Value Function Approximation with Hierarchical Clustering in Soar-RL

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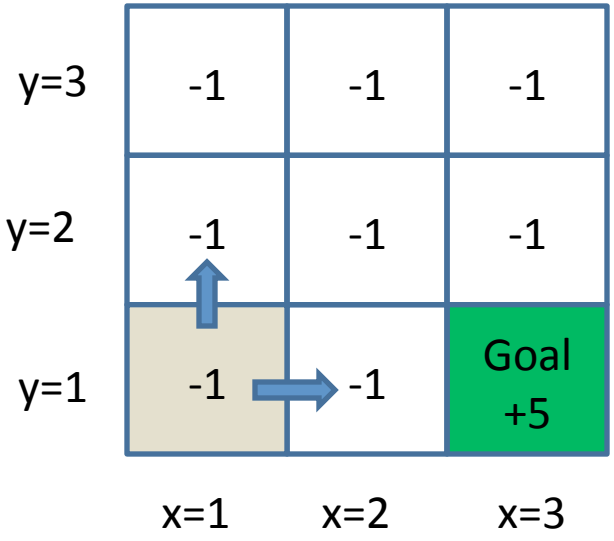
Soar-RL Value Function

- Soar-RL relies on learning the Q value function
  - Q Value Function, Q(state, action)

(x=1, y=1), (move-up) --> Q=1
(x=1, y=1), (move-right) --> Q=3
(x=1, y=1), (move-down) --> Q=2
(x=1, y=1), (move-left) --> Q=2



Soar-RL Value Function

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  - Q Value Function, Q(state, action)
  - Value(state) = max(Q(state, action_i))+r

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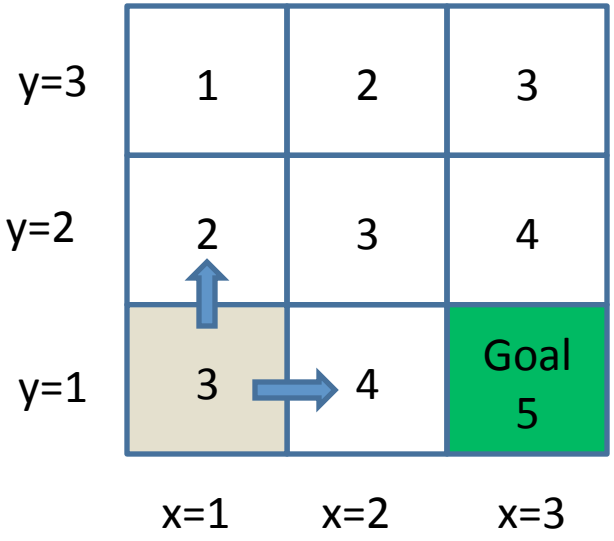

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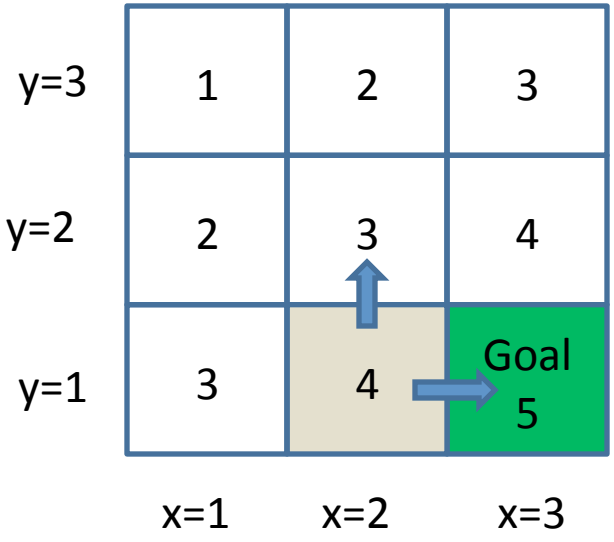
(x=1, y=1), (move-left) --> Q=2
(x=1, y=1), (move-down) --> Q=2

(x=2, y=1), (move-up) --> Q=2
(x=2, y=1), (move-down) --> Q=3
(x=2, y=1), (move-left) --> Q=2
(x=2, y=1), (move-right) --> Q=4



Soar-RL Value Function

- Soar-RL relies on learning the Q value function
  - Q Value Function, Q(state, action)
  - Value(state) = max(Q(state, action_i))
  - What about high dimensional continuous space?

    (x=1, y=1, z=1, … …)
    (x=1.1, y=1, z=1, … …)
    (x=1.2, y=1, z=1, … …)
    … …

  - Need Value Function Approximation

Motivations

- Improve Value Function Approximation in Soar-RL
  - High dimension continuous space
- Evaluate with challenging tasks
  - Characterize the tasks
  - Compare with baselines

Outline

- Background
- Evaluation Task
- Implementation
- Results
- Nuggets & Coal

Value Function Approximation -Parametric Form

Simple linear model:

Q(x,y,up) = $\mathbf{w_1}x + \mathbf{w_2}y + \mathbf{w_3}$

Q(x,y,down) = $\mathbf{w_1}x + \mathbf{w_2}y + \mathbf{w_4}$

Q(x,y,left) = $\mathbf{w_1}x + \mathbf{w_2}y + \mathbf{w_5}$

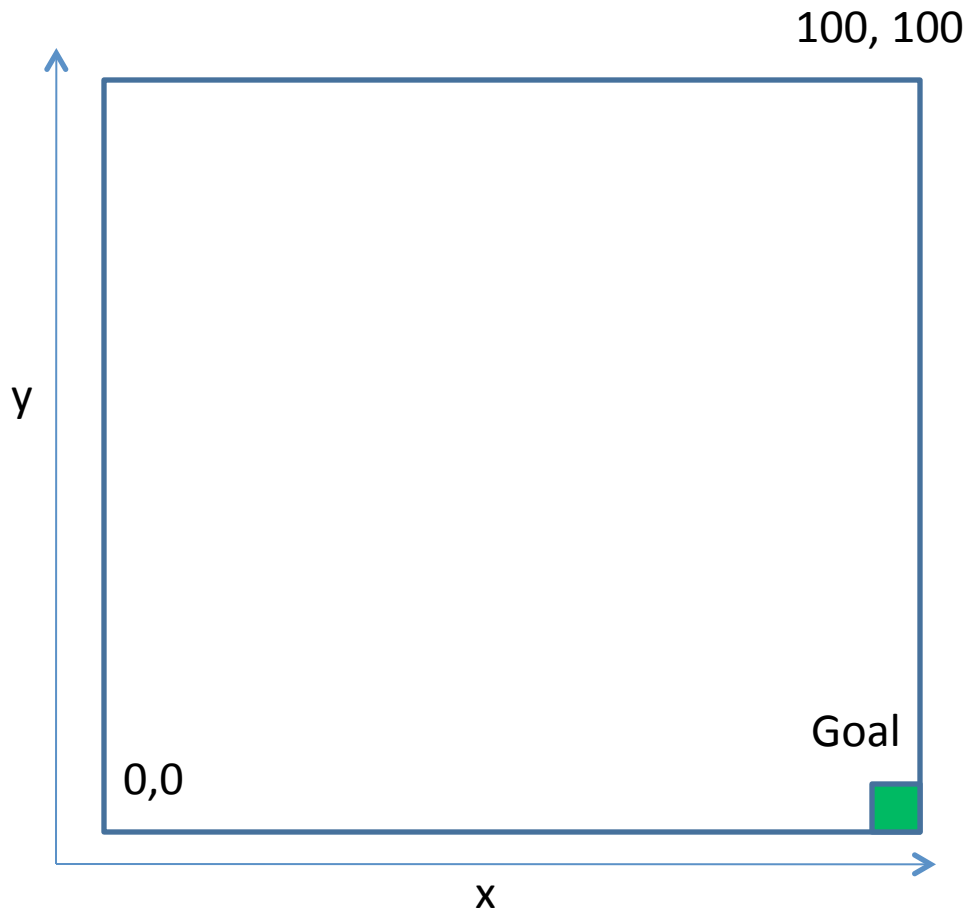
Q(x,y,right) = $\mathbf{w_1}x + \mathbf{w_2}y + \mathbf{w_6}$

Solution:

$\mathbf{w_1 > 0, w_2 < 0}$

$\mathbf{w_3 < w_4}$

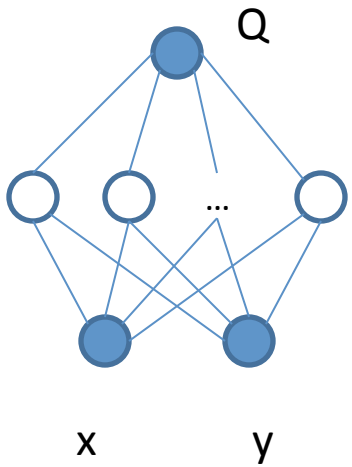
$\mathbf{w_5 > w_6}$

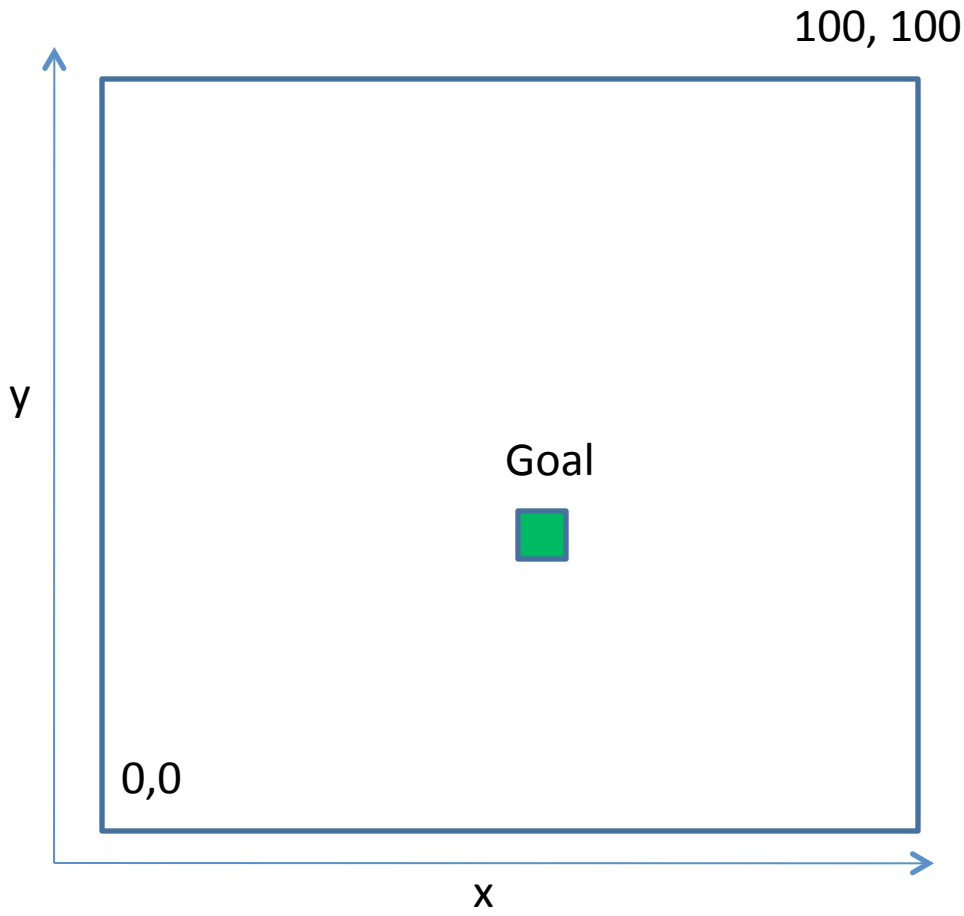


Value Function Approximation -Parametric Form

Simple linear model won't work.
Need nonlinear basis function.

Neural network:

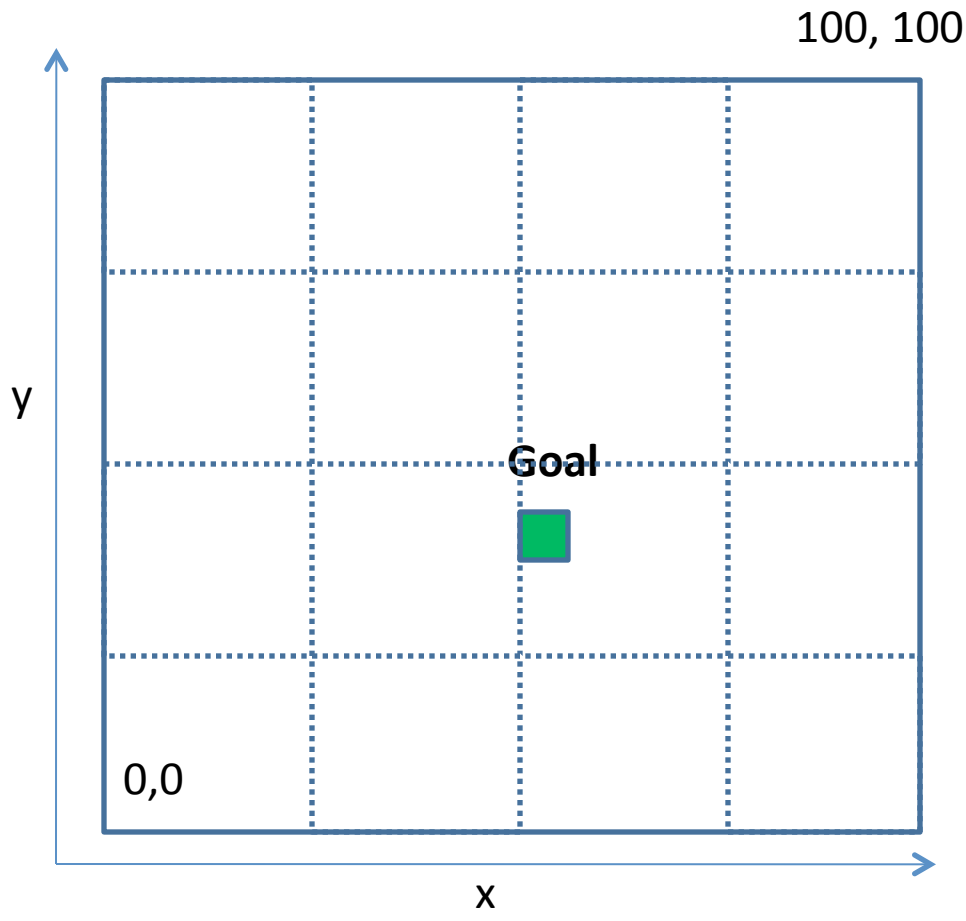




Global Approximators: updates in parameters during learning affects the entire state space

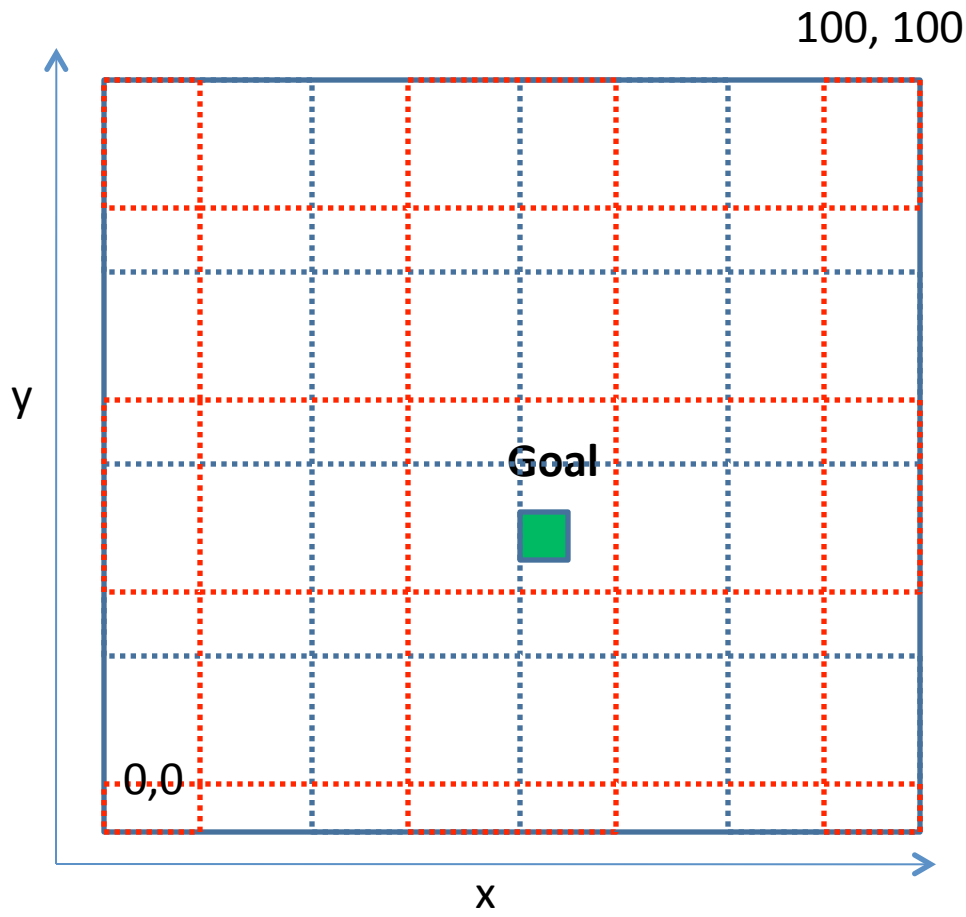
Value Function Approximation -Nonparametric methods

Tile coding



Value Function Approximation -Nonparametric methods

Coarse coding



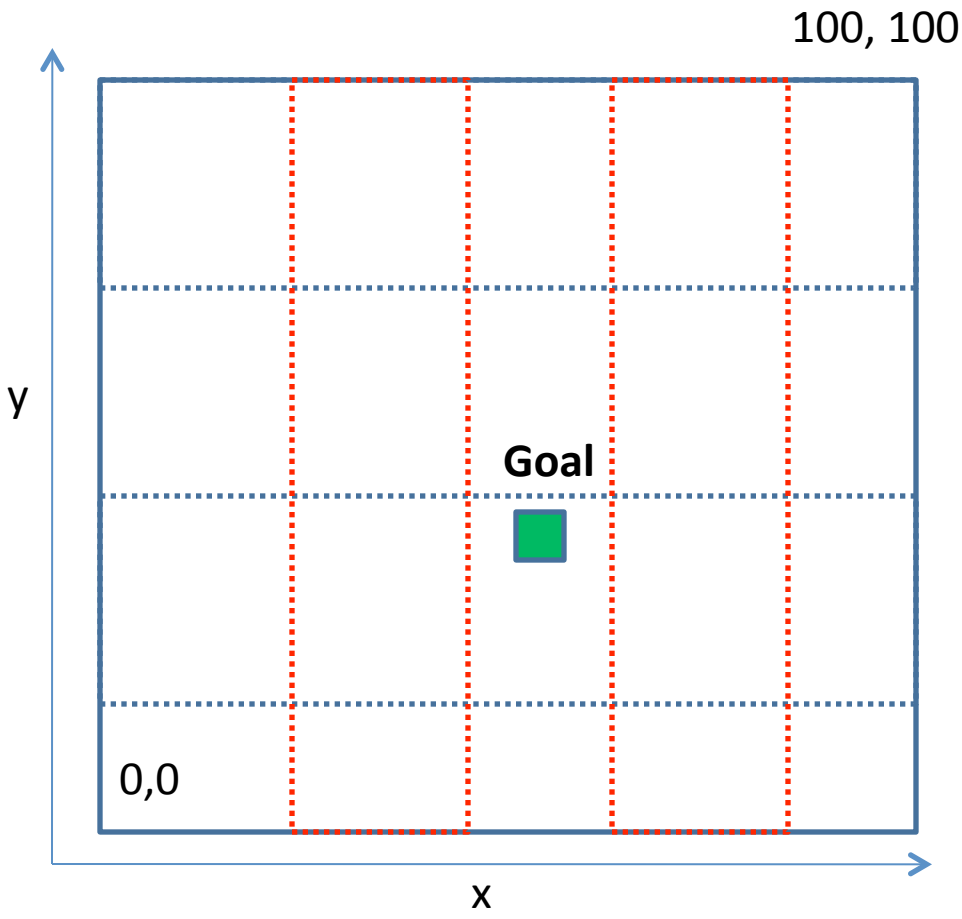
Value Function Approximation -Nonparametric methods

Soar-RL supports arbitrary coarse coding by using "coarse features" in RL rules

RL rule_1: ($x_0 < x < x_1$) -> $Q=q_1$
RL rule_2: ($y_0 < y < y_1$) -> $Q=q_2$
… …
RL rule_n

$Q(x_0 < x < x_1, y_0 < y < y_1) = q_1+q_2$

How to decide the boundaries?
How to encode rules for high dimensional space?

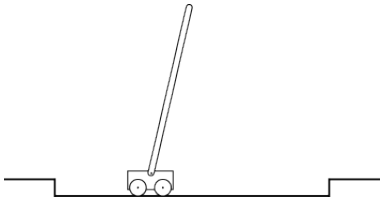


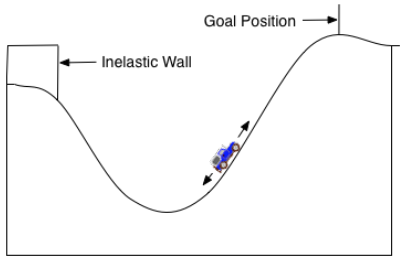
Motivations

- Improve Value Function Approximation in Soar-RL
  - Manually design coarse features can be challenging, even infeasible
  - Learn coarse features automatically
  - Compatible with existing VFA scheme in Soar-RL
- Evaluate with challenging tasks
  - Characterize the tasks
  - Compare with baselines

Traditional RL

- Dynamic control problem
  - Pole balancing
  - Mountain car
  - Robotic arm
  - Helicopter





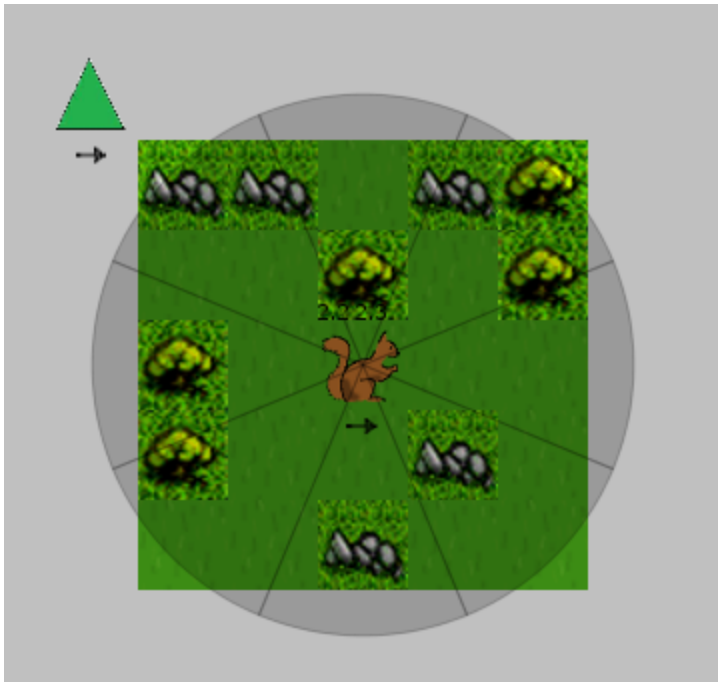
Object Oriented RL

- Object Oriented MDP (OOMDP) framework
  - *Diuk* et al. 2008
  - Representation and learning of action models, not value function approximation
  - Limited object diversity

Motivations

- Improve Value Function Approximation in Soar-RL
  - Manually design coarse features can be challenging
  - Learn coarse features by hierarchical clustering
  - Compatible with existing VFA scheme in Soar-RL
- Evaluate with challenging tasks (Object oriented environments)
  - State representation consists of objects
  - Objects are functionally and perceptually diverse, represented by feature vectors
  - Complex interactions among objects

Evaluation Environment



Distance: 3
Obstacles: bush at 1, rock at 2

Prey:

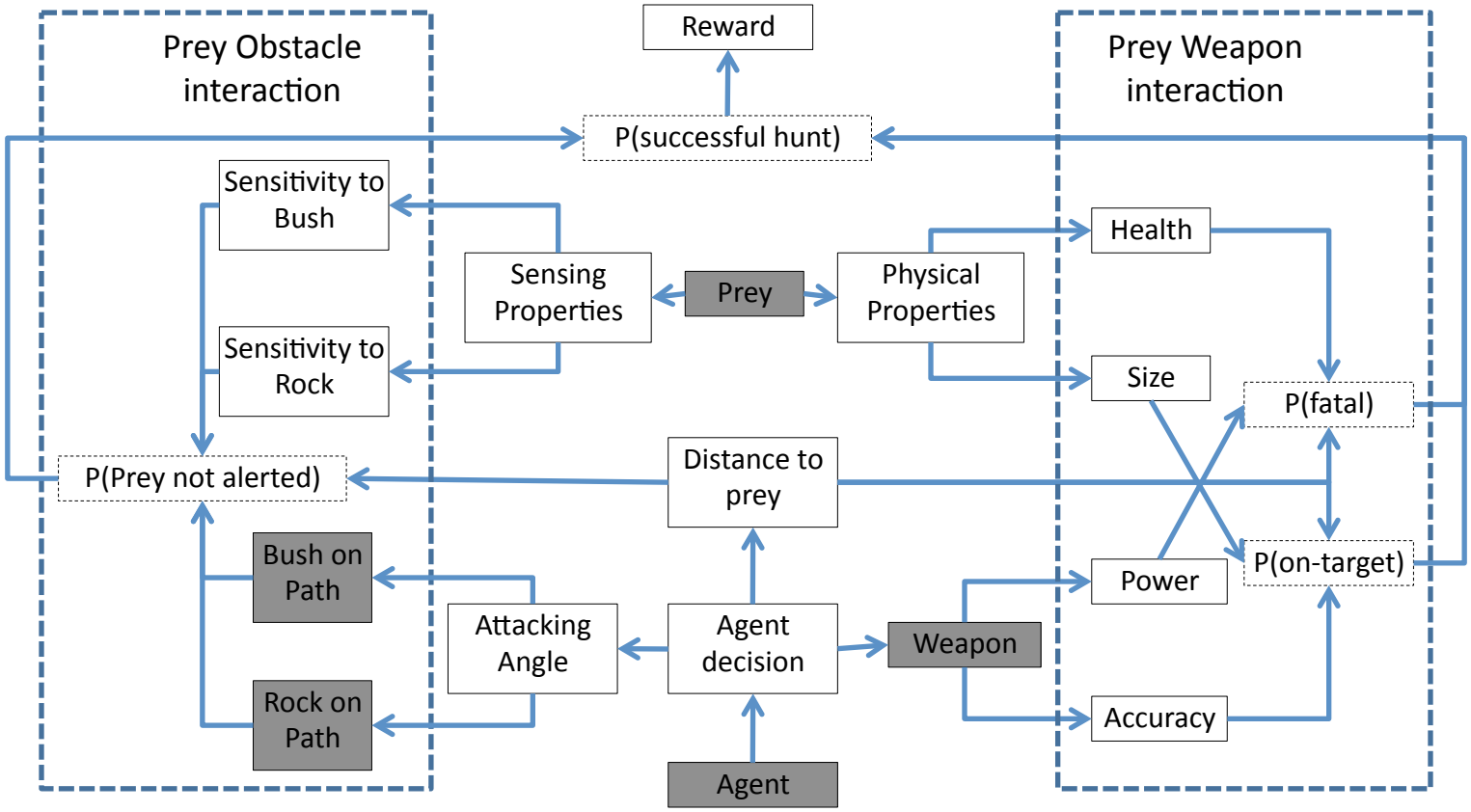
size	health	bush-sensitivity	rock-sensitivity
1	2	2	4

Weapon:

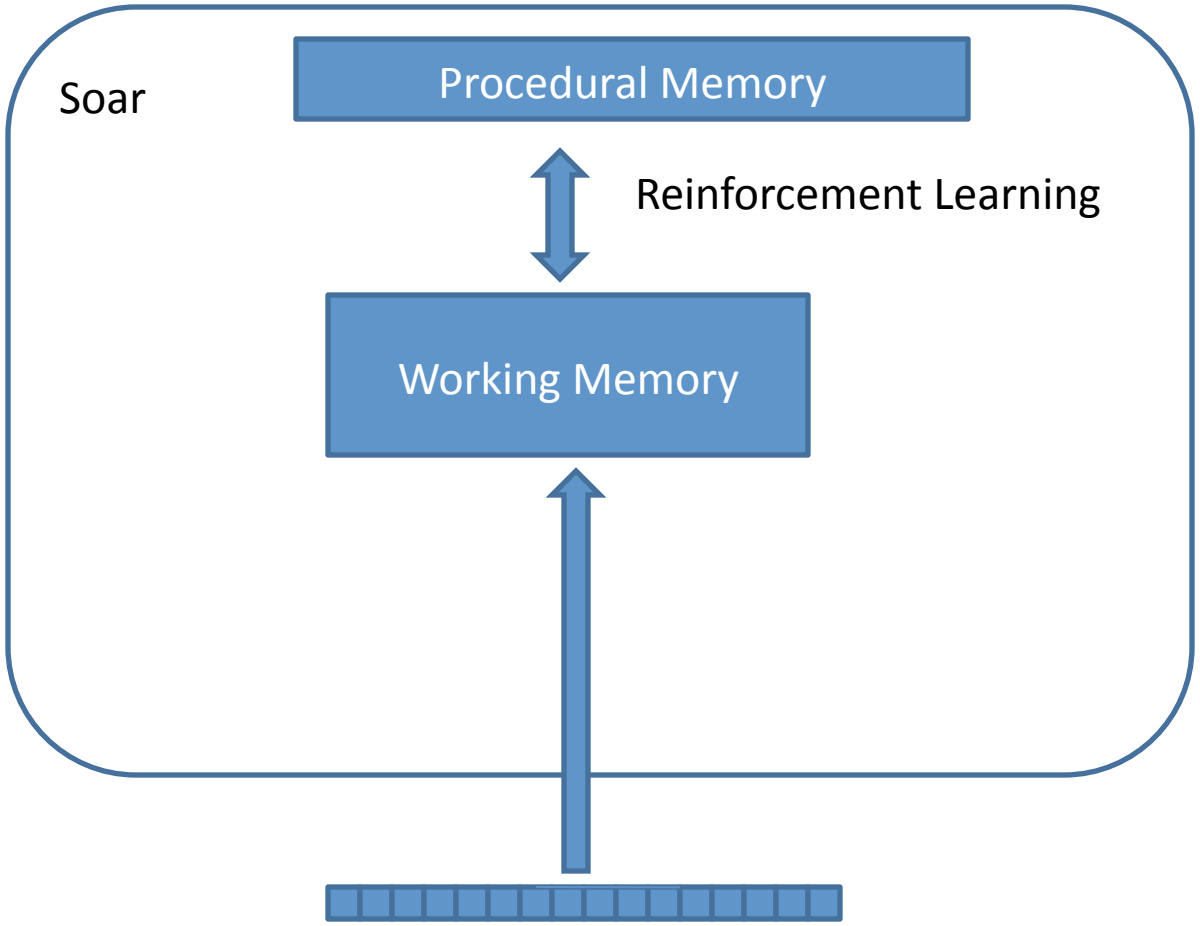
accuracy	power
5	2

1. Not alert the prey
2. Shot on target
3. Fatally wound the prey
4. Reward

Environment Model

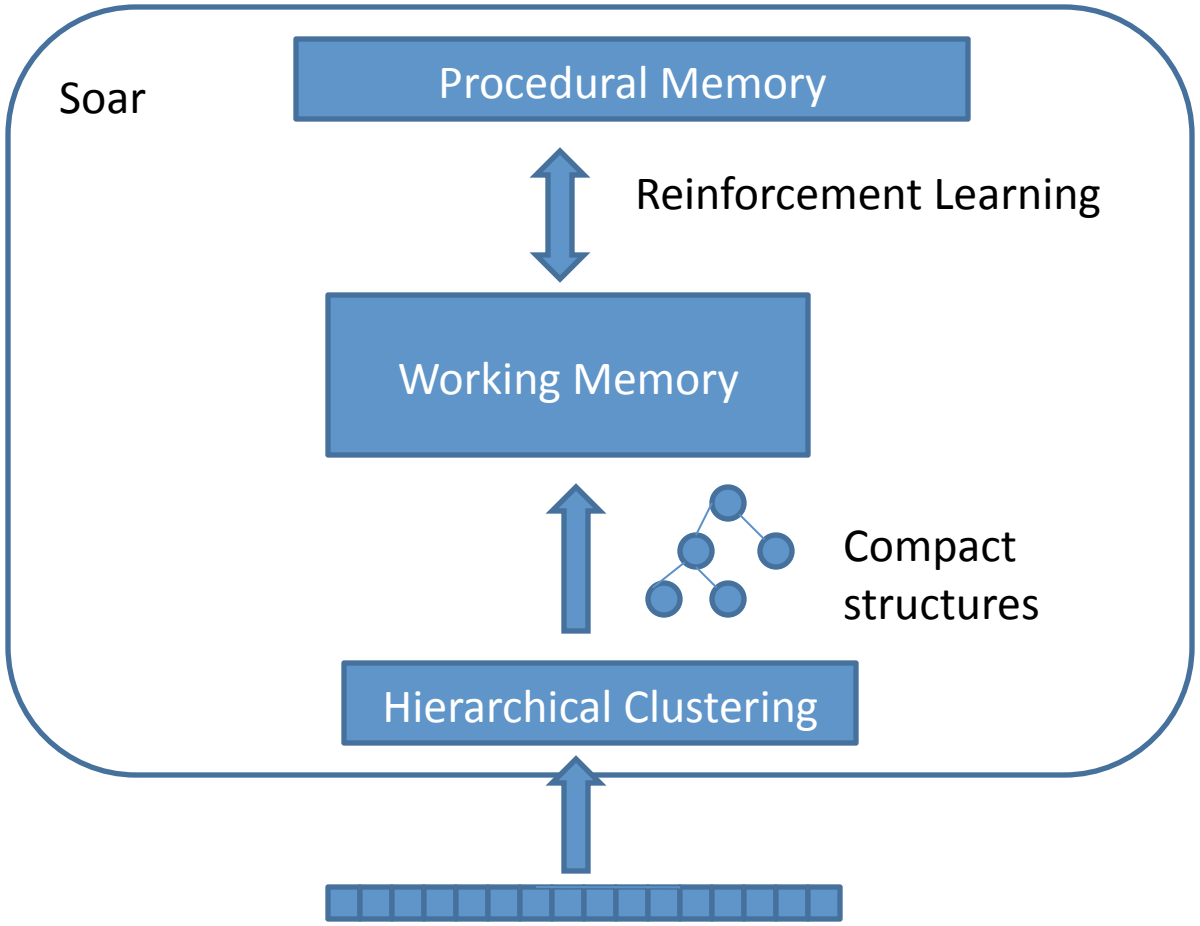


Integrate Hierarchical Clustering with Soar-RL



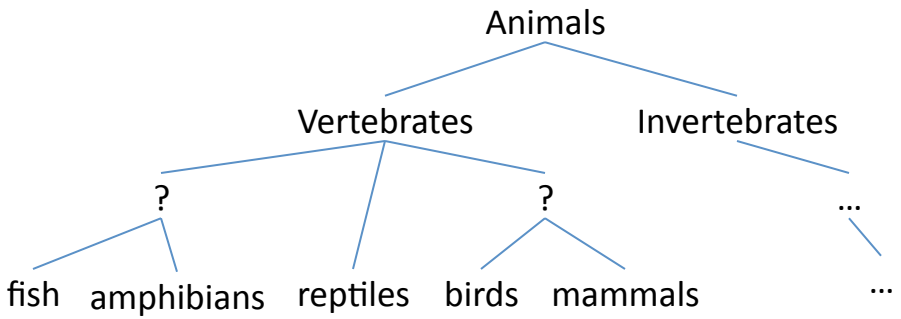
High dimension, continuous state space

Integrate Hierarchical Clustering with Soar-RL



Integrate Category Learning with RL

- COBWEB (D. Fisher 1987)
  - Incremental learning
    - process one instance a time
  - Hierarchical clustering
    - Take numeric feature vector as input
    - Automatically create category symbols
    - Hierarchical structure

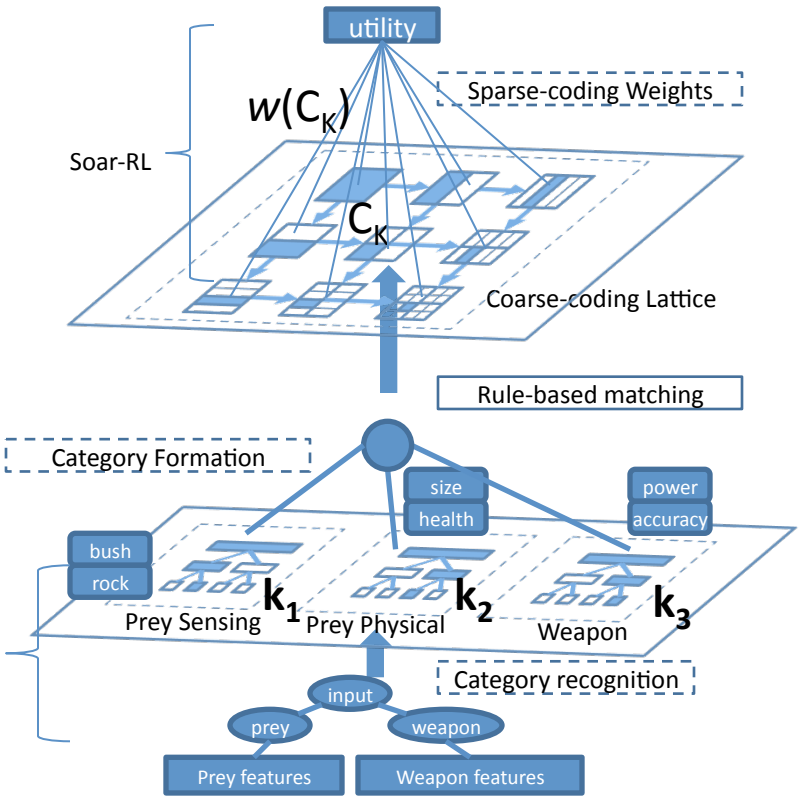


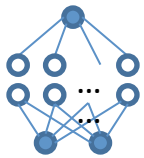
Details of the Algorithm

Procedural Memory

Working Memory

COBWEB





Vector K = (k_1, k_2, k_3), represents the activated clusters from each of the three hierarchies.

A cell C_K, represents the rule matching the clusters K, and $a(C_K)$ is the activation:

$$a(C_K) = \begin{cases} 1 \; if \; matches \\ 0 \; if \; not \; matches \end{cases}$$

Connection weight $w(C_K)$ is the Q value associated with the RL rule. The predicted value:

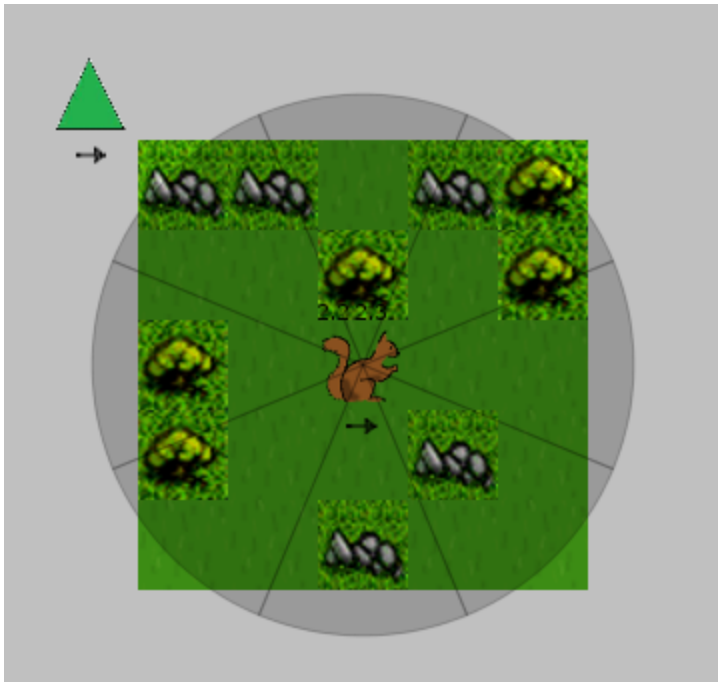
$$y = \sum_{C_K} w(C_K) a(C_K)$$

Update in Soar-RL is calculated in the same way as in stochastic gradient descent methods

$$\Delta w(C_K) = \frac{\alpha}{\sum_{C_K} a(C_K)} (t - y) a(C_K)$$

Like two-hidden-layer network, except for competitive learning and sparse activity in the "hidden layer".

Evaluation Environment



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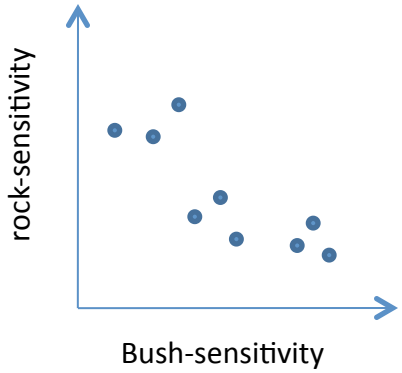
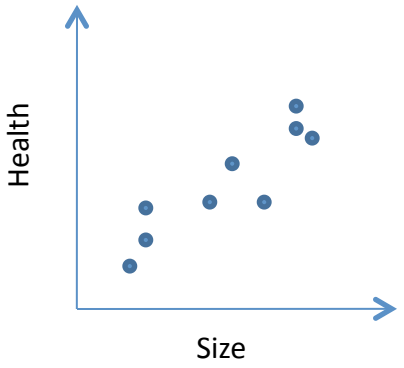
Data Used for Evaluation

Prey

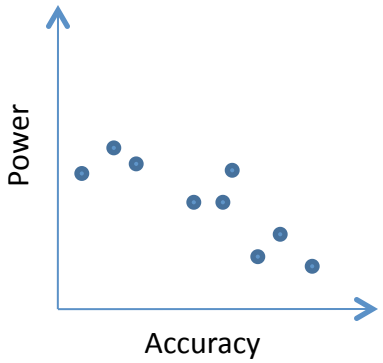


Prey adapted to specific terrain



Health and size are positively correlated

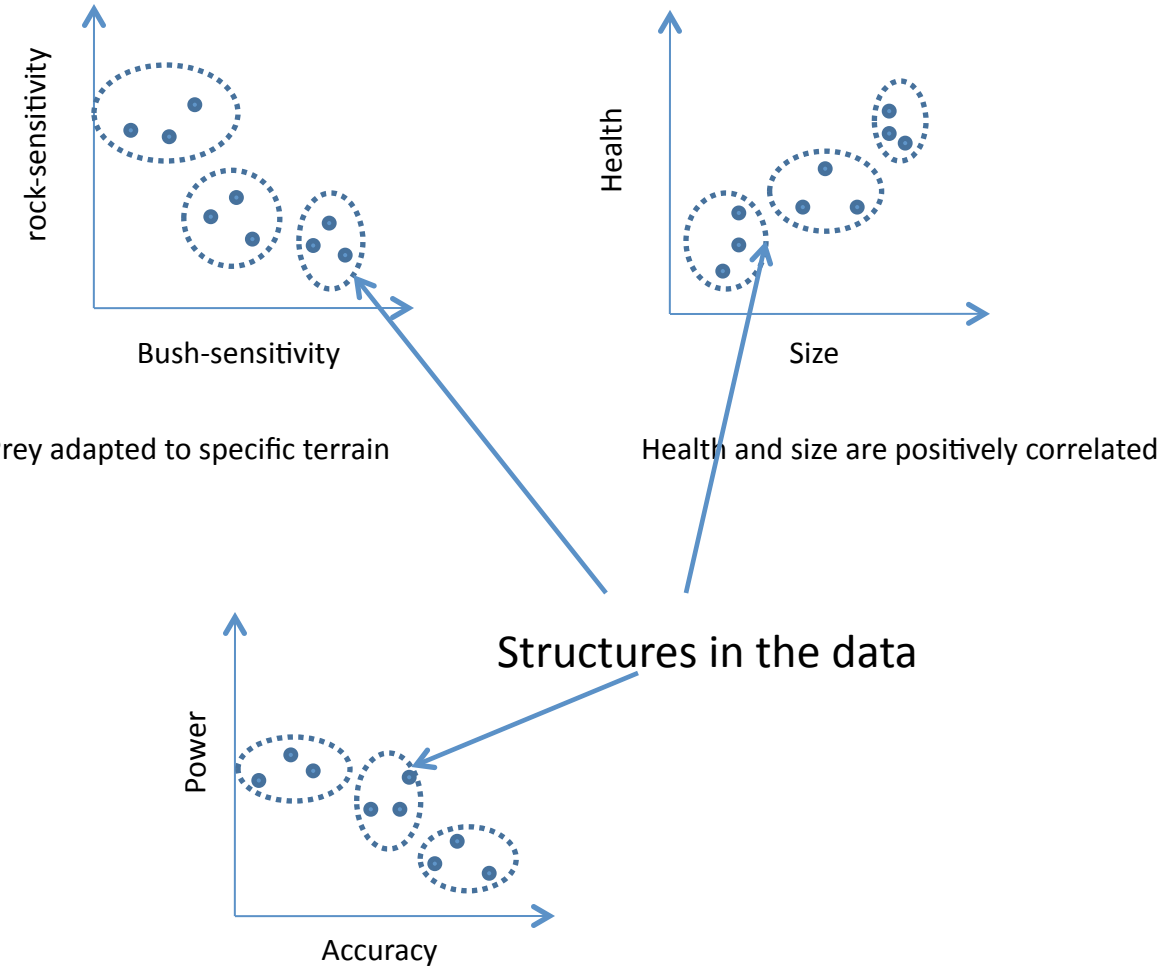
Weapon



Power and accuracy are negatively correlated

Data Used for Evaluation

Prey

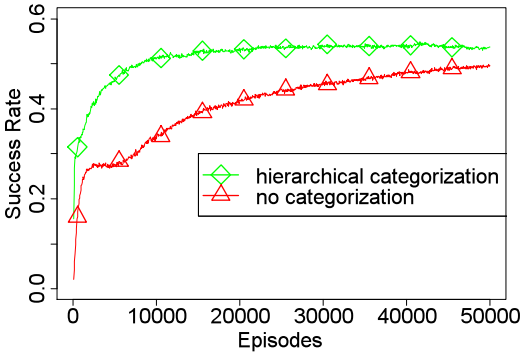


Weapon

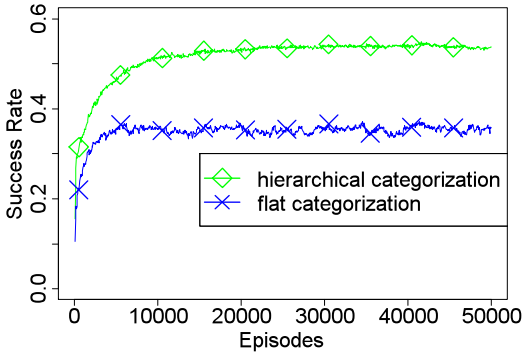
Evaluation

- Target system (Hierarchical clustering + RL)
  - Hierarchical Categorization
  - Using specific functional features
    - prey sensing, prey physical, weapon
- Baseline 1
  - No categorization
  - No generalization, slow learning
- Baseline 2
  - Flat categorization
  - Can be over-general, fail to discriminate more specific cases
- Baseline 3
  - A single hierarchy for prey including all perceptual features
  - Hierarchy with lower quality: some perceptual features are irrelevant to the task (such as color)

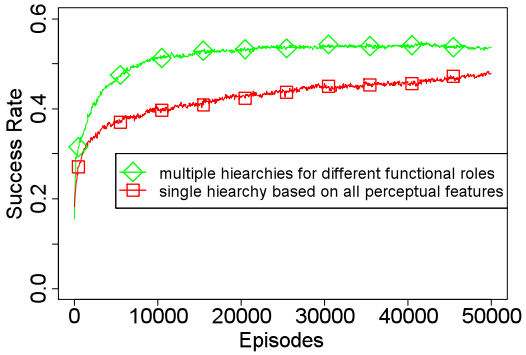
Results



Against baseline1
No generalization



Against baseline2
Over-generalization



Against baseline3
Hierarchy of lower quality

	Categorization	Hierarchical	Functional Hierarchies
Target	Yes	Yes	Yes
Baseline1	No	NA	Yes
Baseline2	Yes	No	Yes
Baseline3	Yes	Yes	No

Nuggets & Coal

- Nuggets
  - Integrated hierarchical category learning and Soar-RL for object-oriented environments with complex features
  - Provide means to take advantage of prior knowledge about functional features
- Coal
  - Single point evaluation
  - Limited complexity in object diversity
  - Only one way flow of information: from categorization to VFA