Learning and Transferring Relational Instance-Based Policies

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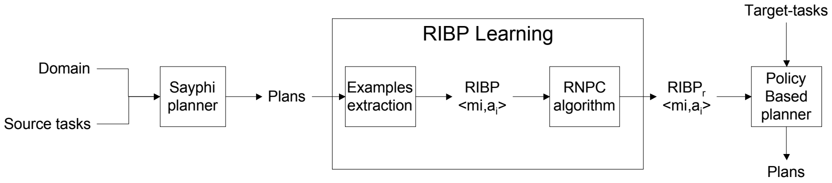
Content

Motivation

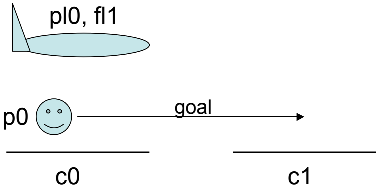
- Planners can solve simple problems optimally, but they can not solve most complex problems
- Solutions:
  - Manually defining efficient domain-independent heuristics
  - Learning control knowledge
- Traditionally, learning has been casted as a transfer learning approach (without explicitly using that terminology)
- Our goal is to transfer knowledge (a relational policy) learned in simple problems (source problems) to help planning systems to solve complex ones (target problems)
- Transferring of a policy is possible given that:
  - The same relational representation is used for all tasks in the same domain (universal policy)
  - A nearest neighbor approach is applied (partial matching)
  - The policy is simplified, so it is fast to use (utility problem)

The learning process



1. **Training**:
    - Generation of plans
    - Extraction of examples
    - Reduction of the examples(RNPC algorithm [Fernández and Isasi, 2004])
2. **Test**: more complex random target problems to solve using the RIBP$_r$.

Deliberative planning



state$_0$:

(at p0 c0) (at pl0 c0)
(fuel-level pl0 fl1)
(next fl0 fl1) (next fl1 fl2)
(next fl2 fl3) (next fl3 fl4)
(next fl4 fl5) (next fl5 fl6)

goal: (goal-at p0 c1)

Solution plan:

action$_0$: (board p0 pl0) $\longrightarrow$ state$_1$: (in p0 pl0), (at pl0 c0), …
action$_1$: (fly pl0 c0 c1 fl1 fl0) $\longrightarrow$ state$_2$: (in p0 pl0), (al pl0 c1), …
action$_2$: (debark p0 pl0 c1) $\longrightarrow$ FINISH

A Relational Instance-Based Policy (RIBP)

A relational policy, π, is defined by:

- $\pi : M \rightarrow A$ is a mapping from a meta-state to an action

Meta-state m_i (s_i+pending goals)		**Action** a_i	
m_0	(at pl0 c0), (at p0 c0), (fuel-level pl0 fl1), (next pl0 pl1)... , (goal-at p0 c1)	a_0	(board p0 pl0 c0)
m_1	(at pl0 c0), (in p0 pl0), (fuel-level pl0, fl1), (next pl0, pl1)..., (goal-at p0 c1)	a_1	(fly pl0 c0 c1 fl1 fl0)
m_2	(at pl0 c1), (in p0 pl0), (fuel-level pl0, fl0), (next pl0, pl1)..., (goal-at p0 c1)	a_2	(debark p0 'pl0 c1)

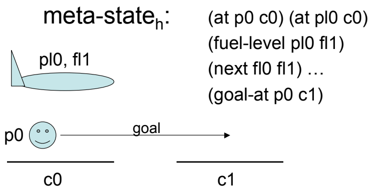
The **RIBP**, π, is defined by a tuple $< P, d >$, where:

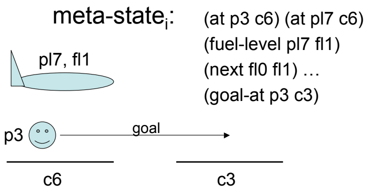
- P: set of tuples $< m_i, a_i >$
- d: relational distance metric
- $\pi(m) = \arg_a \min_{(<m',a'>\in P)} dist(m, m')$

The RIBL distance

- The RIBL distance [Kirsten, Wrobel and Horváth, 2001]
  - $d(m_1, m_2) = \sqrt{\frac{\sum_{k=1}^{K} w_k d_k(m_1,m_2)^2}{\sum_{k=1}^{K} w_k}}$
  - $d_k(m_1, m_2) = \frac{1}{N} \sum_{i=1}^{N} \min_{p \in P_k(m_2)} d'_k(P_k^i(m_1), p)$
  - $d'_k(p_k^1, p_k^2) = \sqrt{\frac{1}{M} \sum_{l=1}^{M} \delta(p_k^1(l), p_k^2(l))}$ where $p_k^i(l)$ is the lth argument of literal p_k^i, and $\delta(p_k^1(l), p_k^2(l))$ returns 0 if both values are the same, and 1 if they are different

An example





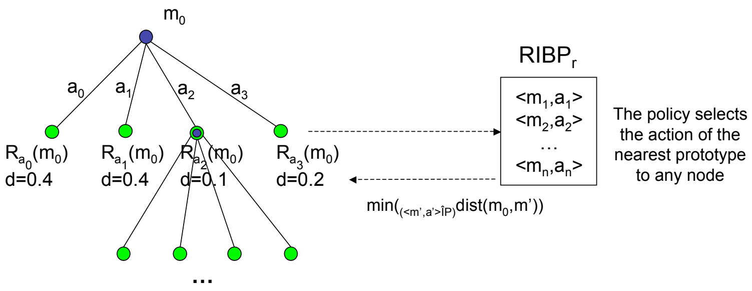
$$d(m_h, m_i) = \sqrt{\frac{d_{at}(m_h,m_i)^2 + d_{in}(m_h,m_i)^2 + d_{fuel-level}(m_h,m_i)^2 + d_{next}(m_h,m_i)^2 + d_{goal-at}(m_h,m_i)^2}{5}} = 0.707$$

- **Problem**: The distance between two instances depends on the similarity between the names of both sets of objects
- **Partial solution**: The meta-states are renamed to keep some kind of relevance level of the objects

Example of use

Sayphi (=MetricFF): heuristic planner with forward search

Heuristic+RIBP$_r$ (greedy algorithm):



a_i: suggested action by the heuristic

$R_{a_i}(m_0)$: renamed meta-state m_0 with the a_i

● Evaluated node with the heuristic

🟢 Renamed node and evaluated node with RIBP$_r$

Experiments in the Zenotravel domain

- Source problems: 250 random problems; 50 with (1,3,1); 100 with (1,3,2); and 100 with (2,3,3), where (planes,cities,persons-goals)
- Training time bound: 180 seconds
- RIBP: 1509 training instances from the solution plans
- RIBP$_r$: average number of prototypes: 18 (after running RNPC 10 times)
- Target problems:
  - 180 problems of different **complexity**. Nine subsets of 20 problems: (1,3,3), (1,3,5), (2,5,10), (4,7,15), (5,10,20), (7,12,25), (9,15,30), (10,17,35) and (12,20,40)
  - 20 problems from the third IPC
- Test time bound: 1800 seconds (standard in the IPC)

Results in the Zenotravel domain (I)

#Problems (#goals)	Approach	Solved	Time	Cost	Nodes
20 (3)	Sayphi	20	0.46	166	683
	RIBP$_r$	20	1.47	275	296
20 (5)	Sayphi	20	0.49	236	868
	RIBP$_r$	20	1.40	291	314
20 (10)	Sayphi	20	5.84	535	3277
	RIBP$_r$	20	8.11	719	743
20 (15)	Sayphi	20	82.54	749	10491
	RIBP$_r$	20	40.69	1285	1307
20 (20)	Sayphi	20	607.32	1293	21413
	RIBP$_r$	20	133.25	2266	2287
20 (25)	Sayphi	13	629.06	961	26771
	RIBP$_r$	20	112.41	1880	1896
20 (30)	Sayphi	8	221.92	712	9787
	RIBP$_r$	20	72.22	1340	1353
20 (35)	Sayphi	0	—	—	—
	RIBP$_r$	15			
20 (40)	Sayphi	1	30.20	120	1420
	RIBP$_r$	6	25.82	298	301

Results in the Zenotravel domain (II)

	solved	time	cost	nodes
Sayphi	18	2578.84	512	30023
RIBP	20	2761.69	1081	1102
RIBP_r	20	111.62	1248	1267

Conclusions

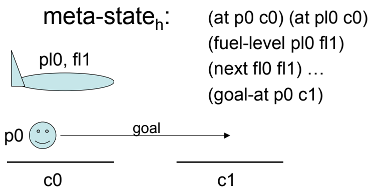
- We have used a Relational Nearest Neighbor approach to learn a reduced policy ($< state - goal, action >$), as control knowledge, to guide the search in planning
- RIBP implements a partial matching of control knowledge
- RIBP$_r$ reduces time and memory in different more complex tasks
- RIBP$_r$ can solve more problems although with worse quality

In the future

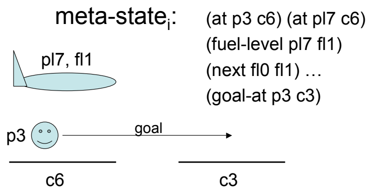
- Extend the experiments to others planners and other domains (IPC08)
- Focus on the distance metric in planning (enumerating variables, splitting goals, creating more relation levels, etc)
- Study and compare different distance metrics for planning domains
- Extend the idea to probabilistic domains where scale-up is more complex

Thank you

An example



(at p0 c0) (at pl0 c0)
(fuel-level pl0 fl1)
(next fl0 fl1) …
(goal-at p0 c1)



(at p3 c6) (at pl7 c6)
(fuel-level pl7 fl1)
(next fl0 fl1) …
(goal-at p3 c3)

$$d(m_h, m_i) = \sqrt{\frac{d_{at}(m_h,m_i)^2+d_{in}(m_h,m_i)^2+d_{fuel-level}(m_h,m_i)^2+d_{next}(m_h,m_i)^2+d_{goal-at}(m_h,m_i)^2}{5}} = 0.707$$

$$d_{at}(m_h, m_i) = \frac{1}{2}(min(1.0, 1.0) + min(1.0, 1.0)) = 1.0$$

d'_{at}	(at p3 c6)	(at pl7 c6)
(at p0 c0)	1.0	1.0
(at pl0 c0)	1.0	1.0

$$d'_{at}((at\ p0\ c0), (at\ p3\ c6)) = \sqrt{\frac{1+1}{2}} = 1.0$$

Renaming the objects

m_h: (at p0 c0)	→	m_h: (at **@p0** **@c0**)	→	m_h: (at **@p0** **@c0**)	→	m_h: (at **@p0** **@c0**)
(at pl0 c0)		(at **@pl0** **@c0**)		(at **@pl0** **@c0**)		(at **@pl0** **@c0**)
(fuel-level pl0 fl1)		(fuel-level **@pl0** fl1)		(fuel-level **@pl0** **fl1**)		(fuel-level **@pl0** **@fl0**)
(next fl0 fl1)		(next fl0 fl1)		(next **fl0** **fl1**)		(next **@fl1** **@fl0**)
(next fl1 fl2)		(next fl1 fl2)		(next **fl1** **fl2**)		(next **@fl0** **@fl2**)
…		…		…		…
(goal-at p0 c1)		(goal-at **@p0** **c1**)		(goal-at **@p0** **@c1**)		(goal-at **@p0** **@c1**)

a_h: (board **p0** **pl0** **c0**)

m_i: (at p3 c6)	→	m_i: (at **@p0** **@c0**)	→	m_i: (at **@p0** **@c0**)	→	m_i: (at **@p0** **@c0**)
(at pl7 c6)		(at pl7 **@c0**)		(at pl7 **@c0**)		(at pl7 **@c0**)
(fuel-level pl7 fl1)		(fuel-level **@pl0** fl1)		(fuel-level **@pl0** **fl1**)		(fuel-level **@pl0** **@fl0**)
(next fl0 fl1)		(next fl0 fl1)		(next **fl0** **fl1**)		(next **@fl1** **@fl0**)
(next fl1 fl2)		(next fl1 fl2)		(next **fl1** **fl2**)		(next **@fl0** **@fl2**)
…		…		…		…
(goal-at p3 c3)		(goal-at **@p0** **c3**)		(goal-at **@p0** **@c1**)		(goal-at **@p0** **@c1**)

a_i: (board **p3** **pl7** **c3**)

Renaming with this order we try to keep some kind of relevance level of the objects to find a better similarity between two instances.