Learning and Transferring Relational Instance-Based Policies

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Motivation

- Planners can solve simple problems optimally, but they cannot 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)
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

pl0, fl1

p0          goal

<table>
<thead>
<tr>
<th></th>
<th>c0</th>
<th>c1</th>
</tr>
</thead>
<tbody>
<tr>
<td>state0</td>
<td>(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)</td>
<td></td>
</tr>
<tr>
<td>goal</td>
<td>(goal-at p0 c1)</td>
<td></td>
</tr>
</tbody>
</table>

Solution plan:

action0: (board p0 pl0)  →  state1: (in p0 pl0), (at pl0 c0), ...
action1: (fly pl0 c0 c1 fl1 fl0)  →  state2: (in p0 pl0), (al pl0 c1), ...
action2: (debark p0 pl0 c1)  →  FINISH
A Relational Instance-Based Policy (RIBP)

A relational policy, $\pi$, is defined by:

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

<table>
<thead>
<tr>
<th>Meta-state $m_i$ (s_i + pending goals)</th>
<th>Action $a_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_0$ (at pl0 c0), (at p0 c0), (fuel-level pl0 fl1), (next pl0 pl1)..., (goal-at p0 c1)</td>
<td>$a_0$ (board p0 pl0 c0)</td>
</tr>
<tr>
<td>$m_1$ (at pl0 c0), (in p0 pl0), (fuel-level pl0, fl1), (next pl0, pl1)..., (goal-at p0 c1)</td>
<td>$a_1$ (fly pl0 c0 c1 fl1 fl0)</td>
</tr>
<tr>
<td>$m_2$ (at pl0 c1), (in p0 pl0), (fuel-level pl0, fl0), (next pl0, pl1)..., (goal-at p0 c1)</td>
<td>$a_2$ (debark p0 'pl0 c1)</td>
</tr>
</tbody>
</table>

The RIBP, $\pi$, is defined by a tuple $< P, d >$, where:

- $P$: set of tuples $< m_i, a_i >$
- $d$: relational distance metric
- $\pi(m) = \arg \min_{<m',a'> \in P} \text{dist}(m, m')$
The RIBL distance [Kirsten, Wrobel and Horváth, 2001]

- \( d(m_1, m_2) = \sqrt{\frac{\sum_{k=1}^{K} w_k d_k(m_1, m_2)^2}{\sum_{k=1}^{K} w_k}} \)

- \( d_k(m_1, m_2) = \frac{1}{N} \sum_{i=1}^{N} \min_{p \in P_k(m_2)} d'_k(P^i_k(m_1), p) \)

- \( d'_k(p^1_k, p^2_k) = \sqrt{\frac{1}{M} \sum_{l=1}^{M} \delta(p^1_k(l), p^2_k(l))} \) where \( p^i_k(l) \) is the \( l \)th argument of literal \( p^i_k \), and \( \delta(p^1_k(l), p^2_k(l)) \) returns 0 if both values are the same, and 1 if they are different.
**An example**

```plaintext
meta-state_h:

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

meta-state_i:

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

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

- **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** (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

The policy selects the action of the nearest prototype to any node.
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
- RIBPₚ: 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)

<table>
<thead>
<tr>
<th>#Problems (#goals)</th>
<th>Approach</th>
<th>Solved</th>
<th>Time</th>
<th>Cost</th>
<th>Nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 (3)</td>
<td>Sayphi</td>
<td>20</td>
<td>0.46</td>
<td>166</td>
<td>683</td>
</tr>
<tr>
<td></td>
<td>RIBP_r</td>
<td>20</td>
<td>1.47</td>
<td>275</td>
<td>296</td>
</tr>
<tr>
<td>20 (5)</td>
<td>Sayphi</td>
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<td>0.49</td>
<td>236</td>
<td>868</td>
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<tr>
<td></td>
<td>RIBP_r</td>
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<td>1.40</td>
<td>291</td>
<td>314</td>
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<td>Sayphi</td>
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<td>5.84</td>
<td>535</td>
<td>3277</td>
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<tr>
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<td>20</td>
<td>8.11</td>
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<tr>
<td>20 (15)</td>
<td>Sayphi</td>
<td>20</td>
<td>82.54</td>
<td>749</td>
<td>10491</td>
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<tr>
<td></td>
<td>RIBP_r</td>
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<td>40.69</td>
<td>1285</td>
<td>1307</td>
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<tr>
<td>20 (20)</td>
<td>Sayphi</td>
<td>20</td>
<td>607.32</td>
<td>1293</td>
<td>21413</td>
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<tr>
<td></td>
<td>RIBP_r</td>
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<td>133.25</td>
<td>2266</td>
<td>2287</td>
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<tr>
<td>20 (25)</td>
<td>Sayphi</td>
<td>13</td>
<td>629.06</td>
<td>961</td>
<td>26771</td>
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<tr>
<td></td>
<td>RIBP_r</td>
<td>20</td>
<td>112.41</td>
<td>1880</td>
<td>1896</td>
</tr>
<tr>
<td>20 (30)</td>
<td>Sayphi</td>
<td>8</td>
<td>221.92</td>
<td>712</td>
<td>9787</td>
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<tr>
<td></td>
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<td>72.22</td>
<td>1340</td>
<td>1353</td>
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<tr>
<td>20 (35)</td>
<td>Sayphi</td>
<td>0</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>RIBP_r</td>
<td>15</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>20 (40)</td>
<td>Sayphi</td>
<td>1</td>
<td>30.20</td>
<td>120</td>
<td>1420</td>
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<tr>
<td></td>
<td>RIBP_r</td>
<td>6</td>
<td>25.82</td>
<td>298</td>
<td>301</td>
</tr>
</tbody>
</table>
## Results in the Zenotravel domain (II)

<table>
<thead>
<tr>
<th></th>
<th>solved</th>
<th>time</th>
<th>cost</th>
<th>nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sayphi</td>
<td>18</td>
<td>2578.84</td>
<td>512</td>
<td>30023</td>
</tr>
<tr>
<td>RIBP</td>
<td>20</td>
<td>2761.69</td>
<td>1081</td>
<td>1102</td>
</tr>
<tr>
<td>RIBP&lt;sub&gt;r&lt;/sub&gt;</td>
<td>20</td>
<td>111.62</td>
<td>1248</td>
<td>1267</td>
</tr>
</tbody>
</table>
Conclusions

- We have used a Relational Nearest Neighbor approach to learn a reduced policy ($\langle \text{state} - \text{goal, action} \rangle$), 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**

\[ \text{meta-state}_h: \begin{align*} & (\text{at } p0, c0) (\text{at } pl0, c0) \\ & (\text{fuel-level } pl0, fl1) \\ & (\text{next } fl0, fl1) \ldots \\ & (\text{goal-at } p0, c1) \end{align*} \]

\[ \text{meta-state}_i: \begin{align*} & (\text{at } p3, c6) (\text{at } pl7, c6) \\ & (\text{fuel-level } pl7, fl1) \\ & (\text{next } fl0, fl1) \ldots \\ & (\text{goal-at } p3, c3) \end{align*} \]

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

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

<table>
<thead>
<tr>
<th>( d'_{at} )</th>
<th>(at p3, c6)</th>
<th>(at pl7, c6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(at p0, c0)</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>(at pl0, c0)</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

\[ d'_{at}((\text{at } p0, c0), (\text{at } p3, c3)) = \sqrt{\frac{1+1}{2}} = 1.0 \]
Renaming the objects

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