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Sarsa Algorithm

$(s_t, a_t, r_t, s_{t+1}, a_{t+1})$

Characteristics

Monte Carlo

Dynamic Programming

Time Difference (TD)

On Policy

Algorithm

Initialize $Q(s, a)$ arbitrarily

Repeat (for each episode):

 Initialize s

 Choose a from s using policy derived from Q (e.g., ε -greedy)

 Repeat (for each step of episode):

 Take action a , observe r, s'

 Choose a' from s' using policy derived from Q (e.g., ε -greedy)

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma Q(s', a') - Q(s, a)]$$

$s \leftarrow s'; a \leftarrow a'$;

 until s is terminal

Algorithm

Model

1	2	3	4	5	6
7	8	9	10	11	12
13	14	15	16	17	18
19	20	21	22	23	24
25	26	27	28	29	30
31	32	33	34	35	36

Rewards

30 → 36:	2
35 → 36:	2
Else:	0

Why 0?

Because the algorithm does not know when and in which direction it has to go.

Algorithm

Structure Q(s,a)

X₁: U₁ R₁ D₁ L₁

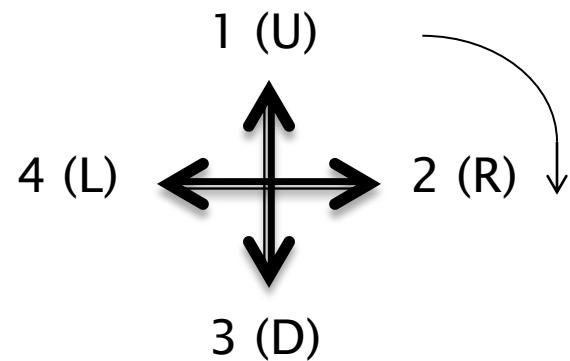
X₂: U₃ R₂ D₂ L₂

X₃: U₂ R₃ D₃ L₃

...

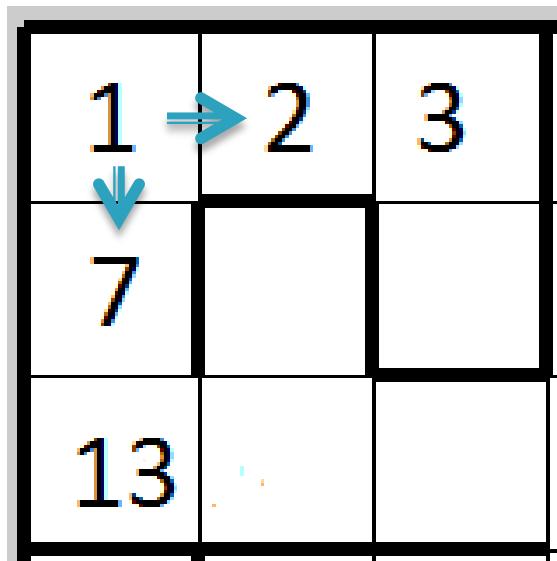
...

X₃₆: U₃₆ R₃₆ D₃₆ L₃₆



Algorithm

First iteration



S: state 1

A: best action →

R:

S:

B:

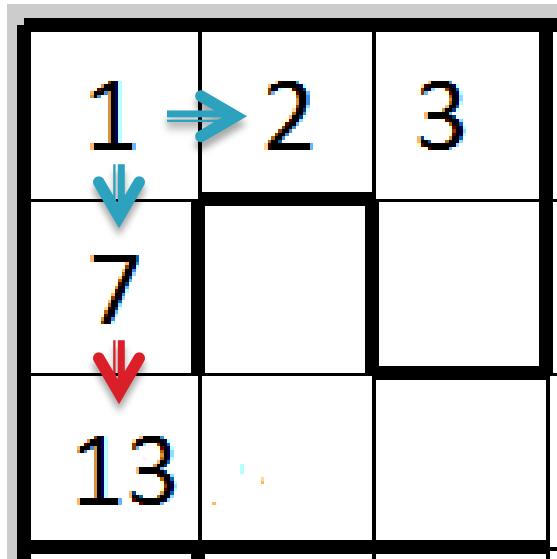
- ϵ prob. to choose a random action.
- if same reward, random action



Both have a reward of 0, so it will choose a random action.

Algorithm

First iteration



S: state 1

A: action 3 (down)

R: reward 0

S: state 7

A: best action →

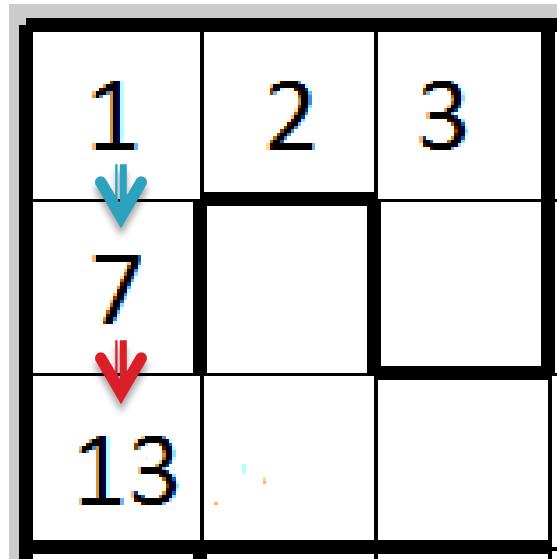
- ϵ prob. to choose a random action.
- if same reward, random action



Both have a reward of 0, so it will choose a random action.

Algorithm

First iteration



S: state 1

A: action 3 (down)

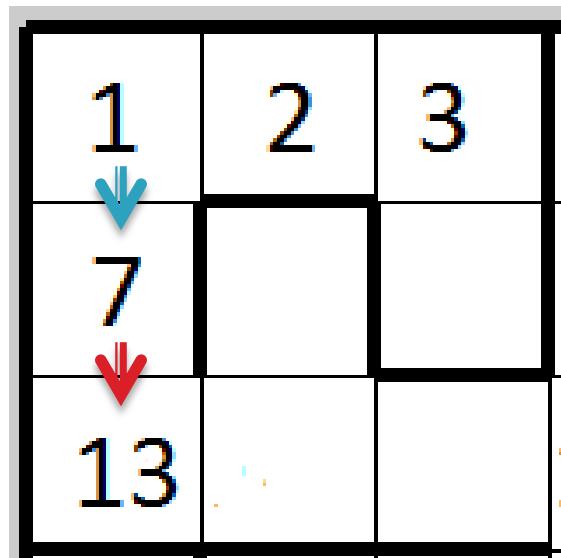
R: reward 0

S: state 7

A: action 3 (down)

Algorithm

First iteration



Algorithm

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a') - Q(s,a)]$$

$$Q(1,3) \leftarrow Q(1,3) + \alpha[0 + \gamma Q(7,3) - Q(1,3)]$$

α : learning rate

r: reward

γ : discount factor

Algorithm

After many iterations

1	2	3	4	5	6
7	8	9	10	11	12
13	14	15	16	17	18
19	20	21	22	23	24
25	26	27	28	29	30
31	32	33	34	35	36

Final Q(s,a)

1:	0	0.0000	0.0007	0
7:	0.0002	0	0.0033	0
13:	0.0006	0.0143	0	0
14:	0.0007	0.0276	0	0.0001
15:	0	0.0758	0	0.0055
16:	0.0043	0	0.3093	0.0239
22:	0.0814	0.4906	0	0.0546
23:	0	0.0063	0.9059	0.1223
29:	0.2403	0	1.3936	0
35:	0.4974	1.9444	0	0

Explanation

Complementary explanation

<http://laid.delanover.com/reinforcement-learning-sarsa-algorithm-a-practical-case>

Video

<https://www.youtube.com/watch?v=MZSK-Ho2-NA>