function LIKELIHOOD-WEIGHTING($X$, $e$, $bn$, $N$) returns an estimate of $P(X|e)$

inputs: $X$, the query variable
$e$, observed values for variables $E$
$bn$, a Bayesian network specifying joint distribution $P(X_1, \ldots, X_n)$
$N$, the total number of samples to be generated

local variables: $W$, a vector of weighted counts for each value of $X$, initially zero

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

function WEIGHTED-SAMPLE($bn$, $e$) returns an event and a weight

$w \leftarrow 1$; $x \leftarrow$ an event with $n$ elements initialized from $e$

foreach variable $X_i$ in $X_1, \ldots, X_n$ do
    if $X_i$ is an evidence variable with value $x_i$ in $e$
        then $w \leftarrow w \times P(X_i = x_i | parents(X_i))$
    else $x[i] \leftarrow$ a random sample from $P(X_i | parents(X_i))$
return $x$, $w$

Figure 14.14 The likelihood-weighting algorithm for inference in Bayesian networks. In WEIGHTED-SAMPLE, each nonevidence variable is sampled according to the conditional distribution given the values already sampled for the variable’s parents, while a weight is accumulated based on the likelihood for each evidence variable.

function GIBBS-ASK($X$, $e$, $bn$, $N$) returns an estimate of $P(X|e)$

local variables: $N$, a vector of counts for each value of $X$, initially zero
$Z$, the nonevidence variables in $bn$
$x$, the current state of the network, initially copied from $e$

initialize $x$ with random values for the variables in $Z$
for $j = 1$ to $N$ do
    for each $Z_i$ in $Z$ do
        set the value of $Z_i$ in $x$ by sampling from $P(Z_i | mb(Z_i))$
        $N[x] \leftarrow N[x] + 1$ where $x$ is the value of $X$ in $x$
return NORMALIZE($N$)

Figure 14.15 The Gibbs sampling algorithm for approximate inference in Bayesian networks; this version cycles through the variables, but choosing variables at random also works.