Model-free reinforcement learning: Q-learning and SARSA

Model-free reinforcement learning: what if we do not know transitions *P* and reward function *r* of an MDP?

The Mystery Game:
https://programmingheroes.blogspot.com/2016/02/udacity-reinforcement-learning-mystery-game.html

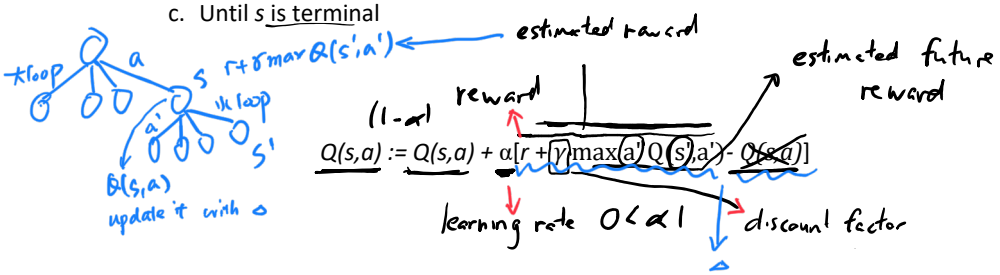
Model-based vs model-free

MDP:
- Set of states *S*
- Transition probabilities *P_a(s' | s)*
- Reward function *r(s, a, s')* in real
- Discount factor γ

unknown P → can't calculate reward directly
→ experience → policy
→ simulation-based RL

Q-learning

1. Initialise *Q(s,a)* arbitrarily
2. For each episode:
   a. Initialise *s* (go to the initial state)
   b. Repeat for each step in the episode
      i. Select the next action *a* to apply from *s* (using e.g. epsilon greedy, UCT) using *Q(s,a)*
      ii. Execute action *a* and observe the reward *r* and new state *s'*
      iii. $Q(s,a) := Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
      iv. $s := s'$
   c. Until *s* is terminal

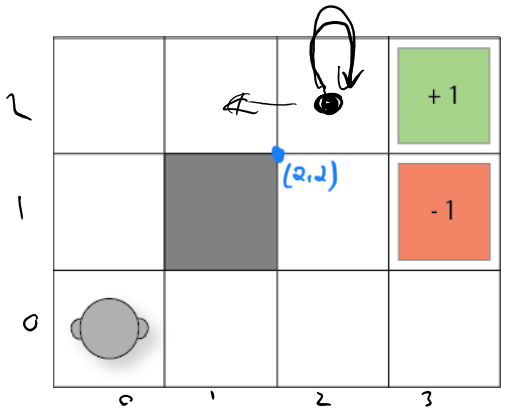


Q-Tables

State	Action			
	North	South	East	West
(0,0)	0.53	0.36	0.36	0.21
(0,1)	0.61	0.27	0.23	0.23
. . .				
(2,2)	0.79	0.72	0.90	0.72
(2,3)	0.90	0.78	0.99	0.81

Q-learning

SARSA example



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$Q(s,a) := Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$

Learning rate $\alpha = 0.1$

Discount reward factor $\gamma = 0.9$

Q-learning:

Q((2,2), North) = 0.79 + 0.1*(0 + 0.9*0.9 - 0.79) = 0.792

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

SARSA, with assumption that a' is West (on-policy action)

Q((2,2), North) = 0.79 + 0.1* (0 + 0.9*0.72 -0.79)=0.7758

If a' was East is for SARSA, the update would be just the same as for Q-learning because East is the max action from (2,2)

whether update the value based on policy or not.

Q-learning: Off-policy

1. Initialise *Q(s,a)* arbitrarily
2. For each episode:
   a. Initialise *s* (go to the initial state)
   b. Repeat for each step in the episode
      i. Select the next action *a* to apply from *s* (using e.g. epsilon greedy, UCT) use *Q(s,a)*
      ii. Execute action *a* and observe the reward *r* and new state *s'*
      iii. $Q(s,a) := Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
      iv. *s := s'*
   c. Until *s* is terminal

SARSA: On-policy learning

1. Initialise *Q(s,a)* arbitrarily
2. For each episode:
   a. Initialise *s* (go to the initial state)
   b. Select the next action *a* to apply from *s* (using e.g. epsilon greedy, UCT)
   c. Repeat for each step in the episode
      i. Execute action *a* and observe the reward *r* and new state *s'*
      ii. Select the next action *a'* to apply from *s'* (using e.g. epsilon greedy, UCT)
      iii. $Q(s,a) := Q(s,a) + \alpha[r + \gamma Q(s',a') - Q(s,a)]$
      iv. *s := s'; a := a';*
   d. Until *s* is terminal

from observations (both) Algo

$Q(S,a) = Q(S,a) + \alpha[r + \gamma V(S') - Q(S,a)]$

Q-learning

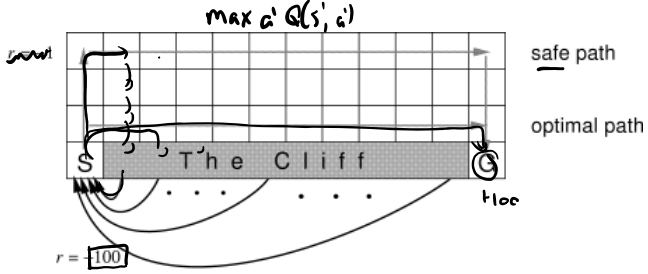
$\max Q(S',a')$ $a' \in A(S')$

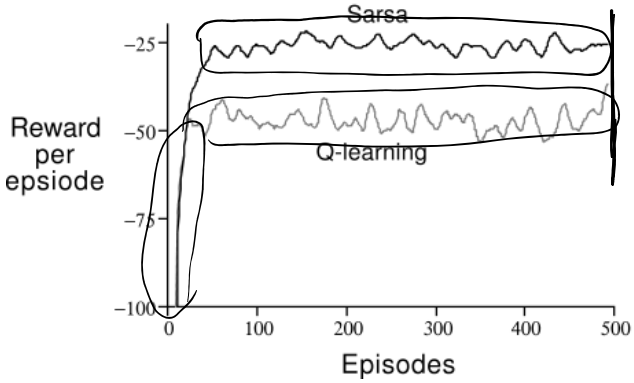
chosen by

SARSA ⇒ follow the actual policy

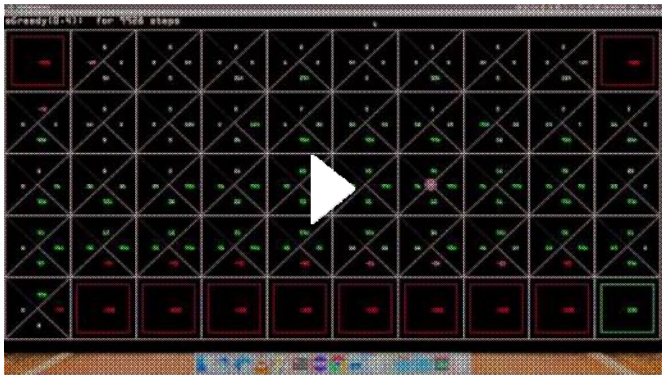
$Q(S',a')$

Off-policy vs. on-policy learning





Gridworld Q-Learning - Example 3 - The Cliff



Learning to Play Freeway, using Reinforcement Learning