Practical Introduction to Reinforcement Learning with Gym in Python

21st IEEE Latin American Robotics Symposium

Material available at www.miguelsolis.info

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Robotics

Disciplines

- Mobile Robotics
- Bio-inspired Robotics
- Intelligent Robotics
- Cognitive Robotics
- Evolutive Robotics
- Human-Robot Interaction
- Micro-Robotics
- Nano-Robotics
- Tele-Operated Robotics
- Swarm Robotics

Action and Perception

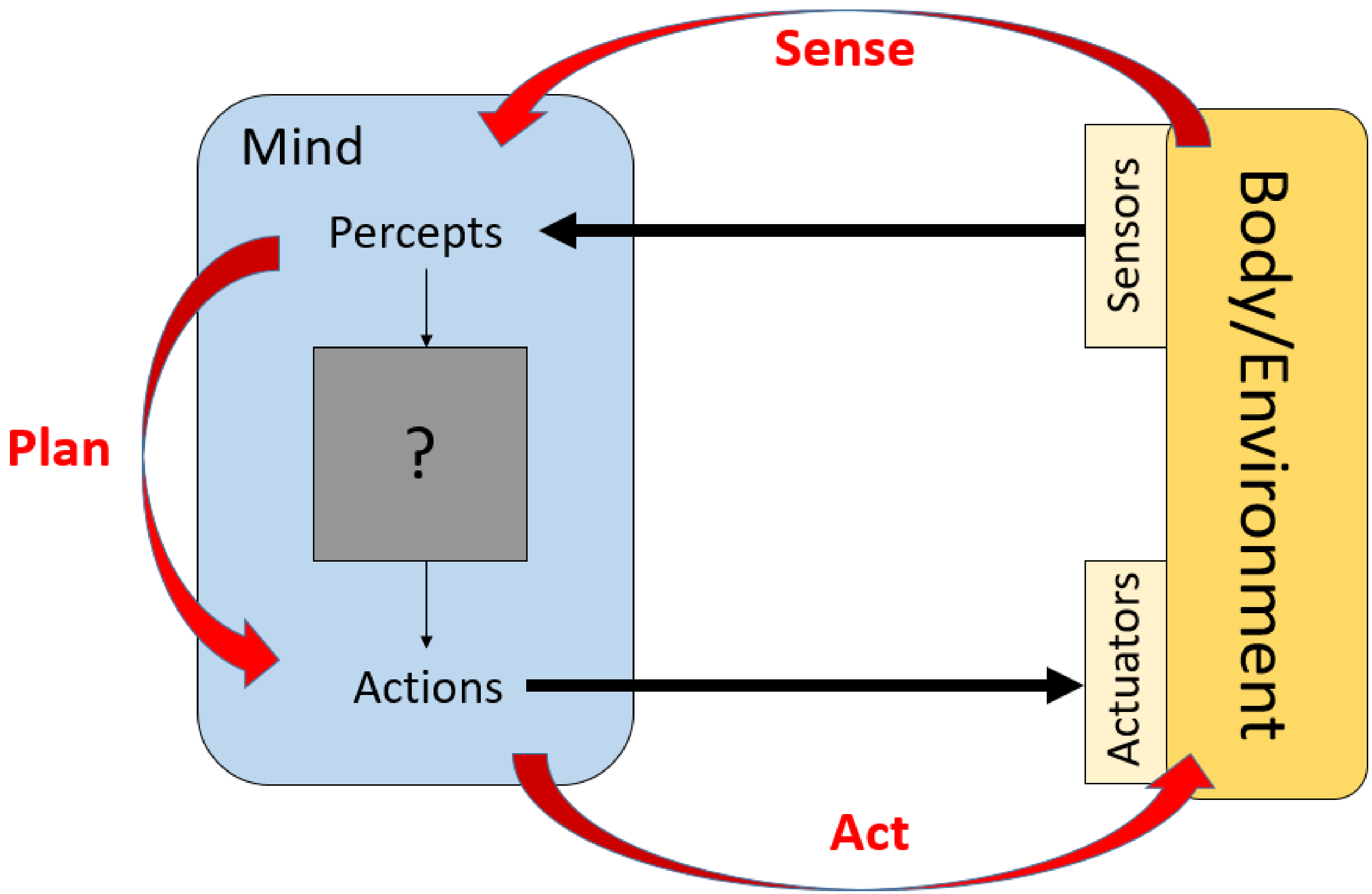


Image extracted from “Robotic Systems”, Kris Hauser, University of Illinois at Urbana-Champaign.

Decision Making

Ways of interacting between agent/environment:

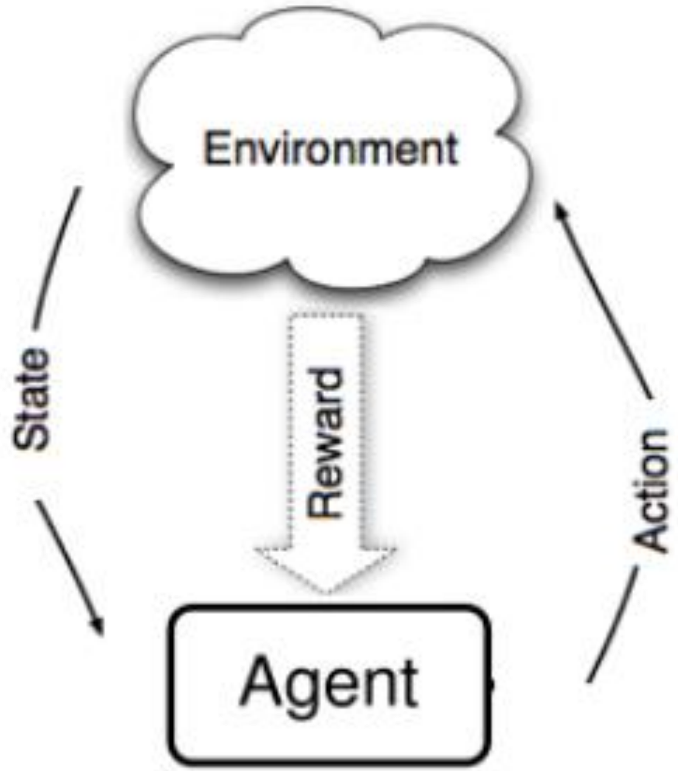
- reactive: simplest way of decisión making through finite states machine (if A when X, then execute B leaving on Y)

Decision Making

Ways of interacting between agent/environment:

- intelligent: behavior shaping through heuristics
- incremental learning: behavior shaping through patterns recognition and prediction of outcomes from the environment

Reinforcement learning



- Learning through interactions with environment.
- Applications

  Sequential decisión problems

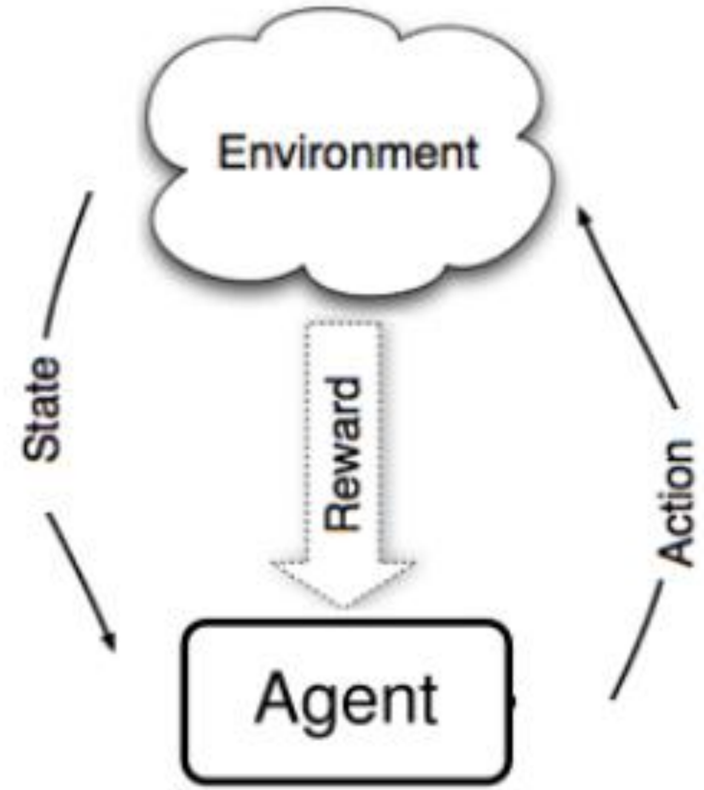
  Adaptive systems

Reinforcement learning and conductism

Edward L. Thorndike – Animal Intelligence: An experimental study of the associate processes in animals (1898).

Animal modifies its behavior according to trial-and-error interactions with the environment.

Reinforcement learning and conductism



- Agent perceives current state, s.
- Agent executes action, a, as output.
- Agent receives a reward, r, as reinforcement signal.

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Markov Process

- A reinforcement learning problema is formally formulated through an MDP.

- MDP: Markov Decision Process.

A given state s_k comes from a (first-order) Markov Process if and only if:

$$Pr\{s_{k+1}|s_k\} = Pr\{s_{k+1}|s_1, ..., s_k\}.$$

Reinforcement learning elements

A reinforcement learning problema, formulated as an MDP is given by the tuple (S, A, T, R) where:

- S: set of states
- A: set of actions
- T: S x A x S → [0, 1] (transition function, unknown)
- R: S x A x S → $\mathbb{R}$ (rewards function)
- π : S → A (policy)

Reinforcement learning elements

State on time step k:

$$s_k \in \mathcal{S}$$

Action executed on time step k:

$$a_k \in \mathcal{A}$$

State-transition function:

$$s_{k+1} = T(s_k, a_k)$$

Rewards

$$r_k = R(s_k, a_k, s_{k+1})$$

- $r_k > 0$
- $r_k = 0$
- $r_k < 0$

Policy $\pi : \mathcal{S} \to \mathcal{A}$

A policy is said to be optimal, if it maximizes the long-term reward

Return

Value function:
$$V^{\pi}(s_k) = r_k + \gamma r_{k+1} + \gamma^2 r_{k+2} + \dots$$
$$= \sum_{i=0}^{\infty} \gamma^i r_{k+i}.$$

Constraints:

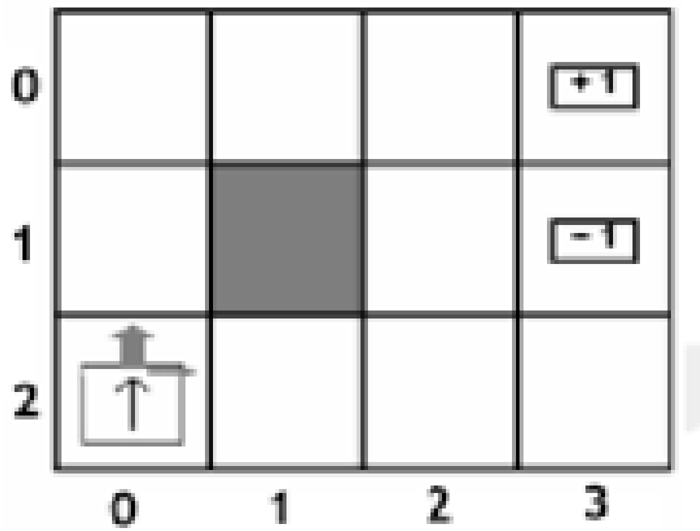
$$0 \le \gamma < 1.$$

r_k bounded

A policy π^* is optimal if value function for that policy is optimal:

$$V^*(s) = V^{\pi^*}(s) \ge V^{\pi}(s) \quad \forall s, \pi$$

Toy example: Grid World



- States: location within the grid.
- Actions: up, left, right, down.
- Rewards: +1 , -1 , -0.1

Classical algorithms

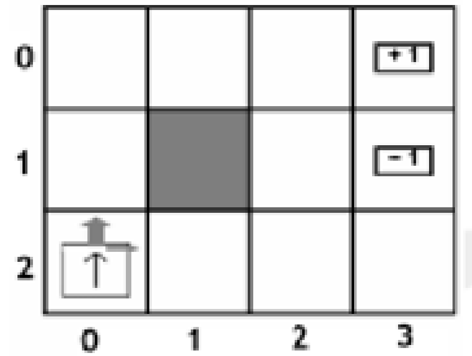
- Value Iteration
- Policy Iteration
- Temporal Difference
    - Q-Learning
    - SARSA

Value Iteration

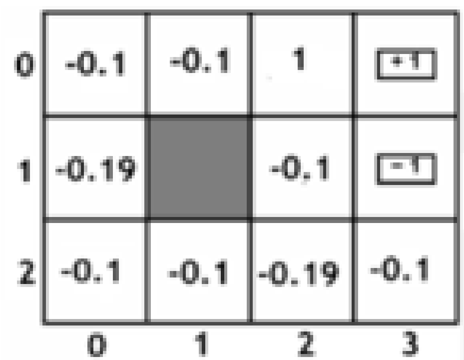
It consists on k iterations, until $V_k(s) - V_{k-1}(s)$ is small enough (according to a given tolerance), with updates given by:

$$V_k(s) = \max_a \sum_{s'} Pr\{s', s, a\} \cdot (R(s', s, a) + \gamma V_{k-1}(s'))$$

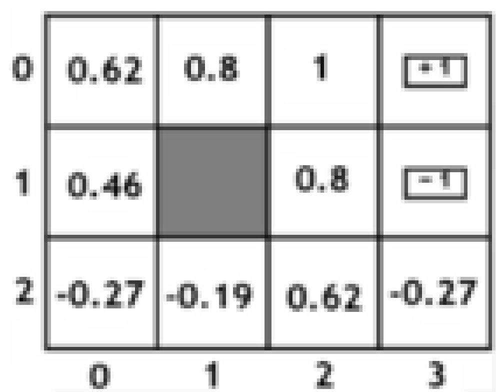
Toy example



- After 1 iteration:



- After 2 iterations:



Toy example

- After 2 iterations:

	0	1	2	3
0	0.62	0.8	1	+1
1	0.46		0.8	-1
2	0.31	0.46	0.62	0.46

- On convergence:

	0	1	2	3
0	0.62	0.8	1	+1
1	0.46		0.8	-1
2	0.31	0.46	0.62	0.46

Q values

Just as V(s) gives some value related to state, Q(s,a) gives some value to taking a certain action on such state.

Optimal policy π^* satisfies:

$$Q^{\pi^*}(s,a) \geq Q^{\pi}(s,a) \quad \forall s, a, \pi$$

Q-learning

Consists on iterating over every (state,action) pair, for given hyperparameters (alpha and gamma).

Update expression:

$$Q(s_k, a_k) \leftarrow (1-\alpha)Q(s_k, a_k) + \alpha \left(r_{k+1} + \gamma \max_a Q(s_{k+1,a}) \right)$$

Assuming $\hat{Q} = Q^*$, then optimal action for every state could be obtained by means of maximizing:

$$\pi^*(s_k) = arg \max_{a_k} Q^*(s_k, a_k)$$

Image extracted from “Introduction to Q-learning with OpenAI Gym”, Gelana Tostaeva, Medium.

Toy example: Grid World

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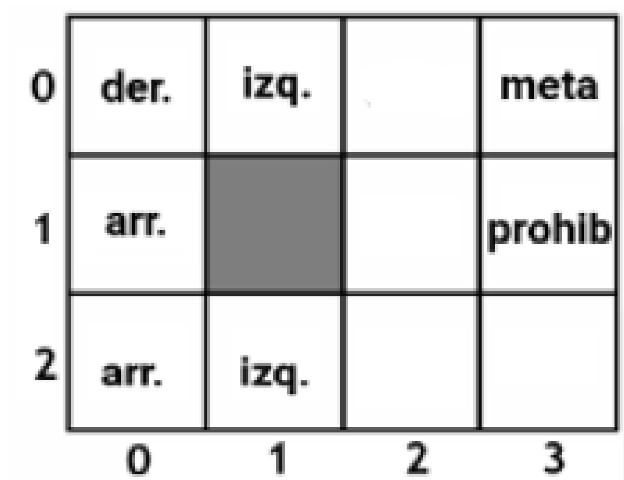
Algorithm does not iterate over the whole states space, just those visited states.

This (toy) example is episodic (when agent gets to final state, episode finish and a new episode starts with the agent starting again).

Must pay attention to local optimum.



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Toy example: Grid World

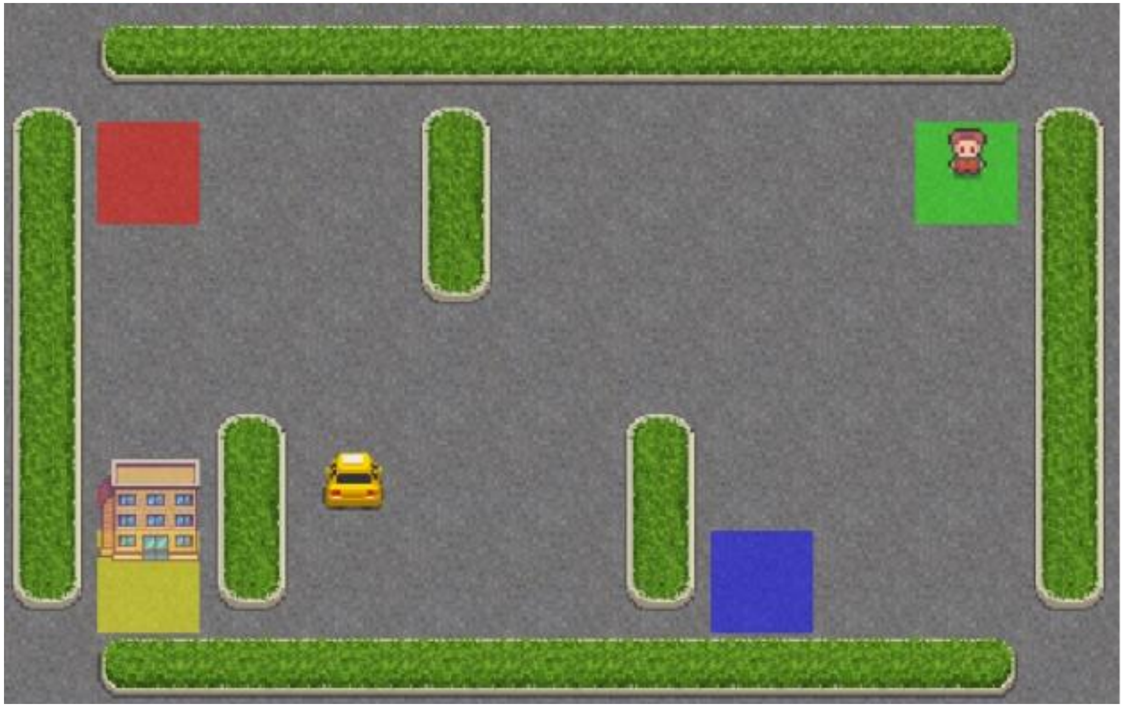
Local optimum stuck:

	0	1	2	3
0	der.	izq.		meta
1	arr.			prohib
2	arr.	izq.		

Including exploration

	0	1	2	3
0	der.	der.	der.	meta
1	arr.			prohib
2	arr.	izq.		

Taxi problem (Gym)



Actions

```
+---------+
|R: | : :G|
| : | : : |
| : : : : |
| | : | : |
|Y| : |B: |
+---------+
```

0: south
1: north
2: east (right)
3: west (left)
4: pick up passenger
5: leave passenger

States and Actions Space

Actions: 6

States: 500 (passenger_location, taxi_location, destination)

4 possible destinations
passenger_location: 4 possible locations for origin, or same location as the taxi
taxi_location: 25 possible locations according to the map

Gym verification:

env.action_space
env.observation_space

Rewards

- Passenger left on correct location: 20 points

- Discount of 1 point anytime taxi moves with passenger without arriving to destination

- Discount of 10 points for leaving passenger on illegal location

Python Notebook

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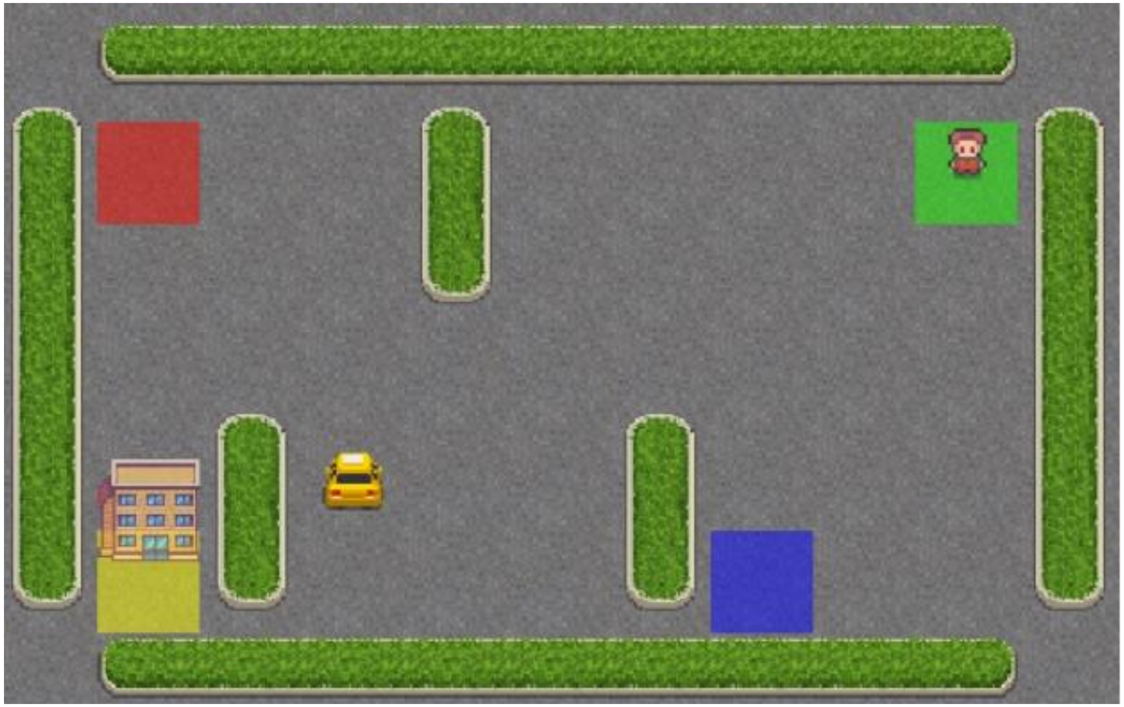
12112024_Tutorial_MSolis.ipynb



Open with any Python Notebook Interpreter, or colab.research.google.com

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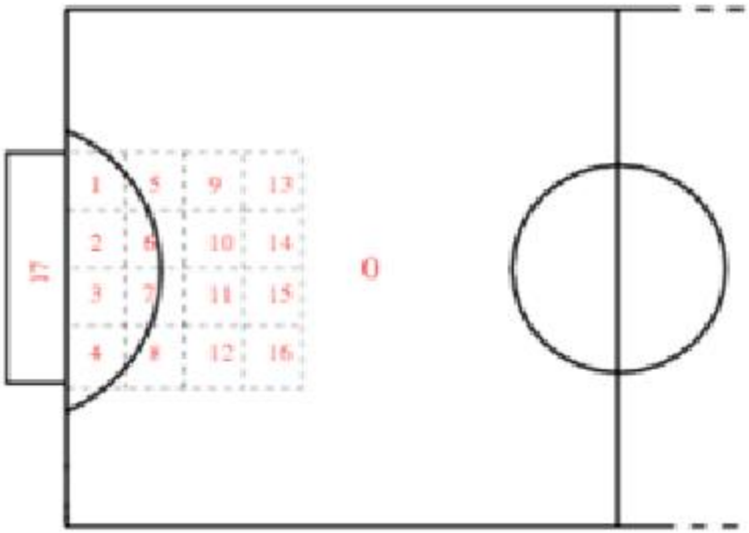
More examples

- G.A. Ahumada, C.J. Nettle and M.A. Solis, ‘Accelerating Q-learning through Kalman Filter Estimations applied in a RoboCup SSL Simulation’, **Proceedings** of the 10th IEEE Latin American Robotics Symposium, 2013.



More examples

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Deffensive strategy generation

State is composed by

- dist(Keeper, ball) , dist(Taker, ball)
- Dist(Keeper_Team_A, Keeper_Team_B)
- Dist(Keeper_Team_A, Taker_Team_B)
- Angle(Keeper_Team_A, Taker_Team_B)

Ollino, F., Solis, M. A., & Allende, H. (2018). Batch reinforcement learning on a RoboCup Small Size League keepaway strategy learning problem. In 4th Congress on Robotics and Neuroscience, CRoNe 2018. CEUR-WS.

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Important challenges

Rewards design

Delay on actions execution

Tabular representation

Some current topics

- affordances

(Object, Action, Effect)

Given an object and a certain action, what effect does it have?

Given an object and a desired effect, what is the required action?

- continual reinforcement learning (open-ended)

Final questions?

(material available at www.miguelsolis.info)