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

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

Figure 14.12   A sampling algorithm that generates events from a Bayesian network. Each variable is sampled according to the conditional distribution given the values already sampled for the variable's parents.

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**
      $\mathbf{x} \leftarrow$ PRIOR-SAMPLE(bn)
      if x is consistent with **e then**
         $\mathbf{N}[x] \leftarrow \mathbf{N}[x]$+1 where x is the value of X in **x**
   return NORMALIZE($\mathbf{N}$)

Figure 14.13   The rejection-sampling algorithm for answering queries given evidence in a Bayesian network.

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function LIKELIHOOD-WEIGHTING(X, **e**, bn, N) **returns** an estimate of $\mathbf{P}(X|\mathbf{e})$
  inputs: X, the query variable
          e, observed values for variables **E**
          bn, a Bayesian network specifying joint distribution $\mathbf{P}(X_1, \ldots, X_n)$
          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**
      $\mathbf{x}, w \leftarrow$ WEIGHTED-SAMPLE(bn, **e**)
      $\mathbf{W}[x] \leftarrow \mathbf{W}[x] + w$ where x is the value of X in $\mathbf{x}$
  return NORMALIZE(**W**)

---

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

  $w \leftarrow 1$; $\mathbf{x} \leftarrow$ 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 $w \leftarrow w \times P(X_i = x_i \mid parents(X_i))$
          else $\mathbf{x}[i] \leftarrow$ a random sample from $\mathbf{P}(X_i \mid parents(X_i))$
  return $\mathbf{x}$, 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.

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function GIBBS-ASK(X, **e**, bn, N) **returns** an estimate of $\mathbf{P}(X|\mathbf{e})$
  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 $\mathbf{x}$ 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 $\mathbf{x}$ by sampling from $\mathbf{P}(Z_i|mb(Z_i))$
          $\mathbf{N}[x] \leftarrow \mathbf{N}[x] + 1$ where x is the value of X in $\mathbf{x}$
  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.