Deliberative Acting, Online Planning and Learning with Hierarchical Operational Models

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Abstract

The most common representation formalisms for automated planning are descriptive models that abstractly describe what the actions do and are tailored for efficiently computing the next state(s) in a state-transition system. However, real-world acting requires operational models that describe how to do things, with rich control structures for closed-loop online decision-making in a dynamic environment. To use a different action model for planning than the one used for acting causes problems with combining acting and planning, in particular for the development and consistency verification of the different models.

As an alternative, we define and implement an integrated acting-and-planning system in which both planning and acting use the same operational models, which are written in a general-purpose hierarchical task-oriented language offering rich control structures. The acting component, called Reactive Acting Engine (RAE), is inspired by the well-known PRS system, except that instead of being purely reactive, it can get advice from the planner. Our planner uses a UCT-like Monte Carlo Tree Search procedure, called UPOM (UCT Procedure for Operational Models), whose rollouts are simulations of the actor’s operational models. We also present learning strategies for use with RAE and UPOM that acquire, from online acting experiences and/or simulated planning results, a mapping from decision contexts to method instances as well as a heuristic function to guide UPOM. Our experimental results show that UPOM and our learning strategies significantly improve the acting efficiency and robustness of RAE. We discuss the asymptotic convergence of UPOM by mapping its search space to an MDP.

Keywords: Acting and planning, Operational Models, Hierarchical Actor, Real Time Planning, Supervised Learning

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1. Introduction

While several representations have been proposed for describing and reasoning about actions, most planning algorithms work with descriptive models, which represent actions with abstract preconditions and effects. This representation is inherited from the early STRIPS system [20], formalized in the PDDL description languages [62, 22, 23, 33] and their variants for nondeterministic and probabilistic domains, e.g., PPDDL [94] and RDDL [76].

Operational models are tailored to efficiently compute abstract state transitions; they specify what might happen as a result of an action, assuming that the problem of how to achieve the action is dealt with by other means. When plans are intended to be carried out by an autonomous actor, the usual planning approaches require to map the descriptive models used for planning into the more complex operational models that the actor needs in order to perform its actions. Acting requires a context dependent reasoning about ongoing activities, reacting and adapting to an unfolding situation. Operational models address this need by describing how to perform the actions, with rich control structures for closed-loop online decision-making.
Some approaches for the integration of planning and acting use descriptive action models for planning, and operational action models for acting [42]. However, this decomposition has several drawbacks. First, it fails to take into account the highly interconnected reasoning that is required between planning and deliberative acting in most practical settings. Second, in several applications, the mapping between descriptive and operational models is complex. A guarantee of the consistency of this mapping is required in safety-critical applications, such as self-driving cars [34], collaborative robots working directly with humans [85], or virtual coaching systems to help patients with chronic diseases [73]. However, to verify the consistency between the two different models is usually difficult (e.g., see the work on formal verification of operational models such as PRS-like procedures, using model checking and theorem proving [78, 5]). Finally, modeling is always a costly bottleneck; reducing the corresponding efforts is beneficial in most applications.

Therefore, it is highly desirable to have a single representation for both acting and planning. If such a representation were solely descriptive, it wouldn’t provide sufficient functionality. Instead, the planner needs to be able to reason directly with the actor’s operational models.

This paper describes an integrated planning and acting system in which both planning and acting use the actor’s operational models. The acting component, called Refinement Acting Engine (RAE), is inspired by the well-known PRS system [41]. RAE uses a hierarchical task-oriented operational representation in which an expressive, general-purpose language offers rich programming control structures for online decision-making. A collection of refinement methods describes alternative ways to handle tasks and react to events. A method can be any complex algorithm, including subtasks, which need to be refined recursively, and primitive actions, which query and change the world non-deterministically. We assume at this stage that methods are manually programmed (approaches for learning method bodies are discussed in Section 8).

Rather than behaving purely reactively, RAE interacts with a planner. To choose how best to refine tasks, the planner uses a Monte Carlo Tree Search procedure, called UPOM, which assesses the utility of possible alternatives and finds an approximately optimal one. Two utility functions are proposed favoring respectively the acting efficiency (reciprocal of the cost) and robustness (success ratio). Planning is performed with the same constructs and operations of the operational model, except that methods and actions are executed in a simulated world rather than the real one. When a refinement method contains an action, UPOM takes samples of its possible outcomes, using either a domain-dependent generative simulator, when available, or a probability distribution of its effects.

UPOM is used by RAE as a progressive deepening, receding-horizon anytime planner. Its scalability requires heuristics. However, operational models lead to quite complex search spaces not easily amenable to the usual techniques for

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1 Prior results about this approach have been presented in [28, 69, 70, 71]. The last paragraph of Section 2 describes what the current paper adds to that work.
domain-independent heuristics. Fortunately, this issue can be addressed with a learning approach to acquire a mapping from decision contexts to method instances; this mapping provides the base case of the anytime strategy. Learning can also be used to acquire a heuristic function to guide the search. We do not claim any contribution on the learning techniques per se, but on the integration of learning, planning, and acting. We use an off-the-shelf learning library with appropriate adaptation for our experiments. The learning algorithms do not provide the operational models needed by the planner, but they do several other useful things. First, they speed up the online planning search. Second, they enable both the planner and the actor to find better solutions, thereby improving the actor’s performance. Third, they allow the human domain author to write refinement methods without needing to specify a preference ordering in which the planner or actor should try instances of those methods.

The paper is structured as follows. Following a discussion of the state of the art, Section 3 describes the hierarchical operational models. In Sections 4, 5, and 6, respectively, we present the acting component RAE, the planning component UPOM, and the learning procedures for RAE and UPOM. We provide an experimental evaluation of the approach in Section 7, followed by a discussion and conclusion. The planner’s asymptotic convergence to optimal choices is detailed in Appendix A, and Appendix B is a table of notation.

2. Related Work

To our knowledge, no previous approach has proposed the integration of planning, acting and learning directly with operational models.

Our acting algorithm and operational models are based on the Refinement Acting Engine, RAE algorithm [28, Chapter 3], which in turn is inspired from PRS [41]. If RAE needs to choose among several eligible refinement method instances for a given task or event, they make the choice without trying to plan ahead. This approach has been extended with some planning capabilities in PropicePlan [13] and SeRPE [28]. Unlike our approach, those systems model actions as classical planning operators; they both require the action models and the refinement methods to satisfy classical planning assumptions of deterministic, fully observable and static environments, which are not acceptable assumptions for most acting systems. Moreover, these works do not perform any kind of learning.

Various acting approaches similar to PRS and RAE have been proposed, e.g., [21, 79, 81, 3, 64, 66]. Some of these have refinement capabilities and hierarchical models, e.g., [86, 88, 4]. While such systems offer expressive acting environments, e.g., with real time handling primitives, none of them provides the ability to plan with the operational models used for acting, and thus cannot integrate acting and planning as we do. Most of these systems do not reason about alternative refinements, and do not perform any kind of learning.

Online planning and acting is addressed in many approaches, e.g., [65, 30, 29], but their notion of “online” is different from ours. For example, in [65], the old plan is executed repeatedly in a loop while the planner synthesizes a new
plan, which isn’t installed until planning has been finished. In UPOM, hierarchical task refinement is simulated to do the planning, and can be interrupted anytime when RAE needs to act.

The Reactive Model-based Programming Language (RMPL) [40] is a comprehensive CSP-based approach for temporal planning and acting, which combines a system model with a control model. The system model specifies nominal as well as failure state transitions with hierarchical constraints. The control model uses standard reactive programming constructs. RMPL programs are transformed into an extension of Simple Temporal Networks with symbolic constraints and decision nodes [89, 11]. Planning consists in finding a path in the network that meets the constraints. RMPL has been extended with error recovery, temporal flexibility, and conditional execution based on the state of the world [15]. Probabilistic RMPL are introduced in [77, 57] with the notions of weak and strong consistency, as well as uncertainty for contingent decisions taken by the environment or another agent. The acting system adapts the execution to observations and predictions based on the plan. RMPL and subsequent developments have been illustrated with a service robot which observes and assists a human. Our approach does not handle time; it focuses instead on hierarchical decomposition with Monte Carlo rollout and sampling.

Behavior trees (BT) [7, 8, 10] can also respond reactively to contingent events that were not predicted. In [7, 8], BT are synthesized by planning. In [10] BT are generated by genetic programming. Building the tree refines the acting process by mapping the descriptive action model onto an operational model. We integrate acting, planning, and learning directly in an operational model with the control constructs of a programming language. Moreover, we learn how to select refinement methods and method instances in a natural and practical way to specify different ways of accomplishing a task.

Our methods are significantly different from those used in HTNs [67]: to allow for the operational models needed for acting, we use rich control constructs rather than simple sequences of primitives. Learning HTN methods has also been investigated. HTN-MAKER [39] learns methods given a set of actions, a set of solutions to classical planning problems, and a collection of annotated tasks. This is extended for nondeterministic domains in [37]. [38] integrates HTN with Reinforcement Learning (RL), and estimates the expected values of the learned methods by performing Monte Carlo updates. At this stage, we do not learn the methods but only how to choose the appropriate one.

A wide literature on MDP planning and Monte Carlo Tree Search refers to simulated execution, e.g., [17, 18, 43] and sampling outcomes of action models e.g., RFF [84], FF-replan [92], or hindsight optimization [93]. In particular, our UPOM procedure is an adaptation of the popular UCT algorithm [53], which has been used for various games and MDP planners, e.g., in PROST for RDDL domains [50]. The main conceptual and practical difference with our work is that these approaches use descriptive models, i.e., abstract actions on finite MDPs. Although most of the papers refer to online planning, they plan using descriptive models rather than operational models. There is no integration of acting and planning, hence no concerns about the planner’s descriptive models versus the
actor’s operational models. Moreover, they have no notion of hierarchy and refinement methods, and do not provide any learning mechanism.

There has been a lot of work in robotics to integrate planning and execution. They propose various techniques and strategies to handle the inconsistency issues that arise when execution and planning are done with different models. [54] shows how HTN planning can be used in robotics. [25] and [26] integrates task and motion planning for robotics. The approach of [63] addresses a problem similar to ours but specific to robot navigation. Several methods for performing a navigation task and its subtasks are available, each with strong and weak points depending on the context. The problem of choosing a best method instance for starting or pursuing a task in a given context is stated as a receding horizon planning in an MDP for which a model-explicit RL technique is proposed. Our approach is not limited to navigation tasks; it allows for richer hierarchical refinement models and is combined with a powerful Monte-Carlo tree search technique.

The Hierarchical Planning in the Now (HPN) of [46] is designed for integrating task and motion planning and acting in robotics. Task planning in HPN relies on a goal regression hierarchized according to the level of fluents in an operator preconditions. The regression is pursued until the preconditions of the considered action (at some hierarchical level) are met by current world state, at which point acting starts. Geometric reasoning is performed at the planning level (i) to test ground fluents through procedural attachment (for truth, entailment, contradiction), and (ii) to focus the search on a few suggested branches corresponding to geometric bindings of relevant operators using heuristics called geometric suggesters. It is also performed at the acting level to plan feasible motions for the primitives to be executed. HPN is correct but not complete; however when primitive actions are reversible, interleaved planning and acting is complete. HPN has been extended in a comprehensive system for handling geometric uncertainty [47].

The integration of task and motion planning problem is also addressed in [90], which uses an HTN approach. Motion primitives are assessed with a specific solver through sampling for cost and feasibility. An algorithm called SAHTN extends the usual HTN search with a bookkeeping mechanism to cache previously computed motions. In comparison to this work as well as to HPN, our approach does not integrate specific constructs for motion planning. However, it is more generic regarding the integration of planning and acting.

Approaches based on temporal logics and situation calculus [14, 32, 6, 19] specify acting and planning knowledge through high-level descriptive models and not through operational models like in RAE. Moreover, these approaches integrate acting and planning without exploiting the hierarchical refinement approach described here.

Our approach shares some similarities with the work on planning by reinforcement learning (RL) [45, 83, 27, 55, 24], since we learn by acting in a (simulated) environment. However, most of the works on RL learn policies that map states to actions to be executed, and learning is performed in a descriptive model. We learn how to select refinement method instances in an operational
model that allows for programming control constructs. This main difference holds also with works on hierarchical reinforcement learning, see, e.g., [91], [68], [75]. Works on user-guided learning, see e.g., [60], [59], use model based RL to learn relational models, and the learner is integrated in a robot for planning with exogenous events. Even if relational models are then mapped to execution platforms, the main difference with our work still holds: Learning is performed in a descriptive model. [44] uses RL for user-guided learning directly in the specific case of robot motion primitives.

Learning planning domain models has been investigated along several approaches. In probabilistic planning, for example [74], or [49], learn a POMDP domain model through interactions with the environment, in order to plan by reinforcement learning or by sampling methods. In these cases, no integration with operational models and hierarchical refinements is provided.

Here is how the current paper relates to our prior work on this topic. A pseudocode version of RAE first appeared in [28]. An implementation of RAE, and three successively better planners for use with it, were described in [69, 70, 71]. The current paper is based on [71], with the following additional contributions. We provide complete formal specifications and explanations of the actor RAE and planner UPOM. We present a learning strategy to learn values of uninstantiated method parameters, with experimental evaluation. We have an additional experimental domain, called Deliver. We propose a new performance metric, called Retry Ratio, and evaluate it on our five experimental domains. We perform experiments with success-ratio (or probability of success) as the utility function optimized by UPOM, We compare success ratio with efficiency. We perform experiments with varying the parameters, number of rollouts and maximum rollout length, of UPOM. We provide a proof of convergence of UPOM to a plan with optimal expected utility.

3. Hierarchical Operational Models

The usual preconditions-effects representation of actions is tailored for the efficient exploration of a state-transition system. It does not describe how to perform an action in a particular context, or how to react to dynamic events. For that, we rely here on a representation based on the formalism described in [28, Chapter 3], which has been designed for acting and reacting in a dynamic environment. It provides a hierarchical representation of tasks through alternative refinement methods and primitive actions.

This representation is called operational since it allows an actor to perform the tasks requested by users and to react to events. The actor perceives the current state of the world and interacts with the environment for sensing and actuation through an execution platform (see Figures 1(a) for the general architecture, and 1(b) for the integration of planning, learning and refinement acting explained in subsequent sections). Let us describe the main ingredients.

**States.** We rely on a parameterized state variable representation, i.e., a finite collection of mappings from typed sets of objects of the planning domain into
Figure 1: (a) Architecture of an actor reacting to events and tasks through an execution platform; (b) Integration of refinement acting, planning and learning.

some range, such as door-status(d) ∈ {closed, open, cracked, unknown} which describes the status of a door d. Let X be a finite set of state variables; variable x ∈ X takes values from the set Range(x), assumed at this stage to be finite.

A state is a total assignment of values to state variables. The world state ξ is updated through observation by the execution platform, reflecting the dynamics of the external world. For the purpose of the planning lookahead, ξ may be simplified into an abstract state s ∈ S which evolves by reasoning; s gets updated from ξ each time the actor calls the planner (see Section 5). Both ξ and s are defined with the same set X of state variables. In general, s is a domain dependent abstraction of ξ, in which some state variables are ignored or range over sparser ranges. A given world state ξ is mapped to a single abstract state; an abstract state s may correspond to a subset of world states.

To provide a convenient notation for handling partial knowledge, we extend the range of values of every state variable to include a special symbol, unknown, which is the default value of any state variable that has not been set or updated to another value.

It is also convenient to have a distinct set of variables, which we call internal variables. For example, stable(o, pose) ∈ {⊤, ⊥}, means that object o in some particular pose is stable, as a result of some geometric and dynamic computation. Internal variables are updated by assignment statements inside methods. An assignment statement is of the form x ← expr, where expr may be either a ground value in Range(x), or a computational expression that returns a ground value in Range(x). Such an expression may include, for example, calls to specialized software packages.

Tasks. A task is a label naming an activity to be performed. It has the form task-name(args), where task-name designates the task considered, arguments args
is an ordered list of objects and values. Tasks specified by a user are called root
tasks, to distinguish them from the subtasks in which they are refined.

**Events.** An event designates an occurrence of some type detected by the exec-
cution platform; it corresponds to an exogenous change in the environment to
which the actor may have to react, e.g., the activation of an emergency signal. It has the form event-name(args).

**Actions.** An action is a primitive function with instantiated parameters that
can be executed by the execution platform through sensory motor commands. It has nondeterministic effects. For the purpose of planning, we do not represent
actions with formal templates, as usually done with descriptive models. Instead,
we assume to have a generative nondeterministic sampling simulator, denoted Sample. A call to Sample(a, s) returns a state s′ randomly drawn among the
possible states resulting from the execution of a in s. Sample can be implemented
simply through a probability distribution of the effects of a (see Section 5).

When the actor triggers an action a for some task or event, it waits until
a terminates or fails before pursuing that task or event. To follow its execution progress, when action a is triggered, there is an internal variable, denoted
evaluation-status(a) ∈ {running, done, failed}, which expresses the fact that the execution of a is going on, has terminated or failed. A terminated action returns
a value of some type, which can be used to branch over various followup of the
activity.

**Refinement Methods.** A refinement method is a triple of the form (task, precondition, body) or (event, precondition, body). The first field, either a task or an event, is its role; it tells what the method is about. When the precondition holds in the current state, the method is applicable for addressing
the task or event in its role by running a program given in the method’s body.
This program refines the task or event into a sequence of subtasks, actions, and
assignments. It may use recursions and iteration loops, but its sequence of steps
is assumed to be finite.2

Refinement methods are specified as parameterized templates with a name and list of arguments method-name(arg1, ..., argk). An instance of a method is
given by the substitution of its arguments by constants that are the values of
(internal) state variables.

A method instance is applicable for a task if its role matches a current task
or event, and its preconditions are satisfied by the current values of the state
variables. A method may have several applicable instances for a current state,

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2One way to enforce such a restriction would be as follows. For each iteration loop, one
could require it to have a loop counter that will terminate it after a finite number of iterations.
For recursions, one could use a level mapping (e.g., see [16, 36]) that assigns to each task t
a positive integer ℓ(t), and require that for every method m whose task is t and every task
t′ that appears in the body of m, ℓ(t′) < ℓ(t). However, in most problem domains it is
straightforward to write a set of methods that don’t necessarily satisfy this property but still
don’t produce infinite recursion.
task, and event. An applicable instance of a method, if executed, addresses a
task or an event by refining it, in a context dependent manner, into subtasks,
actions, and possibly state updates, as specified in its body.

The body of a method is a sequence of lines with the usual programming
control structure (if-then-else, while loops, etc.), and tests on the values of state
variables. A simple test has the form \((x \circ v)\), where \(\circ \in \{=, \neq, <, >\}\). A
compound test is a negation, conjunction, or disjunction of simple or compound
tests. Tests are evaluated with respect to the current state \(\xi\). In tests, the
symbol unknown is not treated in any special way; it is just one of the state
variable’s possible values.

The following example of a simplified search-and-rescue domain illustrates
the representation.

Example 1. Consider a set \(R\) of robots performing search and rescue operations
in a partially mapped area. The robots have to find people needing help in some
area and leave them a package of supplies (medication, food, water, etc.). This
domain is specified with state variables such as robotType\(r\) \(\in\) \{UAV, UGV\},
\(r \in R\), a finite set of robot names; hasSupply\(r\) \(\in\) \{\top, \bot\}; loc\(r\) \(\in\) \(L\), a finite
set of locations. A rigid relation adjacent \(\subseteq L^2\) gives the topology of the domain.

These robots can use actions such as DETECT\(r,\) camera, class which de-
tects if an object of some class appears in images acquired by camera of \(r\),
TRIGGERALARM\(r, l\), DROP_SUPPLY\(r, l\), LOAD_SUPPLY\(r, l\), TAKEOFF\(r, l\),
LAND\(r, l\), MOVE_TO\(r, l\), FLY_TO\(r, l\). They can address tasks such as:
search\(r,\) area, which makes a UAV \(r\) survey in sequence the locations in area,
survey\(r, l\), navigate\(r, l\), rescue\(r, l\), getSupplies\(r\).

Here is a refinement method for the survey task:

\begin{verbatim}
ml-survey\(l, r\)
  task: survey\(l\)
    pre: robotType\(r\) = UAV and loc\(r\) = \(l\) and status\(r\) = free
    body: for all \(l'\) in neighbouring areas of \(l\) do:
      moveTo\(r, l'\)
      for cam in cameras\(r\):
        if DETECTPERSON\(r, cam\) = \top then:
          if hasSupply\(r\) then rescue\(r, l'\)
          else TRIGGERALARM\(r, l'\)
This method specifies that in the location \(l\) the UAV \(r\) detects if a person
appears in the images from its camera. In that case, it proceeds to a rescue
task if it has supplies; if it does not it triggers an alarm event. This event is
processed (by some other methods) by finding the closest robot not involved in a
current rescue and assigning to it a rescue task for that location.

ml-getSupplies\(r\)
  task: GetSupplies\(r\)
    pre: robotType\(r\) = UGV
    body: moveTo\(r, loc(BASE)\)
      REPLENISHSUPPLIES\(r\)
\end{verbatim}
m2-GetSupplies(r)

task: GetSupplies(r)
pre: robotType(r) = UGV
body: $r_2 = \text{argmin}_r \{\text{EuclideanDistance}(r, r') | \text{hasMedicine}(r') = \text{TRUE}\}$
if $r_2 = \text{None}$ then FAIL
else:
    moveTo(r, loc(r_2))
    Transfer($r_2$, r)

Specification of an acting domain. We model an acting domain $\Sigma$ with the specification of a tuple $\Sigma = (\Xi, \mathcal{T}, \mathcal{M}, \mathcal{A})$ where:

- $\Xi$ is the set of world states the actor may be in.
- $\mathcal{T}$ is the set of tasks and events the actor may have to deal with.
- $\mathcal{M}$ is the set of methods for handling tasks or events in $\mathcal{T}$, phantomsection
  $\text{Applicable}(\xi, \tau)$ is the set of method instances applicable to $\tau$ in state $\xi$.
- $\mathcal{A}$ is the set of actions the actor may perform. phantomsection We let $\gamma(\xi, a)$ be the set of states that may be reached after performing action $a$ in state $\xi$.

We assume that $\Xi$, $\mathcal{T}$, $\mathcal{M}$, and $\mathcal{A}$ are finite.

The deliberative acting problem can be stated informally as follows: given $\Sigma$ and a task or event $\tau \in \mathcal{T}$, what is the “best” method instance $m \in \mathcal{M}$ to perform $\tau$ in a current state $\xi$. Strictly speaking, the actor does not require a plan, i.e., an organized set of actions or a policy. It requires a selection procedure which designates for each task or subtask at hand the “best” method instance for pursuing the activity in the current context.

The next section describes a reactive actor which relies on a predefined preference order of methods in $\text{Applicable}(\xi, \tau)$. Such an order is often natural when specifying the set of possible methods for a task. In Section 5 we detail a more informed receding horizon look-ahead mechanism using an approximately optimal planning algorithm which provides the needed selection procedure.

4. Acting with RAE

RAE (for Refinement Acting Engine) is adapted from [28, Chapter 3]. It maintains an Agenda consisting of a set of refinement stacks, one for each root task or event that needs to be addressed. A refinement stack $\sigma$ is a LIFO list of tuples of the form $(\tau, m, i, \text{tried})$ where $\tau$ is an identifier for the task or event; $m$ is a method instance to refine $\tau$ (set to $\text{nil}$ if no method instance has been chosen yet); $i$ is a pointer to a line in the body of $m$, initialized to 1 (first line in the body); and $\text{tried}$ is a set of refinement method instances already tried for $\tau$ that failed to accomplish it. A stack $\sigma$ is handled with the usual push, pop and top functions.
RAE:

\[ \text{Agenda} \leftarrow \text{empty list} \]

\[ \text{while True do} \]

\[ 1 \quad \text{for each new task or event } \tau \text{ to be addressed do} \]

\[ 2 \quad \text{observe current state } \xi \]

\[ 3 \quad m \leftarrow \text{Select}(\xi, \tau, \langle(\tau, \text{nil}, 1, \emptyset), d_{\text{max}}, n_{\text{ro}}\rangle) \]

\[ 4 \quad \text{if } m = \emptyset \text{ then output}(\tau, \text{"failed"}) \]

\[ \text{else } \text{Agenda} \leftarrow \text{Agenda} \cup \{\langle(\tau, m, 1, \emptyset)\rangle\} \]

\[ 5 \quad \text{for each } \sigma \in \text{Agenda do} \]

\[ 6 \quad \text{observe current state } \xi \]

\[ 7 \quad \text{if } \sigma = \emptyset \text{ then} \]

\[ \text{Agenda} \leftarrow \text{Agenda} \setminus \sigma \]

\[ \text{output}(\tau, \text{"succeeded"}) \]

\[ \text{else if } \sigma = \text{rettrial-failure} \text{ then} \]

\[ \text{Agenda} \leftarrow \text{Agenda} \setminus \sigma \]

\[ \text{output}(\tau, \text{"failed"}) \]

\[ \text{Algorithm 1: Refinement Acting Engine RAE} \]

When RAE addresses a task \( \tau \), it must choose a method instance \( m \) for \( \tau \). This is performed by function Select (lines 3 of RAE, 5 of Progress, and 2 of Retry). Select takes five arguments: the current state \( \xi \), task \( \tau \), and stack \( \sigma \), and two control parameters \( d_{\text{max}}, n_{\text{ro}} \) which are needed only for planning. In purely reactive mode (without planning), Select returns the first applicable method instance, according to a pre-defined ordering, which has not already been tried (\( \text{tried} \) is given in \( \sigma \)). Note that this choice is with respect to the current world state \( \xi \). Lines 2, 4, 1 in RAE, Progress and Retry respectively, specify to get an update of the world state from the execution platform. If \( \text{Applicable}(\xi, \tau) \subseteq \text{tried} \), then Select returns \( \emptyset \), i.e., there is no applicable method instances for \( \tau \) in \( \xi \) that has not already been tried, meaning a failure to address \( \tau \).

The first inner loop of RAE (line 1) reads each new root task or event \( \tau \) to be addressed and adds to the Agenda its refinement stack, initialized to \( \langle(\tau, m, 1, \emptyset)\rangle \), \( m \) being the method instance returned by Select, if there is one. The root task \( \tau \) for this stack will remain at the bottom of \( \sigma \) until solved; the subtasks in which \( \tau \) refines will be pushed onto \( \sigma \) along with the refinement. The second loop of RAE progresses by one step in the topmost method instance of each stack in the Agenda.

To progress a refinement stack \( \sigma \), Progress (Algorithm 2) focuses on the tuple \( (\tau, m, i, \text{tried}) \) at the top of \( \sigma \). If the current line \( m[i] \) is an action already triggered, then the execution status of this action is checked. If the action \( m[i] \) is still running, this stack has to wait, but RAE goes on for other pending stacks in the Agenda. If \( m[i] \) failed, Retry examines alternative method instances. Otherwise the action \( m[i] \) is done: RAE will proceed in the following iteration with
Algorithm 2: Progress returns an updated stack taking into account the execution status of the ongoing action, or the type of the next step in method instance $m$.

the next step in method instance $m$, as defined by the function Next (Algorithm 3).

Algorithm 3: Next step in a method instance $m$ for a given $\sigma$. 

Next($\sigma, \xi$): 
repeat 
| $(\tau, m, i, tried) \leftarrow \text{top}(\sigma)$ 
| pop($\sigma$) 
| if $\sigma = \emptyset$ then return $\emptyset$ 
until $i$ is not the last step of $m$ 

Algorithm 3: Next step in a method instance $m$ for a given $\sigma$. 

Next($\sigma, \xi$) advances within the body of the topmost method instance $m$ in $\sigma$ as well as with respect to $\sigma$. If $i$ is the last step in the body of $m$, the current tuple is removed from $\sigma$: method instance $m$ has successfully addressed $\tau$. If $\tau$ is a root task; Next and Progress return $\emptyset$, meaning that $\tau$ succeeded; its stack $\sigma$ is removed from the Agenda. If $i$ is not the last step in $m$, RAE proceeds to the next step in the body of $m$. This step $j$ following $i$ in $m$ is defined with respect to the current state $\xi$ and the control instruction in line $i$ of $m$, if any. 

Starting from line 3 in Progress, $i$ points to the next line of $m$ to be processed.
If \( m[i] \) is an assignment, the corresponding update of \( \xi \) if performed; \textit{RAE} proceeds with the next step. If \( m[i] \) is an action \( a \), its execution is triggered; \textit{RAE} will wait until \( a \) finishes to examine the \textbf{Next} step of \( m \). If \( m[i] \) is a task \( \tau' \), a refinement with a method instance \( m' \), returned by \textit{Select}, is performed. The corresponding tuple is pushed on top of \( \sigma \). If there is no applicable method instance to \( \tau' \), then the current method instance \( m \) failed to accomplish \( \tau \), a \textit{Retry} with other method instances is performed.

\begin{algorithm}
\begin{align*}
\text{Retry}(\sigma): \quad & (\tau, m, i, \textit{tried}) \leftarrow \text{pop}(\sigma) \\
& \textit{tried} \leftarrow \textit{tried} \cup \{m\} \quad \triangleright \text{ \textit{m failed}} \\
& \text{observe current state } \xi \\
& m' \leftarrow \text{Select}(\xi, \tau, \sigma, d_{\text{max}}, n_{\text{ro}}) \\
& \text{if } m' \neq \emptyset \text{ then return } \text{push}(\tau, m', 1, \textit{tried}), \sigma) \\
& \text{else if } \sigma \neq \emptyset \text{ then return } \text{Retry}(\sigma) \\
& \text{else return retrial-failure}
\end{align*}
\end{algorithm}

\textbf{Algorithm 4:} \textit{Retry} examines untried alternative method instances, if any, and returns an updated stack.

\textit{Retry} (Algorithm 4) adds the failed method instance \( m \) to the set of method instances that have been tried for \( \tau \) and failed. It removes the corresponding tuple from \( \sigma \). It retries refining \( \tau \) with another method instance \( m' \) returned by \textit{Select} which has not been already tried (line 3). If there is no such \( m' \) and if \( \sigma \) is not empty, \textit{Retry} calls itself recursively on the topmost stack element, which is the one that generated \( \tau \) as a subtask: retrial is performed one level up in the refinement tree. If stack \( \sigma \) is empty, then \( \tau \) is the root task or event: \textit{RAE} failed to accomplish \( \tau \).

\textit{RAE} fails either (i) when there is no method instance applicable to the root task in the current state (line 4 of \textit{RAE}), or (ii) when all applicable method instances have been tried and failed (line 7). A method instance fails either (i) when one of its actions fails (line 2 in \textit{Progress}) or (ii) when all applicable method instances for one of its subtasks have been tried and failed (line 4 in \textit{Retry}).

Note that \textit{Retry} is not a backtracking procedure: it does not go back to a previous \textit{computational node} to pick up another option among the candidates that were applicable when that node was first reached. It finds another method instance among those that are \textit{now} applicable for the \textit{current} state of the world \( \xi \). \textit{RAE} interacts with a dynamic world: it cannot rely on the set \textit{Applicable}(\xi, \tau) computed earlier, because \( \xi \) has changed, new method instances may be applicable. However, the same method instance that failed at some point may succeed later on and may merit retrials. We discuss this issue in \textbf{Section 8}.
5. Planning for RAE

In Section 3, we informally defined the deliberative acting problem as the problem of selecting the “best” method instance \( m \in M \) to perform \( \tau \) in a current state \( \xi \) for a domain \( \Sigma = (\Xi, T, M, A) \). A refinement planning domain is a tuple \( \Phi = (S, T, M, A) \), where \( S \) is the set of states that are abstractions of states in \( \Xi \), and \( T, M, A \) are the same as in \( \Sigma \).

Recall that if RAE is run purely reactively, Select chooses a refinement method instance from a predefined order of refinement methods, without comparing alternative options in the current context. In this section, we define a utility function to assess and compare method instances in \( \text{Applicable}(\xi, \tau) \) to select the best one. This function might, in principle, be used by an exact optimization procedure for finding the optimal method instance for a task. We propose a more efficient Monte Carlo Tree Search approach for finding an approximately optimal method instance. The planner relies on a function, called \( \text{UPOM} \), inspired from the Upper Confidence bounds search applied to Trees (UCT). \( \text{UPOM} \) (UCT Procedure for Operational Models) is parameterized for rollout depth \( d \) and number of rollouts, \( n_{\text{ro}} \). It relies on a heuristic function \( h \) for estimating the criterion at the end of the rollouts when \( d < \infty \).

The proposed approach runs multiple simulations using the method instances and a generative sampling model of actions. This model is defined as a function \( \text{Sample}: S \times A \to S \). \( \text{Sample}(s, a) \) returns a state \( s' \) randomly drawn from \( \gamma(s, a) \), with \( \gamma : S \times A \to 2^S \cup \{\text{failed}\} \). The transition function \( \gamma \) is augmented with the token \( \text{failed} \) to account for possible failures of \( a \). We assume, as usual, that the sampling reflects the probability distribution of the action’s real-world outcomes.

A simulation of a method instance \( m \) for a task \( \tau \) during planning goes successively through the steps of \( m \), as required by the control flow for the current context, and generates a sequence of simulated states \( \langle s_0, \ldots, s_i, \ldots \rangle \), where initially \( s_0 \) corresponds to an abstraction of the current real world state \( \xi \). The utility function is computed along such a sequence, taking into account the deterministic refinements of method instances and the nondeterministic outcomes of actions (see Figure 2). In simulation during planning, we do not Retry, as in RAE, but we take into account possible failures. We assume the simulations to be fast enough with respect to the real world dynamics. Hence, we do not consider possible changes in \( \xi \) during a simulation. These changes, if any, are dealt with at the acting level.

### 5.1. Utility criteria and optimal approach

The appropriate utility function can be application dependent. One may consider a function combining rewards for desirable or undesirable states, and costs for the time and resources of actions. To keep the formal presentation simple, we assume that there are no rewards in states. We studied two utility functions measuring respectively the actor’s efficiency and robustness. Regarding the former, instead of minimizing costs, the efficiency utility function
maximizes values to easily account for failures. For the latter, the actor seeks a method instance that has a good chance to succeed.

We first define two value functions for actions, \( v_e \) and \( v_s \), which lead to the two proposed utility functions for method instances.

**Efficiency.** Let \( \text{Cost} : S \times A \times (S \cup \{\text{failed}\}) \rightarrow \mathbb{R}^+ \) be a cost function. \( \text{Cost}(s, a, s') \) is the cost of performing action \( a \) in state \( s \) when the outcome is \( s' \). Note that the cost of an action \( a \) is finite even when \( a \) fails. This is the case since in general an actor is able to figure out that an attempted action failed to limit its cost. However, a failed action \( a \) in a method instance \( m \) leads to the failure of \( m \); its efficiency is simply 0. Hence we define the efficiency value of an action as follows:

\[
v_e(s, a, s') = \begin{cases} 0 & \text{if } s' = \text{“failed”}, \\ 1/\text{Cost}(s, a, s') & \text{otherwise}. \\ \end{cases}
\] (1)

If we let \( v_{e1} \oplus v_{e2} \) denote the cumulative efficiency value of two successive actions whose efficiency values are \( v_{e1} = 1/c_1 \) and \( v_{e2} = 1/c_2 \), then

\[
v_{e1} \oplus v_{e2} = 1/(c_1 + c_2) = 1/(v_{e1} + v_{e2}) = v_{e1} \times v_{e2}/(v_{e1} + v_{e2}). \tag{2}
\]

**Success Ratio.** Here, we measure the utility of a method instance as its probability of success over all possible outcomes of its actions. Hence we simply take a value 0 for an action that fails, and 1 if the action succeeds.

\[
v_s(s, a, s') = \begin{cases} 0 & \text{if } s' = \text{“failed”}, \\ 1 & \text{otherwise}. \\ \end{cases}
\] (3)

If we let \( v_{s1} \oplus v_{s2} \) denote the cumulative success ratio for two successive actions in a method instance whose success ratios are \( v_{s1} \) and \( v_{s2} \), then

\[
v_{s1} \oplus v_{s2} = v_{s1} \times v_{s2}. \tag{4}
\]

For both value functions \( v_e \) and \( v_s \), the operator \( \oplus \) is associative, which is needed for combining successive steps. For both value functions, we let \( I \) denote the identity element for operation \( \oplus \), i.e., \( x \oplus I = x \):

- For \( v_e \) in Equation 1, \( I = \infty \), corresponding to a cost of \( 1/I = 0 \). If \( v_{e1} = I \), then \( v_{e1} \oplus v_{e2} = 1/(0 + 1/v_{e2}) = v_{e2} \) for every \( v_{e2} \).
- For \( v_s \) in Equation 3, we have \( I = 1 \), corresponding to success (task is already accomplished).

Note that if either of two actions in a method instance \( m \) fails, their combined value is 0, since \( m \) also fails.

Let us now define a utility function for method instances using either \( v_e \) or \( v_s \). In order to compute the expected utility of a method instance \( m \) we need to consider possible traces of the execution of \( m \) for a task \( \tau \). In RAE, an execution
trace was conveniently represented through the evolution of $\sigma$ for the task $\tau$. In planning, we similarly use $\sigma$ as a LIFO list of tuples $(\tau, m, i, tried)$, as defined in RAE.\(^3\) For a given simulation of $m$ for $\tau$, $\sigma$ is initialized as a copy of the current stack in RAE. We progress in the simulation of $m$ step by step using the function $Next$ (Algorithm 3), pushing in $\sigma$ a new tuple when a step requires a refinement into a subtask.

Let $top(\sigma)$ be the stack tuple $(\tau, m, i, tried)$. The utility of a particular simulation of $i^{th}$ step of $m$ for $\tau$ is given by the following recursive equation:

$$U(m, s, \sigma) = \begin{cases} 
U(m, s', Next(\sigma, s)) & \text{if } m[i] \text{ is an assignment}, \\
v(s, a, s') \oplus U(m, s', Next(\sigma, s)) & \text{if } m[i] \text{ is an action } a, \\
U(m', s, push((\tau', m', 1, \emptyset), Next(\sigma, s))) & \text{if } m[i] \text{ is a subtask } \tau', \\
I & \text{if } \sigma = \emptyset. 
\end{cases}$$

(5)

Here, $v$ is either $v_e$ or $v_s$. An assignment step changes the state from $s$ to $s'$ but does not change the utility $U$. An action $a$ changes the state nondeterministically to $s'$; the utility is the combined value of $a$ and the utility of the remaining step. A refinement step does not change the state; it is addressed in this particular simulation by refining $\tau$ into $\tau'$ with $m'$. The function $Next$ moves to the following step, and to the empty stack at the end of every simulated execution.

From Equation 5 we derive the maximal expected utility of $m$ for $\tau$ by maximizing recursively over all possible refinements in $m$ and averaging over all possible outcomes of actions, including failures:

$$U^*(m, s, \sigma) = \begin{cases} 
U^*(m, s', Next(\sigma, s)) & \text{if } m[i] \text{ is an assignment}, \\
\sum_{s' \in \gamma(s, a)} Pr(s'|s, a) \times [v(s, a, s') \oplus U^*(m, s', Next(\sigma, s))] & \text{if } m[i] \text{ is an action } a, \\
max_{m' \in \text{Applicable}(s, \tau')} U^*(m', s, push((\tau', m', 1, \emptyset), Next(\sigma, s))) & \text{if } m[i] \text{ is a subtask } \tau', \\
I & \text{if } \sigma = \emptyset. 
\end{cases}$$

(6)

In the above equation, $\gamma(s, a)$ includes the token “failed”. We assume as usual that if $\text{Applicable}(s, \tau) = \emptyset$ then $\max_{m \in \text{Applicable}(s, \tau)} U^*(m, s, \sigma) = 0$, meaning a refinement failure. Instantiating $v$ as either $v_e$ or $v_s$ gives the two utility functions, the efficiency and the success ratio of method instances, respectively.

The optimal method instance for a task $\tau$ in a state $s$ for the utility $U^*$ is:

$$m^*_{\tau, s} = \arg\max_{m \in \text{Applicable}(s, \tau)} U^*(m, s, ((\tau, m, 1, \emptyset)))$$

(7)

\(^3\)We do not need for the moment to keep track of already $tried$ method instances, but we’ll see in a moment the usefulness of this term.
It is possible to implement Equation 6 directly as a recursive backtracking optimization algorithm and to make the planning algorithm return \( m^*_s \), as defined above. However, this would be too computationally demanding and not practical for an online planner. We propose instead to seek an approximately optimal method instance with an anytime controllable procedure using a Monte Carlo Tree Search algorithm in the space of operational models.

5.2. A planning algorithm based on UCT

To find an approximation \( \tilde{m} \) of \( m^* \), we propose a progressive deepening Monte Carlo Tree Search procedure with \( n_{ro} \) rollouts, down to a depth \( d_{max} \) in the refinement tree of a task \( \tau \) (see Figure 2). The basic ideas are the following:

- at an action node of the search tree, we average over the value of the corresponding \( n_{ro} \) rollouts;
- at a task node, we choose the refinement method instance with the highest expected utility;
- starting from \( d = d_{max} \), we decrease \( d \) for a refinement step and an action step, but not in an assignment step;
- we take a heuristic estimate of the utility of the remaining refinements at the tip of a rollout, i.e., at \( d = 0 \);
- we stop a rollout at a failure of an action or a refinement, and return a value \( U_{\text{Failure}} = 0 \); we also stop when the stack is empty and return \( U_{\text{Success}} = 1 \).

\[
\text{Select}(\xi, \tau, \sigma, d_{max}, n_{ro});
\]

\[
\begin{align*}
(\tau, m, i, \text{tried}) & \leftarrow \text{top}(\sigma) \\
M & \leftarrow \text{Applicable}(\xi, \tau) \setminus \text{tried} \\
\text{if} \quad M = \emptyset \text{ then return } \emptyset \\
\text{if} \quad |M| = 1 \text{ then return } m \\
\quad s & \leftarrow \text{Abstract}(\xi); \sigma & \leftarrow \text{copy of } \sigma; \quad d \leftarrow 0 \\
1 & \quad \tilde{m} \leftarrow \operatorname{argmax}_{m \in M} h(\tau, m, s) \\
2 & \quad \text{repeat} \\
3 & \quad \text{for } n_{ro} \text{ times do} \\
4 & \quad \quad \text{UPOM}(s, \text{push}(\langle \tau, \text{nil}, 1, \emptyset \rangle, \sigma), d) \\
5 & \quad \quad \tilde{m} \leftarrow \operatorname{argmax}_{m \in M} Q_{\sigma, s}(m) \\
6 & \quad \text{until } d = d_{max} \text{ or search time is over} \\
\text{return } \tilde{m}
\end{align*}
\]

Algorithm 5: A progressive deepening procedure using UPOM for finding an approximately optimal method instance.

This is detailed in algorithms 5 and 6. Select is called by RAE with five parameters: \( \xi, \tau, \) and \( \sigma \), and the control parameters, \( d_{max} \) the maximum rollout depth, and \( n_{ro} \) the number of UCT rollouts. Recall that on a new root task \( \tau \), RAE calls Select with \( \sigma = \langle \langle \tau, \text{nil}, 1, \emptyset \rangle \rangle \). Select returns \( \tilde{m} \), an approximately...
Algorithm 6: Monte Carlo tree search procedure UPOM; performs one rollout recursively down the refinement tree of a method instance to compute an estimate of its optimal utility.

optimal method instance for \( \tau \), or \( \emptyset \) if no method instance is found, i.e., if there is no applicable method instances for \( \tau \) in \( \xi \), but of those already tried by RAE for this task. Select uses a copy of RAE’s current stack \( \sigma \), and a simulation state \( s \), which is an abstraction of the current execution state \( \xi \) (e.g., in Example 1, \( l \) can be a precise metric location for acting and topological reference for planning). It initializes \( \tilde{m} \) with a heuristic estimates (line 1). It performs a succession of simulations at progressively deeper refinement levels using the function \( \text{UPOM} \) to evaluate the utility of a candidate method instance. The progressive deepening loop (line 2) is pursued until reaching the maximum rollout depth, or until the actor interrupts the search because of time limit or any other reason, at which point the current \( \tilde{m} \) is returned and will be tried by RAE. Select is an anytime
procedure: it returns a solution whenever interrupted. $Q_{\sigma,s}(m)$ is a global data structure that approximates the utility $U^*(m,s,\sigma)$.

**UPOM** (Algorithm 6) takes as arguments a simulation state $s$, a stack $\sigma$, and the rollout depth $d$. It performs one rollout over recursive calls for a method instance $m$ and its refinements. On the first call of a rollout, $m = \text{nil}$, meaning that no method instance has yet been chosen. A method instance $m_c$ is chosen among untried method instances (line 3). If all method instances have been tried, $m_c$ is chosen (line 4) according to a tradeoff between exploration and exploitation. The constant $C > 0$ fixes this tradeoff for the exploration less sampled method instances (high $C$) versus the exploitation or more promising ones (low $C$).

$Q_{\sigma,s}(m)$ is calculated as follows. $Q_{\sigma,s}(m)$ combines the value of a sampled action with the utility of the remaining part of a rollout (line 8), and it updates $Q$ by averaging over previous rollouts (line 6). The value function $v$ (line 8) is either $v_e$ or $v_s$ depending on the chosen utility function, efficiency or success ratio. For both function, $U_{\text{Success}} = 1$ and $U_{\text{Failure}} = 0$.

A significant difference between the pseudocode in Algorithm 6 and Equation 6 is the restriction of Applicable to method instances that have not been tried before by RAE for the same task. This is a conservative strategy, because at this point the actor has no means for distinguishing failures of tried method instances that require retrials from those that don’t. We’ll come back to a retrial strategy in Section 8.

Another difference shows up in the initialization of $\sigma$ in Select. This is explained by going back to how Select is used by RAE. At a root task $\tau$, when
Select is called the first time (line 3 of RAE), $\sigma = \langle (\tau, \text{nil}, 1, \emptyset) \rangle$. If RAE proceeds for $\tau$ with a method instance $m$ returned by Select, at the next refinement call of RAE, e.g., for $\tau_1$ (see Figure 2) Select needs to consider the utility of the method instances for $\tau_1$, but also their impact on the remaining steps in $m$, here on $a_2$ and $\tau_2$. In other words, the actor requires the best method instance for $\tau_1$ in the context of its current execution state, taking into account the remaining steps of the method instance $m$ it is executing. This best method instance for $\tau_1$ may be different from that given by Equation 7. The need to keep track of previously tried method instances and pending tasks explains why $\sigma$ is taken as a copy of the current $\sigma$ in RAE for the root task at hand. However, this does not lead to reconsider previously made choices of method instances the actor is currently executing, e.g., in Figure 2, $m'$ is not reassessed. Note that UPOM does not pursue a rollout at an internal refinement node with the method instance maximizing the current utility evaluation $Q$, but with the best method instance according to the UCT exploration/exploitation tradeoff (line 4).

The two control parameters $d_{\text{max}}$ and $n_{\text{ro}}$ are dependent because of the following reason. The rationale of UCT is that exploration should examine an untried method instance before pursuing a rollout on an already tried one. Exploration would be complete if $n_{\text{ro}} > \mu$, where $\mu = \sum_i \max_s [\text{Applicable}(s, \tau_i)]$ over all subtasks $\tau_i$, down to a refinement depth of the root task. But $\mu$ increases with $d_{\text{max}}$. In our experiments, we keep a large constant $n_{\text{ro}}$ and increase $d$ in the progressive deepening loop until the max depth $d_{\text{max}}$. An alternative control of Select can be the following:

- for a given $d$, pursue the rollouts (line 3) until there are $K$ successive exploitation rollouts, i.e., for which $\text{Untried} = \emptyset$, for some constant $K$;\footnote{The probabilistic roadmap motion planning algorithm uses a similar idea to stop after $K$ configuration samples unsuccessful for augmenting the roadmap.}
- pursue the progressive deepening loop (line 2) until no subtask is left unrefined for the $K$ exploitation rollouts or until the search time is over.

This is an adaptive control strategy that requires only two constants $C$ and $K$.

Finally, let us discuss the important issue of the depth cutoff strategy. Two options may be considered: (i) $d$ is the number of steps of a rollout (as in MDP algorithms), or (ii) $d$ is the refinement depth of a rollout. The pseudocode in Algorithm 6 takes the former option: $d$ decreases at every recursive call, for an action step as well as for a task refinement step. The advantage is that the cutoff at $d = 0$ stops the current evaluation. The difficulty is that the root method instance, and possibly its refinements, are only partially evaluated. For example in Figure 2, if $j > d_{\text{max}}$, steps $a_2$ and $\tau_2$ of $m$ will never be considered; similarly for the remaining steps in $m_1$: rollouts will go in deep refinements and never assess all the steps of evaluated method instances. The value returned by UPOM can be arbitrarily far from $U^*$. The other issue of this strategy is that the heuristic estimate has to take into account remaining refinements lower down the cutoff point as well as remaining steps higher up in the refinement tree, i.e.,
what remains to be evaluated in $\sigma$.

In the alternative option where $d$ is the refinement depth of a rollout, $d$ decreases at a task refinement step only, not at an action step. The advantage is to allow each rollout to go through all the steps of every developed method instance. Furthermore, the heuristic estimate at a cutoff is focused in this case on a subtask and its applicable method instances, whose simulation will not be started (nondeveloped method instances). The disadvantage is that one needs an estimate of the state following the achievement of a task with a nondeveloped method instance in order to pursue the sibling steps. In Figure 2 with $d = 1$ for example, $\tau_1$ will not be refined; $\alpha_2$ and remaining steps of $m$ will be based on an estimated state following the achievement of $\tau_1$. The definition of a default state change following a task is domain dependent and might not be easily specified in general.

The modifications needed in UPOM to implement this option (ii) are the following:

- In order to be able to go back to higher levels of $d$ when the simulation is pursued in parent method instances after a cutoff, it is convenient to maintain $d$ as part of the simulation stack: a fifth term $d$ is added in every tuple of $\sigma$.
- The arguments of UPOM are modified according to the previous point.
- Line 1 in UPOM has to pursue the evaluation higher up in $\sigma$: if $d = 0$ then return $h(\tau, m, s) \oplus$ UPOM($g(s, \tau, m), pop(\sigma), b, k$), where $g(s, \tau, m)$ is a default state after the achievement of $\tau$ with $m$ in $s$.

For our experimental results (see Section 7), we have implemented a mixture of the two options: we take $d$ as the refinement steps of a rollout (decreasing $d$ at a task refinement step only), but we stop the evaluation when reaching $d = 0$, taking heuristic estimates for the remaining steps of pending method instances. This has the disadvantage of a partial evaluation, but its advantages are to allow easily defined heuristic and not require a following state estimate.

6. Learning for RAE and UPOM

Purely reactive RAE chooses a method instance for a task using an a priori ordering or a heuristic. RAE with anytime receding horizon planning uses UPOM to find an approximately optimal method instance to refine a task or a subtask. At maximum rollout depth, UPOM needs also heuristic estimates.

The classical techniques for domain independent heuristics in planning do not work for operational refinement models. Specifying by hand efficient domain-specific heuristics is not an acceptable solution. However, it is possible to learn such heuristics automatically by running UPOM offline in simulation over numerous cases. For this work we relied on a neural network approach, using both linear and rectified linear unit (ReLU) layers.

We developed three learning procedures to guide RAE and UPOM:
- **Learn** learns a policy which maps a context defined by a task \( \tau \), a state \( s \), and a stack \( \sigma \) to a refinement method \( m \) in this context, to be chosen by RAE when no planning can be performed.
- **Learn** learns the values of instantiated parameters of refinement method \( m \) chosen by **Learn**.
- **LearnH** learns a heuristic evaluation function to be used by UPOM.

### 6.1. Learning to choose methods (**Learn**)

In a first approach, **Learn** learns a mapping from contexts to partially instantiated methods. A parameter of a method instance can inherit its value from the task at hand. However, different instances of a method may be applicable in a given state to the same task. This is illustrated in Example 1 by method \( m_1 \)-survey \((l,r)\) where \( l \) is inherited from the task, but \( r \) can be instantiated as any robot such that \( \text{status}(r) = \text{free} \). **Learn** simplifies the learning by abstracting all these applicable method instances to a single class. To use the learn policy, RAE chooses randomly among all applicable instances of the learned method for the context at hand. **Learn** learning procedure consists of the following four steps, which are schematically depicted in Figure 3.

**Step 1: Data generation.** Training is performed on a set of data records of the form \( r = ((s, \tau), m) \), where \( s \) is a state, \( \tau \) is a task to be refined and \( m \) is a method for \( \tau \). Data records are obtained by making RAE call the planner offline with randomly generated tasks. Each call returns a method instance of the method \( m \). We tested two approaches (the results of the tests are in Section 7):

- **Learn** adds \( r = ((s, \tau), m) \) to the training set if RAE succeeds with \( m \) in accomplishing \( \tau \) while acting in a dynamic environment.
- **Learn** adds \( r \) to the training set irrespective of whether \( m \) succeeded during acting.

**Step 2: Encoding.** The data records are encoded according to the usual requirements of neural net approaches. Given a record \( r = ((s, \tau), m) \), we encode \((s, \tau)\) into an input-feature vector and encode \( m \) into an output label, with the
refinement stack $\sigma$ omitted from the encoding for the sake of simplicity.\(^5\) Thus the encoding is

$$((s, \tau), m) \mapsto \left(\left[ w_s, w_\tau \right], w_m \right),$$

(8)

with $w_s$, $w_\tau$, and $w_m$ being One-Hot representations of $s$, $\tau$, and $m$. The encoding uses an $N$-dimensional One-Hot vector representation of each state variable, with $N$ being the maximum range of any state variable. Thus if every $s \in S$ has $V$ state-variables, then $s$’s representation $w_s$ is $V \times N$ dimensional. Note that some information may be lost in this step due to discretization.

**Step 3: Training.** Our multi-layer perceptron (MLP) $nn_\pi$ consists of two linear layers separated by a ReLU layer to account for non-linearity in our training data. To learn and classify $[w_s, w_\tau]$ by refinement methods, we used a SGD (Stochastic Gradient Descent) optimizer and the Cross Entropy loss function. The output of $nn_\pi$ is a vector of size $|M|$ where $M$ is the set of all refinement methods in a domain. Each dimension in the output represents the degree to which a specific method is optimal in accomplishing $\tau$.

**Step 4: Integration in RAE.** RAE uses the trained network $nn_\pi$ to choose a refinement method whenever a task or sub-task needs to be refined. Instead of calling the planner, RAE encodes $(s, \tau)$ into $[w_s, w_\tau]$ using Equation 8. Then, $m$ is chosen as

$$m \leftarrow \text{Decode}(\arg\max_i(nn_\pi([w_s, w_\tau])[i])),$$

where $\text{Decode}$ is a one-one mapping from an integer index to a refinement method.

6.2. Learning to choose method instances ($\text{Learn}\pi_i$)

Here, we extend the previous approach to learn a mapping from context to fully instantiated methods. The $\text{Learn}\pi_i$ procedure learns over all the values of uninstantiated parameters using a multi-layered perceptron (MLP).

**Step 1: Data generation.** For each uninstantiated method parameter $v_{un}$, training is performed on a set of data records of the form $r = ((s, v_\tau), b)$, where $s$ is the current state, $v_\tau$ is a list of values of the task parameters, and $b$ is the value of the parameter $v_{un}$. Data records are obtained by making RAE call $\text{UPOM}$ offline with randomly generated tasks. Each call returns a method instance $m$ and the value of its parameters.

**Step 2: Encoding.** Given a record $r = ((s, v_\tau), b)$, we encode $(s, v_\tau)$ into an input-feature vector and encode $b$ into an output label. Thus the encoding is

$$((s, v_\tau), b) \mapsto \left(\left[ w_s, w_{v_\tau} \right], w_b \right),$$

(9)

with $w_s$, $w_{v_\tau}$, and $w_b$ being One-Hot representations of $s$, $v_\tau$, and $b$.

---

\(^5\)Technically, the choice of $m$ depends partly on $\sigma$. However, since $\sigma$ is a program execution stack, including it would greatly increase the input feature vector’s complexity, and the neural network’s size and complexity.
Step 3: Training. We train a multi-layered perceptron (MLP) for each uninstantiated task parameter $v_{un}$. Each such MLP $nn_{v_{un}}$ consists of two linear layers separated by a ReLU layer to account for non-linearity in our training data. To learn and classify $[w_s, w_{v_{un}}]$ by the values of $v_{un}$, we used a SGD (Stochastic Gradient Descent) optimizer and the Cross Entropy loss function. The output of $nn_{v_{un}}$ is a vector of size $|Range(v_{un})|$. Each dimension in the output represents the degree to which $v_{un}$ takes a specific value.

Step 4: Integration in RAE. After RAE has chosen a refinement method $m$ for task $\tau$, we have RAE use the trained network $nn_{v_{un}}$ to choose a value for each uninstantiated parameter $v_{un}$. RAE encodes $(s, v_{\tau})$ into $[w_s, w_{v_{\tau}}]$ using Equation 9. Then, the value for $v_{un}$, $b$ is chosen as

$$b \leftarrow Decode(\text{argmax}_j(nn_{v_{un}}([w_s, w_{v_{un}}])[j]),$$

where $Decode$ is a one-one mapping from integer indices to $Range(v_{un})$.

6.3. Learning a heuristic function (LearnH)

The LearnH procedure tries to learn an estimate of the utility $u$ of accomplishing a task $\tau$ with a method instance $m$ in state $s$. One difficulty with this is that $u$ is a real number. In principle, an MLP could learn the $u$ values using either regression or classification. To our knowledge, there is no rule to choose between the two; the best approach depends on the data distribution. Further, regression can be converted into classification when the range of the target values is finite. In our case, we don’t need an exact utility value. We only need to compare candidate method instances. Experimentally, we observed that classification performed better than regression. We divided the range of utility values into $K$ intervals. By studying the range and distribution of utility values, we chose $K$ and the range of each interval such that the intervals contained approximately equal numbers of data records. LearnH learns to predict interval($u$), i.e., the interval in which $u$ lies. The steps of LearnH are the following (see Figure 4):

![Figure 4: A schematic diagram for the LearnH procedure.](image-url)
**Step 1: Data generation.** We generate data records in a similar way as in the Learnπ procedure, with the difference that each record \( r \) is of the form \( ((s, \tau, m), u) \) where \( u \) is the estimated utility value calculated by UPOM.

**Step 2: Encoding.** In a record \( r = ((s, \tau, m), u) \), we encode \((s, \tau, m)\) into an input-feature vector using \( N \)-dimensional One-Hot vector representation, omitting \( \sigma \) for the same reasons as before. If \( interval(u) \) is as described above, then the encoding is

\[
((s, \tau, m), interval(u)) \xrightarrow{\text{Encoding}} ([w_s, w_{\tau}, w_m], w_u)
\]  

with \( w_s, w_{\tau}, w_m \) and \( w_u \) being One-Hot representations of \( s, \tau, m \) and \( interval(u) \).

**Step 3: Training.** LearnH’s MLP \( nn_H \) is the same as Learnπ’s, except for the output layer. \( nn_H \) has a vector of size \( K \) as output where \( K \) is the number of intervals into which the utility values are split. Each dimension in the output of \( nn_H \) represents the degree to which the estimated utility lies in that interval.

**Step 4: Integration in RAE.** RAE calls the planner with a limited rollout length \( d \), giving UPOM the following heuristic function to estimate a rollout’s remaining utility:

\[
h(\tau, m, s) \leftarrow \text{Decode}(\text{argmax}_i(nn_H([w_s, w_{\tau}, w_m])[i])),
\]

where \([w_s, w_{\tau}, w_m]\) is the encoding of \((\tau, m, s)\) using Equation 10, and \( \text{Decode} \) is a one-one mapping from a utility interval to its mid-point. Before the progressive deepening loop over calls to UPOM, Select initializes \( \tilde{m} \) in line 1 according to this heuristic \( h \).

6.4. Incremental online learning

The proposed approach supports incremental online learning (although not yet experimented with). The initialization can be performed either (i) without a heuristic by running RAE+UPOM online with \( d_{\max} = \infty \), or (ii) with an initial heuristic obtained from offline learning on simulated data. The online acting, planning and incremental learning is performed as follows:

- Augment the training set by recording successful methods (with the values of uninstantiated parameters) and \( U \) values; train the models using Learnπ and LearnH with \( Z \) records, and then switch RAE to use either Learnπ alone when no search time is available, or UPOM with current heuristic \( h \) and finite \( d_{\max} \) when planning time available.
- Repeat the above steps every \( X \) runs (or on idle periods) using the most recent \( Z \) training records (for \( Z \) about a few thousands) to improve the learning on both LearnH and Learnπ.
7. Experimental Evaluation

7.1. Domains

We have implemented and tested our framework on five domains which illustrate service and exploration robotics scenarios with aerial and ground robots.

The S&R domain extends the search and rescue setting of Example 1 with several UAVs surveying a partially mapped area and finding injured people in need of help. UGVs gather supplies, such as medicines, and go to rescue the localized persons. Exogenous events are weather conditions and debris in paths.

In Explore, several chargeable UGVs and UAVs explore a partially known terrain and gather information by surveying, screening, monitoring, e.g., for ecological studies. They need to go back to the base regularly to deposit data or to collect a specific equipment. Appearance of animals simulate exogenous events.

In Fetch domain, several robots are collecting objects of interest. The robots are rechargeable and may carry the charger with them. They can’t know where objects are, unless they do a sensing action at the object’s location. They must search for an object before collecting it. A task reaches a dead end if a robot is far away from the charger and runs out of charge. While collecting objects, robots may have to attend to some emergency events happening in certain locations.

The Nav domain has several robots trying to move objects from one room to another in an environment with a mixture of spring doors (which close unless they’re held open) and ordinary doors. A robot can’t simultaneously carry an object and hold a spring door open, so it must ask for help from another robot. A free robot can be the helper. The type of each door isn’t known to the robots in advance.

The Deliver domain has several robots in a shipping warehouse that must co-operatively package incoming orders, i.e., lists of items of different types and weights to deliver to customers. Items for a single order have be placed in a machine, which packs them together; packages have to be placed in the shipping doc. To process multiple orders concurrently, items can be moved to a pallet before transfer to a machine. Robots have limited capacities.

S&R, Explore, Nav and Fetch have sensing actions. S&R, Explore, Fetch and Deliver can have dead-ends. The features of these domains are in Table 1. Please recall from Section 3 that $\mathcal{M}$ is the set of all refinement methods, and $\mathcal{M}$ is the set of all refinement method instances.

| Domain  | $|\mathcal{T}|$ | $|\mathcal{M}|$ | $|\mathcal{M}|$ | $|\mathcal{A}|$ | Dynamic events | Dead ends | Sensing | Robot collaboration | Concurrent tasks |
|---------|----------------|----------------|----------------|----------------|----------------|------------|---------|-------------------|-----------------|
| S&R     | 8              | 16             | 16             | 14             | ✓              | ✓         | ✓       | ✓                 | ✓               |
| Explore | 9              | 17             | 17             | 14             | ✓              | ✓         | ✓       | ✓                 | ✓               |
| Fetch   | 7              | 10             | 10             | 9              | ✓              | ✓         | ✓       | –                 | ✓               |
| Nav     | 6              | 9              | 15             | 10             | ✓              | –         | ✓       | ✓                 | ✓               |
| Deliver | 6              | 6              | 50             | 9              | ✓              | ✓         | –       | ✓                 | ✓               |

Table 1: Features of the test domains
7.2. Planning parameters

Here we analyze the effect of the two planning parameters, \( n_{ro} \) and \( d_{\text{max}} \), on the two utility functions we considered, the efficiency, and the success ratio, as well as on the retry ratio of RAE. We tested \( n_{ro} \in [0, 1000] \) and \( d_{\text{max}} \in [0, 30] \). The case \( n_{ro} = 0 \) rollout corresponds to purely reactive RAE, without planning. We only report for \( n_{ro} \in [0, 250] \) since no significant additional effect was observed beyond \( n_{ro} > 250 \). We tested each domain on 50 randomly generated problems. A problem consists of one or two root tasks that arrives at a random time points in RAE’s input stream, together with other randomly generated exogenous events. For each problem we recorded 50 runs to account for the nondeterministic effects of actions. We measured

- the efficiency of RAE for a task, i.e., the reciprocal of the sum of the costs of the actions executed by RAE for accomplishing that task;
- the success ratio of RAE for a run, i.e., the number of successful task over the total of tasks for that run; and
- the retry ratio of RAE for a run, i.e., the number of call to Retry over the total of tasks for that run.

Note that the measured efficiency takes into account the execution context with concurrent tasks and exogenous events; hence it is different for the corresponding utility function optimized in UPOM (i.e., the expected efficiency of Equation 6); similarly for the success ratio. We used a 2.8 GHz Intel Ivy Bridge processor. The cut-off time for a run was set to 30 minutes.

Comparison of the two utility functions. We studied two utility functions that are not totally independent but assess different criteria. The success ratio is useful as a measure of robustness. Suppose method instance \( m_1 \) is always successful but has a large cost, whereas \( m_2 \) sometimes fails but costs very little...
when it works: $m_1$ has a higher success ratio, but $m_2$ has higher expected efficiency.

Figure 5 shows the measured efficiency and success ratio of RAЕ for the two utility functions, averaged over all domains. Each data point is the average of $10^4$ runs, with the error bars showing 95% confidence interval; we plot relative values with respect the base case of $U$ for $n_{ro} = 0$. As expected, the measured efficiency is higher when the optimized utility function of UPOM is the expected efficiency. Similarly for the success ratio. However, optimizing one criteria has also a good effect on the other one, since the two are not independent. We also observe that 5 rollouts have already a significant effect on the efficiency, with slight improvements as UPOM does more rollouts. In contrast, the success-ratio increases smoothly from no planning to planning with 250 rollouts. This can be due to the difference between the two criteria: a task that succeeds in its first attempt and a task that succeeds after several retries of RAЕ have both a success-ratio of 1, but the efficiency in the latter case is lower. This point is analyzed next.

**Retry ratio.** Figure 6 shows the retry ratio, i.e., the number of calls to Retry, divided by the total number of tasks. Recall that when a chosen method instance fails, Retry tries another applicable method instance that hasn’t been tried already. The retry ratio measures the execution effectiveness. Performing many retries is not desirable, since this has a high cost and faces the uncertainty of execution. We observe that the retry ratio drops sharply from purely reactive RAЕ to calling UPOM with 5 rollouts. From then onwards, until 250 rollouts, the retry ratio continues to decrease gradually. The behavior is similar in all domains, so we have combined the results together to show the average values in a single plot.

**Efficiency across domains.** In Figure 7 we detail for each domain the measured efficiency of RAЕ when the utility of UPOM was set to expected efficiency, for varying $n_{ro}$ and $d_{max} = \infty$. Each data point is the average of 2500 runs.
We observe that the efficiency generally improves with the number of rollouts. However, there is not much improvement with increase in \( n_{ro} \) in the Fetch domain, and in the Deliver domain, the efficiency drops slightly when \( n_{ro} = 250 \). We conjectured that this can be due to concurrent interfering tasks. Hence, we measured for Fetch and Deliver domains the efficiency for test cases with only one root task; the results in Figure 8 confirmed this conjecture.

![Figure 7: Measured efficiency of RAE for \( n_{ro} \in [0, 250] \) and \( d_{max} = \infty \) (relative values with respect to the base case of U for \( n_{ro} = 0 \)).](image)

![Figure 8: Measured efficiency averaged over only test cases with one root task, in Fetch and Deliver domains with \( d_{max} = \infty \) (relative values with respect to the base case of U for \( n_{ro} = 0 \)).](image)

**Success ratio across domains.** Figure 9 shows for each domain the measured success ratio of RAE when the utility of UPOM was set to expected success ratio, for varying \( n_{ro} \) and \( d_{max} = \infty \). The success-ratio generally increases with increase in the number of rollouts. Again, a slight drop is observed in the Deliver domain. Figure 10 shows that for test cases with only one root task the success-ratio improves in the Fetch domain, and remains constant in the Deliver domain.
The success ratio remains 1 in the Deliver domain because all test cases with one root task succeed eventually, with or without retries. In the domains with dead ends, the improvement in success ratio is more substantial than domains without dead ends because planning is more critical for cases where one bad choice of refinement method instance can lead to permanent failure.

**Depth and Heuristics.** We ran UPOM at different values of $d_{max} \in [0, 30]$, without progressive deepening in Select. At the depth limit, UPOM estimates the remaining efficiency using one of the following heuristic functions:

- $h0$ always returns $\infty$;
- $hD$ is a hand written domain specific heuristic;
- $hLearnH$ is the heuristic function learned by the LearnH procedure (Section 6.3).
The results, in Figure 11, show that the efficiency generally increases with depth across all domains. In the Nav domain, the \textit{hLearnH} performs better than \textit{h0} and \textit{hD} with 95% confidence at depths 2 and 3. In the Explore domain, \textit{hLearnH} performs better than \textit{h0} and \textit{hD} at depth 1 with 95% confidence. The same is true for Fetch at depth 2. In the Deliver domain, the learned heuristic performs better than the others with 95% confidence for all depths $>= 1$. The performance difference between the three different heuristics are due to the properties of the domain, how the refinement methods are designed and how much of it is learnable by the \textit{LearnH} procedure.

![Figure 11: Measured efficiency with limited depth and three different heuristic functions. The utility function optimized is expected efficiency (relative values with respect to the base case of $U$ for $n_{re} = 0$).](image)

**Measured vs expected efficiency.** We already discussed how the measured efficiency of RAE is different from the expected one computed in UPOM. The difference between the two is given in Figure 12 with respect to the refinement deepness. A root task is refined recursively into sub-tasks. For each sub-task, RAE calls UPOM to choose a method instance. We note that the difference between the measured efficiency and the expected efficiency decreases as RAE makes progress towards accomplishing the root task.

7.3. Assessment of UPOM

We are not aware of any comparable planner for operational models, but of RAEplan [70], a Monte Carlo Tree Search procedure we developed earlier. We discuss here RAE with UPOM \textit{vs} RAEplan.\footnote{We didn’t compare UPOM with any non-hierarchical planning algorithms because it would be very difficult to perform a fair comparison, as discussed in [48].} We configured UPOM to optimize the expected
efficiency as its utility function, the same as RAEplan. In order not to favor the UCT strategy of UPOM with respect to the tree branching strategy of RAEplan, we set $n_{r_o} = 1000$, with $d_{\text{max}} = \infty$ in each rollout.

Figure 13 shows the computation time for a single run of a problem (one or two root tasks), averaged across all domains and problems, i.e., over $10^4$ runs. RAE with UPOM runs more than twice as fast as RAE alone. Note that the computation time of RAE with UPOM runs more than twice as fast as RAE alone. However, in physical experiments, the total time includes sensing and actuation time, hence the planning overhead would not appear as significant as it is here.

![Figure 13: Average computation time in seconds for a single run of a problem, for RAE with and without the planners.](image)

Efficiency. Figure 14 gives the measured efficiency for the five domains, with the 95% confidence intervals. It shows in all domains that RAE with UPOM is more efficient than purely reactive RAE and RAE with RAEplan.

Success ratio. Figure 15 shows RAE’s success ratio both with and without the planners. We observe that planning with UPOM outperforms purely reactive RAE in S&R and Fetch with 95% confidence, and Explore and Nav with 85% confidence. Also, UPOM outperforms RAEplan in Fetch and Nav domains with a 95% confidence, and Explore domain with 85% confidence. In the S&R domain, the success ratio is similar for RAEplan and UPOM.

Asymptotically, UPOM and RAEplan should have near-equivalent efficiency and success ratio metrics. They differ because neither are able to traverse the entire search space due to computational constraints. Our experiments on simulated environments suggest that UPOM is more effective than RAEplan when called online with real-time constraints.
Figure 14: Measured efficiency for each domain with purely reactive RAE, RAE with RAEplan, RAE with the policies learned by Learnπ without planning, RAE with UPOM, the heuristic learned by LearnH and \( d_{\text{max}} = 5 \), and RAE with UPOM and \( d_{\text{max}} = \infty \) (relative values with respect to the base case of \( U \) for \( n_{r_0} = 0 \)).

7.4. Assessment of learning procedures

For training purposes, we synthesized data records for each domain by randomly generating root tasks and then running RAE with UPOM. The number of randomly generated tasks in S&R, Nav, Explore, Fetch, and Deliver domains are 96, 132, 189, 123, and 100 respectively. We save the data records according to the Learnπ-1, Learnπ-2, Learnπ, and LearnH procedures, and encode them using the One-Hot schema. We divide the training set randomly into two parts: 80% for training and 20% for validation to avoid overfitting on the training data.

The training and validation losses decrease and the accuracy increases with increase in the number of training epochs (see Figure 16).

The accuracy of Learnπ is measured by checking whether the refinement method instance returned by UPOM matches the template predicted by the MLP \( nn_\pi \), whereas the accuracy of LearnH is measured by checking whether the efficiency estimated by UPOM lies in the interval predicted by \( nn_H \). We chose the learning rate to be in the range \([10^{-3}, 10^{-1}]\). Learning rate is a scaling factor that controls how weights are updated in each training epoch via backpropagation.

Table 2 summarizes the training set size, the number of input features and outputs after data records are encoded using the One-Hot schema, number of training epochs for the three different learning procedures. In the LearnH learning procedure, we define the number of output intervals \( K \) from the training data such that each interval has an approximately equal number of data records. The final validation accuracies for Learnπ are 65%, 91%, 66% and 78% in the domains Fetch, Explore, S&R and Nav respectively. The final validation accuracies for LearnH are similar but slightly lower.
Figure 15: Measured success ratio for each domain with purely reactive RAE, RAE with RAEplan, RAE with the policies learned by Learn\(\pi\) without planning, RAE with UPOM, the heuristic learned by LearnH and \(d_{\text{max}} = 5\), and RAE with UPOM and \(d_{\text{max}} = \infty\) (relative values with respect to the base case of \(U\) for \(n_{\text{ro}} = 0\)).

| Domain | Training Set Size | (#(input features) | Training epochs | #(outputs) |
|--------|------------------|--------------------|----------------|-----------|
|        | LM-1  | LM-2  | LH    | LM-1 and -2 | LH    | LM-1 and -2 | LH    |
| S&R    | 250   | 654   | 342   | 350  | 401  | 225   | 250   | 16   | 10   |
| Nav    | 1686  | 5331  | 16251 | 126  | 144  | 750   | 150   | 9    | 75   |
| Explore| 2391  | 6883  | 10503 | 182  | 204  | 1000  | 250   | 17   | 200  |
| Fetch  | 262   | 508   | 1084  | 97   | 104  | 430   | 250   | 10   | 100  |
| Deliver| -     | 2001  | -     | -    | 627  | -     | 250   | -    | 10   |

Table 2: The size of the training set, number of input features and outputs, and the number of training epochs for three different learning procedures: Learn\(\pi\)-1, Learn\(\pi\)-2, and LearnH. We note LM-1 = Learn\(\pi\)-1, LM-2 = Learn\(\pi\)-2, and LH = LearnH.

The accuracy values may possibly improve with more training data and encoding the refinement stacks as part of the input feature vectors.

To test the learning procedures we measured the efficiency and success ratio of RAE with the policies learned by Learn\(\pi\)-1 and Learn\(\pi\)-2 without planning, and RAE with UPOM and the heuristic learned by LearnH. We use the same test suite as in our experiments with RAE using RAEplan and UPOM, and do 20 runs for each test problem. When using UPOM with LearnH, we set \(d_{\text{max}}\) to 5 and \(n_{\text{ro}}\) to 50, which has about 88\% less computation time compared to using UPOM with infinite \(d_{\text{max}}\) and \(n_{\text{ro}} = 1000\). Since the learning happens offline, there is almost no computational overhead when RAE uses the learned models for online acting.

**Efficiency.** Figure 14 shows that RAE with UPOM + LearnH is more efficient than
both purely reactive RAE and RAE with RAЕplan in three domains (Explore, S&R and Nav) with 95% confidence, and in the Fetch domain with 90% confidence. The efficiency of RAE with Learnп-1 and Learnп-2 lies in between RAE with RAЕplan and RAE with UPOM + LearnH, except in the S&R domain, where they perform worse than RAE with RAЕplan but better than purely reactive RAE. This is possibly because the refinement stack plays a major role in the resulting efficiency in the S&R domain.

**Success ratio.** In these last experiments, UPOM optimizes for the efficiency, not the success ratio. It is however interesting to see how we perform for this criteria even when it is not the chosen utility function. In Figure 15, we observe that RAE with UPOM + LearnH outperforms purely reactive RAE and RAE with RAЕplan in three domains (Fetch, Nav and S&R) with 95% confidence in terms of success ratio. In Explore, there is only slight improvement in success-ratio possibly because of high level of non-determinism in the domain’s design.

In most cases, we observe that RAE does better with Learnп-2 than with Learnп-1. Recall that the training set for Learnп-2 is created with all methods returned by UPOM regardless of whether they succeed while acting or not, whereas Learnп-1 leaves out the methods that don’t. This makes Learnп-1’s training set much smaller. In our simulated environments, the acting failures due to random exogenous events don’t have a learnable pattern, and a smaller training set makes Learnп-1’s performance worse.

**Learning Method Instances.** Two of our simulated domains, Nav and Deliver, have refinement methods with parameters that are not inherited from the task at hand. For these domains, Learnп-1 and Learnп-2 give only partially instantiated methods, while Learnп is more discriminate. To test its benefit, we trained a MLP for each parameter not specified in the task. The size of the training set, number of input features and number of outputs are summarized in Table 3.

Figure 17 compares the efficiency of RAE with Learnп, vs purely reactive RAE and RAE with RAЕplan, Learnп-1, Learnп-2, LearnH, and UPOM. In the Deliver domain, RAE with Learnп is better than purely reactive RAE as well as RAE with Learnп-1 or Learnп-2 with 95% confidence. In the Nav domain, RAE with Learnп also outperforms Learnп-1 and purely reactive RAE with 95% confidence, but not Learnп-2. The performance benefit is significant in the Deliver domain because refinement methods have several uninstatiated parameters.

In summary, for all the domains, planning with UPOM and learning clearly outperforms purely reactive RAE.
### Table 3: The size of the training set, number of input features and outputs for learning method parameters in Learn$\pi_i$.

| Domain     | Method                        | Parameter  | Training Set Size | #input features | #outputs |
|------------|-------------------------------|------------|-------------------|----------------|---------|
| Nav        | MoveThroughDoorway_M2         | robot      | 404               | 1420           | 4       |
|           | Recover_M1                    | robot      | 337               | 5128           | 4       |
|           | Recover_M2                    | robot      | 296               | 633            | 5       |
| Deliver    | Order_M1                      | machine    | 95                | 613            | 5       |
|           | Order_M2                      | objList    | 95                | 613            | 2       |
|           | Order_M2                      | pallet     | 95                | 613            | 4       |
|           | PickupAndLoad_M1              | robot      | 244               | 637            | 7       |
|           | UnloadAndDeliver_M1           | robot      | 219               | 625            | 7       |
|           | MoveToPallet_M1               | robot      | 7                 | 633            | 7       |

Figure 17: The cross hatched blue bars show the performance of RAE with Learn$\pi_1$ (learning method instances) for the two domains, Nav and Deliver, which have methods with parameters not in tasks (relative values with respect to the base case of $U$ for $n_{ro} = 0$).

### 8. Discussion and Conclusion

This paper presented a novel system for integrating acting and planning using hierarchical refinement operational models. The refinement acting engine RAE can either run purely reactively, or it can get advice from an online planner to choose efficient method instances for performing a task. We proposed a planning procedure UPOM, which uses a search strategy inspired by UCT, extended to operate in a more complicated search space. UPOM provides near-optimal method instances with respect to a quite general utility functions and converges asymptotically. Two distinct utility function, favoring respectively efficiency and robustness, have been proposed. UPOM is integrated to RAE within receding horizon, anytime progressive deepening procedure. We further designed three learning strategies: Learn$\pi$, to learn a mapping from a task in a given context to a good method, Learn$\pi_i$, to learn values of uninstantiated method parameters and LearnH, to learn a domain specific heuristic function for our hierarchical refinement framework. We have shown how incremental learning could be integrated online with acting and planning.

We presented empirical results over five domains that have challenging features such as dynamicity, dead-ends, exogenous events, sensing and information gathering actions, collaborative and concurrent tasks. While most often the experimental evaluation of systems addressing acting and planning is simply performed on the sole planning functionality, we devised here a simulation and a measure to assess the over-
all performance to act, with and without planning and learning, taking into account
exogenous events and failure cases.

We measured the actor’s efficiency, success ratio and retry ratio, and discussed
their relationships with respect to the planner’s utility function, maximizing either the
expected efficiency or the expected success ratio. Our results show that $\text{Learn}^\pi$ already
improves the performance of reactive RAE with respect to the three measures; RAE
with UPOM and $\text{LearnH}$ or with UPOM at unbounded depth improve significantly all
the performance measures. Thanks to learning, the computational overhead remains
acceptable for online procedure, since in this case a small number of rollouts bring
already a good benefit. In summary, acting purely reactively in dynamic domains with
dead ends can be costly and risky. The homogeneous and sound integration approach
for acting, planning and learning proposed here is of great benefit reflected through a
higher efficiency or robustness. This approach is backed up with an open-source code
for all algorithms and domains.\footnote{\url{https://bitbucket.org/sunandita/rae/}}

While covering a broad technical material for refinement acting, planning and
learning, we left a few pending issues and assumptions, whose discussion can be of
help to the reader for using and deploying this material in a practical application.

Retrial in RAE. As mentioned earlier, Retry is not a backtracking procedure. Since
RAE interacts with a dynamic world, Retry cannot go back to a previous state. It
selects a method instance among those applicable in the current world state, but of
those that have been tried before and failed. This latter restriction may not always
be necessary, since the same method instance that failed at some point may succeed
later on. A full analysis of the conditions responsible for failures to make sure that
they no longer hold can be complicated. However, RAE can be adapted to retrial of
method instances vulnerable to noisy sensing and execution contexts that merit to be
retried: one extends their parameters with arguments not needed for the logic of the
method instance but that characterize the context (e.g., the pose of a sensor that may
have changed between trials), while bounding the number of retrials.

Retrial can be applied more easily for actions. In RAE, a method instance fails
when one of its actions fails. But actions being non deterministic, it can be worthwhile
retrying an action as assessed by its expected utility. This may be implemented after a
full analysis and the computation of an optimal MDP policy\footnote{This can be done with a sequence of dummy states $s_{\text{fail}}$, such that the effects of action
$a$ in $s$ include $s'_{\text{fail}} \in \gamma(s,a), \ldots, s'_{\text{fail}_{i+1}} \in \gamma(s_{\text{fail}_i},a)$; two actions are applicable to each
$s'_{\text{fail}}$: $a$ and stop-with-failure.}, or simply with an ad-hoc loop on the execution-status
of the actions that merit retrials. Furthermore, the body
of a method being any procedure, complex retrial loop can be specified. For example, a
difficult grasp action in robotics may need several sequences of $<\text{move, sense, grasp}>$
before succeeding or renouncing to the corresponding method instance.

Concurrency. The main loop of RAE progresses concurrently over several Agenda, one
for each top level task. All the domains we experimented with use this facility and
involve concurrent tasks. However, in our current implementation possible conflicts
and needed synchronizations are managed through the specification of the methods.
To ease this specification, it is possible to enrich the body of methods with temporal
and synchronization constructs, such as those used in TCA and TDL [80, 81], and rely
on the execution-status of actions to handle waits. Since both UPOM and learning rely on the simulation of the method instances, they can support such extensions as long as Sample is able to simulate the duration of actions. More research would be needed to integrate to our approach extensions permitting the formal verification of concurrency property (liveness, deadlocks), e.g., as in the Petri-net based reactive system ASPiC [56].

Note that it is possible to extend RAE with refinement into concurrent subtasks (see [28, Sect. 3.2.4]. We have not experimented with this facility.

Learning operational models. The Learnπ and LearnH procedures are limited to improve the decision making of RAE, with or without planning. They are also of help to a domain author, who does not need to design a minimal set of methods associated to a preference ordering. However, assistance in acquiring operational models, which are more detailed than the abstract descriptive models of planning (and which are always needed for acting), would be highly desirable. Let us raise few remarks about this important issue of future work.

Actions and methods, the two main components of operational models, would probably demand different learning techniques. Execution models of actions are domain dependent. For example, in robotics several approaches have been studied, e.g., [72, 51, 35, 12]. They usually rely on Reinforcement Learning (RL), possibly supervised and/or with inverse RL (see survey [52]). Other techniques for learning actions as low levels skills can also be relevant, e.g., [9, 95]. These techniques would provide the procedure Sample, a corner stone in our approach: Sample(s, a) returns a state s′ randomly drawn from γ(s, a) according to the distribution of the outcomes of a in s. UPOM needs Sample (line 7 in Algorithm 6) to simulate the execution of method instances in a rollout. Note that many application areas benefit from a domain simulator which can be very useful learning action models and synthesizing Sample.

Learning refinement methods has been addressed for HTN descriptive models, e.g., [39, 37, 38, 96, 95]. Our refinement methods for operational models can be significantly more complex. Possible investigation avenues for synthesizing these methods are: program synthesis techniques [87, 31], partial programming and RL [1, 58, 82], learning from the demonstrations of a tutor [2].

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Appendix A. Asymptotic Convergence of UPOM

In this appendix we demonstrate the asymptotic convergence of UPOM towards an optimal method in static domains, i.e., domains without exogenous events. We do this by mapping UPOM’s search strategy into UCT, which is demonstrated to converge on a finite horizon MDP with a probability of not finding the optimal action at the root node that goes to zero at a polynomial rate as the number of rollouts grows to infinity (Theorem 6 of [53]).

To simplify the mapping, we first consider UPOM with an additive utility function, and show how to map UPOM’s search space into an MDP. We then discuss how this can be extended to the efficiency and success ratio utility functions defined in 5, using the fact that the UCT algorithm is not restricted to the additive case; it still converges as long as the utility function is monotonic.

A.1. Search Space for Refinement Planning

Let $\Sigma = (\Xi, T, M, A)$ be an acting domain, as specified at the end of Section 3. Throughout this appendix, we will assume that $\Sigma$ is static.

Recall from Section 5 that the space searched by UPOM is a simulated version of $\Sigma$. To talk about this formally, recall that a refinement planning domain is a tuple $\Phi = (S, T, M, A)$, where $S$ is the set of states (recall that these are abstractions of...
states in \( \Xi \), and \( T, M, \) and \( A \) are the same as in \( \Sigma \). Recall from Section 3 that \( \Xi \) (and thus \( S \)), \( T, M, \) and \( A \) are all finite, and that every sequence of steps generated by the methods in \( M \) is finite.

For \( s \in S \) and \( a \in A \), we let \( \gamma(s, a) \subseteq S \) be the set of all states that may be produced by simulating \( a \)'s execution in \( s \). For each \( s' \in \gamma(s, a) \), we let \( P(s, a, s') \) be the probability that state \( s' \) will be produced if we simulate \( a \)'s execution in state \( s \).

Recall from Section 4 that a refinement stack is a LIFO stack in which each element is a tuple \((\tau, m, i, \text{tried})\), where \( \tau \) is a task, \( m \) is a method, \( i \) is an instruction pointer that points to the \( i \)'th line of \( m \)'s body (which is a computer program), and tried is the set of methods previously tried for \( \tau \). We will call the tuple \((\tau, m, i, \text{tried})\) a stack frame, and we will let \( m[i] \) denote the \( i \)'th line of the body of \( m \).

We now can define a refinement planning problem to be a tuple \( \Pi = (\Phi, s_0, \sigma_0, U) \), where \( s_0 \) is the initial state, \( \sigma_0 \) is the initial refinement stack, and \( U \) is a utility function.

**Rollouts.** A rollout in \( \Phi \) is a sequence of pairs

\[
\rho = \langle (\sigma_0, s_0), (\sigma_1, s_1), \ldots, (\sigma_n, s_n) \rangle
\]

satisfying the following properties:

- each \( s_i \) is a state, and each \( \sigma_i \) is a refinement stack;
- for each \( i > 0 \) there is a nonzero probability that \( s_j \) and \( \sigma_j \) are the next state and refinement stack after \( s_{i-1} \) and \( \sigma_{i-1} \);
- \((\sigma_n, s_n)\) is a termination point for UPOM.

If the final refinement stack is \( \sigma_n = \langle \rangle \), i.e., the empty stack, then the rollout \( \rho \) is successful. Otherwise \( \rho \) fails.

In a top-level call to UPOM, the initial refinement stack \( \sigma_0 \) would normally be

\[
\sigma_0 = \langle (\tau_0, m_0, 1, \emptyset) \rangle,
\]

where \( \tau_0 \) is a task, and \( m_0 \) is a method that is relevant for \( \tau_0 \) and applicable in \( s_0 \). In all subsequent refinement stacks produced by UPOM.

We will say that a refinement stack \( \sigma \) is reachable in \( \Phi \) (i.e., reachable from a top-level call to UPOM) if there exists a rollout

\[
\rho = \langle (\sigma_0, s_0), (\sigma_1, s_1), \ldots, (\sigma_n, s_n) \rangle
\]

such that \( \sigma_0 \) satisfies Equation A.2 and \( \sigma \in \{\sigma_0, \ldots, \sigma_n\} \). We let \( R(\Phi) \) be the set of all refinement stacks that are reachable in \( \Phi \). Since every sequence of steps generated by the methods in \( M \) is finite, it follows that \( R(\Phi) \) is also finite.

**Additive utility functions.** The utility function \( U \) is additive if there is either a reward function \( R(s) \) or a cost function \( C(s, a, s') \) (where \( s, a, s' \) is a transition from \( s \) to \( s' \) caused by action \( a \)) such that \( U \) is the sum of the rewards or costs associated with the state transitions in \( \rho \). These state transitions are the points in \( \rho \) where UPOM simulates the execution of an action.

For each pair \((\sigma_j, s_j)\) in \( \rho \), let \((\tau_j, m_j, i_j, \text{tried}_j)\) be the top element of \( \sigma_j \). If \( m_j[i_j] \) is an action, then the next element of \( \rho \) is a pair \((\sigma_{j+1}, s_{j+1})\) in which \( s_{j+1} \) is the state produced by executing the action \( m_j[i_j] \). In \( \Phi \) this corresponds to the state transition \((s_j, m_j[i_j], s_{j+1})\). Thus the set of state transitions in \( \rho \) is

\[
t_\rho = \{ (s_j, m_j[i_j], s_{j+1}) \mid (\sigma_j, s_j) \text{ and } (\sigma_{j+1}, s_{j+1}) \text{ are members of } \rho, \quad (\tau_j, m_j, i_j, \text{tried}_j) = \text{top}(\sigma_j), \text{ and } m_j[i_j] \text{ is an action} \}.
\]
Thus if \( U \) is additive, then
\[
U(\rho) = \begin{cases} 
\sum_{(s,a,s') \in t_\rho} R(s'), & \text{if } U \text{ is the sum of rewards,} \\
\sum_{(s,a,s') \in t_\rho} C(s,a,s'), & \text{if } U \text{ is the sum of costs.}
\end{cases}
\tag{A.4}
\]

A.2. Defining the MDP

We want to define an MDP \( \Psi \) such that choosing among methods in \( \Phi \) corresponds to choosing among actions in \( \Psi \). The easiest way to do this is to let all of \( \Phi \)'s actions and methods be actions in \( \Psi \). Based loosely on the notation in [61], we will write \( \Psi \) as
\[
\Psi = (S^\Psi, A^\Psi, s^\Psi_0, S^g_\Psi, \gamma^\Psi, P^\Psi, U^\Psi) \tag{A.5}
\]
where
- \( S^\Psi = \text{stacks}(\Phi) \times S \) is the set of states,
- \( A^\Psi = \mathcal{M} \cup \mathcal{A} \) is the set of actions,
- \( s^\Psi_0 = (\sigma_0, s_0) \) is the initial state,
- \( S^g_\Psi = \{ (\emptyset, s) | s \in S \} \) is the set of goal states,

and the state-transition function \( \gamma^\Psi \), state-transition probability function \( P^\Psi \), and utility function \( U^\Psi \) are defined as follows.

**State transitions.** To define \( \gamma^\Psi \) and \( P^\Psi \), we must first define which actions are applicable in each state. Let \( (\sigma, s) \in S^\Psi \), and \( (\tau, m, i, t) = \text{top}(\sigma) \). Then the set of actions that are applicable to \( (\sigma, s) \) in \( \Psi \) is
\[
\text{Applicable}^\Psi((\sigma, s)) = \begin{cases} 
\text{Instances}(\mathcal{M}, m[i], s), & \text{if } m[i] \text{ is a task,} \\
\{m[i]\}, & \text{if } m[i] \text{ is an action.}
\end{cases}
\tag{A.6}
\]
Thus if \( a \in \text{Applicable}^\Psi((\sigma, s)) \), then there are two cases for what \( \gamma^\Psi((\sigma, s), a) \) and \( P^\Psi(s, a, s') \) might be:

- **Case 1:** \( m[i] \) is a task in \( \mathcal{M} \), and \( a \in \text{Instances}(\mathcal{M}, m[i], s) \). In this case, the next refinement stack will be produced by pushing a new stack frame \( \phi = (m[i], a, 1, \emptyset) \) onto \( \sigma \). The state \( s \) will remain unchanged. Thus the next state in \( \Psi \) will be \( (\phi + \sigma, s) \), where ‘+’ denotes concatenation. Thus
  \[
  \gamma^\Psi((\sigma, s), a) = \{(\phi + \sigma, s)\};
  \]
  \[
  P^\Psi((\sigma, s), a, (\phi + \sigma, s)) = 1;
  \]
  \[
  P^\Psi((\sigma, s), a, (\sigma', s')) = 0, \text{ if } (\sigma', s') \neq (\phi + \sigma, s).
  \]

- **Case 2:** \( m[i] \) is an action in \( \mathcal{A} \), and \( a = m[i] \). Then \( a \)'s possible outcomes in \( \Psi \) correspond one-to-one to its possible outcomes in \( \Phi \). More specifically, if \( \gamma \) is the state-transition function for \( \Phi \) (see Section 3), then
  \[
  \gamma^\Psi((\sigma, s), a) = \{(\text{Next}(\sigma, s'), s') | s' \in \gamma(\sigma, a)\}
  \]
  and
  \[
  P^\Psi((\sigma, s), a, (\sigma', s'))) = \begin{cases} 
P(s, a, s'), & \text{if } (\sigma', s') \in \gamma^\Psi((\sigma, s), a), \\
0, & \text{otherwise.}
\end{cases}
\]

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Rollouts and utility. A rollout of $\Pi^\Psi$ is any sequence of states and actions of $\Psi$,
$$\rho^\Psi = \langle (\sigma_0, s_0), a_1, (\sigma_1, s_1), a_2, \ldots, (\sigma_{n-1}, s_{n-1}), a_n, (\sigma_n, s_n) \rangle,$$
such that for $i = 1, \ldots, n$, $a_i \in \text{Applicable}(\sigma_i-1, s_{i-1})$ and
$$P^\Psi((\sigma_{i-1}, s_{i-1}), (\sigma_i, s_i), a_i) > 0.$$ The rollout is successful if $(\sigma_n, s_n) \in S^\Phi_g$, and unsuccessful otherwise.

We can define $U^\Psi$ directly from $U$. If $\rho^\Psi$ is the rollout given above, then the corresponding rollout in $\Phi$ is $\rho = \langle (\sigma_0, s_0), (\sigma_1, s_1), \ldots, (\sigma_{n-1}, s_{n-1}), (\sigma_n, s_n) \rangle$, and
$$U^\Phi(\rho^\Psi) = U(\rho).$$ If $U$ is additive, then so is $U^\Psi$. In this case, $\Psi$ satisfies the definition of an MDP with initial state (see [61]).

A.3. Mapping UPOM’s Search to an Equivalent UCT Search

Let
$$\Pi = (\Phi, s_0, \sigma_0, U)$$
be a refinement planning problem, where
$$\Phi = (S, T, M, A).$$
Suppose UPOM($s_0, \sigma_0, \infty$) generates the rollout
$$\rho = \langle (\sigma_0, s_0), (\sigma_1, s_1), \ldots, (\sigma_n, s_n) \rangle,$$
where $\sigma_j = (\tau_j, m_j, i_j, \text{tried}_j)$, for $j = 1, \ldots, n$. UPOM generates $\rho$ by choosing $m_1$ and then recursively calling UPOM($s_j, \sigma_j, \infty$). Consequently, UPOM’s probability of generating $\rho$ is
$$p = p_1 \times \ldots \times p_n,$$
where each $p_j$ is the probability that UPOM($s_j, \sigma_j, \infty$) will choose $m_j$ before making its recursive call. The value of $p_j$ will depend on UPOM’s metadata for $\Pi$, e.g., the number of times each method for a task $\tau$ has been tried in each state $s$, and the average utility obtained over those tries.

We want to show that UPOM’s search of $\Pi$ corresponds to an equivalent UCT search of $\Psi$. Below, Theorem 1 accomplishes this in the case where the utility function $U$ is additive. After the proof of the theorem, we discuss how to generalize the theorem to cases where $U$ is not additive.

Theorem 1. Let $\Pi$, $\Phi$, $\rho$ and $p$ be as in Equations A.7–A.10, let $U$ be additive, let UPOM’s metadata for $\Pi$ be as described above, and let $\Psi = (S^\Psi, A^\Psi, \gamma^\Psi, P^\Psi, U^\Psi)$ be the MDP corresponding to $\Pi$. If UCT searches $\Psi$ using the same metadata that UPOM used, then the probability that UCT generates the rollout
$$\rho^\Psi = \langle (\sigma_0, s_0), m_1, (\sigma_1, s_1), m_2, \ldots, (\sigma_{n-1}, s_{n-1}), m_n, (\sigma_n, s_n) \rangle$$
is the same probability $p = p_1 \times \ldots \times p_n$ as in Equation A.10.
Sketch of proof. The proof is by induction on \(n\), the length of \(\rho\). The base case is when \(n = 0\), i.e., \(\rho = (s_0, s_0)\). If \(n = 0\) then it must be that \(\text{Applicable}(s_0) = \emptyset\). Thus \(\text{Applicable}^\Psi((s_0, s_0)) = \emptyset\), so in this case the theorem is vacuously true.

For the induction step, suppose \(n > 0\), and consider UPOM’s recursive call to UPOM\((s_1, \sigma_1, \infty)\). In this case, the refinement planning problem is \(\Pi_1 = (\Phi, s_1, \sigma_1, U)\), and we let \(\Psi_1\) be the corresponding MDP.

Given the same metadata as above, UPOM\((s_1, \sigma_1, \infty)\) will generate the rollout \(\rho_1 = (\sigma_1, s_1), \ldots, (\sigma_n, s_n)\) with probability \(p_2 \times \ldots \times p_n\). The induction assumption is that with that same probability, a UCT search of \(\Psi_1\) will generate the rollout \(\rho_\Psi^1 = (\sigma_1, s_1), m_2, \ldots, (\sigma_{n-1}, s_{n-1}), m_n, (\sigma_n, s_n)\).

Before applying the induction assumption, we first need to show that if \(p_1\) is the probability that UPOM\((s_0, \sigma_0, U)\) chooses \(m_1\) before making its recursive call, then a UCT search of \(\Psi_1\) will choose \(m_1\) with the same probability \(p_1\). There are two cases:

- Case 1: \(m_1\) is a method in \(\Phi\). As shown in Algorithm 6, UPOM\((s_0, \sigma_0, U)\) chooses \(m_1\) using the same UCB-style computation that a UCT search in \(\Psi\) would use at \((\sigma_0, s_0)\). Thus, omitting the details about how to compute \(p_1\) from the metadata, it follows that if UPOM\((s_0, \sigma_0, U)\) chooses \(m_1\) with probability \(p_1\), then so does the UCT search.

- Case 2: \(m_1\) is an action in \(\Phi\). Then UPOM’s computation (in lines line 8 through the end of Algorithm 6) is not a UCT-style computation, but this does not matter, because there is only one possible choice, namely \(m_1\). In this case, UPOM’s probability of choosing \(m_1\) is \(p_1 = 1\), and the same is true for the UCT search.

In both cases, it follows from the induction assumption that in \(\Pi\), UPOM’s probability of generating \(\rho = p_1 \times p_2 \times \ldots \times p_n\), and in \(\Pi^\Psi\), UCT’s probability of generating \(\rho_\Psi^1\) is also \(p_1 \times p_2 \times \ldots \times p_n\). This concludes the sketch of the proof. \(\square\)

Generalizing beyond MDPs. If the utility function \(U\) is not additive, Equation A.5 produces a probabilistic planning problem that looks similar to an MDP, the only difference being that the utility function \(U^\Psi\) is not additive. Furthermore, Theorem 1 still holds even when \(U\) is not additive, if we modify the proof to remove the claim that \(\Psi\) is an MDP.

We note that the UCT algorithm [53] is not restricted to the case where \(U^\Psi\) is additive; it will still converge as long as \(U^\Psi\) is monotonic. If \(U\) is monotonic, then so is \(U^\Psi\). In this case it follows that UCT—and thus UPOM—will converge to an optimal solution. In particular, UPOM will converge to an optimal solution when using the efficiency and success ratio utility functions in Section 5.1.

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## Appendix B. Table of Notation

| Notation | Meaning | Page defined |
|----------|---------|--------------|
| \( \Sigma = (\Xi, T, M, A) \) | an acting domain | 11 |
| \( s, S \) | predicted state, set of states for the planner | 8 |
| \( \xi, \Xi \) | actual state, set of world states for the actor | 8 |
| \( \tau, T \) | task or event, set of tasks and events | 11 |
| \( m, M \) | method/method instance, set of methods for \( T \) | 11 |
| \( \mathcal{M} \) | set of method instances of \( M \) | 11 |
| \( m[i] \) | the \( i \)th step of \( m \) | 12 |
| \( \text{Applicable}(\xi, \tau) \) | set of method instances applicable to \( \tau \) in state \( \xi \) | 11 |
| \( a, A \) | action, set of actions | 11 |
| \( \gamma(\xi, a) \) | possible states after performing \( a \) in \( \xi \) | 11 |
| \( \sigma \) | a refinement stack with tuples of the form \((\tau, m, i, \text{tried})\) | 11 |
| \( v_e, v_s \) | value functions for efficiency and success ratio | 16 |
| \( v_e1 \oplus v_e2 \) | cumulative efficiency value of two successive actions | 16 |
| \( v_s1 \oplus v_s2 \) | cumulative success ratio of two successive actions | 16 |
| \( \mathbb{I} \) | the identity element for \( \oplus \), i.e. \( x \oplus \mathbb{I} = x \) | 16 |
| \( U(m, s, \sigma) \) | the utility of \( m \) for \( \tau \) and \( \sigma \) | 17 |
| \( U^*(m, s, \sigma) \) | the maximal expected utility of \( m \) for \( \tau \) | 17 |
| \( U_{\text{Success}}, U_{\text{Failure}} \) | the utility of a success, the utility of a failure | 20 |
| \( m^*_{\tau, s} \) | the optimal method instance for \( \tau \) in \( s \) for utility \( U^* \) | 17 |
| \( d, d_{\text{max}}, n_{\text{ro}} \) | depth, max depth, number of rollouts | 18 |
| \( h(\tau, m, s) \) | heuristic estimate to solve \( \tau \) with \( m \) in \( s \) | 18 |
| \( h0, hD \) | always returns \( \infty \), hand written heuristic | 31 |
| \( \text{hLearnH} \) | learned heuristic | 31 |
| \( Q_{\tau, s}(m) \) | approximation of \( U^*(m, s, \sigma) \) | 20 |
| \( C \) | tradeoff parameter between exploration and exploitation | 20 |
| \( \mu, K \) | suggested control parameters for \( n_{\text{ro}} \) | 21 |
| \( g(s, \tau, m) \) | default state after accomplishing \( \tau \) with \( m \) in \( s \) | 22 |
| \( r \) | a data record of the form \((s, \tau, m)\) | 23 |
| \( w_s, w_\tau, w_m, w_u \) | One-Hot representations of \( s, \tau, m, \) and \text{interval}(u) | 24 |
| \( v_{\text{un}} \) | uninstantiated method parameter | 24 |
| \( v_\tau \) | list of values of task parameters | 24 |
| \( b \) | value of the parameter \( v_{\text{un}} \) | 24 |
| \( V \) | number of state variables | 24 |
| \( nn_\pi \) | MLP for \text{Learn}\(\pi\) | 24 |
| \( nn_{v_{\text{un}}} \) | MLP for each \( v_{\text{un}} \) | 25 |
| \( Z \) | Number of training records | 26 |
| \( \Phi = (S, T, M, A) \) | a refinement planning domain | 15 |
| \( P(s, a, s') \) | probability that \( a \)'s execution in \( s \) returns \( s' \) | 46 |
| \( \Pi = (\Phi, s_0, \sigma_0, U) \) | a refinement planning problem | 46 |
| \( \rho \) | a rollout in \( \Phi \) | 48 |
| \( \mathcal{R}(\Phi) \) | the set of all refinement stacks that are reachable in \( \Phi \) | 46 |
| \( R(s), C(s, a, s') \) | reward function, cost function | 46 |
| \( \Psi \) | an MDP | 47 |