Soar-RL
A Year of "Learning"

Nate Derbinsky

University of Michigan

Outline

- The Big Picture
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- Soar-RL Performance
- Nuggets & Coal
- Additional Resources

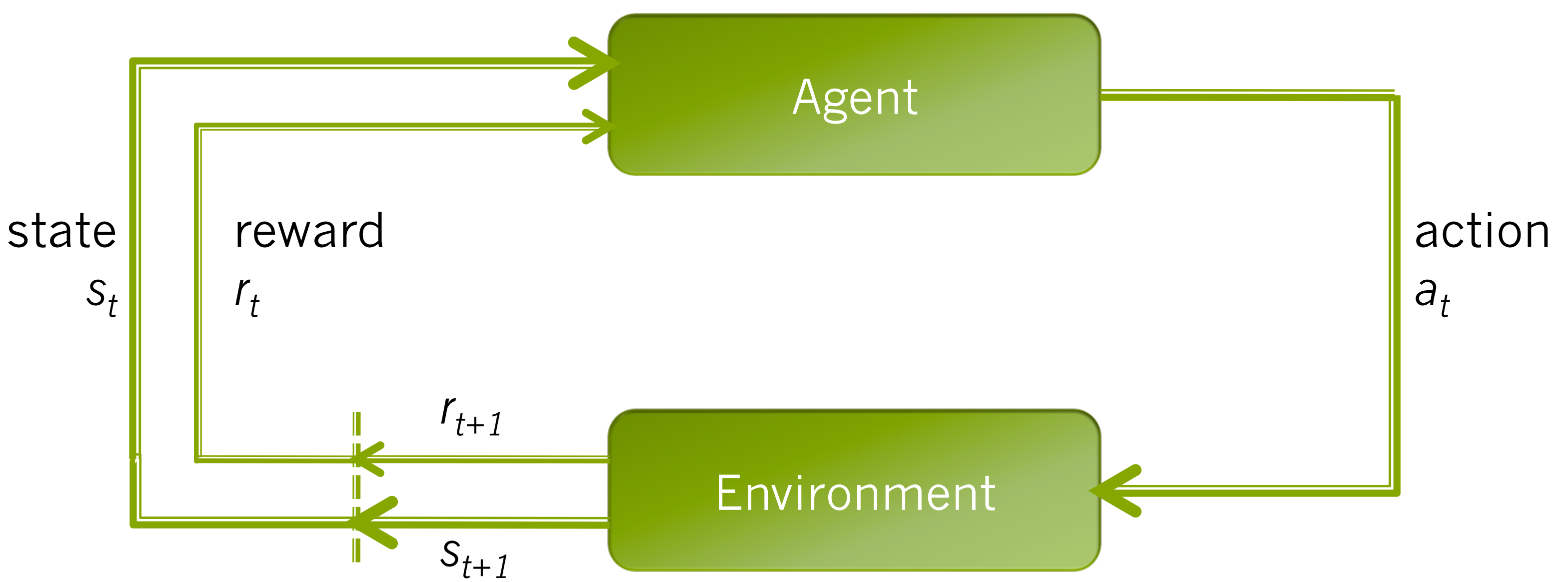
Outline

- **The Big Picture**
  - The Path to Release
  - How Soar-RL Affects Agent Behavior
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- Soar-RL Performance
- Nuggets & Coal
- Additional Resources

The Path to Release

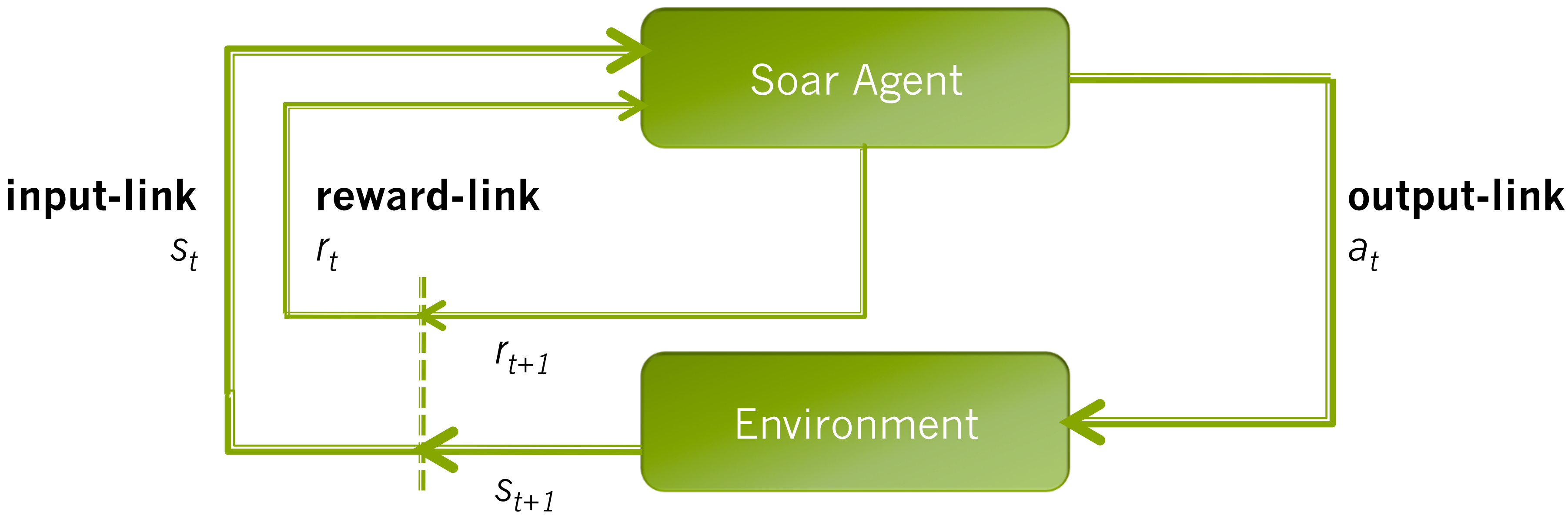
- Credit for most system functionality and all research to make Soar-RL possible should go to Shelley Nason and John Laird
  - Nason, S. and Laird, J. E., Soar-RL, Integrating Reinforcement Learning with Soar, International Conference on Cognitive Modeling, 2004.
- The work being presented today deals with the engineering efforts to effectively and efficiently integrate Soar-RL with the Soar trunk
  - Nate Derbinsky, Nick Gorski, John Laird, Bob Marinier, Jonathan Voigt, Yongjia Wang

The RL Agent-Environment Interface



Sutton, R.S., and Barto, A.G., Reinforcement Learning: An Introduction.

Soar-RL Agent-Environment Interface



Numeric Indifferent Preferences

- (<state> ^operator <operator> = number)
  - **number**, the *value* of the preference, is a numeric constant
- The value of the numeric indifferent preference may bias selection of the **operator** from amongst indifferent preferences
  - **numeric-indifferent-mode** determines how values combine
  - **indifferent-selection** sets the policy for deciding amongst indifferent preferences

How Soar-RL Affects Agent Behavior

- Over time, Soar-RL modifies numeric indifferent preference values such as to maximize the expected receipt of future reward
- Altering preference values in procedural memory allows Soar-RL to modify the outcome of operator selection, and thus affect agent behavior

Water Jug Demonstration

Outline

- The Big Picture
- **Developing Soar-RL Agents**
  - Soar-RL Rules
  - Templates
  - Reward
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- Soar-RL Performance
- Nuggets & Coal
- Additional Resources

Soar-RL Rules

```
sp {my*rl*rule
   (state <s> ^operator <o> +
              ^attrib-a alpha
              ^attrib-b beta)
   (<o> ^name my-op)
-->
   (<s> ^operator <o> = 2.3)
}
```

- LHS can be anything
- RHS must be single numeric indifferent preference
- Soar-RL rules form a representation of a value function
  - Q(s, o) = 2.3

Water-Jug Agent Example

```
sp {water-jug*empty*small*0*0
   (state <s> ^name water-jug ^operator <op> +
              ^jug <j1> <j2>)
   (<op> ^name empty ^empty-jug.volume 3)
   (<j1> ^volume 3 ^contents 0)
   (<j2> ^volume 5 ^contents 0)
-->
   (<s> ^operator <op> = 0)
}
```

Soar-RL Rule Usage

- In order for Soar-RL to affect selection of an operator in a particular state, a Soar-RL rule must exist whose LHS matches the state-operator pair
- With complex agents, the requirement of manually representing the Q-function with Soar-RL rules is unreasonable
  - Solutions: scripting or **templates**

Soar-RL Templates

```
sp {my*rl*template
   :template
   (state <s> ^operator <o> +
              ^attrib-a <a>
              ^attrib-b <b>)
   (<o> ^name my-op)
-->
   (<s> ^operator <o> = 2.3)
}
```

- Must have **:template** flag
- LHS can be anything
- RHS must be single numeric indifferent preference
- A Soar-RL template is a representation of the <u>initial</u> value function of a set of state-operator pairs

Water-Jug Agent Example

```
sp {water-jug*empty
   :template
   (state <s> ^name water-jug ^operator <op> +
              ^jug <j1> <j2>)
   (<op> ^name empty ^empty-jug.volume <evol>)
   (<j1> ^volume 3 ^contents <c1>)
   (<j2> ^volume 5 ^contents <c2>)
-->
   (<s> ^operator <op> = 0)
}
```

Soar-RL Template Behavior

- During proposal phase, the template rule is supplied to the matcher
  - Matches are used to create new Soar-RL productions that contribute to the current cycle and future decisions
- The new production has naming pattern **rl*template-name*id**
  - template-name – original template rule
  - id – auto incrementing counter

Water-Jug Agent Example

```
sp {rl*water-jug*empty*1
   (state <s> ^name water-jug ^operator <op> +
              ^jug <j1> <j2>)
   (<op> ^name empty ^empty-jug.volume 3)
   (<j1> ^volume 3 ^contents 0)
   (<j2> ^volume 5 ^contents 0)
-->
   (<s> ^operator <op> = 0)
}
```

Reward

- The agent programmer must supply reward information to guide the reinforcement learning process
- Location of reward is a new structure, a state's **reward-link**
  - state.reward-link.reward.value
    - **`state ^reward-link.reward.value 1.2`**
    - **`state ^reward-link.reward.value -2`**
- The **reward-link** is not part of the **io-link** and is <u>not</u> modified directly by the environment

Water-Jug Agent Example

```
sp {water-jug*detect*goal*achieved
   (state <s> ^name water-jug
              ^jug <j> ^reward-link <r>)
   (<j> ^volume 3 ^contents 1)
-->
   (write (crlf) |The problem has been solved.|)
   (<r> ^reward.value 10)
   (halt)}
```

Outline

- The Big Picture
- Developing Soar-RL Agents
- **Controlling the Soar-RL Algorithm**
  - Operator Selection
  - Reinforcement Learning
  - Manipulating Soar-RL Parameters
- Debugging Soar-RL
- Soar-RL Performance
- Nuggets & Coal
- Additional Resources

Operator Selection

- The purpose of learning a Q-function is that the agent can act optimally by selecting the operator with the highest Q-value
- In Soar preference semantics, symbolic preferences take precedence over numeric preferences
  - Only if there would be a tie are numeric preferences considered

Exploration vs. Exploitation

- For reinforcement learning to discover the optimal policy, it is necessary that the agent sometimes choose an action that does not have the maximum predicted value
  - Often occurs during initial learning and as a result of a change in the task
- Control of the exploration policy takes place via the **indifferent-selection** command

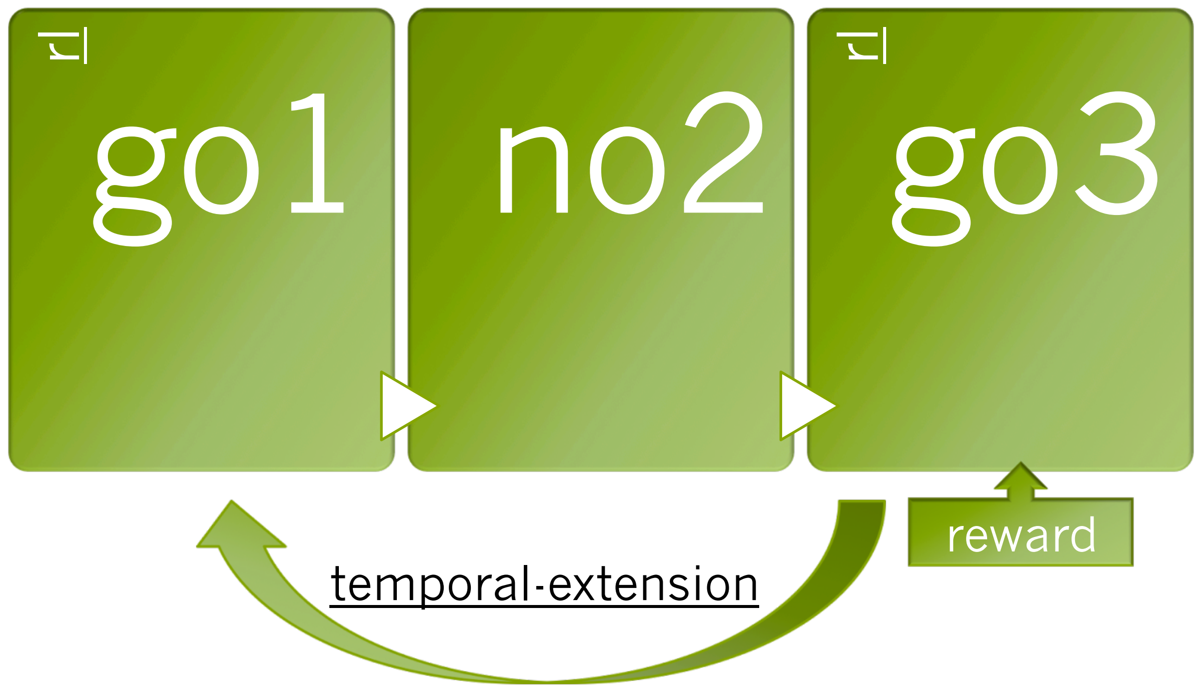
Preference Updates

- Soar-RL does Temporal Difference (TD) learning:
  - update = α(target – current)
- Current estimate = Q(s_t, o_t)
- α = Learning rate
- Target estimate and application of update are affected by a number of Soar-RL parameters
- Updates are applied at the beginning of the next <u>decision phase</u>

Gaps in Rule Coverage

- Since TD updates are transmitted backwards through the stored Q-function, it would seem necessary that the function be well-represented by Soar-RL rules at each decision cycle
- To address this practical issue, Soar-RL provides preliminary support for automatic propagation of updates over "gaps"
- By default, Soar-RL will automatically propagate updates over gaps, discounted exponentially with respect to the length of the gap
- This behavior can be enabled/disabled by manipulating the **temporal-extension** parameter

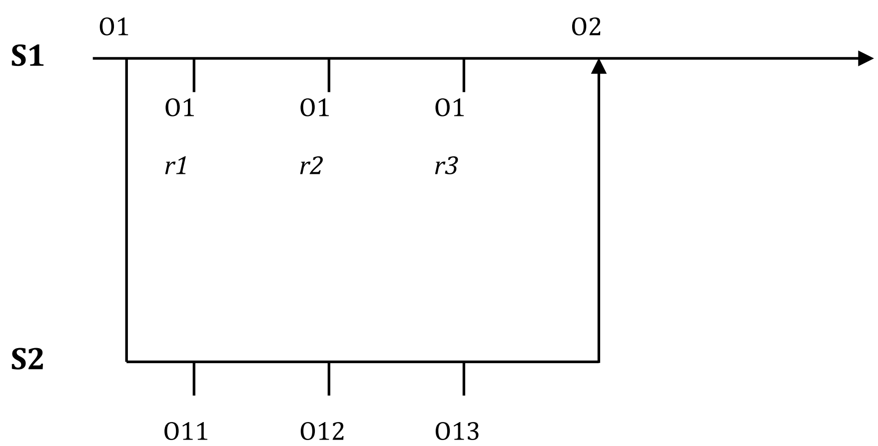
Gaps Example



Hierarchical Reinforcement Learning

- HRL is RL done over a hierarchically decomposed structure
  - Learning can be done to improve subtask performance, as well as selection amongst subtasks
- Hierarchical Soar-RL is built on Soar's impasse structure

Op No-Change Example



- Rewards at S1 after O1 are attributed to O1, discounted with respect to the number of decision cycles
- Rewards at S2 are attributed to the respective operator
- After O13, reward is checked at S2 and, if present, attributed directly to O13

Other Soar-RL Features

- Exploration Policies
  - Boltzmann, Epsilon Greedy, Softmax, First, Last
- Learning Policies
  - On-policy, Off-policy
- Reward Discounting
- Reward Accumulation
- Eligibility Traces

Manipulating Soar-RL Parameters

- Get a parameter
  - rl [-g|--get] <name>
- Set a parameter
  - rl [-s|--set] <name> <value>
- Get all values
  - rl
- Get Soar-RL statistics
  - rl [-S|--stats] <statistic>

Outline

- The Big Picture
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- **Debugging Soar-RL**
- Soar-RL Performance
- Nuggets & Coal
- Additional Resources

Debugging Soar-RL

- New `watch` switches
  - --indifferent-selection = view numeric preferences for each operator
  - --template = view firing of templates
  - --rl = debugging information
- New `print` and `excise` switches
  - --rl = all Soar-RL rules
  - --template = all Soar-RL templates

```
rl*water-jug*empty*46  1.  0.
rl*water-jug*pour*45  1.  3.
```

New Decision Cycle Commands

- `select <id>`
  - Forces the selection of an operator
- `predict`
  - Determines which operator will be chosen during the next decision phase
  - If operator selection will require probabilistic selection predict will manipulate the random number generator to enforce its prediction (assuming no preference changes)

Outline

- The Big Picture
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- **Soar-RL Performance**
  - TestSoarPerformance
  - Rules vs. Templates
- Nuggets & Coal
- Additional Resources

TestSoarPerformance

	8.6.4	RL	Δ
OS X (RL on)	8.067	8.231	**2.0%**
OS X (RL off)		8.201	**1.7%**
Linux (RL on)	3.593	3.660	**1.9%**
Linux (RL off)		3.637	**1.2%**
Windows XP (RL on)	3.703	3.765	**1.7%**
Windows XP (RL off)		3.725	**0.6%**

Rules vs. Templates

	Rules	Templates	Δ
Water Jug			
OS X	.043	.065	**51%**
Linux	.024	.033	**38%**
Windows XP	.125	.140	**12%**

Outline

- The Big Picture
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- Soar-RL Performance
- **Nuggets & Coal**
- Additional Resources

Nuggets & Coal

- Nuggets
  - Soar-RL is an integration of reinforcement learning with Soar
  - Soar-RL provides a highly configurable new learning mechanism with a relatively small performance cost
  - Soar-RL$_{\text{beta}}$ is available for download today!
- Coal
  - Current template implementation takes a heavy toll

Outline

- The Big Picture
- Developing Soar-RL Agents
- Controlling the Soar-RL Algorithm
- Debugging Soar-RL
- Soar-RL Performance
- Nuggets & Coal
- **Additional Resources**

Additional Resources

- http://winter.eecs.umich.edu/soar
  - Binaries
  - Tutorial
  - Manual
    - Programmer Reference