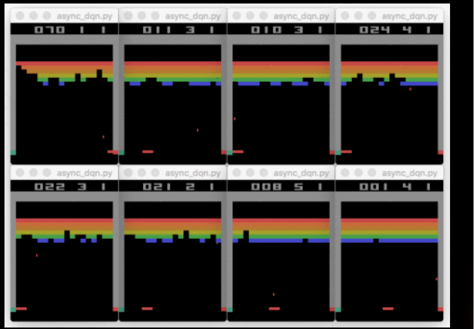

Robótica inteligente mediante Reinforcement Learning

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SUMMER SCHOOL
CEA Comité Español de Automática
ALMA

Robótica inteligente mediante Reinforcement Learning

- ❑ **Reinforcement Learning dentro de la IA**
- ❑ **Conceptos Principales en RL**
- ❑ **Ejemplos de Algoritmos en RL**
- ❑ **Robótica: Expert Rules hasta End-to-end**
- ❑ **Conclusiones y recursos**

Artificial Intelligence

- Artificial General Intelligence (AGI)
- Narrow AI
  - Optimization (Gradient Descent, Evol. Comput...)
  - Good Old-Fashioned AI (Cognitivist/Symbolical)
  - Machine Learning (Connectionist/Statistical)

Artificial Intelligence

- Artificial General Intelligence (AGI)
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  - Machine Learning (Connectionist/Statistical)

Machine Learning (Tipos de Problemas)

Supervised Learning

Unsupervised Learning

Reinforcement Learning

Aún más vía Deep Learning
(p.ej. Selfsupervised Learning, Style Transfer, GANs…)

Machine Learning (Tipos de Problemas)

Supervised Learning

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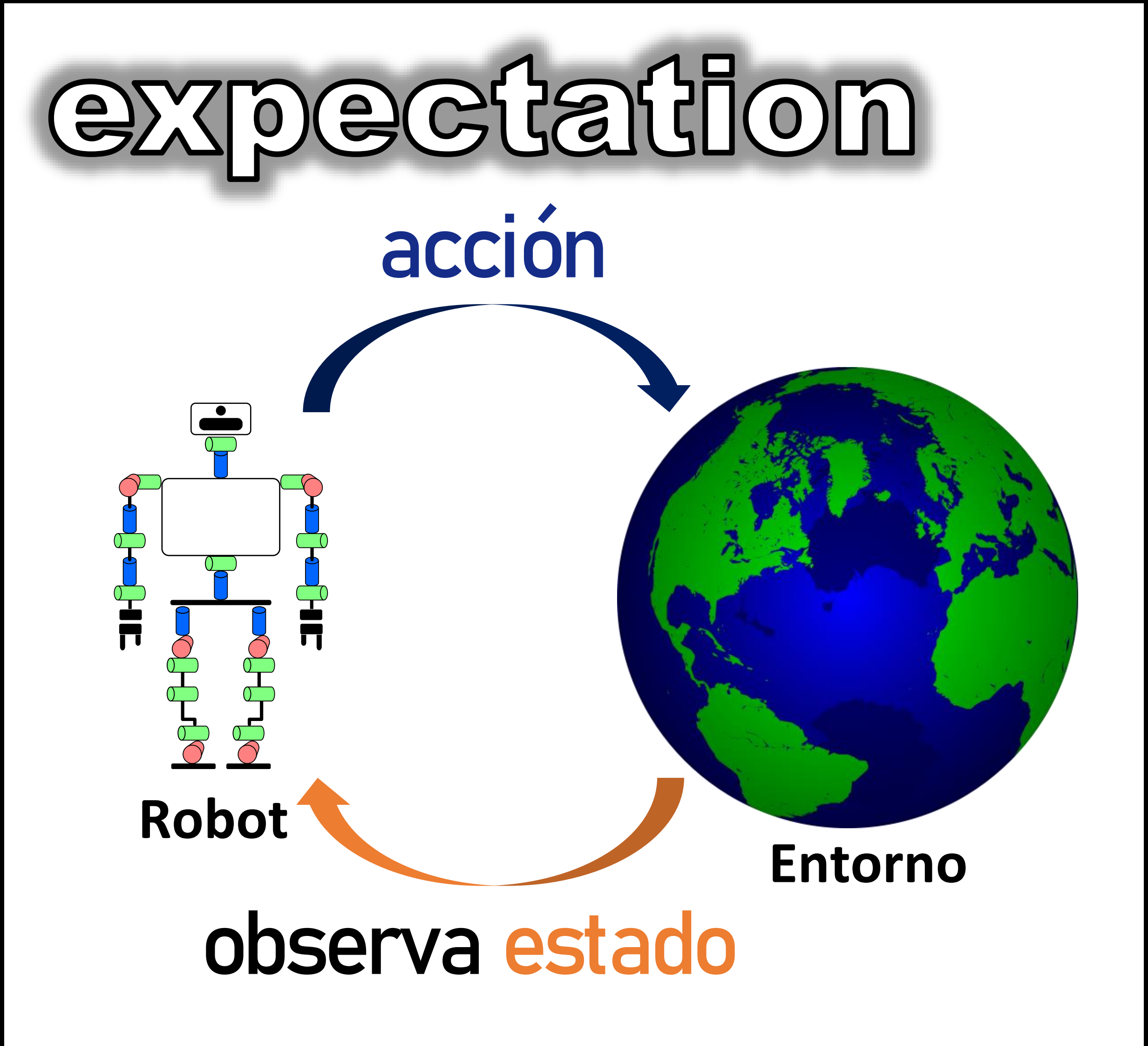
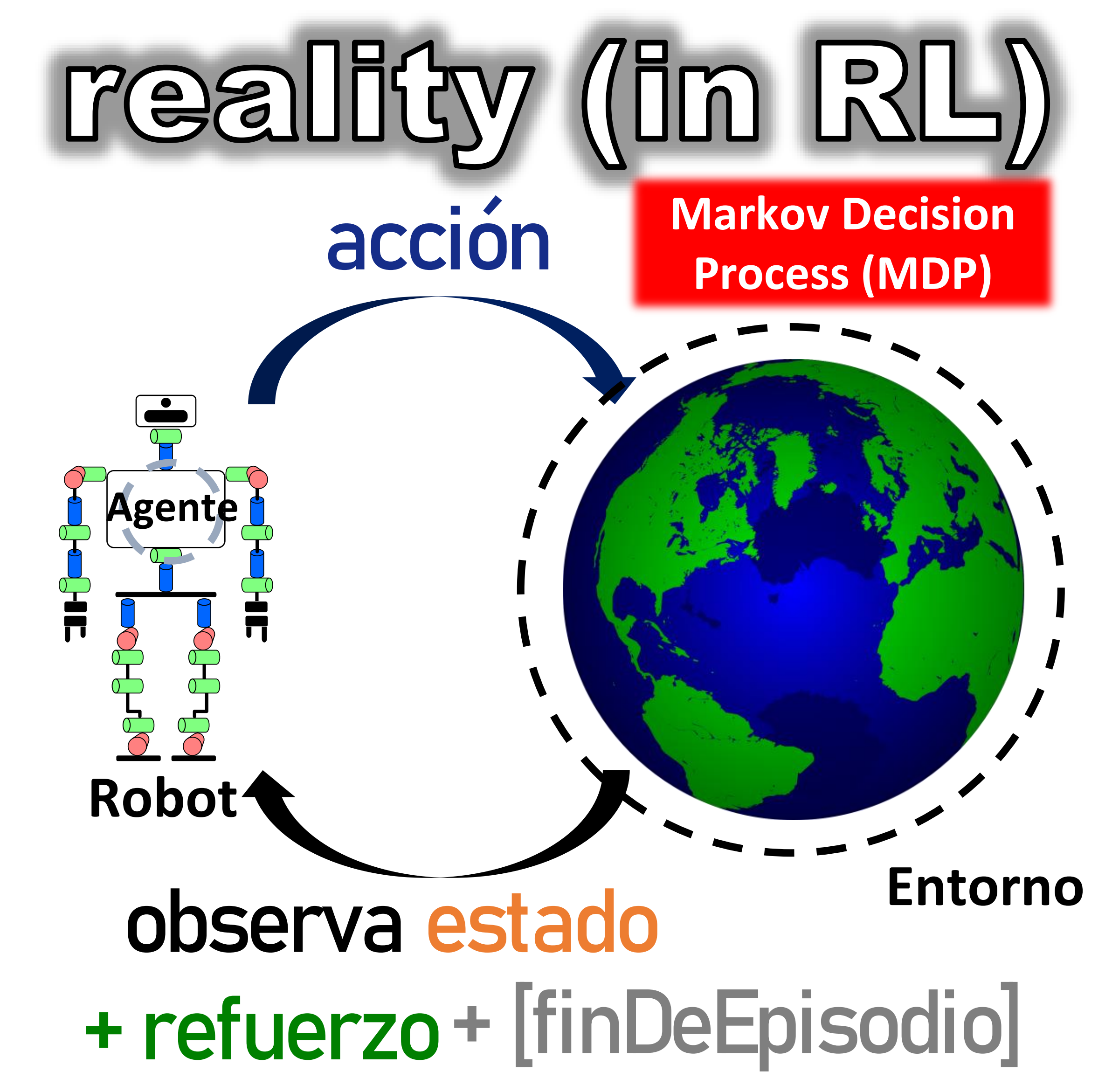
(p.ej. Selfsupervised Learning, Style Transfer, GANs...)

INTERACCIÓN ROBOT-ENTORNO

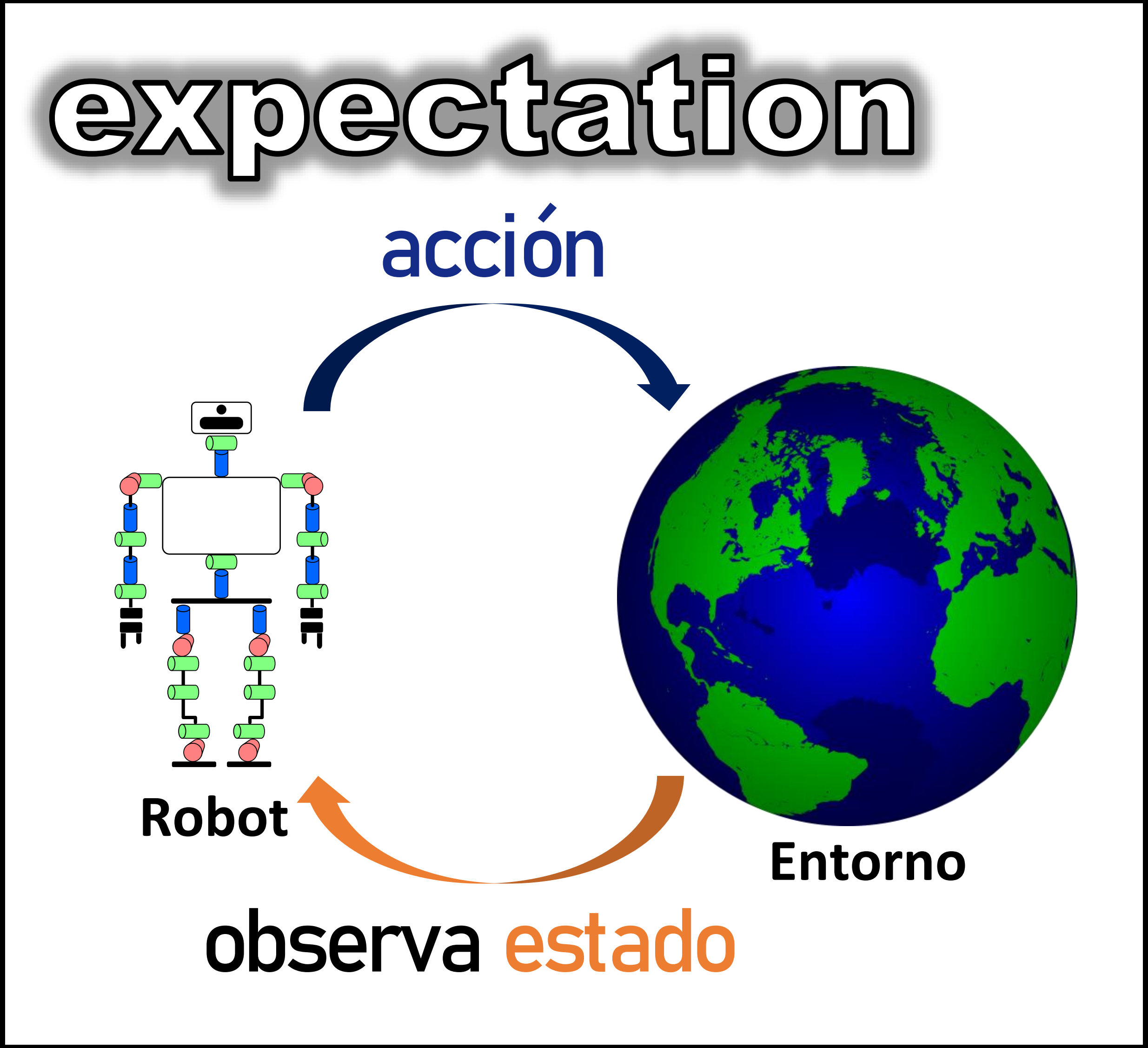
@jgvictores

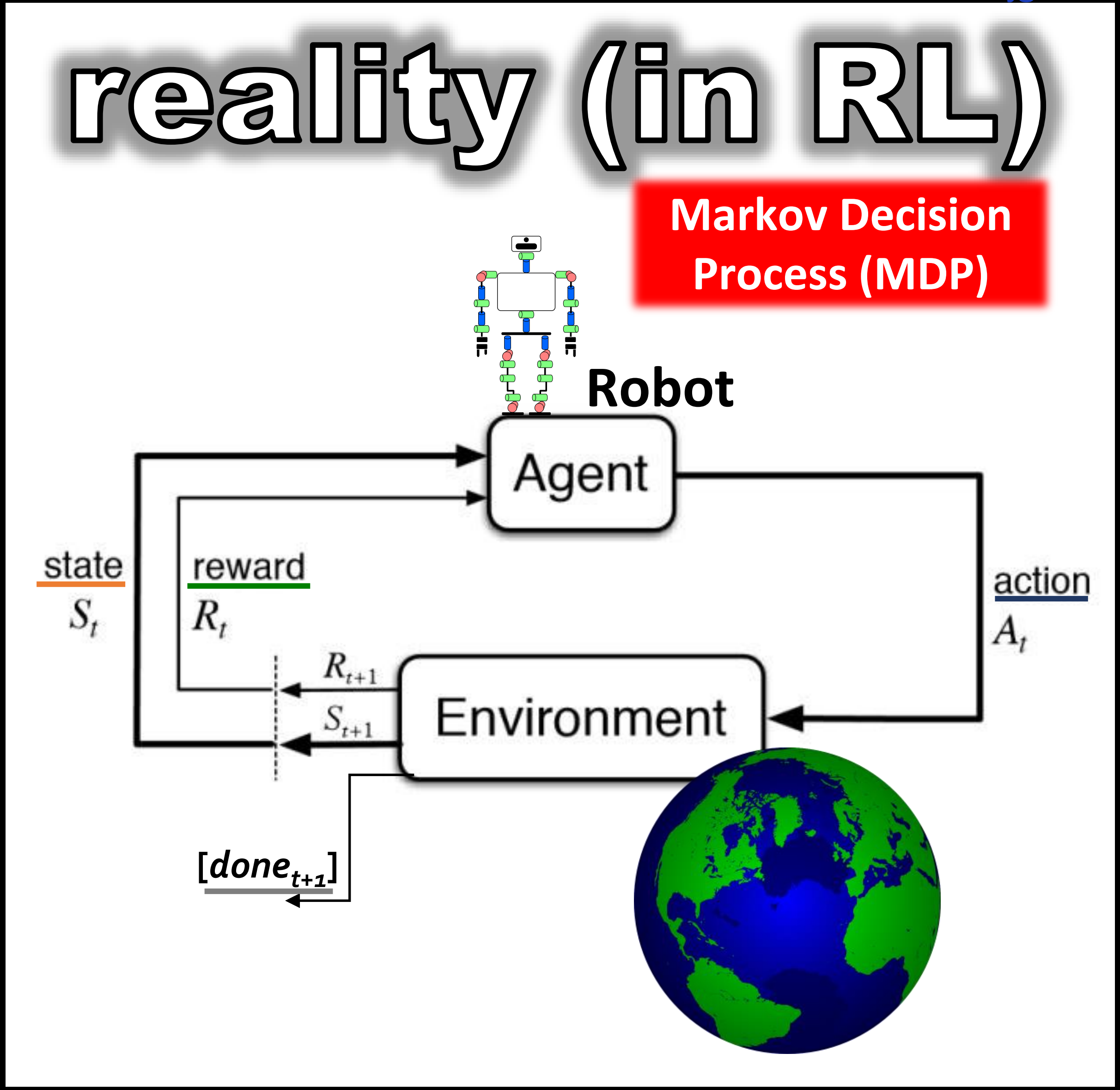




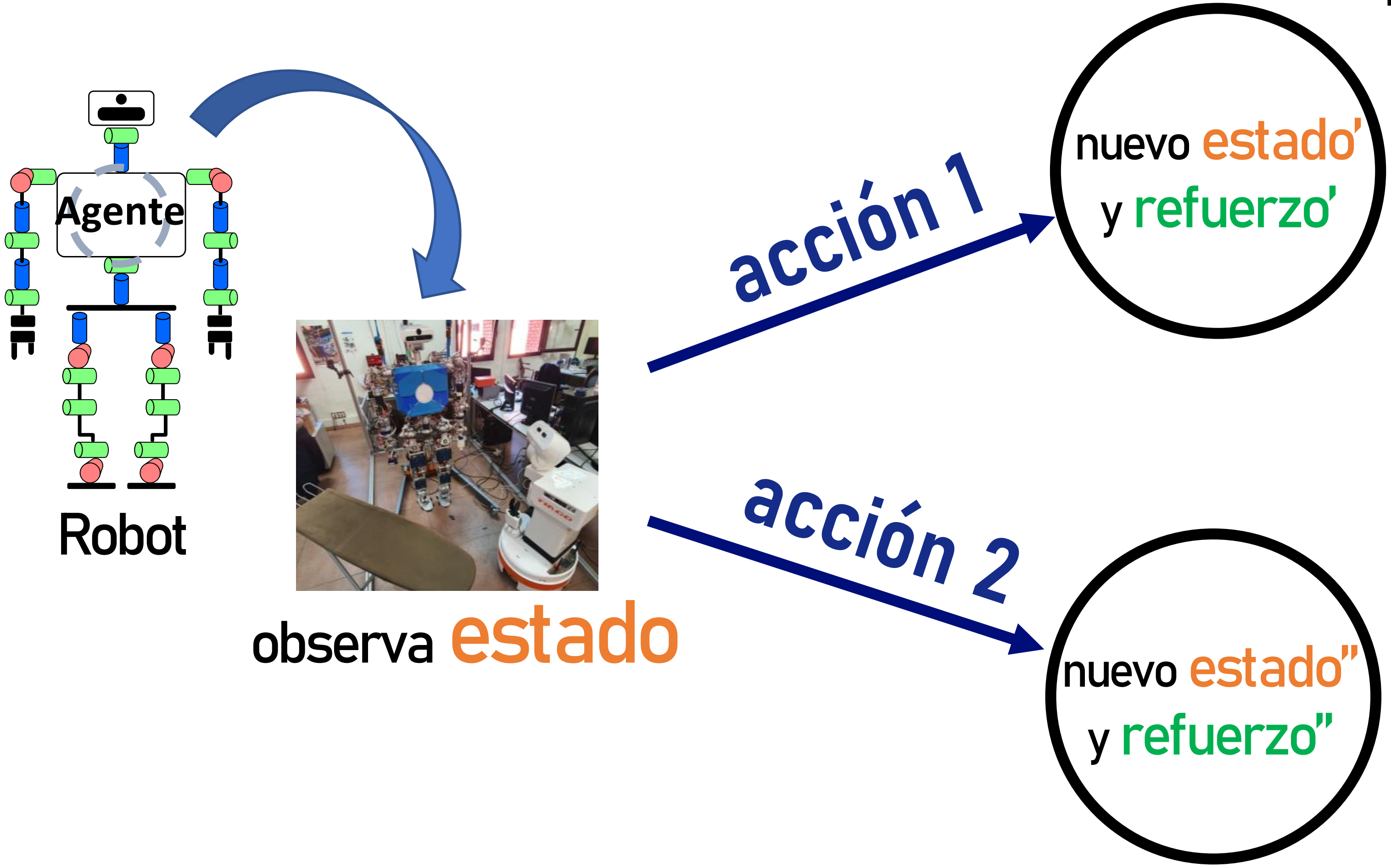
INTERACCIÓN ROBOT-ENTORNO

@jgvictores





Reinforcement Learning (Tipo de Problema)



Toma de decisiones

Objetivo: ley de control

acción = π(estado)

Maximiza: f(refuerzo)

Supuestos:

Markov Assumption

Markov Decision Process

π directa o vía V/Q

Reinforcement Learning: Técnicas

Watkins (1989): Q-Learning

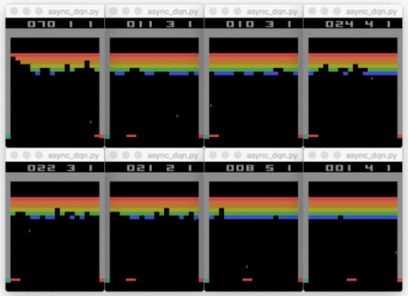
- π(s) / V(s) / Q(s,a) / Actor-Critic

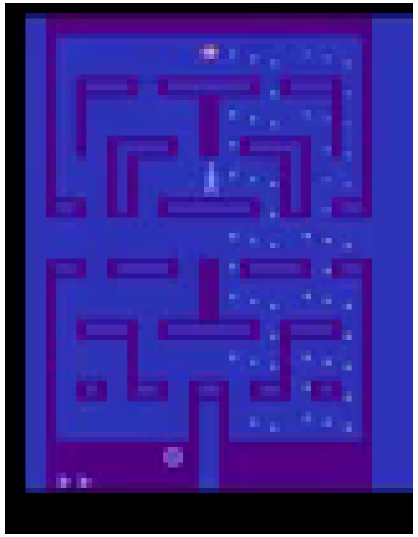
Mnih (2015-): Deep Q-Network (DQN)

- Tabular / Function Approximator
- f(reward): Average / Discounted / (Return)
- Model-free / Model-based
- MDP / POMDP / …
- On-policy / Off-policy

Mnih (2015-): Deep Q-Network (DQN)

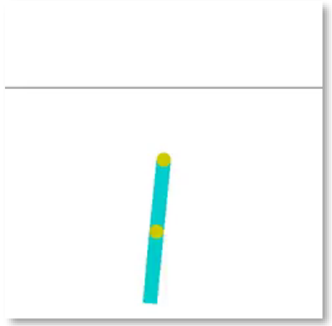
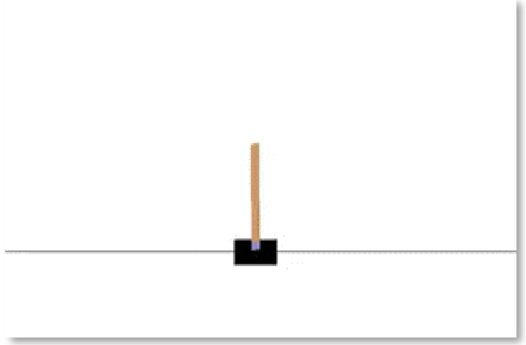
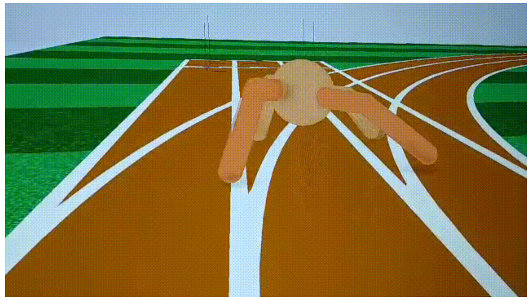
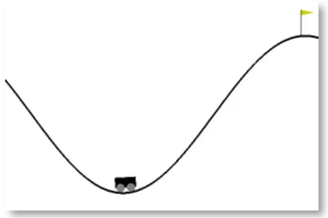
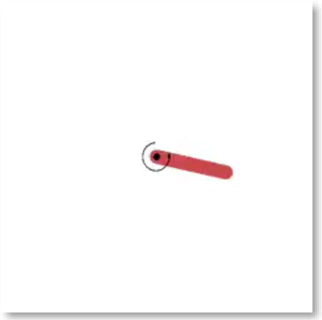
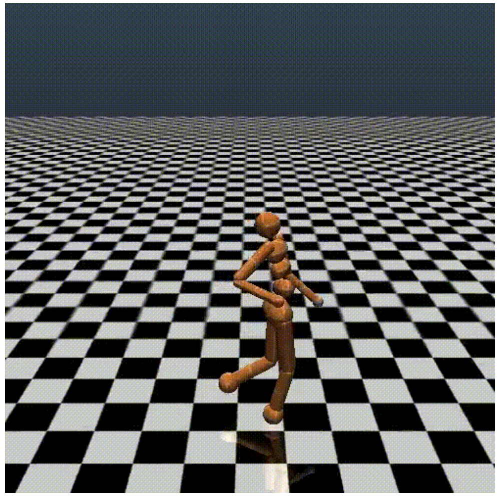
RL+DeepL=DRL: en videojuegos (2015-)





Schulman (2015-): TRPO

DRL: en simuladores de robots (2015-)

DRL: en robots (2015-)

Levine (2015-): End-to-End Training of Deep Visuomotor Policies

Conceptos RL (agente y entorno)

s: estado = x

a: acción = u (управление)

r: refuerzo (recompensa)

Ecuaciones de Bellman (fundamentos y proofs matemáticos)

Conceptos RL (entorno)

Algoritmos "Model-Based": Intentan hallar modelo de P
Algoritmos "Model-Free": El resto (muy habitual)

P: dinámica=transiciones

En un MDP, el entorno devuelve estado completo.
En un Partialy Observable MDP (POMDP), sólo devuelve una parte: la observación

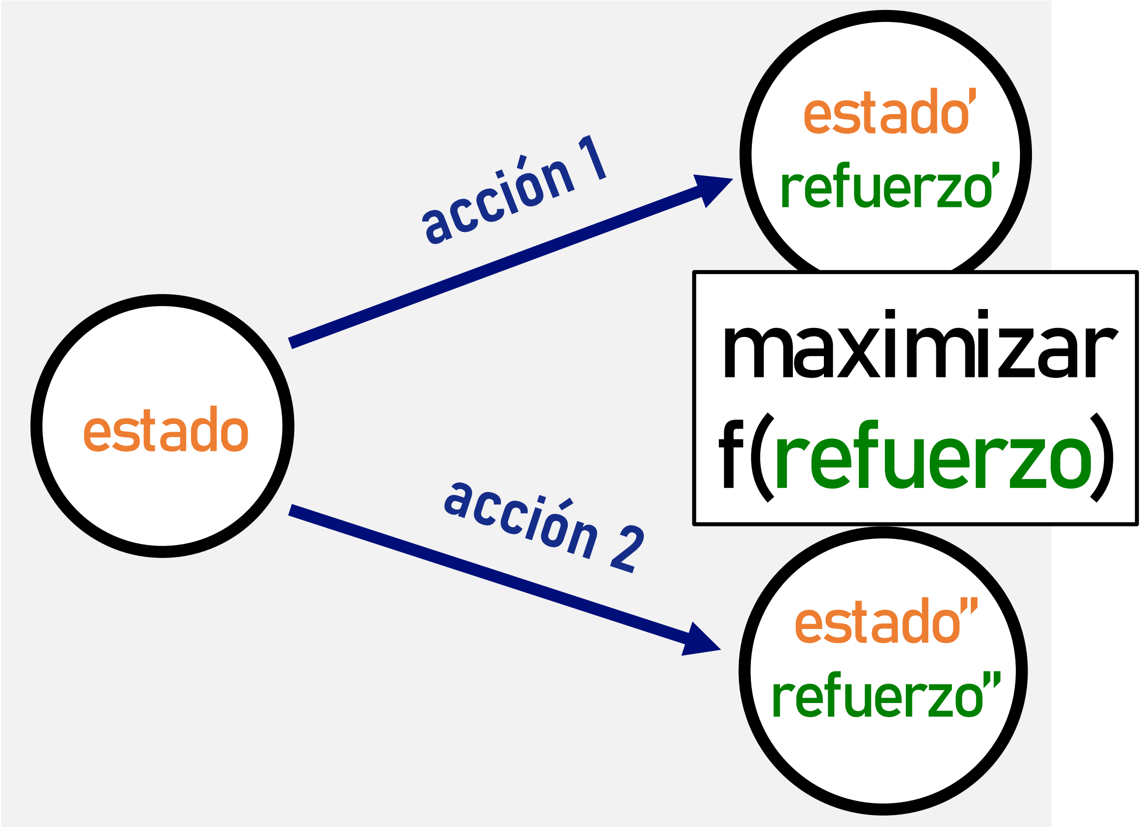
Determinista	Probabilística
s',r',fin = P(s,a)	P(s',r',fin | s,a)

fin: "episodic" (vs. "continuing"="infinite")

isd(s): distribución inicial de estados

Conceptos RL (agente)

π: Ley de control (policy, cómo actúa agente)



Determinista

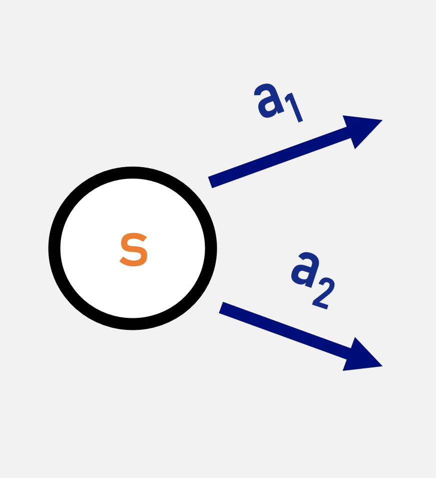
acción=π(estado)

Probabilística

π(acción|estado)

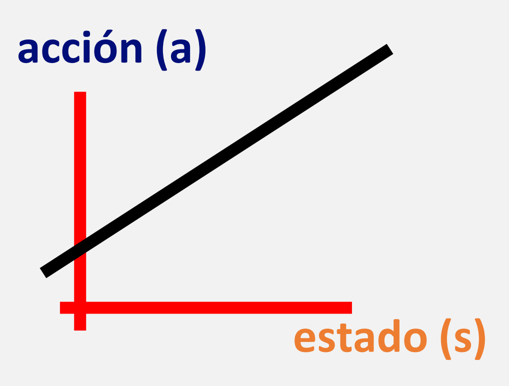
Conceptos RL (agente)

π: Ley de control, acción=π(estado)



- Modelo explícito
  - Tabla
  - Función
- Modelo que depende de Q o V

estado (s)	acción (a)
s_1	...
s_2	...
s_3	...
...	...



Conceptos RL (agente)

Q(s,a): Q-Value, action-value. Modela el valor de cada acción para cada estado.

Es opcional. Tablular / function approx.

π "greedy"
$\pi = \operatorname{argmax}_a(Q(s,a))$

π "ε-greedy"
$\begin{cases} (1-\varepsilon): \operatorname{argmax}_a(Q(s,a)) \\ (\varepsilon): \text{random } a \end{cases}$

Conceptos RL (agente)

V(s): Value, state value. Modelo valor de cada estado.

Es opcional. Tablular / function approx.

Una π “greedy” sería aquella que siempre escoja la a que lleve al s’ (estado contiguo) de mayor V(s’).

Conceptos RL (agente)

- **γ: Discount [0, 1]. Opcional. Pondera importancia del refuerzo futuro.**
- **G: Return. Refuerzos ponderados según discount y caso de uso específico.**

$$G_t = \sum_t^T r_{t+1} + r_{t+2} + \ \dots + r_T$$

$$G_t = \sum_t^\infty r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots$$

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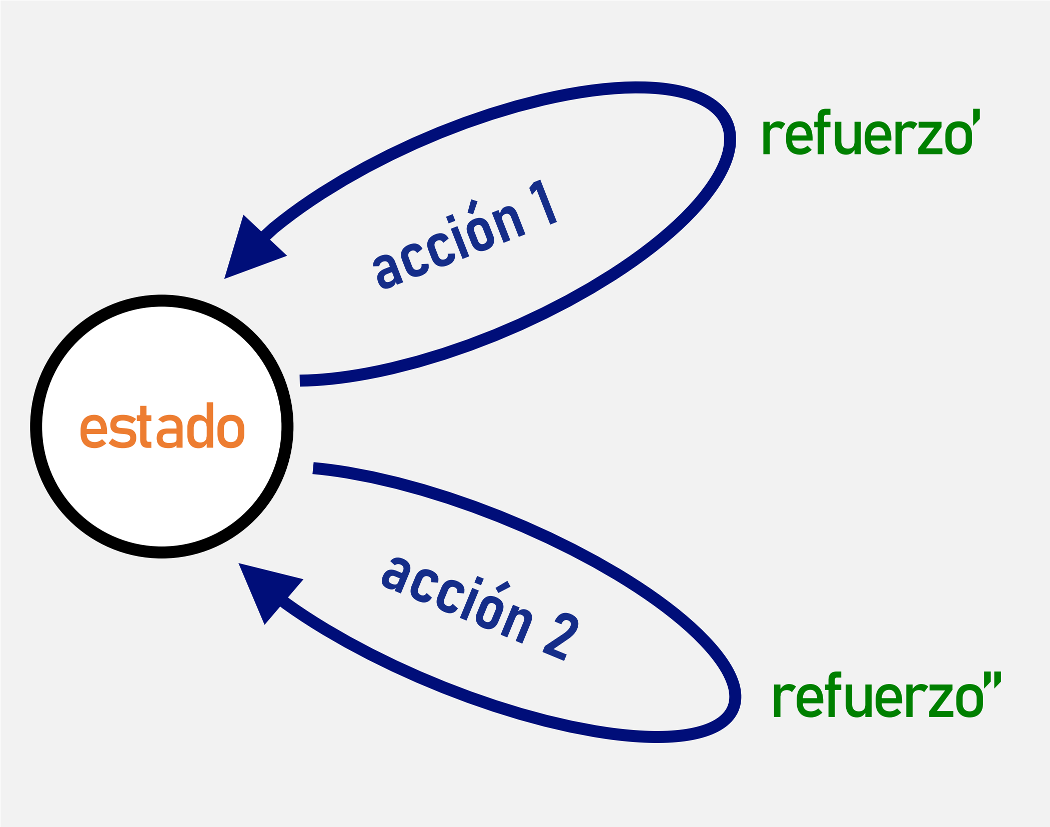
k-armed Bandit: ¡un entorno sin estado!

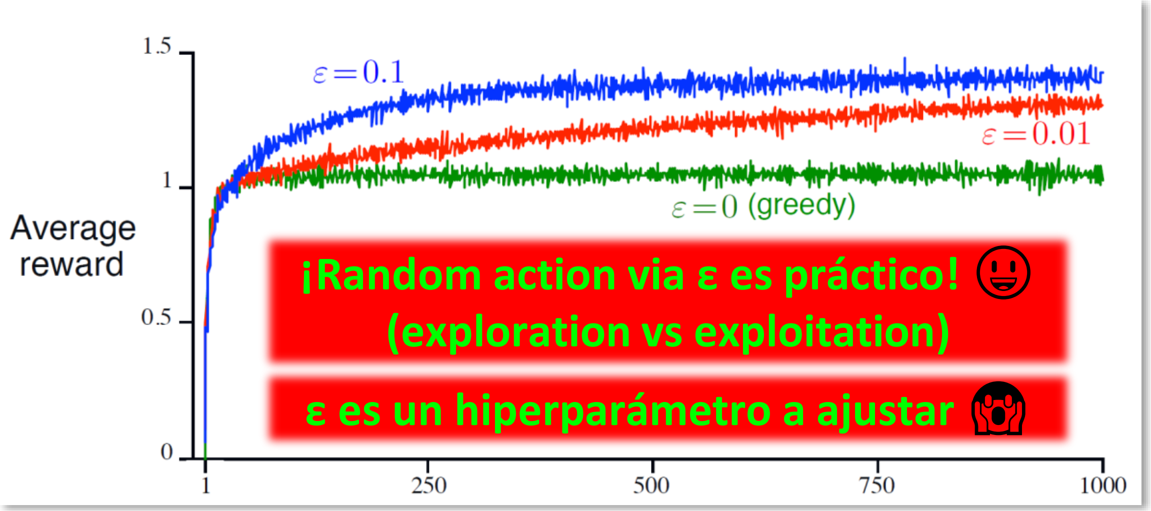
k acciones (c/u proporciona r correspondiente)



k-armed Bandit: una π solución vía Q

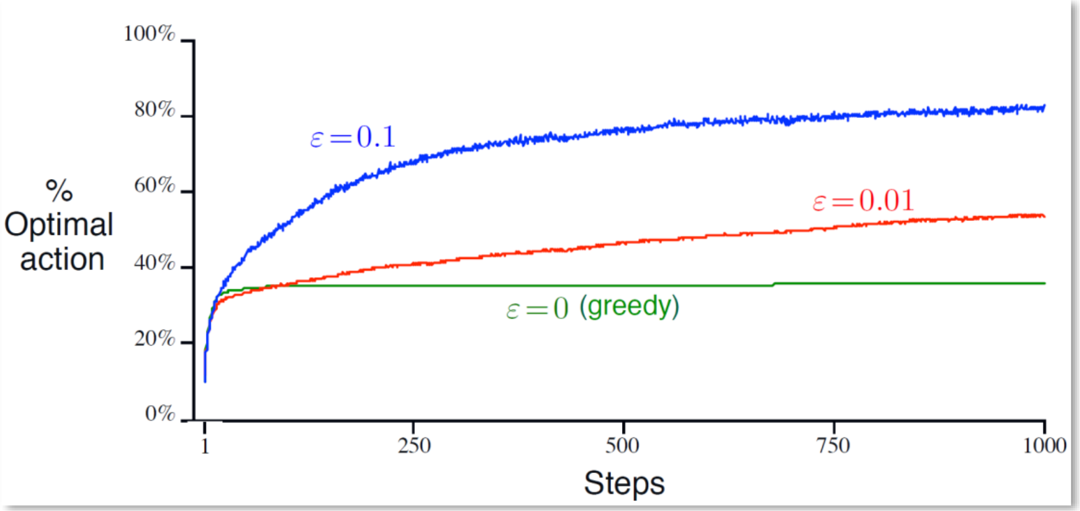
Caso particular: Q(s,a) = Q(a)

Algoritmo: $Q(a) = \dfrac{\Sigma\ r \text{ habiendo seleccionado } a}{\#\text{ veces seleccionado } a}$



¡Random action via ε es práctico! 😃
(exploration vs exploitation)

ε es un hiperparámetro a ajustar 😱



Sutton, Barto, "Reinforcement Learning: An Introduction", 2018

Un algoritmo muy conocido: Q-Learning

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $\boxed{Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]}$
    $S \leftarrow S'$
  until S is terminal

Sutton, Barto, "Reinforcement Learning: An Introduction", 2018

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Un algoritmo muy conocido: Q-Learning

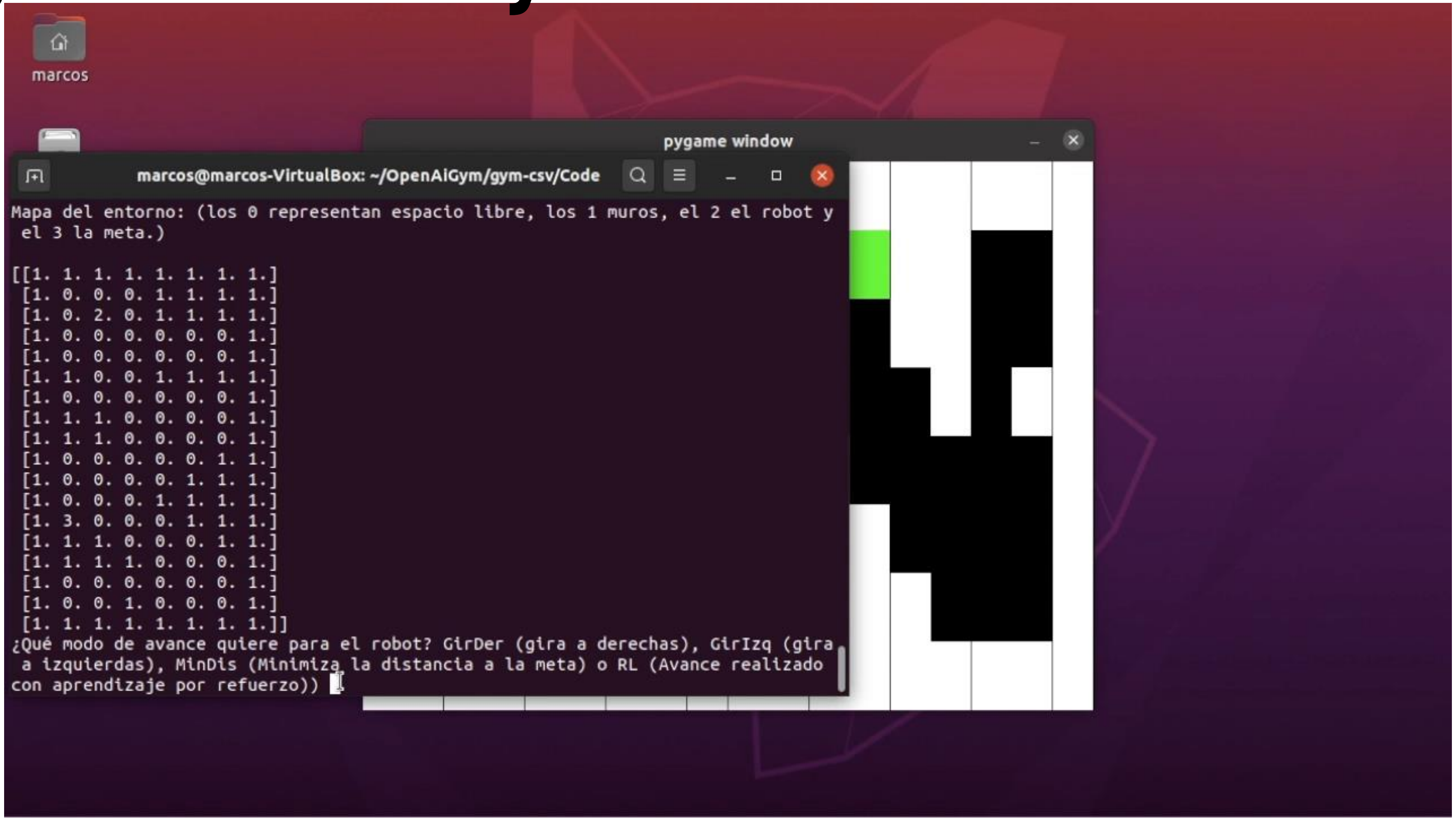
$$Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_a Q(S',a) - Q(S,A)\right]$$

Es un método tabular, s y a valores discretos.

Incorpora hiperparámetro α (learning rate), que se puede ajustar para optimizar en *convergencia* o en *rapidez de aprendizaje*.

```
Q[s,a] = Q[s,a] + alpha*(r + gamma*np.max(Q[s1,:]) - Q[s,a])
```

Un algoritmo muy conocido: Q-Learning

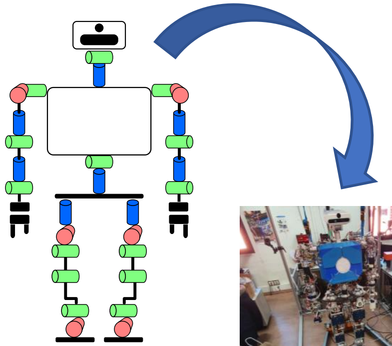


Algoritmos "Deep Reinforcement Learning"

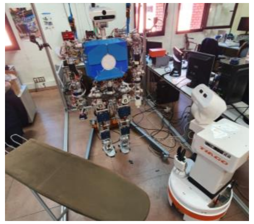
Mnih (2015-): Deep Q-Network (DQN) for Atari

Levine (2015-): End-to-End Training of Deep Visuomotor Policies

entrada = estado (imagen, pose…)



Agente



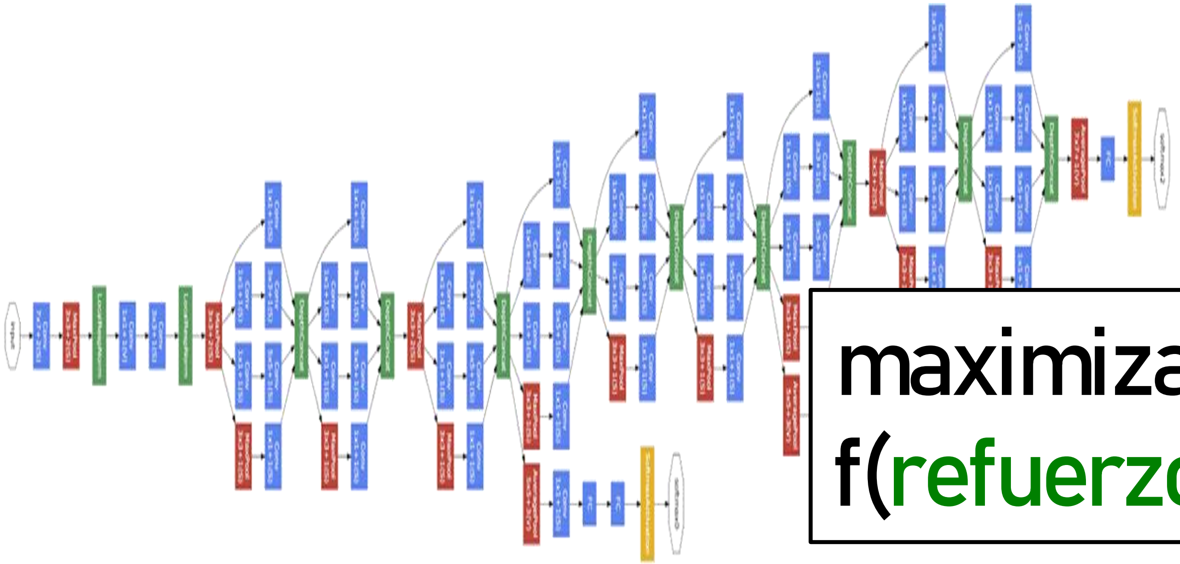
observa estado

acción 1

nuevo estado' y refuerzo'

acción 2

nuevo estado'' y refuerzo''



maximizar f(refuerzo)

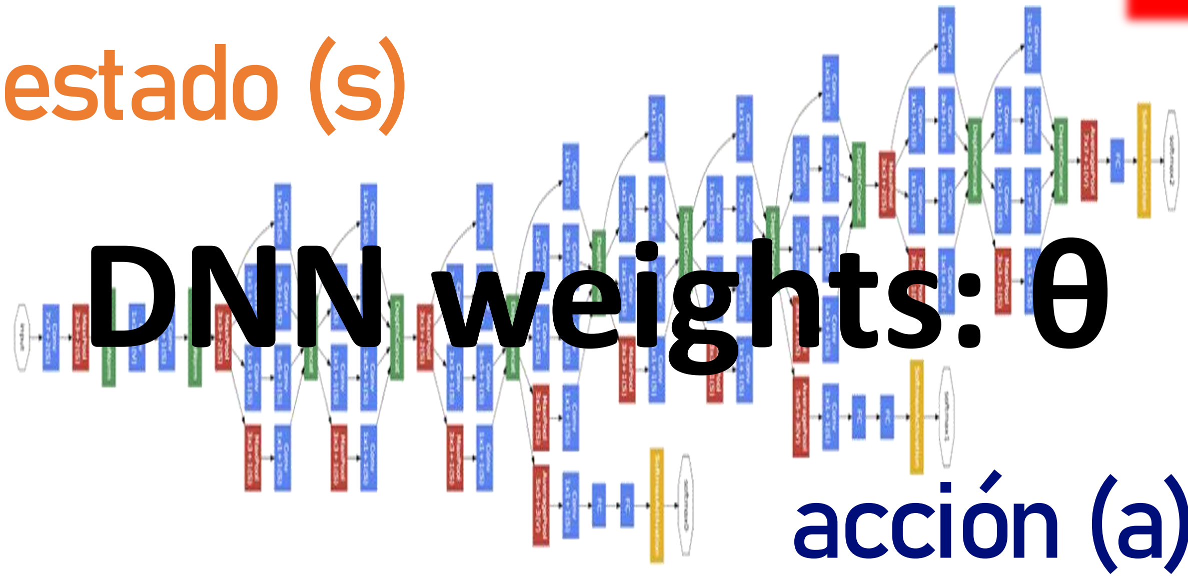
salida = π/V/Q

para acción = π(state)

Algoritmos "Deep Reinforcement Learning"

Modelado directo de π (policy gradient, p.ej. REINFORCE)

estado (s)



DNN weights: θ

acción (a)

Probabilística

π_θ(**acción** | **estado**)

Supervised Learning (DL)

$$\nabla_\theta J_{\mathrm{ML}}(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right)$$

Reinforcement Learning (DL)

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

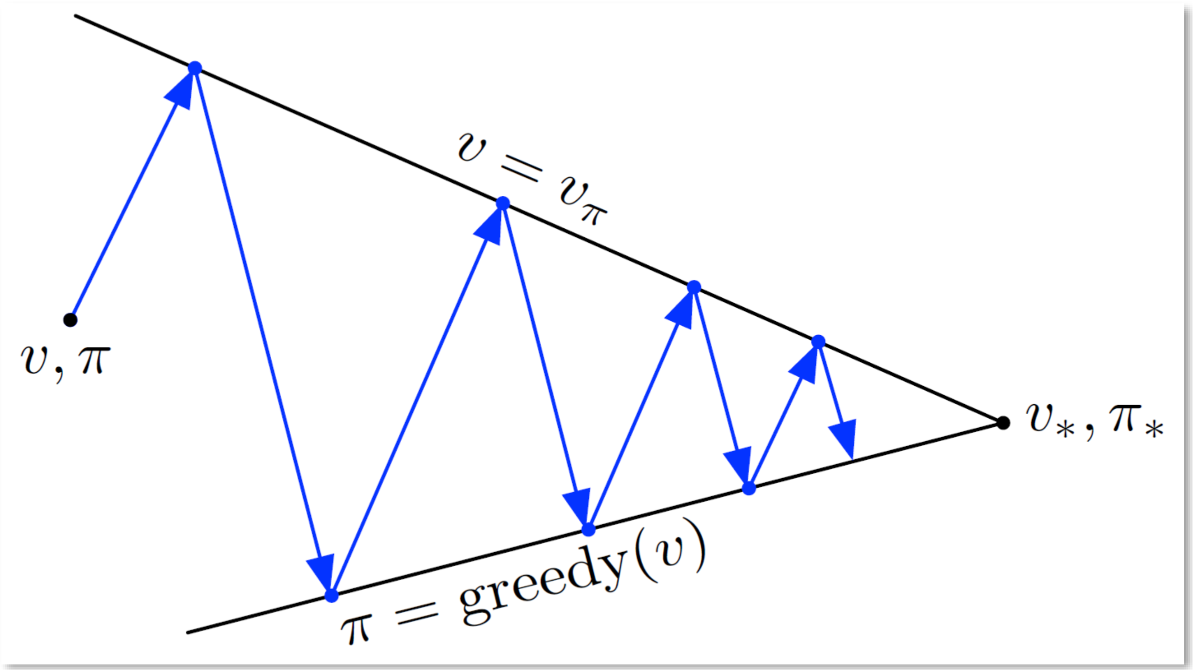
Supervised & Reinforcement Learning Objective Eqs from "Berkeley CS 285 – Fall 2020 (Instructor: Sergey Levine)"

Más posibilidades dentro de RL

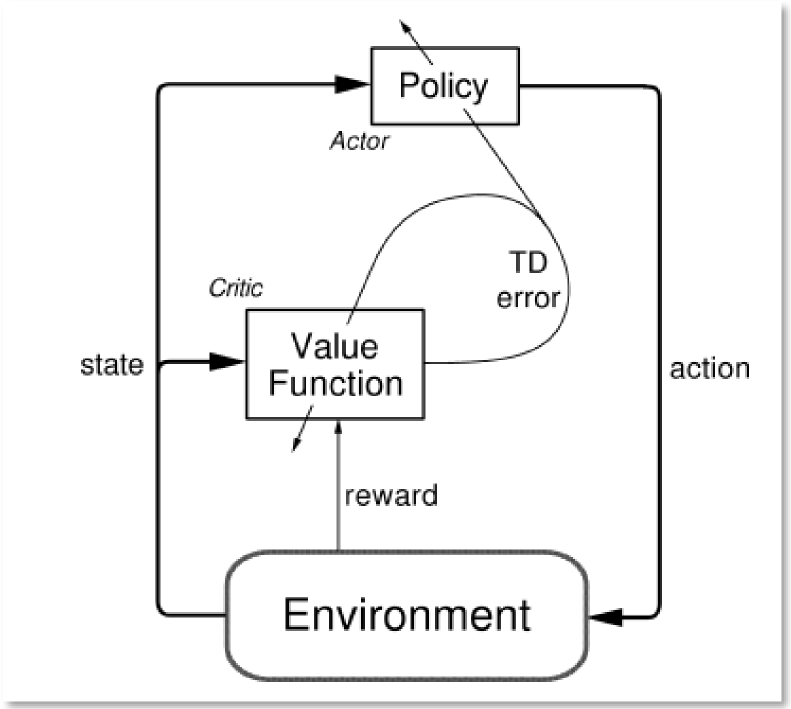
- En “on-policy”, el agente mejora sus parámetros a través de su interacción.
- En “off-policy”, es capaz de mejorar sus parámetros en base a los datos de interacción de otro agente (herramienta: “importance sampling”).

Más posibilidades dentro de RL

Modelos simultáneos: Generalized Policy Iteration (GPI)



Actor-Critic: A3C, TRPO, SAC…



Más posibilidades dentro de RL (Avanzado)

Inverse Reinforcement Learning

Metalearning

AutoML

…

…

…

Robótica inteligente mediante Reinforcement Learning

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- ❑ **Conclusiones y recursos**

Robótica: Expert Rules hasta End-to-End

- Component Based Software Engineering (CBSE)
  - Sistemas Expertos (Rule-Based: IF-ELSE)
  - Planificación, Cinemática, Control
  - Learning w/hand-crafted Features
  - All Learned Features
- End-to-End (p.ej. Via DRL)

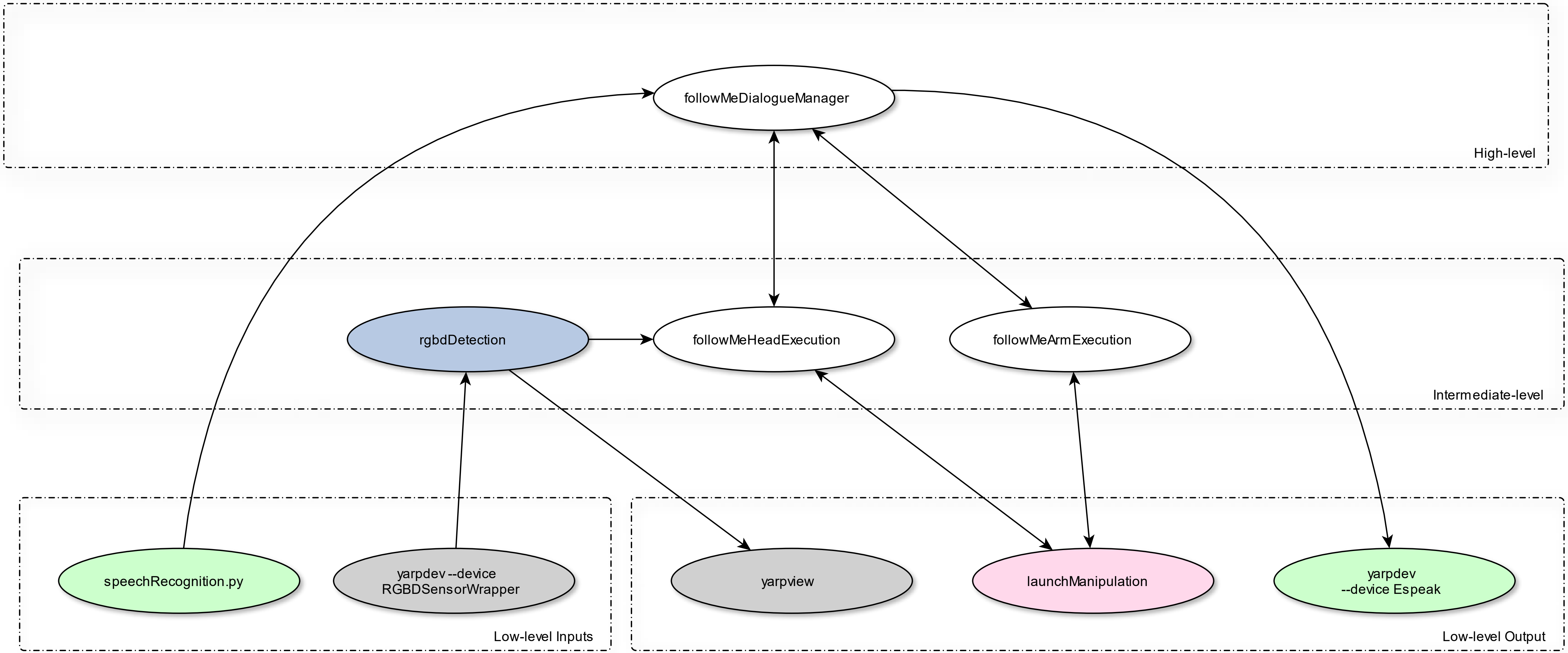
Hyperparameters
- Hand-crafted
- Automated search

Expert (Coding)

"generic/ agnostic" Algorithms

Learning (Data+Model +Algorthms)

Robótica: CBSE (rules & generic & learning)



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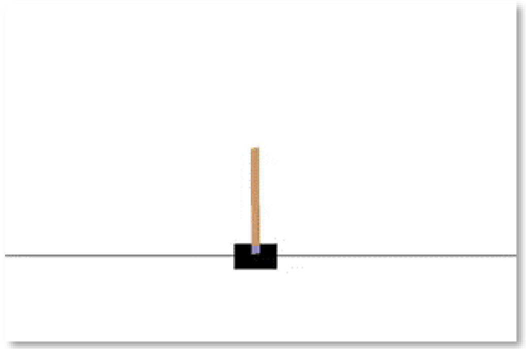
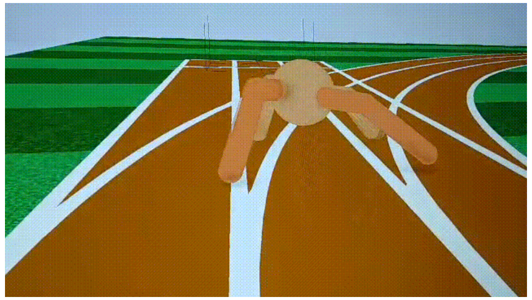
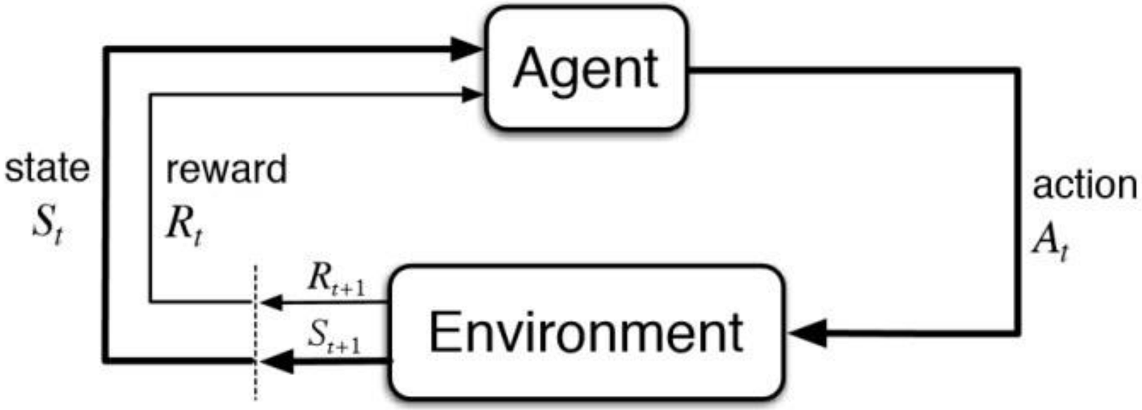
Recursos (software): OpenAI Gym

- Python API: Utilizar entornos [1]



```
import gym
env = gym.make('CartPole-v0')
env.reset()
for _ in range(1000):
    env.render()
    env.step(env.action_space.sample()) # take a random action
```

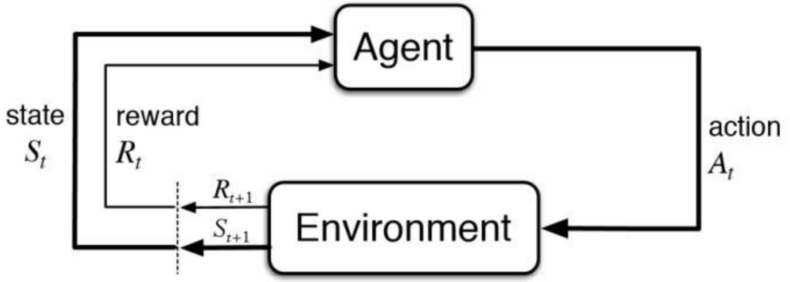




Recursos (software): OpenAI Gym

- Python API: Utilizar entornos [1]

```
import gym
env = gym.make('CartPole-v0')
for i_episode in range(20):
    observation = env.reset()
    for t in range(100):
        env.render()
        print(observation)
        action = env.action_space.sample()
        observation, reward, done, info = env.step(action)
        if done:
            print("Episode finished after {} timesteps".format(t+1))
            break
```



Recursos (software): OpenAI Gym

- **Python API: Crear entornos [1]**

```
import gym
from gym import error, spaces, utils
from gym.utils import seeding

class FooEnv(gym.Env):
  metadata = {'render.modes': ['human']}

  def __init__(self):
    ...
  def step(self, action):
    ...
  def reset(self):
    ...
  def render(self, mode='human'):
    ...
  def close(self):
    ...
```

Recursos (software): OpenAI Gym

- **Python API: Crear entornos [1]**

```python
class DiscreteEnv(Env):

    """
    Has the following members
    - nS: number of states
    - nA: number of actions
    - P: transitions (*)
    - isd: initial state distribution (**)

    (*) dictionary dict of dicts of lists, where
      P[s][a] == [(probability, nextstate, reward, done), ...]
    (**) list or array of length nS


    """
```

```python
def __init__(self, nS, nA, P, isd):
    self.P = P
    self.isd = isd
    self.lastaction = None # for rendering
    self.nS = nS
    self.nA = nA

    self.action_space = spaces.Discrete(self.nA)
    self.observation_space = spaces.Discrete(self.nS)

    self.seed()
    self.s = categorical_sample(self.isd, self.np_random)
    self.lastaction=None

def seed(self, seed=None):
    self.np_random, seed = seeding.np_random(seed)
    return [seed]

def reset(self):
    self.s = categorical_sample(self.isd, self.np_random)
    self.lastaction = None
    return self.s

def step(self, a):
    transitions = self.P[self.s][a]
    i = categorical_sample([t[0] for t in transitions], self.np_random)
    p, s, r, d= transitions[i]
    self.s = s
    self.lastaction = a
    return (s, r, d, {"prob" : p})
```

Recursos (software):

1. https://gym.openai.com
2. https://github.com/openai/gym
3. https://github.com/openai/gym/blob/master/docs/environments.md#third-party-environments
4. https://github.com/jgvictores/awesome-deep-reinforcement-learning#rldrl-gyms
5. https://github.com/hill-a/stable-baselines

Recursos (libros, cursos, proyectos)

Guili, “Deep Learning with TensorFlow 2 and Keras”, 2019

https://www.coursera.org/specializations/deep-learning

Sutton, Barto, “Reinforcement Learning: An Introduction”, 2018

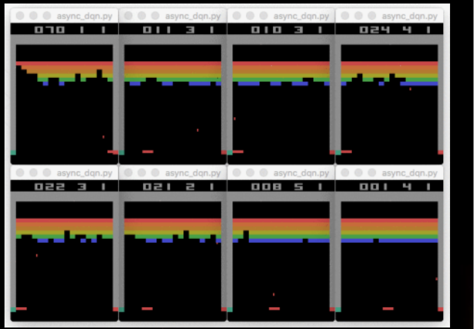
https://www.coursera.org/specializations/reinforcement-learning

http://rail.eecs.berkeley.edu/deeprlcourse

Máster Universitario en Robótica y Automatización (UC3M)
(p.ej. Planificación, Aprendizaje, Simuladores…)

ALMA: Human Centric Algebraic Machine Learning (H2020-EIC-FETPROACT-2019)

https://github.com/jgvictores/awesome-deep-reinforcement-learning



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