Ayudantía 11 Reinforcement Learning

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Reinforcement Learning

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El problema se modela como un MDP



Markov decision process

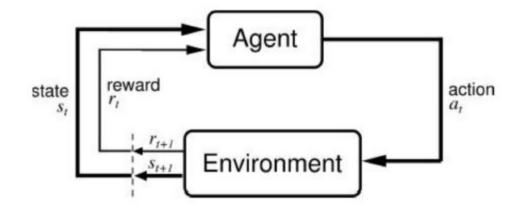
MDP se compone:

- Set finito de estados: s₁,, s_n
- Set de recompensas: $r_1, ..., r_n$
- Set de acciones: a₁,, a_n
- Set de probabilidades de transición entre estados:

$$P_{ij}^k = P(s_j|s_i, a_k)$$

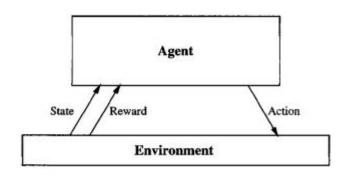
Reinforcement Learning

Se busca aprender a comportarse en el entorno (aprender una política).



Factor de descuento

Determina la importancia de las recompensas futuras



$$s_0 \stackrel{a_0}{\xrightarrow{r_0}} s_1 \stackrel{a_1}{\xrightarrow{r_1}} s_2 \stackrel{a_2}{\xrightarrow{r_2}} \dots$$

Goal: Learn to choose actions that maximize

$$r_0 + \gamma r_1 + \gamma^2 r_2 + \dots$$
, where $0 \le \gamma < 1$

$$V(s) = E\left\{\sum_{t=0}^{\infty} \gamma^{t} r_{t}^{\pi}\right\}$$

Recompensa total que el agente recibe al iniciar en el estado s y seguir la política π

Política de recompensa π

• Se busca encontrar la política π que maximice la value function:

$$V^*(s) = \max_{\pi} E\left\{\sum_{t=0}^{\infty} \gamma^t r_t^{\pi}\right\}$$

Se utilizan las ecuaciones de Bellman:

$$V^*(s) = \max_{a} \left\{ R(s, a) + \gamma \sum_{s' \in S} T(s, a, s') V^*(s') \right\}, \quad \forall s \in S$$

Recompensa del estado actual

Recompensa futura esperada

Interesan las acciones que maximizan la función

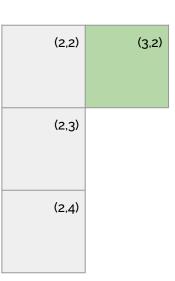
$$V^*(s) = \underset{a}{\operatorname{arg max}} \left\{ R(s, a) + \gamma \sum_{s' \in S} T(s, a, s') V^*(s') \right\}, \quad \forall s \in S$$

```
Initialize V(s) arbitrarily loop until policy good enough loop for s \in S loop for a \in A Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop \hat{V}(s) := \max_{a} Q(s,a) end loop end loop return \{\hat{V}(s)\}
```

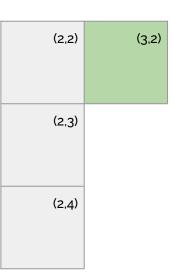
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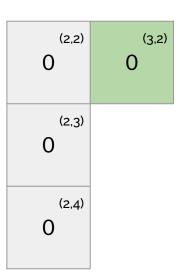
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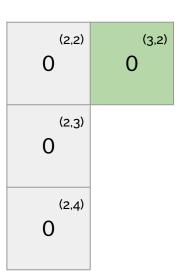
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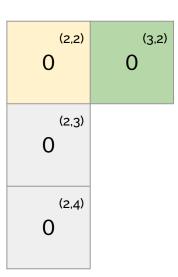
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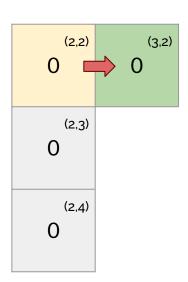
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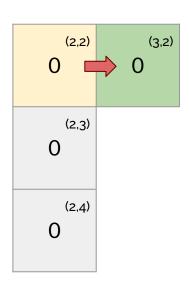
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```



```
Initialize V(s) arbitrarily loop until policy good enough loop for s \in S \frac{100p \text{ for } a \in A}{Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')} end loop \hat{V}(s) := \max_{a} Q(s,a) end loop end loop return \{\hat{V}(s)\}
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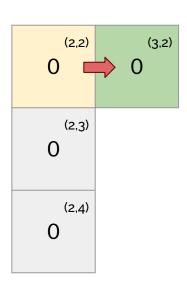


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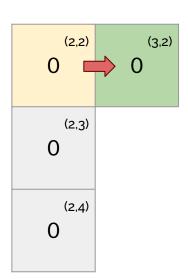
$$Q([2,2],r) = R([2,2],r) + \gamma \cdot T([2,2],r,[3,2]) \cdot V_0([3,2])$$



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Initialize V(s) arbitrarily loop until policy good enough loop for s \in S loop for a \in A Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')
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$$Q([2,2],r) = R([2,2],r) + \gamma \cdot T([2,2],r,[3,2]) \cdot V_0([3,2])$$

= 1 + 0,9 \cdot 0,25 \cdot 0

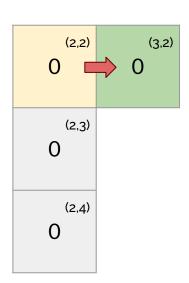


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$$= 1 + 0.9 \cdot 0.25 \cdot 0$$

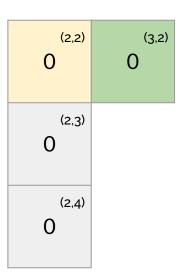
$$= 1.$$



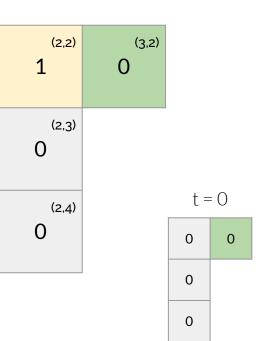
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Initialize V(s) arbitrarily loop until policy good enough loop for s \in S loop for a \in A Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop
```

$$Q([2, 2], r) = 1$$

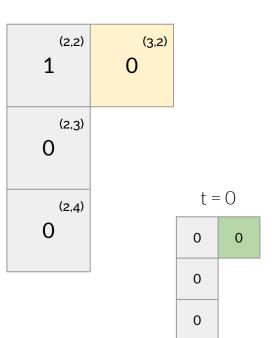
 $Q([2, 2], l) = 0$
 $Q([2, 2], u) = 0$
 $Q([2, 2], d) = 0$



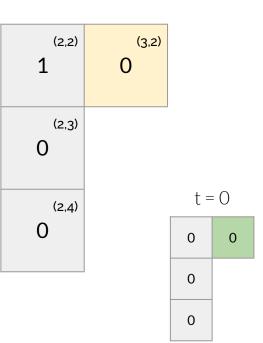
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Initialize V(s) arbitrarily
loop until policy good enough
      loop for s \in S
              loop for a \in A
                     Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')
               end loop
               \hat{V}(s) := \max_{a} Q(s, a)
                      Q([2,2],r)=1
                      Q([2,2],l)=0
                      Q([2,2],u)=0
                      Q([2,2],d)=0
```



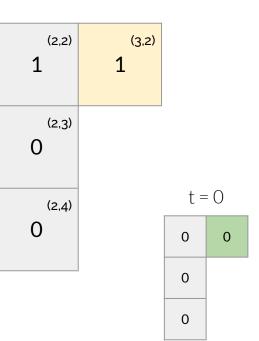
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Initialize V(s) arbitrarily loop until policy good enough \frac{\text{loop for } s \in S}{\text{loop for } a \in A} Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop
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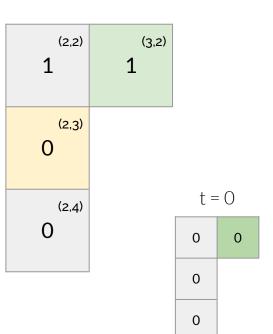
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      loop for s \in S
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                    Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')
              end loop
                     Q([3,2],r)=1
                     Q([3,2],l)=0
                    Q([3,2],u)=1
                     Q([3,2],d)=1
```



```
Initialize V(s) arbitrarily
loop until policy good enough
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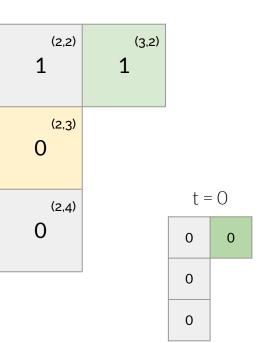
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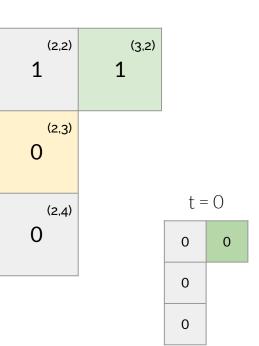
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```

$$Q([2,3],r) = 0$$

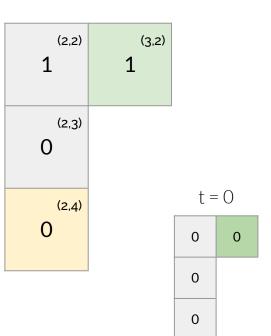
 $Q([2,3],l) = 0$
 $Q([2,3],u) = 0$
 $Q([2,3],d) = 0$



```
Initialize V(s) arbitrarily
loop until policy good enough
      loop for s \in S
              loop for a \in A
                     Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')
               end loop
               \hat{V}(s) := \max Q(s, a)
                        Q([2,3],r)=0
                        Q([2,3],l) = 0
                       Q([2,3],u)=0
                       Q([2,3],d) = 0
```



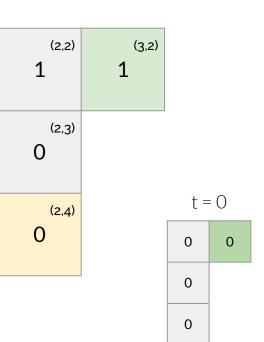
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Initialize V(s) arbitrarily loop until policy good enough \frac{\text{loop for } s \in S}{\text{loop for } a \in A} Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop
```



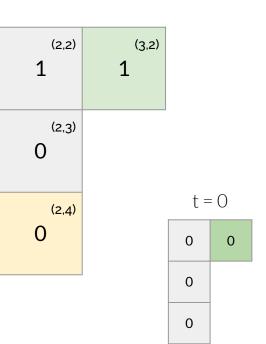
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Initialize V(s) arbitrarily loop until policy good enough loop for s \in S loop for a \in A Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop
```

$$Q([2,4],r) = 0$$

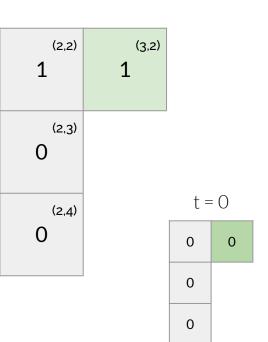
 $Q([2,4],l) = 0$
 $Q([2,4],u) = 0$
 $Q([2,4],d) = 0$



```
Initialize V(s) arbitrarily
loop until policy good enough
      loop for s \in S
              loop for a \in A
                     Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s')
               end loop
               \hat{V}(s) := \max Q(s, a)
                        Q([2,4],r)=0
                        Q([2,4],l) = 0
                       Q([2,4],u)=0
                       Q([2,4],d) = 0
```



```
Initialize V(s) arbitrarily loop until policy good enough loop for s \in S loop for a \in A Q(s,a) := R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \hat{V}(s') end loop \hat{V}(s) := \max_{a} Q(s,a) end loop end loop return \{\hat{V}(s)\}
```



```
\gamma = 0.9
```

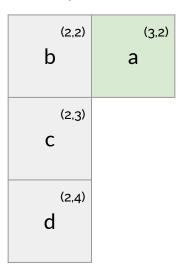
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```

t = 1

(2,2) 1	(3,2) 1
O ^(2,3)	
0 (2,4)	

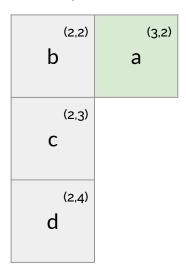
(...)

t->inf

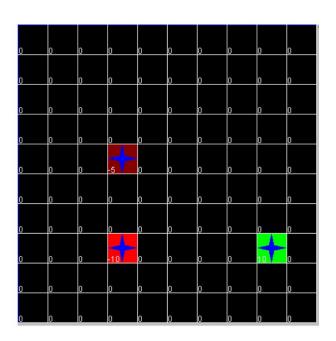


¿ Qué relación existirá entre a, b, c y d?

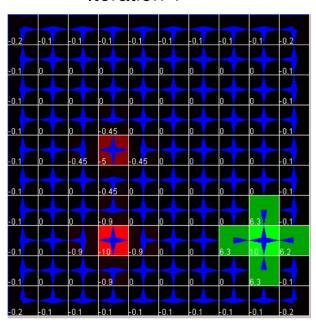
t -> inf

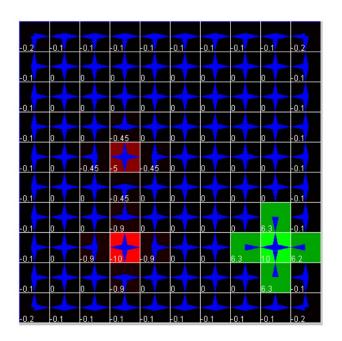


Para este caso en particular



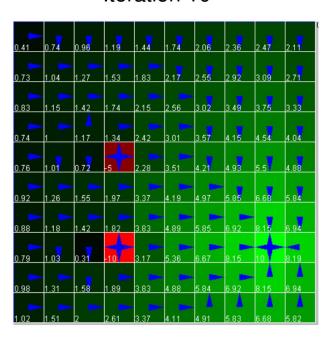
Iteration 1





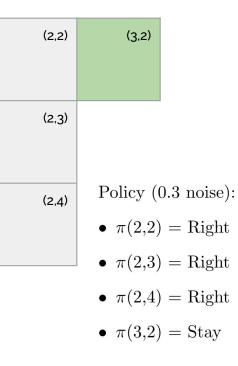


Iteration 10



```
Choose an arbitray policy \pi'
Loop \pi:=\pi'
Compute value function of policy \pi:
\# solve \ \ linear \ equations
V_{\pi}(s):=R(s,\pi(s))+\gamma\sum_{s'\in S}T(s,\pi(s),s')V_{\pi}(s')
Improve the policy at each state \pi'(s):=\arg\max_{a}\left(R(s,a)+\gamma\sum_{s'\in S}T(s,a,s')V_{\pi}(s')\right) until \pi=\pi'
```

```
Choose an arbitray policy \pi'
Loop \pi := \pi'
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\# solve \ linear \ equations
V_{\pi}(s) := R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') V_{\pi}(s')
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until \pi = \pi'
```



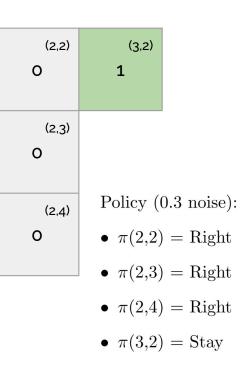
Choose an arbitray policy π'

Loop

 $\pi := \pi'$ Compute value function of policy π :

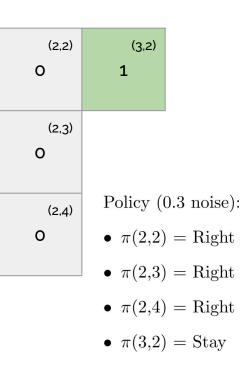
#solve linear equations $V_{\pi}(s) := R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') V_{\pi}(s')$ Improve the policy at each state $\pi'(s) := \arg\max \left(R(s, a) + \gamma \sum_{s' \in S} T(s, a, s') V_{\pi}(s') \right)$

until $\pi = \pi'$



Choose an arbitray policy π' Loop

until $\pi = \pi'$



Choose an arbitray policy π' Loop

$$\pi := \pi'$$

Compute value function of policy π :

#solve linear equations

$$V_{\pi}(s) := R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') V_{\pi}(s')$$

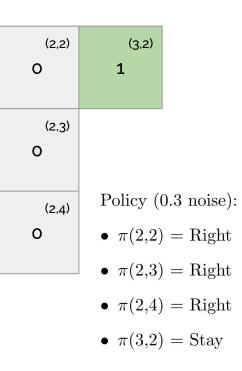
Improve the policy at each state

$$\pi'(s) := \arg\max\left(R(s, a) + \gamma \sum_{s' \in S} T(s, a, s') V_{\pi}(s')\right)$$

until $\pi = \pi'$

(2,2)	(3,2)	
0	1	
(2,3)		
0		
(2,4)	Policy (0.3 noise
0	• $\pi(2,2)$	= Righ
	• $\pi(2,3)$	= Righ
	 π(2,4) 	= Righ
	• $\pi(3,2)$	= Stay

```
Choose an arbitray policy \pi'
Loop \pi := \pi'
Compute value function of policy \pi:
\# solve \ linear \ equations
V_{\pi}(s) := R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') V_{\pi}(s')
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until \pi = \pi'
```



$$\gamma = 0.9$$

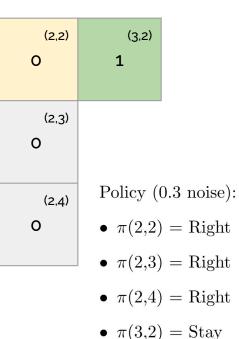
$$V_{\pi}(s) := R(s, \pi(s)) + \gamma \sum_{s' \in S} T(s, \pi(s), s') V_{\pi}(s')$$

$$V([2, 2]) = R([2, 2], \pi) + \gamma ($$

$$T([2, 2], \pi, [3, 2]) \cdot V([3, 2]) +$$

$$T([2, 2], \pi, [2, 2]) \cdot V([2, 2]) +$$

$$T([2, 2], \pi, [2, 3]) \cdot V([2, 3])$$



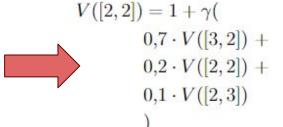
$$\gamma = 0.9$$

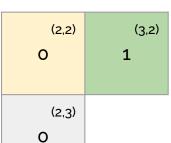
$$V([2,2]) = R([2,2],\pi) + \gamma($$

$$T([2,2],\pi,[3,2]) \cdot V([3,2]) +$$

$$T([2,2],\pi,[2,2]) \cdot V([2,2]) +$$

$$T([2,2],\pi,[2,3]) \cdot V([2,3])$$
)





Policy (0.3 noise):
• $\pi(2,2) = \text{Right}$

0

- $\pi(2,3) = \text{Right}$
- $\pi(2,4) = \text{Right}$
- $\pi(3,2) = \text{Stay}$

$$\gamma = 0.9$$

$$V([2,2]) = 1 + \gamma (\qquad V([3,2]) = 1 + \gamma (0,7 \cdot V([3,2]) + \qquad 1 \cdot ([3,2]) 0,2 \cdot V([2,2]) + \qquad) 0,1 \cdot V([2,3]))$$

$$V([3,2]) = 1 + \gamma($$

 $0,7 \cdot V([3,2]) +$
 $0,2 \cdot V([2,2]) +$
 $V([3,2]) = 1 + \gamma($
 $1 \cdot ([3,2])$

$$V([2,3]) = 0 + \gamma($$

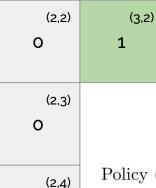
$$0.8 \cdot V([2,3]) +$$

$$0.1 \cdot V([2,2]) +$$

$$0.1 \cdot V([2,4])$$
)

$$V([2,4]) = 0 + \gamma($$

 $0.9 \cdot V([2,4]) +$
 $0.1 \cdot V([2,3])$
)



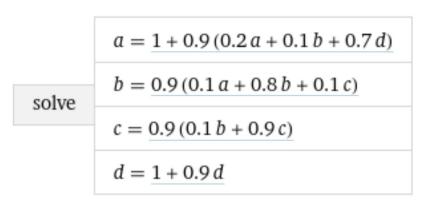
0

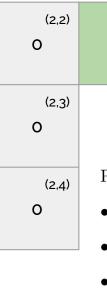
Policy (0.3 noise):

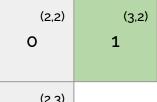
- $\pi(2,2) = \text{Right}$
- $\pi(2,3) = \text{Right}$
- $\pi(2,4) = \text{Right}$
- $\pi(3,2) = \text{Stay}$

$$\gamma = 0.9$$

```
V([2,2]) = 1 + \gamma(
           0.7 \cdot V([3,2]) +
           0,2 \cdot V([2,2]) +
           0.1 \cdot V([2,3])
V([2,3]) = 0 + \gamma(
          0.8 \cdot V([2,3]) +
          0,1 \cdot V([2,2]) +
          0.1 \cdot V([2,4])
V([2,4]) = 0 + \gamma(
          0.9 \cdot V([2,4]) +
          0.1 \cdot V([2,3])
V([3,2]) = 1 + \gamma(
           1 \cdot ([3, 2])
```





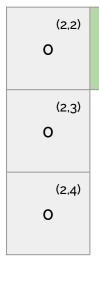


Policy (0.3 noise):

- $\pi(2,2) = \text{Right}$
- $\pi(2,3) = \text{Right}$
- $\pi(2,4) = \text{Right}$
- $\pi(3,2) = \text{Stay}$

$$\gamma = 0.9$$

V([2, 2])	_	9,289
V([2, 3])	=	3,522
V([2, 4])	_	1,668
V([3, 2])	=	10



Policy (0.3 noise):

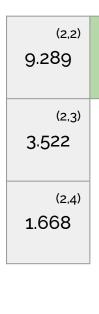
(3,2)

1

- $\pi(2,2) = \text{Right}$
- $\pi(2,3) = \text{Right}$
- $\pi(2,4) = \text{Right}$
- $\pi(3,2) = \text{Stay}$

$$\gamma = 0.9$$

V([2,2]) = 9,289
V([2,3]) = 3,522
V([2,4]) = 1,668
V([3,2]) = 10



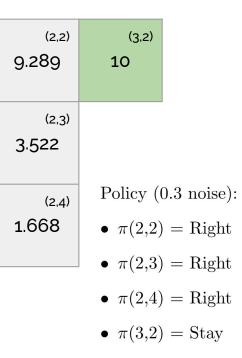
Policy (0.3 noise):

(3,2)

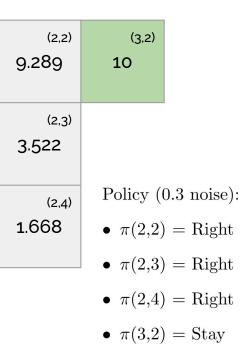
10

- $\pi(2,2) = \text{Right}$
- $\pi(2,3) = \text{Right}$
- $\pi(2,4) = \text{Right}$
- $\pi(3,2) = \text{Stay}$

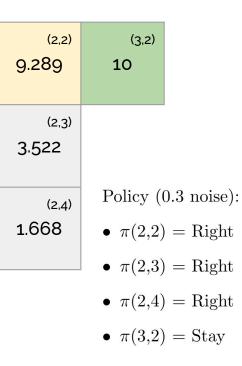
$$\gamma = 0.9$$



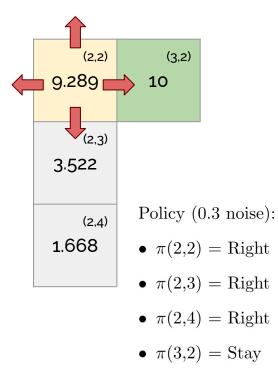
$$\gamma = 0.9$$



$$\gamma = 0.9$$



$$\gamma = 0.9$$

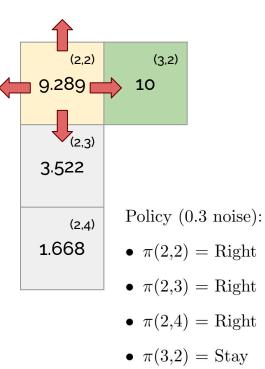


$$R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V_{\pi}(s')$$

$$\gamma = 0.9$$

$$R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V_{\pi}(s')$$

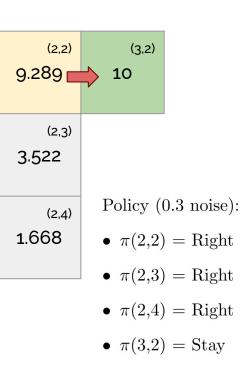
$$\begin{aligned} right &\to 1 + 0.9 \cdot (0.7 \cdot 10 + 0.2 \cdot 9.289 + 0.1 \cdot 3.522) = 9.289 \\ left &\to 0 + 0.9 \cdot (0.8 \cdot 9.289 + 0.1 \cdot 10 + 0.1 \cdot 3.522) = 7.90506 \\ up &\to 0 + 0.9 \cdot (0.8 \cdot 9.289 + 0.1 \cdot 10 + 0.1 \cdot 3.522) = 7.90506 \\ down &\to 0 + 0.9 \cdot (0.7 \cdot 3.522 + 0.2 \cdot 9.289 + 0.1 \cdot 10) = 4.79088 \end{aligned}$$



$$\gamma = 0.9$$

$$\underset{a}{\operatorname{arg\,max}} \left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V_{\pi}(s') \right)$$

$$\begin{aligned} right &\to 1 + 0.9 \cdot (0.7 \cdot 10 + 0.2 \cdot 9.289 + 0.1 \cdot 3.522) = 9.289 \\ left &\to 0 + 0.9 \cdot (0.8 \cdot 9.289 + 0.1 \cdot 10 + 0.1 \cdot 3.522) = 7.90506 \\ up &\to 0 + 0.9 \cdot (0.8 \cdot 9.289 + 0.1 \cdot 10 + 0.1 \cdot 3.522) = 7.90506 \\ down &\to 0 + 0.9 \cdot (0.7 \cdot 3.522 + 0.2 \cdot 9.289 + 0.1 \cdot 10) = 4.79088 \end{aligned}$$



$$\gamma = 0.9$$

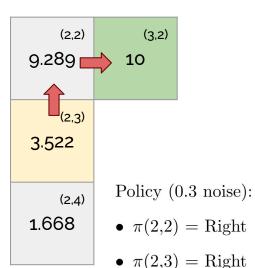
$$\arg\max_{a} \left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V_{\pi}(s') \right)$$

$$right \to 0 + 0.9 \cdot (0.8 \cdot 3.522 + 0.1 \cdot 9.289 + 0.1 \cdot 1.668) = 3.52197$$

$$left \to 0 + 0.9 \cdot (0.8 \cdot 3.522 + 0.1 \cdot 9.289 + 0.1 \cdot 1.668) = 3.52197$$

$$up \to 1 + 0.9 \cdot (0.7 \cdot 9.289 + 0.2 \cdot 3.522 + 0.1 \cdot 1.668) = 7.63615$$

$$down \to 0 + 0.9 \cdot (0.7 \cdot 1.668 + 0.2 \cdot 3.522 + 0.1 \cdot 9.289) = 2.52081$$



• $\pi(2,4) = \text{Right}$

• $\pi(3,2) = \text{Stay}$

$$\gamma = 0.9$$

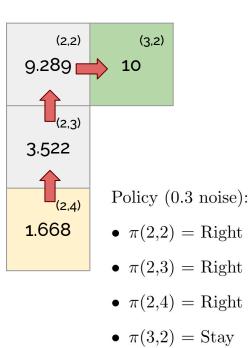
$$\underset{a}{\operatorname{arg\,max}} \left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') V_{\pi}(s') \right)$$

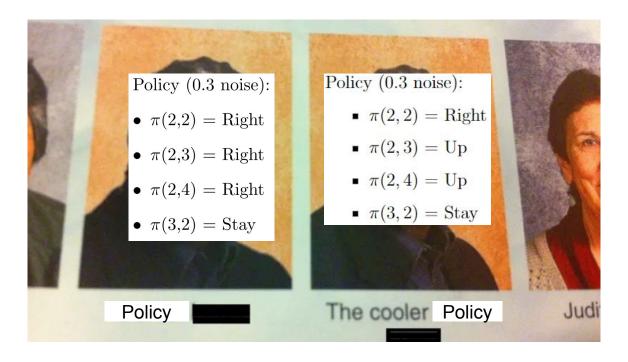
$$right \rightarrow 0 + 0.9 \cdot (0.9 \cdot 1.668 + 0.1 \cdot 3.522) = 1.66806$$

$$left \rightarrow 0 + 0.9 \cdot (0.9 \cdot 1.668 + 0.1 \cdot 3.522) = 1.66806$$

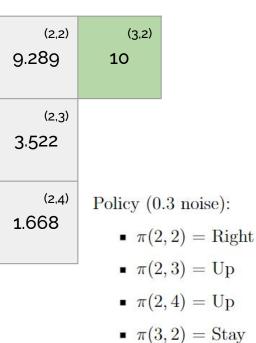
$$up \rightarrow 1 + 0.9 \cdot (0.7 \cdot 3.522 + 0.3 \cdot 1.668) = 3.66922$$

$$down \rightarrow 0 + 0.9 \cdot (0.9 \cdot 1.668 + 0.1 \cdot 3.522) = 1.66806$$

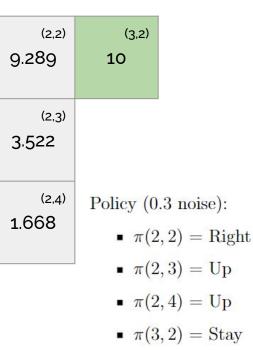




$$\gamma = 0.9$$



$$\gamma = 0.9$$



 (\dots)

Q learning algorithm

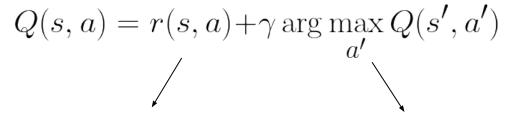
For each s, a initialize the table entry $\hat{Q}(s, a)$ to zero. Observe the current state s

Do forever:

- Select an action a and execute it
- Receive immediate reward r
- Observe the new state s'
- Update the table entry for $\hat{Q}(s, a)$ as follows:

$$\hat{Q}(s,a) \leftarrow r + \gamma \max_{a'} \hat{Q}(s',a')$$

• $s \leftarrow s'$

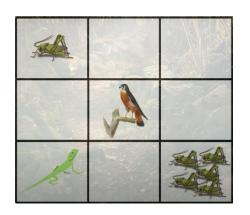


Recompensa

adquirida tras realizar la acción *a* en *s* Valor que entrega la mejor acción en el próximo estado

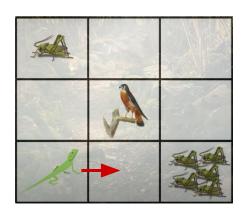


Estado	Recompensa	
Un grillo	+1	
Vacío	-1	
Cinco grillos	+10	
Pájaro	-10	



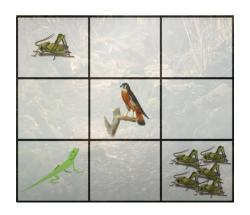
Estado	Recompensa		
Un grillo	+1		
Vacío	-1		
Cinco grillos	+10		
Pájaro	-10		

	Arriba	Abajo	Izq.	Der.
1 grillo	0	0	0	0
Vacío 1	0	0	0	0
Vacío 2	0	0	0	0
Vacío 3	0	0	0	0
Pájaro	0	0	0	0
Vacío 4	0	0	0	0
Vacío 5	0	0	0	0
Vacío 6	0	0	0	0
5 grillos	0	0	0	0



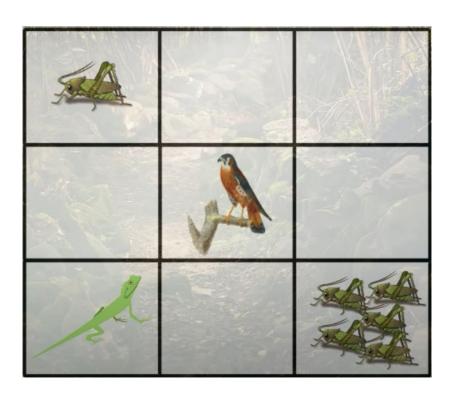
Estado	Recompensa	
Un grillo	+1	
Vacío	-1	
Cinco grillos	+10	
Pájaro	-10	

$$Q(s, a) = r(s, a) + \gamma \arg \max_{q} Q(s', a')$$



Estado	Recompensa	
Un grillo	+1	
Vacío	-1	
Cinco grillos	+10	
Pájaro	-10	

	Arriba	Abajo	Izq.	Der.
1 grillo	0	0	0	0
Vacío 1	0	0	0	0
Vacío 2	0	0	0	0
Vacío 3	0	0	0	0
Pájaro	0	0	0	0
Vacío 4	0	0	0	0
Vacío 5	0	0	0	-1
Vacío 6	0	0	0	0
5 grillos	0	0	0	0



Q learning algorithm

For each s, a initialize the table entry $\hat{Q}(s, a)$ to zero. Observe the current state s

Do forever:

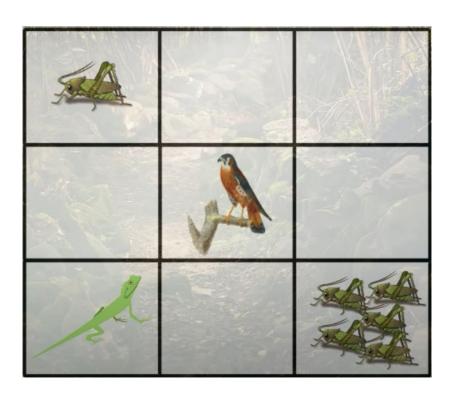
- Select an action a and execute it
- Receive immediate reward r
- Observe the new state s'
- Update the table entry for $\hat{Q}(s, a)$ as follows:

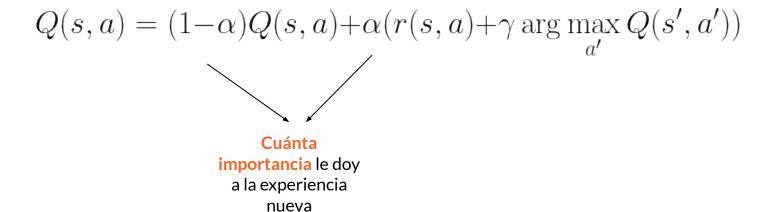
$$\hat{Q}(s,a) \leftarrow r + \gamma \max_{a'} \hat{Q}(s',a')$$

s ← s'

ε- greedy

- ε-greedy exploration policy:
 - With probability 1ϵ :
 - Choose the current optimal action: $\arg \max \hat{Q}(s, a)$.
 - With probability ϵ :
 - Select a random action.





Ayudantía 11 Reinforcement Learning

Sarah Everke - Daniel Florea