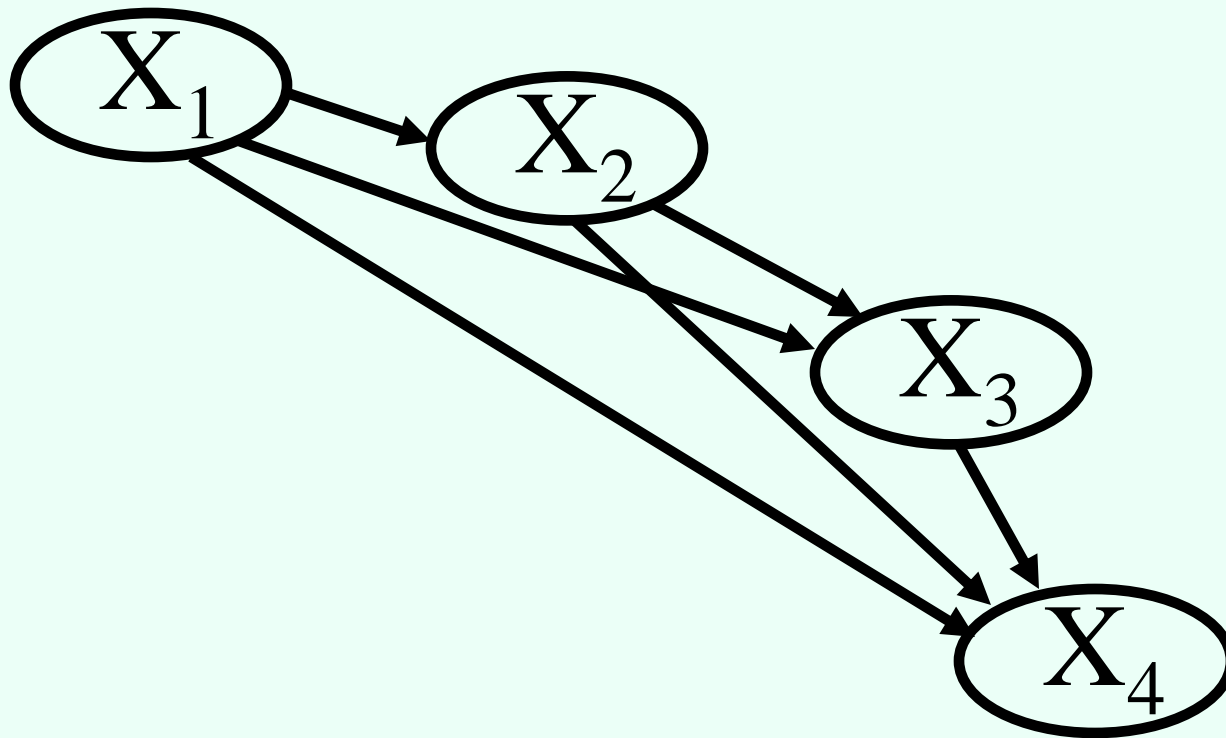
# Specifying probability distributions

- Specifying a probability for every atomic event is impractical
- We have already seen it can be easier to specify probability distributions by using (conditional) independence
- **Bayesian networks** allow us
  - to specify any distribution,
  - to specify such distributions concisely if there is (conditional) independence, in a natural way

# A general approach to specifying probability distributions

- Say the variables are  $X_1, \dots, X_n$
- $P(X_1, \dots, X_n) = P(X_1)P(X_2|X_1)P(X_3|X_1, X_2)\dots P(X_n|X_1, \dots, X_{n-1})$
- Can specify every component
- If every variable can take  $k$  values,
- $P(X_i|X_1, \dots, X_{i-1})$  requires  $(k-1)k^{i-1}$  values
- $\sum_{i=\{1, \dots, n\}} (k-1)k^{i-1} = \sum_{i=\{1, \dots, n\}} k^i - k^{i-1} = k^n - 1$
- Same as specifying probabilities of all atomic events – of course, because we can specify any distribution!

# Graphically representing influences

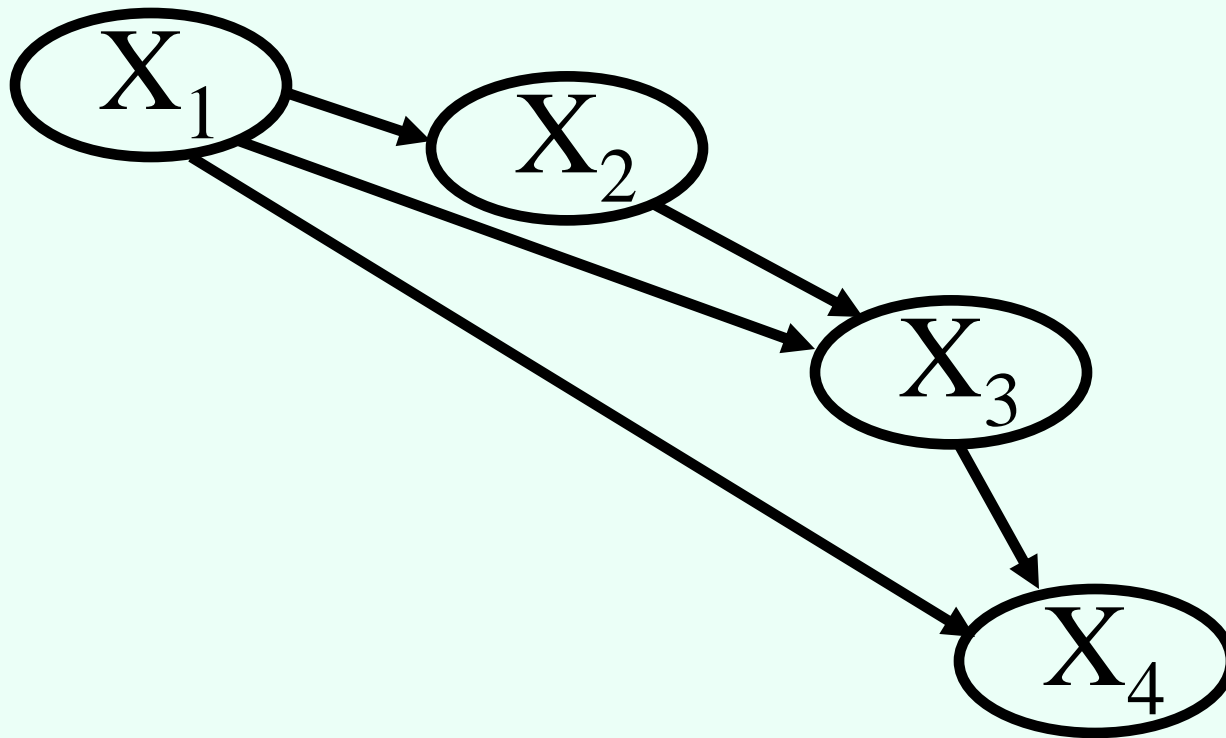


# Conditional independence to the rescue!

- Problem:  $P(X_i | X_1, \dots, X_{i-1})$  requires us to specify too many values
- Suppose  $X_1, \dots, X_{i-1}$  partition into two subsets,  $S$  and  $T$ , so that  $X_i$  is conditionally independent from  $T$  given  $S$
- $P(X_i | X_1, \dots, X_{i-1}) = P(X_i | S, T) = P(X_i | S)$
- Requires only  $(k-1)k^{|S|}$  values instead of  $(k-1)k^{i-1}$  values

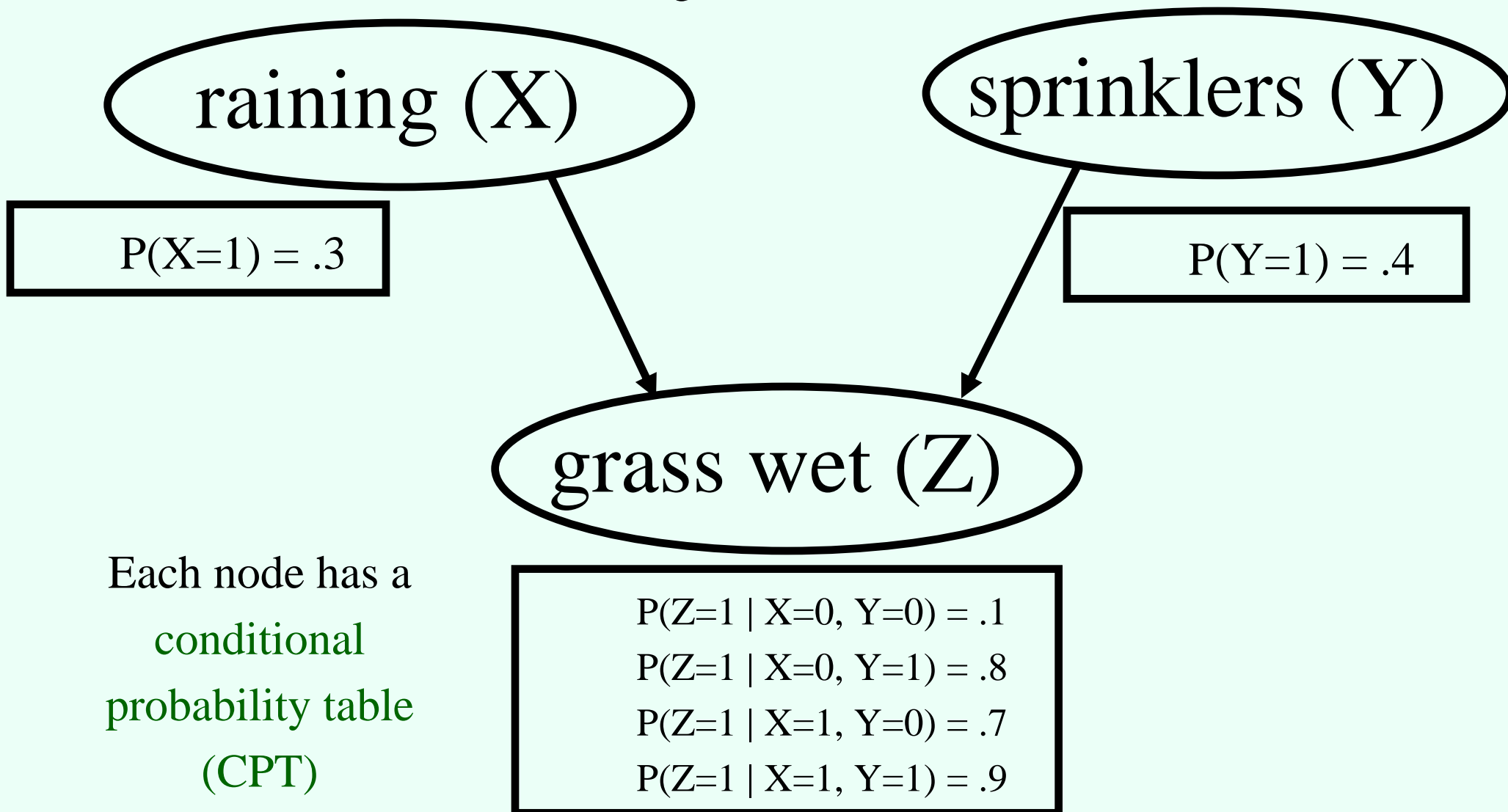
# Graphically representing influences

- ... if  $X_4$  is conditionally independent from  $X_2$  given  $X_1$  and  $X_3$

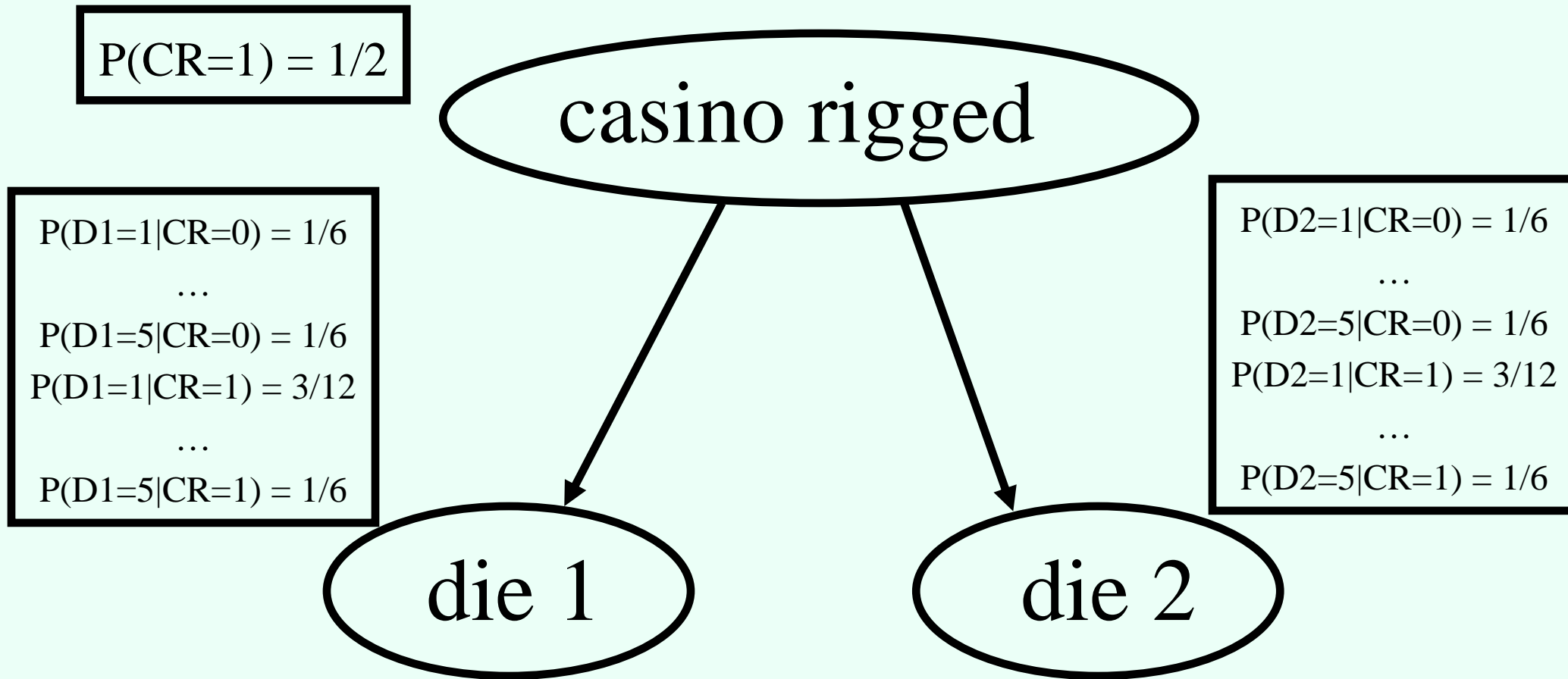


# Rain and sprinklers example

sprinklers is independent of raining, so no edge between them



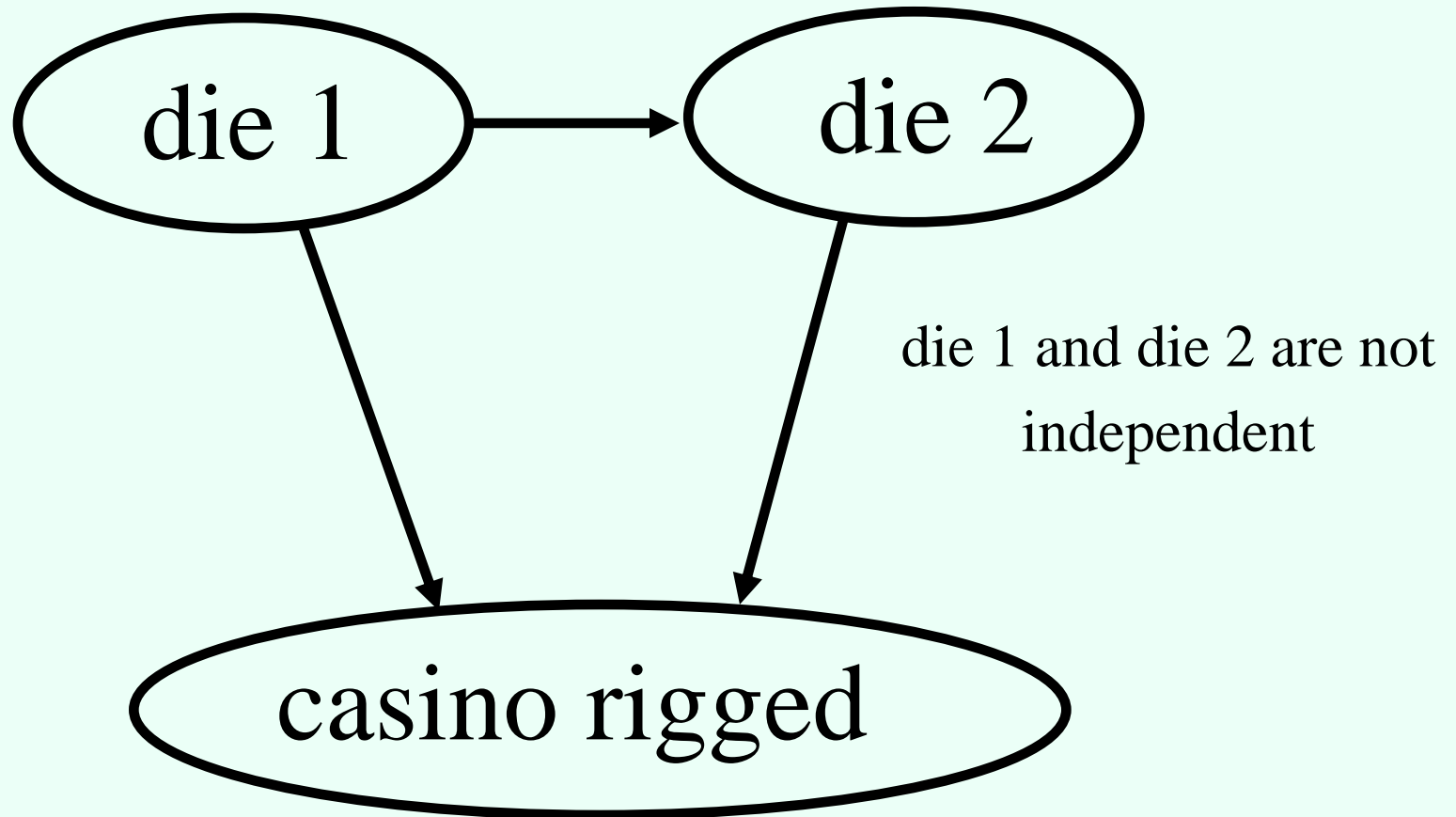
# Rigged casino example



die 2 is conditionally independent of die 1 given  
casino rigged, so no edge between them



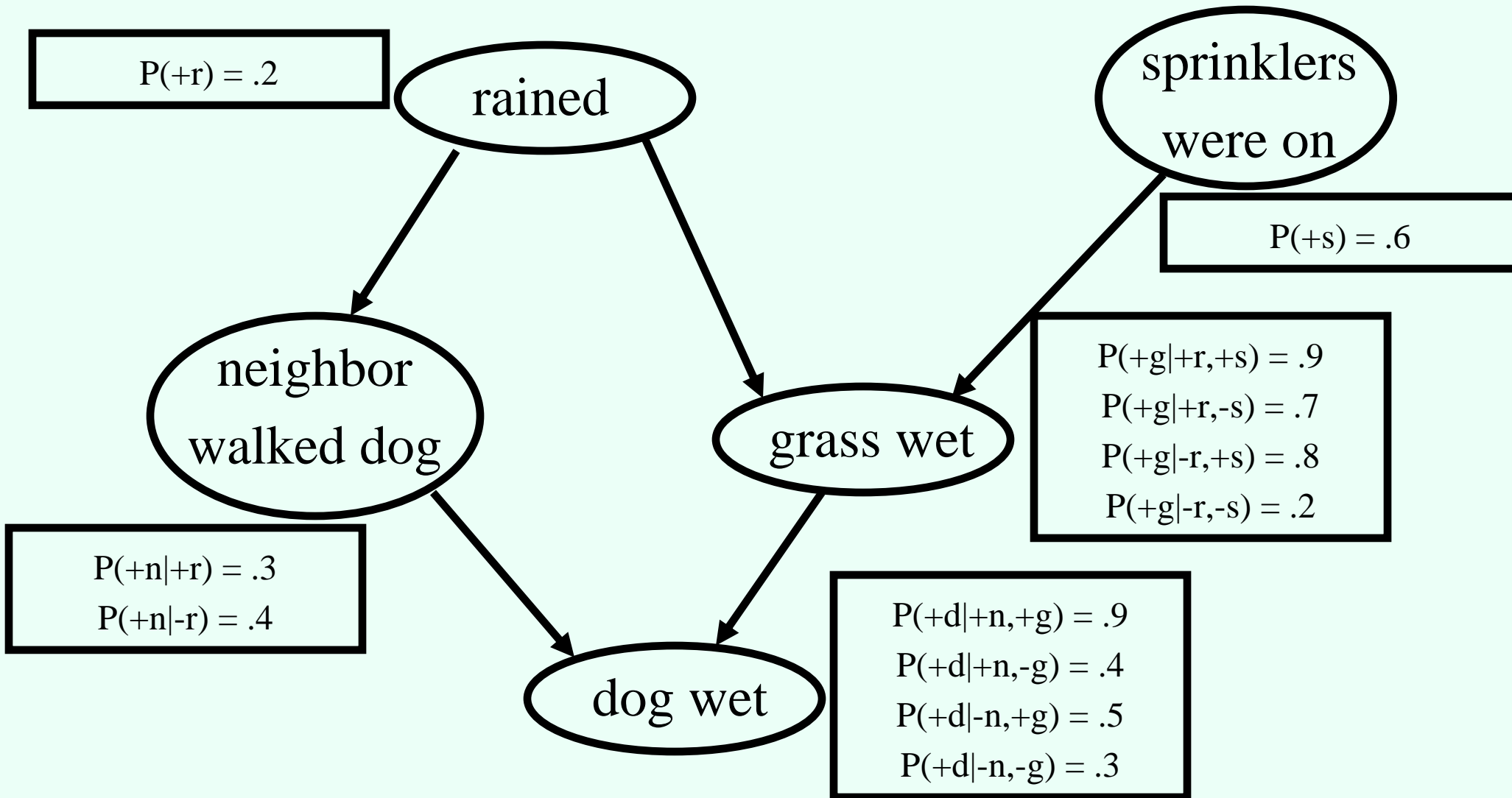
# Rigged casino example with poorly chosen order



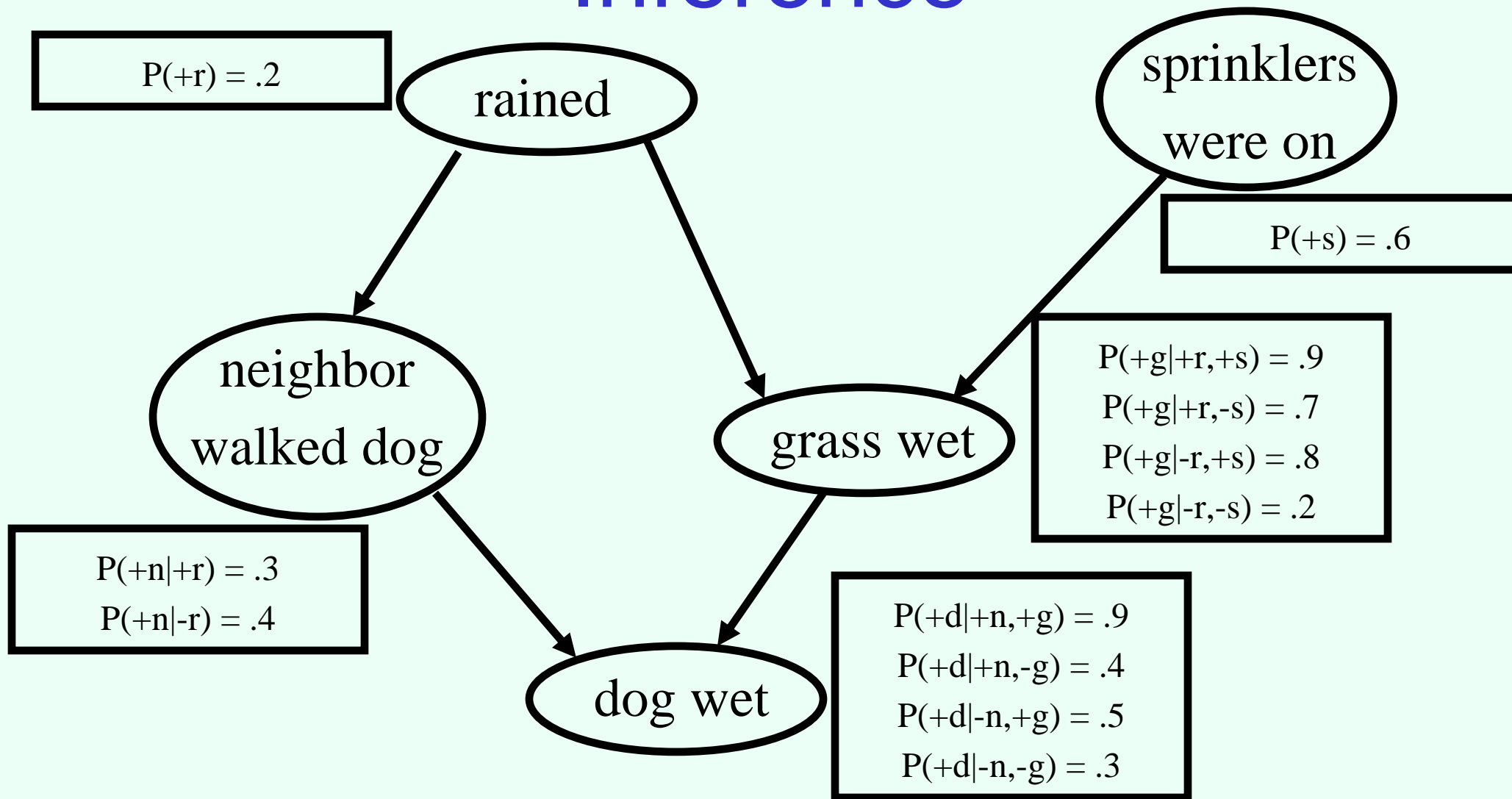
both the dice have relevant information for whether the casino is rigged

need 36 probabilities here!

# More elaborate rain and sprinklers example

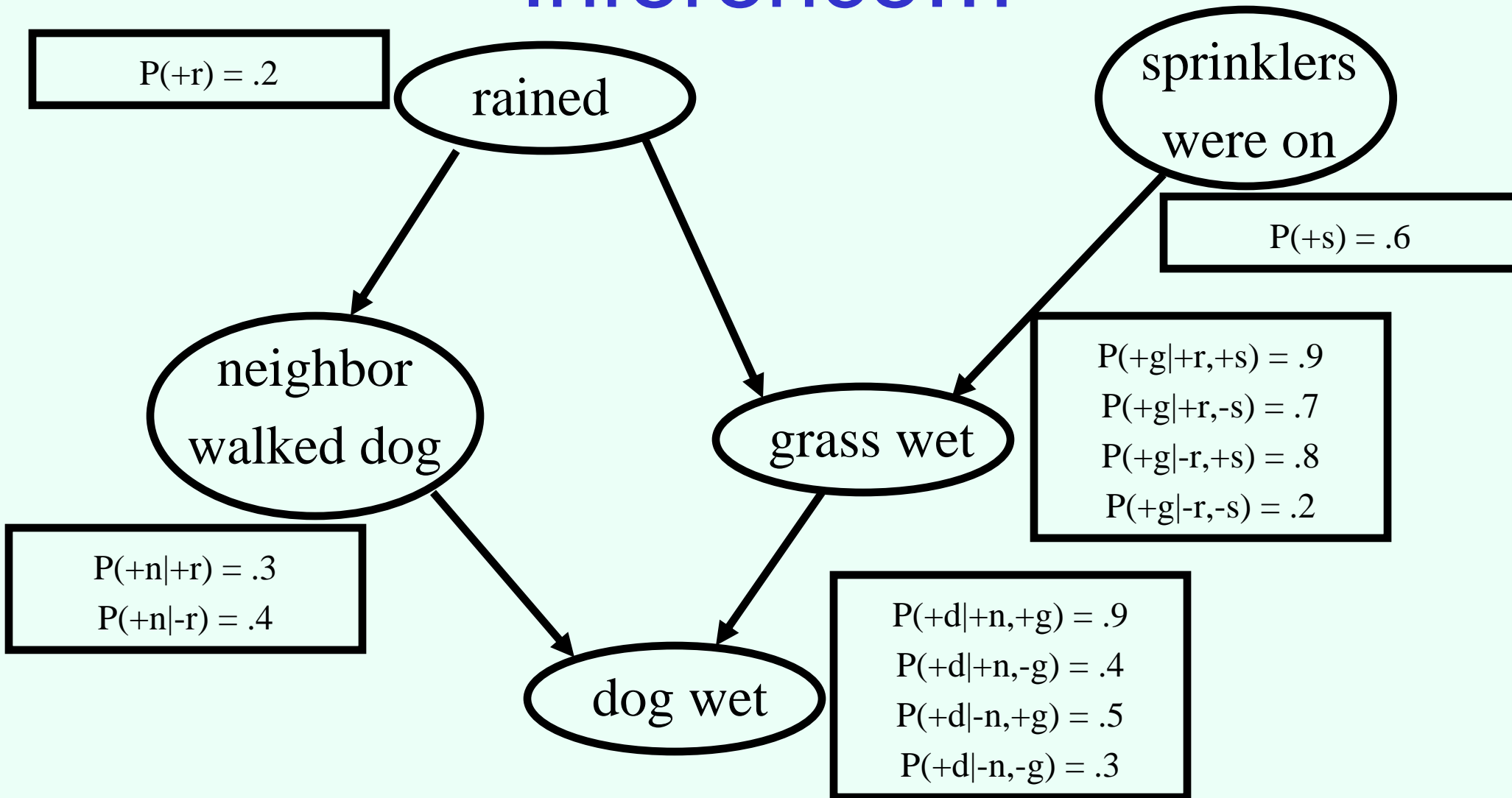


# Inference



- Want to know:  $P(+r|+d) = P(+r,+d)/P(+d)$
- Let's compute  $P(+r,+d)$

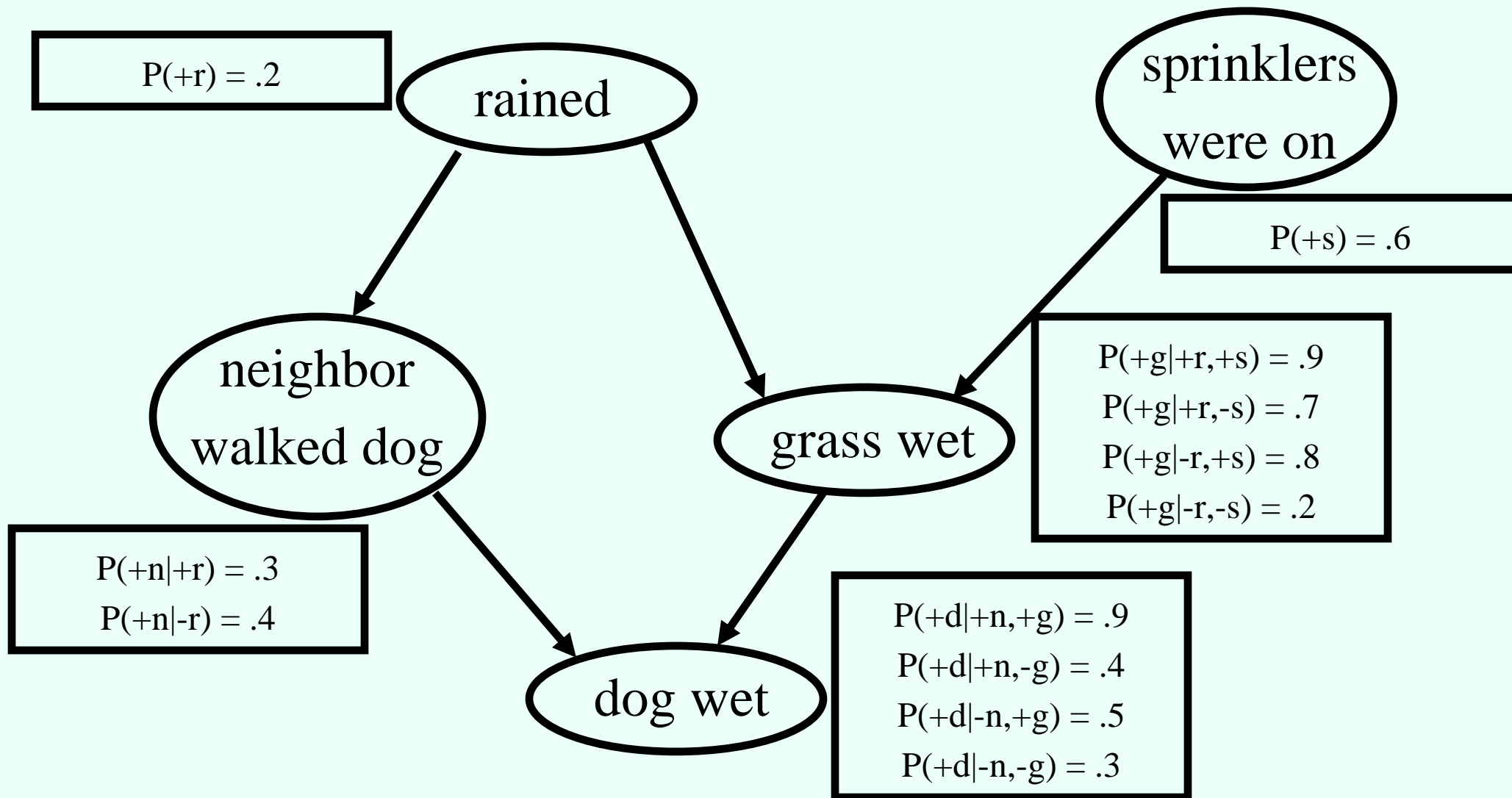
# Inference...



- $$P(+r,+d) = \sum_s \sum_g \sum_n P(+r)P(s)P(n|+r)P(g|+r,s)P(+d|n,g) =$$

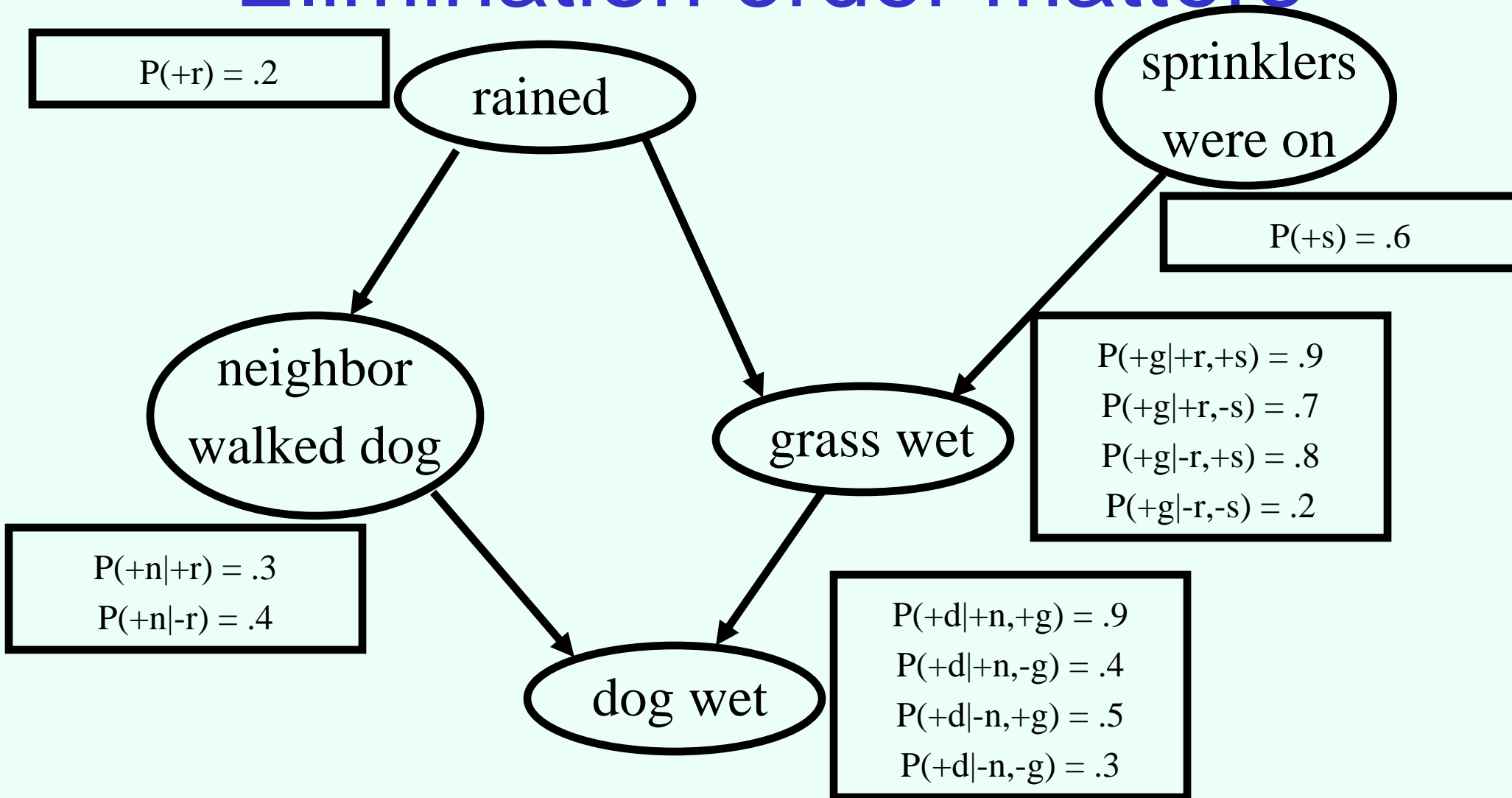
$$P(+r) \sum_s P(s) \sum_g P(g|+r,s) \sum_n P(n|+r)P(+d|n,g)$$

# Variable elimination



- From the factor  $\sum_n P(n|+r)P(+d|n,g)$  we sum out  $n$  to obtain a factor only depending on  $g$
- $[\sum_n P(n|+r)P(+d|n,+g)] = P(+n|+r)P(+d|+n,+g) + P(-n|+r)P(+d|-n,+g) = .3*.9+.7*.5 = .62$
- $[\sum_n P(n|+r)P(+d|n,-g)] = P(+n|+r)P(+d|+n,-g) + P(-n|+r)P(+d|-n,-g) = .3*.4+.7*.3 = .33$
- Continuing to the left,  $g$  will be summed out next, etc. (continued on board)

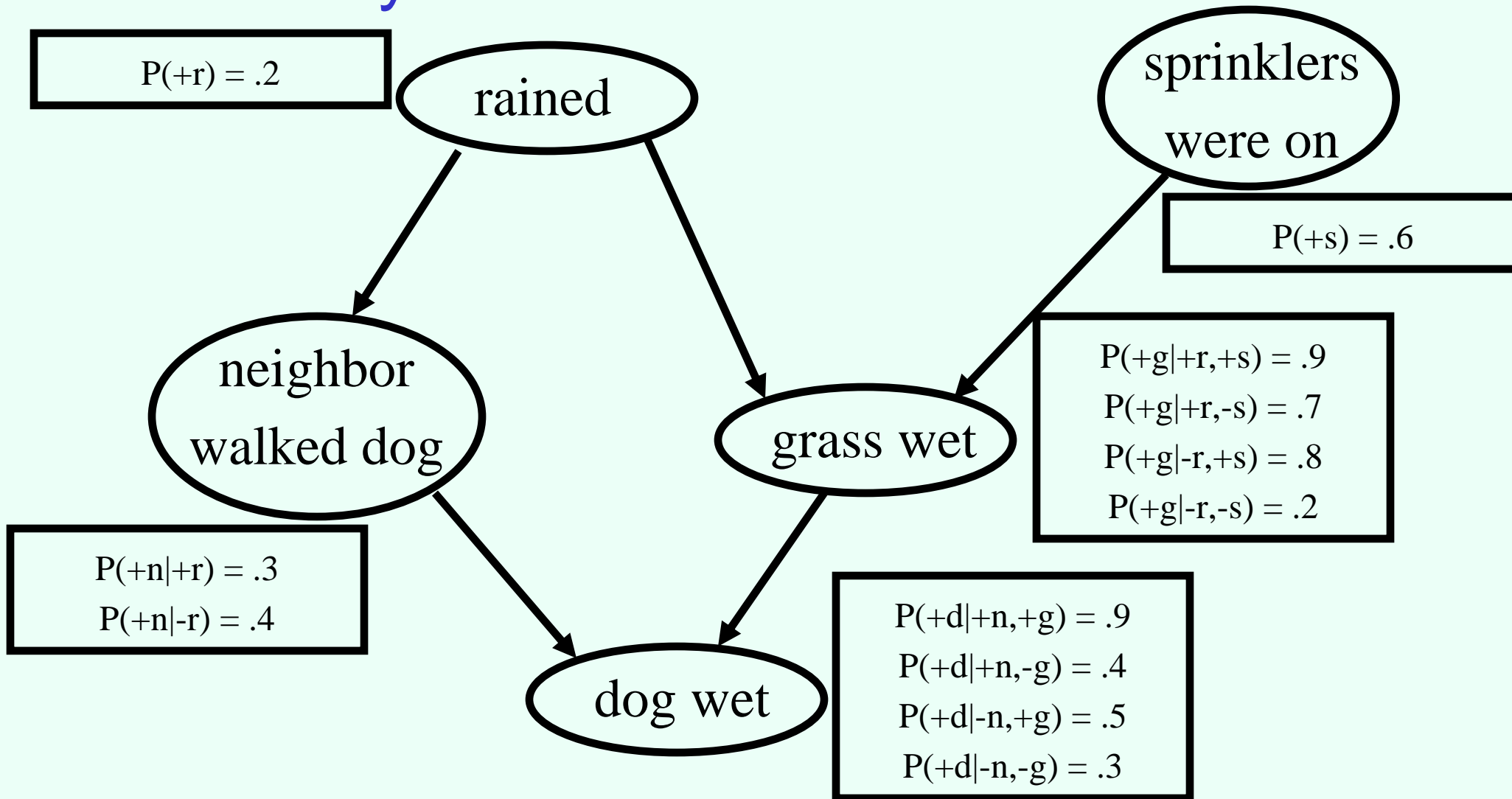
# Elimination order matters



- $$P(+r,+d) = \sum_n \sum_s \sum_g P(+r)P(s)P(n|+r)P(g|+r,s)P(+d|n,g) =$$

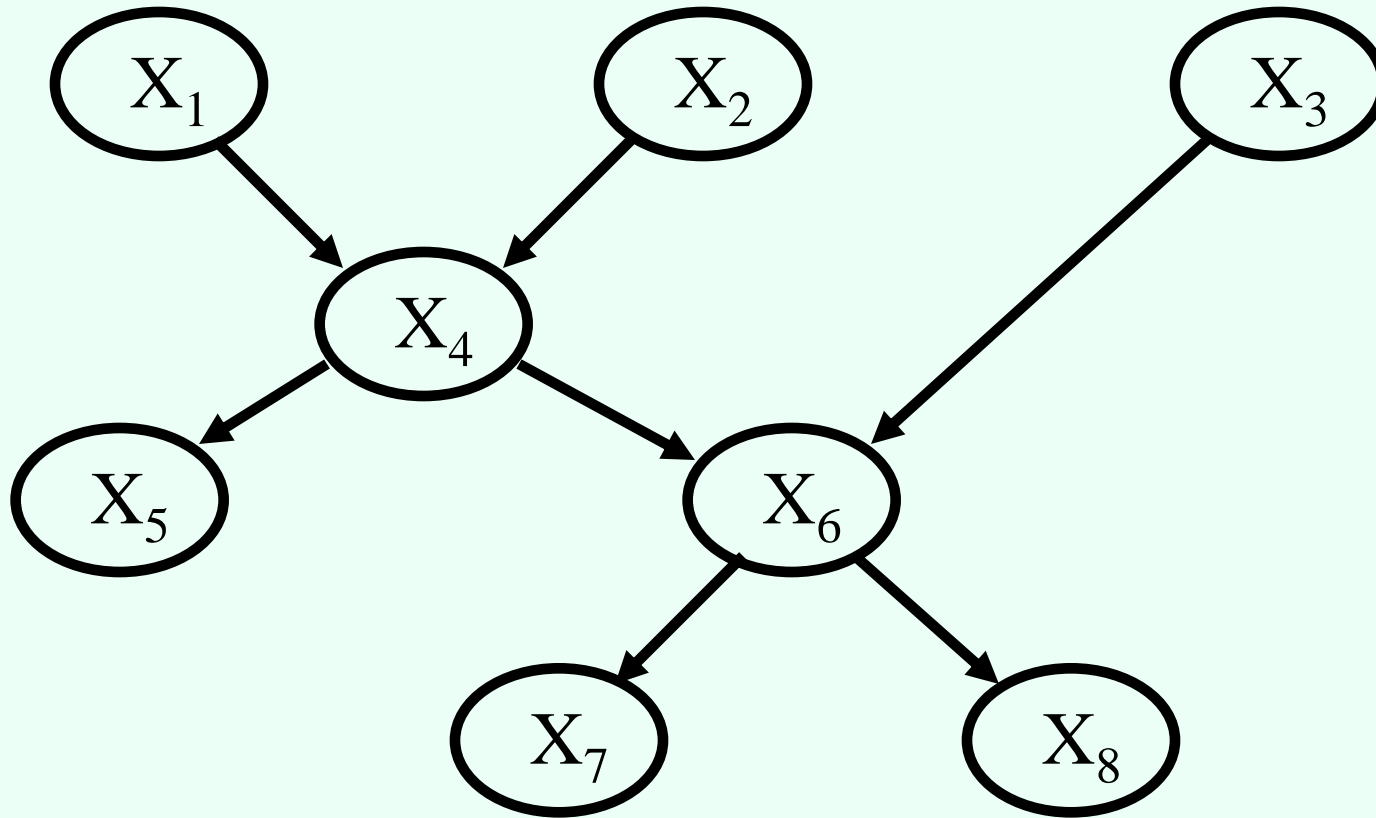
$$P(+r) \sum_n P(n|+r) \sum_s P(s) \sum_g P(g|+r,s)P(+d|n,g)$$
- Last factor will depend on two variables in this case!

# Don't always *need* to sum over **all** variables



- Can drop parts of the network that are irrelevant
- $P(+r, +s) = P(+r)P(+s) = .6 \cdot .2 = .012$
- $P(+n, +s) = \sum_r P(r, +n, +s) = \sum_r P(r)P(+n|r)P(+s) = P(+s) \sum_r P(r)P(+n|r) = P(+s)(P(+r)P(+n|+r) + P(-r)P(+n|-r)) = .6 \cdot (.2 \cdot .3 + .8 \cdot .4) = .6 \cdot .38 = .228$
- $P(+d | +n, +g, +s) = P(+d | +n, +g) = .9$

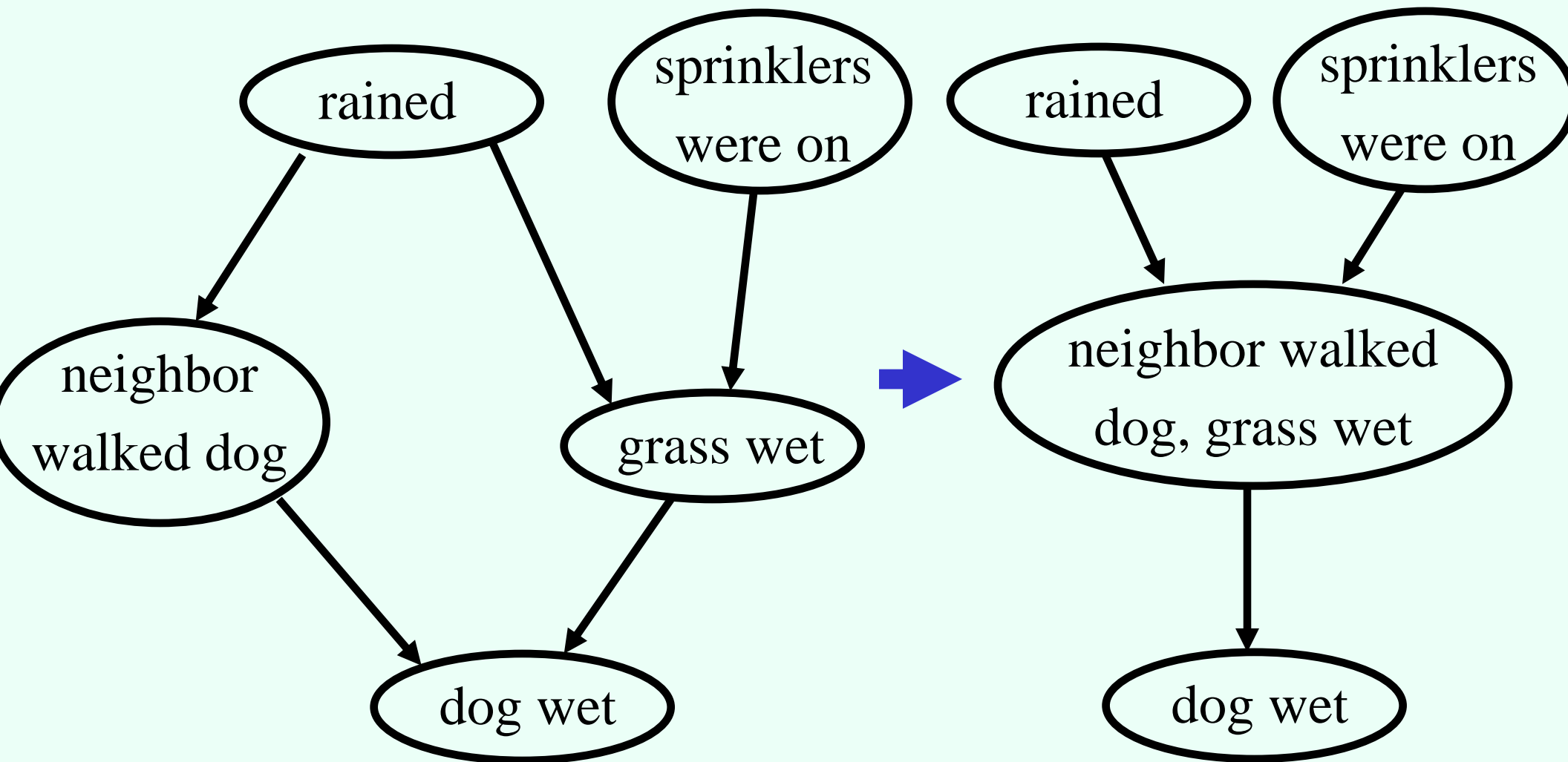
# Trees are easy



- Choose an extreme variable to eliminate first
- Its probability is “absorbed” by its neighbor
- $\dots \sum_{x_4} P(x_4|x_1, x_2) \dots \sum_{x_5} P(x_5|x_4) = \dots \sum_{x_4} P(x_4|x_1, x_2) [\sum_{x_5} P(x_5|x_4)] \dots$



# Clustering algorithms

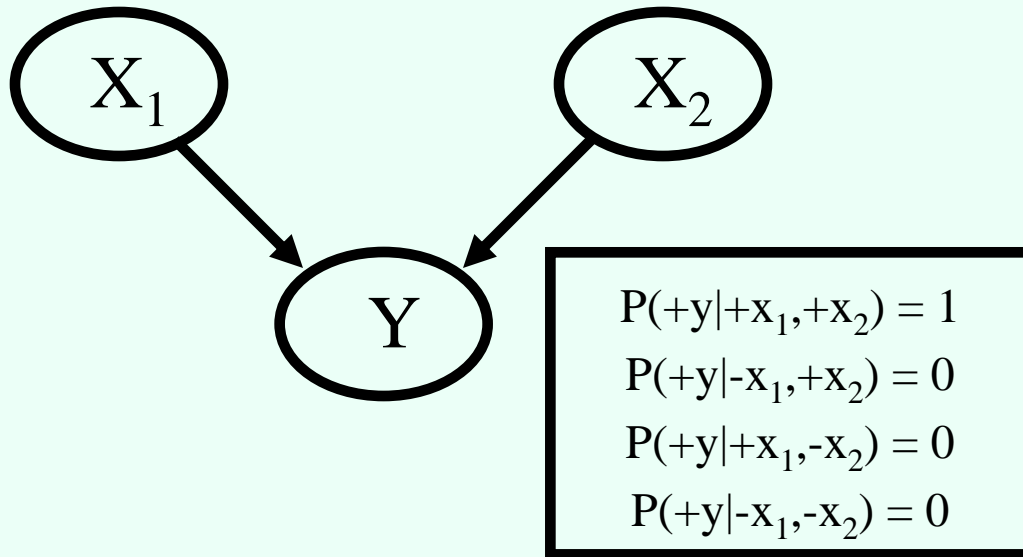


- Merge nodes into “meganodes” until we have a tree
  - Then, can apply special-purpose algorithm for trees
- Merged node has values  $\{+n+g, +n-g, -n+g, -n-g\}$ 
  - Much larger CPT

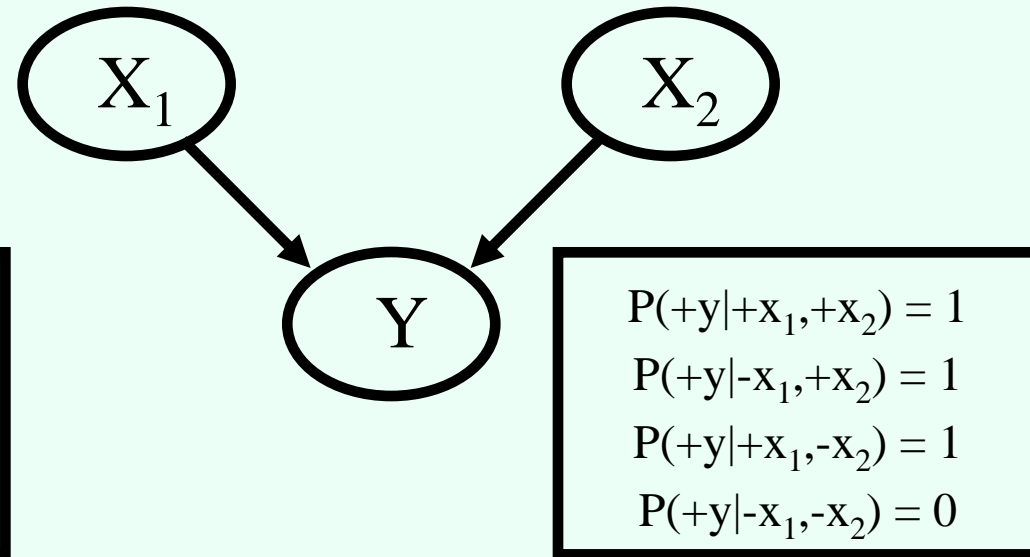
# Logic gates in Bayes nets

- Not everything needs to be random...

AND gate

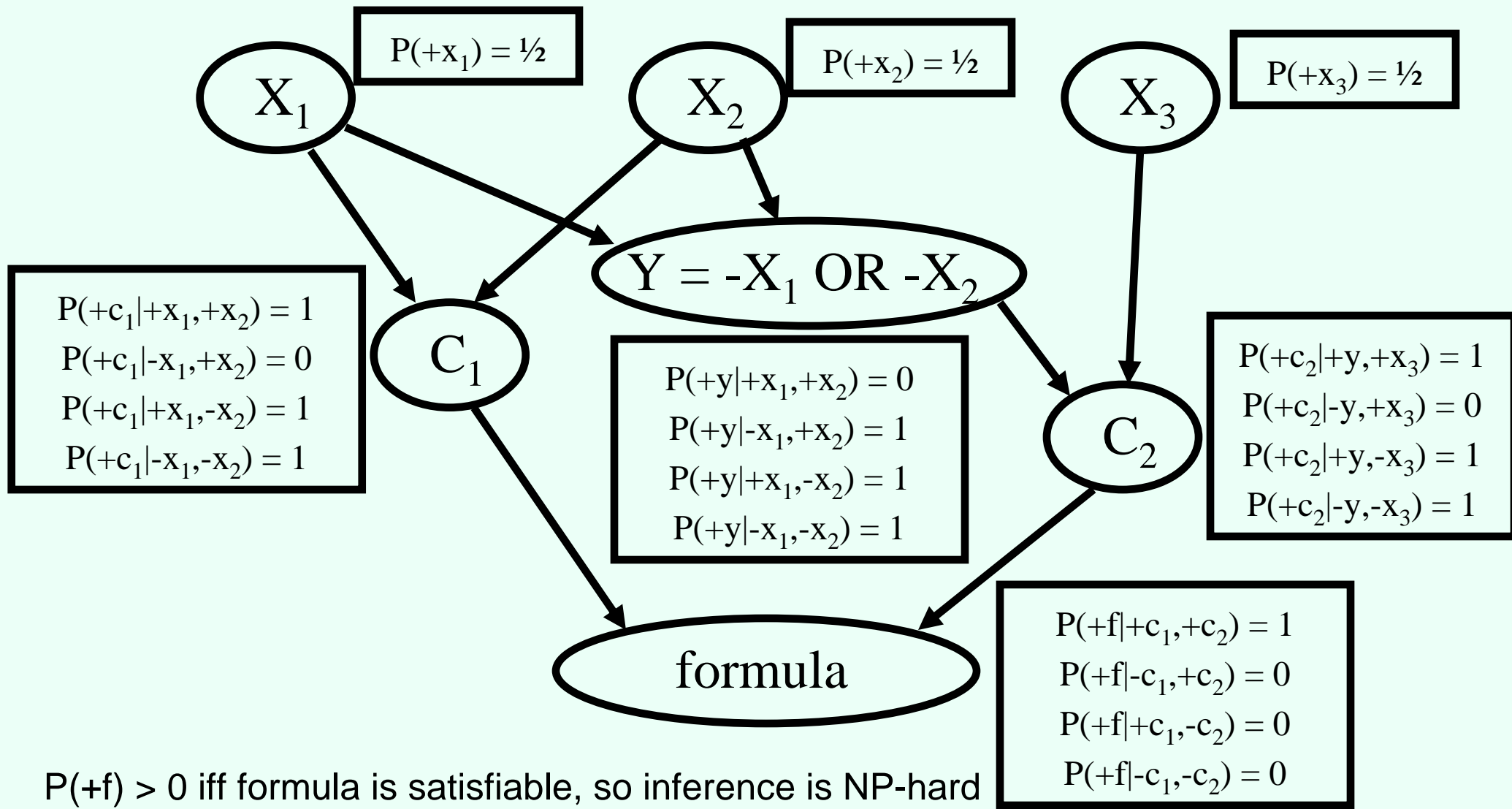


OR gate



# Modeling satisfiability as a Bayes Net

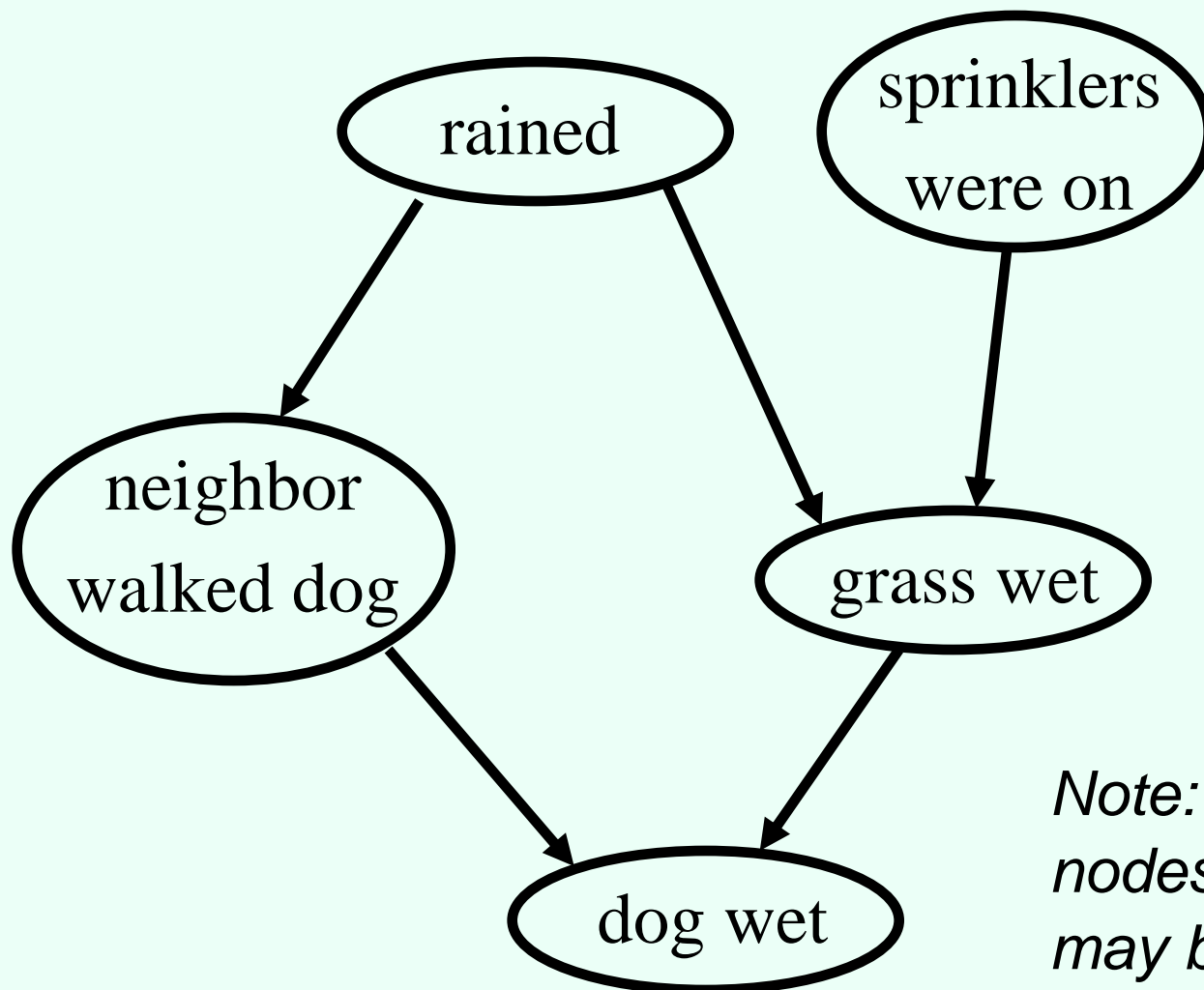
- $(+X_1 \text{ OR } -X_2) \text{ AND } (-X_1 \text{ OR } -X_2 \text{ OR } -X_3)$



- $P(+f) > 0$  iff formula is satisfiable, so inference is NP-hard
- $P(+f) = (\#\text{satisfying assignments}/2^n)$ , so inference is #P-hard (because counting number of satisfying assignments is)

# More about conditional independence

- A node is conditionally independent of its non-descendants, given its parents
- A node is conditionally independent of everything else in the graph, given its parents, children, and children's parents (its **Markov blanket**)

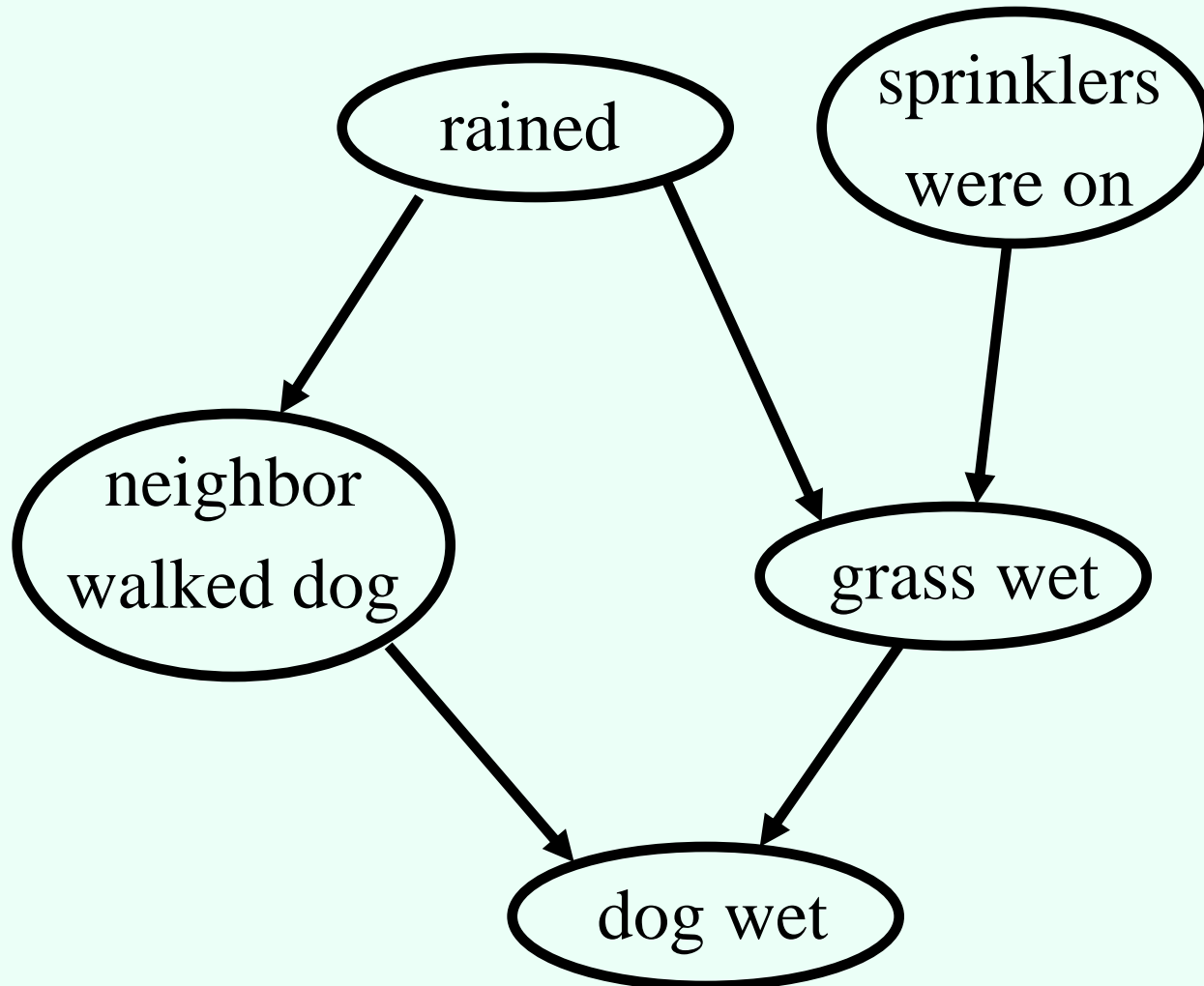


- N is independent of G given R
- N is **not** independent of G given R and D
- N is independent of S given R, G, D

*Note: can't know **for sure** that two nodes are not independent: edges may be dummy edges*

# General criterion: d-separation

- Sets of variables  $X$  and  $Y$  are conditionally independent given variables in  $Z$  if all paths between  $X$  and  $Y$  are blocked; a path is **blocked** if one of the following holds:
  - it contains  $U \rightarrow V \rightarrow W$  or  $U \leftarrow V \leftarrow W$  or  $U \leftarrow V \rightarrow W$ , and  $V$  is in  $Z$
  - it contains  $U \rightarrow V \leftarrow W$ , and neither  $V$  nor any of its descendants are in  $Z$



- N is independent of G given R
- N is not independent of S given R and D