

Learning Context Conditions for BDI Plan Selection

Tracking Number: 170

ABSTRACT

An important drawback to the popular Belief, Desire, and Intentions (BDI) paradigm is that such systems include no element of learning from experience. In particular, the so-called *context conditions* of plans, on which the whole model relies for plan selection, are restricted to be boolean formulas that are to be specified at design/implementation time. To address these limitations, we propose a novel BDI programming framework that, by suitably modeling context conditions as *decision trees*, allows agents to *learn* the probability of success for plans based on previous execution experiences. By using a probabilistic plan selection function, the agents can balance exploration and exploitation of their plans. We develop and empirically investigate two extreme approaches to learning the new context conditions and show that both can be advantageous in certain situations. Finally, we propose a generalization of the probabilistic plan selection function that yields a middle-ground between the two extreme approaches, and which we thus argue is the most flexible and simple approach.

1. INTRODUCTION

In this paper, we are concerned with one of the key aspects of the BDI agent-oriented programming paradigm, namely, that of *intelligent plan selection* [12, 7]. Specifically, we explore the details of how effective plan selection can be learnt based on ongoing experience.

There are a plethora of agent programming languages and development platforms in the BDI tradition, such as PRS [7], JACK [5], 3APL [9] and 2APL [6], Jason [3], and SRI's SPARK [11], among others. Generally speaking, these systems enable *abstract plans* written by programmers to be combined and used in real-time, in a way that is both flexible and robust. Concretely, a BDI agent is built around a *plan library*, a collection of pre-defined *hierarchical plans* indexed by goals and representing the standard operational procedures of the domain (e.g., landing a plane). The so-called *context condition* attached to each plan states the conditions under which the plan is a sensible strategy to address the corresponding goal in a given situation (e.g., it is not raining). The execution of a BDI system relies then entirely on *context sensitive subgoal expansion*, allowing agents to “act as they go” by making *plan choices* at each level of abstraction with respect to the current situation.

The fact that both the actual behaviours (the plans) and the situ-

ations for which they are appropriate (their context conditions) are fixed at design time has important implications for the whole programming approach. First, it is often difficult or impossible for the programmer to craft the *exact* conditions under which a plan would succeed. Second, once deployed, the plan selection mechanism is fixed and may not adapt to potential variations of different environments. Finally, since plan execution often involves interaction with a *partially observable* external world, it is desirable to measure success in terms of probabilities rather than boolean values.

In [1] the authors detail why it may be problematic for learning if the BDI hierarchical structure is not taken into account. They showed why it can be problematic to assume a mistake at a higher level in the hierarchy, when a poor outcome may have been related to a mistake in selection further down. Their empirical work suggested that perhaps the advantages of an aggressive approach, where all failures were considered meaningful, outweighed the advantages of careful consideration. In this work, we show that the aggressive scheme, though simpler, can at times lead to a complete inability to learn, thus yielding a much less robust performance than the conservative alternative. Informally, the difference between the two approaches is that whereas the aggressive approach accounts for every execution failure, the conservative approach instead considers failures only when decisions made during the execution are deemed sufficiently “informed.”

In order to obtain a flexible middle-ground between the above two approaches, we devise an extended probabilistic plan selection that includes a *confidence* measure based on how much the agent has explored the space of possible executions of a given plan (Section 6). The more this space has been “covered” by previous executions, the more the agent “trusts” the estimation of success provided by the plan’s decision tree. It turns out that an agent based on the aggressive learning scheme together with the enhanced plan selection mechanism provides a flexible and simple compromise between the two extreme approaches.

We point out that our new account of plans’ context conditions is *compatible* with the standard formula-based one. Indeed, our approach can be easily combined with the standard plan selection mechanism, by allowing the agent programmer to provide initial context conditions that could be later automatically “refined” by the agent system. By doing so, one can effectively take a BDI program and “tune it” using our learning framework. For simplicity, though, context conditions are learnt from scratch in our experimental work.

2. BDI PROGRAMMING

BDI agent-oriented programming is a popular, well-studied, and practical paradigm for building intelligent agents situated in complex and dynamic environments with (soft) real-time reasoning and

control requirements [7, 2].

In a BDI-style system, an agent consists, basically, of a belief base (akin to a database), a set of recorded pending goal events, a plan library, and an intention base. While the belief base encodes the agent’s knowledge about the world, the pending events stand for the *goals* the agent wants to achieve/resolve. The *plan library*, in turn, contains *plan rules*, or simply *plans*, of the general form $e : \psi \leftarrow \delta$ encoding the standard domain operational procedure δ (that is, a program) for achieving the event-goal e when the so-called *context condition* ψ is believed true—program δ is a reasonable strategy to resolve event e whenever ψ holds. Among other operations, the plan-body program δ will typically include the execution of actions (*act*) in the environment and subgoal events (! e) that ought to be in turn resolved by selecting suitable plans for that subgoal event. Lastly, the intention base accounts for the current, partially instantiated, plans that the agent has already committed to in order to handle or achieve some event-goal.

The basic reactive goal-oriented behavior of BDI systems involves the system responding to events, the inputs to the system, by committing to handle one pending event-goal, *selecting a plan* from the library, and placing its program body into the intention base. A plan may be selected if it is *relevant* and *applicable*, that is, if it is a plan designed for the event in question and its context condition is believed true, respectively. In contrast with traditional planning, execution happens at each step. The assumption is that the use of plans’ context-preconditions to make choices as late as possible, together with the built-in goal-failure mechanisms, ensures that a successful execution will eventually be obtained while the system is sufficiently responsive to changes in the environment.

For the purposes of this paper, we shall mostly focus on the plan library, as we investigate ways of learning how agents can make a better use of it over time. It is not hard to see that, by grouping together plans responding to the same event type, the plan library can be seen as a set of *goal-plan tree* templates: a goal (or event) node has children representing the alternative relevant plans for achieving it; and a plan node, in turn, has children nodes representing the subgoals (including primitive actions) of the plan. These structures, can be seen as AND/OR trees: for a plan to succeed all the subgoals and actions of the plan must be successful (AND); for a subgoal to succeed one of the plans to achieve it must succeed (OR).

Consider, for instance, the structure depicted in Figure 1. A link from a goal to a plan means that this plan is relevant (i.e., potentially suitable) for achieving the goal (e.g., $P_1 \dots P_4$ are the relevant plans for event goal G); whereas a link from a plan to a goal means that the plan needs to achieve that goal as part of its (sequential) execution (e.g., plan P_A needs to achieve goal G_{A1} first and then G_{A2}). For compactness, an edge with a label $\times n$ states that there are n edges of such type. Leaf plans directly interact with the environment and so, in a given world state, they can either succeed or fail when executed; this is marked accordingly in the figure for *some particular world* (of course, in other states, such plans may behave differently). In some world, given successful completion of G_A first, the agent may achieve goal G_B by selecting and executing P_B , followed by selecting and executing 2 leaf working plans to resolve goals G_{B1} and G_{B2} . If the agent succeeds with goals G_{B1} and G_{B2} , then it succeeds for plan P_B , achieving thus goal G_B and the top-level goal G itself. There is no possible successful execution, though, if the agent decides to carry on any of the three plans labelled P'_{B2} for achieving the low-level goal G_{B2} .

As one can easily observe, the problem of *plan-selection* is at the core of the whole BDI approach: *which plan should the agent commit to in order to achieve a certain goal?* This problem amounts, at least partly, to what has been referred to as *means-end analysis*

in the agent foundational literature [12, 4], that is, the decision of *how* goals are achieved. To tackle the plan-selection task, state-of-the-art BDI systems leverage domain expertise by means of the context conditions of plans. However, crafting fully correct context conditions at design-time can, in some applications, be a demanding and error-prone task. In addition, fixed context conditions do not allow agents to adapt to changing environments. In the rest of the paper, we shall provide an extended framework for BDI agent systems that allows agents to learn/adapt plans’ context conditions, and discuss and empirically evaluate different approaches for such learning task.

3. A BDI LEARNING FRAMEWORK

The problem that we are interested in is as follows: *given past execution data and the current world state, determine which plan to execute next in order to address an event.*

To address this “learnable” plan-selection task, we start by modeling the context condition of plans with *decision trees*, rather than with logical formulas.¹ Decision trees [10] provide a natural classification mechanism for our purposes, as they can deal well with noise (generally due to partially observable and predictable environments), and they are able to support disjunctive hypotheses. They are also readily convertible to rules, which are the standard representation for context conditions in BDI systems.

We associate each plan in the agent’s library with a decision tree that will classify world states into an expectation of whether the plan will succeed or fail. Then for each relevant plan, the plan’s decision tree (induced based on previous executions) will give the agent information regarding how likely it is to succeed/fail in a particular world state.

Given this new context for BDI programming, there are two issues that ought to be addressed. First, one has to decide *when and what kind of execution data the agent should collect in order to be able to “learn” (useful) decision trees for plans*. Roughly speaking, data is collected regarding whether a plan is considered to have succeeded or failed in the world for which it was selected. Whereas successful executions are always recorded, the recording of failure runs of a plan may be subject to some analysis; this is the topic of the following section.

The second issue to be addressed is how to use the plans’ decision trees for plan selection. More concretely: *given a goal to be resolved and a set of relevant plans with their corresponding context decision trees, what plan should the agent commit for execution?* Typical BDI platforms offer various mechanisms for plan selection, including plan precedence and meta-level reasoning. However, these mechanisms are pre-programmed and do not take into account the experience of the agent. In our framework for context learning, we must consider the standard dilemma of *exploitation vs exploration*. To that end, we use an approach in which plans are selected with a probability proportional to their relative expected success (in the world state of interest). Moreover, in Section 6, we discuss how to further enhance such plan selection account by considering how much each candidate plan has been explored, relative to its “complexity.”

For the purpose of our analysis, we have used algorithm J48, a version of c4.5 [10], from the well-known weka learning package [17]. Currently we recreate decision trees from scratch after each new piece of data is collected. Of course, for a real-world implementation, one should appeal to algorithms for *incremental* induction of the decision tree, such as those described in [14, 16].

¹The logical formulae of the classical BDI framework can of course be combined with decision trees.

The weka J48 algorithm for inducing decision trees aims to balance compactness of representation with accuracy. Consequently, it maintains in each decision tree information about the number of instances (or world states in our case) from the training data correctly and incorrectly classified by each decision tree leaf node. Subsequently, whenever a plan’s decision tree is used to classify a new instance (world state), weka returns not only the classification (i.e. success or failure), but also a classification probability (i.e. to what degree it believes that the classification is correct). We then use this probability as an estimate of the plan’s chances of success for the world in question.

Finally, we should point out a number of assumptions that were made in order to focus on the core issues we are concerned with. First, we assume that actions in the environment may fail with some probability (if an action is not possible in a world state this probability is 1.0). Second, we assume no external changes in the environment during execution other than those made by the agent. Although this may appear too limiting, the fact that actions may fail with some probability mitigates against over-simplification by capturing external changes as non-deterministic failures. Third, we consider the execution of a single intention; learning in the context of multiple, possibly interacting, intentions poses other extra challenges that would complicate our study substantially (see [15]). Lastly, we assume no automated failure handling, whereby the BDI system retries a goal with alternative options, if the selected plan happens to fail. Integrating failure handling would not alter any of our results, but it would complicate our implementation framework and the understanding of the basic mechanisms.

4. CONTEXT LEARNING: 2 APPROACHES

With the classical BDI programming framework extended with decision trees and a probabilistic plan selection scheme, we are now ready to develop mechanisms for learning context decision trees based on online experiences, in order to improve plan selection over time. To that end, in this section, we explore two approaches for learning the context condition of plans.

Recall that our objective is to learn which plans are best for achieving a particular goal event in the various world states that may ensue. Given that, in this work, we have no measure of cost for plans,² a good plan for a given world state is simply one which (usually) succeeds in such state. In order to learn the context decision tree for a plan, the agent keeps track of previous experiences she has had when running the plan in question. More precisely, if a plan P is tried in world state w with certain outcome $o \in \{succ, fail\}$, the agent may record the tuple $\langle w, o \rangle$ as part of the training set for plan P . Interestingly, while it is always meaningful to record successful executions, some failures may not be worth recording. Based on this observation, we shall develop and compare two different algorithms that differ on how past experiences are taken into account by the agent. Before then, though, let us explain better this issue by means of an example.

Consider the example in Figure 1. Suppose that in some execution, plan P_i , for some $i \in \{1, \dots, 4\}$, is selected in order to resolve top-goal G in some world state w_1 . The plan involves, in turn, the successful resolution of sequential goals G_A and G_B . Suppose further that subgoal G_A has been resolved successfully, yielding new state w_2 , and that plan P_B has been chosen next to try and achieve the second subgoal G_B . Suppose next that the first subgoal of plan P_B , namely G_{B1} has been successfully resolved, yielding new state w_3 , but that the non-working plan P'_{B2} for sub-

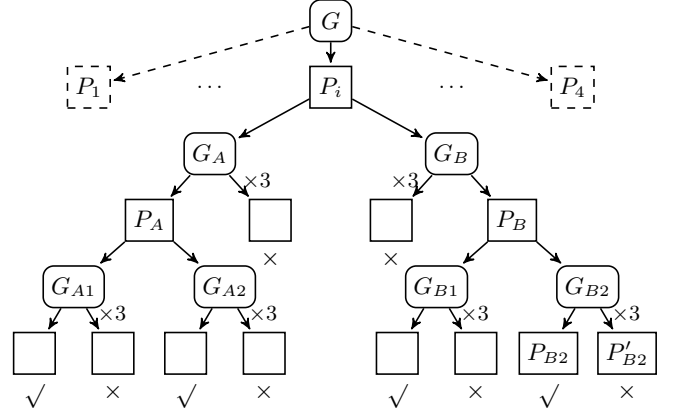


Figure 1: Goal-plan hierarchy T_3 . There are 2^4 worlds whose solutions are distributed evenly in each of the 4 top level plans. Successful execution traces are of length 4. Within each subtree P_i , BUL is expected to perform better for a given world, but it suffers in the number of worlds. Overall, ACL and BUL perform equally well in this structure.

goal G_{B2} is selected in w_3 and execution thus fails. As there is no failure recovery, this failure will be propagated upwards in the hierarchy, causing goals G_{B2} as well as G_B and top-level goal G itself to fail. First of all, the failure (in world state w_3) must be recorded in the decision tree of the plan where the failure originated, namely, plan P'_{B2} . Such bottom-level plans have no subgoals, so they interact with the external world directly, and over time we can expect to learn such interactions. On the other hand, as we will show below, it is not so clear whether the failure should also be recorded in the decision trees for plans higher up in the hierarchy (e.g., plans P_B and P_i).

In order to discuss further *which* data should be recorded *where*, we define the notion of an *active execution trace*, as a sequence of the form $G_0[P_0 : w_0] \cdot G_1[P_1 : w_1] \cdot \dots \cdot G_n[P_n : w_n]$, which represents the sequence of currently active goals, along with the plans which have been selected to achieve each of them, and the world state in which the selection was made—plan P_i has been selected in world state w_i in order to achieve the i -th active subgoal G_i . In our example, the trace at the moment of failure is as follows:

$$\lambda = G[P_i : w_1] \cdot G_B[P_B : w_2] \cdot G_{B2}[P'_{B2} : w_3].$$

So, when the final goal of λ fails, namely G_{B2} , it is clear that the decision tree of the plan being used to achieve such goal ought to be updated, and a failure should be recorded for the world state w_3 against the decision tree attached to plan P'_{B2} . By recording every outcome for the lowest plans, i.e., plans with no subgoals, the system eventually learns how such plans perform in the environment.

What is more difficult to determine is whether the decision trees of plans associated with *earlier goals* in λ should also be updated. More concretely, should failure cases in world states w_2 and w_1 be recorded against plans P_B and P_i , respectively? The point is that it is conceivable that the failure of subgoal G_{B2} in plan P_B , for instance, could indeed have been avoided, had the alternative plan P_{B2} , been chosen instead. Therefore, recording a failure against plan P_B would not be justified—it is not true that plan P_B is a “bad” one in world state w_2 . Informally, one could argue that it is more appropriate to *wait* before recording failures against a plan until one is reasonably confident that subsequent choices down the

²This could also be a useful addition, but is not part of standard BDI programming languages.

goal-plan tree hierarchy were “well informed.” In our case, if the agent knows that the plan selection for goal G_{B2} was as good and informed as possible, then recording the failure for world w_2 in plan P_B would also be justified. Similarly, if the agent considers that the plan selection for subgoal G_B was an informed choice, then recording the failure for world w_1 against P_i ’s decision tree would be justified too.

The judgment as to whether plan choices were sufficiently “well informed,” is however not a trivial one. A plan P is considered to be *stable* for a particular world state w if the rate of success of P in w is changing below a certain threshold ϵ . In such a case, the agent can start to build confidence about the applicability level of P . The stability notion extends to goals as follows: a goal is considered *stable* for world state w if all its relevant plans are stable for w . When a goal is stable, we regard the plan selection for such goal as a “well informed” one. Thus, a failure is recorded in the plan for a given world if the subgoal that failed is stable for the respective world in which it was resolved. In our example, we record the failure in plan P_B (P_i) if goal G_{B2} (G_B) is deemed stable in world state w_3 (w_2), that is, if the selection of option P'_{B2} (P_B) was an informed one.

The RecordFailedTrace algorithm below shows how a failed execution run λ is recorded. Function $\text{StableGoal}(G, w, k, \epsilon)$ returns true iff goal G is considered *stable* for world state w , for success rate change threshold $0 < \epsilon \leq 1$ and minimal number of executions $k \geq 0$. The algorithm starts by recording the failure against the last plan P_n in the trace. Next, if the choice of executing plan P_n to achieve goal G_n was deemed an informed one (that is, goal G_n was stable for w_n), then the procedure should be repeated for the previous goal-plan nodes, if any. If, on the other hand, the last goal G_n in the trace is not considered stable enough, the procedure terminates and no more failure data is assimilated. Observe that, in order to update the decision tree of a certain plan that was chosen along the execution, it has to be the case that the (failed) decisions taken during execution must have all been informed ones.

Algorithm 1 RecordFailedTrace(λ, k, ϵ)

Require: $\lambda = G_0[P_0 : w_0] \dots G_n[P_n : w_n]$; $k \geq 0$; $\epsilon > 0$

Ensure: Propagates DT updates for plans

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1: RecordWorldDT( $P_n, w_n, fail$ )
2: if StableGoal( $G_n, w_n, k, \epsilon$ )  $\wedge |\lambda| > 1$  then
3:    $\lambda' := G_0[P_0 : w_0] \dots G_{n-1}[P_{n-1} : w_{n-1}]$ 
4:   RecordFailedTrace( $\lambda', k, \epsilon$ ) // recursive call
5: end if
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So, in the remainder of the paper, we shall consider two learning approaches compatible with the framework developed in the previous section. The first, which we call *aggressive concurrent learning* (ACL), corresponds to the more traditional approach where all data is always assimilated by the learner, that is, we take $\epsilon = 1$ and $k = 0$. In other words, every plan and every goal is always considered stable and, as a result, a failure in a plan is always recorded. The assumption is that misleading information, as discussed above, will eventually disappear as noise. The second one, which we refer to as *bottom-up learning* (BUL), is more cautious and records a failure execution experience when the success rate has stabilised i.e. is not changing by more than ϵ . In our work, we have taken $\epsilon = 0.3$ and $k = 3$, that is, the context condition of a plan is considered stable (for a world state) if at least 3 past execution experiences have been recorded and the change in the rate of success over the last two experiences is less than 0.3. Note that the lower ϵ is and the higher k is, the more conservative the agent is in considering its decisions “well informed.”

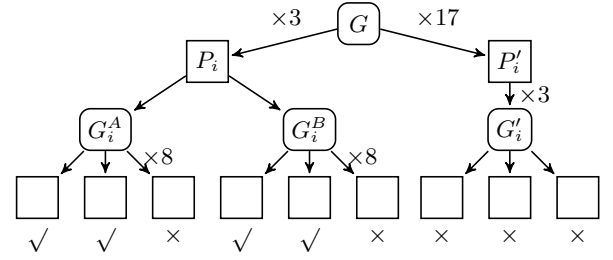


Figure 2: Goal-plan tree structure T_1 . To succeed, an agent needs to make three correct choices, including selecting P_i at the top-level. The solutions to 2^3 worlds are distributed evenly in the 3 plans P_i . ACL outperforms BUL in this structure.

In the following section, we shall explore these two approaches against different programs with different structures.

5. EXPERIMENTAL RESULTS

In order to explore the difference between BUL and ACL, we set up testbed programs composed of several goals and plans combined in a hierarchical manner and yielding goal-plan tree structures of different shapes.³ In particular, we crafted goal-plan tree structures representing different cases of BDI programs with one main top-level goal, i.e., the event to be resolved. In addition, for each structure there is always a way of addressing the main goal, i.e. there is at least one successful execution of the top-level event provided the right plan choices are made. Observe that such successful (plan) choices are different for different world states. When it comes to describing the possible (observable) world states, we have used a set of logical (binary) propositions, representing the so-called fluents or features of the environment that are observable to the agent (e.g., fluent proposition *DoorLocked* states whether the door is believed open or not). Finally, we assume the agent is acting in a non-deterministic environment, in which actions that are expected to succeed may still fail with some (small) probability. In our experiments, we assumed a 0.1 probability of uncontrolled failure for all actions.⁴

The experiments consisted in posting the top-level goal repetitively under random world states, running the corresponding BDI learning agent, and finally recording whether the execution terminated successfully or not. We calculate the average rate of success of the goal by first averaging the results at each time step over 5 runs of the same experiment, and then smoothing using a moving average of the previous 100 time steps to get the trends reported in the figures. We ran the tests with both a BUL-based agent and a ACL-based agent, ensuring the same sampling of random world states for each.

From our set of experiments, we have selected three hierarchical structures that best illustrate the results that we have obtained, namely:

(Tree T_1 ; Figure 2) For each world state, the goal has a few plans

³We have implemented the learning agent system in the JACK BDI platform [5]. The fact that JACK is a Java-based system and provides powerful meta-level reasoning capabilities, allows us to integrate weka and probabilistic plan-selection mechanisms with not much effort. Nonetheless, all the results are independent on this and any other BDI agent system could have been used.

⁴See Discussion section on how our results generalize to a framework with world state built from non-binary fluents and with more complex accounts for stochastic actions.

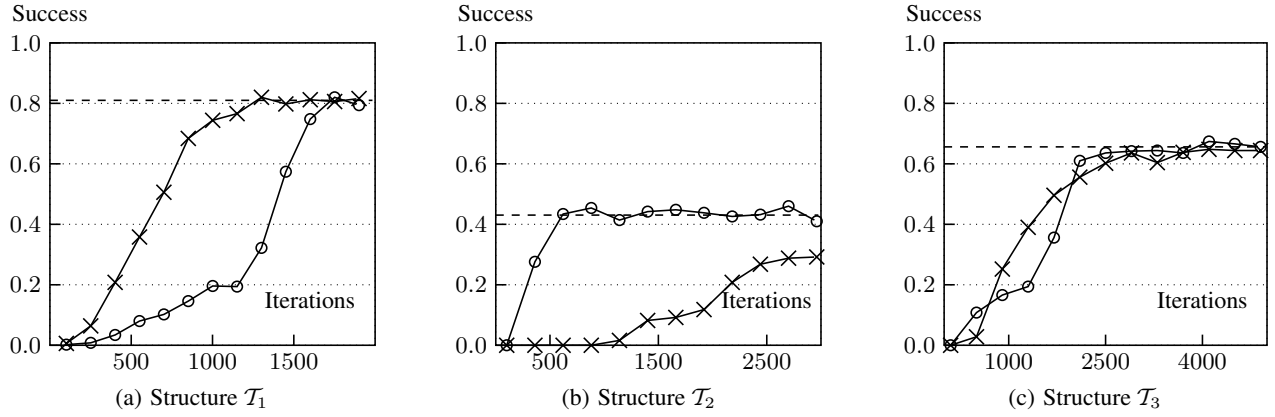


Figure 4: Agent performance under BUL (circles) and ACL (crosses) schemes. Each point represents results from 5 experiment runs using an averaging window of 100 samples. The dashed line represents optimal performance (Note that outcomes are always 0 or 1 so more than expected consecutive successes may seem like “above” optimal performance when averaged).

for a certain event goal, that event goal is failed right away.

To understand the impact of applicability in our BDI learning framework, we modified the probabilistic plan selection so that the agent does *not* consider plans whose chances of success are deemed below a threshold; in our case we set this threshold to 0.2. For simplicity, we removed the non-determinism in the model of the environment: actions either fail or succeed in each world state.

Using the structure T_3 we found that whereas the BUL scheme maintains its performance (and in fact may slightly improve due to truly failing leaf plans being ruled out earlier), the ACL approach may not be able to learn at all and could end up eventually failing the top-level goal *always*. This is reported in Figure 6 (dotted lines).

The explanation for this undesirable behavior under ACL is as follows. Initially, the agent tries all top-level plans for the top-level goal, including the ones containing potential successful executions. Because of their complexity, the chance of finding a successful execution immediately is very low, and most executions fail initially. With each failure, ACL decreases the feasibility of all plans tried, including the top-level one. After several failures, all plans for the top-level goal eventually go below the applicability threshold of the system (including the “good” plans). When that happens, the system has no more applicable plans for the goal and will therefore fail it always. This behavior does not arise in the original system, because even if all plans perform very poorly, the agent would always pick one anyway, the successful path would be eventually be found, and the context decision trees of the plans associated with such a path would then start “recovering.”

The reason BUL exhibits more robust behaviour here is that false negative executions (i.e., failing executions of plans that do encode successful runs) will *not* be recorded. The BUL approach relies on a *confidence* test—stability—that checks whether we are sufficiently well informed to trust that the current failure is indicative of future attempts. In the next section, we explore an alternative approach to confidence that takes account of how sure we are of the decision tree when we use it, rather than using stability as a confidence measure for deciding when to record.

6. INFORMED PLAN SELECTION

Our new approach relies on the idea that confidence in a plan’s decision tree increases as more of the possible choices below the plan in the goal-plan structure are explored.

So, with each plan in the goal-plan tree hierarchy, we identify its set of potential *choices* as the set of all potential execution paths *below* the plan in the hierarchy. This can easily be computed offline. Intuitively, a plan’s decision tree is more *informed* for a world state if it is based on a larger number of choices having been explored in that state. We say that a plan has a higher degree of *coverage* as more of its underlying choices are explored and accounted for in the corresponding decision tree. Technically, given a decision tree T for a certain plan, we define its coverage for the world state w as $c_T(w) \in [0, \dots, 1]$. Initially, when the plan has not yet been executed in a world w , its coverage in such state is $c_T(w) = 0$ and the agent has no basis for confidence in the likelihood of success estimated by T for w . As the different ways of executing the plan in the world state w are explored, the value of $c_T(w)$ approaches 1. When all choices have been tried, $c_T(w) = 1$ and the agent may rely fully on the decision tree estimation of success. In this way, coverage provides a confidence measure for the decision tree classification.

We then construct a probabilistic plan selection function that includes the coverage-based confidence measure. Formally, we define the plan selection weight $\Omega'(w)$ as a function of the decision tree determined success expectation $p_T(w)$ and the degree of coverage $c_T(w)$:

$$\Omega'_T(w) = 0.5 + [c_T(w) * (p_T(w) - 0.5)].$$

Initially the selection weight of the plan for a previously unseen world state w takes the default value of 0.5. Over time, as the various execution paths below the plan are tried in w , its coverage increases and the selection weight approaches the true value estimated by the plan’s decision tree.

Each time a plan execution result is recorded, the coverage $c_T(w)$ for a world w is calculated and stored. It requires, in principle, $\tau \times |S|$ *unique* executions of a plan for it to reach *full* coverage, where τ is the total number of choices below the plan and $|S|$ is the number of possible worlds. Practically, however, it takes significantly less since choices below a plan are effectively an AND/OR tree, and each time an AND node fails, the subsequent nodes are not tried and are counted as covered for the world in question. Also, a plan is generally not executed in every world state, so in practice it will only need to be assessed in the subset of the world states that is relevant to it.

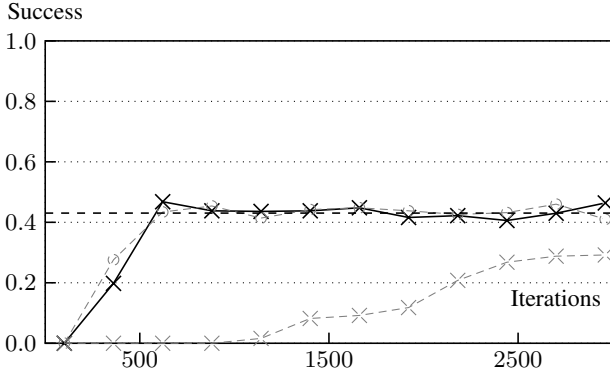


Figure 5: Performance of ACL+Ω' (solid crosses) in structure \mathcal{T}_2 compared against the earlier results for ACL+Ω and BUL+Ω (both in dotted grey).

We are now ready to revisit the two learning approaches ACL and BUL from the previous section, but this time using the modified selection weighting based on coverage. We will refer to the new approaches as ACL+Ω' and BUL+Ω', respectively. Similarly, ACL+Ω and BUL+Ω correspond to the approaches using the *original* selection weighting that only uses its decision tree success expectation, that is, $\Omega_T(w) = p_T(w)$.

Our first observation is that the BUL+Ω and BUL+Ω' approaches show similar performance. This is not surprising, as the stability test performed by these agents at each plan node inherently results in close to full coverage. Indeed, for a plan to become “stable,” the agent needs to (substantially) explore all possible ways of executing it. The stability check, then, effectively reduces $\Omega'_T(w)$ to $\Omega_T(w)$. So, for simplicity, we shall not give a further account of the BUL+Ω' approach in this section.

We now focus on the ACL approach. For the ACL-favouring structure \mathcal{T}_1 , we find that the performance of ACL+Ω' matches that of ACL+Ω reported earlier in Figure 4(a). Similarly, for the balanced structure \mathcal{T}_3 where previously both ACL and BUL performed equally well, the performance of ACL+Ω' was the same as that reported for ACL+Ω earlier in Figure 4(c). Thus, for the cases where ACL+Ω was performing reasonably well, the new ACL+Ω approach maintains comparable performance.

The benefit of the coverage-based approach is apparent, though, when one considers the goal-plan structure \mathcal{T}_2 in which the ACL+Ω performed poorly (cf. Figure 4(b)). Here, the ACL+Ω' scheme showed a dramatic improvement over ACL+Ω. Figure 5 shows this change with the results for the new approach to plan selection ACL+Ω' superimposed over the original results from Figure 4(b). The reason why the new plan selection mechanism improves the ACL learning scheme is that even though the success estimation $p_T(w)$ for a given plan P_i would still be low initially (remember that ACL, in contrast with BUL, would record all initial failure outcomes for P_i), the agent would not be very confident in such estimation until the plan's coverage increases; therefore the selection weight $\Omega'_T(w)$ will initially bias towards the default weight of 0.5. In other words, the false negative outcomes collected by the agent for plan P_i would not be considered so seriously due to low plan coverage. As full coverage is approached, one would expect the agent to have discovered the success execution encoded in P_i .

Even more interesting is the impact of the new plan selection mechanism on agents that work with an applicability threshold, i.e., agents that may not select plans that are deemed unlikely

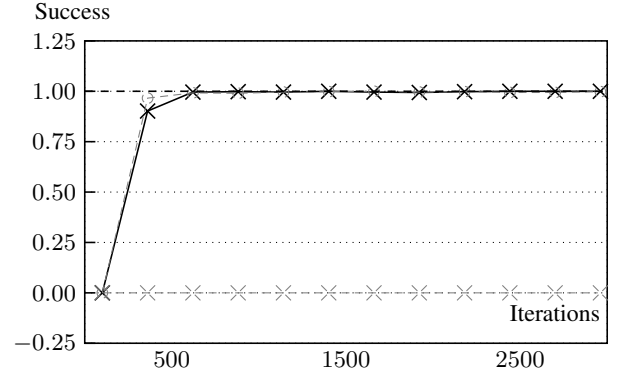


Figure 6: Performance of ACL+Ω' (solid crosses) compared against ACL+Ω and BUL+Ω (both in dotted grey) in structure \mathcal{T}_2 using an applicability threshold of 0.2.

to succeed. Here, the original ACL+Ω approach completely fails, as it collects many negative experiences early on, quickly causing plans' success expectation to fall below the selection threshold. For ACL+Ω', even if a plan is deemed with very low expectation of success, its selection weight would be biased towards the default value of 0.5 if it has not been substantially “covered.” Hence, provided that the applicability threshold is lower than the default plan selection weight, then ACL+Ω' is indeed able to find the solution(s). Figure 6 shows the ACL+Ω' performance in goal-plan structure \mathcal{T}_2 for an applicability threshold of 0.2.

The above results show that the coverage-based confidence weighting can improve the performance of the ACL approach in those cases where it performed poorly due to false negative experiences, i.e., failure runs for a plan that includes successful executions. Furthermore, coverage provides a flexible mechanism for tuning agent behaviour depending on application characteristics. Consider equation $\Omega'_T(w)$ with the coverage term modified to $c_T(w)^{1/\alpha}$, with parameter $\alpha \in [0, \dots, \infty)$. Interestingly, as $\alpha \approx 0$, ACL+Ω' will behave more like BUL+Ω: $c_T(w)^{1/\alpha}$ transitions directly from 0 to 1 when $c_T(w)$ reaches 1 (and remains zero otherwise). On other hand, when $\alpha \approx \infty$, ACL+Ω' will behave more like the ACL+Ω: $c_T(w)^{1/\alpha}$ transitions from 0 to 1 faster and $\Omega'(w) \approx p_T(w)$. With $\alpha = 1$ we get our initial equation. It follows then that ACL+Ω' provides a *middle ground* between the ACL+Ω and BUL+Ω schemes.

Finally, we note that coverage-based selection weights encourage the agent to explore all available options. This further ensures that all solutions are systematically found, allowing the agent to decide which solution is optimal faster. For some domains this may be an important feature.

7. DISCUSSION AND CONCLUSION

In this paper, we proposed a technique to enhance the typical plan selection mechanism in BDI systems by allowing agents to learn and adapt the context conditions of plans in the agent's plan library. As designing adequate context conditions that take full account of the agent's environment for its complete life-cycle is a non-trivial task, a framework that allows for the *refinement* of (initial) context conditions of plans *based on online experience* is highly desirable. To this end, we extended the typical BDI programming framework to use decision trees as (part of) plan's context conditions and provided a probabilistic plan selection mechanism that caters for both exploration and exploitation of plans. After empirically evaluating different learning strategies suitable for

BDI agents against various kinds of plan libraries, we concluded that an aggressive learning approach combined with a plan selection scheme that uses a confidence measure based on the notion of plan coverage is the best candidate for the general setting. The work carried out here is significant for the BDI agent-oriented programming community, in that it provides a solid foundation for going beyond the standard static kind of BDI agents.

The framework presented here made a number of simplifying assumptions. We did not consider the effects of conflicting interactions between sub-goals of a plan. In fact, the way a sub-goal is resolved may affect how the next sub-goal can be addressed or even if it can be resolved at all. Our current approach will not detect and learn such interactions; each subgoal is treated “locally.” To handle such interactions, the selection of a plan for resolving a sub-goal should also be predicated on the goals higher than the sub-goal, that is, it should take into account the “reasons” for the sub-goal. Similarly, we did not consider the effects of using goal failure recovery, under which alternative plans for a goal are tried upon the failure of a plan. Also, we have only dealt with domains described via boolean propositions. To handle continuous attributes (e.g., discretize *temperature*), our approach requires that either these attributes are discretized (e.g., *cold*, *warm*, and *hot*) or additional discrete attributes be used to test the continuous ones (e.g. $temperature < 25.2$).

One critique of the coverage-based confidence measure used is that it has a defined end state, namely $c_T(w) = 1$. In a real system, however, learning and re-learning will occur indefinitely, as the agent continually tries to *adapt* to a changing environment. This implies that an agent’s confidence in a decision tree’s classification would also require calibration when the environment has changed. If the change was deliberate, then our confidence could be reset and subsequently *re-built*. Without such an explicit signal, the agent must rely on other methods for determining when the environment has changed significantly. An appealing measure for recognising environmental changes is through the relatedness of its features. For instance, an observation that the grass is *wet* may have a high correlation to the fact that it is *raining*. If at some point, the agent were to witness a world where it is not raining but the grass is indeed wet (for some other new reasons), then this world would be “atypical,” and as a result, the agent may have reason to reduce its confidence in a plan’s decision tree classification of this new world. It turns out that efficient algorithms exist—some already included in the weka library—that perform inference in and learning of Bayesian networks [10], which the agent can appeal to in building a model of the environment for the purposes just described.

The issue of combining learning and deliberative approaches for decision making in autonomous systems has not been widely addressed. In [13], learning is used *prior to deployment* for acquiring low level robot soccer skills that are then treated as fixed methods in the deliberative decision making process once deployed. Hernández et al. [8] give a preliminary account of how decision trees may be induced on plan failures in order to find an alternative logical context conditions in a deterministic paint-world example. More recently, [18] proposes a method for learning hierarchical task network (HTN) method preconditions under partial observations. There, a set of constraints are constructed from observed decomposition trees that are then solved *offline* using a constraint solver. Despite HTN systems being automated planning frameworks, rather than execution frameworks, these are highly related to BDI agent systems when it comes to the *know-how* information used—learning methods’ preconditions amounts to learning plan’s context conditions. In contrast, in our work, learning and deliberation are fully integrated in a way that one impacts the other and

the classical exploration/exploitation dilemma applies.

Our work is similar to that of [1] and in fact borrows from there the strategy of using decision trees for modeling plan’s context conditions. Nonetheless, there are major differences between that work and ours. First, our conservative learning approach, based on the notion of plan “stability,” is substantially more grounded than the one used in [1], where a plan is just required to be executed a *fixed* number of times for failure executions to be recorded. Second, only one goal-plan hierarchical structure was used for experimentation in the mentioned work; we instead considered different structures identifying various types of plan libraries. More importantly, in our work, we explored the realistic case of agents with plan applicability thresholds. Contrary to what was implied in [1], our results do suggest that some sort of *confidence* test is indeed worthwhile—this was the motivation behind our coverage-based approach.

8. REFERENCES

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