Abstract

Bayesian networks are directed acyclic graphs representing independence relationships among a set of random variables. A random variable can be regarded as a set of exhaustive and mutually exclusive propositions. We argue that there are several drawbacks resulting from the propositional nature and acyclic structure of Bayesian networks.

To remedy these shortcomings, we propose a probabilistic network where nodes represent unary predicates and which may contain directed cycles. The proposed representation allows us to represent domain knowledge in a single static network even though we cannot determine the instantiations of the predicates beforehand. The ability to deal with cycles also enables us to handle cyclic causal tendencies and to recognize recursive plans.

1 INTRODUCTION

Bayesian networks [Pearl, 1988] are directed acyclic graphs which encode independence relationships among random variables represented by the nodes. Applications of Bayesian networks have been found in diagnosis [Pearl, 1988; Heckerman, 1990], decision analysis [Henrion et al., 1991], story understanding [Charniak and Goldman, 1989; Charniak and Goldman, 1991], etc.

Reasoning in Bayesian networks takes the form of assigning values to a set of random variables in the network and then propagating the influence of these assignments to other nodes in the network. One of the important kinds of inference performed by Bayesian networks is abduction. Abduction is the inference to the best explanation. Many AI tasks such as diagnosis [Peng and Reggia, 1990; Lin and Goebel, 1991a], plan recognition [Kautz, 1987; Lin and Goebel, 1991b] can be formulated as abduction. In Bayesian networks, observations are be represented by assignments to a subset of variables in the network. An explanation of the observations is an assignment of all the variables in the network [Charniak and Goldman, 1991; Pearl, 1988] or the subset of variables in the network that are relevant to the observations [Shimony, 1991].

1.1 DRAWBACKS OF BAYESIAN NETWORK

Bayesian network formulation of abduction offers many advantages over other models of abduction. Abduction is unsound inference. There are typically multiple explanations for any given set of observations. Bayesian network approach defines the best explanation to be the most probable one. Goldman and Charniak argued [Charniak and Goldman, 1991] that the disadvantage of many non-probabilistic approaches to plan recognition is that "it cannot decide that a particular plan, no matter how likely, explains a set of actions, as long as there is another plan, no matter how unlikely, which also explain the actions."

Bayesian networks are acyclic graphs. Each random variable represented by a node in a Bayesian network can be regarded as a set of exhaustive and mutually exclusive propositions. There are several drawbacks as a result of the acyclicity and the propositional nature of Bayesian networks:

Multiple instances

In cases where there are multiple instances of the same type of events, each event has to be represented by a separate node in a Bayesian network. Analogous to the limitation of propositional logic, propositional Bayesian network must represent common properties of the same types of events separately and explicitly for each instance. In medical diagnosis, there are typically at most one event of a particular type in each case. However, consider this:

Arnold dropped in at Bob's house. Bob was sneezing and having a headache. When Arnold went back home, he also began to sneeze and have headaches.

An explanation of this is that Bob had a flu and, since flu is contagious, Arnold got it from Bob. The knowledge used to make this inference include that flu causes sneezing and headache and that flu is contagious. This knowledge, however, is difficult to encode in a Bayesian network, because we cannot determine the instances of flu and
sneezing events beforehand. Therefore, a Bayesian network must be dynamically constructed for each case [Charniak and Goldman, 1991; Goldman and Charniak, 1990; Horsch and Poole, 1990].

The disadvantage of dynamic construction is that the network construction mechanism has to depend on another representation scheme such as a deductive database [Charniak and Goldman, 1991; Goldman and Charniak, 1990] or logic schemas [Horsch and Poole, 1990] to represent domain knowledge. It then has to identify what is the relevant part of knowledge with regard to the current case. One of the most important advantages of Bayesian network over other representation schemes is that it is easier to identify what’s relevant or not. Dynamic construction loses this advantage. Further more, the dynamically constructed Bayesian network is often, in effect, a representation of all the possible solutions to the problem. Bayesian network is only used to choose the most probable among the all possible ones. This reduce the usefulness of Bayesian network significantly.

Acyclicity
Since Bayesian networks are acyclic graphs, they cannot represent recursive relations. In plan recognition, a plan may contain another plan of the same type as one of its components. For example, a plan to sort a list involves sorting sublists and then merge the results. One may argue that if the links in Bayesian network represent causal relations, then the acyclic assumption does not affect the expressive power, because causal relationships are acyclic. We believe that this not necessarily true. There are two notions of causation: token causation and causal tendency. Token causation refers to a particular instance of causation, happening at a unique spatio-temporal location. For example, "Socrates’s drinking of hemlock caused his death" is a token causation. Causal tendency, other hand, refers the tendency of events of one type to cause events of another type. For example, "flu tends to cause sneezing" is a causal tendency.

While token causations are acyclic, causal tendencies can be cyclic. For example, one person’s flu may cause another person to catch flu. The cause and the effect are of the same type. The relationship between hens and eggs provides another example: hens engender eggs, and eggs hens.

Imprecise Observation
The inputs to Bayesian network inference are variable assignments. Sometimes, however, an observation may not be in enough detail to warrant a variable assignment. For example, in auto-engine diagnosis, one of the most common symptoms is abnormal sound. There are several attributes that characterize different kinds of abnormal sound: the sound may be banging or pinging; its occurrence may be continual or intermittent. These different attribute values have different implications in diagnosis. A Bayesian network either represents abnormal sound as a single variable which takes values from the different combinations of the attributes, or represents each combinations of attributes as a single variable. In both cases, an observation of abnormal sound must specify every one of its attribute values, e.g., a continual, pinging sound. However, a novice may not be able to make these distinctions. He may only be able to tell the sound is abnormal. Such an observation is not in enough detail to assign a value to a variable in the network.

Overly specific explanations
An explanation in Bayesian network is an assignment to the variables in the network. A problem with this definition of explanations is that explanations may be overly specific. For example, Figure 1 shows a Bayesian network. Supposing Mr. Holmes receives a message on his desk that his house alarm went off. The most likely explanation is that someone broke into his house and triggered the alarm. One of his concerned neighbour then phoned his office. Another explanation, which is less likely, is that the secretary played a practical joke on him and gave him this phony message. However, if Mr. Holmes has 50 neighbours, the node "neighbour’s call" has 50 different values. Each break-in explanation must commit to one of them. As a result, each break-in explanation is less likely than the practical joke explanation even though break-in is more likely to be the case. This is obviously a situation we want to avoid. Shimony [Shimony, 1991] proposed assigning values to variables only to the relevant variables in the network. His proposal, however, will not resolve the problem in our example, because neighbour’s call is relevant. One may wonder why should we distinguish between 50 different neighbours. The answer is that which person phoned may indeed be important. For example, if Mr. Holmes has a neighbour Jack who is notorious for making things up and Mr. Holmes knows the message is from Jack, then he might have more doubt on whether there was a break in than he would otherwise.

1.2 A PREDICATIVE APPROACH
In this paper, we introduce a probabilistic network for abductive reasoning, where nodes are interpreted as unary predicates instead of propositions. There is no acyclic restriction on the network. An observation is a description of an event that includes the type of the event, and a set of attribute values of the event. An explanation of the observations is a scenario which contains events that match the descriptions in the observations.

The domain knowledge is represented by a single static network. Given a set of observations, the inference algorithm retrieves the most probable explanation from the network. The explanation may contain multiple instantiations of the
same node. Similar to Bayesian networks, the best explanation is defined to be the most probable one. We show that our approach overcomes the difficulties discussed earlier.

2 EVENT NETWORK

In our approach, the domain is partitioned into events and their attribute values. Attributes are characteristics that can be ascribed to events. Attributes are represented by functions that map events to attribute values. For example, agent is an attribute. If \( x \) is an event, then \( \text{agent}(x) \) is the agent of \( x \).

An event type is a unary predicate over the set of events. For example, flu is an event type, and \( \text{flu}(x) \) is true if \( x \) is a flu event. The event types are organized in generalization-specialization hierarchies.

The structural/causal relationships between events are represented by unary functions, called features. When the interpretation of a feature is causal, it represents the causal tendency between the two types of events that are the domain and the range of the feature function. For example, since flu tends to cause sneezing, there is a feature sneeze-effect that maps a flu event to a sneezing event. That is \( \text{sneeze-effect}(x) \) is the sneezing effect of a flu event \( x \).

There is a distinguished element in the domain to represent the intuitive notion of undefined. For example, if flu event \( x \) did not cause a sneezing event, then \( \text{sneeze-effect}(x) = \perp \).

The events, features, and attributes are axiomatized in the language \( L_p \), an extension of the first order logic (FOL) developed by Bacchus [Bacchus, 1988] to represent and reason with both logical and probabilistic information.

The taxonomic relationships between event types are represented by abstraction axioms, which are sentences in the form:
\[
\forall x. \ c_1(x) \rightarrow c_2(x)
\]
where \( c_1 \) and \( c_2 \) are event types. For example, that flu is a subclass of disease is represented by the sentence:
\[
\forall x. \ \text{flu}(x) \rightarrow \text{disease}(x)
\]

For each feature \( f \) that maps events of type \( c_1 \) to events of type \( c_2 \), there is a feature restriction axiom:
\[
\forall x. \ c_1(x) \land f(x) \neq \perp \rightarrow c_2(f(x))
\]

The relationships between event types forms an event network.

**Definition 2.1 (Event Network)** A event network is a directed graph whose nodes represent event types and whose links are as follows:

"isa" and specialization links: Corresponding to each abstraction axiom \( \forall x. c_1(x) \rightarrow c_2(x) \), there is an "isa" link from \( c_1 \) to \( c_2 \) with the label "isa", and a specialization link from \( c_2 \) to \( c_1 \) with the label "spec."

feature links: Corresponding to each feature restriction axiom
\[
\forall x. (c_1(x) \land f(x) \neq \perp) \rightarrow c_2(f(x))
\]

there is a feature link from \( c_1 \) to \( c_2 \) and labeled \( f \).

Figure 2 shows an example. The solid lines represent feature links. A bidirectional broken line represents a pair of "isa" and specialization links. The upward arrow represents the "isa" link and the downward arrow represents the specialization link.

A major source of complexity for many abductive reasoning systems is consistency checking. In our representation scheme, we restrict the consistency conditions to constraints on attribute values so that the consistency can be established efficiently.

There are two kinds of attribute value constraints: local constraints and percolation constraints.

Local constraints specify the relationships between the attributes of a single event and are expressed in the sentences in the following form:
\[
\forall x. c(x) \rightarrow r(a_1(x), \ldots, a_k(x))
\]
where \( c \) is an event type and \( a_1, \ldots, a_k \) are attributes, \( r \) is a k-nary relation over attribute values. For example, that the infectee of a flu event is a different person than the agent can be represented by the local constraint:
\[
\forall x. \text{flu}(x) \rightarrow \text{agent}(x) \neq \text{infectee}(x)
\]

Percolation constraints specify the relationships between the attributes of an event and its direct features. For example, suppose infect is the feature that represent flu causing flu, then we have the following percolation constraint:
\[
\forall x, v. \ (\text{flu}(x) \land \text{flu}(\text{infect}(x)) \land \text{agent}(\text{infect}(x)) = v \rightarrow \text{infectee}(x) = v)
\]

Intuitively, this says that the agent of a flu event that is caused by another flu is the value of infectee attribute of the cause event. In general, percolation constraints are in the form:
\[
\forall x, v. \ (c_1(x) \land c_2(f(x)) \land a'(f(x)) = v) \rightarrow a(x) = v
\]

where \( c_1, c_2 \) are event types, \( f \) is feature of \( c_1, a, a' \) are attributes.

Together, the above examples of local and percolation constraints state that the agents of two flu events where one causing another are different.
So far, the axioms have all been FOL formulas. Lp's extension to FOL is the ability to represent and reason with probabilistic knowledge, which are represented by probabilistic terms. Somewhat simplified, a probabilistic term in Lp is a formula in the form: $[\alpha(z)]_x$, where $\alpha(z)$ is a FOL formula with open variable $z$. It denotes the probability of an random individual in the domain satisfies the formula $\alpha(z)$. For example, $[\text{flu}(x)]_x$ is the probability of an random event in the domain being a flu event. Conditional probabilities can also be conveniently expressed in Lp: $[\beta(z)\mid \alpha(x)]_x$ denotes the conditional probability of $\beta$ being true of a random element $x$ in the domain, given $\alpha(x)$ is true.

The probabilities we use to compute the probabilities of explanations are prior and conditional probabilities of event descriptions.

**Definition 2.2 (Event description)** An event description specifies the type of an event and its attribute values. It is a formula in the following form:

$$D(x) \equiv c(x) \land V(x)$$

where $c$ is a event type and $V(x)$ is a conjunction of attribute value assignments: $V(x) \equiv a_1(x) = v_1 \land a_2(x) = v_2 \land \ldots a_k(x) = v_k$, where $a_1, a_2, \ldots, a_k$ are attributes and $v_1, v_2, \ldots, v_k$ are attribute values. An event $x$ is said to match a description $D$ if $D(x)$ is true.

The probabilistic knowledge in the domain are represented as category statistics in either of the following two forms:

$$[D(x)]_x = p \quad \text{or} \quad [D'(f(x))\mid D(x)]_x = p$$

where $D(x) = c(x) \land V(x)$ and $D'(x) = c'(x) \land V'(x)$ are event descriptions. $f$ is a feature that maps events in $c$ to $c'$.

In summary, the domain knowledge is represented by four groups of axioms: Abstraction axioms, feature restriction axioms, attribute value constraints, and category statistics.

**3 SCENARIOS AS EXPLANATIONS**

An observation is an existentially quantified event description. For example, the story about Arnold and Bob contains four observations:

- $\exists x. \text{sneezing}(x) \land \text{agent}(x) = \text{Bob} \land \text{time}(x) = 1$
- $\exists x. \text{headache}(x) \land \text{agent}(x) = \text{Bob} \land \text{time}(x) = 1$
- $\exists x. \text{sneezing}(x) \land \text{agent}(x) = \text{Arnold} \land \text{time}(x) = 2$
- $\exists x. \text{headache}(x) \land \text{agent}(x) = \text{Arnold} \land \text{time}(x) = 2$

An observation can be explained by hypothesizing that the event is a component or caused by another event. Such a relationship forms a directed path in the event network. The "isa" and specialization links in the event network allows one event to inherit causal/structural properties and explanations of its superclasses. Similar to inheritance reasoning in semantic networks, we use path preemption to ensure that information inherited is the most specific.

We denote the closure and the non-empty closure of "isa" links by $\xrightarrow{\text{isa}}$ and $\xrightarrow{\text{isa}^+}$, respectively. The meanings of $\xrightarrow{\text{spec}}$ and $\xrightarrow{\text{spec}^+}$ are similarly defined.

**Definition 3.1 (Path Preemption)**

**Generalization Preemption**: A path $c \xrightarrow{\text{spec}} c_2 \xrightarrow{\text{isa}} c_1 \xrightarrow{\text{spec}} c' \rightarrow c$ is pre­empted if there exists a path $c \xrightarrow{\text{spec}} c_1 \xrightarrow{\text{isa}} c' \rightarrow c$ such that $c_1 \xrightarrow{\text{isa}^+} c_2$ (Figure 3.a).

**Specialization Preemption**: A path $c \xrightarrow{\text{spec}^+} c_2 \xrightarrow{\text{isa}} c_1 \xrightarrow{\text{spec}} c' \rightarrow c$ is pre­empted if there exists a path $c \xrightarrow{\text{spec}^+} c_1 \xrightarrow{\text{isa}} c' \rightarrow c$ such that $c_2 \xrightarrow{\text{isa}} c_1$ (Figure 3.b).

Given a set of observations, an abductive reasoner seeks the best explanation of how the observed events might have been caused by certain culprit events. For example, to explain the sneezing and headache of Bob and those of Arnold after his contact with Bob, we may construct the scenario in Figure 4. This scenario states that Bob's flu caused his sneezing, headache and Arnold's flu, which in turn caused Arnold's sneezing and headache.

**Definition 3.2 (Local Tree)** A local tree is a one level tree whose nodes are event descriptions and whose links are labeled with distinct feature functions such that if there is a link labeled $f$ from $D$ to $D'$ in the local tree, where $D(x) \equiv c(x) \land V(x)$ and $D'(x) \equiv c'(x) \land V'(x)$ are
object descriptions, then there is a non-preempted path $c \rightarrow \pi \rightarrow c'' \rightarrow c'$ in the event network.

**Definition 3.3 (Scenario)** A scenario is defined recursively as follows:

1. The local trees are also scenarios.
2. Suppose $\alpha$ is a scenario. If $D$ is a leaf node of $\alpha$ and $\beta$ is a local tree or a specialization link, whose root is also $D$, then the tree formed by joining the node $D$ in $\alpha$ and the root of $\beta$ is also a scenario.
3. All scenarios are either one of the above.

The scenario in Figure 4 can be decomposed into two local trees. The first one consists of Bob's flu causing his sneezing, headache and Arnold's flu. The second one consists of Arnold's flu causing his sneezing and headache.

A scenario represents a formula that is the conjunction of the event descriptions in it. For example, the scenario in Figure 4 represent the following formula:

$$\alpha(x) \equiv \text{flu}(x) \land V(x) \land \text{sneezing}(g_1(x)) \land V_1(g_1(x)) \land \text{headache}(g_2(x)) \land V_2(g_2(x)) \land \text{sneezing}(g_3(x)) \land V_3(g_3(x)) \land \text{headache}(g_4(x)) \land V_4(g_4(x))$$

where

$$V(x) \equiv \text{agent}(x) = \text{Bob} \land \text{infected}(x) = \text{Arnold} \land \text{time}(x) = 1$$

$$V_1(x) \equiv \text{agent}(x) = \text{Bob} \land \text{time}(x) = 1$$

$$V_2(x) \equiv \text{agent}(x) = \text{Arnold} \land \text{time}(x) = 2$$

$$g_1(x) \equiv \text{sneezing}(x)$$

$$g_2(x) \equiv \text{headache}(x)$$

$$g_3(x) \equiv \text{infected}(x)$$

$$g_4(x) \equiv \text{sneezing}(\text{infected}(x))$$

$$g_5(x) \equiv \text{headache}(\text{infected}(x))$$

**Definition 3.4 (Explanation)** An explanation of a set of observations is a scenario of the event network that is consistent with the knowledge base and logically entails the observations.

Let $\alpha(x)$ denote a scenario, the probability of the scenario is $[\alpha(x)]_x$. The problem of finding a causal explanation of the observations amounts to finding the most probable scenario that explains the observations.

Let $f$ be a feature that represents a causal tendency. When $f(x) \neq \bot$, it means that event $x$ caused another event $f(x)$. We call $f(x) \neq \bot$ a **causation event**. Assuming that given the direct cause of causation event, its probability is independent of indirect causes and other effects of the direct cause, we showed in [Lin, 1992] that the probability of a scenario is the product of the causation event involved in the scenario and the prior probability of the culprit (the root node of a scenario), which are available as category statistics in the knowledge base.

For example, if $\alpha(x)$ denotes the scenario in Figure 4, then its probability is:

$$[\alpha(x)]_x = p_0 \times p_1 \times p_2 \times p_3 \times p_1 \times p_2$$

where

$$p_0 = \text{flu}(x)$$

$$p_1 = \text{sneezing(sneez-effect(x))}\text{flu}(x)$$

$$p_2 = \text{headache(headache-effect(x))}\text{flu}(x)$$

$$p_3 = \text{flu(infect(x))}\text{flu}(x)$$

### 4 INFERENCE ALGORITHM

Since we have used only a restricted subset of $L_p$ to represent the observations, scenarios and domain knowledge, a specialized inference algorithm can be used to find the most probable explanation. Abductive inference is performed by a message passing algorithm operating over the network. Each of the nodes in the network is also a computing agent that communicates with neighboring agents by passing messages across the links in the network. The messages represent partial explanations of the observations, which are explanations of a subset of observations. The partial explanations are combined with others at the nodes to construct explanations for larger subsets of observations. Dynamic programming techniques are employed so that the most probable scenarios can be found without enumerating all those possible. A detailed description of the algorithm can be found in [Lin, 1992].

### 5 PLAN RECOGNITION

Dynamic Bayesian network construction is most often used in plan recognition. We now use an example to demonstrate that we can represent domain knowledge in a static network and use it directly in plan recognition.

![Figure 5: A working/shopping world](image)

Figure 5 is shows a network representation of a fraction of working/shopping world. We briefly explain the knowledge encoded in the network:

- To work, one first goes to work place and then do whatever job he/she is suppose to do. Thus the feature
links from work to goto-workplace and do-job. For bureaucrats, doing their job means reading comics in newspapers.

- Some kinds of work require the workers to wear uniforms. Supermarket cashier's work is one of them.
- A cashier goes to supermarket to work and the job is to collect payment.
- To shop, one first goes to a shop, get the merchandise, and then pay the cashier.
- Shopping in supermarket is a kind of shopping, where one goes to a supermarket and gets the merchandise by picking them up from the shelves.

Once the network is created, we can use it to understand the stories about the domain. Consider the following example from [Ng and Mooney, 1990]:

"John went to the supermarket. He put on the uniform."

The two sentences are represented as two observations:

\[ \exists x. \text{go-to-supermarket}(x) \land \text{agent-name}(x) = \text{John} \]
\[ \exists x. \text{put-on-uniform}(x) \land \text{agent-sex}(x) = \text{male} \]

Two scenarios explaining the observations are shown in Figure 6. The scenario in (1) explains the observation by postulating that John is going to supermarket to work. The scenario (2), on the other hand, says that John went to the supermarket to shop and someone (not necessarily John) put on uniform to work. Assuming the probabilities:

\[ \Pr(\text{work-in-supermarket}(x)) \]
\[ \Pr(\text{do-things}(x)) \times \Pr(\text{do-things}(\text{rest}(x))) \times \Pr(\text{shop-in-supermarket}(x)) \times \Pr(\text{do-one-thing}(x)) \times \Pr(\text{work-in-uniform}(x)) \]

are 1.0, the probability of scenario (1) is

\[ \Pr(\text{work-in-supermarket}(x)) \]

whereas the probability of scenario (2) is

\[ \Pr(\text{do-things}(\text{first}(x)) \times \Pr(\text{do-things}(x)) \times \Pr(\text{shop-in-supermarket}(x)) \times \Pr(\text{do-one-thing}(x)) \times \Pr(\text{work-in-uniform}(x)) \]

Therefore, the first scenario tends to be more probable than the second unless work-in-supermarket is an extremely unlikely event.

The ability to deal with networks with directed cycles also allows us to represent and recognize recursive plans. In [Lin, 1992], we showed that our scheme can be used for program recognition. We represent programs as hierarchies of recursive plans. Given a sequence of basic actions performed by a program, e.g., comparing and exchanging positions of two elements in an array, our plan recognition algorithm is able to infer which algorithm (plan) the program is using.

6 IMPRECISE OBSERVATIONS

Consider an example from auto-engine diagnosis: misfiring (mf) causes uneven sound (us). There are two possible causes of mf: bad spark (bs) and impure fuel (im). The former is an ignition system problem and tends to happen
continually. On the other hand, the latter tends to be intermittent. The causal relationships between these events can be represented in the causal network in Figure 9.

![Figure 9: Causes of uneven sound](image)

Since the occurrence attribute \( \text{occ} \) of \( \text{bs} \) is continual (cont), we have a local constraint at the node \( \text{bs} \):

\[
\forall x. \text{bs}(x) \rightarrow \text{occ}(x) = \text{cont} \quad \ldots \quad (a)
\]

On the other hand, since \( \text{im} \) is intermittent (int), we have:

\[
\forall x. \text{im}(x) \rightarrow \text{occ}(x) = \text{int} \quad \ldots \quad (b)
\]

We also have percolation constraints:

\[
\begin{align*}
\forall x, v. \text{bs}(x) \land \text{mf}(f_1(x)) \land \text{occ}(f_1(x)) = v \rightarrow \text{occ}(x) = v \\
\forall x, v. \text{im}(x) \land \text{mf}(f_2(x)) \land \text{occ}(f_2(x)) = v \rightarrow \text{occ}(x) = v \\
\forall x, v. \text{im}(x) \land \text{us}(f_3(x)) \land \text{occ}(f_3(x)) = v \rightarrow \text{occ}(x) = v
\end{align*}
\]

Then if the observation is \( \exists x. \text{us}(x) \), then we have two explanations in Figure 10. Both \( \text{bs} \) and \( \text{im} \) are possible explanations.

![Figure 10: Explanations of uneven sound](image)

If the observation is given in more detail:

\[
\exists x. \text{us}(x) \land \text{occ}(x) = \text{cont}
\]

then the attribute value \( \text{occ} = \text{cont} \) percolates from \( \text{us} \) to \( \text{mf} \) and then to \( \text{bs} \) and \( \text{im} \) (see Figure 11). In Figure 11.2, the attribute value \( \text{occ} = \text{cont} \) at the node \( \text{im} \) violates the local constraint \( (b) \). Therefore the scenario in Figure 11.2 is inconsistent with the knowledge base and subsequently eliminated as a candidate explanation. On the other hand, the scenario in Figure 11.1 is consistent with the knowledge base and logically implies the observations. Therefore, it is an explanation of the observation.

### 7 SPECIFICITY OF EXPLANATION

In our formulation of abduction, specificity of explanation is treated as follows: Each individual explanation is maximally specific with respect to the observations it explains, because explanations do not contain preempted path. Since the more general explanations are more probable, the most general explanation that logically entails the observations is preferred.

![Figure 11: Misfiring scenarios](image)

For example, suppose Mr. Holmes knowledge about phone message, house alarm, etc., represented in Figure 12. The shaded nodes represent events based upon which Mr. Holmes makes his decisions. The root node of an explanation must be one of the shaded nodes. They are similar to end nodes in Kautz's plan hierarchy [Kautz, 1987].

Suppose Mr. Holmes's only observation is the phone message, then he has three explanations shown in Figure 13. The scenario shown in Figure 14.2 is deemed to be less likely than the one in Figure 13.2 because the probability of the former is the probability of the latter times the probability of a random neighbour of Mr. Holmes being Jack. Now suppose Mr. Holmes has an independent source confirming that Jack made a call, then the two explanations are those in Figure 14. The scenario in Figure 13.2 is no longer an explanation because it does not explain Jack's call. If Mr. Holmes further heard on radio that there was an earthquake, then his explanation became the scenario in Figure 15. Earthquake was not considered as explanations previously because its prior probability is much lower than the prior of break-ins. The scenario becomes preferable because other scenarios do not explain radio announcement.

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1. By a more general explanation, we do not mean an explanation that explain a wider range of data, rather, we mean the explanation is stated in more general terms.
8 CONCLUSION

We pointed out several drawbacks of Bayesian networks in abduction, due to its propositional nature and acyclic structure. We proposed a predicative interpretation of probabilistic network which is similar to Bayesian network in that the independence relationships between events are represented in a network structure but is different in that the nodes represent unary predicates instead of propositions. We have used several examples to show that our approach overcomes several difficulties encountered in Bayesian networks.

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