Model-Based Default Refinement of Partial Information within an Ambient Agent

Fiemke Both, Charlotte Gerritsen, Mark Hoogendoorn, and Jan Treur

Vrije Universiteit Amsterdam, Department of Artificial Intelligence
De Boelelaan 1081, 1081 HV Amsterdam, The Netherlands
{fboth, cg, mhoogen, treur}@cs.vu.nl
http://www.few.vu.nl/~{fboth, cg, mhoogen, treur}

Abstract. Ambient agents react on humans on the basis of partial information obtained by sensoring. Appropriate types of reactions depend on in how far an ambient agent is able to interpret the available information (which is often incomplete, and hence multi-interpretable) in order to create a more complete internal image of the environment, including humans. This interpretation process, which often has multiple possible outcomes, can make use of an explicitly represented model of causal and dynamic relations. Given such a model representation, the agent needs a reasoning method to interpret the partial information available by sensoring, by generating one or more possible interpretations. This paper presents a generic model-based default reasoning method that can be exploited to this end. The method allows the use of software tools to determine the different default extensions that form the possible interpretations.

1 Introduction

Ambient Intelligence [1, 2, 16] applications usually involve sensor information about the environment, including humans. As this information is often incomplete, applications that require a high level of context awareness (see also [17, 18, 19]) depend on the availability of methods to analyse such information. One way is to include computational models about environmental and human functioning in ambient agents. However, even when incomplete sensor information is refined on the basis of such models to create a more complete internal image of the environment's and human's state, still this may result in partial information that can be interpreted in different manners. Reactions of ambient agents then depend on in how far they are able to handle the available multi-interpretable information. To do this, the agent needs a reasoning method to generate one or more of the possible interpretations. Tools from the area of nonmonotonic logic can provide adequate analysis tools for reasoning processes concerning partial information. Within nonmonotonic logic approaches it is possible to formalise reasoning processes that deal with multiple possible outcomes, which can be used to model different possibilities of interpretation; see [10] for a similar perspective on the application of nonmonotonic logic tools.

This paper presents a generic model-based default reasoning method that can be exploited to this end. The method exploits the available causal model and allows the use of software tools to determine the different default extensions that form the possible interpretations, given the sensor information and the causal model. Moreover, by formally specifying the default rules in an executable temporal format, according to the approach put forward in [8, 9], explicit default reasoning processes can be generated.

Section 2 describes two case studies used to illustrate the approach. In Section 3 the basic concepts used are briefly introduced. Section 4 presents the approach to use default logic in conjunction with causal graphs to refine partial information by defining multiple interpretations. Finally, Section 5 is a discussion.

2 Case Studies

Two case studies are used throughout this paper; they are introduced below.

Wristband for Elderly

As a case study, the reasoning concerning conditions that occur amongst elderly people is used. Figure 1 shows a simplified causal model for such conditions. On the left hand side five conditions are shown: awake, asleep, syncope (fainted), myocardial infarction (heart attack) and cardiac arrest. The output of the model consists of symptoms that can be measured with a wristband, which are pulse, blood pressure and body temperature. Such a causal model can help in finding out the current condition of an elderly person based on sensory information from the wristband.

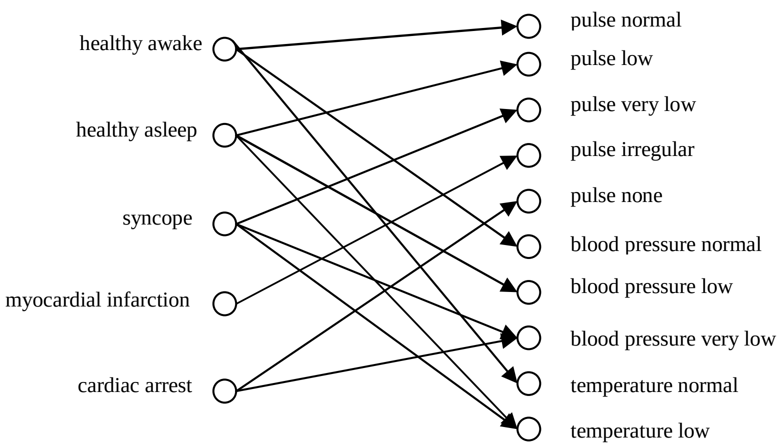

Fig. 1. Causal model for the condition of an elderly person

Crime Case

In this case study, a system is used that can help the police solve a crime using ambient intelligence facilities. A Dutch company (Sound Intelligence) developed microphones that can distinguish aggressive sounds. Consider the situation in which these microphones are distributed at crucial points in the city, similar to surveillance cameras. Furthermore, suppose in this scenario that for some persons ankle bracelets are used as a form of punishment, which can measure the level of ethanol in the person’s perspiration, and indicate their position.

In this example scenario, someone is beaten up nearby a microphone. The microphone picks up the sound of the fight and records this. After an investigation, the police have three suspects. The first suspect is known to have a high level of testosterone, which often leads to aggressive behaviour. The second suspect is someone who is sensitive for alcohol (causing aggression) and wears an ankle bracelet that measures the level of ethanol in his system. He has been seen in a nearby cafe. The third suspect is diagnosed with Intermittent Explosive Disorder (IED), which is a disorder that can lead to a terrible outburst of rage after an unpleasant or stressful meeting. Witnesses saw suspect 2 in the company of someone else.

Figure 2 shows a causal model that is used for this situation that can help the police officers to figure out what information is missing and help them to plan their strategy. For example, did suspect 2 have a conflict with the person he was with? Did suspect 3 drink alcohol? Aggressive sounds are caused by persons that are aggressive, according to the model. Three possible causes for this aggressiveness are considered, as can be seen in Figure 2: someone can have a high level of testosterone, someone can just have been in a situation of conflict or someone can have a high level of alcohol.

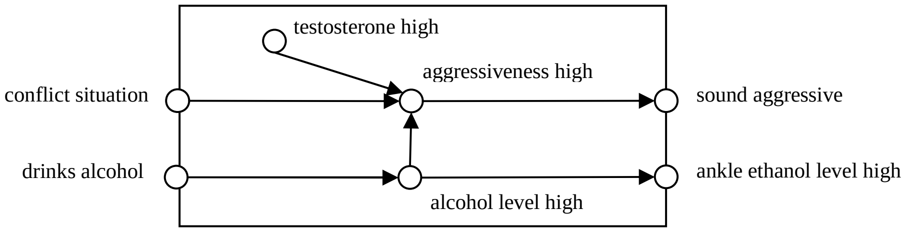

Fig. 2. Causal model for the crime case

3 Basic Concepts Used

In this section the basic concepts used in the paper are briefly introduced.

Causal models

In this paper, this dynamic perspective on reasoning is applied in combination with facts that are labelled with temporal information, and models based on causal or temporal relationships that relate such facts. To express the information involved in an agent's internal reasoning processes, the following ontology is used.

leads_to_after(I:INFO_EL, J:INFO_EL, D:REAL)	state property I leads to state property J after duration D
at(I:INFO_EL, T:TIME)	state property I holds at time T

Multiple Interpretation

Reasoning to obtain an interpretation of partial information can be formalised at an abstract generic level as follows. A particular interpretation for a given set of formulae considered as input information for the reasoning, is formalised as another set of formulae, that in one way or the other is derivable from the input information (output of the reasoning towards an interpretation). In general there are multiple possible outcomes. The collection of all possible interpretations derivable from a given set of formulae as input information (i.e., the output of the reasoning towards an interpretation) is formalised as a collection of different sets of formulae. A formalisation describing the relation between such input and output information is described at an abstract level by a multi-interpretation operator.

The input information is described by propositional formulae in a language L_1. An interpretation is a set of propositional formulae, based on a language L_2.

a) A *multi-interpretation operator* MI with input language L_1 and output language L_2 is a function $MI : P(L_1) \rightarrow P(P(L_2))$ that assigns to each set of input facts in L_1 a set of sets of formulae in L_2.
b) A multi-interpretation operator MI is *non-inclusive* if for all $X \subseteq L_1$ and $S, T \in MI(X)$, if $S \subseteq T$ then $S = T$.
c) If $L_1 \subseteq L_2$, then a multi-interpretation operator MI is *conservative* if for all $X \subseteq L_1$, $T \in MI(X)$ it holds $X \subseteq T$.

The condition of non-inclusiveness guarantees a relative maximality of the possible interpretations. Note that when MI(X) has exactly one element, this means that the set $X \subseteq L_1$ has a unique interpretation under MI. The notion of multi-interpretation operator is a generalisation of the notion of a nonmonotonic belief set operator, as introduced in [6]. The generalisation was introduced and applied to approximate classification in [10]. A reasoner may explore a number of possible interpretations, but often, at some point in time a reasoner will focus on one (or possibly a small subset) of the interpretations. This selection process is formalised as follows (see [10]).

a) A *selection operator* s is a function $s : P(P(L)) \rightarrow P(P(L))$ that assigns to each nonempty set of interpretations a nonempty subset: for all A with $\phi \neq A \subseteq P(L)$ it holds $\phi \neq s(A) \subseteq A$. A selection operator s is *single-valued* if for all non-empty A the set s(A) contains exactly one element.
b) A *selective interpretation operator* for the multi-interpretation operator MI is a function $C : P(L_1) \rightarrow P(L_2)$ that assigns one interpretation to each set of initial facts: for all $X \subseteq L_1$ it holds $C(X) \in MI(X)$.

Representation in Default Logic

The *representation problem* for a nonmonotonic logic is the question whether a given set of possible outcomes of a reasoning process can be represented by a theory in this logic. More specifically, representation theory indicates what are criteria for a set of possible outcomes, for example, given by a collection of deductively closed sets of formulae, so that this collection can occur as the set of outcomes for a theory in this nonmonotonic logic. In [13] the representation problem is solved for default logic, for the finite case. Given this context, in the current paper Default Logic is chosen to represent interpretation processes. For the empirical material analysed, default theories have been specified such that their extensions are the possible interpretations.

A *default theory* is a pair $\langle D, W \rangle$. Here W is a finite set of logical formulae (called the background theory) that formalise the facts that are known for sure, and D is a set of default rules. A default rule has the form: $\alpha: \beta / \gamma$. Here α is the precondition, it has to be satisfied before considering to believe the conclusion γ, where the β, called the justification, has to be consistent with the derived information and W. As a result γ might be believed and more default rules can be applied. However, the end result (when no more default rules can be applied) still has to be consistent with the justifications of all applied default rules. *Normal default theories* are based on defaults of the form $\alpha: \beta / \beta$. In the approach *supernormal* default rules will be used: normal default rules where α is trivial: true. Such supernormal rules are denoted by β / β or $: \beta / \beta$; they are also called prerequisite-free normal defaults. For more details on Default Logic, such as the notion of extension, see e.g. [12, 15].

Temporal Specification of Reasoning Processes

In this paper a dynamic perspective on reasoning is taken, following, e.g. [8, 9]. In practical reasoning situations usually different lines of reasoning can be generated, each leading to a distinct set of conclusions. In logic semantics is usually expressed in terms of models that represent descriptions of conclusions about the world and in terms of entailment relations based on a specific class of this type of models. In the (sound) classical case each line of reasoning leads to a set of conclusions that are true in all of these models: each line of reasoning fits to each model. However, for non-classical reasoning methods the picture is different. For example, in default reasoning or abductive reasoning methods a variety of mutually contradictory conclusion sets may be possible. It depends on the chosen line of reasoning which one of these sets fits.

The general idea underlying the approach followed here, and inspired by [8, 9], is that a particular reasoning line can be formalised by a sequence of *information states* $M_0, M_1, \ldots\ldots$. Here any M_t is a description of the (partial) information that has been derived up to time point t. From a dynamic perspective, an inference step, performed in time duration D is viewed as a transition $M_t \rightarrow M_{t+D}$ of a current information state M_t to a next information state M_{t+D}. Such a transition is usually described by application of a deduction rule or proof rule, which in the dynamic perspective on reasoning gets a temporal aspect. A particular reasoning line is formalised by a sequence $(M_t)_{t \in T}$ of subsequent information states labelled by elements of a flow of time T, which may be discrete, based on natural numbers, or continuous, based on real numbers.

An information state can be formalised by a set of statements, or as a three-valued (false, true, undefined) truth assignment to ground atoms, i.e., a partial model. In the latter case, which is followed here (as in [8, 9]), a sequence of such information states or reasoning trace can be interpreted as a partial temporal model. A transition relating a next information state to a current one can be formalised by temporal formulae the partial temporal model has to satisfy.

Executable Temporal Specification

To specify models and to execute these models, the language LEADSTO, an executable sublanguage of Temporal Trace Language (TTL), is used. The basic building blocks of this language are causal relations of the format $\alpha \twoheadrightarrow_{e, f, g, h} \beta$, which means:

if   state property α holds for a certain time interval with duration g,
then after some delay (between e and f) state property β will hold
for a certain time interval of length h.

where α and β are state properties of the form ‘conjunction of literals’ (where a literal is an atom or the negation of an atom), and e, f, g, h non-negative real numbers. For the sake of simplicity, especially when they are always the same, these subscripts may be left out of the notation and indicated separately. As an example, a modus ponens deduction rule in time duration D can be specified in temporal format as:

$$\text{derived}(I) \wedge \text{derived}(\text{implies}(I, J)) \twoheadrightarrow_D \text{derived}(J)$$

So, inference rules are translated into temporal rules thus obtaining a temporal theory describing the reasoning behaviour. Each possible line of reasoning can be described by a linear time model of this theory (in temporal partial logic). This representation format will be used to formalise this and other types of model-based reasoning methods, as is shown more extensively in Appendix A[†].

[†] http://www.few.vu.nl/~fboth/default-refinement

4 Representing Model-Based Interpretation in Default Logic

In this section it is discussed how a model-based interpretation operator can be represented in default Logic.

4.1 Default logic for model-based refinement of partial information

The *causal theory* CT of the agent consists of a number of statements $a \rightarrow b$ for each causal relation from a to b, with a and b atoms. Sometimes included in this set are some facts to indicate that some atoms exclude each other (for example, ¬(has_value(temperature, high) ∧ has_value(temperature, low) assuming that temperature can only be high or low), or that at least one of a set of atoms is true, (for example: has_value(pulse, high) ∨ has_value(pulse, normal) ∨ has_value(pulse, low)). A set of literals S is *coherent* with CT if $S \cup CT$ is consistent. The set S is called a *maximal coherent* set for CT if it is coherent, and for all sets T coherent with CT with $S \subseteq T$ it holds S = T. Let X be a set of formulae. The multi-interpretation operator $MI_{CT}(X)$ is defined by

$$MI_{CT}(X) = \{ Cn(X \cup CT \cup S) \mid S \text{ maximal coherent with CT} \}$$

This operator defines for the partial information the agent may have at some point in time (indicated by set of literals X) the set of all complete refinements of X which are coherent with the causal model. This operator has been defined above in an abstract manner, and only indicates the possible outcomes of a reasoning process, not the steps of the reasoning process itself. A next step is to obtain a representation of this operator in a well-known formalism such as default logic. Based on this default logic representation, reasoning processes can be defined that can be performed to obtain one or more of the interpretations.

The following Default Theory $\Delta_{CT}(X) = \langle W, D \rangle$ can be used to represent the multi-interpretation operator MI_{CT} (notice that this is a supernormal default theory); see also [13], Theorem 5.1:

$$W = CT \cup X$$
$$D = \{ (\text{true}: a / a) \mid a \text{ literal for an atom occurring in CT} \}$$

Here a literal is an atom or a negation of an atom. That this default theory represents MI_{CT} means that for any set X indicating partial information the set of interpretations defined by $MI_{CT}(X)$ can be obtained as the set of all extensions of the default theory $\Delta_{CT}(X)$. This representation allows to determine the interpretations by using known methods and tools to determine the extensions of a default theory. One of these methods is worked out in a tool called Smodels, based on answer set programming; cf. [14]. The use of this for the two case studies will be discussed in the next two Subsections 4.2 and 4.3. Another method to determine the extensions of a default theory is by controlled or prioritised default reasoning. This method is illustrated in Appendix A.

4.2 A Default Theory for the Wristband for Elderly Case

In order to represent the knowledge introduced in Section 2.1, the following default theory has been specified. First, the causal background theory (W = CT) is defined, based on the causal graph shown in Figure 1. Furthermore, inconsistent values are defined for the various facets (i.e. pulse, temperature, blood pressure, and condition):

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inconsistent_values(pulse, normal, low)
inconsistent_values(condition, healthy_awake, healthy_asleep)
etc.
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If an attribute has a certain value and this value is inconsistent with another value, then this other value is not the case.

has_value(y, x1) $\wedge$ inconsistent_values(y, x1, x2) $\rightarrow \neg$ has_value(y, x2)

Besides the background theory, also the default theory Δ_{CT} has been generated from this causal theory CT. The default rules for the atoms are simply as follows:

has_value(condition, healthy_awake) / has_value(condition, healthy_awake)
has_value(condition, healthy_asleep) / has_value(condition, healthy_asleep)
has_value(condition, syncope) / has_value(condition, syncope)
has_value(condition, myocardial_infarction) / has_value(condition, myocardial_infarction)
has_value(condition, cardiac_arrest) / has_value(condition, cardiac_arrest)
has_value(pulse, normal) / has_value(pulse, normal)
has_value(pulse, low) / has_value(pulse, low)
has_value(pulse, very_low) / has_value(pulse, very_low)
has_value(pulse, irregular) / has_value(pulse, irregular)
has_value(pulse, none) / has_value(pulse, none)
has_value(blood_pressure, normal) / has_value(blood_pressure, normal)
has_value(blood_pressure, low) / has_value(blood_pressure, low)
has_value(blood_pressure, very_low) / has_value(blood_pressure, very_low)
has_value(temperature, normal) / has_value(temperature, normal)
has_value(temperature, low) / has_value(temperature, low)

Besides these default rules, similar defaults for the negations of these atoms are included. Using a system called Smodels [14], the extensions for the default theory specified can be calculated. Using the theory above, 30 extensions result. Hereby, in 19 out of 30 cases neither of the 5 conditions holds (i.e. awake, asleep, syncope, myocardial infarction and cardiac arrest). However, by adding strict rules which express that at least one of the conditions holds, only 11 extensions are found. The extensions that follow after adding these strict rules are shown in Table 1.

Table 1. All extensions of the default theory

#	Condition	Values	#	Condition	Values
1	healthy_awake	has_value(pulse, normal) has_value(blood_pressure, normal) has_value(temperature, normal)	7	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, normal) has_value(temperature, low)
2	healthy_asleep	has_value(pulse, low) has_value(blood_pressure, low) has_value(temperature, low)	8	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, low) has_value(temperature, low)
3	syncope	has_value(pulse, very_low) has_value(blood_pressure, very_low) has_value(temperature, low)	9	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, very_low) has_value(temperature, low)
4	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, normal) has_value(temperature, normal)	10	cardiac_arrest	has_value(pulse, none) has_value(blood_pressure, very_low) has_value(temperature, normal)
5	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, low) has_value(temperature, normal)	11	cardiac_arrest	has_value(pulse, none) has_value(blood_pressure, very_low) has_value(temperature, low)
6	myocardial_ infarction	has_value(pulse, irregular) has_value(blood_pressure, very_low) has_value(temperature, normal)			

Partial information X may be given that includes the information that the person has a normal temperature. Such a set X can be added to the background theory W. Table 2 shows the extensions resulting when the following facts are added to W:

X = { has_value(temperature, normal), has_value(pulse, irregular) }

Table 2. All extensions given the changed background theory

#	Condition	Values
1	myocardial_infarction	has_value(pulse, irregular) has_value(blood_pressure, normal) has_value(temperature, normal)
2	myocardial_infarction	has_value(pulse, irregular) has_value(blood_pressure, low) has_value(temperature, normal)
3	myocardial_infarction	has_value(pulse, irregular) has_value(blood_pressure, very_low) has_value(temperature, normal)

Finally, Table 3 shows the extensions when the following set X is added to W:

X = { has_value(temperature, normal) , has_value(pulse, normal) , has_value(blood_pressure, normal) }

Table 3. All extensions of the default theory

#	Condition	Values
1	healthy_awake	has_value(pulse, normal) has_value(blood_pressure, normal) has_value(temperature, normal)

4.3 Crime Case Default Theory

Similar to the Elderly Wristband, the default theory Δ_{CT} for the crime case has been generated from the causal model:

has_value(situation, conflict) / has_value(situation, conflict)
has_value(situation, drinks_alcohol) / has_value(situation, drinks_alcohol)
has_value(testosterone, high) / has_value(testosterone, high)
has_value(sounds, aggressive) / has_value(sounds, aggressive)
has_value(ankle_ethanol_level, high) / has_value(ankle_ethanol_level, high)
has_value(aggressiveness, high) / has_value(aggressiveness, high)
has_value(alcohol_level, high) / has_value(alcohol_level, high)
not(has_value(situation, conflict) / not(has_value(situation, conflict))
not(has_value(situation, drinks_alcohol) / not(has_value(situation, drinks_alcohol))
not(has_value(testosterone, high) / not(has_value(testosterone, high))
not(has_value(sounds, aggressive) / not(has_value(sounds, aggressive))
not(has_value(ankle_ethanol_level, high) / not(has_value(ankle_ethanol_level, high))
not(has_value(aggressiveness, high) / not(has_value(aggressiveness, high))
not(has_value(alcohol_level, high) / not(has_value(alcohol_level, high))

Furthermore, aggressive sound has been observed, therefore the following fact is added to W:

X = {has_value(sound, aggressive)}

The resulting number of extensions is 18. Hereby however, the reasoning has not been performed using a closed world assumption, whereby values can only occur in case they result from a known causal relation or in case they are input variables (i.e. the situation). In order to perform reasoning with such a closed world assumption, the following rules have been added. First, a rule expressing that in case there is only one source from which a value can be derived, then this source should have the appropriate value (in this case, this holds for all variables except for aggressiveness).

has_value(X1, Y1) $\wedge$ leads_to(has_value(X2, Y2), has_value(X1, Y1)) $\wedge$ X1 $\neq$ aggressiveness $\rightarrow$
has_value(X2, Y2)

For the aggressiveness a different set of rules is used, since only one out of three conditions needs to hold. An example of one instance of such a rule is the following:

has_value(aggressivness, high) ∧ not(has_value(testosterone, high) ∧ not(has_value(situation, conflict) → has_value(alcohol_level, high)

Given that these rules are added, 7 extensions result using Smodels as shown in Table 4. Note that the sound is not shown since that is fixed in advance already. The last column shows to which suspect this extension is applicable. Hereby the suspect with high testosterone is marked with 1, the oversensitive alcohol suspect with 2, and the IED suspect with 3.

Table 4. Extensions given that aggressive sound has been observed

#	Situation	Testosterone	Aggressiveness	Alcohol level	Ankle Ethanol level	Suspect
1	¬conflict; ¬drinks_alcohol	high	high	¬high	¬high	1
2	conflict; ¬drinks_alcohol	high	high	¬high	¬high	1
3	conflict; ¬drinks_alcohol	¬high	high	¬high	¬high	3
4	conflict; drinks_alcohol	high	high	high	high	1
5	conflict; drinks_alcohol	¬high	high	high	high	2, 3
6	¬conflict; drinks_alcohol	¬high	high	high	high	2
7	¬conflict; drinks_alcohol	high	high	high	high	1

5 Discussion

This paper shows how a number of known techniques and tools developed within the area of nonmonotonic reasoning and AI can be applied to analyse model-based interpretation. The formal techniques exploited in the approach, are causal graphs and causal reasoning in conjunction with techniques from the nonmonotonic reasoning area such as: multi-interpretation operators as an abstract formalisation multiple interpretation and a default theory to represent this multi-interpretation operator. Model-based default refinement can be useful to obtain (on top of sensor information) a high level of context awareness; see also [17, 18, 19]. The properties and default rules presented in this paper have all been specified in a generic fashion, such that they can easily be reused for studying other cases.

More formalisms for handling causal or temporal reasoning within ambient intelligence have been proposed, see e.g. [11]. The application of nonmonotonic logic as put forward in this paper adds the possibility to specify human like reasoning in a natural way, possibly even resulting in multiple stable sets that can be the outcome of such a reasoning process.

Currently, the approach put forward is a theoretical framework, whereby case studies have been conducted on paper. Future work is to see how well such a theoretical framework can be applied in a practical setting, for example for elderly care or crime analysis. Issues such as how to extract the appropriate information needed within the system from domain experts, how useful the system can be in supporting human decision makers, and how accessible the method can be made for people not familiar with formal methods will need to be addressed.

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