Parallel Transfer Learning in Multi-Agent Systems: What, when and how to transfer?

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Reinforcement Learning (RL) in Multi-Agent Systems (MAS)

- Learning takes time:
  - ★ Performance of RL-based systems depends on the speed of learning
  - ✗ More agents interaction implies slower learning

- Real-world problems are dynamic and non-stationary:
  - ✗ Once learning is complete, changes can invalidate the learnt policy, so re-learning is required
  - ✔ Additional knowledge can be used in MAS [1]
Transfer Learning (TL)

TL [1] was applied in MAS [2] to transfer learnt policies offline and for multi-agent coordination [3].

Agents require pre-training before transferring fully learnt policies, applied to similar tasks.

PTL enables online knowledge transfers [4] and can be used for multi-objective problems [5]

PTL can result in higher risk of negative transfers (e.g. learning wrong behaviours or un-learning correct ones)
Challenges for PTL

★ How to minimise bad transfers?

★ How to reuse knowledge for different tasks?

★ What information should be transferred?

★ At which frequency?

★ How to integrate knowledge in the locally learnt behaviours without over-writing correct or converged tasks?
Context and objectives
Reinforcement Learning in Multi-Agent Systems
Transfer Learning
Parallel Transfer Learning
Challenges

Parallel Transfer Learning
Components
Data selection methods
Merge methods

Evaluation
Scenarios
Impact of PTL parameters
Effects of learning time

Conclusions and future work

PTL components

Environment

Action
State & Reward

RL Component

Mapping Component

PTL Component

Self-Configuration Component

PTL Agent

Other Agents

Data Selected From
Data to Transfer
Received Knowledge

Transfer to Others
Transfer from Others
Data selection methods (SM)

What and when to transfer?

- **Most visited states**: provides a frequent estimate of the important states
- **Converged states**: provides the highest confidence information
- **Best/Worst states**: share states that are important based on their value
- **Visit threshold**: enables a greater degree of confidence
- **Greatest change**: selects the state in which the most significant learning has occurred since the last transfer
Merge methods (MM)

How and when to incorporate received knowledge?

- We use a decaying linear combination of received and local knowledge:

  \[
  \text{scaledRecieved} = \text{Recieved } Q(S_t, A_t) \times (\text{numCV} - \text{currVC})
  \]

  \[
  \text{scaledLocal} = Q(S_t, A_t) \times \text{currVC}
  \]

  \[
  Q(S_t, A_t) = \frac{\text{scaledRecieved} + \text{scaledLocal}}{\text{numCV}}
  \]

- where \text{currVC} is the current visits count for that state and \text{numCV} is the number of confidence visits required.
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Conclusions and future work
Evaluation: scenarios

Mountain Car

Cooperative predator-prey pursuit

- $2^4$ states (4 directions and binary detection)
- 5 actions
- Q-learning: $\alpha = 0.95$ and $\gamma = 0.2$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value/Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>State: Position</td>
<td>$[-1.2, 0.6]$ (goal at 0.6)</td>
</tr>
<tr>
<td>State: Velocity</td>
<td>$[-0.07, 0.07]$</td>
</tr>
<tr>
<td>Actions</td>
<td>Left $-1$, Neutral $0$ or Right $1$</td>
</tr>
<tr>
<td>Reward</td>
<td>10 if at the goal, $-1$ otherwise</td>
</tr>
<tr>
<td>Q-learning</td>
<td>$\alpha = 0.1$ and $\gamma = 0.01$</td>
</tr>
</tbody>
</table>
### Impact of PTL parameters (SM and MM) in Mountain Car

<table>
<thead>
<tr>
<th>Selection Method (SM)</th>
<th>Confidence (MM)</th>
<th>Source</th>
<th>Target</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Best States</strong></td>
<td>*1</td>
<td>569.45</td>
<td>382.29</td>
<td>187.16</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>616.59</td>
<td>511.93</td>
<td>104.66</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>476.96</td>
<td>451.52</td>
<td>25.44</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>529.69</td>
<td>526.05</td>
<td>3.64</td>
</tr>
<tr>
<td><strong>Converged</strong></td>
<td>1</td>
<td>524.04</td>
<td>525.52</td>
<td>-1.48</td>
</tr>
<tr>
<td></td>
<td>*4</td>
<td>660.17</td>
<td>397.79</td>
<td>262.38</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>401.83</td>
<td>514.88</td>
<td>-113.05</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>527.03</td>
<td>491.44</td>
<td>35.59</td>
</tr>
<tr>
<td><strong>Greatest Change</strong></td>
<td>1</td>
<td>416.9</td>
<td>514.75</td>
<td>-97.85</td>
</tr>
<tr>
<td></td>
<td>*4</td>
<td>475.32</td>
<td>483.81</td>
<td>-8.49</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>518.3</td>
<td>539.8</td>
<td>-21.5</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>500.17</td>
<td>492.49</td>
<td>7.68</td>
</tr>
<tr>
<td><strong>Visit threshold</strong></td>
<td>1</td>
<td>496.63</td>
<td>502.91</td>
<td>-6.28</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>418.08</td>
<td>438.75</td>
<td>-20.67</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>534.75</td>
<td>511.33</td>
<td>23.42</td>
</tr>
<tr>
<td></td>
<td>*10</td>
<td>508.7</td>
<td>444.08</td>
<td>64.62</td>
</tr>
<tr>
<td><strong>Most Visits</strong></td>
<td>1</td>
<td>438.3</td>
<td>514.18</td>
<td>-75.88</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>364.85</td>
<td>441.4</td>
<td>-76.55</td>
</tr>
<tr>
<td></td>
<td>*7</td>
<td>472.09</td>
<td>523.09</td>
<td>-51</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>403.16</td>
<td>559.53</td>
<td>-156.37</td>
</tr>
</tbody>
</table>
Effects of learning time in Mountain Car

- SM: Best states; MM confidence: 1
- PTL performs better than RL from 10\textsuperscript{th} learning episode
- PTL converges around episode 60 vs. 80 for RL
- Final performance is improved by 27\% after 150 exploration episodes
Effects of learning time in Cooperative predator-prey pursuit

- SM: Greatest Change; MM set as a probability: 0.6

- PTL and RL perform poorly in the early training (as knowledge is missing)

- PTL catches more preys between episodes 500 and 1500 (around 20% more)

- RL and PTL converge to similar level of performance
Conclusions and future work

✓ PTL enables **online knowledge sharing** between RL agents in MAS

✓ It increases the **use of early acquired knowledge**

✓ PTL **speeds up the overall learning process**

✗ Like RL and TL, PTL is **sensitive to parameter selection**, which could be done autonomously: *i.e.*, by **learning (or sharing) transfer parameters**
Thank you for your attention

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