The Autonomous Agent Architecture

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Abstract

In this paper we give a summary of the Autonomous Agent Architecture (AAA architecture for short) for intelligent agents. The AAA architecture is the result of several years of research on the design and implementation of intelligent agents that reason about, and act in, changing environments. In the AAA architecture, the knowledge about the domain where the agent is situated is encoded in Answer Set Prolog and is *shared by all of the reasoning components*. The agent's reasoning components are also formalized in Answer Set Prolog. Typical AAA agents are capable of observing the environment, interpreting the observations, recovering from unexpected observations, and planning to achieve their goals.

1 Introduction

The *Autonomous Agent Architecture* (*AAA architecture* for short) is an architecture for the design and implementation of software components of intelligent agents reasoning about, and acting in, a changing environment. The AAA architecture is based around a control loop, called *Observe-Think-Act Loop*, consisting of the following steps:

1. Observe the world, explain the observations, and update the agent's knowledge base;

2. Select an appropriate goal, G;

3. Find a plan (sequence of actions $a_1, \ldots, a_n$) to achieve G;

4. Execute part of the plan, update the knowledge base, and go back to step 1.

Generally speaking, we view an architecture as a specification of (1) the agent's control, (2) the type and representation of the agent's knowledge, and (3) how the basic operations, or *primitives* (e.g. goal selection, planning), are performed. The agent's control for the AAA architecture is the Observe-Think-Act Loop. The representation of knowledge and the execution of the primitives are based on the following assumptions: (a) The world (including an agent and its environment) can be modeled by a transition diagram whose nodes represent physically possible states of the world and whose arcs are labeled by actions – the diagram therefore contains all possible trajectories of the system; (b) The agent is capable of making correct observations, performing actions, and remembering the domain history; (c) *Normally* the agent is capable of observing all relevant exogenous events occurring in its environment. Notice that the observations made at step 1 of the loop need not be complete, or taken at every iteration. However, according to the assumptions just given, those observations must be correct. The interested reader can refer to [21] for a study of reasoning algorithms that can deal with wrong or false observations.

The knowledge of a AAA agent is encoded by a knowledge base written using Answer Set Prolog (ASP) [17, 18, 11] and the Answer Set Programming methodology [24]. At the beginning of this research, our original goal was in fact to investigate if the knowledge representation capabilities of ASP could be used to represent the agent's knowledge, and if the primitives, such as diagnostics or planning, could be reduced to reasoning with ASP. With time, we came to the realization that, although ASP is sufficient in many situations, in some cases it is not. For these cases, we used CR-Prolog [8, 2, 5] (whose development in fact is rooted in the research on the AAA architecture) and P-log [13, 20, 14]. In the remainder of the discussion, whenever there is no need to make a distinction, we loosely use the term "ASP" to refer to both the original language and its extensions

The AAA architecture was first suggested in [12]. Various reasoning algorithms have been developed and refined along the years, most notably diagnostic reasoning [7], planning [10], and inductive learning [3]. Throughout this paper we illustrate the architecture and its use for agent design using the scenarios based upon a simple electrical circuit. The domain is deliberately simple but we hope it is sufficient to illustrate the basic ideas of the approach. Furthermore, in spite of the simplicity of the domain used here, it is important to note that the corresponding algorithms are rather scalable. In fact, they were successfully used in rather large, industrial size applications [10].

2 Building the Action Description

The electrical circuit that we will be referring to is depicted in Figure 1. Circuit C_0 consists of a battery (*batt*), two safety switches (sw_1, sw_2), and two light bulbs (b_1, b_2). By *safety switches* we mean switches with a locking device. To move a switch from its current position, the switch must first be unlocked. The switch is automatically locked again after it is moved. If all of the components are working properly, closing a switch causes the corresponding bulb to light up.

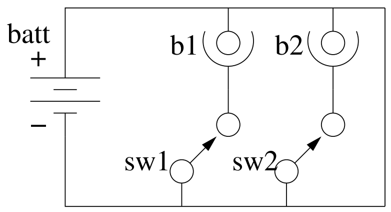


Figure 1: C_0: A simple electrical circuit

Next, we describe in more detail how we model the circuit, and introduce some useful terminology.

The state of the circuit is modeled by the following *fluents* (properties whose truth changes over time): $closed(SW)$: switch SW is closed; $locked(SW)$: switch SW is locked; $on(B)$: bulb B is on; $ab(B)$: bulb B is malfunctioning; $down(BATT)$: battery $BATT$ has run down. When a fluent f is false, we write $\neg f$.

The agent interacts with the circuit by means of the following *actions*: $flip(SW)$: move switch SW from open to closed, or vice-versa; $unlock(SW)$: unlock SW; $replace(BATT)$, $replace(B)$: replace a battery or a bulb.

We allow in the formalization actions whose occurrence is beyond the agent's control (e.g., a bulb blowing up). These actions are called *exogenous*. Relevant exogenous actions for this domain are: $run\_down(BATT)$: battery $BATT$ runs down; $blow\_up(B)$: B blows up. Note that actions can occur concurrently. We distinguish between *elementary actions*, such as the ones listed above, and *compound actions*, i.e. sets of elementary actions, intuitively corresponding to the simultaneous execution of their components. In the remainder of this paper we abuse notation slightly and denote singletons by their unique component. We also use the term "action" to denote both elementary and compound actions.

The behavior of the domain is described by laws. Depending upon the approach used, the laws can be written using *action languages* [19] and later translated to ASP, or encoded directly as ASP rules. To save space, here we adopt the direct encoding in ASP. A possible encoding of the effects of actions $unlock(SW)$ and $close(B)$ is:

$$\neg holds(locked(SW), S+1) \leftarrow occurs(unlock(SW), S).$$

$$holds(closed(SW), S+1) \leftarrow occurs(flip(SW), S),\ \neg holds(closed(SW), S).$$

$$\neg holds(closed(SW), S+1) \leftarrow occurs(flip(SW), S),\ holds(closed(SW), S).$$

$$\begin{aligned} holds(on(B), S) \leftarrow\ & holds(closed(SW), S), \\ & connected(SW, B),\ \neg holds(ab(B), S), \\ & \neg holds(down(batt), S). \end{aligned}$$

where variables SW, B, S range, respectively, over switches, bulbs, and non-negative integers denoting steps in the evolution of the domain. The first law intuitively states that unlocking SW causes it to become unlocked. This is called a *direct effect* of action $unlock(SW)$. Laws describing the direct effects of actions are usually called *dynamic laws*. The second and third laws encode the effects of flipping a switch, and they, too, are dynamic laws. The last law says that, if *SW* is closed and connected to some bulb *B* in working order while the battery is not down, then *B* is lit. This law describes an *indirect effect, or ramification,* of an action. Such laws are usually called *static laws* or *state constraints*.

Similar laws encode the effects of the other actions and the behavior of malfunctioning bulbs and battery. The encoding of the model is completed by the following general-purpose axioms:

$$holds(F,S+1) \leftarrow holds(F,S),\ \text{not}\ \neg holds(F,S+1).$$
$$\neg holds(F,S+1) \leftarrow \neg holds(F,S),\ \text{not}\ holds(F,S+1).$$

where F ranges over fluents, S over steps. The rules encode the principle of inertia "things normally stay as they are."

Now, we turn our attention to the reasoning algorithms, and to the corresponding agent's behavior. For each reasoning algorithm, we select a scenario in which the main reasoning algorithm used is the one of interest. (Because various steps of the Observe-Think-Act loop are interconnected, most scenarios involve multiple algorithms.)

3 Planning Scenario

The idea of planning using Answer Set Programming dates back to [27, 15], where it had been demonstrated that planning could be reduced to computing the answer sets of suitable programs. What was not clear to us was if, and how, the approach could be extended to medium and large sized applications. The conclusions of our research on this issue, initially presented in [25] and later extended in [10], showed that the basic planning technique had to be complemented with control knowledge [23, 22] in order to improve the efficiency of planning in medium and large domains. We also showed that such control knowledge could be easily encoded using ASP, as well as integrated into the planner in an incremental fashion.

To understand how the ASP planning technique is tied into the AAA architecture, consider the following scenario, based upon the domain introduced in the previous section.

Example 1 *Initially, all bulbs of circuit C_0 are off, all switches open and locked, and all components are working correctly. The agent's goal is to turn on b_1.*

The intended agent behavior is as follows. At step 1 of the Observe-Think-Act loop, the agent gathers observations about the environment. Recall that, in general, the observations need not be complete, or taken at every iteration. Let us assume, however, for simplicity that at the first iteration of the agent's observations are complete. At step 2, the agent selects goal $G = on(b_1)$. At step 3, it looks for a plan to achieve G and finds $\langle unlock(sw_1), flip(sw_1)\rangle$. Next, the agent executes $unlock(sw_1)$, records the execution of the action, and goes back to observing the world.

Suppose the agent observes that sw_1 is unlocked. Then, no explanations for the observations are needed. The agent proceeds through steps 2 and 3, and selects the plan $\langle flip(sw_1)\rangle$. Next, it executes $flip(sw_1)$ and observes the world again. Let us assume that the agent indeed discovers that b_1 is lit. Then, the agent's goal is achieved.

The key feature that allows exhibiting the described behavior is in the capability to find a sequence of actions $\langle a_1,\dots,a_k\rangle$ that achieves G. The task involves both *selecting* the appropriate actions, and *ordering* them suitably. For example, the sequence of actions $\langle unlock(sw_2), flip(sw_1)\rangle$ is not a good selection, while $\langle flip(sw_1), unlock(sw_1)\rangle$ is improperly ordered.

To determine if a sequence of actions achieves the goal, the agent uses its knowledge of the domain to predict the effects of the execution of the sequence. This is accomplished by reducing planning to computing answer sets of an ASP program, consisting of the ASP encoding of the domain model, together with a set of rules informally stating that the agent can perform any action at any time (see e.g. [26]).

This technique relies upon the fact that the answer sets of the ASP encoding of the domain model together with facts encoding the initial situation and occurrence of actions are in one-to-one correspondence with the corresponding paths in the transition diagram. This result, as well as most of the results used in this and the next section, is from [7]. We invite the interested reader to refer to that paper for more details. Simple iterative modifications of the basic approach allow one to find shortest plans, i.e. plans that span the smallest number of steps.

To see how this works in practice, let us denote by AD the action description from the previous section, and consider a simple encoding, O_1, of the initial state from Example 1, which includes the facts $\{holds(locked(sw_1),0),\ \neg holds(closed(sw_1),0),\ \neg holds(on(b_1),0)\}$ (more sophisticated encodings are also possible). A simple yet general *planning module* PM_1, which finds plans of up to n steps, consists of the rule:

$$occurs(A,S) \text{ OR } \neg occurs(A,S) \leftarrow cS \leq S < cS+n.$$

where A ranges over agent actions, S over steps, and cS denotes the current step (0 in this scenario). Informally, the rule says that any agent action A may occur at any of the next n steps starting from the current one. The answer sets of program $\Pi_1 = AD \cup O_1 \cup PM_1$ encode all possible trajectories, of length n, from the initial state. For example, the trajectory corresponding to the execution of $unlock(sw_1)$ is encoded by the answer set $O_1 \cup \{occurs(unlock(sw_2),0),\ \neg holds(locked(sw_2),1),\ \neg holds(on(b_1),1),\ \dots\}$. Note that $\neg holds(on(b_1),1)$ is obtained from O_1 and the inertia axioms.

To eliminate the trajectories that do not correspond to plans, we add to Π_1 the following rules:

$$\begin{array}{l} goal\_achieved \leftarrow holds(on(b1),S). \\ \leftarrow \text{not } goal\_achieved. \end{array}$$

which informally say that goal $on(b1)$ must be achieved. Let us denote the new program by Π'_1. It is not difficult to see that the previous set of literals is not an answer set of Π'_1. On the other hand, (if $n \geq 2$) Π'_1 has an answer set containing $O_1 \cup \{occurs(unlock(sw_1),0), \neg holds(locked(sw_1),1), occurs(flip(sw_1),1),$ $holds(closed(sw_1),2), holds(on(b_1),2)\}$, which encode the trajectory corresponding to the execution of the sequence $\langle unlock(sw_1), flip(sw_1)\rangle$.

4 Interpretation Scenario

Another important feature of the AAA architecture is the agent's ability to interpret unexpected observations. Consider for instance the scenario:

Example 2 *Initially, all of the bulbs of circuit C_0 are off, all switches open and locked, and all of the components are working correctly. The agent wants to turn on b_1. After planning, the agent executes the sequence $\langle unlock(sw_1), flip(sw_1)\rangle$, and notices that b_1 is not lit.*

The observation is unexpected, as it contradicts the expected effects of the actions the agent just performed. Intuitively, a possible explanation of this discrepancy is that b_1 blew up while the agent was executing the actions (recall that all of the components were initially known to be working correctly). Another explanation is that the battery ran down.[1]

To find out which explanation corresponds to the actual state of the world, the agent will need to gather additional observations. For example, to test the hypothesis that the bulb blew up, the agent might check the bulb. Suppose it is found to be malfunctioning. Then, the agent can conclude that $blow\_up(b_1)$ occurred in the past. The fact that b_1 is not lit is finally explained, and the agent proceeds to step 3, where it re-plans.

The component responsible for the interpretation of the observations, often called *diagnostic component*, is described in detail in [7]. Two key capabilities are needed to achieve the behavior described above: the ability to detect unexpected observations, and the ability to find sequences of actions that, had they occurred undetected in the past, may have caused the unexpected observations. These sequences of actions correspond to our notion of *explanations*.

The detection of unexpected observations is performed by checking the consistency of the ASP program, Π_d, consisting of the encoding of the domain model, together with the history of the domain, and the Reality Check Axioms and Occurrence-Awareness Axiom, both shown below. The history is encoded by statements of the form $obs(F,S,truth\_val)$ (where $truth\_val$ is either t or f, intuitively meaning "true" and "false") and $hpd(A,S)$, where F is a fluent and A an action. An expression $obs(F,S,t)$ (respectively, $obs(F,S,f)$) states that F was observed to hold (respectively, to be false) at step S. An expression $hpd(A,S)$ states that A was observed to occur at S. The Reality Check Axioms state that it is impossible for an observation to contradict the agent's expectations:

$$\begin{array}{l} \leftarrow holds(F,S), obs(F,S,f). \\ \leftarrow \neg holds(F,S), obs(F,S,t). \end{array}$$

Finally, the Occurrence-Awareness Axiom ensures that the observations about the occurrences of actions are reflected in the agent's beliefs: $occurs(A,S) \leftarrow hpd(A,S)$. It can be shown that program Π_d is inconsistent if-and-only-if the history contains unexpected observations.

To find the explanations of the unexpected observations, the agent needs to search for sequences of exogenous actions that would cause the observations (possibly indirectly), if they had occurred in the past.

[1]Of course, it is always possible that the bulb blew up *and* the battery ran down, but we do not believe this should be the first explanation considered by a rational agent.

In the early stages of our research, we investigated reducing this task to reasoning with ASP [6, 7]. Although the results were positive, we were not able to find an elegant way to specify, in ASP, that diagnoses should be minimal. That led us to the development of CR-Prolog [8, 2, 5], which solves the issue with minimal diagnoses and, overall, allows for rather elegant, declarative formalizations.

In CR-Prolog, programs consist of regular ASP rules and of *cr-rules*. A cr-rule is a statement of the form $r : l_0 \overset{+}{\leftarrow} l_1, \ldots, l_m, \text{not } l_{m+1}, \ldots, \text{not } l_n$, where r is a (possibly compound) term denoting the name of the cr-rule and l_i's are ASP literals. The rule intuitively says "if $l_1, \ldots, l_m$ hold and there is no reason to believe $l_{m+1}, \ldots, l_n$, l_0 *may possibly* hold, but that happens rarely." Informally, this possibility should be used only if the regular rules alone are not sufficient to form a consistent set of beliefs. In the CR-Prolog terminology, we say that cr-rules are used to *restore consistency*. The name of the cr-rule is used in specifying preferences between cr-rules. The interested reader can find more about preferences in [8].

As described in [10], the exogenous nature of an action e can be formalized in CR-Prolog by one or more cr-rules of the form (cr-rules are not needed to encode the direct and indirect effects of the action): $r(e,S) : occurs(e,S) \overset{+}{\leftarrow} \Gamma$, where Γ is a condition under which the exogenous action may occur. The rule informally states that, under those conditions, the exogenous action may possibly occur, but that is a rare event. Then, let EX be the set of cr-rules:

$$r(run\_down(BATT),S) : occurs(run\_down(BATT),S) \overset{+}{\leftarrow} .$$
$$r(blow\_up(B),S) : occurs(blow\_up(B),S) \overset{+}{\leftarrow} .$$

informally stating that $run\_down(BATT)$ and $blow\_up(B)$ may possibly (but rarely) occur. Consider now program Π_2 consisting of AD and the encoding of the initial state O_1 from the previous section[2], together with the Occurrence-Awareness Axiom, EX, and the history $H_1 = \{hpd(unlock(sw_1),0),\ hpd(flip(sw_1),1),\ obs(on(b_1),2,f)\}$. It is not difficult to show that the answer sets of Π_2 correspond to the *set-theoretically minimal* explanations of the observations in H_1. If no unexpected observation is present in H_1, the answer sets encode an empty explanation. Furthermore, specifying preferences between cr-rules allows one to provide information about the relative likelihood of the occurrence of the exogenous actions. More details can be found in [9].

In the next section, we discuss the specification of policies in the AAA architecture.

5 Policies and Reactivity

Here by *policy* we mean the description of those paths in the transition diagram that are not only possible but also *acceptable* or *preferable*. The ability to specify policies is important to improve both the quality of reasoning (and acting) and the agent's capability to *react* to the environment.

In this section we show how the AAA architecture, and in particular the underlying ASP language, allows one to easily specify policies addressing both aspects.

[2]The initial state described by O_1 could also be re-written to use statements $obs(F,S,truth\_val)$.

We begin by considering policies allowing one to improve the quality of reasoning. More details can be found in [1, 10]. In the circuit domain, one policy addressing this issue could be "do not replace a good bulb." The policy is motivated by the consideration that, although technically possible, the action of replacing a good bulb should in practice be avoided. A possible ASP encoding of this policy is $\leftarrow occurs(replace(B),S), \neg holds(ab(B),S)$. Note that, although the rule has the same form as the executability conditions, it is conceptually very different. Also note that this is an example of a *strict* policy because it will cause the action of replacing a good bulb to be *always* avoided.

Often it is useful to be able to specify *defeasible policies*, i.e. policies that are *normally* complied with but may be violated if really necessary. Such policies can be elegantly encoded using CR-Prolog. For example, a policy stating "if at all possible, do not have both switches in the closed position at the same time" can be formalized as:

$$\begin{array}{l} \leftarrow holds(closed(sw_1),S), holds(closed(sw_2),S), \\ \quad \text{not } can\_violate(p_1). \\ r(p_1) : can\_violate(p_1) \overset{+}{\leftarrow} . \end{array}$$

The first rule says that the two switches should not be both in the closed position *unless the agent can violate the policy*. The second rule says that it is possible to violate the policy, but only if strictly necessary (e.g., when no plan exists that complies with the policy).

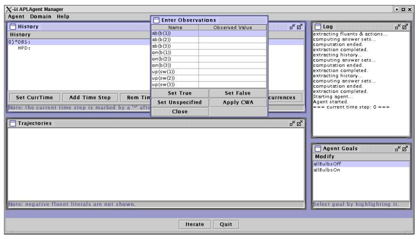
Now we turn our attention to policies improving the agent's *capability to react to the environment*. When an agent is interacting with a changing domain, it is often important for the agent to be able to perform some actions in response to a state of the world. An example is leaving the room if a danger is spotted. Intuitively, selecting the actions to be performed should come as an immediate reaction rather than as the result of sophisticated reasoning. We distinguish two types of reaction: *immediate reaction* and *short reaction*. Immediate reaction is when actions are selected based solely upon observations. An example from the circuit domain is the statement "if you observe a spark from closed switch SW, open it," which can be formalized as (assume SW is unlocked and fluent $spark\_from(SW)$ is available):

$$occurs(flip(SW),S) \leftarrow obs(spark\_from(SW),S),\ obs(closed(SW),S).$$

A short reaction is the occurrence of an action triggered by the agent's beliefs. This includes conclusions *inferred* from observations and possibly other beliefs. An example is the statement "if a battery is failing, replace it," encoded as: $occurs(replace(BATT),S) \leftarrow holds(failing(BATT),S)$. It is worth noting that similar policies can also be used, in reasoning about multi-agent environments, to model the behavior of the other agents [4].

6 Implementation of the AAA Architecture

A prototype that implements the AAA architecture is available from: `http://krlab.cs.ttu.edu/~marcy/APLAgentMgr/`. The program, called *APLAgent Manager*, is implemented in Java and allows the user to specify observations (Figure 2), execute a number of iterations of the Observe-Think-Act Loop, and inspect the agent's decisions (Figure 3) and expectations about the future (Figure 4). APLAgent Manager comes with pre-compiled implementations of the Observe-Think-Act Loop, but also allows using a customized version of the loop.



```
History
0)*OBS:
   HPD:
```

Note: the current time step is marked by a '*' afte

Name	Observed Value
ab(b(1))	
ab(b(2))	
ab(b(3))	
on(b(1))	
on(b(2))	
on(b(3))	
up(sw(1))	
up(sw(2))	
up(sw(3))	

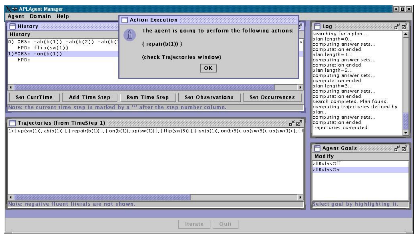
```
extracting fluents & actions...
computing answer sets...
computation ended.
extraction completed.
extracting history...
computing answer sets...
computation ended.
extraction completed.
extracting history...
computing answer sets...
computation ended.
extraction completed.
Starting agent...
Agent started.
=== current time step: 0 ===
```

allBulbsOff
allBulbsOn

Note: negative fluent literals are not shown.

Select goal by highlighting it.

Figure 2: Specifying observations at a given time step.



```
History
0) OBS: -ab(b(1)) -ab(b(2)) -ab(b(
   HPD: flip(sw(1))
1)*OBS: -on(b(1))
   HPD:
```

The agent is going to perform the following actions:

{ repair(b(1)) }

(check Trajectories window)

Note: the current time step is marked by a '*' after the step number column.

```
1) { up(sw(1)), ab(b(1)) }, { repair(b(1)) }, { on(b(1)), up(sw(1)) }, { flip(sw(3)) }, { on(b(1)), on(b(3)), up(sw(3)), up(sw(1)) }, { f
```

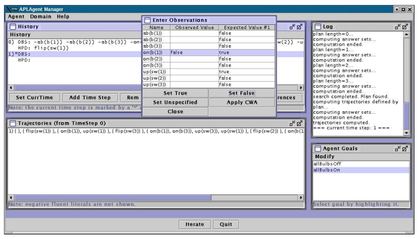
```
searching for a plan...
plan length=0...
computing answer sets...
computation ended.
plan length=1...
computing answer sets...
computation ended.
plan length=2...
computing answer sets...
computation ended.
plan length=3...
computing answer sets...
computation ended.
search completed. Plan found.
computing trajectories defined by
plan...
computing answer sets...
computation ended.
trajectories computed.
```

allBulbsOff
allBulbsOn

Note: negative fluent literals are not shown.

Select goal by highlighting it.

Figure 3: Ready to perform an action.



```
History
0) OBS: -ab(b(1)) -ab(b(2)) -ab(b(3)) -on        w(2)) -u
   HPD: flip(sw(1))
1)*OBS:
   HPD:
```

Note: the current time step is marked by a '*' a

Name	Observed Value	Expected Value #1
ab(b(1))		false
ab(b(2))		false
ab(b(3))		false
on(b(1))	false	true
on(b(2))		false
on(b(3))		false
up(sw(1))		true
up(sw(2))		false
up(sw(3))		false

```
1) { }, { flip(sw(1)) }, { on(b(1)), up(sw(1)) }, { flip(sw(3)) }, { on(b(1)), on(b(3)), up(sw(3)), up(sw(1)) }, { flip(sw(2)) }, { on(b(1
```

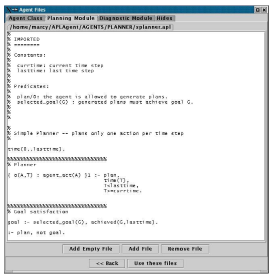
```
plan length=0...
computing answer sets...
computation ended.
plan length=1...
computing answer sets...
computation ended.
plan length=2...
computing answer sets...
computation ended.
plan length=3...
computing answer sets...
computation ended.
search completed. Plan found.
computing trajectories defined by
plan...
computing answer sets...
computation ended.
trajectories computed.
=== current time step: 1 ===
```

allBulbsOff
allBulbsOn

Note: negative fluent literals are not shown.

Select goal by highlighting it.

Figure 4: Inspecting the agent's expectations about the state of the world.



/home/marcy/APLAgent/AGENTS/PLANNER/splanner.apl

```
%
% IMPORTED
% ========
%
% Constants:
%
%  currtime: current time step
%  lasttime: last time step
%
%
% Predicates:
%
%  plan/0: the agent is allowed to generate plans.
%  selected_goal(G) : generated plans must achieve goal G.
%
%
%


%
% Simple Planner -- plans only one action per time step
%

time(0..lasttime).

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Planner

{ o(A,T) : agent_act(A) }1 :- plan,
                              time(T),
                              T<lasttime,
                              T>=currtime.


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Goal satisfaction

goal :- selected_goal(G), achieved(G,lasttime).

:- plan, not goal.
```

Figure 5: Editing a planning module.

When using the pre-compiled implementations of the Observe-Think-Act Loop, APLAgent Manager expects the user to provide formalizations of the domain and of the reasoning modules written in ASP (Figure 5).[3] More information, as well as a tutorial, can be found on the APLAgent Manager web page.

7 Conclusions

In this paper we have described an ASP-based architecture for intelligent agents capable of reasoning about and acting in changing environments. The design is based upon a description of the domain that is shared by all of the reasoning modules. The generation and execution of plans are interleaved with detecting, interpreting, and recovering from, unexpected observations. Although here we focused on explaining unexpected observations by hypothesizing the undetected occurrence of exogenous actions, the architecture has also been extended with a reasoning module capable of modifying the domain description by means of inductive learning [3]. An initial exploration of the issues of inter-agent communication and cooperation can be found in [16]. Dealing with multiple, even prioritized, goals is also possible [4].

[3]In the current version, by default the system is not configured for CR-Prolog, but the user can easily add support for CR-Prolog as well as for any other solver.

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