

INFERENCE IN BAYESIAN NETWORKS

CHAPTER 14.4–5

Outline

- ◇ Exact inference by enumeration
- ◇ Exact inference by variable elimination
- ◇ Approximate inference by stochastic simulation
- ◇ Approximate inference by Markov chain Monte Carlo

Inference tasks

Simple queries: compute posterior marginal $\mathbf{P}(X_i|\mathbf{E} = \mathbf{e})$

e.g., $P(\text{NoGas}|\text{Gauge} = \text{empty}, \text{Lights} = \text{on}, \text{Starts} = \text{false})$

Conjunctive queries: $\mathbf{P}(X_i, X_j|\mathbf{E} = \mathbf{e}) = \mathbf{P}(X_i|\mathbf{E} = \mathbf{e})\mathbf{P}(X_j|X_i, \mathbf{E} = \mathbf{e})$

Optimal decisions: decision networks include utility information;
probabilistic inference required for $P(\text{outcome}|\text{action}, \text{evidence})$

Value of information: which evidence to seek next?

Sensitivity analysis: which probability values are most critical?

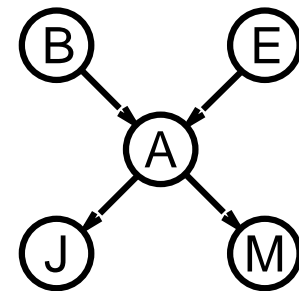
Explanation: why do I need a new starter motor?

Inference by enumeration

Slightly intelligent way to sum out variables from the joint without actually constructing its explicit representation

Simple query on the burglary network:

$$\begin{aligned} & \mathbf{P}(B|j, m) \\ &= \mathbf{P}(B, j, m) / P(j, m) \\ &= \alpha \mathbf{P}(B, j, m) \\ &= \alpha \sum_e \sum_a \mathbf{P}(B, e, a, j, m) \end{aligned}$$



Rewrite full joint entries using product of CPT entries:

$$\begin{aligned} & \mathbf{P}(B|j, m) \\ &= \alpha \sum_e \sum_a \mathbf{P}(B)P(e)\mathbf{P}(a|B, e)P(j|a)P(m|a) \\ &= \alpha \mathbf{P}(B) \sum_e P(e) \sum_a \mathbf{P}(a|B, e)P(j|a)P(m|a) \end{aligned}$$

Recursive depth-first enumeration: $O(n)$ space, $O(d^n)$ time

Enumeration algorithm

function **ENUMERATION-ASK**(X, \mathbf{e}, bn) **returns** a distribution over X

inputs: X , the query variable

\mathbf{e} , observed values for variables \mathbf{E}

bn , a Bayesian network with variables $\{X\} \cup \mathbf{E} \cup \mathbf{Y}$

$Q(X) \leftarrow$ a distribution over X , initially empty

for each value x_i of X **do**

 extend \mathbf{e} with value x_i for X

$Q(x_i) \leftarrow$ **ENUMERATE-ALL**(**VARs**[bn], \mathbf{e})

return **NORMALIZE**($Q(X)$)

function **ENUMERATE-ALL**($vars, \mathbf{e}$) **returns** a real number

if **EMPTY?**($vars$) **then return** 1.0

$Y \leftarrow$ **FIRST**($vars$)

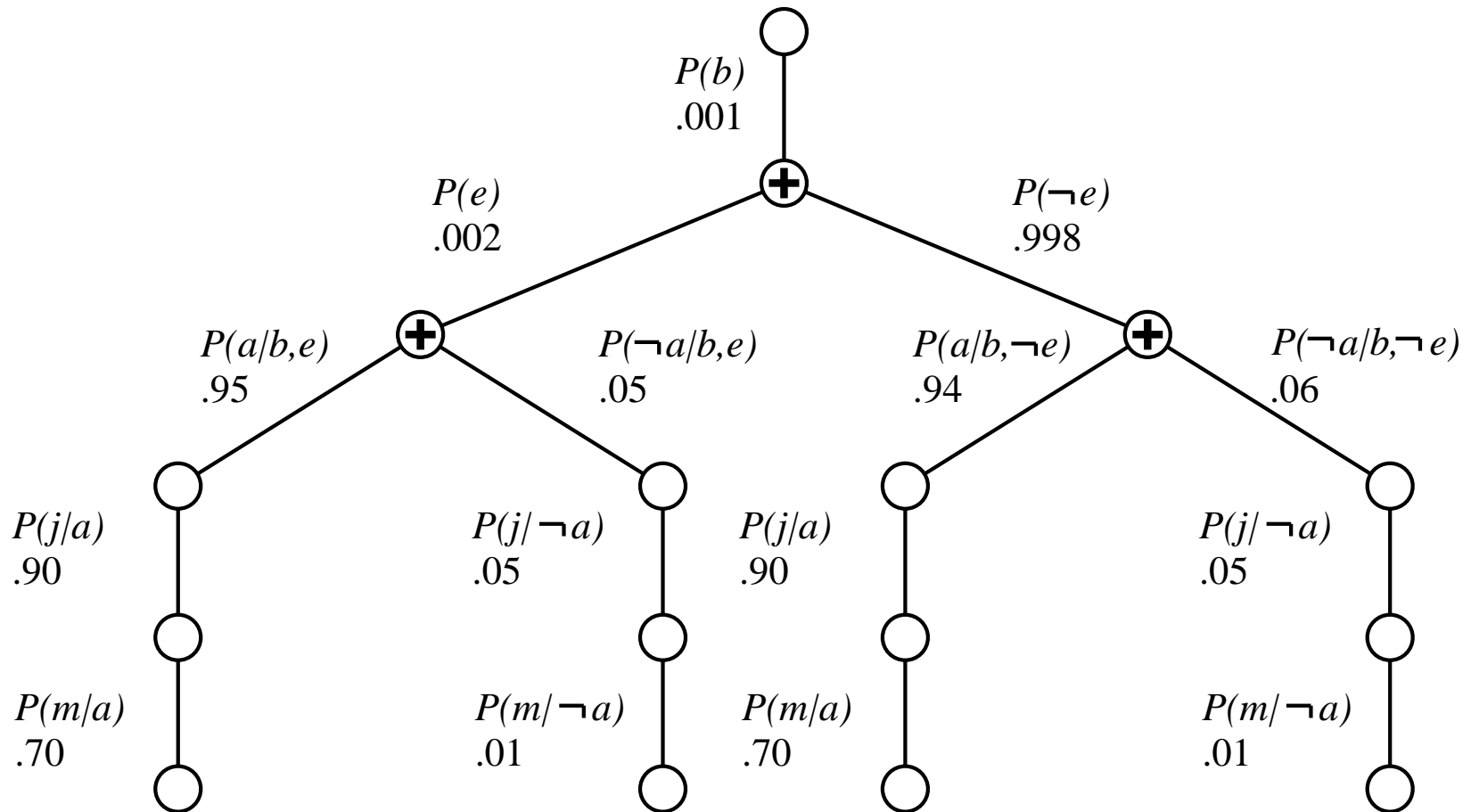
if Y has value y in \mathbf{e}

then return $P(y \mid Pa(Y)) \times$ **ENUMERATE-ALL**(**REST**($vars$), \mathbf{e})

else return $\sum_y P(y \mid Pa(Y)) \times$ **ENUMERATE-ALL**(**REST**($vars$), \mathbf{e}_y)

 where \mathbf{e}_y is \mathbf{e} extended with $Y = y$

Evaluation tree



Enumeration is inefficient: repeated computation
 e.g., computes $P(j|a)P(m|a)$ for each value of e

Inference by variable elimination

Variable elimination: carry out summations right-to-left, storing intermediate results (**factors**) to avoid recomputation

$$\begin{aligned} \mathbf{P}(B|j, m) &= \alpha \underbrace{\mathbf{P}(B)}_B \sum_e \underbrace{P(e)}_E \sum_a \underbrace{\mathbf{P}(a|B, e)}_A \underbrace{P(j|a)}_J \underbrace{P(m|a)}_M \\ &= \alpha \mathbf{P}(B) \sum_e P(e) \sum_a \mathbf{P}(a|B, e) P(j|a) f_M(a) \\ &= \alpha \mathbf{P}(B) \sum_e P(e) \sum_a \mathbf{P}(a|B, e) f_J(a) f_M(a) \\ &= \alpha \mathbf{P}(B) \sum_e P(e) \sum_a f_A(a, b, e) f_J(a) f_M(a) \\ &= \alpha \mathbf{P}(B) \sum_e P(e) f_{\bar{A}JM}(b, e) \text{ (sum out } A) \\ &= \alpha \mathbf{P}(B) f_{\bar{E}\bar{A}JM}(b) \text{ (sum out } E) \\ &= \alpha f_B(b) \times f_{\bar{E}\bar{A}JM}(b) \end{aligned}$$

Variable elimination: Basic operations

Summing out a variable from a product of factors:

move any constant factors outside the summation

add up submatrices in pointwise product of remaining factors

$$\sum_x f_1 \times \cdots \times f_k = f_1 \times \cdots \times f_i \sum_x f_{i+1} \times \cdots \times f_k = f_1 \times \cdots \times f_i \times f_{\bar{X}}$$

assuming f_1, \dots, f_i do not depend on X

Pointwise product of factors f_1 and f_2 :

$$\begin{aligned} & f_1(x_1, \dots, x_j, y_1, \dots, y_k) \times f_2(y_1, \dots, y_k, z_1, \dots, z_l) \\ &= f(x_1, \dots, x_j, y_1, \dots, y_k, z_1, \dots, z_l) \end{aligned}$$

E.g., $f_1(a, b) \times f_2(b, c) = f(a, b, c)$

Variable elimination algorithm

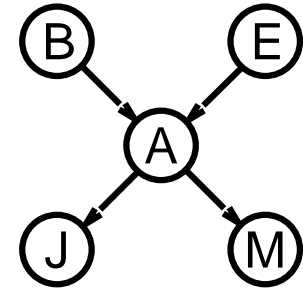
```
function ELIMINATION-ASK( $X, \mathbf{e}, bn$ ) returns a distribution over  $X$   
inputs:  $X$ , the query variable  
           $\mathbf{e}$ , evidence specified as an event  
           $bn$ , a belief network specifying joint distribution  $\mathbf{P}(X_1, \dots, X_n)$   
 $factors \leftarrow []$ ;  $vars \leftarrow \text{REVERSE}(\text{VARS}[bn])$   
for each  $var$  in  $vars$  do  
     $factors \leftarrow [\text{MAKE-FACTOR}(var, \mathbf{e}) | factors]$   
    if  $var$  is a hidden variable then  $factors \leftarrow \text{SUM-OUT}(var, factors)$   
return NORMALIZE( $\text{POINTWISE-PRODUCT}(factors)$ )
```

Irrelevant variables

Consider the query $P(\text{JohnCalls} | \text{Burglary} = \text{true})$

$$P(J|b) = \alpha P(b) \sum_e P(e) \sum_a P(a|b, e) P(J|a) \sum_m P(m|a)$$

Sum over m is identically 1; M is **irrelevant** to the query



Thm 1: Y is irrelevant unless $Y \in \text{Ancestors}(\{X\} \cup \mathbf{E})$

Here, $X = \text{JohnCalls}$, $\mathbf{E} = \{\text{Burglary}\}$, and
 $\text{Ancestors}(\{X\} \cup \mathbf{E}) = \{\text{Alarm}, \text{Earthquake}\}$
so MaryCalls is irrelevant

(Compare this to backward chaining from the query in Horn clause KBs)

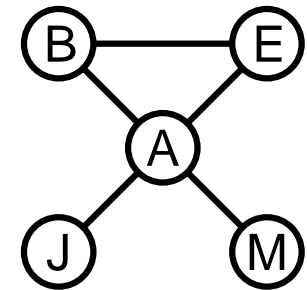
Irrelevant variables contd.

Defn: moral graph of Bayes net: marry all parents and drop arrows

Defn: **A** is m-separated from **B** by **C** iff separated by **C** in the moral graph

Thm 2: **Y** is irrelevant if m-separated from **X** by **E**

For $P(\text{JohnCalls} | \text{Alarm} = \text{true})$, both *Burglary* and *Earthquake* are irrelevant



Complexity of exact inference

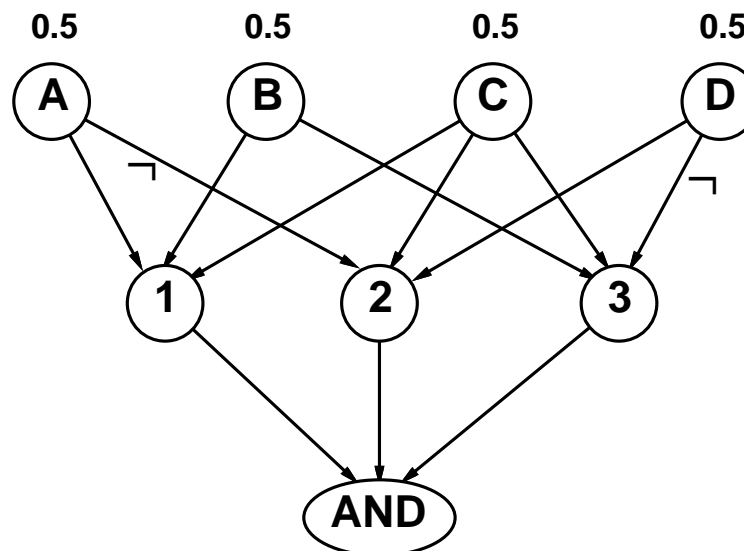
Singly connected networks (or **polytrees**):

- any two nodes are connected by at most one (undirected) path
- time and space cost of variable elimination are $O(d^k n)$

Multiply connected networks:

- can reduce 3SAT to exact inference \Rightarrow NP-hard
- equivalent to **counting** 3SAT models \Rightarrow #P-complete

1. $A \vee B \vee C$
2. $C \vee D \vee \neg A$
3. $B \vee C \vee \neg D$



Inference by stochastic simulation

Basic idea:

- 1) Draw N samples from a sampling distribution S
- 2) Compute an approximate posterior probability \hat{P}
- 3) Show this converges to the true probability P



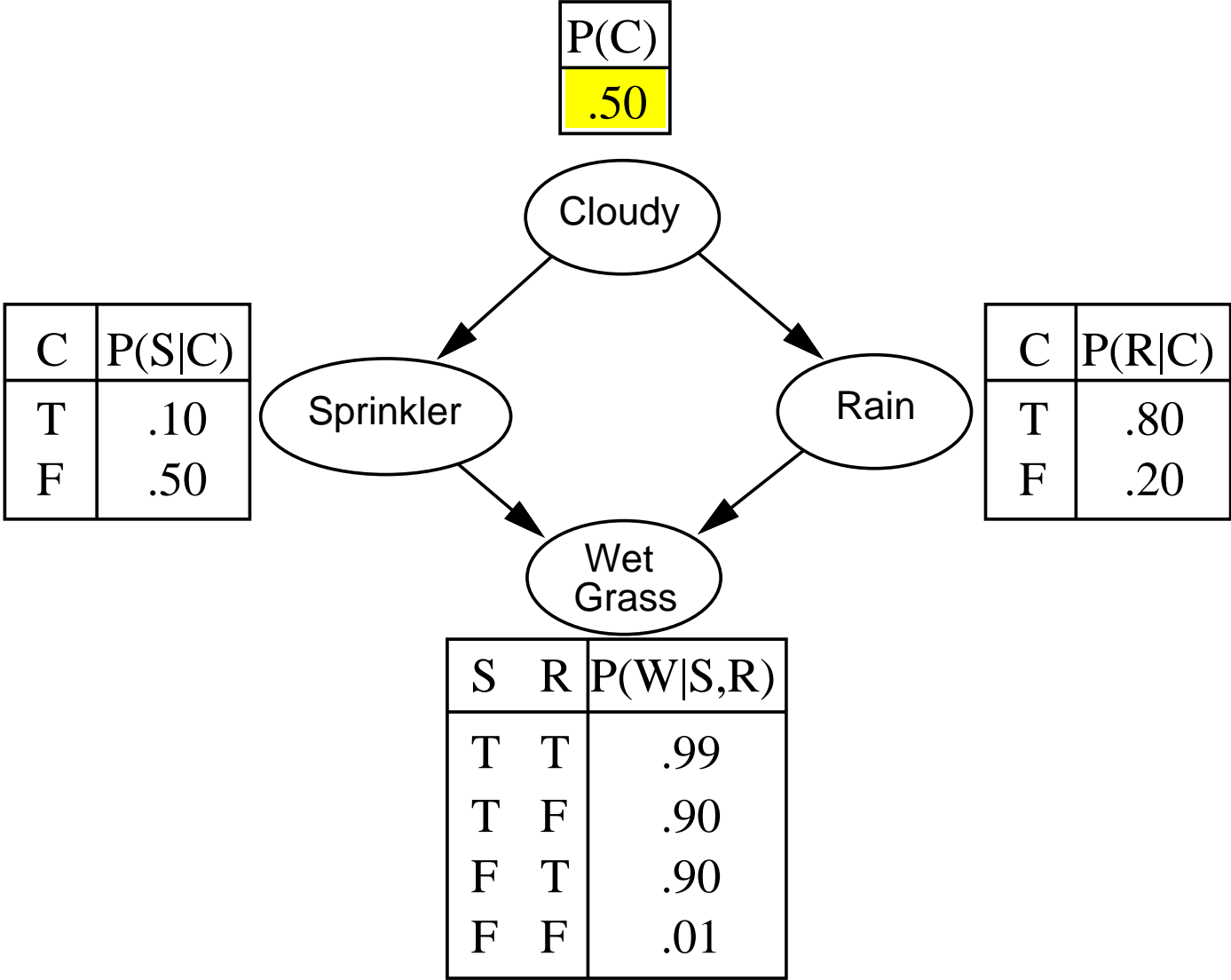
Outline:

- Sampling from an empty network
- Rejection sampling: reject samples disagreeing with evidence
- Likelihood weighting: use evidence to weight samples
- Markov chain Monte Carlo (MCMC): sample from a stochastic process whose stationary distribution is the true posterior

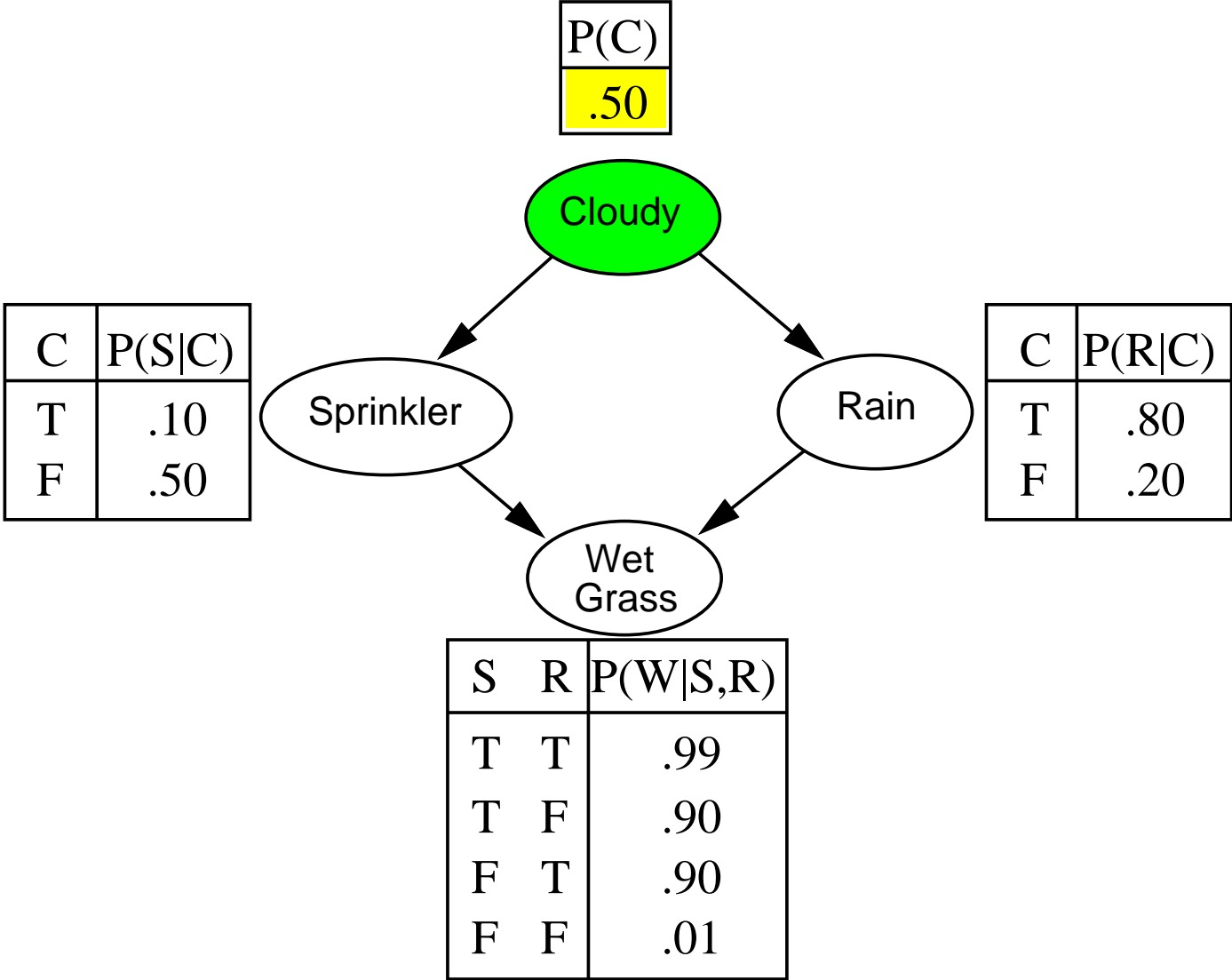
Sampling from an empty network

```
function PRIOR-SAMPLE(bn) returns an event sampled from bn  
inputs: bn, a belief network specifying joint distribution  $\mathbf{P}(X_1, \dots, X_n)$   
x  $\leftarrow$  an event with n elements  
for i = 1 to n do  
    xi  $\leftarrow$  a random sample from  $\mathbf{P}(X_i \mid \text{parents}(X_i))$   
        given the values of Parents(Xi) in x  
return x
```

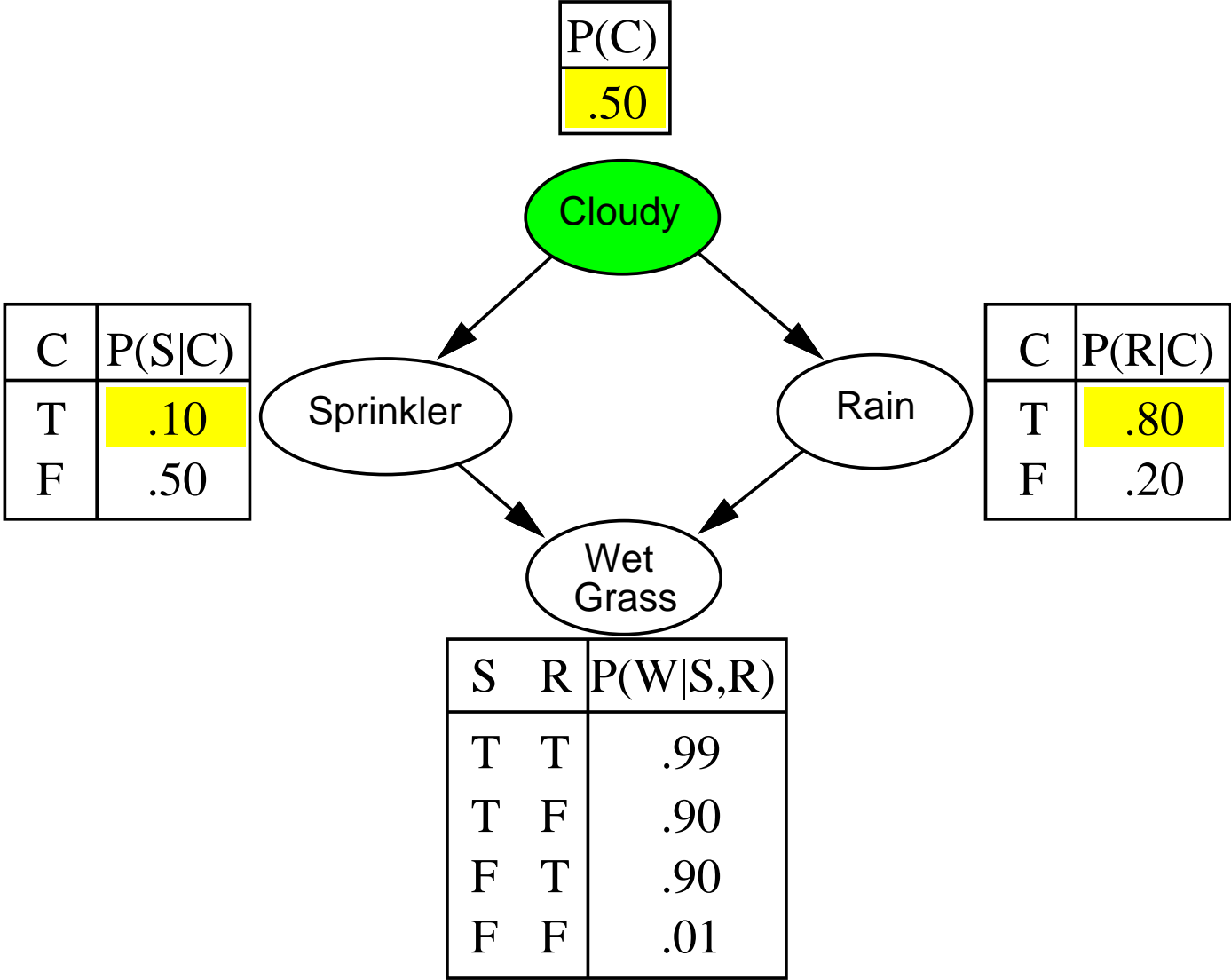
Example



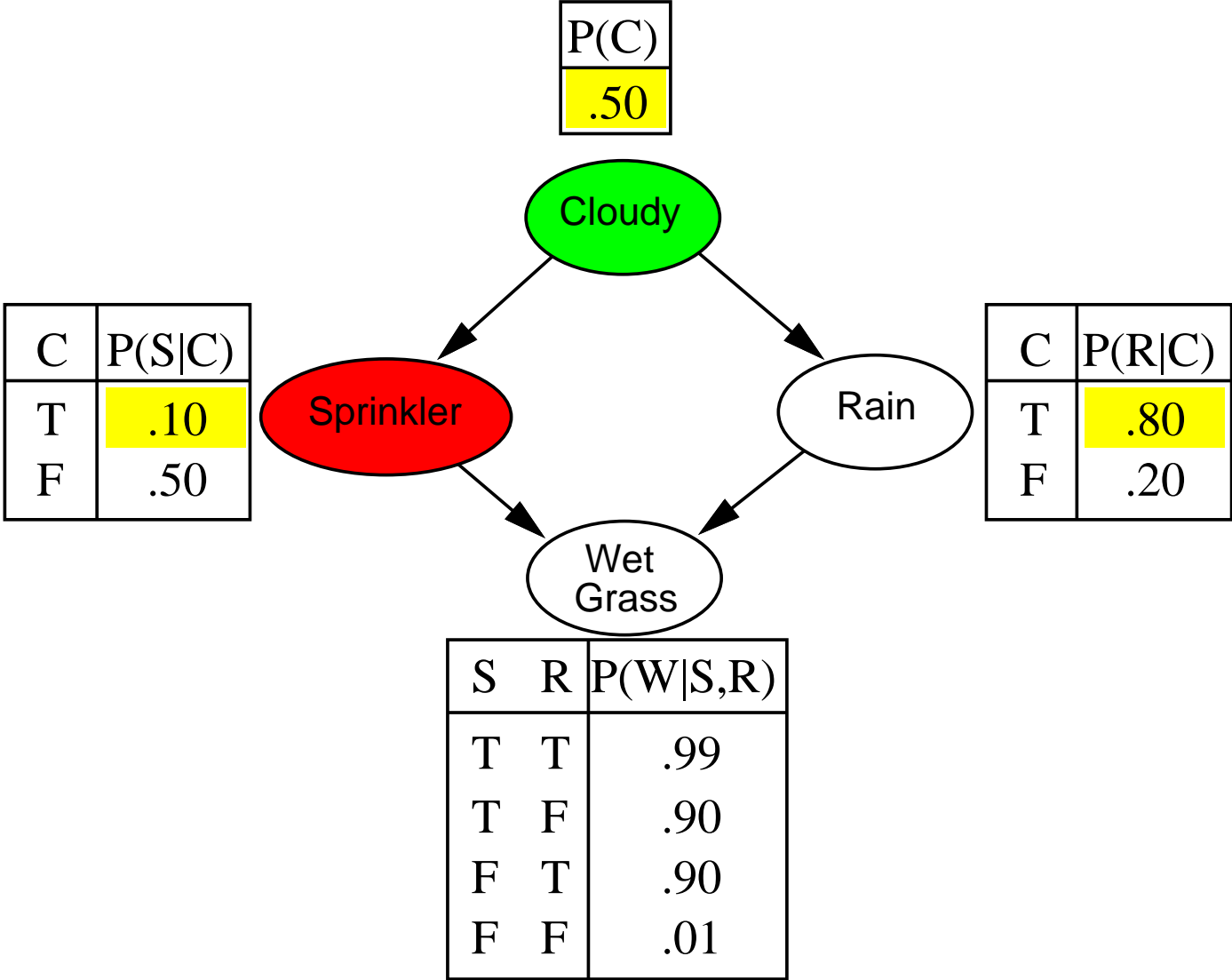
Example



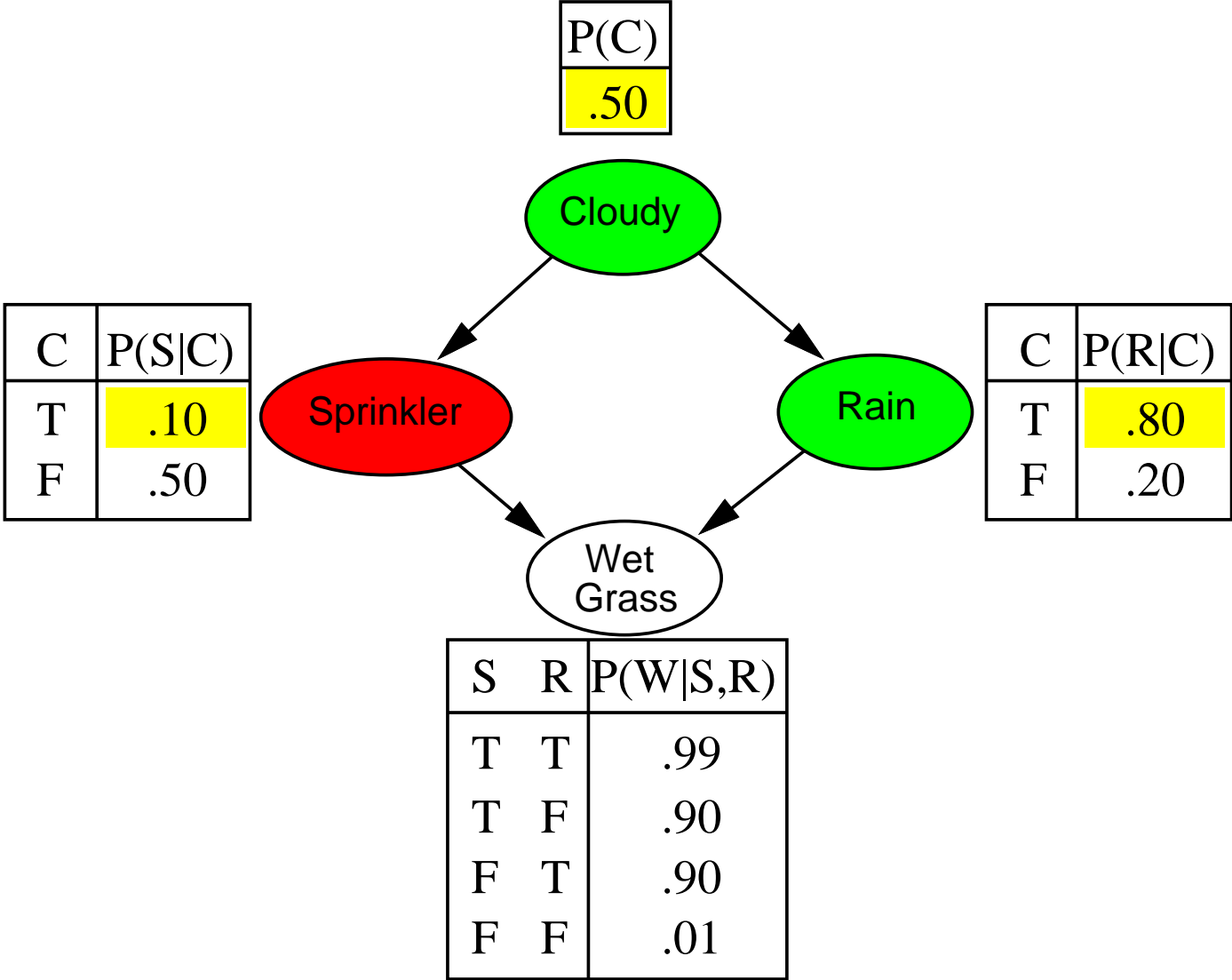
Example



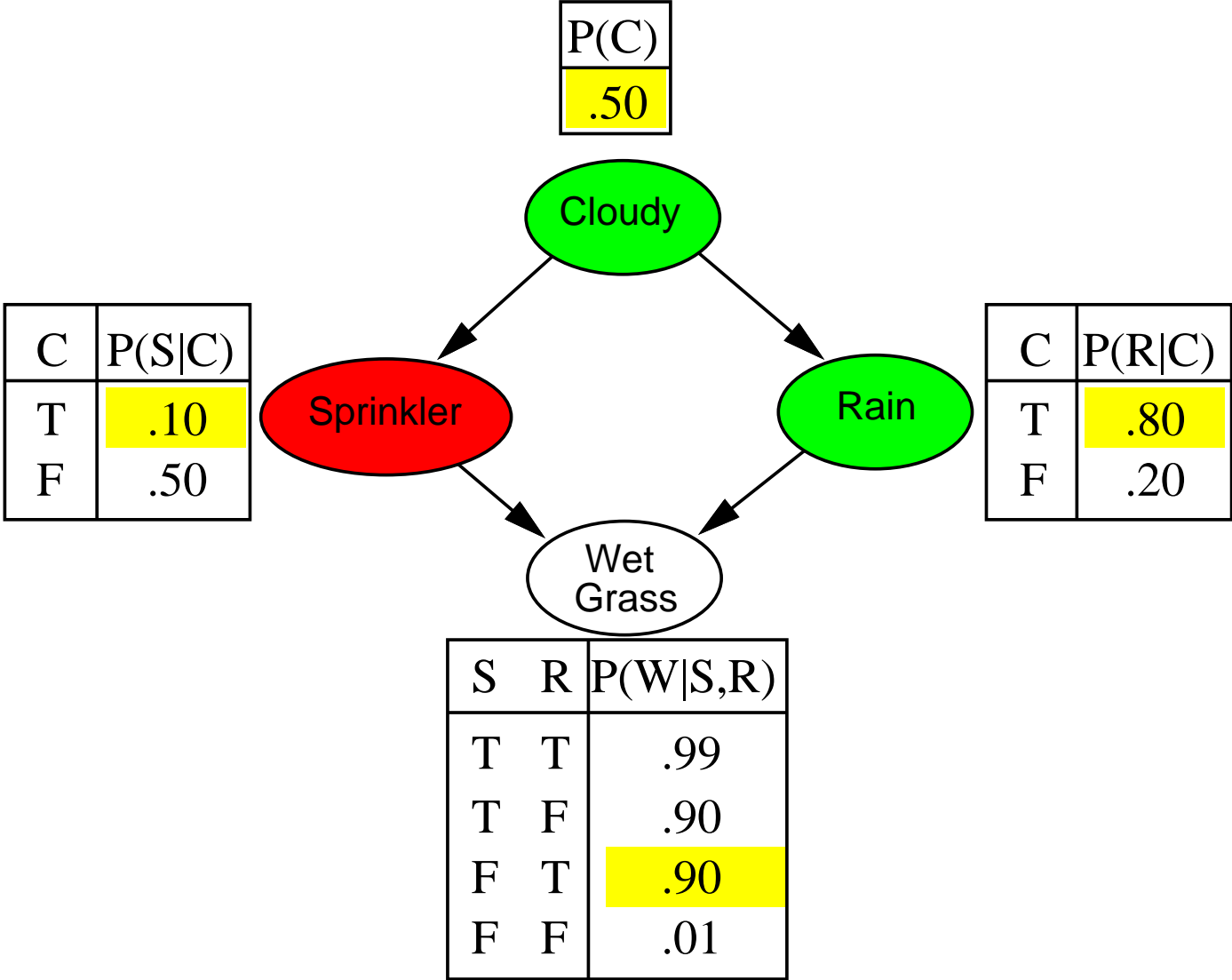
Example



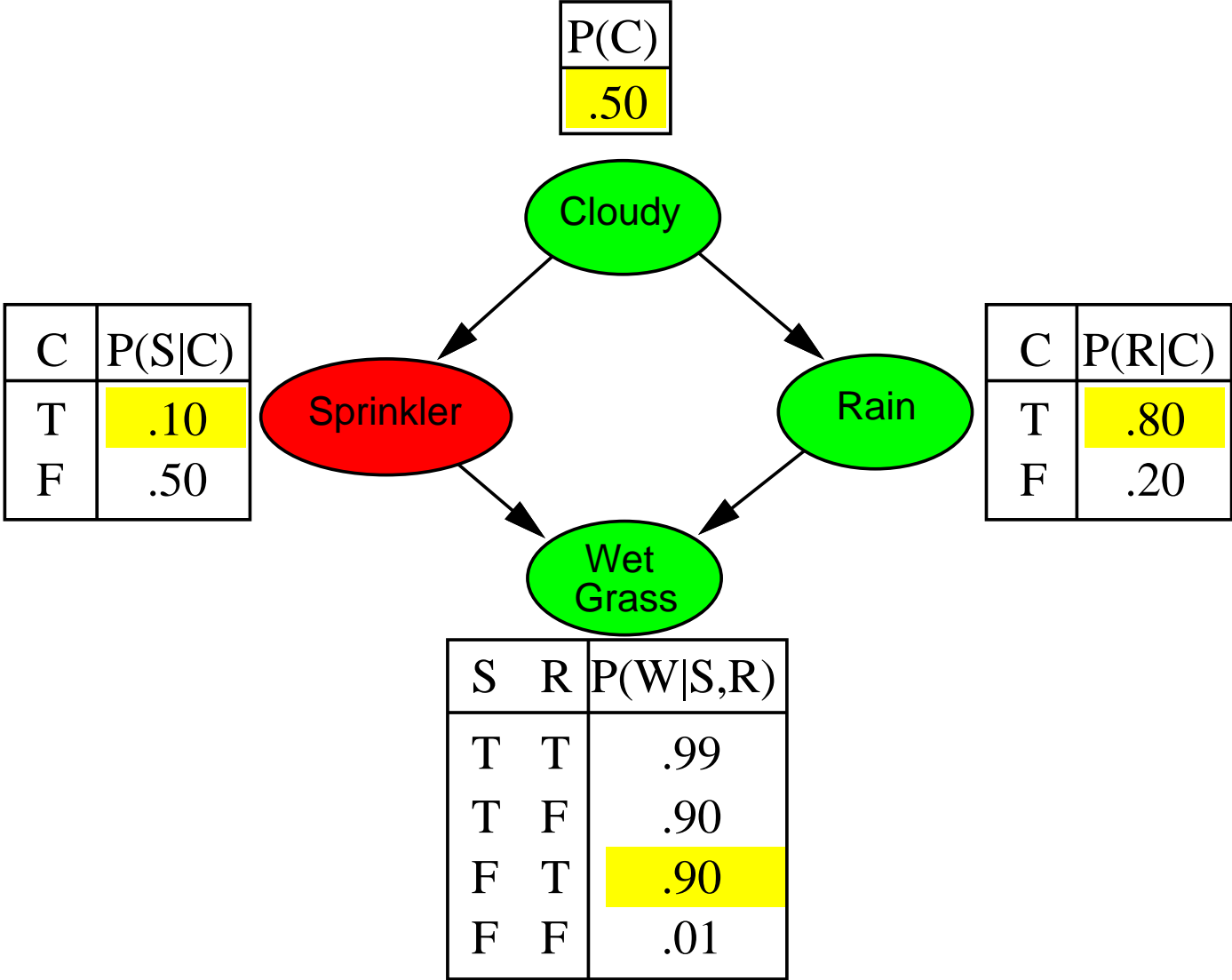
Example



Example



Example



Sampling from an empty network contd.

Probability that PRIORSAMPLE generates a particular event

$$S_{PS}(x_1 \dots x_n) = \prod_{i=1}^n P(x_i | \text{parents}(X_i)) = P(x_1 \dots x_n)$$

i.e., the true prior probability

E.g., $S_{PS}(t, f, t, t) = 0.5 \times 0.9 \times 0.8 \times 0.9 = 0.324 = P(t, f, t, t)$

Let $N_{PS}(x_1 \dots x_n)$ be the number of samples generated for event x_1, \dots, x_n

Then we have

$$\begin{aligned} \lim_{N \rightarrow \infty} \hat{P}(x_1, \dots, x_n) &= \lim_{N \rightarrow \infty} N_{PS}(x_1, \dots, x_n) / N \\ &= S_{PS}(x_1, \dots, x_n) \\ &= P(x_1 \dots x_n) \end{aligned}$$

That is, estimates derived from PRIORSAMPLE are **consistent**

Shorthand: $\hat{P}(x_1, \dots, x_n) \approx P(x_1 \dots x_n)$

Rejection sampling

$\hat{P}(X|\mathbf{e})$ estimated from samples agreeing with \mathbf{e}

```
function REJECTION-SAMPLING( $X, \mathbf{e}, bn, N$ ) returns an estimate of  $P(X|\mathbf{e})$ 
  local variables:  $\mathbf{N}$ , a vector of counts over  $X$ , initially zero
  for  $j = 1$  to  $N$  do
     $\mathbf{x} \leftarrow$  PRIOR-SAMPLE( $bn$ )
    if  $\mathbf{x}$  is consistent with  $\mathbf{e}$  then
       $\mathbf{N}[x] \leftarrow \mathbf{N}[x] + 1$  where  $x$  is the value of  $X$  in  $\mathbf{x}$ 
  return NORMALIZE( $\mathbf{N}[X]$ )
```

E.g., estimate $\mathbf{P}(Rain|Sprinkler = true)$ using 100 samples

27 samples have $Sprinkler = true$

Of these, 8 have $Rain = true$ and 19 have $Rain = false$.

$\hat{P}(Rain|Sprinkler = true) = \text{NORMALIZE}(\langle 8, 19 \rangle) = \langle 0.296, 0.704 \rangle$

Similar to a basic real-world empirical estimation procedure

Analysis of rejection sampling

$$\begin{aligned}\hat{\mathbf{P}}(X|\mathbf{e}) &= \alpha \mathbf{N}_{PS}(X, \mathbf{e}) && \text{(algorithm defn.)} \\ &= \mathbf{N}_{PS}(X, \mathbf{e}) / N_{PS}(\mathbf{e}) && \text{(normalized by } N_{PS}(\mathbf{e})\text{)} \\ &\approx \mathbf{P}(X, \mathbf{e}) / P(\mathbf{e}) && \text{(property of PRIORSAMPLE)} \\ &= \mathbf{P}(X|\mathbf{e}) && \text{(defn. of conditional probability)}\end{aligned}$$

Hence rejection sampling returns consistent posterior estimates

Problem: hopelessly expensive if $P(\mathbf{e})$ is small

$P(\mathbf{e})$ drops off exponentially with number of evidence variables!

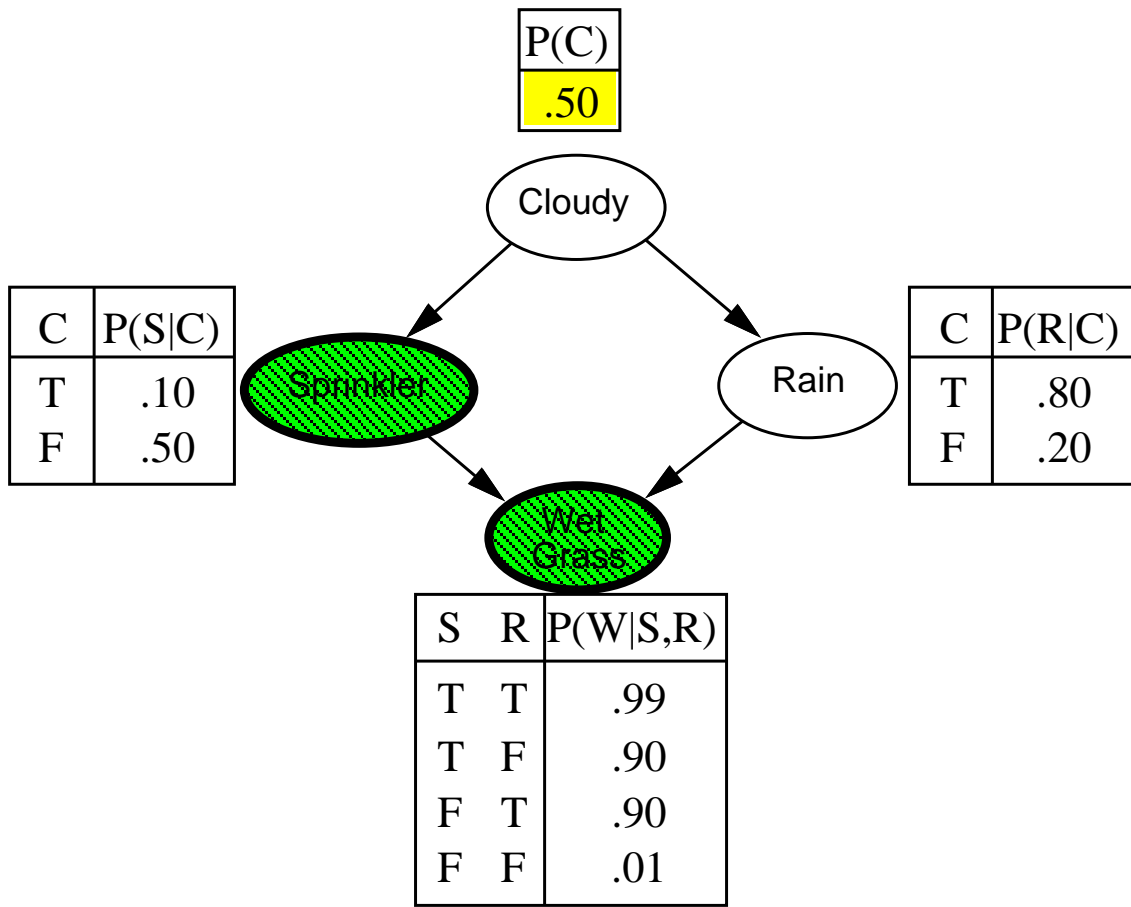
Likelihood weighting

Idea: fix evidence variables, sample only nonevidence variables, and weight each sample by the likelihood it accords the evidence

```
function LIKELIHOOD-WEIGHTING( $X, \mathbf{e}, bn, N$ ) returns an estimate of  $P(X|\mathbf{e})$   
  local variables:  $\mathbf{W}$ , a vector of weighted counts over  $X$ , initially zero  
  for  $j = 1$  to  $N$  do  
     $\mathbf{x}, w \leftarrow$  WEIGHTED-SAMPLE( $bn$ )  
     $\mathbf{W}[x] \leftarrow \mathbf{W}[x] + w$  where  $x$  is the value of  $X$  in  $\mathbf{x}$   
  return NORMALIZE( $\mathbf{W}[X]$ )
```

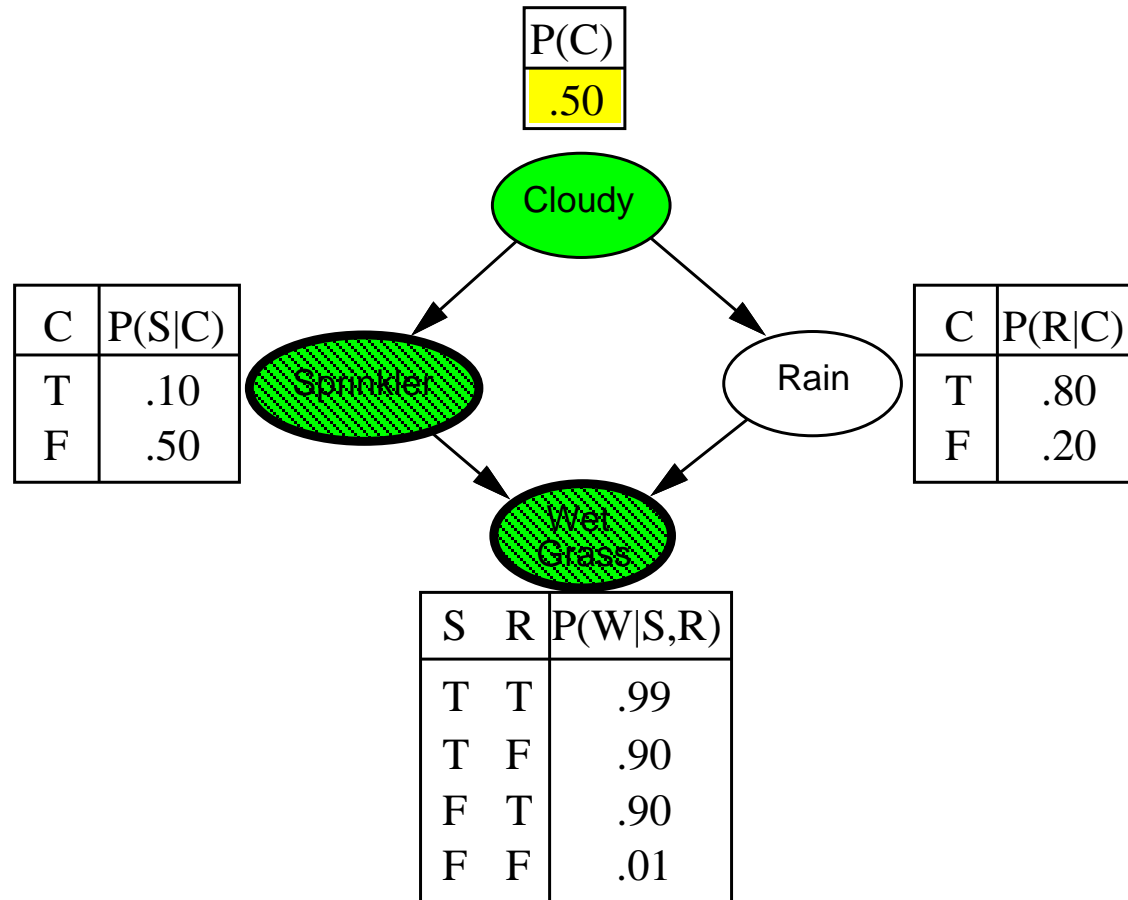
```
function WEIGHTED-SAMPLE( $bn, \mathbf{e}$ ) returns an event and a weight  
   $\mathbf{x} \leftarrow$  an event with  $n$  elements;  $w \leftarrow 1$   
  for  $i = 1$  to  $n$  do  
    if  $X_i$  has a value  $x_i$  in  $\mathbf{e}$   
      then  $w \leftarrow w \times P(X_i = x_i \mid \text{parents}(X_i))$   
      else  $x_i \leftarrow$  a random sample from  $\mathbf{P}(X_i \mid \text{parents}(X_i))$   
  return  $\mathbf{x}, w$ 
```

Likelihood weighting example



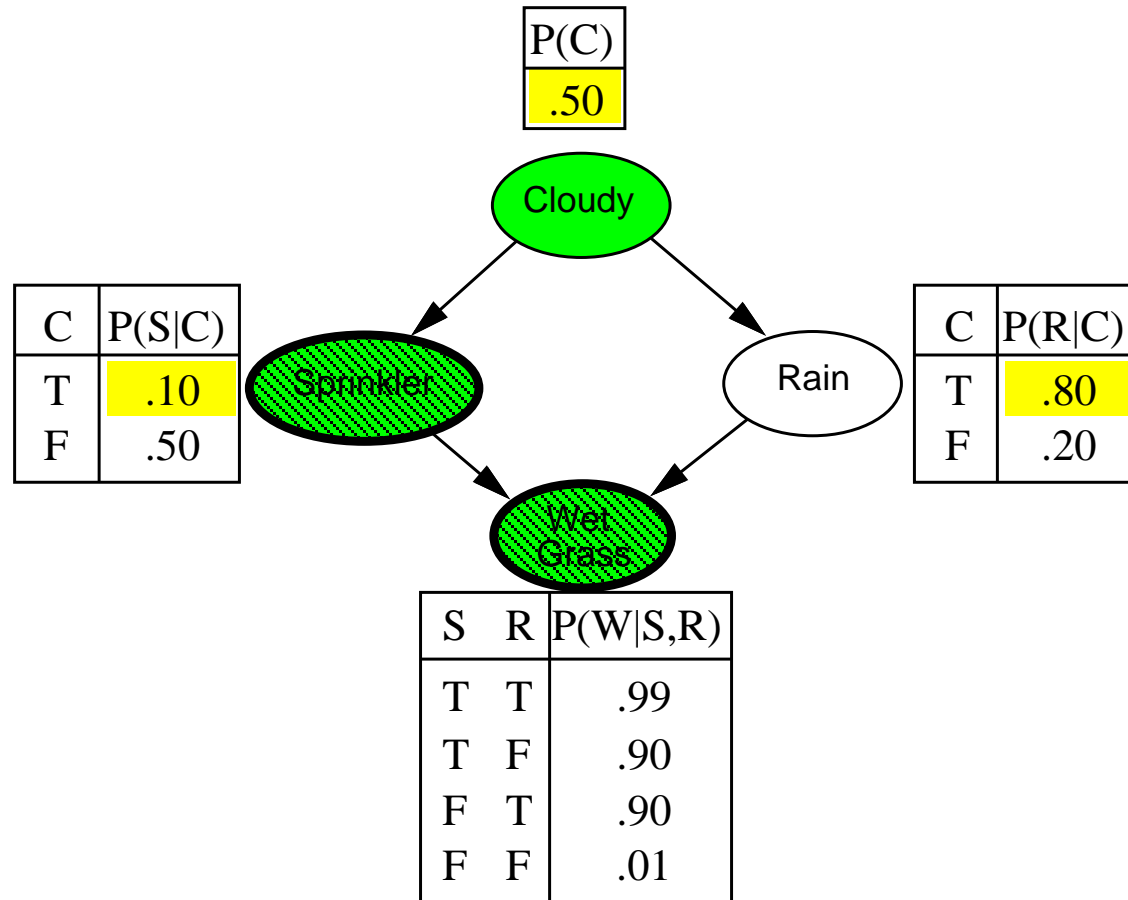
$w = 1.0$

Likelihood weighting example



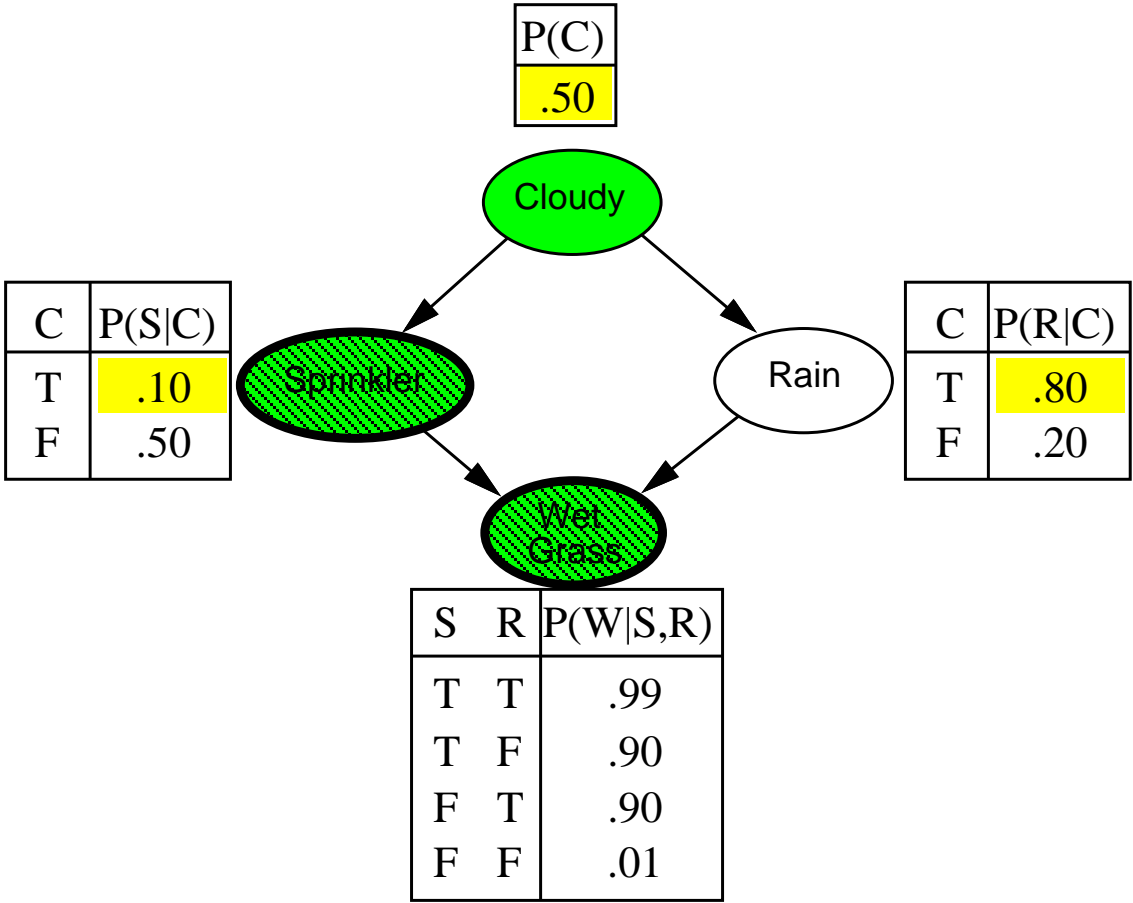
$w = 1.0$

Likelihood weighting example



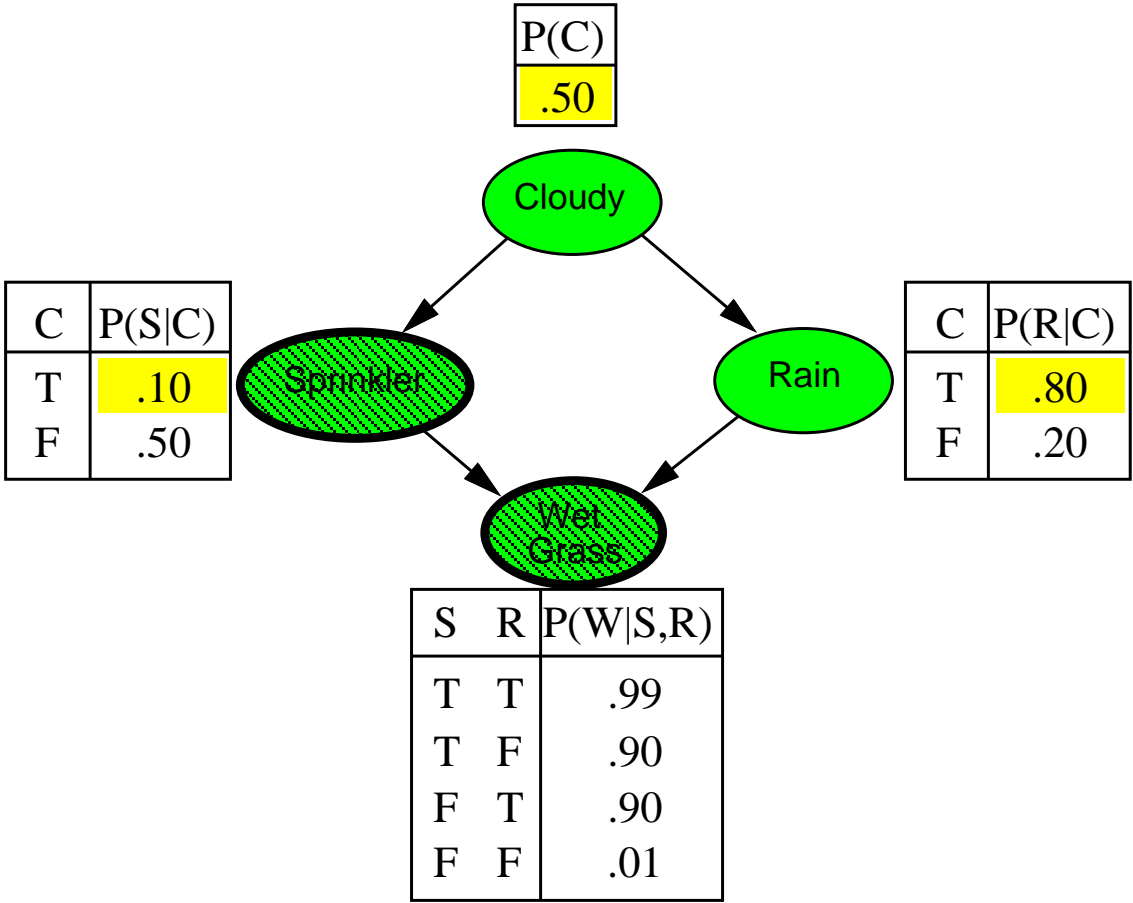
$w = 1.0$

Likelihood weighting example



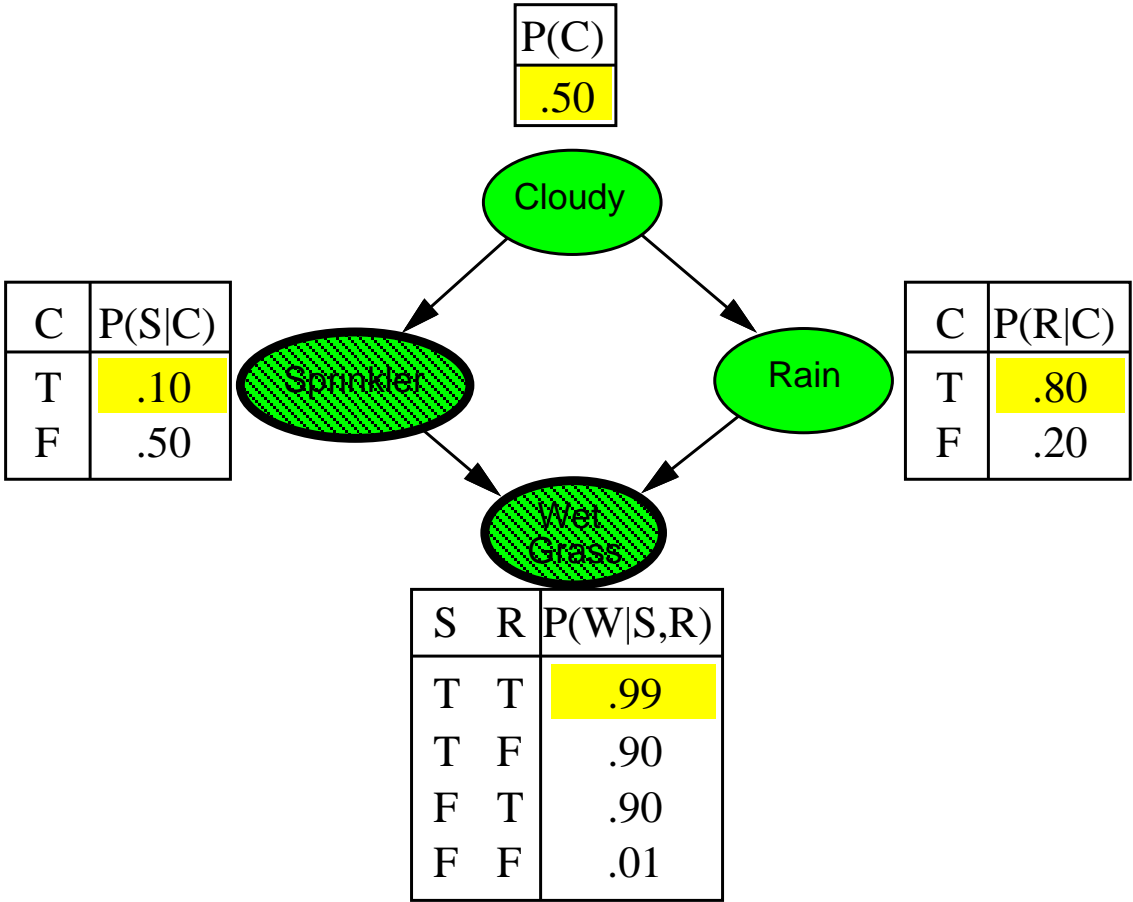
$w = 1.0 \times 0.1$

Likelihood weighting example



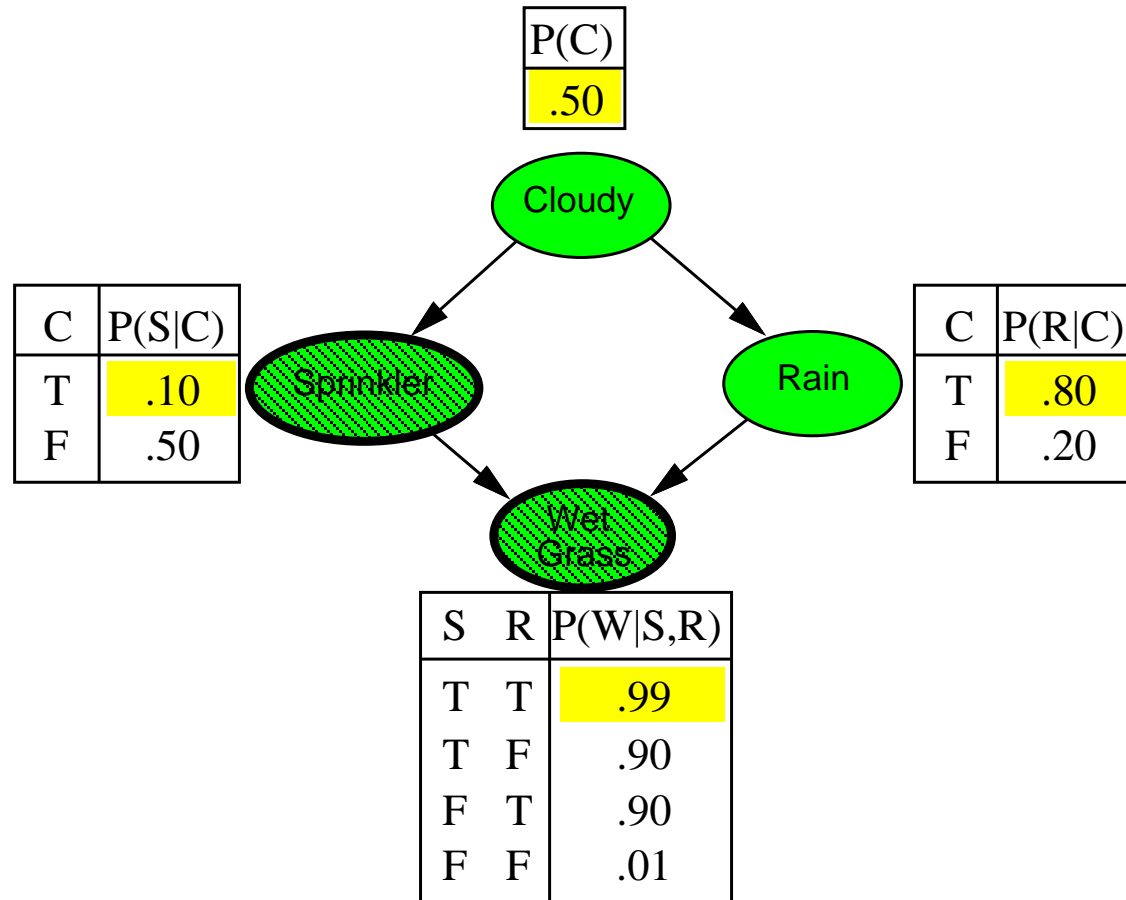
$w = 1.0 \times 0.1$

Likelihood weighting example



$w = 1.0 \times 0.1$

Likelihood weighting example



$$w = 1.0 \times 0.1 \times 0.99 = 0.099$$

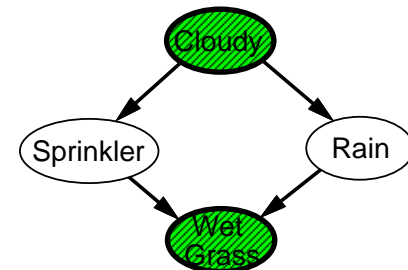
Likelihood weighting analysis

Sampling probability for WEIGHTEDSAMPLE is

$$S_{WS}(\mathbf{z}, \mathbf{e}) = \prod_{i=1}^l P(z_i | \text{parents}(Z_i))$$

Note: pays attention to evidence in **ancestors** only

⇒ somewhere “in between” prior and posterior distribution



Weight for a given sample \mathbf{z}, \mathbf{e} is

$$w(\mathbf{z}, \mathbf{e}) = \prod_{i=1}^m P(e_i | \text{parents}(E_i))$$

Weighted sampling probability is

$$\begin{aligned} & S_{WS}(\mathbf{z}, \mathbf{e}) w(\mathbf{z}, \mathbf{e}) \\ &= \prod_{i=1}^l P(z_i | \text{parents}(Z_i)) \prod_{i=1}^m P(e_i | \text{parents}(E_i)) \\ &= P(\mathbf{z}, \mathbf{e}) \text{ (by standard global semantics of network)} \end{aligned}$$

Hence likelihood weighting returns consistent estimates but performance still degrades with many evidence variables because a few samples have nearly all the total weight

Approximate inference using MCMC

“State” of network = current assignment to all variables.

Generate next state by sampling one variable given Markov blanket

Sample each variable in turn, keeping evidence fixed

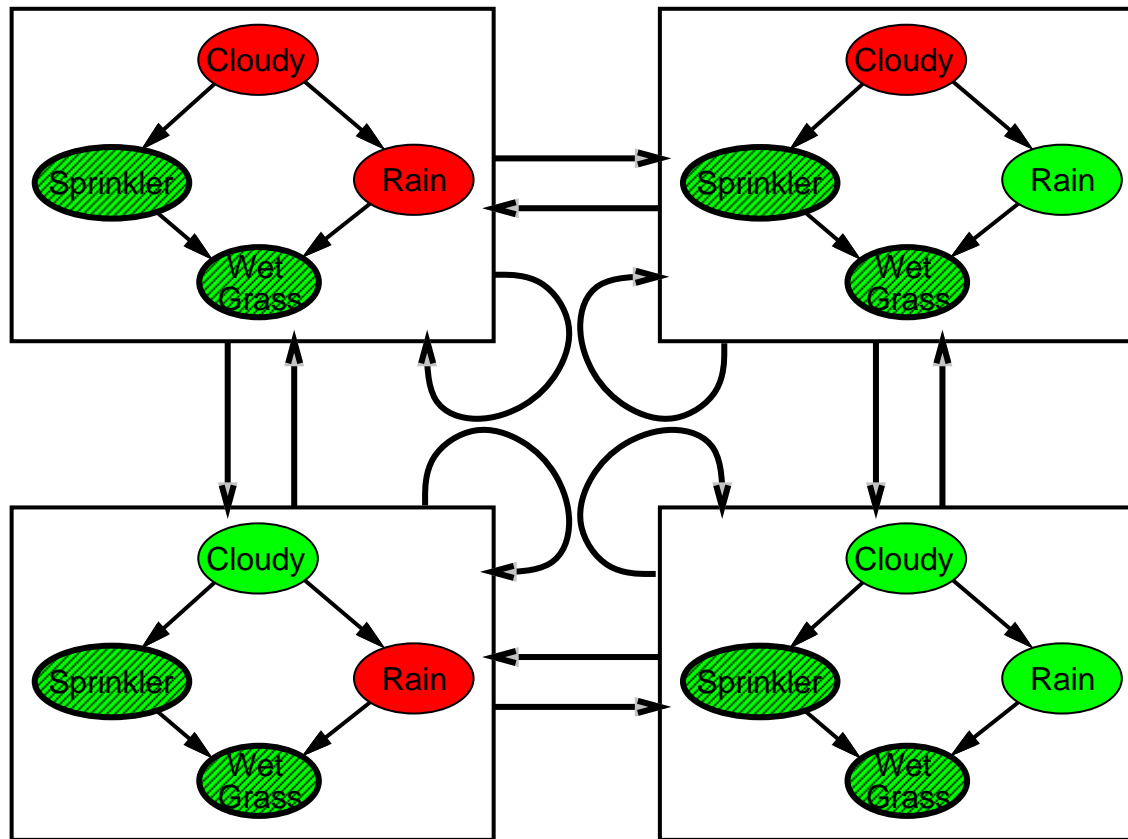
```
function MCMC-Ask( $X, \mathbf{e}, bn, N$ ) returns an estimate of  $P(X|\mathbf{e})$ 
  local variables:  $\mathbf{N}[X]$ , a vector of counts over  $X$ , initially zero
                    $\mathbf{Z}$ , the nonevidence variables in  $bn$ 
                    $\mathbf{x}$ , the current state of the network, initially copied from  $\mathbf{e}$ 

  initialize  $\mathbf{x}$  with random values for the variables in  $\mathbf{Y}$ 
  for  $j = 1$  to  $N$  do
    for each  $Z_i$  in  $\mathbf{Z}$  do
      sample the value of  $Z_i$  in  $\mathbf{x}$  from  $\mathbf{P}(Z_i|mb(Z_i))$ 
        given the values of  $MB(Z_i)$  in  $\mathbf{x}$ 
       $\mathbf{N}[x] \leftarrow \mathbf{N}[x] + 1$  where  $x$  is the value of  $X$  in  $\mathbf{x}$ 
  return NORMALIZE( $\mathbf{N}[X]$ )
```

Can also choose a variable to sample at random each time

The Markov chain

With *Sprinkler = true, WetGrass = true*, there are four states:



Wander about for a while, average what you see

MCMC example contd.

Estimate $\mathbf{P}(Rain|Sprinkler = true, WetGrass = true)$

Sample *Cloudy* or *Rain* given its Markov blanket, repeat.
Count number of times *Rain* is true and false in the samples.

E.g., visit 100 states

31 have *Rain = true*, 69 have *Rain = false*

$$\begin{aligned} \hat{\mathbf{P}}(Rain|Sprinkler = true, WetGrass = true) \\ = \text{NORMALIZE}(\langle 31, 69 \rangle) = \langle 0.31, 0.69 \rangle \end{aligned}$$

Theorem: chain approaches **stationary distribution**:

long-run fraction of time spent in each state is exactly
proportional to its posterior probability

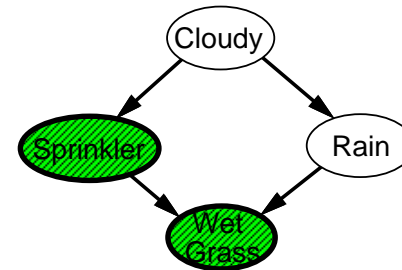
Markov blanket sampling

Markov blanket of *Cloudy* is

Sprinkler and *Rain*

Markov blanket of *Rain* is

Cloudy, *Sprinkler*, and *WetGrass*



Probability given the Markov blanket is calculated as follows:

$$P(x'_i | mb(X_i)) = P(x'_i | parents(X_i)) \prod_{Z_j \in Children(X_i)} P(z_j | parents(Z_j))$$

Easily implemented in message-passing parallel systems, brains

Main computational problems:

- 1) Difficult to tell if convergence has been achieved
- 2) Can be wasteful if Markov blanket is large:

$P(X_i | mb(X_i))$ won't change much (law of large numbers)

Summary

Exact inference by variable elimination:

- polytime on polytrees, NP-hard on general graphs
- space = time, very sensitive to topology

Approximate inference by LW, MCMC:

- LW does poorly when there is lots of (downstream) evidence
- LW, MCMC generally insensitive to topology
- Convergence can be very slow with probabilities close to 1 or 0
- Can handle arbitrary combinations of discrete and continuous variables