In which we explain how to build reasoning systems that use network models to reason with uncertainty according to the laws of probability theory.
Outline

- Knowledge in uncertain domains
- Probabilistic Networks
- Semantic of Bayesian Networks
  - Global Semantic
  - Local Semantic
- Efficient representation of conditions distributions
- Exact inference in Bayesian Networks
- Approximate inference in Bayesian Networks
- Summary
Bayes’-Rule

Why is this rule useful?

- Causal experiences
  C: cause, E: effect

- Diagnostic Inference

\[ P(C \mid E) = \frac{P(E \mid C) P(C)}{P(E)} \]

This simple equation underlies all modern AI systems for probabilistic inference.

Cause
Mistake in technical system

causal inferences

Effect
system behavior shows symptom
diagnostic inferences
Knowledge in uncertain domains

• Joint probability distribution
  – delivers answers to questions that exists in domain
  – Problem: intractable with large number of variables
  – Specification
    Probabilities difficult for atomic events

• Complexity
  – Independence and conditional dependence reduce complexity

• Bayesian Networks
  – Data structure represents dependencies between variables
  – Specification of joint distribution
Syntax

• **Graph-theoretical structure**
  – Set of variables as nodes (discrete, continuous)
  – Each node corresponds to random variable
  – Directed acyclic graph (DAG), links express causal dependencies between variables

• **Conditional probability tables**
  – For each node a table for conditional probabilities
  – Table consists of distribution of probabilities given their parents $P(X_i|\text{Parents}(X_i))$

```
Cavity
```
```
Weather
```
```
Toothache
```
```
Catch
```
Simple Bayesian Network

- Example Alarm
  - New burglar alarm fairly reliable at detecting a burglary
  - Also responds on occasion to minor earthquake
  - Two neighbors, John and Mary have promised to call when they hear the alarm
  - John always calls when he hears alarm, but sometimes confuses the telephone ringing with the alarm and calls then too
  - Mary likes loud music and sometimes misses the alarm altogether
  - Given the evidence of who has or has not called, we would like to estimate the probability of a burglary.
Simple Bayesian Network

Probabilistic Networks
Semantics of Bayesian Networks

- Two views on semantics
  1. Global Semantics: The first is to see the network as a representation of the joint probability distribution
  2. Local Semantics: The second is to view it as an encoding of a collection of conditional independence statements

- Views are equivalent
  - first helpful in understanding how to construct networks
  - second helpful in designing inference procedures
Representing the full joint distribution

• General idea
  – Joint distribution can be expressed as product of local conditional probabilities
  – Every entry in the joint probability distribution can be calculated from the information in the network.
  – Generic entry

\[ P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid \text{Parents}(X_i)) \]
Representing the full joint distribution

• Example
  – Alarm has sounded but neither a burglary nor an earthquake has occurred, and both John and Mary call
  – \[ P(j \land m \land a \land \neg b \land \neg e) \]
    \[ = P(j|a) P(m|a) P(a|\neg b, \neg e) P(\neg b) P(\neg e) \]
    \[ = 0.9 \times 0.7 \times 0.001 \times 0.999 \times 0.998 \]
    \[ \approx 0.00063 \]
Method for Constructing Bayesian Networks

• Generic Rule

\[ P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid \text{Parents}(X_i)) \]

  − Semantic
    but: not how to construct a network
  − Implicitly: conditional independence
  → Help for Knowledge Engineer

• Reformulate the rule

  − Use of conditional probabilities
    → Product rule

\[ P(x_1, \ldots, x_n) = P(x_n \mid x_{n-1}, \ldots, x_1) P(x_{n-1}, \ldots, x_1) \]

• Repeat process

  − Reduction of conjunctive probabilities to a conditional dependency and a smaller conjunction
  − Final: a big product

\[ P(x_1, \ldots, x_n) = P(x_n \mid x_{n-1}, \ldots, x_1) P(x_{n-1}, \ldots, x_1) \prod_{i=1}^{n} P(x_i \mid x_{i-1}, \ldots, x_1) \]
Chain rule

\[ P(x_1, \ldots, x_n) = P(x_n | x_{n-1}, \ldots, x_1) P(x_{n-1} | x_{n-2}, \ldots, x_1) \ldots P(x_2 | x_1) P(x_1) = \prod_{i=1}^{n} P(x_i | x_{i-1}, \ldots, x_1) \]

- Compare with
  \[ P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | \text{Parents}(X_i)) \]
  reveals that specification is equivalent to general assertion

  \[ P(X_i | X_{i-1}, \ldots, x_1) = P(X_i | \text{Parents}(X_i)) \]
  (as long as \( \text{Parents}(X_i) \subseteq \{X_{i-1}, \ldots, X_1\} \))

- I.e.:
  - This last condition is satisfied by labeling the nodes in any order that is consistent with the partial order implicit in the graph structure.
  - The Bayesian network is a correct representation of the domain only if each node is conditionally independent of its predecessors in the node ordering, given its parents.
Construction of Bayesian Networks

• Important while constructing
  – We need to choose parents for each node such that this property holds.

• Intuitive
  – Parents of node $X_i$ should contain all those nodes in $X_1,...,X_{i-1}$ that directly influence $X_i$
  – Example.: 
    • $M$ (is influenced by $B$ or $E$ but not directly)
    • Influenced by $A$, and $J$ calls are not evident

\[ P(M|J,A,E,B) = P(M|A) \]
General Procedure

1. Choose the set of relevant variables $X_i$ that describe the domain.

2. Choose an ordering for the variables.
   (Any ordering works, but some orderings work better than others, as we will see.)

3. While there are variables left:
   a) Pick a variable $X_i$ and add a node to the network for it.
   b) Set $Parents(X_i)$ to some minimal set of nodes already in the net such that the conditional independence property is satisfied.
   c) Define the conditional distribution $P(X_i|Parents(X_i))$
Notes

• Construction method guarantees that the network is acyclic
  – Because each node is connected only to earlier nodes.

• Redundancies
  – No redundant probability values
  – Exception: for one entry in each row of each conditional probability table, if \(P(x_2|x_1) \cdot P(\neg x_2|x_1)\) is redundant

• This means that it is impossible for the knowledge engineer or domain expert to create a Bayesian network that violates the axioms of probability!
Compactness

- Compactness
  - A Bayesian Network is a complete and not-redundant representation of a domain
  - Can be more compact as a joint distribution
  - This is important in practice
  - Compactness is an example for property that we call in local structure (or sparse coded) in general

- Local Structures (also: sparse)
  - Each sub-component is connected to a limited number of other components
  - Complexity: linear instead of exponential
  - With BN: in most domains one variable is influenced by $k$ others, with $n$ variables $2^k$ conditional probabilities, the whole network $n2^k$
  - In contrast, the full joint distribution contains $2^n$ numbers
Node Ordering

• Local structures (example)
  – 30 nodes, each max. 5 parents
  – 960 for BN, > 1 billion with joint distribution

• Construction
  – Not trivial
  – Variable directly influenced only from a few others
  – Set parent node “appropriately” → Network topology
  – “Direct influencers” first
  – Thus: correct order important

• Order
  – Add:
    • root first
    • then direct influencers
    • then down to leaves
  – What happens with “wrong” order?
Example ordering

- Let us consider the burglary example again.
- Suppose we decide to add the nodes in the order
  - M, J, A, B, E
  - M, J, E, B, A
Example

Suppose we choose the ordering $M, J, A, B, E$

$\text{MaryCalls}$

$\text{JohnCalls}$

$P(J|M) = P(J)$?
Example contd.

Suppose we choose the ordering $M, J, A, B, E$

$$P(J|M) = P(J)? \quad \text{No}$$

$$P(A|J, M) = P(A|J)? \quad P(A|J, M) = P(A)?$$
Example contd.

Suppose we choose the ordering $M, J, A, B, E$

$$P(J|M) = P(J)? \quad \text{No}$$
$$P(A|J, M) = P(A|J)? \quad P(A|J, M) = P(A)? \quad \text{No}$$
$$P(B|A, J, M) = P(B|A)?$$
$$P(B|A, J, M) = P(B)?$$
Example contd.

Suppose we choose the ordering $M, J, A, B, E$

\[
P(J|M) = P(J) \quad \text{No}
\]
\[
P(A|J, M) = P(A|J) \quad P(A|J, M) = P(A) \quad \text{No}
\]
\[
P(B|A, J, M) = P(B|A) \quad \text{Yes}
\]
\[
P(B|A, J, M) = P(B) \quad \text{No}
\]
\[
P(E|B, A, J, M) = P(E|A) \quad P(E|B, A, J, M) = P(E|A, B)\]
Example contd.

Suppose we choose the ordering $M, J, A, B, E$

$P(J|M) = P(J)$? No
$P(B|A, J, M) = P(B|A)$? Yes
$P(B|A, J, M) = P(B)$? No
$P(E|B, A, J, M) = P(E|A)$? No
$P(E|B, A, J, M) = P(E|A, B)$? Yes
Example contd.

Deciding conditional independence is hard in noncausal directions
(Causal models and conditional independence seem hardwired for humans!)
Assessing conditional probabilities is hard in noncausal directions
Network is less compact: $1 + 2 + 4 + 2 + 4 = 13$ numbers needed
Example ordering (2)

- Order
  - M,J,E,B,A

- Network
  - 31 probabilities
  - like full joint distribution
  - thus: bad choice

- All three networks represent same probability distribution

- Last two versions
  - simply fail to represent all the conditional independence relationships
  - end up specifying a lot of unnecessary numbers instead.
Conditional independence relations in Bayesian networks

• Before
  – “numerical (global) semantics with probability distribution
  – from this derive conditional independencies

• Idea now
  – opposite direction: topological (local) semantics
  – specifies conditional independencies
  – from this derive numerical semantics

Local Semantics
Conditional independence relations in Bayesian networks

• General idea
  – A node is conditionally independent of its non-descendants given its parents
  – A node is conditionally independent of all other nodes in the network given its parents, children, and children’s parents—that is, given its Markov blanket

• Examples
  J is independent of B and E given A, i.e.
  \[ P(J|A,B,E) = P(J|A) \]

  B is independent of J and M given A and E, i.e.
  \[ P(B|A,E,J,M) = P(B|A,E) \]
Conditional independence relations in Bayesian networks

- Node X is conditionally independent of its non-descendants (e.g., the $Z_{ij}$s) given its parents (the $U_{ij}$s)

- A node X is conditionally independent of all other nodes in the network given its Markov blanket.
Compact conditional distributions

CPT grows exponentially with number of parents
CPT becomes infinite with continuous-valued parent or child

Solution: **canonical** distributions that are defined compactly

Deterministic nodes are the simplest case:
\[ X = f(\text{Parents}(X)) \text{ for some function } f \]

E.g., Boolean functions
\[ \text{NorthAmerican} \Leftrightarrow \text{Canadian} \lor \text{US} \lor \text{Mexican} \]

E.g., numerical relationships among continuous variables
\[
\frac{\partial \text{Level}}{\partial t} = \text{inflow} + \text{precipitation} - \text{outflow} - \text{evaporation}
\]
## Compact conditional distributions

**Noisy-OR distributions** model multiple noninteracting causes:

1. Parents $U_1 \ldots U_k$ include all causes (can add leak node).
2. Independent failure probability $q_i$ for each cause alone.

\[ P(X|U_1 \ldots U_j, \neg U_{j+1} \ldots \neg U_k) = 1 - \prod_{i=1}^{j} q_i \]

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<td>T</td>
<td>0.988</td>
<td>0.012 = 0.6 $\times$ 0.2 $\times$ 0.1</td>
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</table>

Number of parameters **linear** in number of parents.

Efficient Representation of conditional distributions
Bayesian nets with continuous variables

Discrete (Subsidy? and Buys?); continuous (Harvest and Cost)

Option 1: discretization—possibly large errors, large CPTs
Option 2: finitely parameterized canonical families

1) Continuous variable, discrete + continuous parents (e.g., Cost)
2) Discrete variable, continuous parents (e.g., Buys?)
Continuous child variables

Need one **conditional density** function for child variable given continuous parents, for each possible assignment to discrete parents.

Most common is the **linear Gaussian** model, e.g.,:

\[
P(Cost = c | Harvest = h, \text{Subsidy?} = \text{true}) = N(a_th + b_t, \sigma_t^2)(c)
\]

\[
= \frac{1}{\sigma_t \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{c - (a_th + b_t)}{\sigma_t} \right)^2 \right)
\]

Mean **Cost** varies linearly with **Harvest**, variance is fixed.

Linear variation is unreasonable over the full range but works OK if the **likely** range of **Harvest** is narrow.
Continuous child variables

All-continuous network with LG distributions
⇒ full joint distribution is a multivariate Gaussian

Discrete+continuous LG network is a conditional Gaussian network i.e., a multivariate Gaussian over all continuous variables for each combination of discrete variable values
Discrete variable w/ continuous parents

Probability of \( \text{Buys?} \) given \( \text{Cost} \) should be a “soft” threshold:

Probit distribution uses integral of Gaussian:

\[
\Phi(x) = \int_{-\infty}^{x} N(0, 1)(x)dx \\
P(\text{Buys?} = \text{true} \mid \text{Cost} = c) = \Phi((-c + \mu)/\sigma)
\]
Discrete variable w/ continuous parents

1. It's sort of the right shape

2. Can view as hard threshold whose location is subject to noise
Discrete variable w/ continuous parents

Sigmoid (or logit) distribution also used in neural networks:

\[
P(\text{Buys?} = \text{true} \mid \text{Cost} = c) = \frac{1}{1 + \exp\left(-2\frac{c + \mu}{\sigma}\right)}
\]

Sigmoid has similar shape to probit but much longer tails:
Inference tasks

Simple queries: compute posterior marginal $P(X_i|E = e)$
   e.g., $P(\text{NoGas}|Gauge = \text{empty}, Lights = \text{on}, Starts = \text{false})$

Conjunctive queries: $P(X_i, X_j|E = e) = P(X_i|E = e)P(X_j|X_i, E = e)$

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?
Exact inference by enumeration

**Enumeration algorithm**

```
function ENUMERATION-ASK(\(X, e, bn\)) returns a distribution over \(X\)
    inputs: \(X\), the query variable
            \(e\), observed values for variables \(E\)
            \(bn\), a Bayesian network with variables \(\{X\} \cup E \cup Y\)
    \(Q(X)\) ← a distribution over \(X\), initially empty
    for each value \(x_i\) of \(X\) do
        extend \(e\) with value \(x_i\) for \(X\)
        \(Q(x_i)\) ← ENUMERATE-ALL(VARS[\(bn\)], \(e\))
    return NORMALIZE(\(Q(X)\))

function ENUMERATE-ALL(\(vars, e\)) returns a real number
    if EMPTY?(\(vars\)) then return 1.0
    \(Y\) ← FIRST(\(vars\))
    if \(Y\) has value \(y\) in \(e\)
        then return \(P(y \mid Pa(Y)) \times \) ENUMERATE-ALL(REST(\(vars\)), \(e\))
    else return \(\sum_y P(y \mid Pa(Y)) \times \) ENUMERATE-ALL(REST(\(vars\)), \(e_y\))
        where \(e_y\) is \(e\) extended with \(Y = y\)
```

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Exact 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:

\[ P(B|j,m) = \frac{P(B, j, m)}{P(j, m)} = \alpha P(B, j, m) = \alpha \sum_e \sum_a P(B, e, a, j, m) \]

Rewrite full joint entries using product of CPT entries:

\[ P(B|j,m) = \alpha \sum_e \sum_a P(B)P(e)P(a|B, e)P(j|a)P(m|a) = \alpha P(B) \sum_e P(e) \sum_a P(a|B, e)P(j|a)P(m|a) \]

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

\[ P(B|j, m) = \alpha \langle 0.00059224, 0.0014919 \rangle \approx \langle 0.284, 0.716 \rangle \]
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

$$P(B|j, m)$$

$$= \alpha \underbrace{P(B)}_{B} \underbrace{\sum_{e} P(e)}_{E} \underbrace{\sum_{a} P(a|B, e)}_{A} \underbrace{P(j|a)}_{J} \underbrace{P(m|a)}_{M}$$

$$= \alpha P(B) \sum_{e} P(e) \sum_{a} P(a|B, e) P(j|a) f_{M}(a)$$

$$= \alpha P(B) \sum_{e} P(e) \sum_{a} P(a|B, e) f_{J}(a) f_{M}(a)$$

$$= \alpha P(B) \sum_{e} P(e) \sum_{a} f_{A}(a, b, e) f_{J}(a) f_{M}(a)$$

$$= \alpha P(B) \sum_{e} P(e) f_{AJM}(b, e) \text{ (sum out } A)$$

$$= \alpha P(B) f_{EJM}(b) \text{ (sum out } E)$$

$$= \alpha f_{B}(b) \times f_{EJM}(b)$$
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

\[ \sum_x f_1 \times \cdots \times f_k = f_1 \times \cdots \times f_i \sum_x f_{i+1} \times \cdots \times f_k = f_1 \times \cdots \times f_i \times f_{\overline{X}} \]

assuming \( f_1, \ldots, f_i \) do not depend on \( X \)

**Pointwise product** of factors \( f_1 \) and \( f_2 \):

\[ f_1(x_1, \ldots, x_j, y_1, \ldots, y_k) \times f_2(y_1, \ldots, y_k, z_1, \ldots, z_l) = f(x_1, \ldots, x_j, y_1, \ldots, y_k, z_1, \ldots, z_l) \]

E.g., \( f_1(a, b) \times f_2(b, c) = f(a, b, c) \)
Variable elimination algorithm

function \textsc{Elimination-Ask}(X, e, bn) returns a distribution over \( X \)

\textbf{inputs:} \( X \), the query variable
\( e \), observed values for variables \( E \)
\( bn \), a Bayesian network specifying joint distribution \( P(X_1, \ldots, X_n) \)

\[ \text{factors} \leftarrow [] \]

\textbf{for each} \( \text{var} \) \textbf{in} \ \text{Order}(bn.VARS) \ \textbf{do}

\[ \text{factors} \leftarrow [\textsc{Make-Factor}(\text{var}, e)|\text{factors}] \]

\textbf{if} \ \text{var} \ \text{is a hidden variable} \ \textbf{then} \ \text{factors} \leftarrow \textsc{Sum-Out}(\text{var}, \text{factors})

\textbf{return} \ \textsc{Normalize}(\textsc{Pointwise-Product}(\text{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 $Y \in \text{Ancestors} (\{X\} \cup E)$

Here, $X = \text{JohnCalls}$, $E = \{\text{Burglary}\}$, and $\text{Ancestors} (\{X\} \cup E) = \{\text{Alarm}, \text{Earthquake}\}$

so $\text{MaryCalls}$ 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 $P(JohnCalls | Alarm = true)$, 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

![Bayesian Network Diagram]

**Exact inference by enumeration**
Clustering algorithms

• Variable elimination algorithm is simple and efficient for answering individual queries.
• For computation of posterior probabilities for all the variables in a network it can be less efficient: $O(n^2)$.
• Using clustering algorithms (also known as join tree algorithms), this can be reduced to $O(n)$.
• The basic idea of clustering is to join individual nodes of the network to form cluster nodes in such a way that the resulting network is a polytree.
Clustering algorithms

- Multiply connected network can be converted into a polytree by combining Sprinkler and Rain node into cluster node called Sprinkler + Rain.

- Two Boolean nodes replaced by a mega-node that takes on four possible values: TT, TF, FT, FF. The mega-node has only one parent, the Boolean variable Cloudy, so there are two conditioning cases.
APPROXIMATE INFERENCE IN BAYESIAN NETWORKS

• Randomized sampling algorithms, also called Monte Carlo algorithms
• Provide approximate answers whose accuracy depends on the number of samples generated
• Monte Carlo algorithms are used in many branches of science to estimate quantities that are difficult to calculate exactly.
• Here: sampling applied to the computation of posterior probabilities
• Two families of algorithms: direct sampling and Markov chain sampling
Direct sampling methods

• Generation of samples from a known probability distribution

• Example

\[ P(\text{Coin}) = \langle 0.5, 0.5 \rangle \]

• Sampling from this distribution is exactly like flipping the coin: with probability 0.5 it will return heads, and with probability 0.5 it will return tails.
Direct sampling methods

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

$x \leftarrow$ an event with $n$ elements
foreach variable $X_i$ in $X_1, \ldots, X_n$ do

$x[i] \leftarrow$ a random sample from $P(X_i | \text{parents}(X_i))$

return $x$

**Figure 14.13** 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.
Direct sampling methods

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**inputs:** $bn$, a Bayesian network specifying joint distribution $P(X_1, \ldots, X_n)$

$x \leftarrow$ an event with $n$ elements

**foreach** variable $X_i$ in $X_1, \ldots, X_n$ **do**

$x[i] \leftarrow$ a random sample from $P(X_i | \text{parents}(X_i))$

**return** $x$

**Figure 14.13** 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.
Direct sampling methods

- PRIOR-SAMPLE generates samples from the prior joint distribution specified by the network

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

- Each sampling step depends only on the parent values

\[ S_{PS}(x_1 \ldots x_n) = P(x_1 \ldots x_n) \]
Computing answers

- Answers are computed by counting the actual samples generated
- Say, $N$ total samples and $N_{PS}(x_1, \ldots, x_n)$ number of times the event $x_1, \ldots, x_n$ occurs in the samples

$$
\lim_{N \to \infty} \frac{N_{PS}(x_1, \ldots, x_n)}{N} = S_{PS}(x_1, \ldots, x_n) = P(x_1, \ldots, x_n).
$$
Computing answers

\[
\lim_{N \to \infty} \frac{N_{PS}(x_1, \ldots, x_n)}{N} = S_{PS}(x_1, \ldots, x_n) = P(x_1, \ldots, x_n).
\]

- For example, consider the event produced earlier: [true, false, true, true]. The sampling probability for this event is

\[
S_{PS}(true, false, true, true) = 0.5 \times 0.9 \times 0.8 \times 0.9 = 0.324.
\]

- Hence, in the limit of large \( N \), we expect 32.4% of the samples to be of this event.
Rejection sampling

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

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

$e$, observed values for variables $E$

$bn$, a Bayesian network

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

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

for $j = 1$ to $N$ do

$x$ ← PRIOR-SAMPLE($bn$)

if $x$ is consistent with $e$ then

$N[x] ← N[x]+1$ where $x$ is the value of $X$ in $x$

return NORMALIZE($N$)

**Figure 14.14** The rejection-sampling algorithm for answering queries given evidence in a Bayesian network.
Rejection sampling

- Let $\hat{P}(X|e)$ be the estimated distribution. Then from the definition just given

$$\hat{P}(X|e) = \alpha N_{PS}(X, e) = \frac{N_{PS}(X, e)}{N_{PS}(e)} .$$

$$\hat{P}(X|e) \approx \frac{P(X, e)}{P(e)} = P(X|e) .$$

- That is, rejection sampling produces a consistent estimate of the true probability.
Rejection sampling

- Estimate $P(Rain \mid Sprinkler = true)$, using 100 samples. Of the 100 that we generate, suppose that 73 have $Sprinkler = false$ and are rejected, while 27 have $Sprinkler = true$.
- Of the 27, 8 have $Rain = true$ and 19 have $Rain = false$.
- Thus,

$$P(Rain \mid Sprinkler = true) \approx \text{NORMALIZE}(\langle 8, 19 \rangle) = \langle 0.296, 0.704 \rangle$$
Likelihood weighting

- Likelihood weighting avoids the inefficiency of rejection sampling.
- It generates only events that are consistent with the evidence $e$.
- It is a particular instance of the general statistical technique of importance sampling, tailored for inference in Bayesian networks.
- Let’s see how it works...
## Likelihood weighting

**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 $w \leftarrow w \times P(X_i = x_i | \text{parents}(X_i))$
  else $x[i] \leftarrow$ a random sample from $P(X_i | \text{parents}(X_i))$
return $x$, $w$
Likelihood weighting

- *Cloudy* is an evidence variable with value *true*. Therefore, we set \( w \leftarrow w \times P(Cloudy = \text{true}) = 0.5 \).
- Sprinkler is not an evidence variable, so sample from \( P(Sprinkler \mid Cloudy = \text{true}) = \langle 0.1, 0.9 \rangle \); suppose this returns *false*.
- Similarly, sample from \( P(Rain \mid Cloudy = \text{true}) = \langle 0.8, 0.2 \rangle \); suppose this returns *true*.
- *WetGrass* is an evidence variable with value *true*. Therefore, we set \( w \leftarrow w \times P(WetGrass = \text{true} \mid Sprinkler = \text{false}, Rain = \text{true}) = 0.45 \).
Likelihood weighting

• The weight for a given sample $x$ is the product of the likelihoods for each evidence variable given its parents

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

• Multiplying the last two equations we see that the weighted probability of a sample has the particularly convenient form

$$S_{WS}(z, e)w(z, e) = \prod_{i=1}^{l} P(z_i | \text{parents}(Z_i)) \prod_{i=1}^{m} P(e_i | \text{parents}(E_i)) = P(z, e)$$
Likelihood weighting

- For any particular value $x$ of $X$, the estimated posterior probability can be calculated as follows:

\[
\hat{P}(x \mid e) = \alpha \sum_y N_{WS}(x, y, e)w(x, y, e) \quad \text{from LIKELIHOOD-WEIGHTING}
\]

\[
\approx \alpha' \sum_y S_{WS}(x, y, e)w(x, y, e) \quad \text{for large } N
\]

\[
= \alpha' \sum_y P(x, y, e) \quad \text{by Equation (14.9)}
\]

\[
= \alpha' P(x, e) = P(x \mid e) .
\]

- Hence, likelihood weighting returns consistent estimates.
Summary

This chapter has described **Bayesian networks**, a well-developed representation for uncertain knowledge. Bayesian networks play a role roughly analogous to that of propositional logic for definite knowledge.

- A Bayesian network is a directed acyclic graph whose nodes correspond to random variables; each node has a conditional distribution for the node given its parents.
- Bayesian networks provide a concise way to represent **conditional independence** relationships in the domain.
- A Bayesian network specifies a full joint distribution; each joint entry is defined as the product of the corresponding entries in the local conditional distributions. A Bayesian network is often exponentially smaller than the full joint distribution.
Summary (2)

• Inference in Bayesian networks means computing the probability distribution of a set of query variables, given a set of evidence variables. Exact inference algorithms, such as variable elimination, evaluate sums of products of conditional probabilities as efficiently as possible.

• In polytrees (singly connected networks), exact inference takes time linear in the size of the network. In the general case, the problem is intractable.

• Stochastic approximation techniques such as likelihood weighting and Markov chain Monte Carlo can give reasonable estimates of the true posterior probabilities in a network and can cope with much larger networks than can exact algorithms.