

Bayesian Networks



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Contents

- ☐ 7.5.1 About Uncertain Knowledge
- ☐ 7.5.2 Rational Decisions
- ☐ 7.5.3 Algorithm of a Decision-theoretic Agent
- ☐ 7.5.4 Bayes' Rule
- ☐ 7.5.5 Representing Full Joint Distribution
- ☐ 7.5.6 Constructing Bayesian Networks



Contents

- ☐ 7.5.7 Compactness
- ☐ 7.5.8 Node Ordering
- ☐ 7.5.9 Conditional Independence Relations

About Uncertain Knowledge 关于不确定性知识

- Evolution of an intelligent agent: problem solving, reasoning, planning and learning.
智能体的进化：问题求解、推理、规划以及学习。
- Agents may need to handle uncertainty, due to partial observability and non-determinism.
智能体可能需要处理不确定性，由于部分可观察性和不确定性问题。
- To make decision with uncertainty, we need
 - Probability theory,
概率论，
 - Utility theory,
效用论，
 - Decision theory.
决策论。

Example: An uncertainty problem 一个不确定性问题

A_{90} = home to airport 90 minutes by taxi before flight departs.

从家里打车在航班起飞前90分钟到机场

□ Question: 问题

“Will A_{90} get me to the airport on time?”

A_{90} 能使我准时到达机场吗？

□ Answer: 答案

The taxi agent concludes either:

出租汽车公司给出两个结论中的一个：

- the risks falsehood: “ A_{90} will get us there in time”.

有风险的谎言： A_{90} 将使我们及时到达机场。

- the weaker conclusion: “ A_{90} will get us there in time, if there is no traffic jam, I don't get into an accident, the car doesn't break down, and ...”

A_{90} 将使我们及时到达机场，如果没有交通堵塞、不出交通事故、汽车不出故障的话，……

Rational Decisions 理性决策

□ Probability theory 概率论

for dealing with **degrees of belief**.

是用于处理置信度的理论

□ Utility theory 效用论

the quality of being useful.

是有效性的质量

■ to represent and reason with **preferences**, every state has a degree of **usefulness/utility**.

用偏好来表现和推理，每个状态都具有“有效性/效用”的度量值。

□ Decision theory 决策论

the general theory of rational decisions.

是理性决策的通论

■ Decision theory = probability theory + utility theory

决策论 = 概率论 + 效用论

Algorithm of a Decision-theoretic Agent 一种决策论智能体的算法

```
function DECISION-THEORETIC-AGENT(percept) returns an action  
  persistent: belief_state, probabilistic beliefs about the current state of the world  
             action, the agent's action  
  
  update belief_state based on action and percept  
  calculate outcome probabilities for actions,  
    given action descriptions and current belief_state  
  select action with highest expected utility,  
    given probabilities of outcomes and utility information  
return action
```

A decision-theoretic agent that selects rational actions.

一个选择理性动作的决策论智能体

Bayes' Rule 贝叶斯规则

□ Product rule 乘积规则

- Two ways to factor a joint distribution over two variables:

两个变量联合分布的两种计算方法：

$$P(a \wedge b) = P(a | b) P(b) \quad \text{and} \quad P(a \wedge b) = P(b | a) P(a)$$

□ Bayes' rule 贝叶斯规则

$$P(b | a) = \frac{P(a | b) P(b)}{P(a)}$$

- This rule underlies most modern AI for probabilistic inference.

这个规则成为大多数现代人工智能概率推理的基础。

- Why is Bayes' rule useful 为什么贝叶斯定理有用

- Often we have good probability estimates for three terms to compute the fourth.

我们常常需要根据三个项的概率估计值去计算第四个。

Example: Inference with Bayes' Rule 贝叶斯规则进行推理

- Often we perceive as evidence the *effect* of some unknown cause, and would like to determine that *cause*. In that case, Bayes' rule becomes

我们往往想根据一些未知原因的证据，来查明其原因。这样，贝叶斯定理就变成了

$$P(\text{cause} \mid \text{effect}) = \frac{P(\text{effect} \mid \text{cause})P(\text{cause})}{P(\text{effect})}$$

- Knows $P(\text{symptoms} \mid \text{disease})$ and want to derive a diagnosis, $P(\text{disease} \mid \text{symptoms})$.
已知 $P(\text{symptoms} \mid \text{disease})$ (症状 | 疾病)，想要得出一个诊断 $P(\text{disease} \mid \text{symptoms})$ (疾病 | 症状)。

$P(s \mid m) = 0.7$ // conditional probability that meningitis causes a stiff neck 脑膜炎导致颈部僵硬的条件概率

$P(m) = 1/50000$ // prior probability that a patient has meningitis 病人患脑膜炎的先验概率

$P(s) = 0.01$ // prior probability that any patient has a stiff neck 任何病人患有颈部僵硬的先验概率

$$P(m \mid s) = \frac{P(s \mid m)P(m)}{P(s)} = \frac{0.7 \times 1/50000}{0.01} = 0.0014 \quad // \text{a stiff neck to have meningitis 颈部僵硬患有脑膜炎的概率}$$

About Bayesian Networks 贝叶斯网络

- A probabilistic graphical model (a type of statistical model)
一种概率图模型（一种统计模型的类型）
- With a directed acyclic graph (DAG), it represents:
 - a set of random variables, and conditional dependencies between the variables.
采用一种有向无环图 (DAG)，它表示：一组随机变量，以及变量之间的条件相关性。
- Its specification: 它的规范如下：
 - 1) a set of nodes, each corresponds to a random variable, 2) a set of directed links to those nodes, and 3) a conditional probability distribution for each node given its parents:
 - 1) 一组节点，每个节点对应于一个随机变量，2) 一组这对这些节点的有向连接，以及 3) 每个节点在给定双亲下的条件概率分布：

$$\mathbf{P}(X_i \mid \text{Parents}(X_i))$$

About Bayesian Networks 贝叶斯网络

- The name of Bayesian networks is the most common one, but there are many synonyms, including:

贝叶斯网络这个名称是最常用的，但还有许多同义词，包括：

- **belief network**, 信念网络
- **probabilistic network**, 概率网络
- **causal network**. 因果网络

- A Bayesian network represents a set of random variables and their conditional dependencies.

一个贝叶斯网络表示一组随机变量和他们的条件依赖关系。

- E.g., it could represent the probabilistic relationships between diseases and symptoms.

例如：它可以表示疾病与症状之间的概率关系。

Two Views 两个观点

□ The two views to understand semantics of Bayesian networks:

理解贝叶斯网络语义的两个观点：

- 1st: to view the network as a representation of the **joint probability distribution**.

第一、将该网络视为一种联合概率分布的表示。

- 2nd: to view it as an encoding of a collection of **conditional independence statements**.

第二、将其视为一组条件独立语句的一种编码。

□ The two views are equivalent, but: 这两个观点是等价的，但是：

- 1st view: helpful in understanding how to construct networks,

第一种观点：有助于理解如何构建网络，

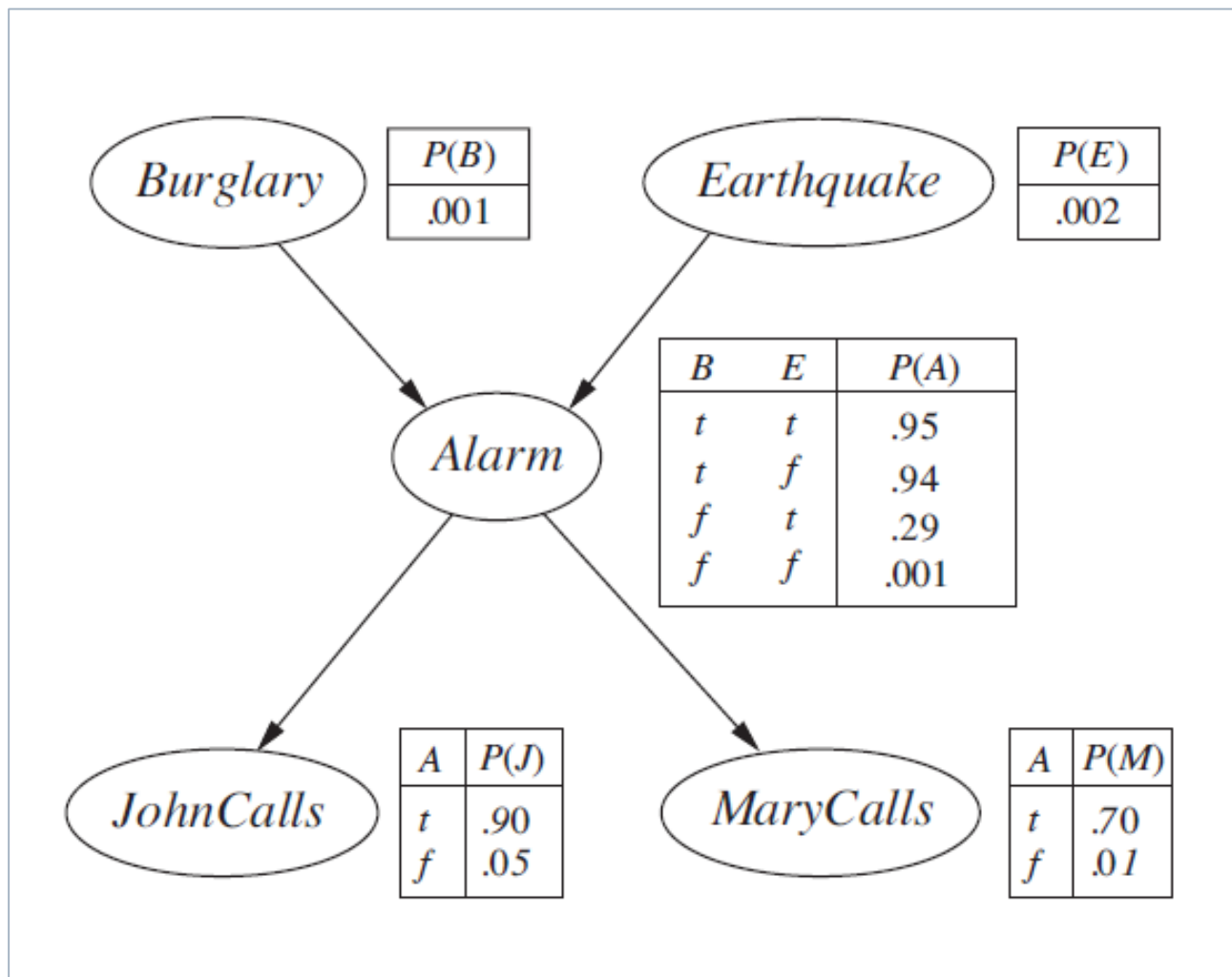
- 2nd view: helpful in designing inference procedures.

第二种观点：有助于设计推理过程。

Example: A typical Bayesian network 一个典型的贝叶斯网络

- A burglar **alarm** installed at home, used to detect a **burglary** or minor **earthquakes**.
房子里安装了一个防盗报警器，用于检测被盗或地震。
- Two neighbors, **John** and **Mary**, who have promised to call you at work when they hear the alarm.
有两个邻居，John和Mary，他们已答应当听到报警时，就给你的办公室打电话。
- Variables 变量: *Burglar, Earthquake, Alarm, JohnCalls, MaryCalls*.
- Network topology reflects the knowledge:
网络的拓扑结构要反应如下知识:
 - A *Burglar* or an *Earthquake* can set the *Alarm*.
盗窃或者地震会导致报警。
 - The *Alarm* can cause *Mary* or *John* to call.
报警会引起Mary或John打电话。

Example: A typical Bayesian network 一个典型的贝叶斯网络



A Bayesian network with the conditional probability tables (CPTs).

一个具有条件概率表 (CPTS) 的贝叶斯网络。

Where 其中

➤ B, E, A, J, M stand for *Burglary, Earthquake, Alarm, JohnCalls, MaryCalls*;

B, E, A, J, M 代表

Burglary, Earthquake, Alarm, JohnCalls, MaryCalls

➤ t and f stand for *true* and *false*;

t 与 f 代表 *true* 和 *false*

➤ Each row shows one number p for $X_i = t$, (the number for $X_i = f$ is just $1 - p$).
 每一行显示 $X_i = t$ 的概率值 p , $X_i = f$ 时概率值则为 $1 - p$

Representing Full Joint Distribution 表征全联合分布

- By the product of the elements of conditional distributions:
采用条件分布元素的乘积:

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

- To illustrate this, we can calculate the probability: Alarm has sounded, but neither a Burglary nor an Earthquake has occurred, and both John and Mary call.
为了说明，我们可以计算概率：报警响起，但盗窃和地震都未发生，而John和Mary打电话。

- We multiply entries from the joint distribution:
我们依据联合分布，将这些项相乘:

$$\begin{aligned} P(j, m, a, \neg b, \neg e) &= P(j | a) P(m | a) P(a | \neg b \wedge \neg e) P(\neg b) P(\neg e) \\ &= 0.90 \times 0.70 \times 0.001 \times 0.999 \times 0.998 = 0.000628 \end{aligned}$$

where j, m, a, b, e stand for *JohnCalls, MaryCalls, Alarm, Burglary, Earthquake*.

其中 j, m, a, b, e 代表 *JohnCalls, MaryCalls, Alarm, Burglary, Earthquake*.

Constructing Bayesian Networks 构建贝叶斯网络

- First, rewrite joint distribution in terms of conditional probability, using **product rule**:
首先，用条件概率公式对联合概率进行改写，使用如下乘积规则：

$$P(a \wedge b) = P(a / b) P(b)$$

$$P(x_1, \dots, x_n) = P(x_n / x_{n-1}, \dots, x_1) P(x_{n-1}, \dots, x_1)$$

- Then, repeat the process, reducing each conjunctive probability to a conditional probability and a smaller conjunction. We end up with one big product.
然后，重复这个过程，将每个合取概率缩减为条件概率和较小的合取。最终得到一个大的乘积。

$$\begin{aligned} P(x_1, \dots, x_n) &= P(x_n / x_{n-1}, \dots, x_1) P(x_{n-1} / x_{n-2}, \dots, x_1) \dots P(x_2 / x_1) P(x_1) \\ &= \prod_{i=1}^n P(x_i | x_{i-1}, \dots, x_1) \end{aligned}$$

This is called **chain rule**, for any set of random variables.

这被称为对任意一组随机变量的链式法则。

Constructing Bayesian Networks 构建贝叶斯网络

- The specification of the joint distribution is equivalent to the general assertion that, for every variable X_i in the network,

联合分布的规格等同于一般性断言，即：对于网络中的每个变量 X_i ，

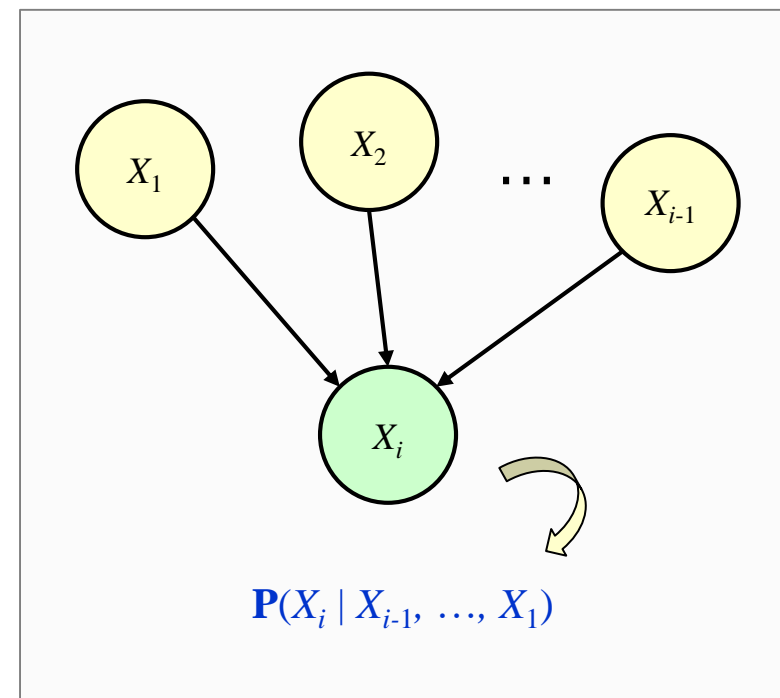
$$\mathbf{P}(X_i | X_{i-1}, \dots, X_1) = \mathbf{P}(X_i | \text{Parents}(X_i))$$

provided that 假设

$$\text{Parents}(X_i) \subseteq \{X_{i-1}, \dots, X_1\}$$

- The equation says: Bayesian network is a correct representation of domain, only if each node is conditionally independent of its other predecessors in the node ordering, given its parents.

该等式说明：贝叶斯网络是域的一个正确表示，仅当给定其父节点，每个节点条件独立于节点序中其它前趋节点时。



Constructing Bayesian Networks 构建贝叶斯网络

□ We can satisfy this condition with this methodology:

我们可以用如下方法来满足该条件:

- 1. *Nodes*: First determine the set of variables to model the domain, $\{X_1, \dots, X_n\}$.
节点: 先确定要对域建模的变量集, $\{X_1, \dots, X_n\}$ 。
- 2. *Links*: For $i = 1$ to n do: 链接: 从 $i = 1$ 至 n , 做:
 - Choose, from X_1, \dots, X_{i-1} , a minimal set of parents for X_i .
从 X_1, \dots, X_{i-1} 中选择 X_i 的父节点的最小集。
 - For each parent insert a link from the parent to X_i .
对每个父节点插入一个从该父节点至 X_i 的连接。
 - Write down the conditional probability table (CPT),
记录 该条件概率表 (CPT),

$$\mathbf{P}(X_i / \text{Parents}(X_i)).$$

The parents of node X_i should contain all nodes in X_1, \dots, X_{i-1} that directly influence X_i .

节点 X_i 的父辈应该包含直接影响 X_i 的 X_1, \dots, X_{i-1} 中的所有节点。

Example: A typical Bayesian network 一种典型的贝叶斯网络

- Suppose we have completed the network, except for the choice of parents for *MaryCalls*.
假设除了*MaryCalls*父节点的选择之外，我们已经完成了该网络。
- *MaryCalls* is not directly influenced by a *Burglary* or an *Earthquake*. Her calling behavior only through their effect on the alarm.
*MaryCalls*并非直接受盗窃或地震的支配，她打电话的行为只受它们对报警器的影响。
- Also, given the alarm state, whether John calls has no influence on Mary's calling.
并且，给定报警状态，John打电话与否并不影响Mary的电话。
- Therefore, the following *conditional independence statement* holds:
因此，如下条件独立语句成立：

$$\mathbf{P}(\textit{MaryCalls} \mid \textit{JohnCalls}, \textit{Alarm}, \textit{Earthquake}, \textit{Burglary}) = \mathbf{P}(\textit{MaryCalls} \mid \textit{Alarm})$$

Compactness 紧凑性

- A Bayesian network is far more *compact* than full joint distribution. Its compactness is a general property of **locally structured** (also called **sparse**) **systems**.

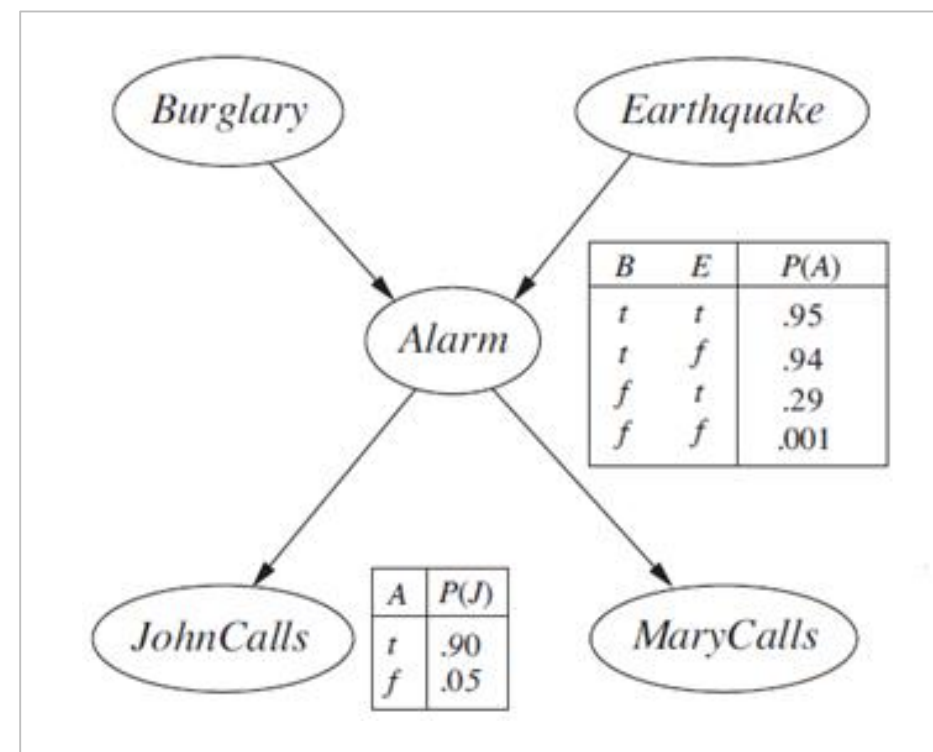
贝叶斯网络远比全联合分布紧凑。它的紧凑性是局部结构化（也称为稀疏）系统的一般特性。

- In a locally structured system, each subcomponent interacts directly with only a bounded number of other components.

在局部结构化系统中，每个子成分仅直接与其它成分的有限数量打交道。

- In Bayesian networks, a CPT (conditional probability table) for a Boolean variable with k parents has 2^k rows.

贝叶斯网络中，具有 k 个父节点的布尔变量的CPT（条件概率表）有 2^k 行。



Compactness 紧凑性

□ Assume there are n Boolean variables: 假设有 n 个布尔变量:

■ **Bayesian networks**: 贝叶斯网络

if each variable has no more than k parents, then the complete network can be specified by $n2^k$ numbers.

如果每个变量的父节点不超过 k 个, 则全部网络可以用 $n2^k$ 个数指定。

■ **Full joint distribution**: 全联合分布

it contains 2^n numbers.

它包含 2^n 个数。

□ E.g., suppose $n = 30$ nodes, each with $k = 5$ parents, then

例如: 设节点 $n = 30$, 每个具有 $k = 5$ 个父节点, 则

■ Bayesian network: $n2^k = 30 \times 2^5 = 960$.

■ Full joint distribution: $2^n = 2^{30} = 1,073,741,824$.

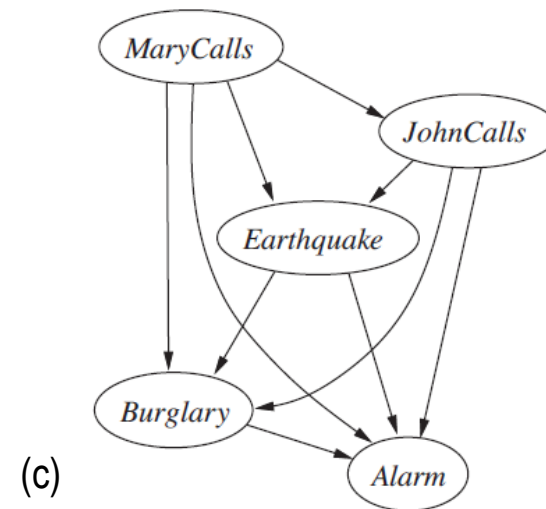
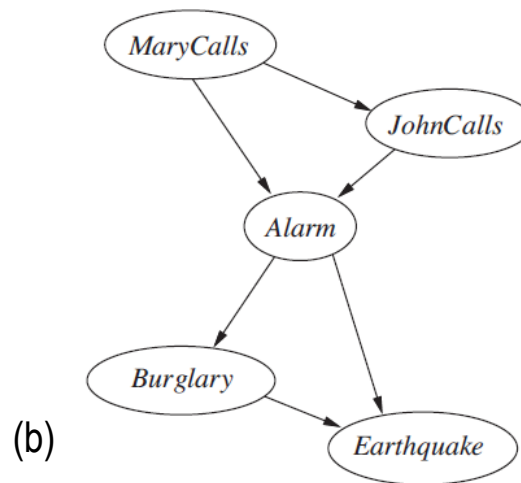
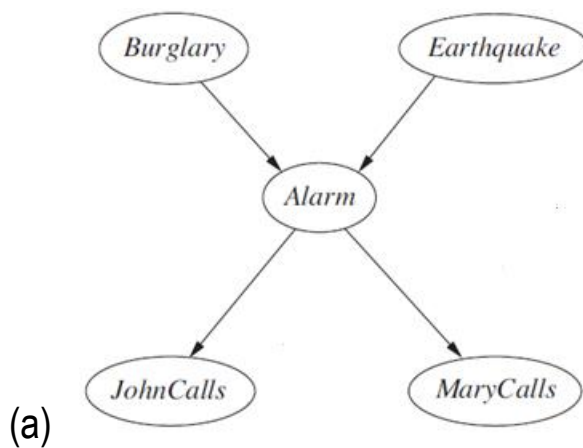
Node Ordering 节点排序

□ We will get a compact Bayesian network only if choose node ordering well (Fig. a).

只有当选择一个好的节点排序（图a），我们才会得到一个紧凑的贝叶斯网络。

□ What happens if we choose the wrong order (Fig. b and c).

如果我们选择一个差的排序会发生什么（图b和c）。



(a) A typical Bayesian network. 一个典型的贝叶斯网络

(b) A bad node ordering 一个差的节点排序: *MaryCalls, JohnCalls, Alarm, Burglary, Earthquake*.

(c) A very bad node ordering 一个更差的节点排序: *MaryCalls, JohnCalls, Earthquake, Burglary, Alarm*.

Conditional Independence Relations 条件独立关系

□ Numerical semantics: 数值语义

a node is conditionally independent of its other predecessors, given its parents.

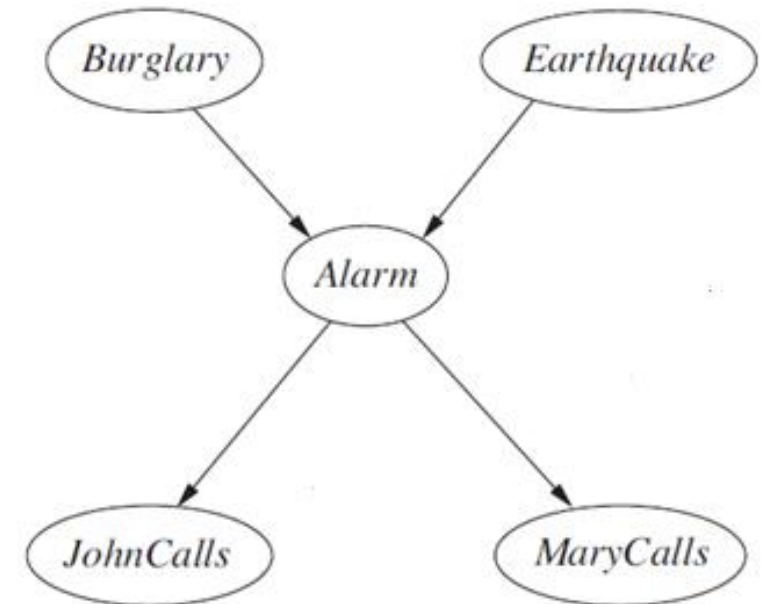
一个节点，给定其父节点后，条件独立于其它前趋节点。

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

Example 举例

$$\begin{aligned} &P(j, m, a, \neg b, \neg e) \\ &= P(j | a) P(m | a) P(a | \neg b \wedge \neg e) P(\neg b) P(\neg e) \\ &= 0.90 \times 0.70 \times 0.001 \times 0.999 \times 0.998 \\ &= 0.000628 \end{aligned}$$

where j, m, a, b, e stand for 其中 j, m, a, b, e 代表
JohnCalls, MaryCalls, Alarm, Burglary, Earthquake.



Conditional Independence Relations 条件独立关系

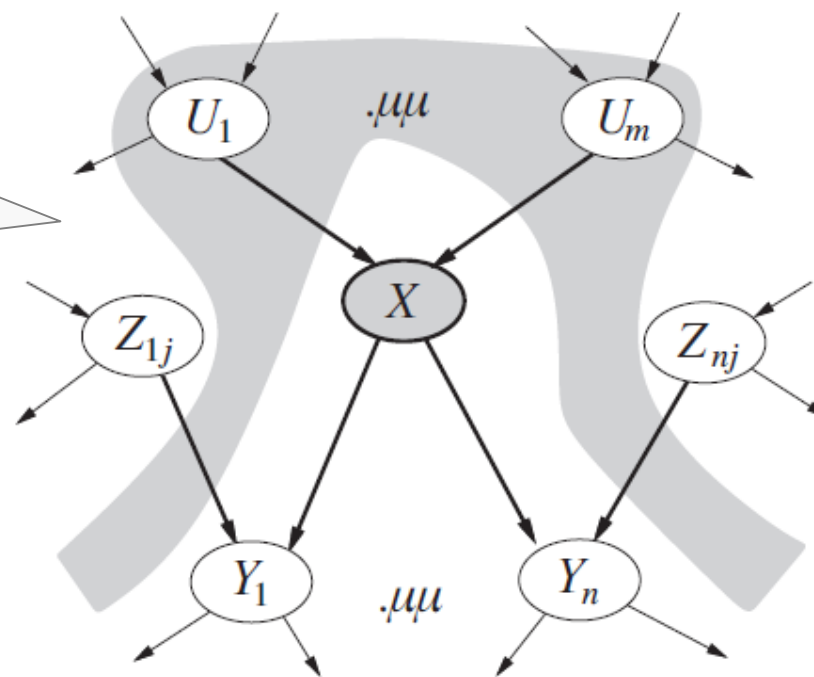
□ Topological semantics: 拓扑语义

each node is conditionally independent of its **non-descendants**, given its parents.

每个节点，给定其父节点后，条件独立于它的非后继节点。

A node X is conditionally independent of its non-descendants Z_{ij} , given its parents U_i (shown in the gray area).

节点 X ，给定其父节点 U_i （灰色区域所示）后，条件独立于它的非后继节点 Z_{ij} 。



Numerical semantics \Leftrightarrow Topological semantics

数值语义 \Leftrightarrow 拓扑语义

Conditional Independence Relations 条件独立关系

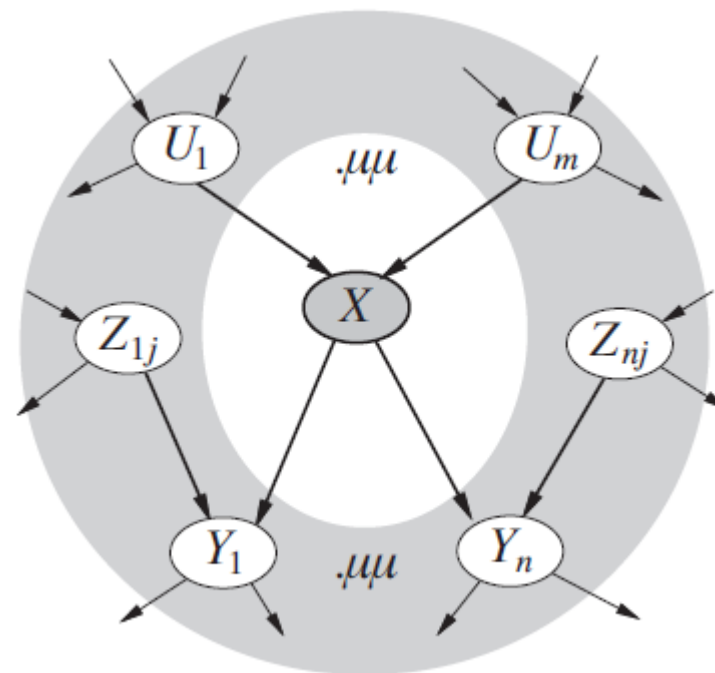
□ Markov blanket 马尔科夫覆盖

a node is conditionally independent of all other nodes in the network, given its Markov blanket (i.e. parents, children, and children's parents).

一个节点，给定其马尔科夫覆盖后，条件独立于网络中的所有其它节点（即：父节点、子节点、以及子节点的其他父节点）。

A node X is conditionally independent of all other nodes in the network given its Markov blanket (the gray area).

一个节点 X ，给定马尔科夫覆盖（灰色区域）后，条件独立于网络中的所有其它节点。



Thank you for your attention!

AI