Reinforcement Learning in Soar

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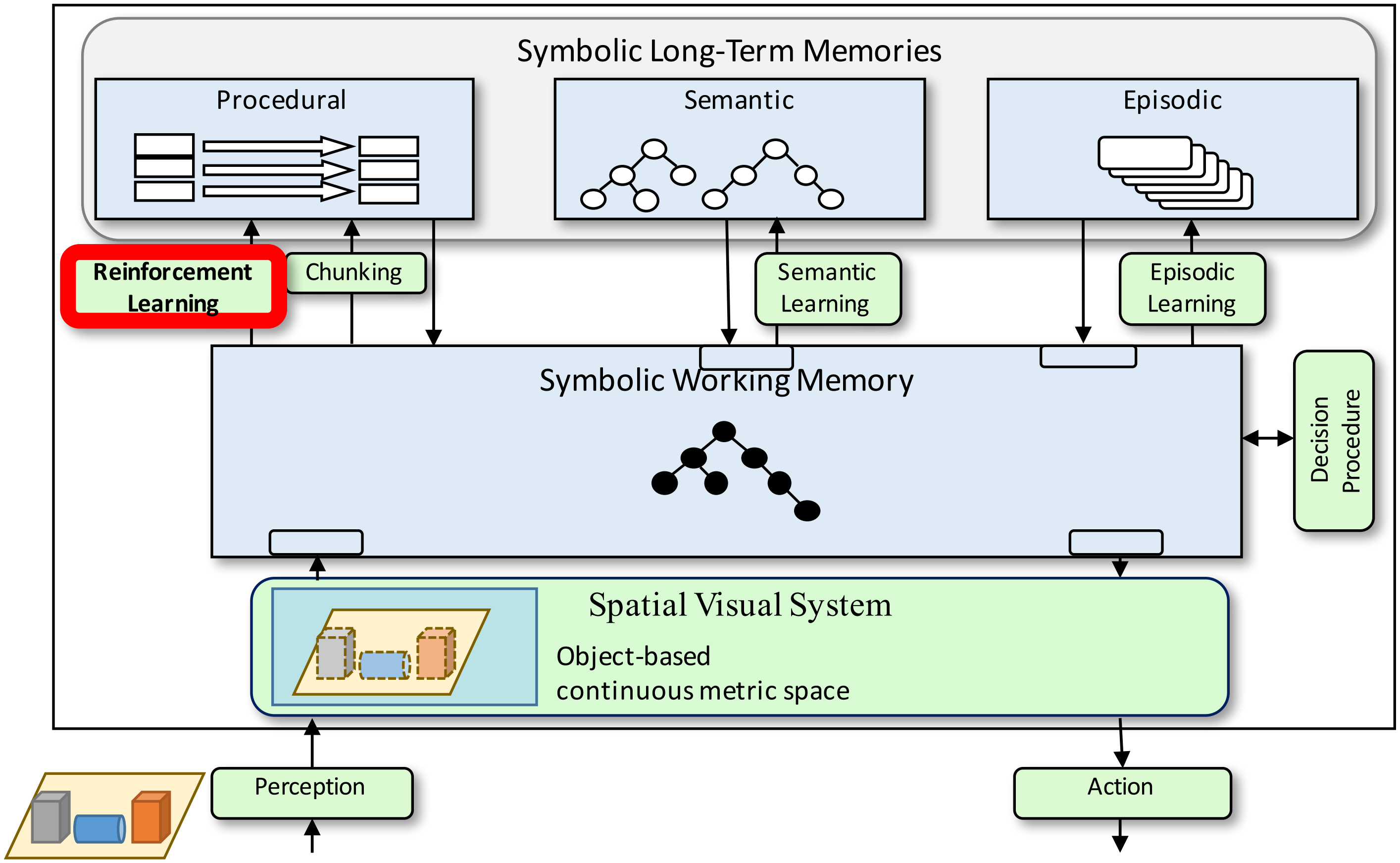
Topics

- RL as a learning mechanism
- Simple example
- Architecture & agent design
- Eater integration

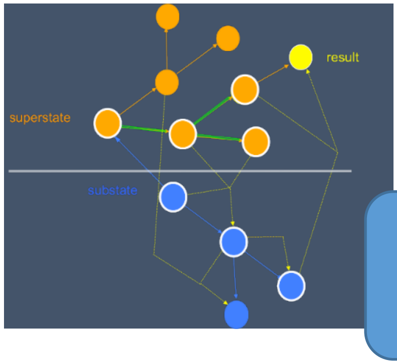
Soar 9


Symbolic Long-Term Memories
Procedural
Semantic
Episodic
Reinforcement Learning
Chunking
Semantic Learning
Episodic Learning
Symbolic Working Memory
Decision Procedure
Spatial Visual System
Object-based
continuous metric space
Perception
Action

Methods for Learning Procedural Knowledge

Chunking

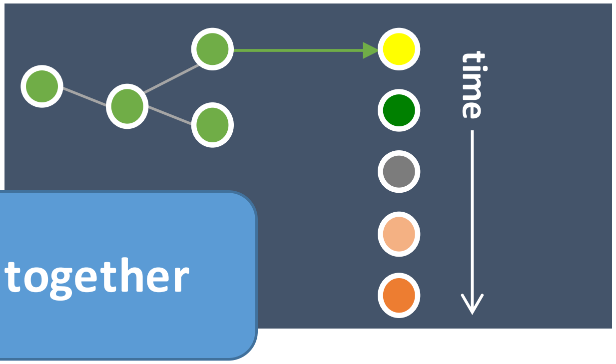
- Converts *deliberation* in substates into *reaction* via rule compilation



- Creates new rules

Reinforcement Learning

- *Tunes* operator numeric preferences to reflect expectation of reward

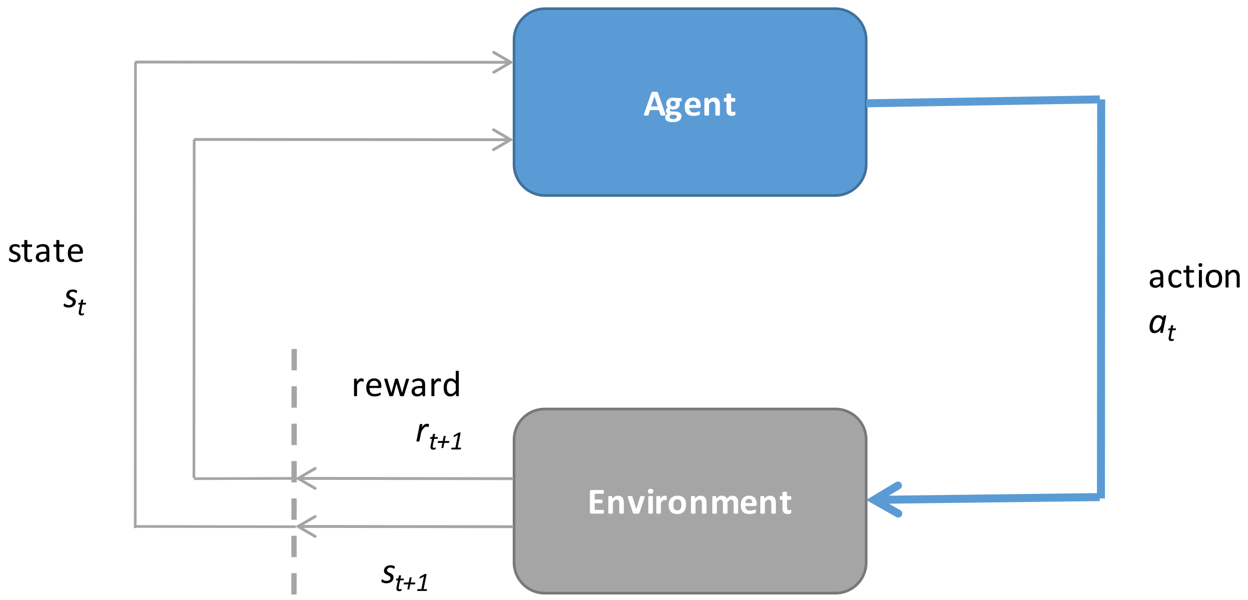


- Updates existing rules

Can be used together

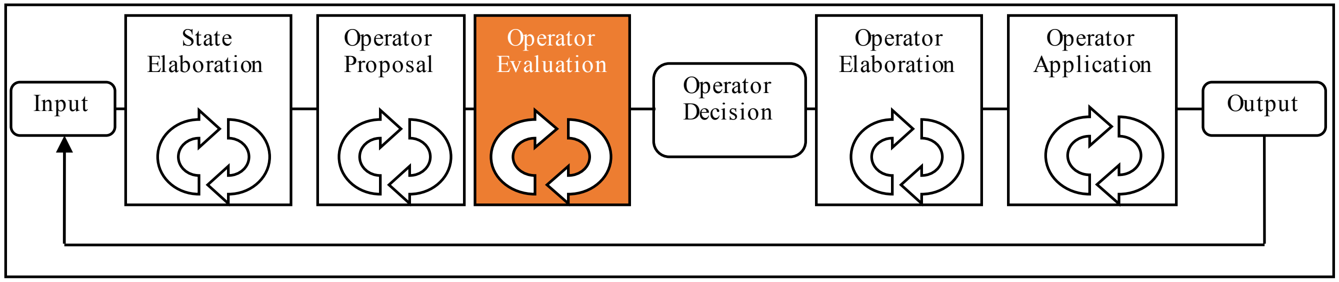
RL Cycle

Goal: learn an action-selection policy such as to maximize expected receipt of future reward



Soar Basic Functions

1. Input from environment
2. Elaborate current situation: *parallel rules*
3. Propose operators via acceptable preferences
4. Evaluate operators via *preferences: Numeric indifferent preference*
5. Select operator
6. Apply operator: Modify internal data structures: *parallel rules*
7. Output to motor system [and access to long-term memories]



Left-Right Demo

1. Soar Java Debugger
2. Source `left-right.soar` file

Left-Right Demo

Script

1. `srand 50412`
2. `step`
3. `run 1 -p`
4. click: `op_pref` tab
   - ➢ note numeric indifferents
5. `print left-right*rl*left`
6. `print left-right*rl*right`
7. `run`
   - ➢ note movement direction
8. `print left-right*rl*left`
9. `print left-right*rl*right`
10. `init-soar`
11. Repeat from #2 (~5 times)

Left-Right: Takeaways

Reinforcement learning changes rules in procedural memory

- Changes are persistent
- Change affects numeric indifferent preferences, which in turn affects the selection of operators
- Change is in the direction of the underlying reward signal (will discuss this more shortly)

RL -> Architecture & Agent Design

Value function

via RL rules [agent]

Reward

via working-memory structures [architecture, agent]

Policy updates

via Temporal Difference (TD) Learning [architecture]

RL Rules

The RL mechanism maintains Q-values for state-operator pairs in specially formulated rules, identified by syntax

- RHS with a single action, asserting a single numeric indifferent preference with a constant value

```
sp {left-right*rl*left
   (state <s> ^name left-right
              ^operator <op> +)
   (<op> ^name move
         ^dir left)
-->
   (<s> ^operator <op> = 0)}
```

```
sp {left-right*rl*right
   (state <s> ^name left-right
              ^operator <op> +)
   (<op> ^name move
         ^dir right)
-->
   (<s> ^operator <op> = 0)}
```

Reward Representation

Each state in WM has a **`reward-link`** structure

Reward is recognized by syntax

```
(<reward-link> ^reward <r>)
(<r> ^value [integer or float])
```

- The reward-link is **not** directly modified by the environment or architecture (i.e. requires agent interpretation/management)
- Reward is collected at the beginning of each *decide* phase
- Reward on a state's reward-link pertains only to that state

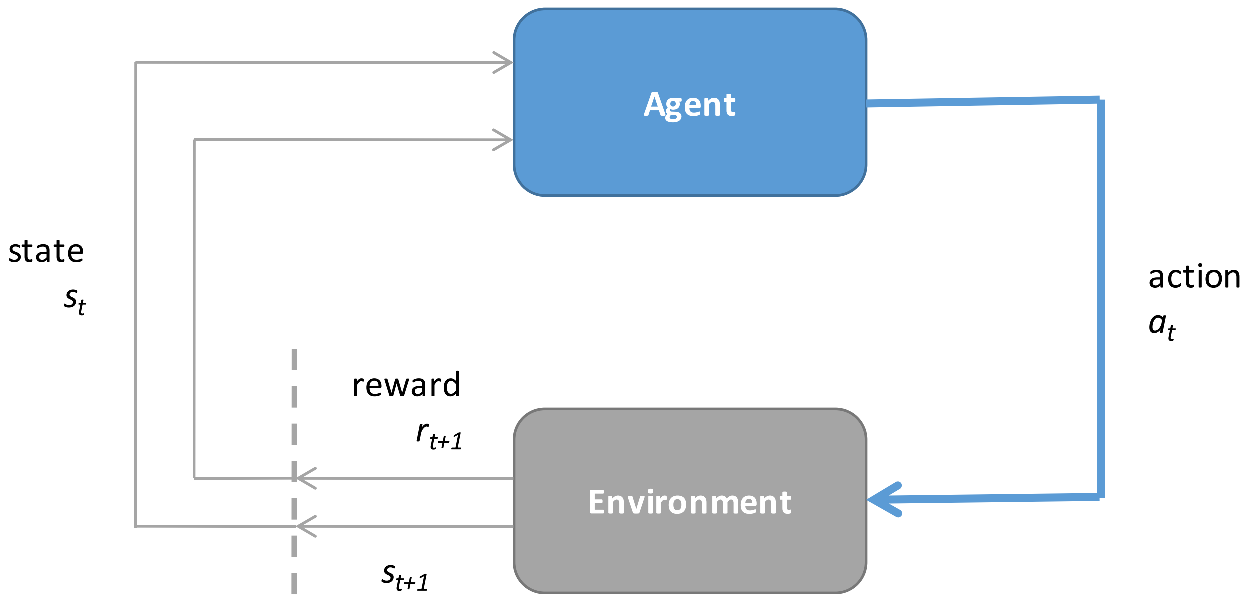
  (more on this later)
- Reward can come from multiple sources: reward values are summed by default

Reward Rule Examples

```
sp {left-right*reward*left
   (state <s> ^name left-right
              ^location left
              ^reward-link <rl>)
-->
   (<rl> ^reward <r>)
   (<r> ^value -1)
}
```

```
sp {left-right*reward*right
   (state <s> ^name left-right
              ^location right
              ^reward-link <rl>)
-->
   (<rl> ^reward <r>)
   (<r> ^value 1)
}
```

RL Cycle



RL Cycle in Soar

	Input	Propose	Decide	Apply	Output
d					
d+1					

RL Cycle in Soar

	Input	Propose	Decide	Apply	Output
d	state_d				
d+1					

RL Cycle in Soar

	Input	**Propose**	**Decide**	**Apply**	**Output**
d	state_d	evaluate operators_d			
d+1					

RL Cycle in Soar

	Input	Propose	Decide	Apply	Output
d	state$_d$	evaluate operators$_d$	select operator$_d$		
d+1					

RL Cycle in Soar

	Input	**Propose**	**Decide**	**Apply**	**Output**
d	state$_d$	evaluate operators$_d$	select operator$_d$		initiate external action(s)
d+1					

RL Cycle in Soar

	Input	**Propose**	**Decide**	**Apply**	**Output**
d	state$_d$	evaluate operators$_d$	select operator$_d$		initiate external action(s)
d+1	state$_{d+1}$ reward$_{d+1}$				

RL Cycle in Soar

	Input	Propose	Decide	Apply	Output
d	state$_d$	evaluate operators$_d$	select operator$_d$		initiate external action(s)
d+1	state$_{d+1}$ reward$_{d+1}$	evaluate operators$_{d+1}$			

RL Cycle in Soar

	Input	Propose	Decide	Apply	Output
d	state$_d$	evaluate operators$_d$	select operator$_d$		initiate external action(s)
d+1	state$_{d+1}$ reward$_{d+1}$	evaluate operators$_{d+1}$	select operator$_{d+1}$ update policy$_d$		

RL Updates

- Takes place during *decide* phase, after operator selection
- For all RL rule instantiations (**n**) that supported the *last* selected operator

$$\text{value}_{d+1} = \text{value}_d + (\delta_d / \mathbf{n})$$

Where, roughly…

$$\delta_d = \alpha[\text{reward}_{d+1} + \Upsilon(q_{d+1}) - \text{value}_d]$$

Where…

- α is a parameter (learning rate)
- Υ is a parameter (discount rate)
- q_{d+1} is dictated by learning policy
  - On-policy (SARSA): value of selected operator
  - Off-policy (Q-learning): value of operator with maximum selection probability

Value Function

Issues

Structure

- What features comprise RL-rule conditions (tradeoff: convergence speed vs. performance)
- High dimensionality -> computationally infeasible

Initialization

- Quality estimates may bootstrap agent performance and reduce time to convergence

Eaters RL: General Idea

- Reward comes from:
  - eating food
  - -1 for movement (push toward efficiency)
- RL rules will learn to select between forward and rotate operators based on reward.

Eaters RL 1: Enable RL

Get your eater code

Add to top of file – turn on RL

- **`rl -s learning on`**
- **`indiff -g`** # use greedy decision making
- **`indiff -e 0.001`** # low epsilon

Eaters RL 2: Modify Proposals

Remove indifferent preference from proposals so RL rules will influence decision.

```
sp {random*propose*forward
   (state <s> ^name eater
              ^io.input-link.time)
-->
   (<s> ^operator <op> +)
   (<op> ^name forward)}

sp {random*propose*rotate
   (state <s> ^name eater
              ^io.input-link.time)
-->
   (<s> ^operator <op> +)
   (<op> ^name rotate)}
```

Eaters RL 3: General RL-Rules: GP

Generate RL rules for every color and operator combination:

```
gp {eater*evaluate*forward
   (state <s> ^name eater
              ^io.input-link.front [ red wall blue empty green purple ]
              ^operator <op> +)
   (<op> ^name forward)
-->
   (<s> ^operator <op> = 0.0)}

gp {eater*evaluate*rotate
   (state <s> ^name eater
              ^io.input-link.front [ red wall blue empty green purple ]
              ^operator <op1> +)
   (<op1> ^name rotate)
-->
   (<s> ^operator <op1> = 0.0)}
```

Each of these will generate 6 rules!

RL will change the value of = 0.0 in each of the rules as it learns

Eaters RL 4: Reward

Add rule that assigns reward: use the change in score:

```
sp {eater*elaborate*state
   (state <s> ^name eater
              ^reward-link <rl>
              ^io.input-link.score-diff <d>)
-->
   (<rl> ^reward.value <d>)
}
```

Eaters RL 5: Run!

- Run eater
- Look at rl rules: `p -r`
- Reset eater (type “r”), run again
- See how rl rules change:
    - Number of updates
    - Value of indifferent preference

- Gets better, but is very limited by the operators available (forward and rotate).