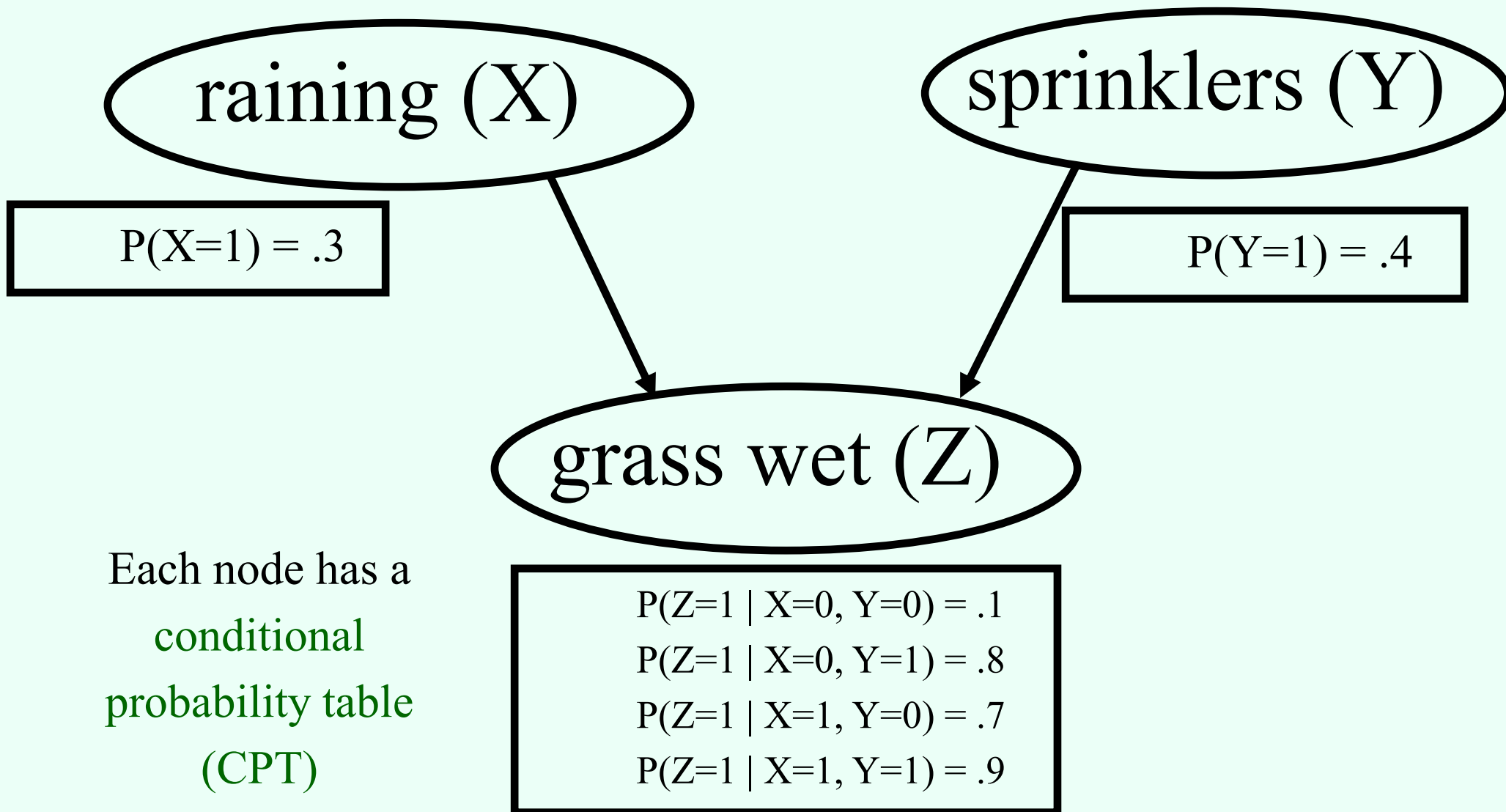


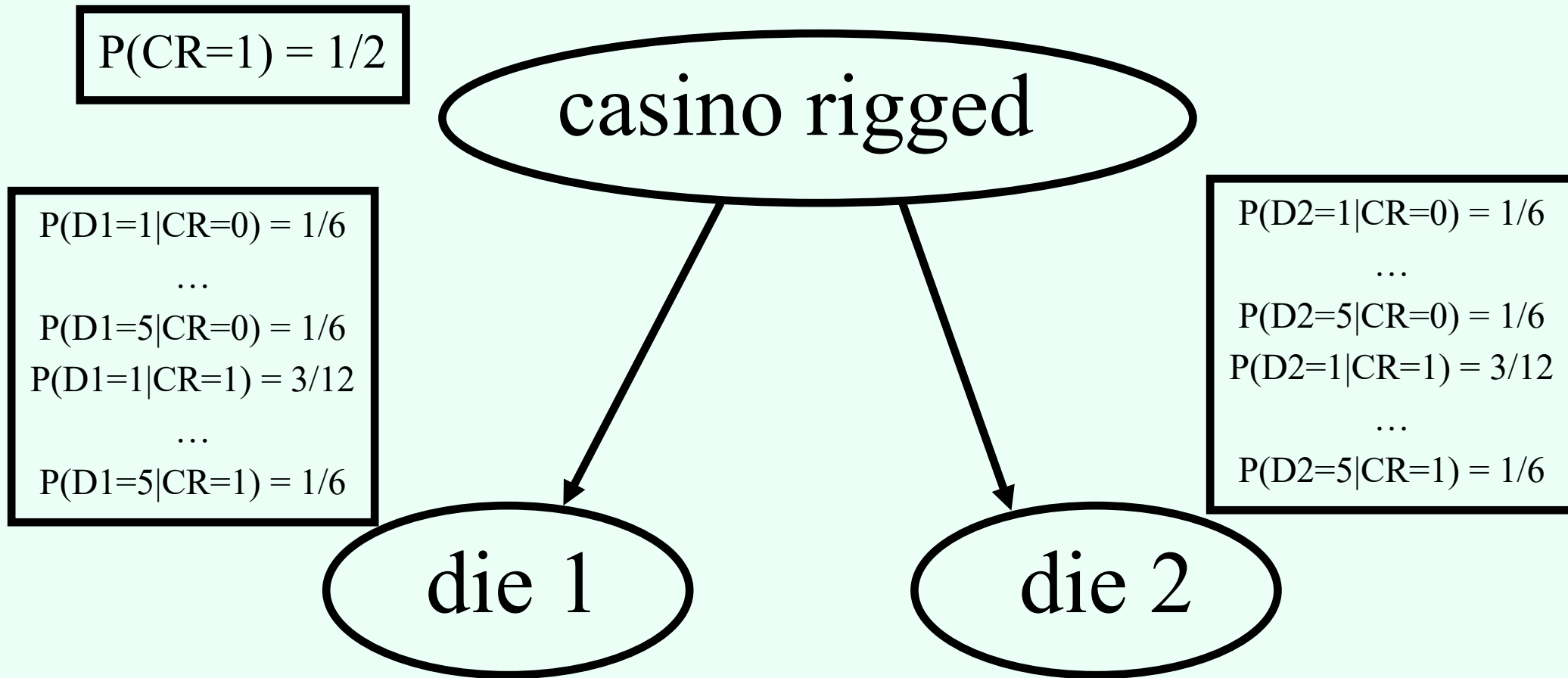
Bayesian networks

Instructor: Vincent Conitzer

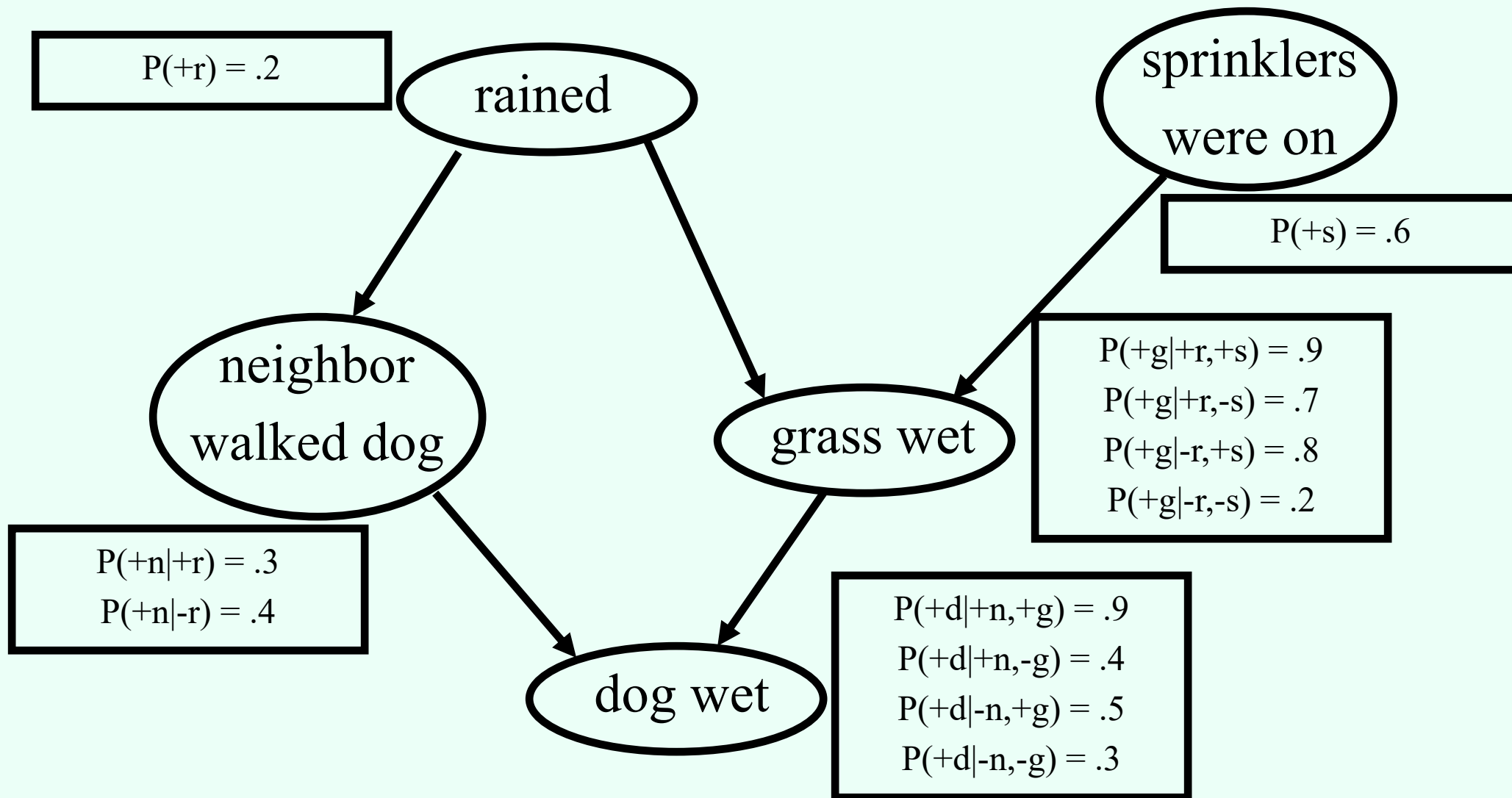
Rain and sprinklers example



Rigged casino example



More elaborate rain and sprinklers example



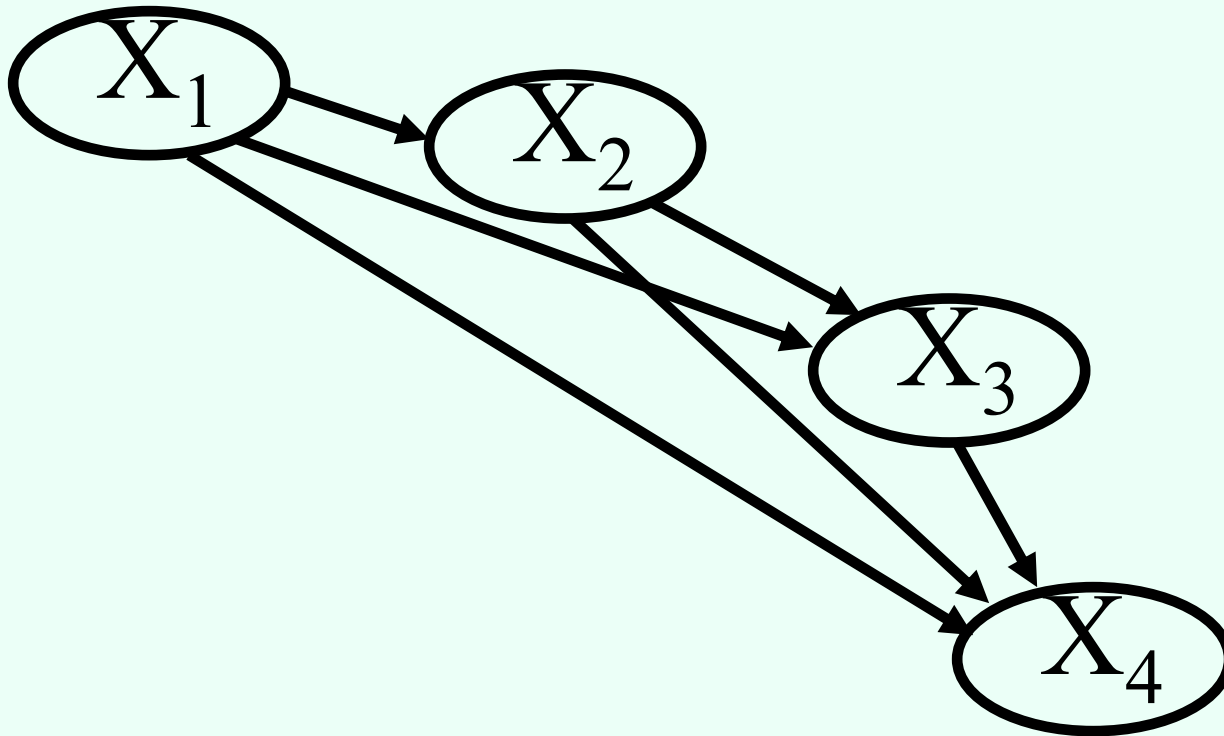
Specifying probability distributions

- Specifying a probability for every atomic event is impractical
- $P(X_1, \dots, X_n)$ would need to be specified for **every** combination x_1, \dots, x_n of values for X_1, \dots, X_n
 - If there are k possible values per variable...
 - ... we need to specify $k^n - 1$ probabilities!
- 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
- $P(X_1, \dots, X_n) = P(X_1)P(X_2|X_1)P(X_3|X_1, X_2)\dots P(X_n|X_1, \dots, X_{n-1})$
- or:
- $P(X_1, \dots, X_n) = P(X_n)P(X_{n-1}|X_n)P(X_{n-2}|X_n, X_{n-1})\dots P(X_1|X_n, \dots, X_2)$
- Can specify every component
 - For **every** combination of values for the variables on the right of |, specify the probability over the values for the variable on the left
- 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

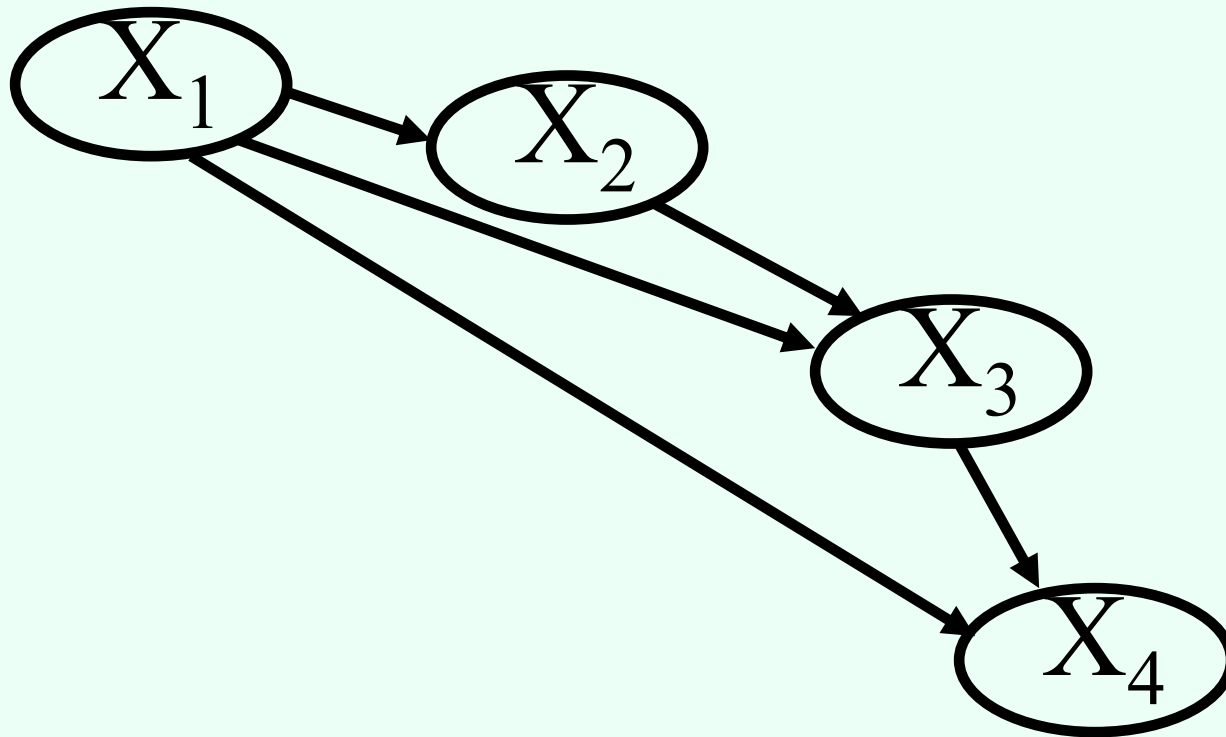


Conditional independence to the rescue!

- 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

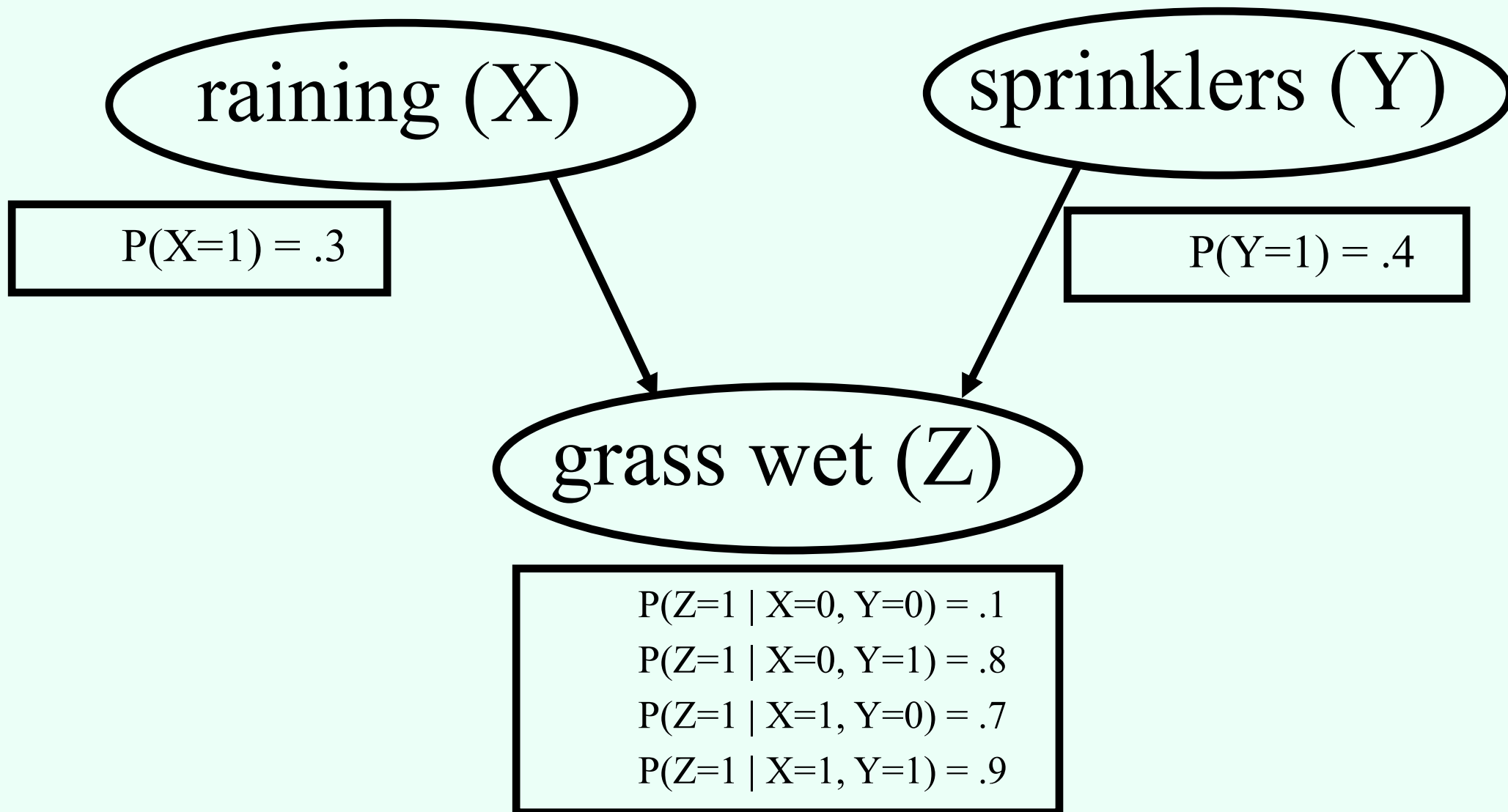
Graphically representing influences

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

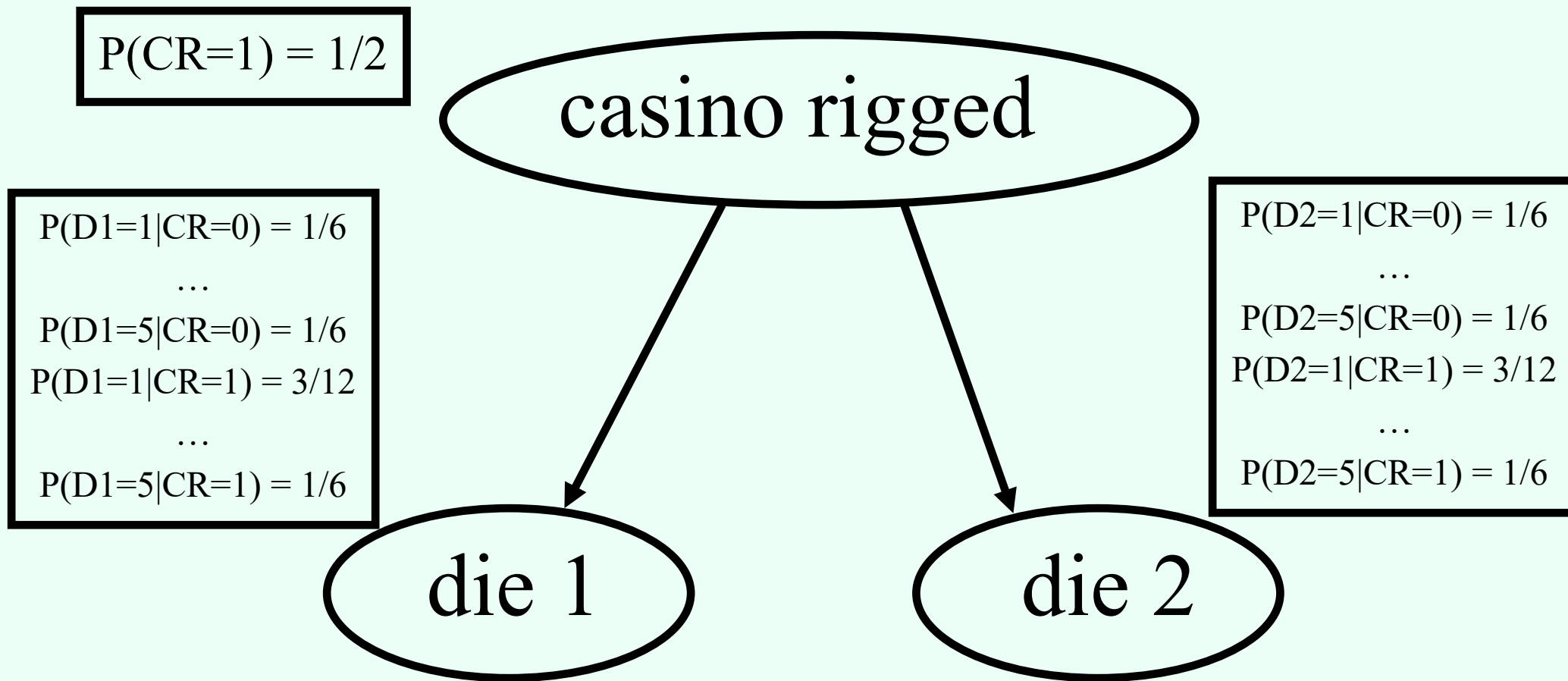


Rain and sprinklers example

sprinklers is independent of raining, so no edge between them

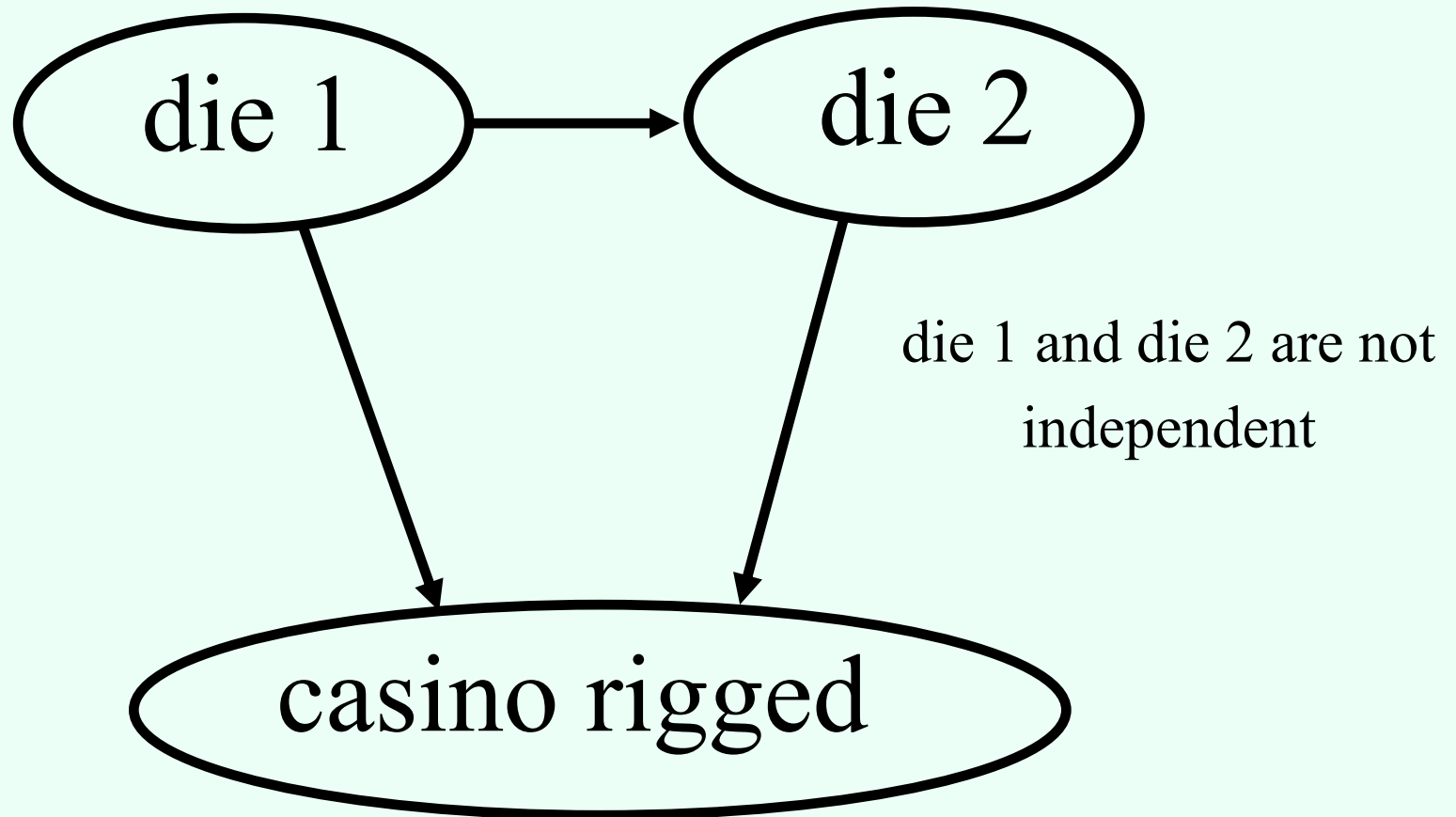


Rigged casino example



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

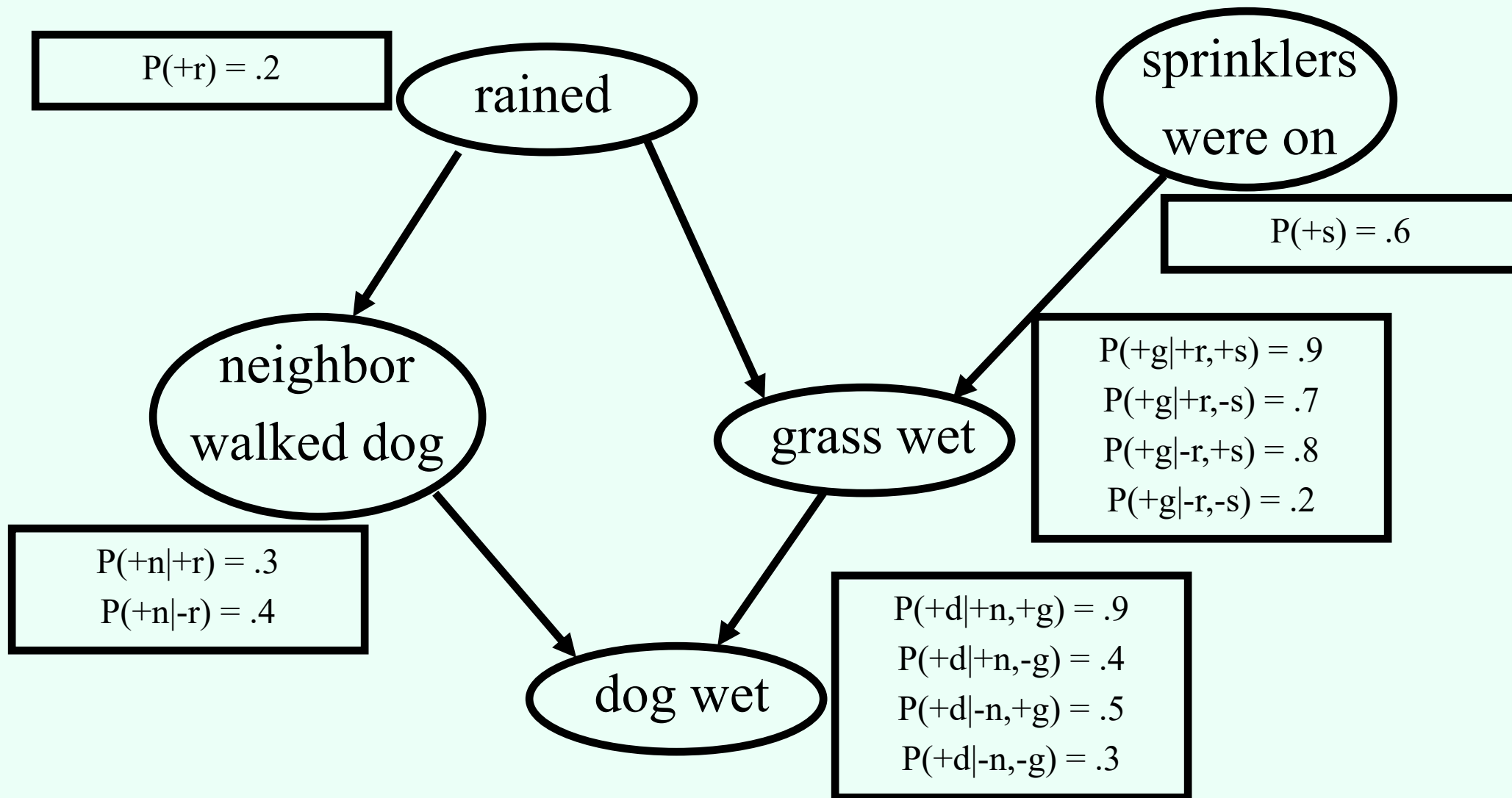
Rigged casino example with poorly chosen order



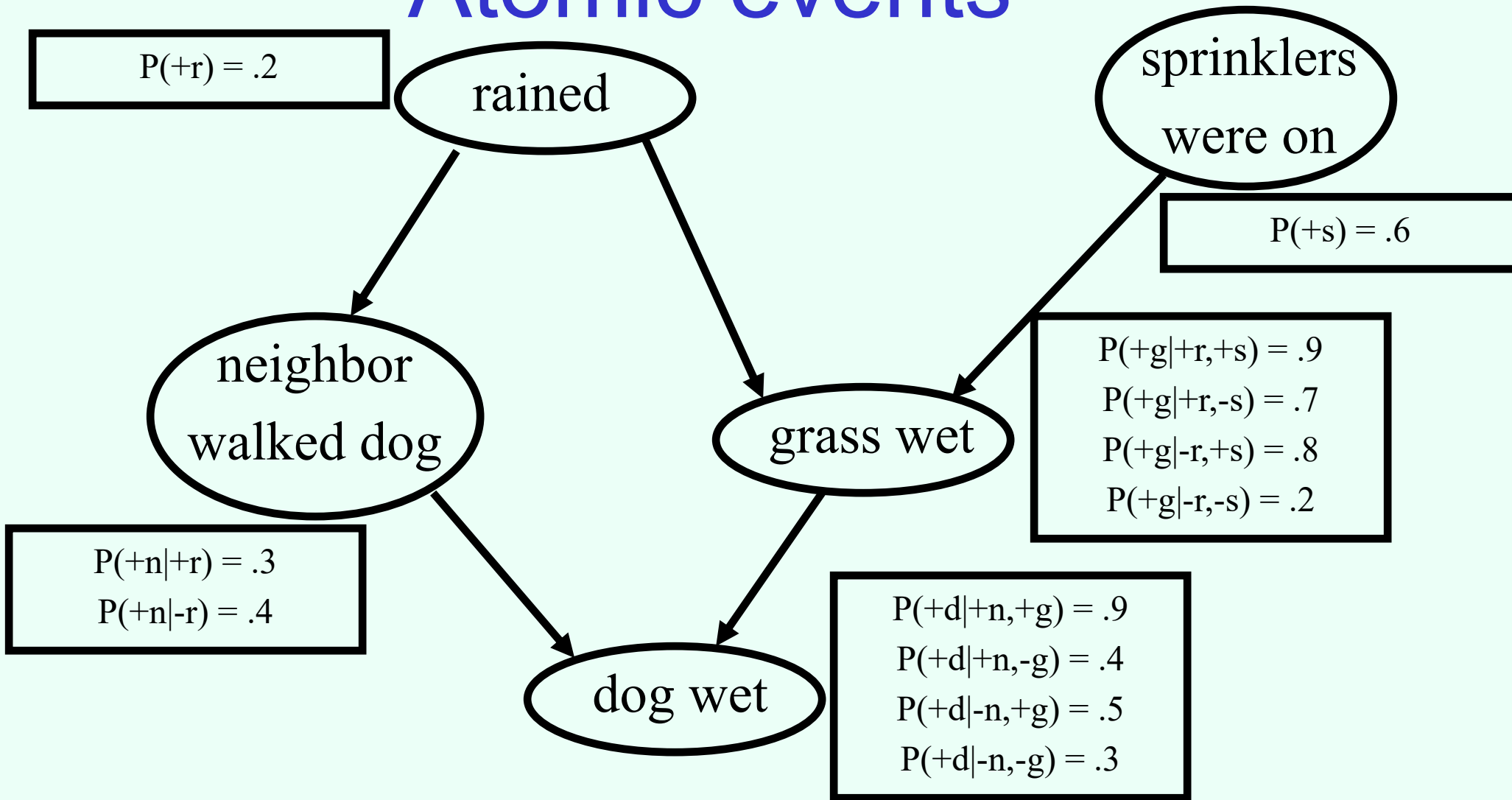
both the dice have relevant information for whether the casino is rigged

need 36 probabilities here!

More elaborate rain and sprinklers example

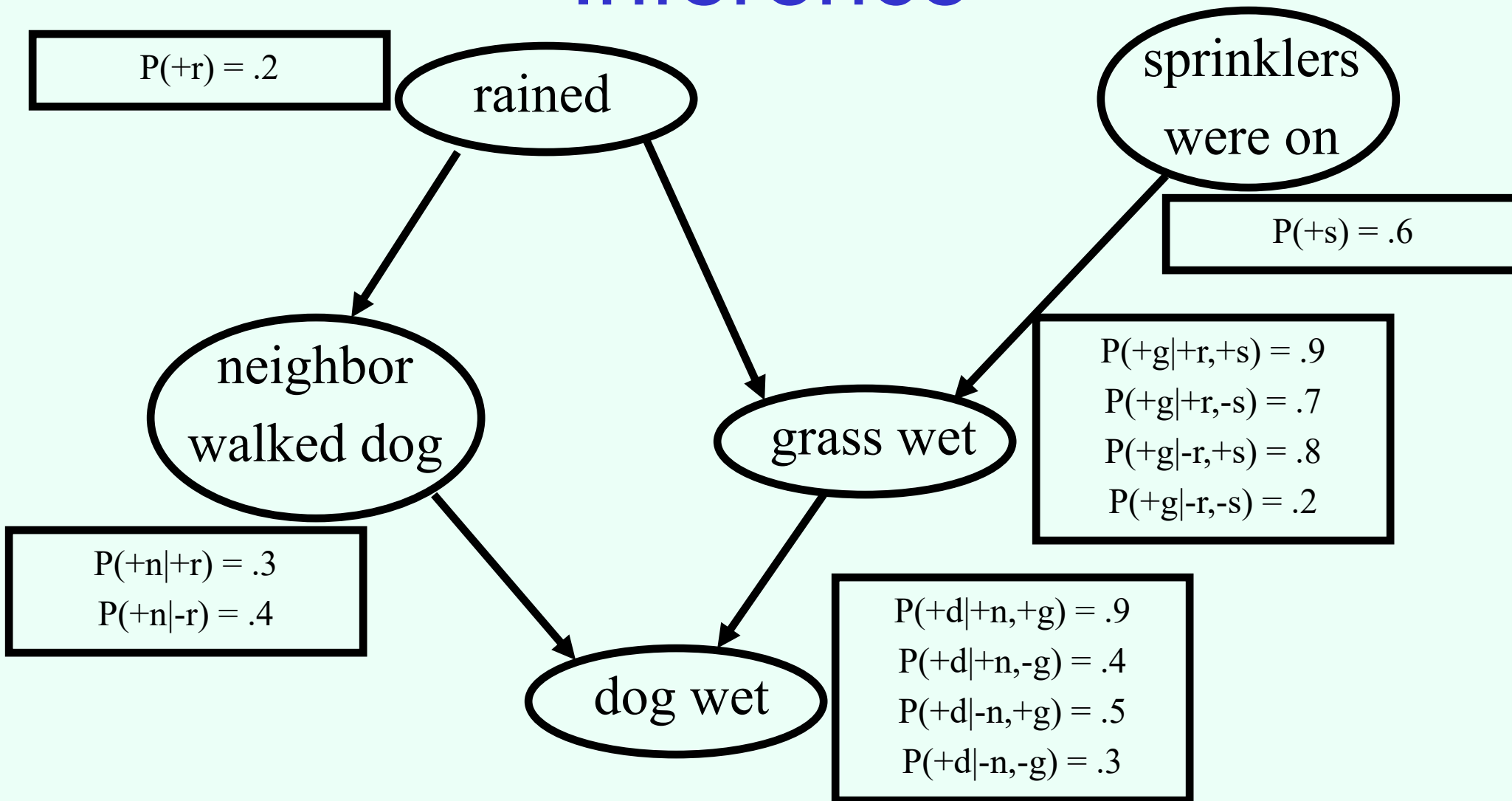


Atomic events



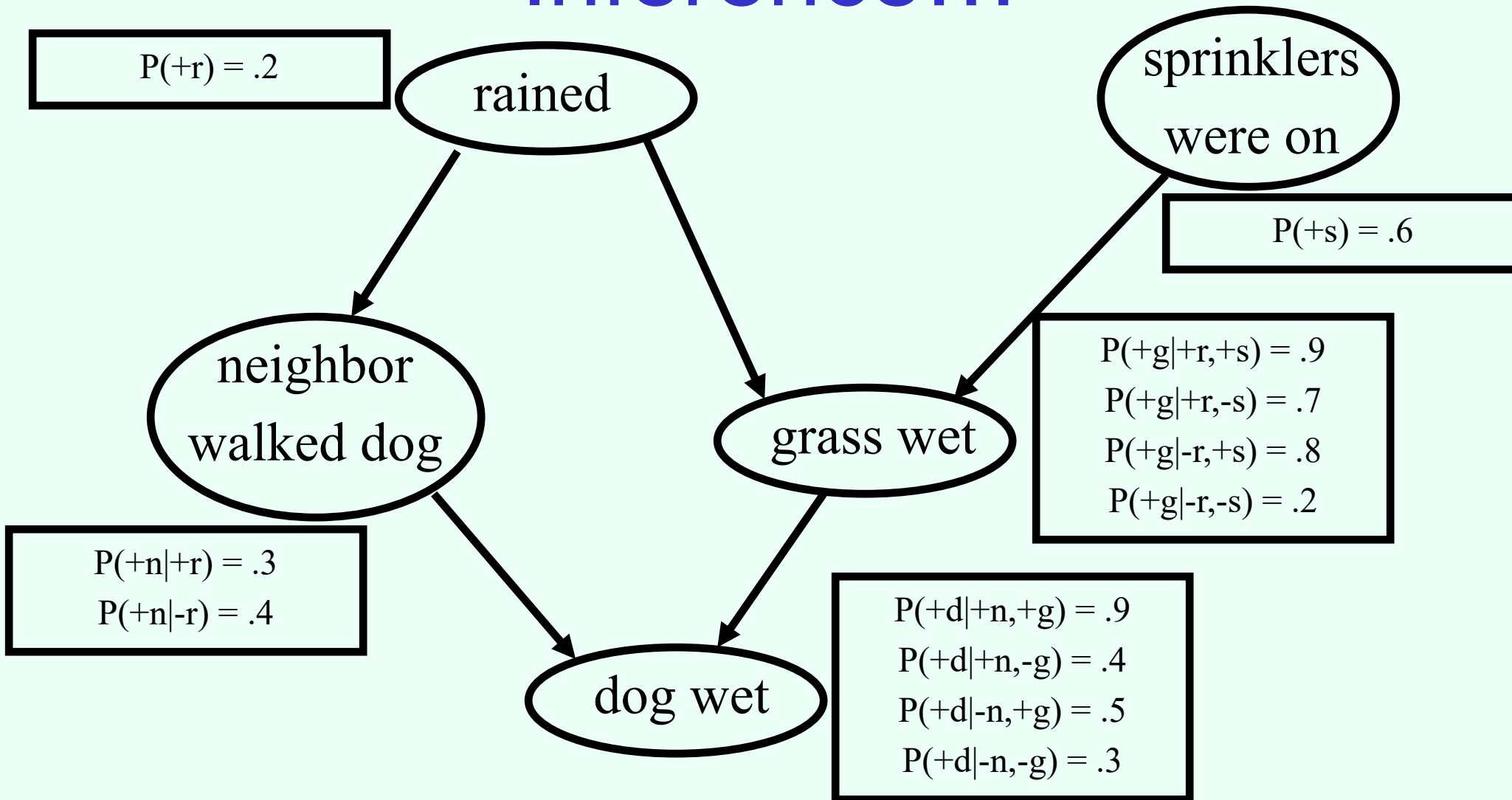
- Can easily calculate the probability of any **atomic** event
- $P(+r,+s,+n,+g,+d) = P(+r)P(+s)P(+n|+r)P(+g|+r,+s)P(+d|+n,+g)$
- Can also **sample** atomic events easily

Inference



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

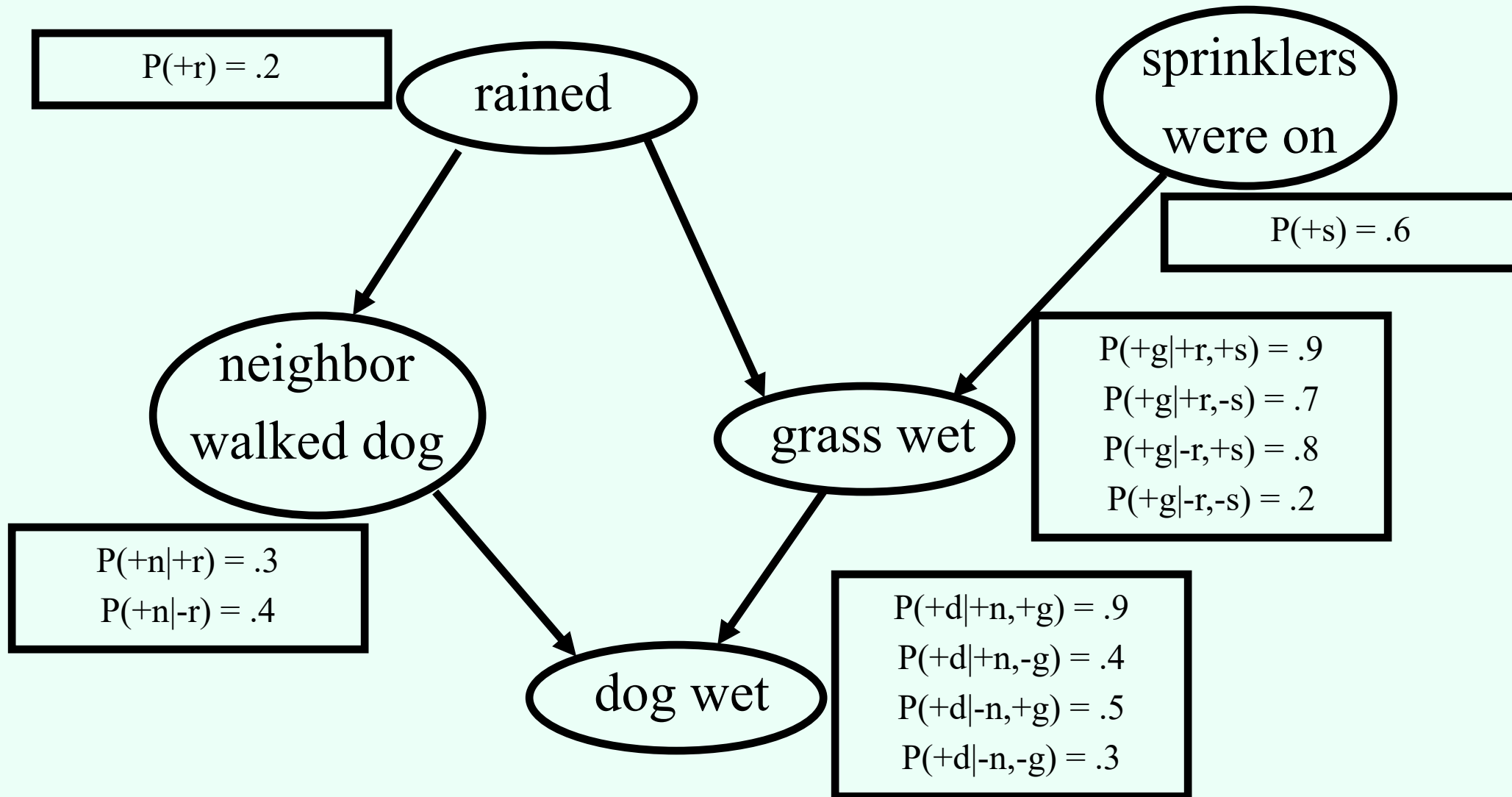
Inference...



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

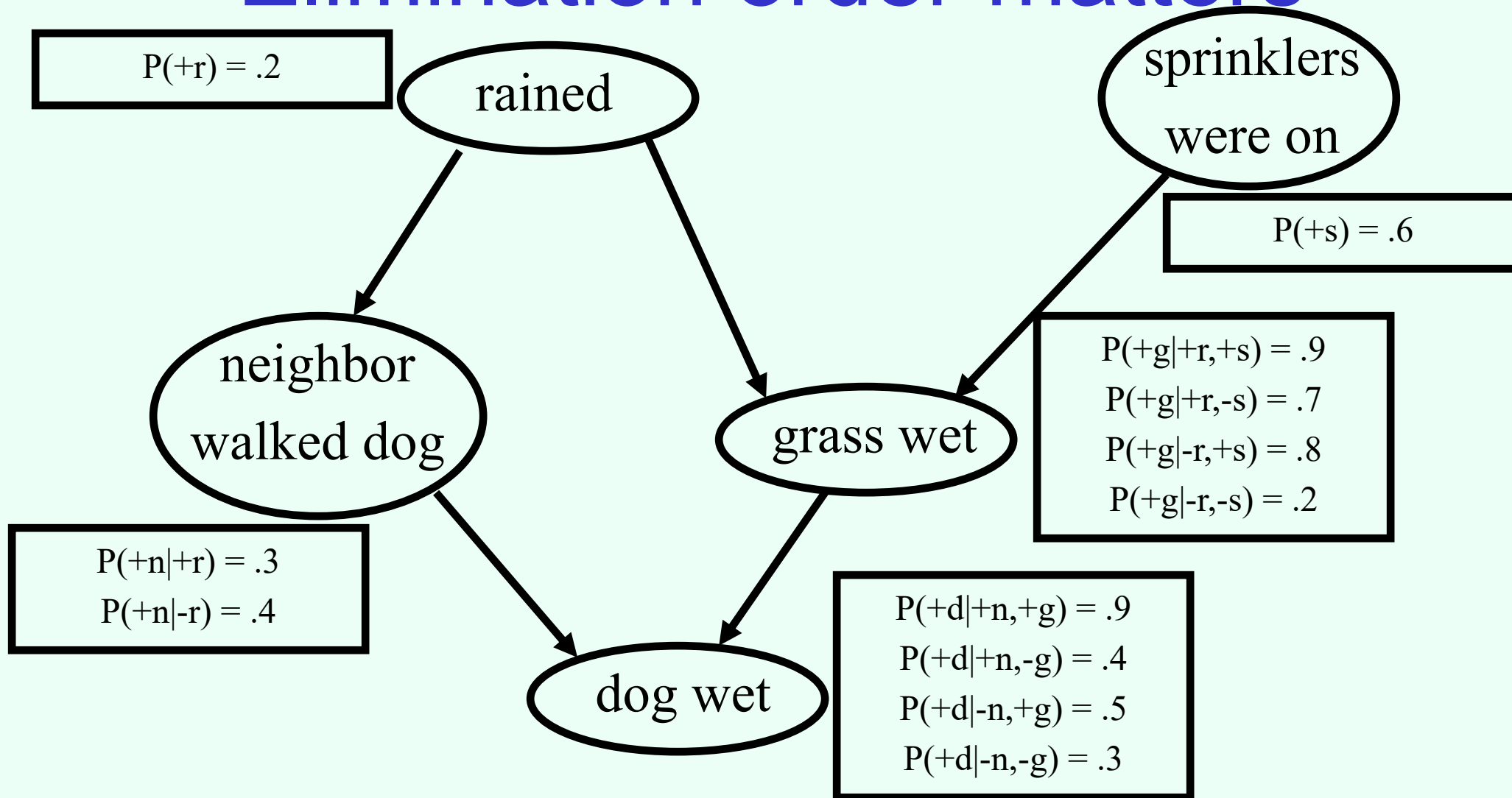
$$P(+r)\sum_s P(s)\sum_g P(g|+r,s)\sum_n P(n|+r)P(+d|n,g)$$

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)

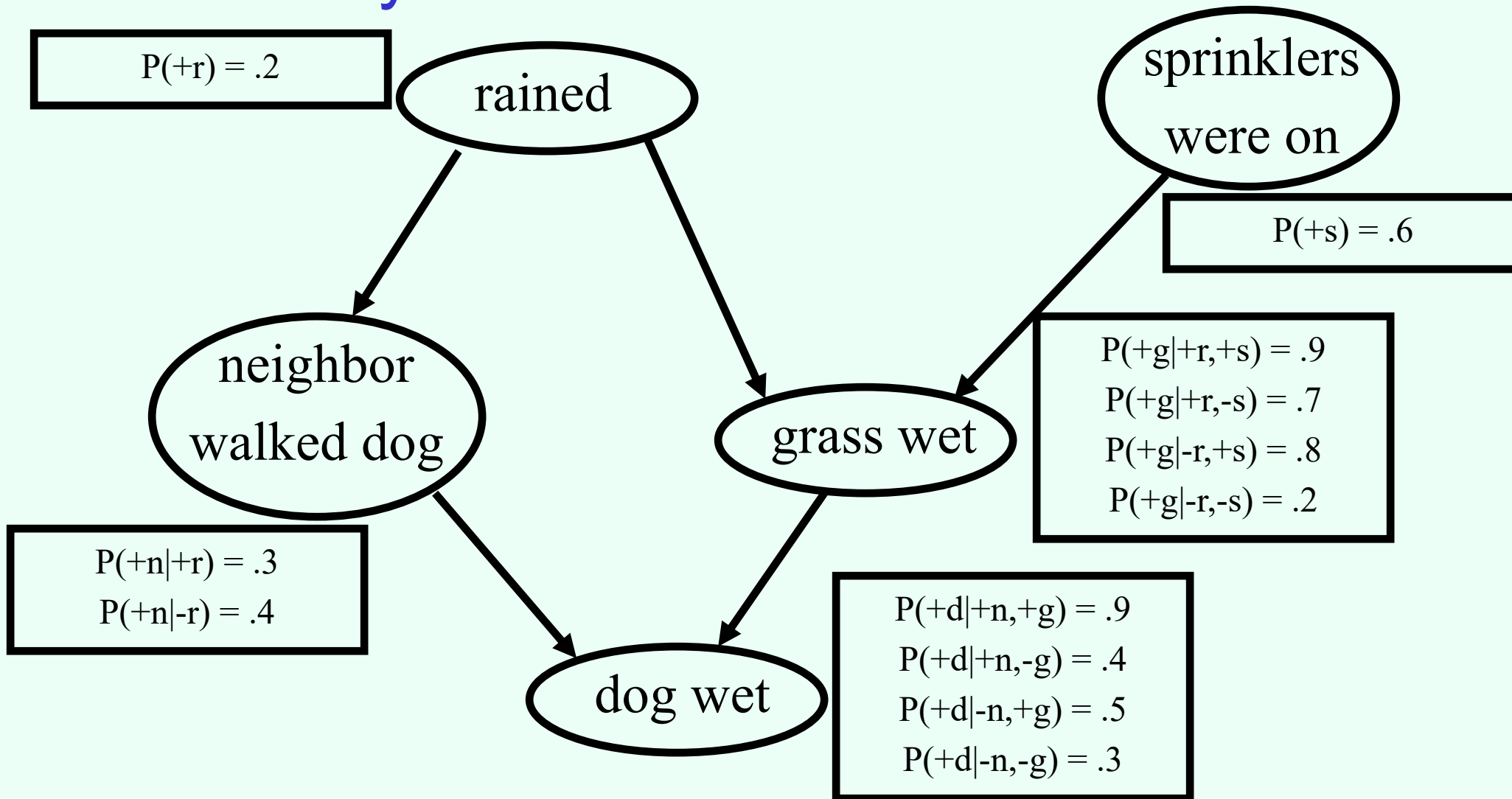
Elimination order matters



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

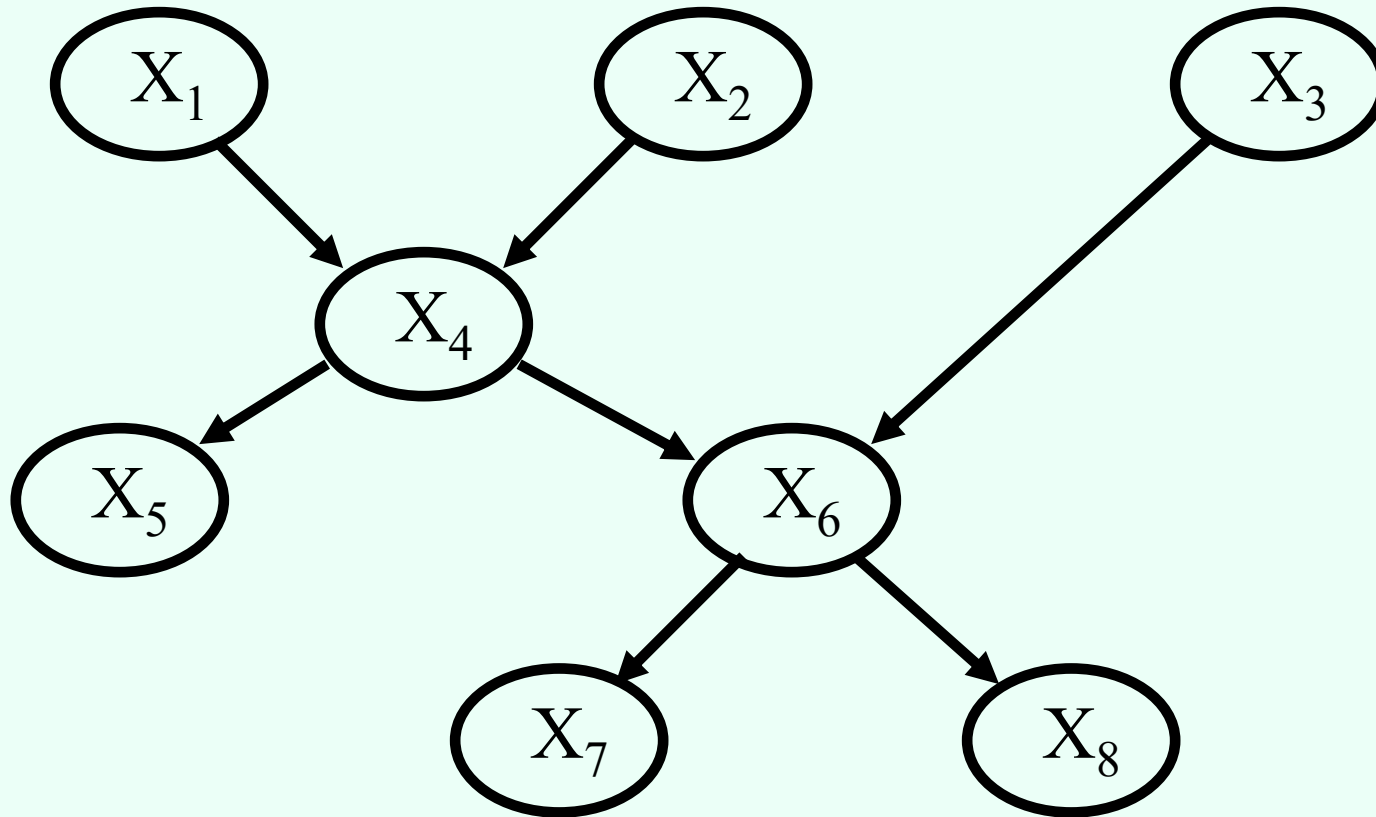
$$P(+r)\sum_n P(n|+r)\sum_s P(s)\sum_g P(g|+r,s)P(+d|n,g)$$
- Last factor will depend on two variables in this case!

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



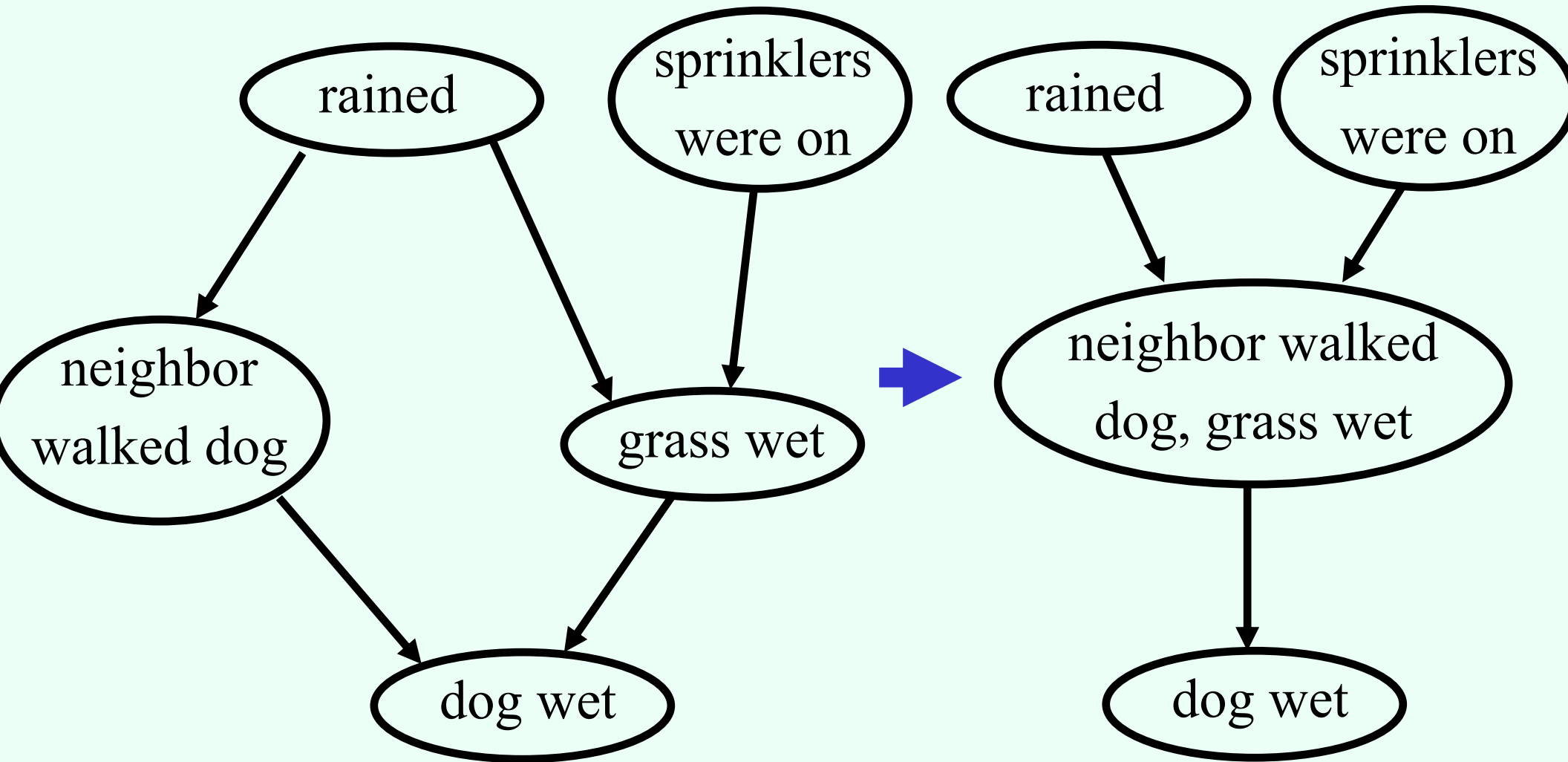
- Can drop parts of the network that are irrelevant
- $P(+r, +s) = P(+r)P(+s) = .6 \cdot .2 = .12$
- $P(+n, +s) = \sum_r P(r, +n, +s) = \sum_r P(r)P(+n|r)P(+s) = P(+s)\sum_r P(r)P(+n|r) = P(+s)(P(+r)P(+n|+r) + P(-r)P(+n|-r)) = .6 \cdot (.2 \cdot .3 + .8 \cdot .4) = .6 \cdot .38 = .228$
- $P(+d | +n, +g, +s) = P(+d | +n, +g) = .9$

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

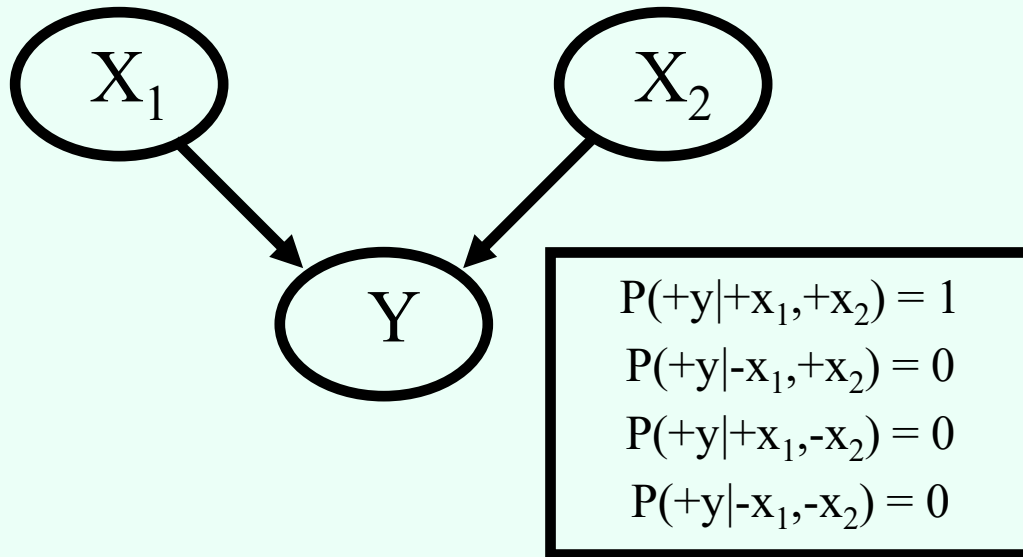


- Merge nodes into “meganodes” until we have a tree
 - Then, can apply special-purpose algorithm for trees
- Merged node has values $\{+n+g, +n-g, -n+g, -n-g\}$
 - Much larger CPT

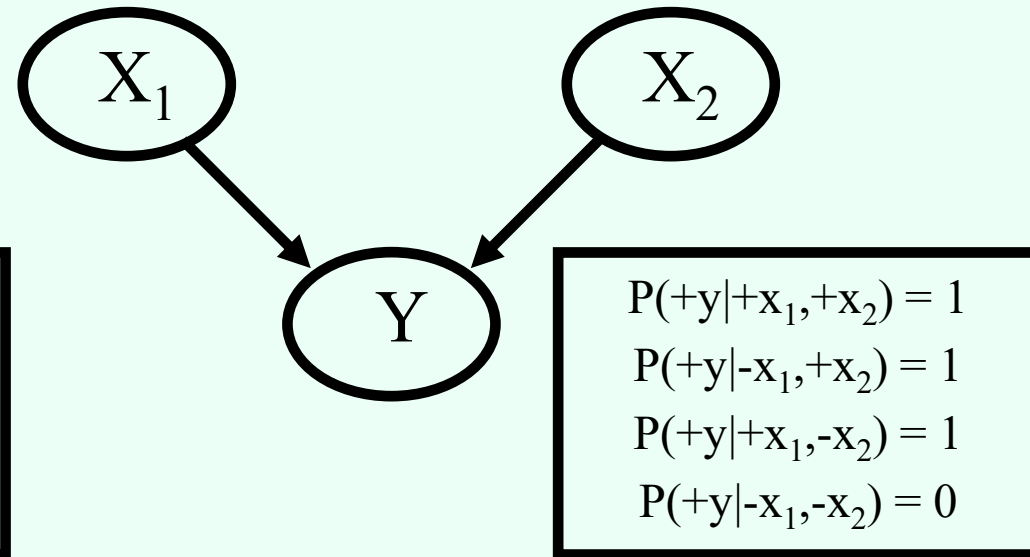
Logic gates in Bayes nets

- Not everything needs to be random...

AND gate

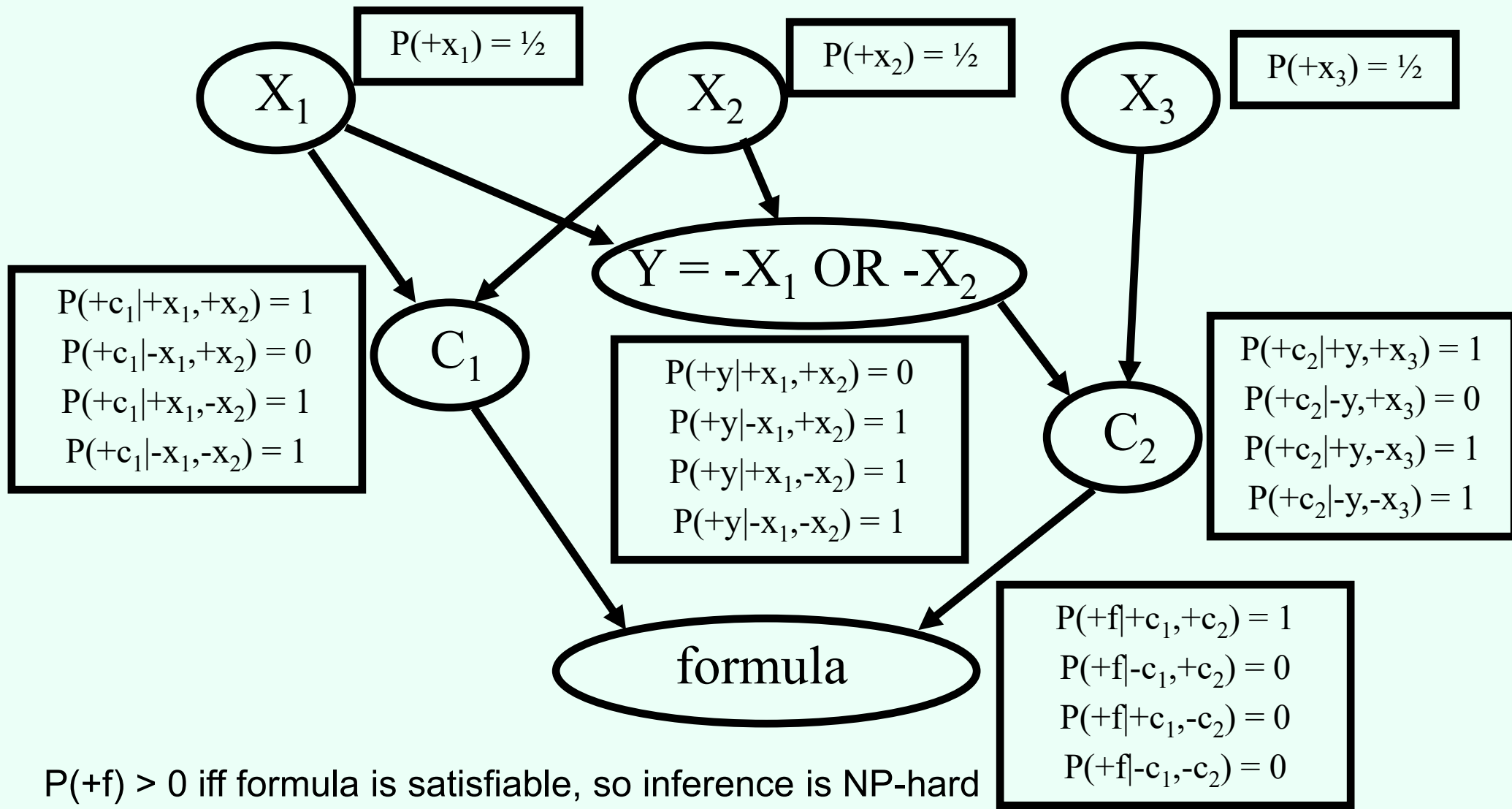


OR gate



Modeling satisfiability as a Bayes Net

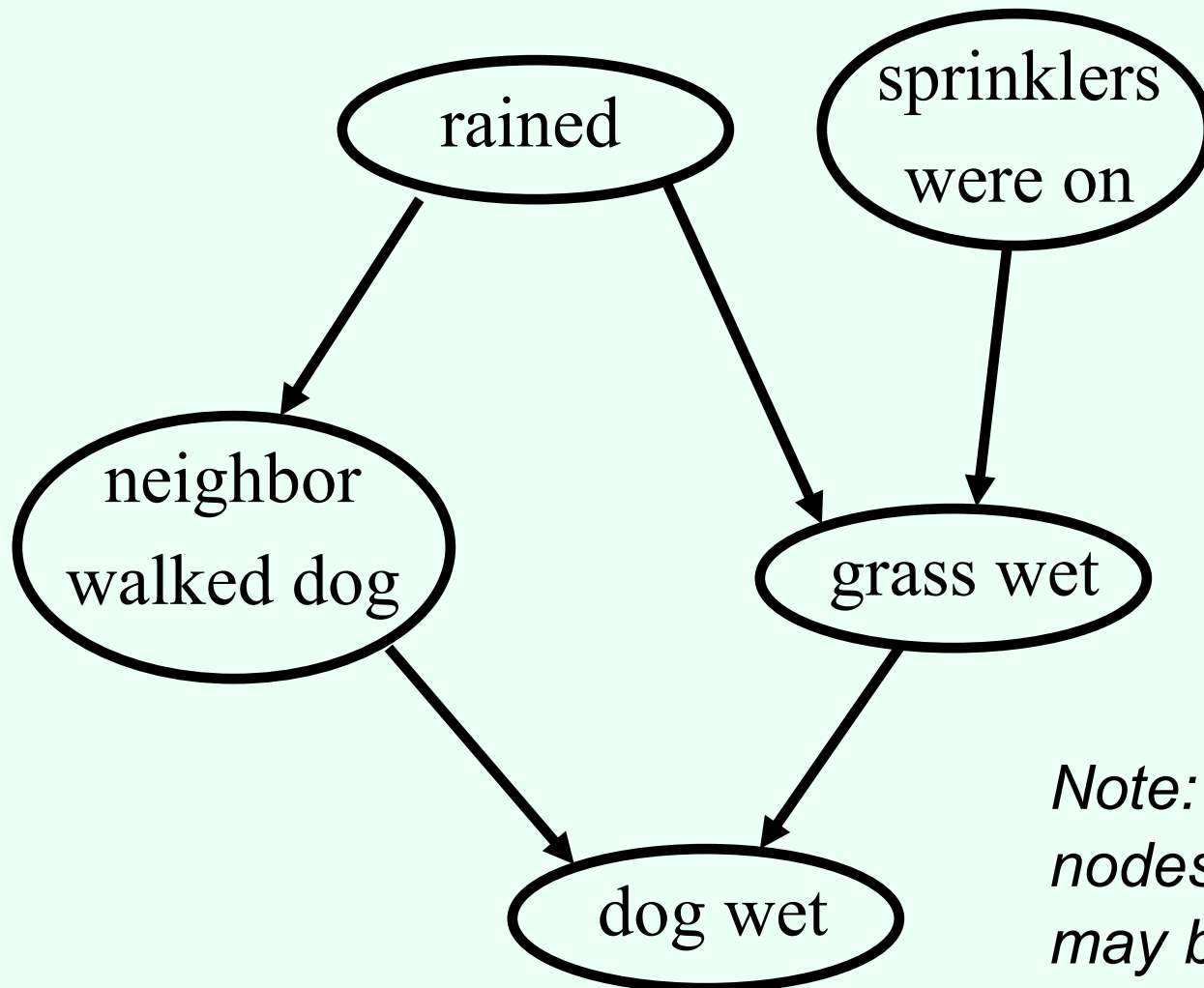
- $(+X_1 \text{ OR } -X_2) \text{ AND } (-X_1 \text{ OR } -X_2 \text{ OR } -X_3)$



- $P(+f) > 0$ 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**)

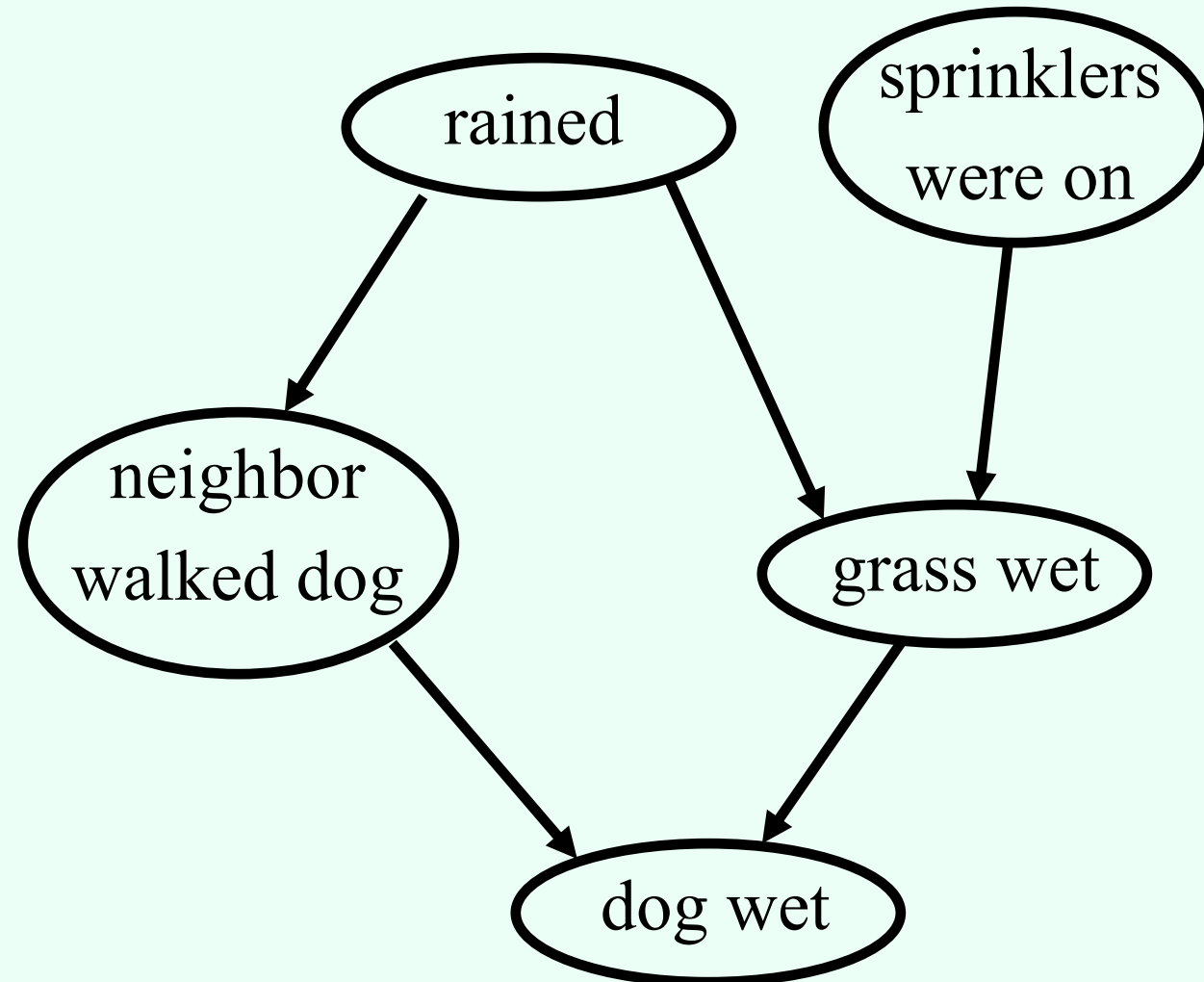


- N is independent of G given R
- N is **not** independent of G given R and D
- N is independent of S given R, G, D

*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