Heuristic Value Function Revision

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Motivation

- Possible to specify an arbitrary value function in Soar
- No way to revise an existing value function because reinforcement learning always make a decision
- **Given the opportunity, it may be possible to improve a value function as specified by RL-rules**
Reinforcement Learning

- Prefer actions leading to positive rewards to actions leading to negative rewards
- Outcomes are characterized as a discounted return, \( \sum_{t=0}^{\infty} \gamma^t r_t \)
- Deriving correct estimates of these returns is integral to many RL algorithms
  - What is essential, however, is learning an optimal policy
- Q-learning and Sarsa in the simplest case map \( S \times A \Rightarrow Q \) in a one-to-one fashion
Soar-RL

- Conditions on RL-rules encode which features to test and how to discretize continuous state, defining the mapping $S \times A \Rightarrow Q$. 
Soar-RL

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  - Potentially arbitrary, non-uniform abstraction
- Traditionally bootstrapped from values set before execution, e.g. 0
  - Can be done simply with GPs or templates
  - Work in John’s talk uses chunking to take advantage of background knowledge instead, deciding ...
    - The mapping $S \times A \Rightarrow Q$
    - Initial Q-values
Decide

1. Reduce candidate set using non-numeric preferences
   - Possible to impasse here

2. Decide using numeric preferences (RL-rules)
   - Always results in a decision (will never impasse)
   - Cannot chunk new RL-rules to modify $S \times A \Rightarrow Q$
     - Prevents using overgeneral conditions early on to promote quick learning
     - Prevents adding conditions on relevant features which were previously believed to be irrelevant
[Munos and Moore, 2001] developed metadata to decide which Q-values...

- Might be important to split (influence)
- Are good candidates for changing values (variance)
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Beyond Initialization

Design Goals

- Initially Chunked RL-Rules
- Heuristically Triggered RL-Rules

- Specify initial value function
  - Condition on features of clear importance
  - Err on side of overgenerality to speed learning

- Track metadata until they indicate an opportunity to improve the value function

- Generate additional RL-rules in tie impasses until metadata indicate improvement
  - Generally condition RL-rules on a smaller part of the state space
blocks world (preliminary)

- Start with creating one RL-rule per move (e.g. A onto B)
- Tie impasse when variance is above a low threshold, 0.002
- Add RL-rules testing features (in-place, on-top)
- Achieved optimal consistently by 50 episodes, ignoring exploration
When Tie Impasses Occur

- Operators without numeric preferences can tie
  - Only acceptable preferences $\rightarrow$ tie impasse
  - Multiple best, no better or worse preferences $\rightarrow$ tie impasse
- Operators with numeric preferences (RL-rules) never tie
  - A somewhat random choice is always made
  - Of course, we can change this
Enabling Tie Impasses for RL-Rules

Figure: Depiction of Q-values, $v_1$ having high variance.

- Must track metadata which summarize experience on which a decision can be based
  - Values have high variance
  - Values have high influence
  - Other metrics...?
Build a Tie Impasse for RL-Rules

- Add subset of ^numeric (^tied <o> ^improve <o>) parallel to ^item <o> in the impasse state
  - ^tied indicates that the operator is involved in the tie
  - ^improve indicates that the operator needs a new preference to resolve the tie
  - Metadata may be exposed under ^numeric in future work, allowing the agent to reason about which preferences could resolve the impasse
Resolve Tie Impasse

- Figure: Depiction of Q-values, $v_1$ having high variance.

- Determine which preference(s) will resolve the impasse
  - The expected case is one RL-rule per operator
  - Current work just adds RL-rules with the value 0
Resolve Tie Impasse

Figure: Depiction of Q-values, $v_1$ now separated in different states

- Rely on chunking to allow improvement over time
  - Test a more complete set of features in blocks world
  - Test a smaller region of continuous state in cart pole
Nuggets and Coal

Nuggets:

- Tie impasses for RL-rules are happening (in a branch)
- Using a *simple* tie-detection procedure, blocks world can converge
- Code can be written fairly generally using an extended problem space description

Coal:

- Not currently achieving good performance in *cart pole*
- Open questions about general tie-detection procedure
  - Must balance need for improved discretization with need for experience
  - Must be feasible to resolve ties with RL-rules, including $= 0$