Integrated Planning and Acting Using Operational Models

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Motivation



Harbor Management

- Multiple levels of abstraction
 - Physical/managerial organization of harbor
- Higher levels:
 - Plan abstract tasks
- Lower levels:
 - Multiple agents, partial observability dynamic change
- Continual online planning
 - Plans are abstract and partial until more detail needed



Hypothetical Worker Robot

- Multiple levels of abstraction
- At higher levels:
 - Plan abstract tasks
- At lower levels:
 - Nondeterminism, partial observability dynamic change
- Continual online planning
 - Plans are abstract and partial until more detail needed



Planning and Acting

Planning

- *Prediction* + *search*
 - Search over predicted states, possible organizations of tasks and actions
- Uses *descriptive* models (e.g., PDDL)
 - predict what the actions will do
 - don't include instructions for performing it

Acting

- *Performing* actions
 - Dynamic, unpredictable, partially observable environment
 - Adapt to context, react to events
- Uses *operational* models
 - instructions telling *how* to perform the actions







- Different methods, depending on what kind of door
 - Sliding or hinged?







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 - Sliding or hinged?
 - Hinge on left or right?







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 - Open toward or away?







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 - Open toward or away?
 - Knob, lever, push bar, …









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 - Hinge on left or right?
 - Open toward or away?
 - Knob, lever, push bar, pull handle, push plate, something else?













• Python implementation:

- https://github.com/sunandita/ICAPS_Summer_School_RAE_2020
- Full code: <u>https://bitbucket.org/sunandita/rae/</u>
- Related publications
 - Patra, Mason, Kumar, Ghallab, Traverso, and Nau (2020). Integrating Acting, Planning, and Learning in Hierarchical Operational Models.

ICAPS-2020. Best student paper honorable mention award. <u>https://www.aaai.org/ojs/index.php/ICAPS/article/view/6743/6597</u>

- Patra, Mason, Ghallab, Dana, and Traverso (2020). Deliberative Acting, Online Planning and Learning with Hierarchical Operational Models. *Submitted for journal publication*. Preprint at <u>https://arxiv.org/abs/2010.01909</u>
- Ghallab, Nau, and Traverso (2016). *Automated Planning and Acting*. Cambridge University Press. Authors' final manuscript at <u>http://projects.laas.fr/planning/</u>



Outline

1. Motivation

- 2. **Representation** state variables, commands, tasks, refinement methods
- **3.** Acting Rae (Refinement Acting Engine)
- 4. **Planning** UPOM (UCT-like Planner for Operational Models)
- **5.** Acting with Planning Rae + UPOM
- **6.** Using the implementation Rae code, UPOM code, examples

Representation



- Objects
 - *Robots* = {r1, r2}
 - *Containers* = {c1, c2}
 - Locations = {loc1, loc2, loc3, loc4}
- Rigid relations (properties that won't change)
 - adjacent(loc0,loc1), adjacent(loc1,loc0), adjacent(loc1,loc2), adjacent(loc2,loc1), adjacent(loc2,loc3), adjacent(loc3,loc2), adjacent(loc3,loc4), adjacent(loc4,loc3)

- State variables (fluents)
 - where $r \in Robots$, $c \in Containers$, $l \in Locations$
 - ▶ $loc(r) \in Locations$
 - ► cargo(r) ∈ Containers U {empty}
 - ▶ $pos(c) \in Locations \cup Robots \cup \{unknown\}$
 - view(l) \in {T, F}
 - Whether a robot has looked at location *l*
 - If view(l) = T then pos(c) = l for every container c at l
- Commands to the execution platform:
 - take(r,o,l): r takes object o at location l
 - put(r,o,l): r puts o at location l
 - perceive(r,l): robot r perceives what objects are at l
 - move-to(r,l): robot r moves to location l

Tasks and Methods

- *Task*: an activity for the actor to perform
 - taskname($arg_1, ..., arg_k$)
- For each task, one or more *refinement methods*
 - Operational models telling how to perform the task

```
method-name(arg_1, ..., arg_k)
                                       m-fetch1(r,c)
                                          task: fetch(r,c)
  task: task-identifier
                                          pre: pos(c) = unknown
         test
  pre:
  body:
                                          body:
                                             if \exists l (view(l) = F) then
        a program
                                                 move-to(r,l)
                                                 perceive(r,l)
                                                 if pos(c) = l then
                                                 \rightarrow take(r,c,l)
                         command
                                                 else fetch(r,c) \leftarrow task
                                             else fail
```



m-fetch2(r,c) task: fetch(r,c) pre: pos(c) \neq unknown body: if loc(r) = pos(c) then take(r,c, pos(c)) else do move-to(r, pos(c)) take(r,c, pos(c))

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Rae (Refinement Acting Engine)

- Performs multiple tasks in parallel
 - Purely reactive, no lookahead
- For each task or event τ , a *refinement stack*
 - execution stack
 - corresponds to current path in Rae's search tree for τ
- *Agenda* = {all current refinement stacks}







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```
m-fetch1(r,c)

task: fetch(r,c)

pre: pos(c) = unknown

body:

if \exists l (view(l) = F) then

move-to(r,l)

perceive(r,l)

if pos(c) = l then

take(r,c,l)

else fetch(r,c)

else fail
```

```
m-fetch2(r,c)

task: fetch(r,c)

pre: pos(c) \neq unknown

body:

if loc(r) = pos(c) then

take(r,c,pos(c))

else do

move-to(r,pos(c))

take(r,c,pos(c))
```

Example

Search tree



procedure Rae:

loop:

for every new external task or event τ do

choose a method instance m for τ

create a refinement stack for τ , *m*

add the stack to Agenda

for each stack σ in *Agenda*

 $Progress(\sigma)$

if σ is finished then remove it



- Partially observable
 - Robot only sees current location





























Extensions to Rae

- Methods for events
 - e.g., an emergency
- Methods for goals
 - special kind of task: achieve(goal)
 - sets up a monitor to see if the goal has been achieved
- Concurrent subtasks

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Why Plan?

procedure Rae:

loop:

for every new external task or event τ do choose a method instance *m* for τ create a refinement stack for τ , *m* add the stack to *Agenda* for each stack σ in *Agenda* Progress(σ) if σ is finished then remove it

- Bad choice may lead to
 - more costly solution
 - failure, need to recover
 - unrecoverable failure
- Idea: do simulations to predict outcomes



Planner

• Basic ideas

- Repeated Monte Carlo rollouts on a single task t
- Choose method instances using a UCT-like formula
- Simulated execution of commands

$\mathsf{UPOM}(\tau)$:

choose a method instance m for τ

create refinement stack σ for τ and m

loop while Simulate-Progress(σ) \neq *failure*

if σ is completed then return (*m*, *utility of outcome*) return *failure*

UPOM-Lookahead (task τ):

Call UPOM(τ) multiple times

Return the $m \in Candidates$ that has the highest average utility



Simulating a command

- Simplest case:
 - probabilistic action template

$$a(x_1, ..., x_k)$$

pre: ...
 $(p_1) \text{ eff}_1: e_{11}, e_{12}, ...$
...
 $(p_m) \text{ eff}_m: e_{m1}, e_{m2}, ...$

- Choose randomly, each eff_i has probability p_i
- Use eff_i to update the current state
- More general:
 - Arbitrary computation, e.g., physics-based simulation
 - Run the code to get prediction of effects





- Rollouts on MDPs
 - At each state, choose action at random, get random outcome
- UCT algorithm

Converges to

optimal choice

at root of tree

 Choice of action balances exploration vs exploitation

action

action

state

state

possible

choices

state

action

possible

′outcomes`

action

state

state

sample from

possible results

 m_1

Monte Carlo Rollouts

pre: . . . • UPOM search tree more complicated body: action a_1 > tasks, methods, commands, code execution task τ_1 • If no exogenous events, can map it into UCT action a_2 on a complicated MDP task τ_2 proof of convergence to optimal task τ disjunction among alternative choices m m sequence of code execution a_1 a_2 τ_2 disjunction state

sample

 n^+

n

state

method instance m

task: τ

disjunction

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RAE + UPOM

procedure Rae:

loop:

for every new external task or event τ do choose a method instance *m* for τ create a refinement stack for τ , *m* add the stack to *Agenda* for each stack σ in *Agenda* Progress(σ) if σ is finished then remove it

• Whenever RAE needs to choose a method instance, use UPOM-Lookahead to make the choice



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Summary of Experimental Results

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

- Five different domains, different combinations of characteristics
- Evaluation criteria:
 - Efficiency, successes vs failures, how many retries
- Result: planning helps
 - Rae operates better with UPOM than without
 - Rae operates better with more planning than with less planning

Other Details

• Receding horizon

- Cut off search before accomplishing τ
 - e.g., depth d_{max} or when we run out of time
- At leaf nodes, use heuristic function
- Learning a heuristic function
 - Supervised learning



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Code Demo

- Github repository: https://github.com/sunandita/ICAPS_Summer_School_RAE_2020
- System requirements:
 - Unix based operating system preferred
 - Have Docker or the Python Conda environment preinstalled
- Things to play with:
 - Domain file: ICAPS_Summer_School_RAE_2020/domains/domain_x.py
 - Problem file: ICAPS_Summer_School_RAE_2020 /problems/x/problemId_x.py
 - x ∈ [chargeableRobot, explorableEnv, searchAndRescue, springDoor, orderFulfillment]
- How to run?
 - cd ICAPS_Summer_School_RAE_2020/RAE_and_UPOM
 - python3 testRAEandUPOM.py –h