A Logic Programming Approach
to Regression Based Repair of Incorrect Initial Belief States

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This paper introduces a combination of regression and belief revision to allow agents to deal with inconsistencies while executing plans. Starting from an inconsistent history consisting of actions and observations, the proposed framework **(1)** computes the initial belief states that support the actions and observations and **(2)** uses a belief revision operator to repair the false initial belief state. The framework operates on domains with static causal laws and supports arbitrary sequences of actions. The paper illustrates how logic programming can be effectively used to support these processes.

1 Introduction

In reasoning about actions and change, sensing actions have been considered as the mean for agents to *refine* their knowledge in presence of incomplete knowledge. A sensing action helps an agent to determine the truth value of an *unknown* fluent. For example, the action *look* helps the agent to determine whether the light in the kitchen is *on* or off ($\neg on$). Initially, the agent's knowledge about the state of the world is described by the set $\{\{on\}, \{\neg on\}\}$, which represents the set of *possible states* that she thinks she might be in. The execution of the *look* action will help the agent to decide whether the current state of the world is $\{on\}$ or $\{\neg on\}$. A sensing action *does not change the world* and its effect is about the knowledge of the agent. Current approaches to dealing with sensing actions in action languages or situation calculus, such as those proposed in [4, 7], often make a fundamental implicit assumption: the reasoning agent has *correct* information. This also means that these approaches cannot be directly applied to situations in which the reasoning agent has completely *incorrect* information (or beliefs) about the world. For example, when the agent believes that the light is *on*, but after executed action *look*, she observes that the light is actually off ($\neg on$). In this case, the agent has to *correct* her initial belief that the light is off. Generally, it means that agents need to be able to incorporate observations and update their beliefs while executing a plan. In this paper, we propose an approach that combines regression and belief revision to allow agents to correct their initial belief state.

2 Background: The Action Language $\mathscr{B}_S$

We adopt the language $\mathscr{B}_S$ introduced in [2]. An action theory in $\mathscr{B}_S$ is defined over two disjoint sets, a set of actions **A** and a set of fluents **F**. A *fluent literal* is either a fluent $f \in \mathbf{F}$ or its negation $\neg f$. A *fluent formula* is a propositional formula constructed from fluent literals. An action theory is composed

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of statements of the following forms:

$$e \textbf{ if } \{p_1,\ldots,p_n\} \quad (1) \qquad a \textbf{ executable\_if } \{p_1,\ldots,p_n\} \quad (3)$$

$$a \textbf{ causes } \{e_1,\ldots,e_n\} \textbf{ if } \{p_1,\ldots,p_m\} \quad (2) \qquad a \textbf{ determines } f \quad (4)$$

where a is an action, f is a fluent, e, e_i are literals representing *effects* and p_i are literals indicating *preconditions*. (1) represents a *static causal law*. (2) represents a *dynamic causal law*. (3) encodes an *executability condition*. (4) is called a *knowledge producing law*. We assume that sensing actions do not occur in dynamic causal laws. An *action theory* is a pair (D,Ψ_0) where Ψ_0 is a fluent formula, describing the *initial state*, and D, called *action domain*, consists of laws of the form (1)–(4). The notions of a state, a belief state, entailment between states or belief states and formula, etc. are defined as usual. For a fluent formula ψ, $\Sigma_\psi = \{s \mid s \text{ is a state in } D \text{ s.t. } s \models \psi\}$, i.e., Σ_ψ is the belief state satisfying ψ. A domain D defines a transition function Φ_D between belief states (see, e.g., [2]). This function is extended to define $\widehat{\Phi}_D$ for reasoning about the effects of action sequences in the usual way.

Definition 1. *Let $T = (D,\Psi_0)$ be an action theory. A* history *of T is a sequence of pairs of actions and observations $\alpha = [(a_1,\psi_1),\ldots,(a_n,\psi_n)]$ where a_i is an action and ψ_i is a fluent formula. We assume that if a_i is a sensing action for the fluent f, then either $\Psi_i \models f$ or $\Psi_i \models \neg f$. We say that the history α is* inconsistent *with T if there exists some k, $1 \le k \le n$, such that $\widehat{\Phi}([a_1,\ldots,a_k],\{\Sigma_{\Psi_0}\}) \not\models \psi_k$.*

Given an inconsistent history α, we are interested in the problem of identifying the correct initial belief state of the agent, say Ψ'_0, such that for every k, $1 \le k \le n$, such that $\widehat{\Phi}([a_1,\ldots,a_k],\{\Sigma_{\Psi'_0}\}) \models \psi_k$.

3 Recovering from Inconsistent Histories

We propose a method that combines regression and belief revision for recovering from inconsistent histories. We start with the definition of a regression function. This function is different for sensing and non-sensing actions.

Regression by non-sensing actions. Let a be a non-sensing action and ψ and φ be conjunctions of fluent literals. We say φ is a *result* of the regression of a from ψ, denoted by $\varphi \stackrel{a}{\to} \psi$, if $\forall s \in \Sigma_\varphi.(\Phi(a,s) \models \psi)$.

Regression by sensing actions. Let a be a sensing action and ψ and φ be conjunctions of fluent literals. We say φ is a *result* of the regression of a from ψ, denoted by $\varphi \stackrel{a}{\to} \psi$, if there exists some $\Sigma \in \Phi(a,\Sigma_\varphi)$ such that $\Sigma \models \psi$.

We define the *regression of action a from ψ*, denoted by $\mathscr{R}(a,\psi)$, as follows:

$$\mathscr{R}(a,\psi) = \bigvee_{\varphi \stackrel{a}{\to} \psi} \varphi \quad (5) \qquad \mathscr{R}(a,\psi) = \bigvee_{i=1}^{k} \mathscr{R}(a,\psi_i) \quad (6)$$

where ψ is a conjunction of literal in (5) and in (6) it is a DNF formula. We also extend the regression function in order to deal with a history $\alpha = [(a_1,\psi_1),\ldots,(a_n,\psi_n)]$ for $n \ge 1$ as $\widehat{\mathscr{R}}(\alpha)$.

Definition 2. *Let (D,Ψ_0) be an action theory. Let $\alpha = [(a_1,\psi_1),\ldots,(a_n,\psi_n)]$ be a history and $\widehat{\Phi}(\alpha,\{\Sigma_{\Psi_0}\}) \not\models \psi_n$. The corrected initial belief state of (D,Ψ_0) is defined by $\Psi_0 \star \widehat{\mathscr{R}}(\alpha)$.*

There are several proposals for the operator $\star$, and as pointed out in [1], only the operator proposed in [3] satisfies all AGM postulates. In this paper, we make use of the following two operators.

- Satoh's revision operator [5]
- Dalal's belief revision operator [3]

4 A Logic Programming Implementation and Results

The main purpose of the Prolog implementation is to guide the development of the definitions in the previous section and validate our ideas as we proceeded. Moreover it gives an overview of strengths and weakness of the theory from a pragmatic point of view. We modified the robot-rooms example from [6] to test our code, it is described as follows.

Example 1. *Initially, the robot is in the room n and believes that all lights are on. It makes a tour, from room n to* $1,\ldots,n-1$*. In each room, the robot looks at the light. At the end of the tour, it realizes that its initial belief is incorrect (*$\neg on(n-1)$ *is observed and it supposed to be* $on(n-1)$*).*

We tested with $n = 1,\ldots,10$ and the system returns the result within 30 minutes. We observe that the size of the domain, in terms of the number of fluents and the number of actions, plays a significant role in the performance of the system. For $n = 10$, we have 20 fluents and the number of potential regression results for a non-sensing action (e.g., `leave(k)`) is small but checking whether or not a potential regression result is a computed regression result involves checking the number of possible states given a set of formulae, which could range from 2^1 to 2^{19}. We observe that the system spends most of the time doing just that.

5 Conclusions

In this paper, we explore the problem of correcting the initial beliefs of an agent who, after executing a sequence of actions and making observations along the history, realizes that her initial beliefs are incorrect. Given an inconsistent history, the approach starts by regressing from the final to the first observation and revising the initial beliefs using the result of the regression. Unlike similar approaches explored in the literature, we consider sensing actions in the presence of static causal laws and propose algorithms for computing the correct initial beliefs.

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