Aprendizaje Profundo por Refuerzo
03. Aprendizaje por refuerzo

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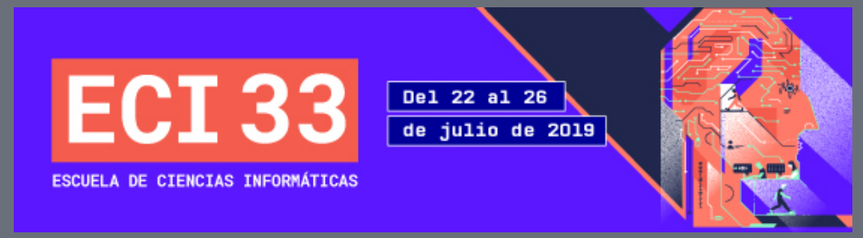

Aprendizaje por refuerzo

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1 MDP

PROCESOS DE DECISIÓN DE MARKOV

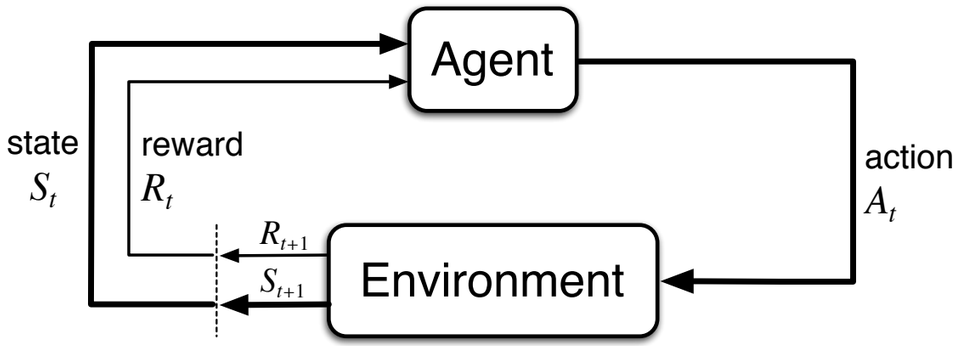
MDP

Introducción

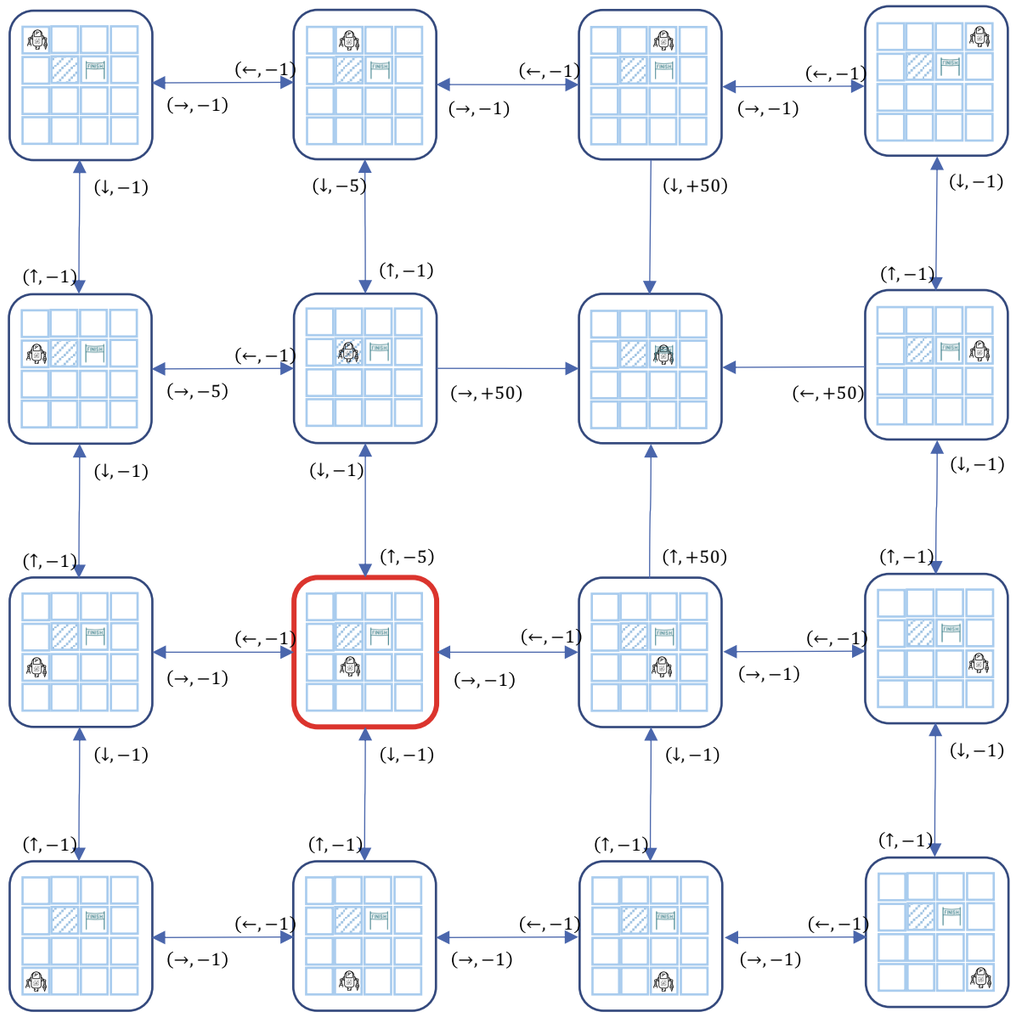
Aprendizaje por refuerzo

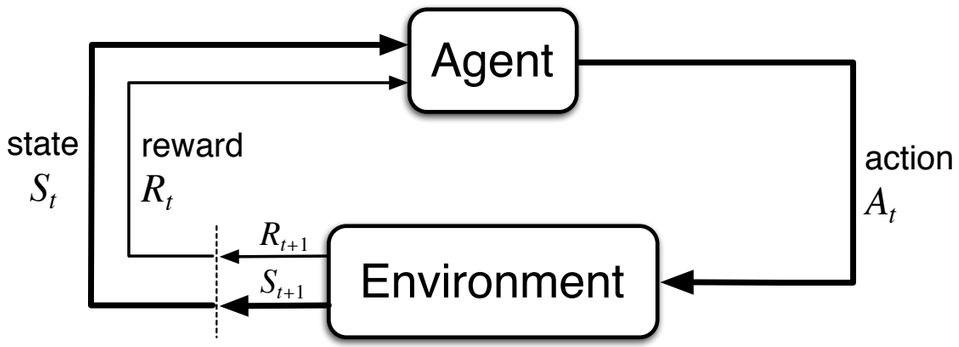
Problema de búsqueda en el grafo de estados y transiciones.

Optimizar la función de recompensa acumulada (*max*)



R.S. Sutton, A.G. Barto (2018) **Reinforcement Learning**. MIT Press.





R.S. Sutton, A.G. Barto (2018) **Reinforcement Learning**. MIT Press.

Markov Decision Process - MDP

tiempo: $0, 1, 2, \ldots$

estado: $S_t \in \mathcal{S}$

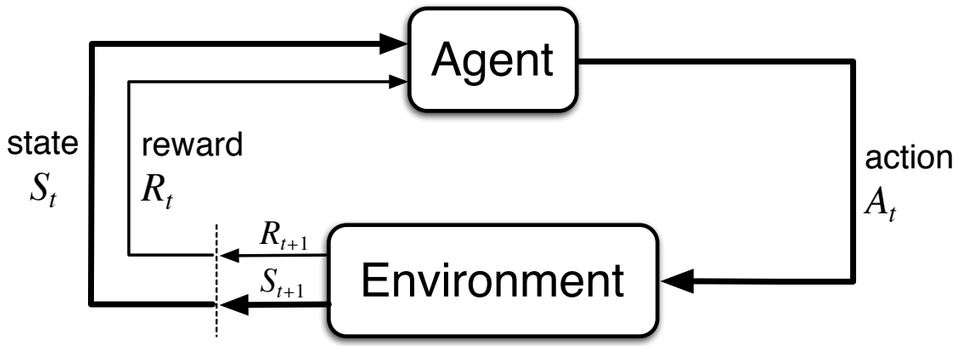
acción: $A_t \in \mathcal{A}(S_t)$

recompensa: $R_{t+1} \in \mathcal{R} \subset \mathbb{R}$

estado siguiente: $S_{t+1} \in \mathcal{S}$

secuencia:
$S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, \ldots$

dinámica del MDP:
$p(s', r|s, a) \doteq Pr\{S_t = s', R_t = r \mid S_{t-1} = s, A_{t-1} = a\}$



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Markov Decision Process - MDP

Recompensa acumulada:

$$G_t \doteq R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$$

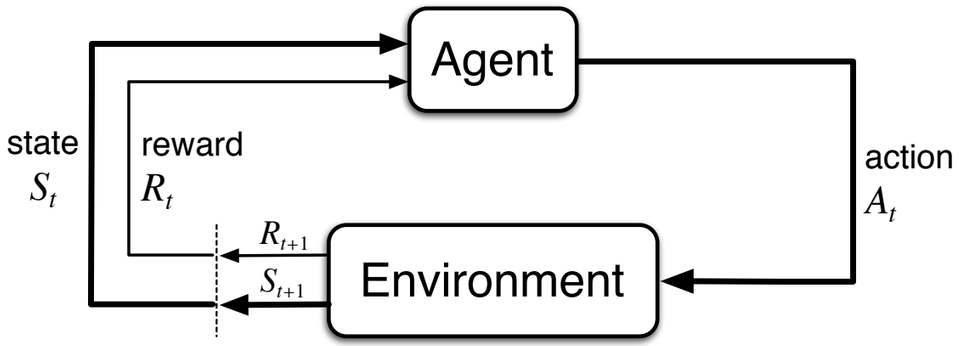
Recompensa con descuento:

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{T} \gamma^k R_{t+k+1}$$

Política de actuación: π

Acción según π : $\pi(a|s)$

Política de actuación óptima: π_*



R.S. Sutton, A.G. Barto (2018) **Reinforcement Learning**. MIT Press.

Markov Decision Process - MDP

Función de estado-valor [*state value*] (para todo s):

$$v_\pi(s) \doteq \mathbb{E}_\pi[G_t \mid S_t = s] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s\right]$$

Función de acción-valor *[action value]* (para todo (s, a)):

$$q_\pi(s,a) \doteq \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s, A_t = a\right]$$

Comparación de políticas de actuación y política óptima

$\pi \geq \pi' \Leftrightarrow v_\pi(s) \geq v'_\pi(s)$

$\pi_* \geq \pi' \; \forall \pi'$ *(garantizada)*

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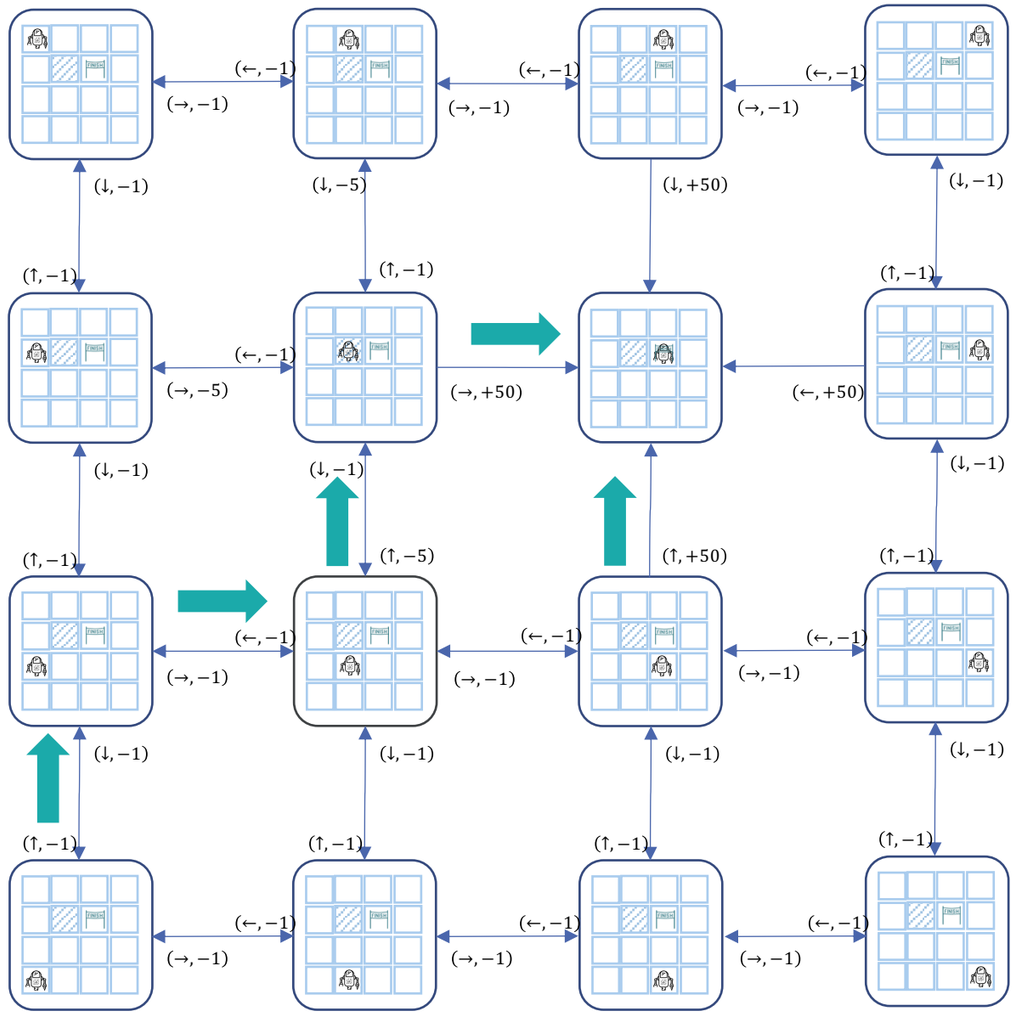
Formulación

$$v_\pi(s) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s\right]$$

Política π_1 $(\gamma = 1)$:

Estado	Acción
$(3,0)$	$\uparrow$
$(2,0)$	$\rightarrow$
$(2,1)$	$\uparrow$
$(1,1)$	$\rightarrow$
$(2,2)$	$\uparrow$
...	

$$v_{\pi_1}(\langle 2,1\rangle) = -5 + 50 = 45$$
$$v_{\pi_1}(\langle 2,2\rangle) = 50$$
$$v_{\pi_1}(\langle 3,0\rangle) = -1 - 1 - 5 + 50 = 43$$
$$v_{\pi_1}(\langle 2,0\rangle) = -1 - 5 + 50 = 42$$



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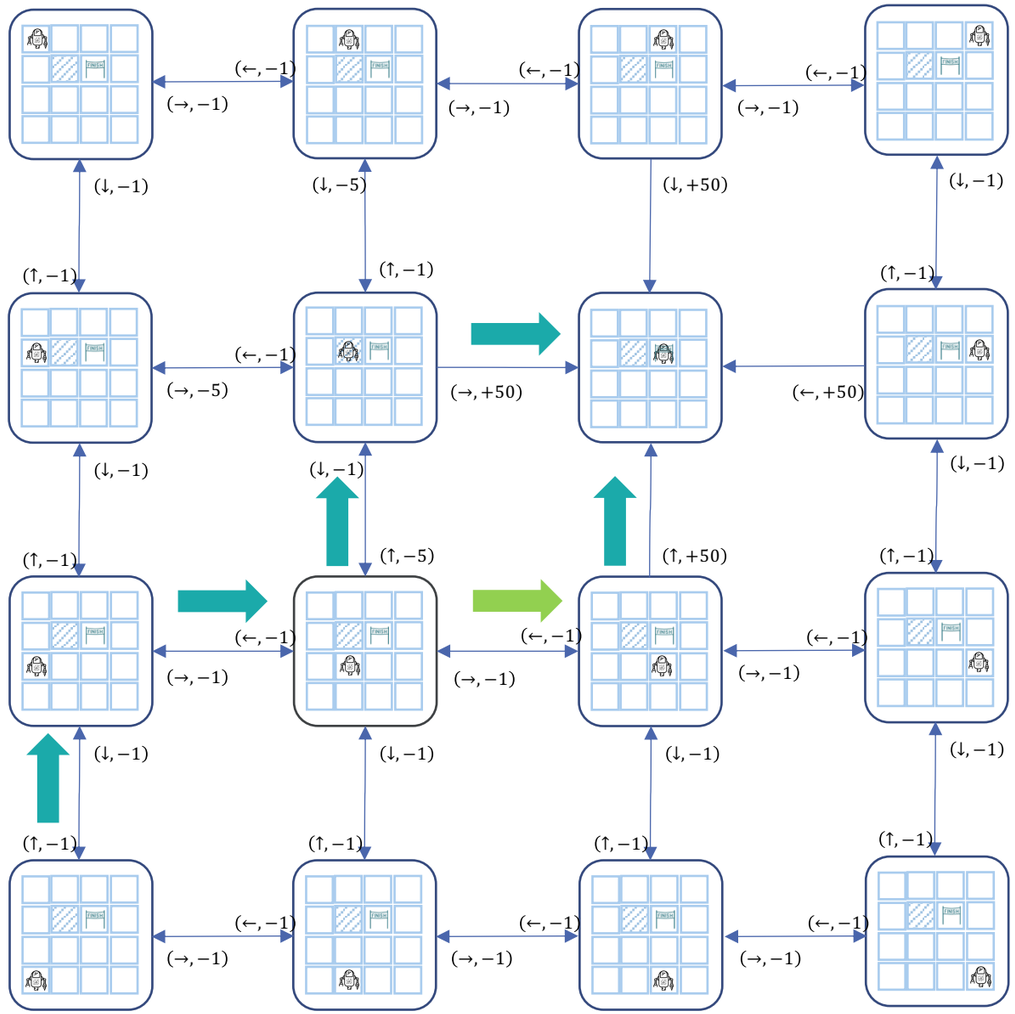
Formulación

$$v_\pi(s) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s\right]$$

Política π_2 $(\gamma = 1)$:

Estado	Acción
$(3,0)$	$\uparrow$
$(2,0)$	$\rightarrow$
$(2,1)$	$\rightarrow$
$(1,1)$	$\rightarrow$
$(2,2)$	$\uparrow$
...	

$$v_{\pi_2}(\langle 2,1\rangle) = -1 + 50 = 49 \geq 45$$
$$v_{\pi_2}(\langle 2,2\rangle) = 50 \geq 50$$
$$v_{\pi_2}(\langle 3,0\rangle) = -1 - 1 - 1 + 50 = 47 \geq 43$$
$$v_{\pi_2}(\langle 2,0\rangle) = -1 - 1 + 50 = 48 \geq 42$$



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Formulación

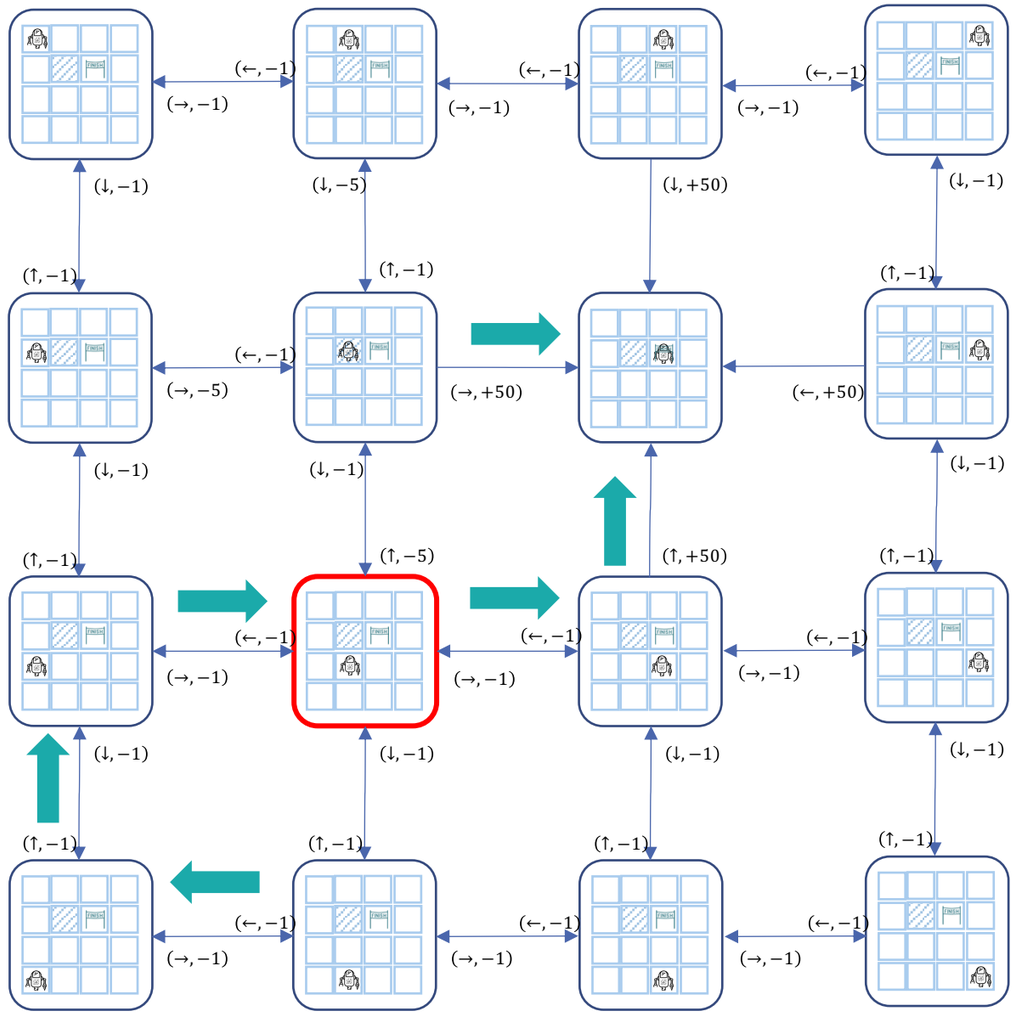
$$q_\pi(s,a) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1} \;\middle|\; S_t = s, A_t = a\right]$$

Política π_2 $(\gamma = 1)$:

Estado	Acción
$(3,0)$	$\uparrow$
$(2,0)$	$\rightarrow$
$(2,1)$	$\rightarrow$
$(1,1)$	$\rightarrow$
$(2,2)$	$\uparrow$
$(3,1)$	$\leftarrow$
...	

$$v_\pi(s) = q_\pi(s, \pi(a|s))$$

$q_{\pi_2}(\langle 2,1\rangle, \uparrow) = -5 + 50 = 45$
$q_{\pi_2}(\langle 2,1\rangle, \rightarrow) = -1 + 50 = \mathbf{49}$
$q_{\pi_2}(\langle 2,1\rangle, \leftarrow) = -1 - 1 - 1 + 50 = 47$
$q_{\pi_2}(\langle 2,1\rangle, \downarrow) = -1 - 1 - 1 - 1 - 1 + 50 = 45$



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Formulación

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Ecuación de Bellman (recursividad de v_π)

$$v_\pi(s) \doteq \mathbb{E}_\pi[G_t \mid S_t = s]$$

$$= \mathbb{E}_\pi[R_{t+1} + \gamma G_{t+1} \mid S_t = s]$$

$$= \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s]$$

recompensa al realizar acción — *valor del siguiente estado*

Ecuación de Bellman (optimalidad de v_*)

$$v_{\pi_*}(s) = \max_{a \in \mathcal{A}(s)} q_{\pi_*}(s, a)$$

valoración de un estado (política óptima) — *valoración de la mejor acción desde ese estado (política óptima)*

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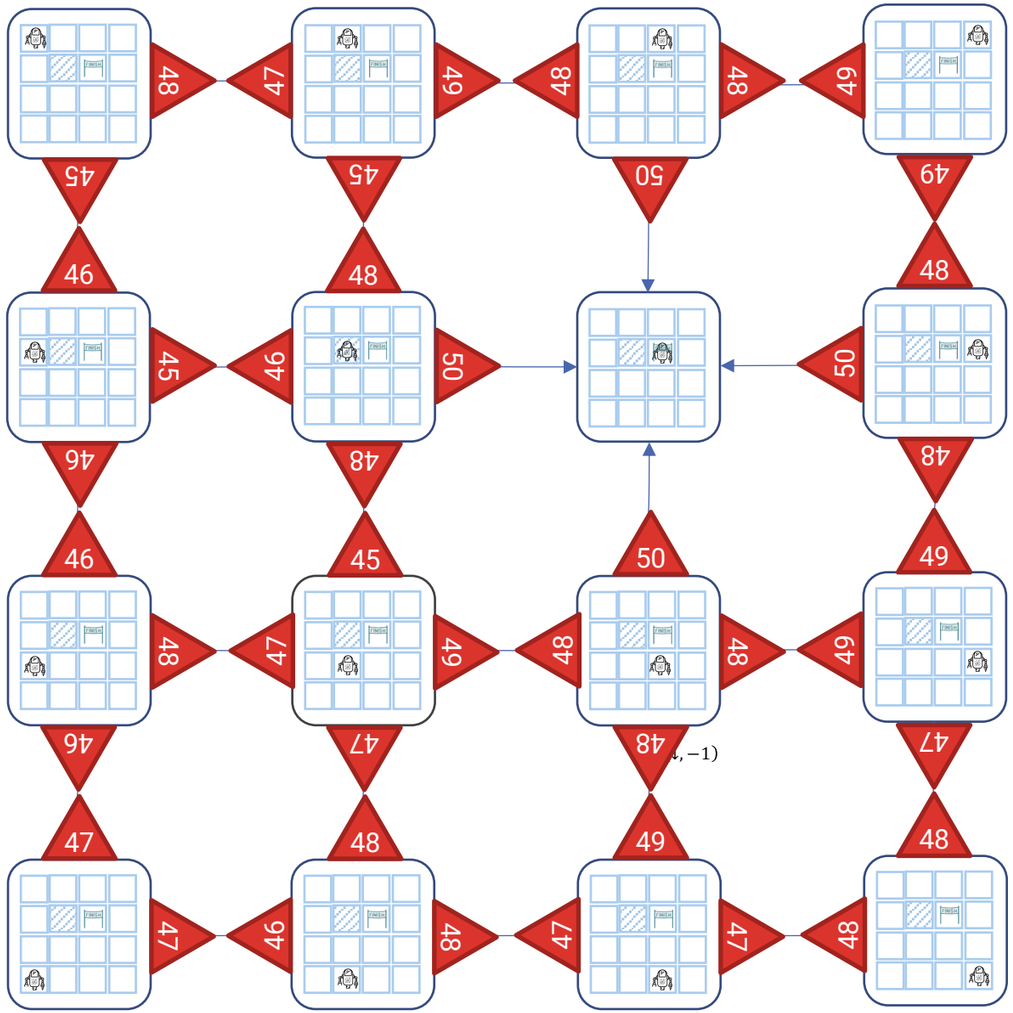
Formulación

$q_{\pi_*}(s, a)$



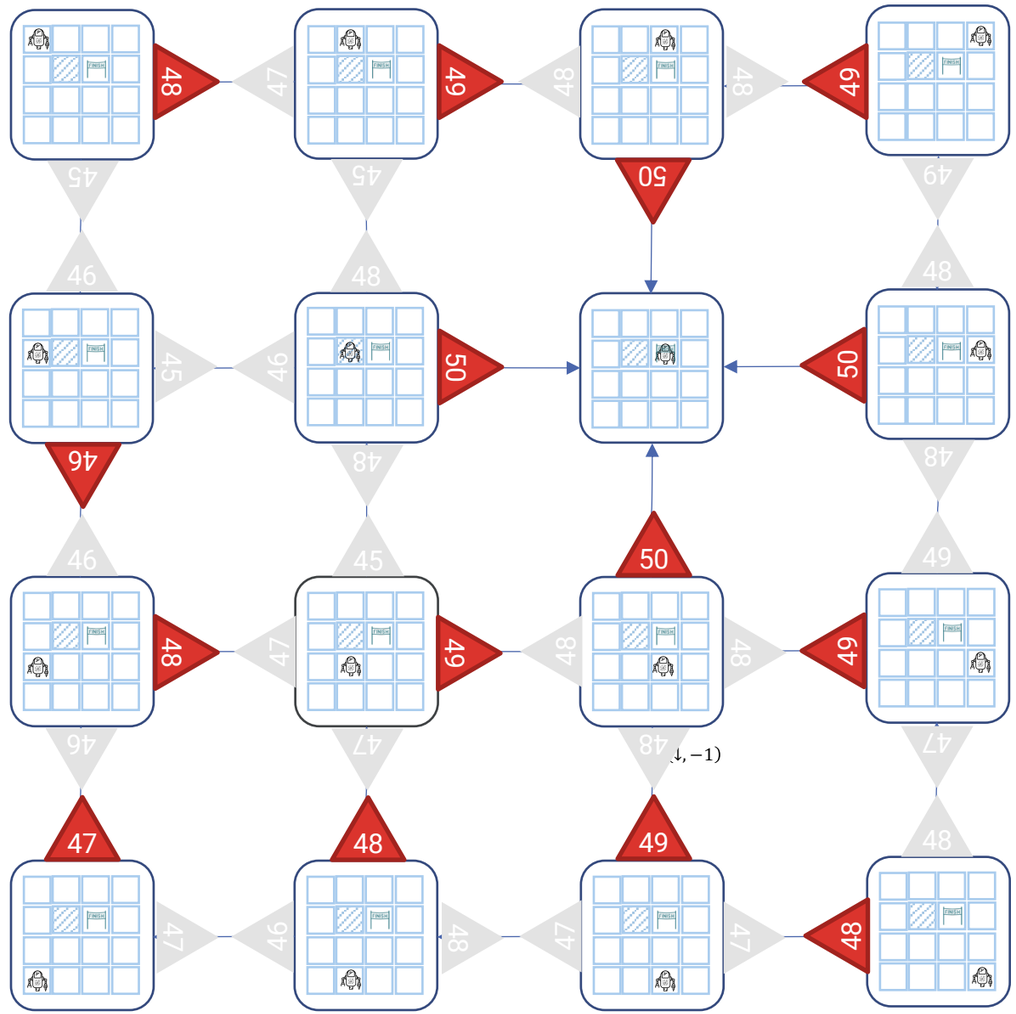
MDP

Formulación

$$q_{\pi_*}(s,a)$$

Resaltar valor máximo de cada estado:

$$v_*(s) = \max_{a \in \mathcal{A}(s)} q_{\pi_*}(s,a)$$



MDP

Formulación

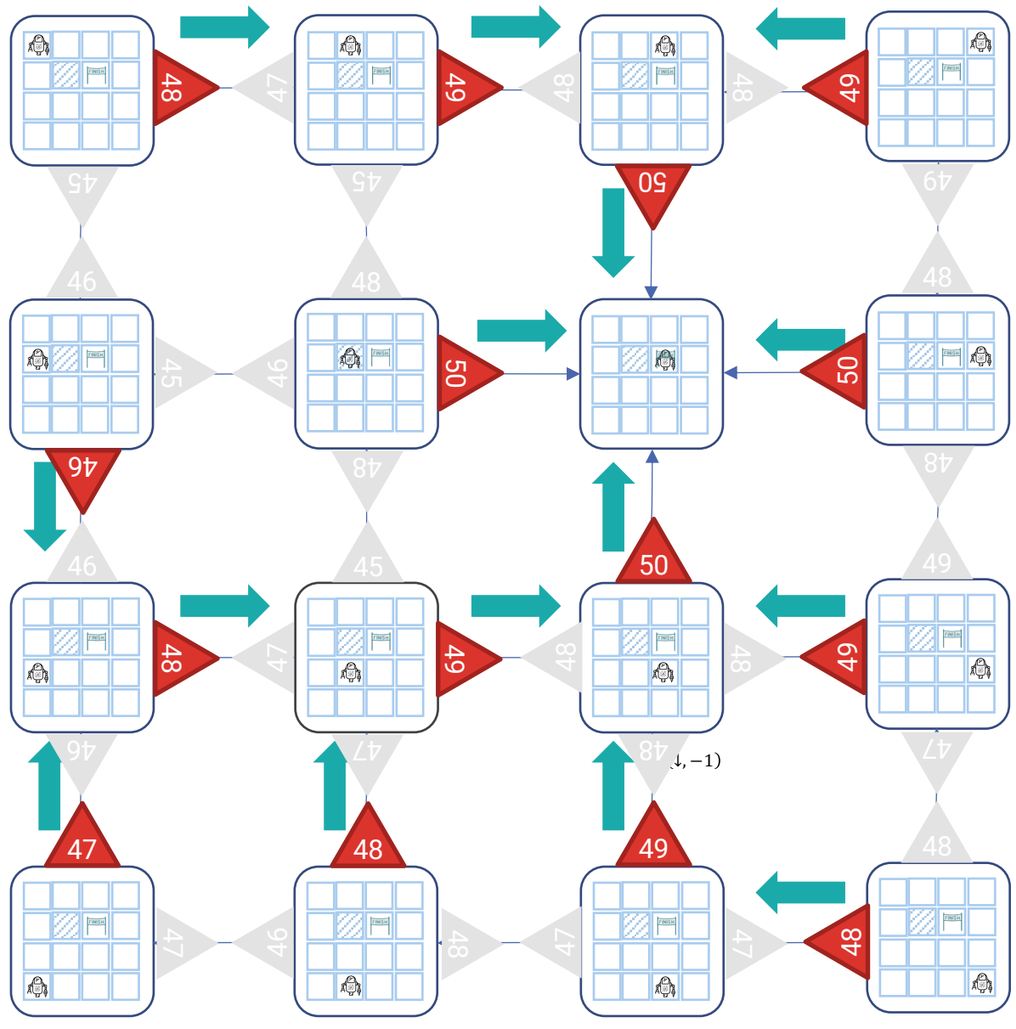
$$q_{\pi_*}(s,a)$$

Resaltar valor máximo de cada estado:

$$v_*(s) = \max_{a \in \mathcal{A}(s)} q_{\pi_*}(s,a)$$

Reconstruir π_*

Estado	Acción
$(3,0)$	$\rightarrow$
$(2,0)$	$\uparrow$
...	



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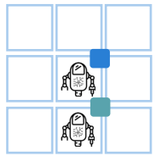
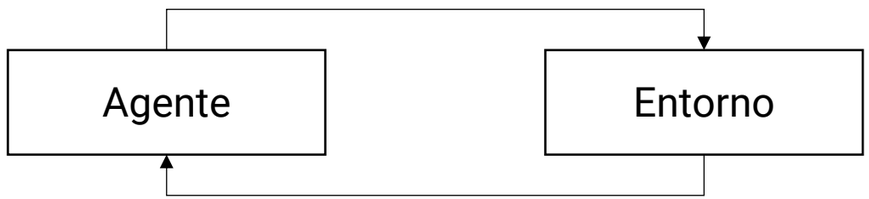
Aprendizaje por refuerzo



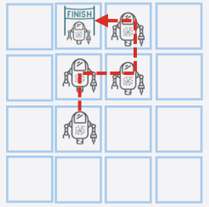
acción $\sim \pi(a|s)$



recompensa r**, nuevo estado** s'

Episodios de entrenamiento

Episodio #1

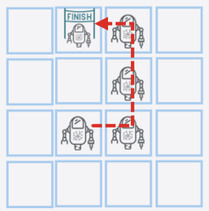


$\pi(a|s)$

(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$R = \sum r_{a_i}$

Episodio #2

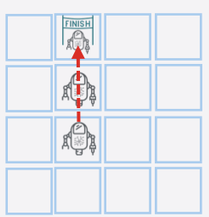


$\pi(a|s)$

(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$R = \sum r_{a_i}$

Episodio #n



$\pi(a|s)$

(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$R = \sum r_{a_i}$

training

Estado	Acción	q
$(3, 0)$	$\uparrow$	10
$(2, 0)$	$\rightarrow$	12
...		...

training

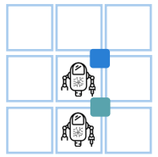
$$\pi' = \arg\max_{\pi} \sum_{t=0} \gamma^t * r_{a_t}(s_t, s_{t+1})$$

con $a_t \sim \pi(a|s)$

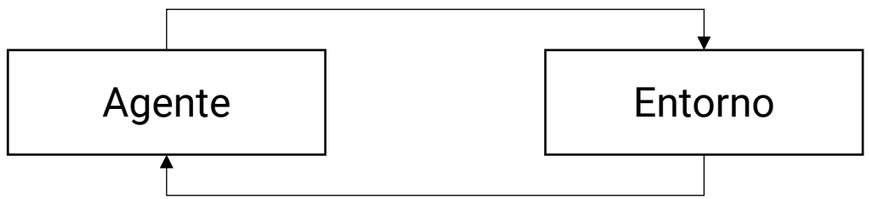
$\gamma \in [0, 1]$: tasa de descuento

MDP

Aprendizaje por refuerzo



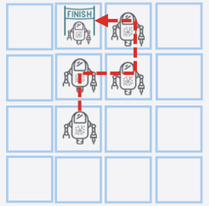
acción $\sim \pi(a|s;\ \Theta)$



recompensa r**, nuevo estado** s'

Episodios de entrenamiento

Episodio #1

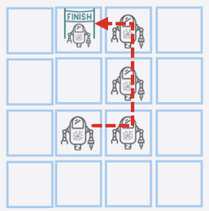


(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$\pi(a|s)$

$R = \sum r_{a_i}$

Episodio #2

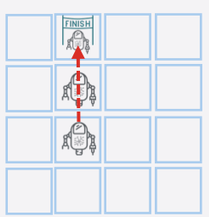


(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$\pi(a|s)$

$R = \sum r_{a_i}$

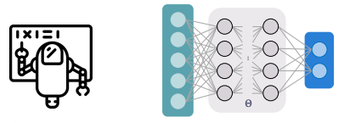
Episodio #n



(s_0, a_0, r_{a_0}, s_1)
(s_1, a_1, r_{a_1}, s_2)
(s_2, a_2, r_{a_2}, s_3)
...

$\pi(a|s)$

$R = \sum r_{a_i}$



training

$$\Theta' = \arg\max_{\Theta} \sum_{t=0} \gamma^t * r_{a_t}(s_t, s_{t+1})$$

con $a_t \sim \pi(s;\ \Theta)$

$\gamma \in [0, 1]$: tasa de descuento

2 Método de Montecarlo

FORMULACIÓN, IMPLEMENTACIÓN

Método de Montecarlo

Formulación

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Método de Montecarlo (con mejora incremental de política)

params: tabla Q inicial, política inicial π_0 , n_episodios

for i = {0, …, n_episodios}

generar episodio según π_i

actualizar Q : $Q'(s,a) \approx Q(s,a) + \hat{q}_{\pi_i}(s,a)$

obtener política mejorada π_{i+1} a partir de Q

Estado	Acción	Q
$(3,0)$	$\uparrow$	10
$(3,0)$	$\rightarrow$	12
$(3,1)$	$\rightarrow$	9
…		

Consideraciones

Si un par *<estado, acción>* se visita más de una vez en un episodio, se puede:

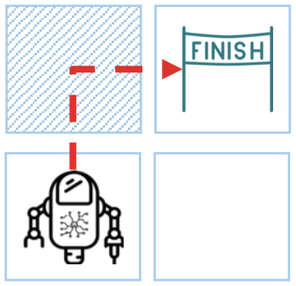
- Tomar la media de los valores G obtenidos (predicción *every visit*)
- Quedarse con el valor G de la primera visita (predicción *first visit*)

Para explorar más espacio, en lugar de π se utiliza ϵ-greedy(Q):

- con probabilidad ϵ se toma una acción aleatoria
- con probabilidad $1-\epsilon$ se toma la acción de π

Método de Montecarlo

Ejemplo



S_t	A_t	R_{t+1}
<1, 0>	↑	−5
<0, 0>	→	+50

```
for i_episode in range(1, num_episodes+1):

    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
    # - obtener gamma para aplicar descuentos
    discounts = np.array([gamma**i for i in range(len(rewards)+1)])
    # - actualizar suma de recompensa, numero de visitas y Q para cada (estado, accion)
    for i, state in enumerate(states):
        returns_sum[state][actions[i]] += sum(rewards[i:]*discounts[:-(1+i)])
        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

Método de Montecarlo

Ejemplo

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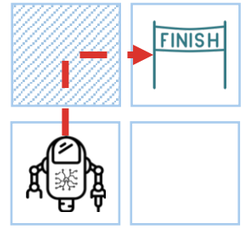

S_t	A_t	R_{t+1}
<1, 0>	↑	−5
<0, 0>	→	+50

```python
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
    # - obtener gamma para aplicar descuentos
    discounts = np.array([gamma**i for i in range(len(rewards)+1)])
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    for i, state in enumerate(states):
        returns_sum[state][actions[i]] += sum(rewards[i:]*discounts[:-(1+i)])
        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

Método de Montecarlo

Ejemplo

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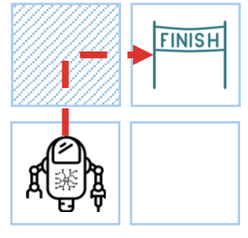

$\gamma = 0.9$

discounts

γ^0	γ^1
1	0.9

```
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
    # - obtener gamma para aplicar descuentos
    discounts = np.array([gamma**i for i in range(len(rewards)+1)])
    # - actualizar suma de recompensa, numero de visitas y Q para cada (estado, accion)
    for i, state in enumerate(states):
        returns_sum[state][actions[i]] += sum(rewards[i:]*discounts[:-(1+i)])
        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

Método de Montecarlo

Ejemplo

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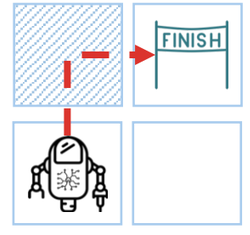
S_t	A_t	R_{t+1}
<1, 0>	↑	−5
<0, 0>	→	+50

discounts

γ^0

γ^1

$$q_\pi(s,a) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1} \,\middle|\, S_t = s, A_t = a\right]$$



returns_sum

S_t	A_t ↑	→	↓	←
<0, 0>				
<0, 1>				
<1, 0>				
<1, 1>				

sum([−5, +50] • [1, 0.9]) = **40**

```
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
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        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

Método de Montecarlo

Ejemplo

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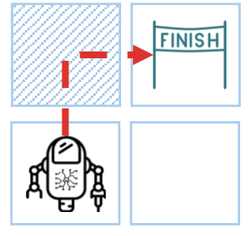

Q		A_t			
		↑	→	↓	←
S_t	<0, 0>				
	<0, 1>				
	<1, 0>	**40**			
	<1, 1>				

```
for i_episode in range(1, num_episodes+1):
# generar episodio
episode = generate_episode(env, Q, epsilon)

# actualizar tabla Q
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```

Método de Montecarlo

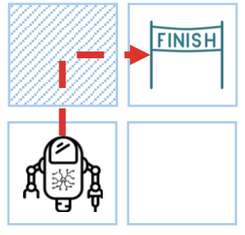
Ejemplo

S_t	A_t	R_{t+1}
<1, 0>	↑	−5
<0, 0>	→	+50

discounts

γ^0

$$q_\pi(s,a) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1} \,\middle|\, S_t = s, A_t = a\right]$$



returns_sum

S_t	A_t ↑	→	↓	←
<0, 0>				
<0, 1>				
<1, 0>	**40**			
<1, 1>				

sum([+50] • [1]) = **50**

```
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
    # - obtener gamma para aplicar descuentos
    discounts = np.array([gamma**i for i in range(len(rewards)+1)])
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        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```
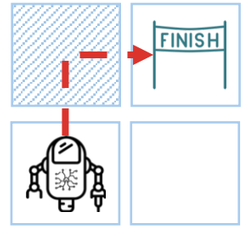

Método de Montecarlo

Ejemplo



Q		A_t			
		↑	→	↓	←
S_t	<0, 0>		**50**		
	<0, 1>				
	<1, 0>	**40**			
	<1, 1>				

```python
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
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        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```
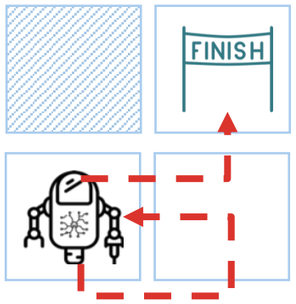

Método de Montecarlo

Ejemplo



S_t	A_t	R_{t+1}
<1, 0>	→	−1
<1, 1>	←	−1
<1, 0>	→	−1
<1, 1>	↑	+50

```
for i_episode in range(1, num_episodes+1):

    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
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        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

Método de Montecarlo

Ejemplo

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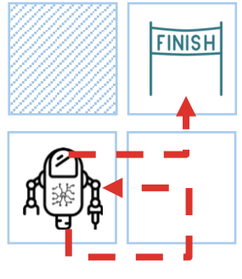

Q		A_t			
		↑	→	↓	←
S_t	<0, 0>		**50**		
	<0, 1>				
	<1, 0>	**40**	**38.9**		
	<1, 1>	**50**			**38.6**

```
for i_episode in range(1, num_episodes+1):
    # generar episodio
    episode = generate_episode(env, Q, epsilon)

    # actualizar tabla Q
    # - obtener estados, acciones y recompensas del episodio
    states, actions, rewards = zip(*episode)
    # - obtener gamma para aplicar descuentos
    discounts = np.array([gamma**i for i in range(len(rewards)+1)])
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        N[state][actions[i]] += 1.0
        Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

3 Q-Learning

FORMULACIÓN, IMPLEMENTACIÓN

Q-Learning

Limitaciones del método de Montecarlo

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En el método de Montecarlo, Q se actualiza en cada episodio:

- Una acción queda *diluida* entre todas las de su episodio

  Recordemos que: $q_\pi(s,a) \doteq \mathbb{E}_\pi\left[\sum_{k=0}^{T} \gamma^k R_{t+k+1} \mid S_t = s, A_t = a\right]$

  El valor estimado para una acción depende mucho de cómo continúe el episodio

- Una acción queda *diluida* entre las realizadas en todos los episodios

  Recordemos que la actualización sobre Q considera valores de todos los episodios anteriores

Montecarlo

```
for i_episode in range(1, num_episodes+1):
        episode = generate_episode(env, Q, epsilon, render)
        states, actions, rewards = zip(*episode)
        discounts = np.array([gamma**i for i in range(len(rewards)+1)])

        # actualizar suma de recompensa, numero de visitas y Q para cada (estado, accion) del episodio

        for i, state in enumerate(states):
            returns_sum[state][actions[i]] += sum(rewards[i:]*discounts[:-(1+i)])
            N[state][actions[i]] += 1.0
            Q[state][actions[i]] = returns_sum[state][actions[i]] / N[state][actions[i]]
```

El algoritmo puede tardar mucho en converger

Q-Learning

Formulación

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Métodos de diferencia temporal

1. Consideran un paso dentro del episodio
2. Actualizan Q después de cada paso con:
   recompensa inmediata (1 paso) [dada por el entorno] +
   estimación recompensa futura (t−1 pasos) [dada por Q ; i.e. *bootstrapping*]
3. Ponderan la importancia de la recompensa inmediata respecto a la recompensa futura

$\pi \leftarrow \epsilon$–greedy(Q)

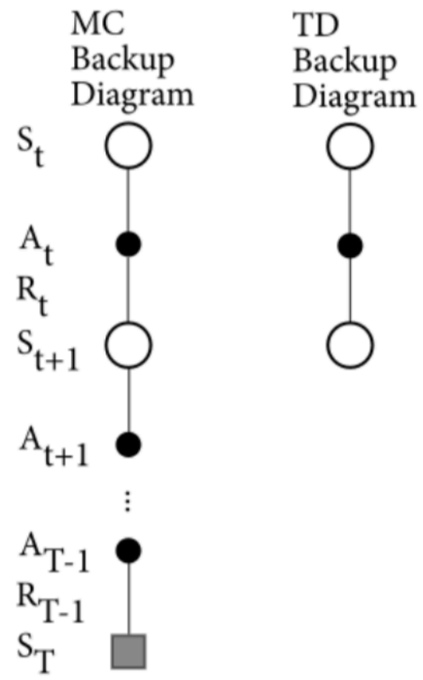
$S_0\ A_0\ R_1\ S_1 \quad | \quad A_1\ R_2\ S_2 \quad |$

$$Q(S_0, A_0) \leftarrow Q(S_0, A_0) + \alpha\left(R_1 + \gamma \max_{a \in \mathcal{A}} Q(S_1, a) - Q(S_0, A_0)\right)$$

$\pi \leftarrow \epsilon_0$–greedy$(Q)$

$$Q(S_1, A_1) \leftarrow Q(S_1, A_1) + \alpha\left(R_2 + \gamma \max_{a \in \mathcal{A}} Q(S_2, a) - Q(S_1, A_1)\right)$$

$\pi \leftarrow \epsilon_0$–greedy$(Q)$



MC update equation:
$G_t = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-1} R_T$
$V(S_t) = V(S_t) + \alpha(G_t - V(S_t))$

TD update equation:
$V(S_t) = V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$

M. Morales (2019) **Grokking Reinforcement Learning**. Manning

Q-Learning

Formulación

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Q-Learning (SARSA-max)

params: Q inicial, n_episodios, α

for i = {0, …, n_episodios}

while *episodio no terminado*

elegir acción A_t con política ϵ−greedy(Q)

aplicar A_t y obtener R_{t+1}, S_{t+1}

Actualizar Q

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left(R_{t+1} + \gamma \max_{a \in \mathcal{A}} Q(S_{t+1}, a) - Q(S_t, A_t) \right)$$

Índice

Aprendizaje por refuerzo

Temas avanzados

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Otras variantes de diferencia temporal

SARSA, Expected SARSA, Double Q-Learning

Demostraciones de *optimalidad* y convergencia de los métodos

Discretización en problemas con espacio de estados continuo

Discretización en problemas con espacio de acciones continuo

Recompensas dispersas (*sparse rewards*)

Planificación y aprendizaje

Random-sample one-step tabular Q-planning

Montecarlo Tree Search (MCTS)