

# Bayesian Networks II

## Advanced Artificial Intelligence: Workshop

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# Prior Sampling

- Download (from Blackboard) and run the following program:  
**PriorSampling.py**
- The program above implements the *PRIOR-SAMPLE* algorithm below in order to return an event of the form  $[true, false, true, true]$  — use the Sprinkler and Burglary networks<sup>1</sup> for testing your program

**function** PRIOR-SAMPLE( $bn$ ) **returns** an event sampled from the prior specified by  $bn$   
**inputs:**  $bn$ , a Bayesian network specifying joint distribution  $\mathbf{P}(X_1, \dots, X_n)$

$\mathbf{x} \leftarrow$  an event with  $n$  elements  
**foreach** variable  $X_i$  **in**  $X_1, \dots, X_n$  **do**  
     $\mathbf{x}[i] \leftarrow$  a random sample from  $\mathbf{P}(X_i \mid \text{parents}(X_i))$   
**return**  $\mathbf{x}$

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<sup>1</sup>Note that you have two versions of the Burglary network, one from the book and the other one from your own calculations (last week)

# Implementation of Approximate Inference: Today

- Implement the Rejection Sampling algorithm and use the Sprinkler and Burglary networks for testing your program<sup>2</sup>

**function** REJECTION-SAMPLING( $X, \mathbf{e}, bn, N$ ) **returns** an estimate of  $\mathbf{P}(X|\mathbf{e})$

**inputs:**  $X$ , the query variable

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

$bn$ , a Bayesian network

$N$ , the total number of samples to be generated

**local variables:**  $\mathbf{N}$ , a vector of counts for each value of  $X$ , initially zero

**for**  $j = 1$  to  $N$  **do**

$\mathbf{x} \leftarrow \text{PRIOR-SAMPLE}(bn)$

**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( $\mathbf{N}$ )

- Test your program varying the value  $N$  (e.g.  $10, 10^2, 10^3, 10^4, 10^5$ ). How many samples would you use and why?

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<sup>2</sup>Feel free to reuse the code in PriorSampling.py

# Implementation of Approximate Inference: Homework

Implement the algs. below and test them with the Sprinkler/Burglary nets

```
function LIKELIHOOD-WEIGHTING( $X, \mathbf{e}, bn, N$ ) returns an estimate of  $\mathbf{P}(X|\mathbf{e})$ 
  inputs:  $X$ , the query variable
            $\mathbf{e}$ , observed values for variables  $\mathbf{E}$ 
            $bn$ , a Bayesian network specifying joint distribution  $\mathbf{P}(X_1, \dots, X_n)$ 
            $N$ , the total number of samples to be generated
  local variables:  $\mathbf{W}$ , a vector of weighted counts for each value of  $X$ , initially zero

  for  $j = 1$  to  $N$  do
     $\mathbf{x}, w \leftarrow \text{WEIGHTED-SAMPLE}(bn, \mathbf{e})$ 
     $\mathbf{W}[x] \leftarrow \mathbf{W}[x] + w$  where  $x$  is the value of  $X$  in  $\mathbf{x}$ 
  return NORMALIZE( $\mathbf{W}$ )
```

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```
function WEIGHTED-SAMPLE( $bn, \mathbf{e}$ ) returns an event and a weight
   $w \leftarrow 1$ ;  $\mathbf{x} \leftarrow$  an event with  $n$  elements initialized from  $\mathbf{e}$ 
  foreach variable  $X_i$  in  $X_1, \dots, X_n$  do
    if  $X_i$  is an evidence variable with value  $x_i$  in  $\mathbf{e}$ 
      then  $w \leftarrow w \times P(X_i = x_i \mid \text{parents}(X_i))$ 
    else  $\mathbf{x}[i] \leftarrow$  a random sample from  $\mathbf{P}(X_i \mid \text{parents}(X_i))$ 
  return  $\mathbf{x}, w$ 
```

```
function GIBBS-ASK( $X, \mathbf{e}, bn, N$ ) returns an estimate of  $\mathbf{P}(X|\mathbf{e})$ 
  local variables:  $\mathbf{N}$ , a vector of counts for each value of  $X$ , 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  $\mathbf{Z}$ 
  for  $j = 1$  to  $N$  do
    for each  $Z_i$  in  $\mathbf{Z}$  do
      set the value of  $Z_i$  in  $\mathbf{x}$  by sampling from  $\mathbf{P}(Z_i \mid \text{mb}(Z_i))$ 
     $\mathbf{N}[x] \leftarrow \mathbf{N}[x] + 1$  where  $x$  is the value of  $X$  in  $\mathbf{x}$ 
  return NORMALIZE( $\mathbf{N}$ )
```