MACHINE LEARNING

University Master's Degree in Intelligent Systems

reinforcement learning

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a quote

"When it is not in our power to determine what is true, we ought to follow what is most probable."

— René Descartes

french philosopher, mathematician and scientist

1596 – 1650

introduction to reinforcement learning

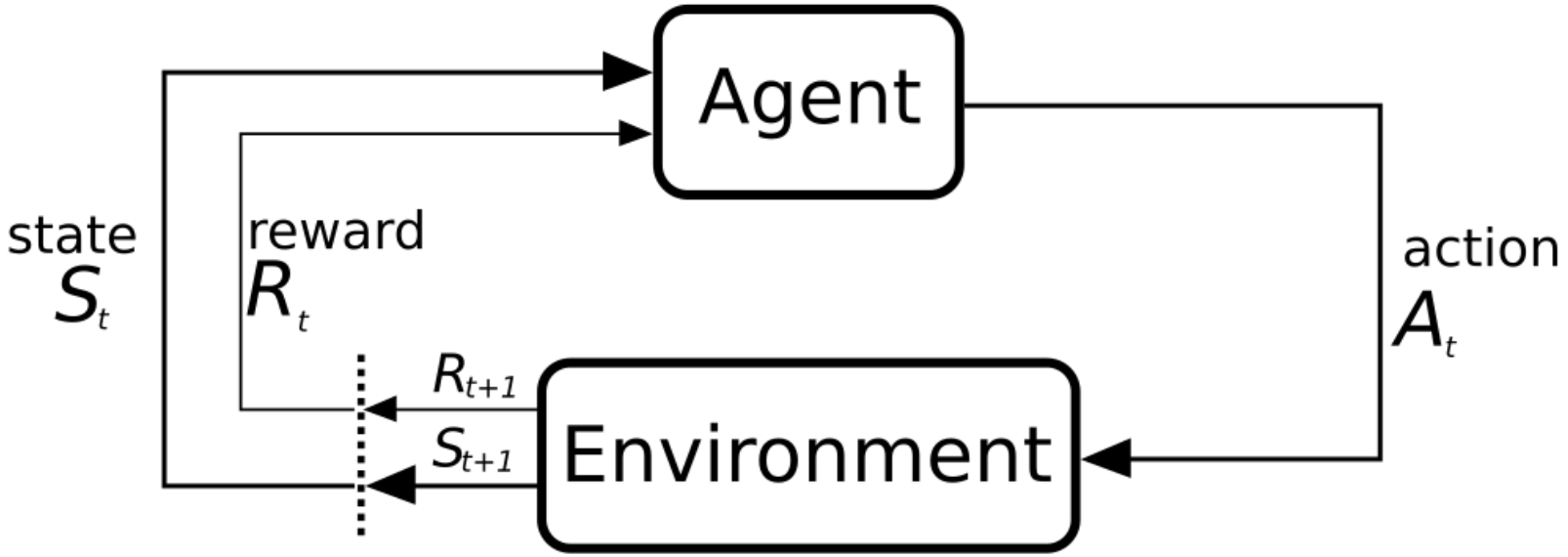
use case

A mobile robot decides whether it should enter a new room in search of more trash to collect or start trying to find its way back to its battery recharging station. It makes its decision based on the current charge level of its battery and how quickly and easily it has been able to find the recharger in the past.

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

introduction

pipeline



sample actions, observe rewards, tune the policy

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introduction

use case

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goal?
agent?
state?
action?
environment?
short-term rewards?
long-term rewards?

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

introduction

goal

RL approach involves learning how

to map states to actions,

so as to gain

the highest long-term cumulative reward.

introduction

RL summary

1. Environment observation (the agent observes the environment state)
2. Deciding how to act using some strategy (or policy)
3. Acting accordingly (the agent acts according to the policy)
4. Receiving a reward or penalty (based on sensor reading)
5. Learning from the experiences and refining our strategy
6. Iterate until an optimal strategy is found

Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

introduction

key principles

- it is a closed-loop problem: system's actions affect later inputs.
- actions may affect not only the immediate reward but also the next states and, through that, all subsequent rewards.
- the agent is not taught what action to take on each state (as in supervised learning); instead, it must discover which action maximizes immediate and future rewards (by interacting with the environment).

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

introduction

exploitation – exploration dilemma / trade-off

exploit known actions

that have proven to be effective (positive rewards)

OR

explore new (unknown) actions

to discover more promising solutions

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

introduction

learning paradigms

- unsupervised learning…
  - discovers similarities between data samples
  - identifies clusters based on similarities
  - is able to detect anomalous data
- supervised learning…
  - learns the correlations between data instances and data labels
  - learns a mapping from instances to data labels
  - requires a labelled dataset
  - uses labels to guide, correct and monitor the learning process
- reinforcement learning…
  - given a state, there exists an optimal action, but it is not known!
  - takes actions based on short- and long-term reward (strategy learning)
  - is guided by sparse and uncertain feedback / supervision.

Source: Chris V. Nicholson. A Beginner's Guide to Deep Reinforcement Learning. Pathmind Inc., 2023.

introduction

key elements

- a policy π: the core of a RL agent
  - a mapping from perceived states to actions to be taken
  - a stimulus-response rule
- a reward signal: what is good in an immediate sense
  - the output of a mapping from the agent's action given an environment state
  - measures the effectiveness of the agent's action (the agent cannot alter it)
- a value function: what is good in the long run (accumulated rewards)
  - the long-term cumulative reward an agent can expect from a state
  - a quality measure of (some sequence of) actions taken from a state
  - policy tuning is based on value judgments
- a model of the environment: it mimics the behavior of the environment
  - given a state and action, it moves to the next state and reward

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

policy

agent's goal

objective function over an episode

$$\sum_{t=0}^{\infty} \gamma^t r\big(s(t), a(t)\big)$$

t: time step

r: reward function

γ: discount factor

$s(t)$: state at a given time step/epoch t

$a(t) = \pi\big(s(t)\big)$

policy

agent's goal

policy

agent's goal

$$\pi^* = argmax_\pi \sum_{t=0}^{\infty} \gamma^t \, r\left(s(t), \pi\left(s(t)\right)\right)$$

$\pi : \mathcal{S} \rightarrow \mathcal{A}$

$\mathcal{S}$ ~ state space

$\mathcal{A}$ ~ action space

RL paradigms

tabular solutions: the action-value function is represented as an array or a table

approximate, gradient-descent, solutions: the state-action spaces involve continuous domains or complex representations (e.g. an image)

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

tabular solutions

representative methods

tabular solutions

- Q-learning: off policy, model-free RL
- State-Action-Reward-State-Action (SARSA): on policy, model-free RL

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

Q-learning*

off policy, model-free RL algorithm

- Q-learning approximates the optimal action-value function Q^* that maximizes the expected value over all successive steps**

$$Q: S \times A \rightarrow \mathbb{R}$$

- Q-learning does not require an environment model (model-free)
- π (policy) depends on Q
- Q depends on π (π determines which state-action pair should be updated)
- Q's update does not depend on π (off policy)

** Watkins, C.J.C.H., Dayan, P. Q-learning. Mach Learn 8, 279–292 (1992). https://doi.org/10.1007/BF00992698.*

*** Q has been shown to converge with probability 1 to q^* under minimal requirements.*

Q-learning

Bellman equation

$$Q(s_t, a_t) = (1 - \alpha) \cdot Q(s_t, a_t) + \alpha \cdot \left(r_{t+1} + \gamma \cdot max_a Q(s_{t+1}, a)\right)$$

where…

- $a_t = \pi(s_t)$
- r_{t+1} is the reward associated to the state-action pair (s_t, a_t)
- s_{t+1} is the new state after selecting the action a_t at state s_t
- α is the learning rate $(0 \leq \alpha \leq 1)$; the extent to which our Q-values are being updated in every iteration
- γ is the discount factor $(0 \leq \gamma \leq 1)$; relevance of future rewards (uncertain)
- $max_a Q(s_{t+1}, a)$ is the maximum value from state s_{t+1} (given the current Q)

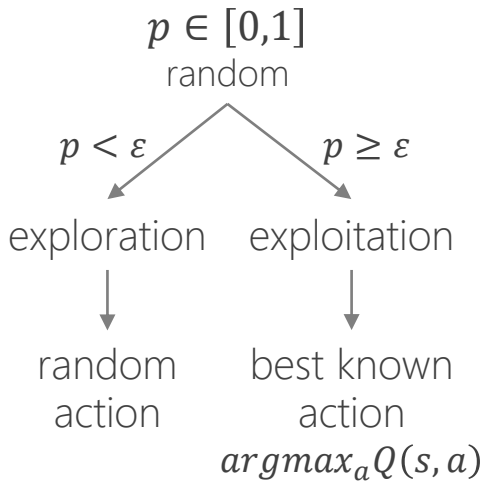
Source: Q-learning. Wikipedia.org.

Q-learning

off-policy learning

$$Q(s_t, a_t) = (1 - \alpha) \cdot Q(s_t, a_t) + \alpha \cdot \left(r_{t+1} + \gamma \cdot max_a Q(s_{t+1}, a)\right)$$

- Q's update does not involve the current (agent, behavior) policy π
- Q's update depends on $max_a Q(s_{t+1}, a)$, a greedy action from s_{t+1}
  - it is usually assumed an ε-greedy (agent, behavior) policy π



Q-learning

Bellman equation: remarks

- the Bellman equation is a recursion that computes the weighted average of the current value and the new learned value
- an episode of the algorithm ends when state s_{t+1} is a final state
- action values are finite even when no final state exists (provided that $\gamma < 1$)
- for final states s_f, $Q(s_f, a)$ is set to the reward observed and is never updated
- α determines to what extent newly acquired information overrides old information
  - $\alpha = 0$ makes the the agent learn nothing (exclusively exploiting prior knowledge)
  - $\alpha = 1$ makes the agent ignore prior knowledge (to explore new possibilities)
- γ determines the importance of future rewards
  - $\gamma = 0$ makes the agent "myopic"
  - $\gamma \geq 1$ the action values might diverge
- Q-learning fails with an infinite (or even large) number of states/actions

Source: Q-learning. Wikipedia.org.

Q-learning

algorithm

Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q (e.g., ϵ-greedy)
        Take action A, observe R, S'
        $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
        $S \leftarrow S'$;
    until S is terminal

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

SARSA: State-Action-Reward-State-Action*

on policy, model-free RL algorithm

- SARSA estimates $Q_\pi(s, a)$ for the current agent policy π and for all state-action pairs (s, a).

$$Q_\pi: S \times A \to \mathbb{R}$$

- SARSA does not require an environment model (model-free)

- π depends on Q; Q depends on π (π determines which state-action pair should be updated), and Q's update does depend on π (on policy)

- SARSA makes up a transition from one state-action pair to the next

** RUMMERY, G.A.; NIRANJAN, M. On-line Q-learning using connectionist systems. Univ. of Cambridge, Dept. of Engineering, UK, 1994.*

SARSA: State-Action-Reward-State-Action

Bellman equation

$$Q(s_t, a_t) = (1 - \alpha) \cdot Q(s_t, a_t) + \alpha \cdot \left(r_{t+1} + \gamma \cdot Q(s_{t+1}, a_{t+1})\right)$$

where…

- $a_t = \pi(s_t)$, $a_{t+1} = \pi(s_{t+1})$
- r_{t+1} is the reward associated to the state-action pair (s_t, a_t)
- s_{t+1} is the new state after selecting the action a_t at state s_t
- α is the learning rate $(0 \leq \alpha \leq 1)$
- γ is the discount factor $(0 \leq \gamma \leq 1)$
- $Q(s_{t+1}, a_{t+1})$ is the accumulated reward determines by the current π

Source: Q-learning. Wikipedia.org.

SARSA: State-Action-Reward-State-Action

on-policy learning

$$Q(s_t, a_t) = (1 - \alpha) \cdot Q(s_t, a_t) + \alpha \cdot \left(r_{t+1} + \gamma \cdot \underbrace{Q(s_{t+1}, a_{t+1})}_{a_{t+1} = \pi(s_{t+1})}\right)$$

- Q's update does depend on the current (agent, behavior) policy π

SARSA: State-Action-Reward-State-Action *algorithm*

Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
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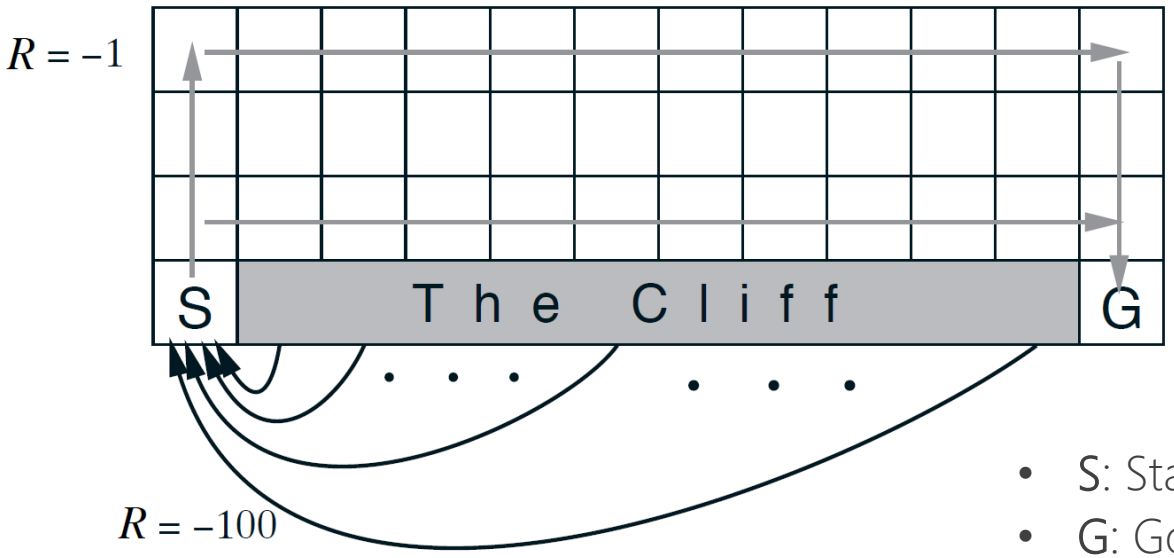
    until S is terminal

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

Q-learning versus SARSA

Cliff walking example

which path do you think was learned by each method?



- S: Start state
- G: Goal state
- actions: up, down, right, and left
- reward = -1 except into "The Cliff"
- reward = -100 in the "The Cliff"
- $\varepsilon = 0.1$

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

Q-learning versus SARSA

Cliff walking example

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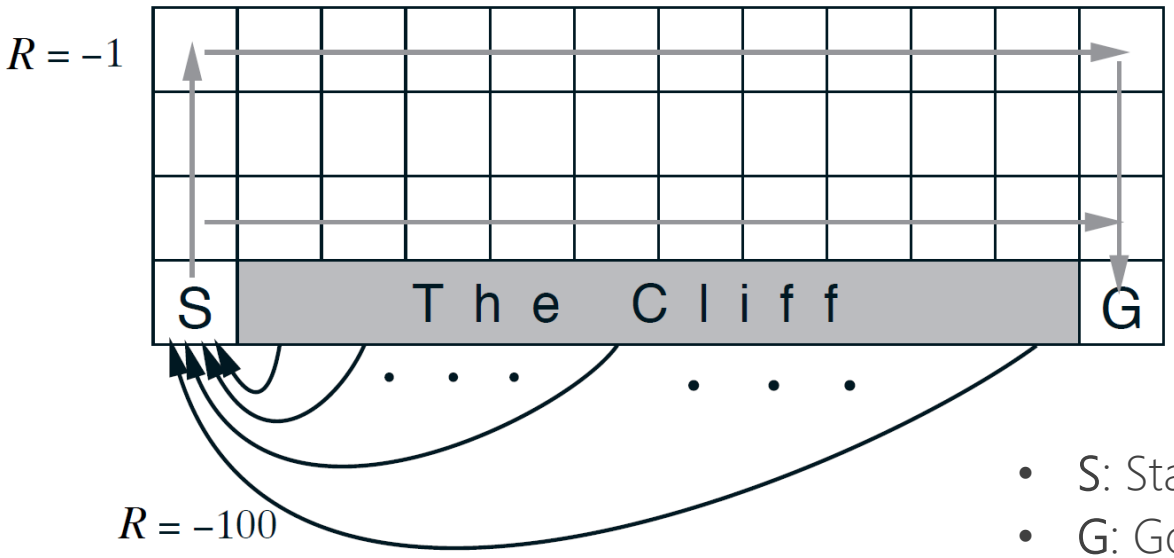

safe path -> SARSA

optimal path -> Q-learning

- S: Start state
- G: Goal state
- actions: up, down, right, and left
- reward = -1 except into "The Cliff"
- reward = -100 in the "The Cliff"
- $\varepsilon = 0.1$

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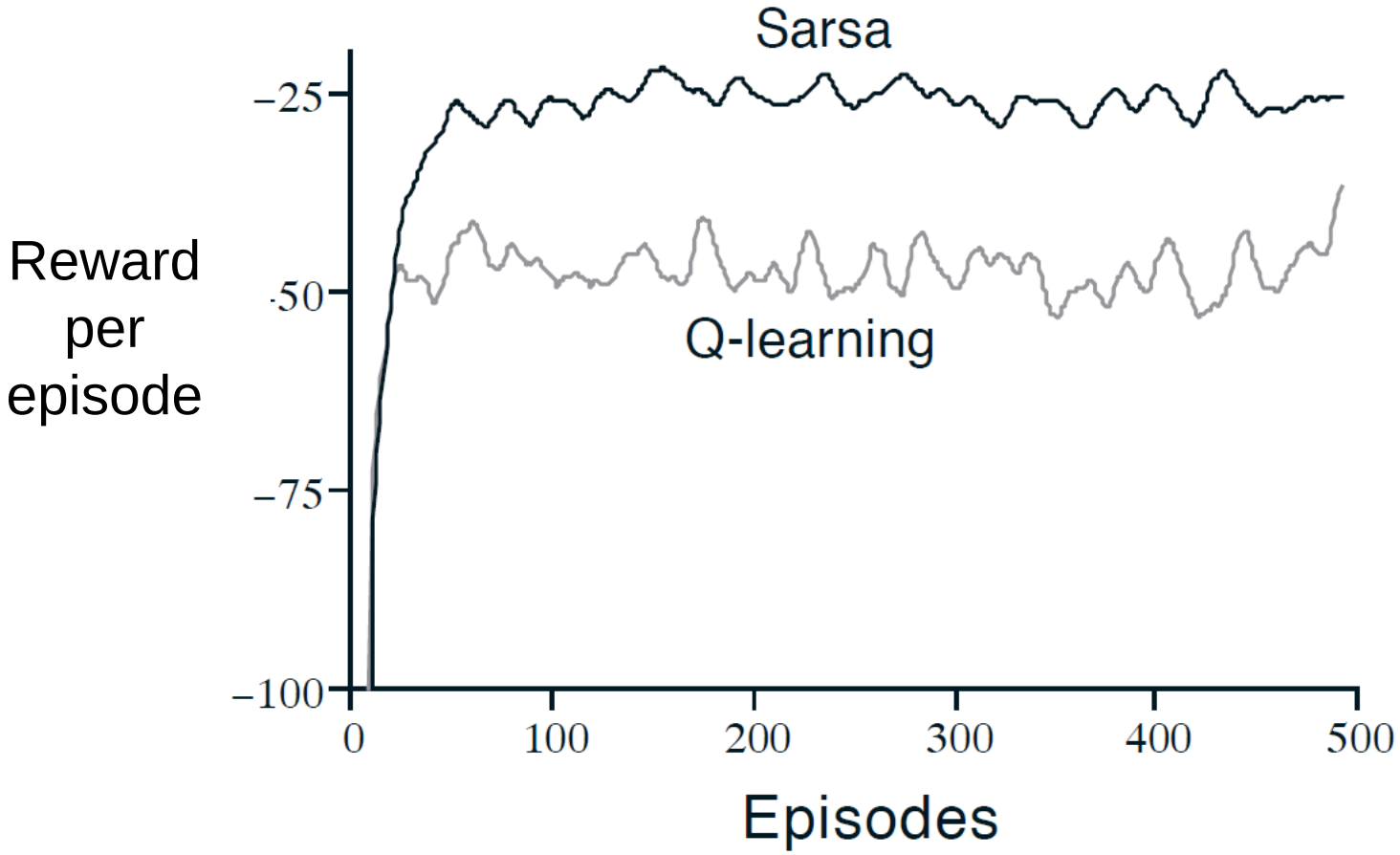
Q-learning versus SARSA

Cliff walking example



Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

tabular solutions

limitations

- assumption: value estimates are represented as a table with one entry for each state or for each state-action pair
- memory problems: it is limited to tasks with small numbers of states and actions; if not, there could be memory problems
- generalization problems: large tables also need large volumes of data and time to generalize (fill) them properly
- unobserved states: in many RL tasks, most states encountered will never have been experienced exactly before

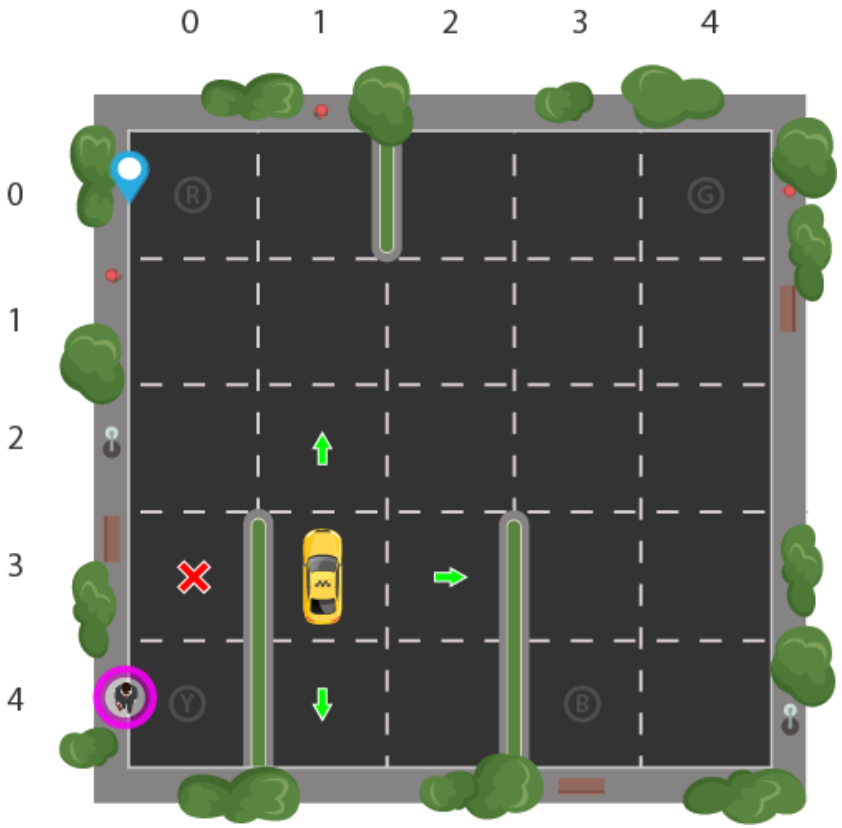
Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

a self-driving cab

case study

smart-cab goals are…

- pick up a passenger at one location
- drop off the passenger to the right location
- save time by taking the shortest path
- ensure passenger safety
- comply with rules



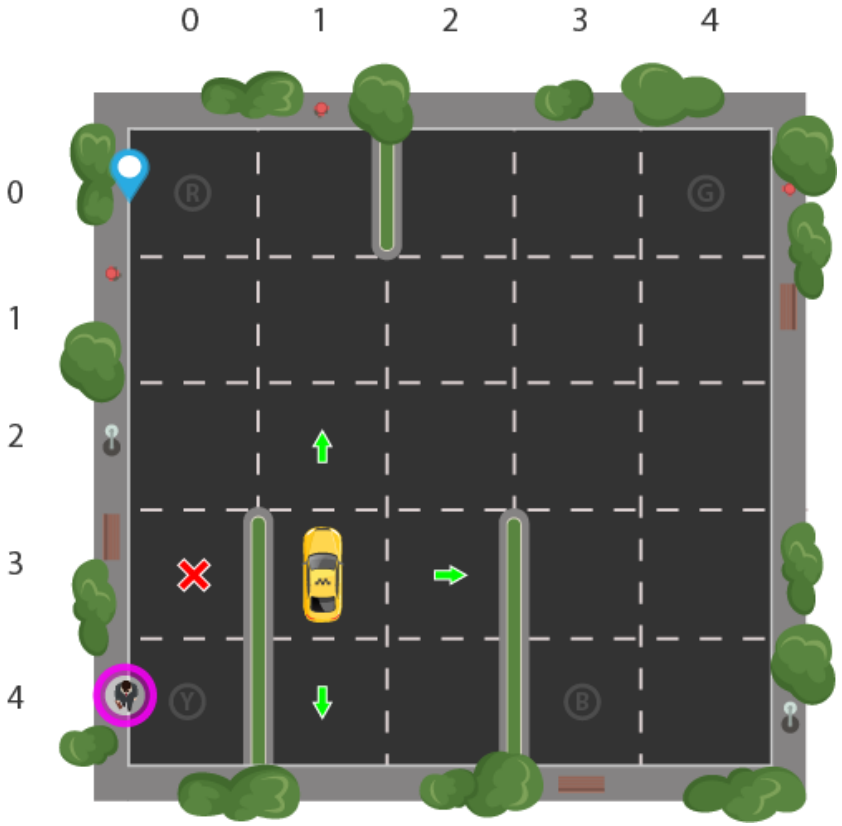
Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

a self-driving cab

state space

state space

- taxi locations: a coordinate in a 5 x 5 grid
- passenger locations: 5 = 4 coord. to pick up the passenger (R, G, Y, B) + 1 (taxi location)
- destination locations: 4 (R + G + Y + B)
- state space size = 5 x 5 x 5 x 4 = 500 states
- state example: (3, 1, 2, 0) -> 328
  - taxi location: coordinate (3, 1)
  - passenger location: 2 (Y coordinate)
  - destination location: 0 (R coordinate)
  - internal code: 328 ∈ [0, 499]



Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

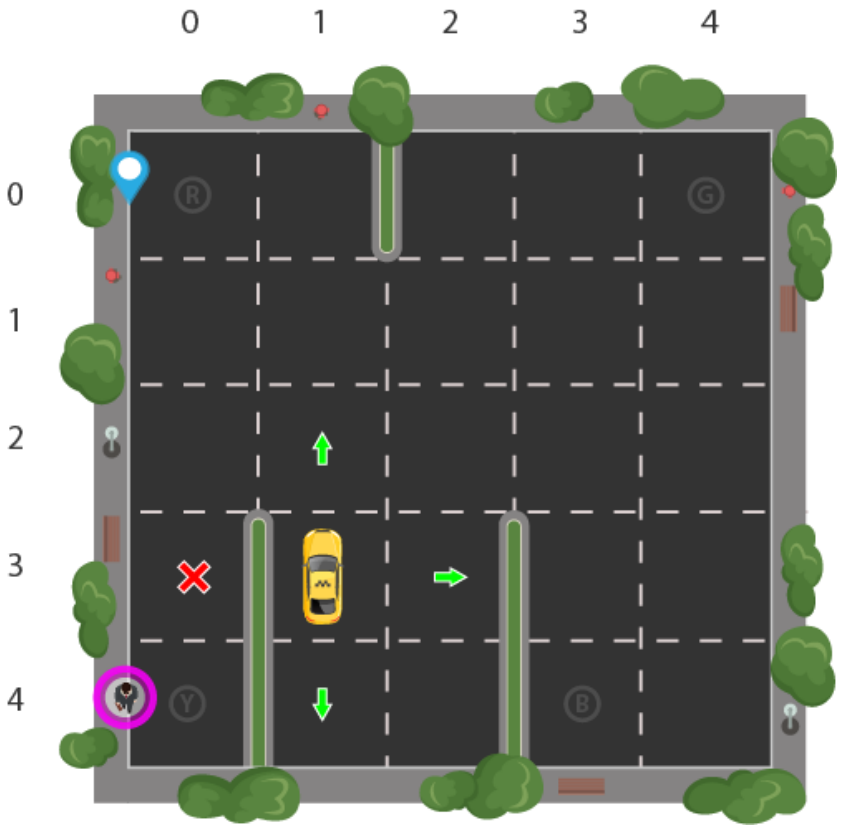
a self-driving cab

action space

action space (set of all the actions)

1. south
2. north
3. east
4. west
5. pickup
6. dropoff

- action space size = 6 actions
- some actions are impossible due to walls
- wall hits are penalized:
  - penalty/reward: -1
  - the taxi does not move anywhere



Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

a self-driving cab

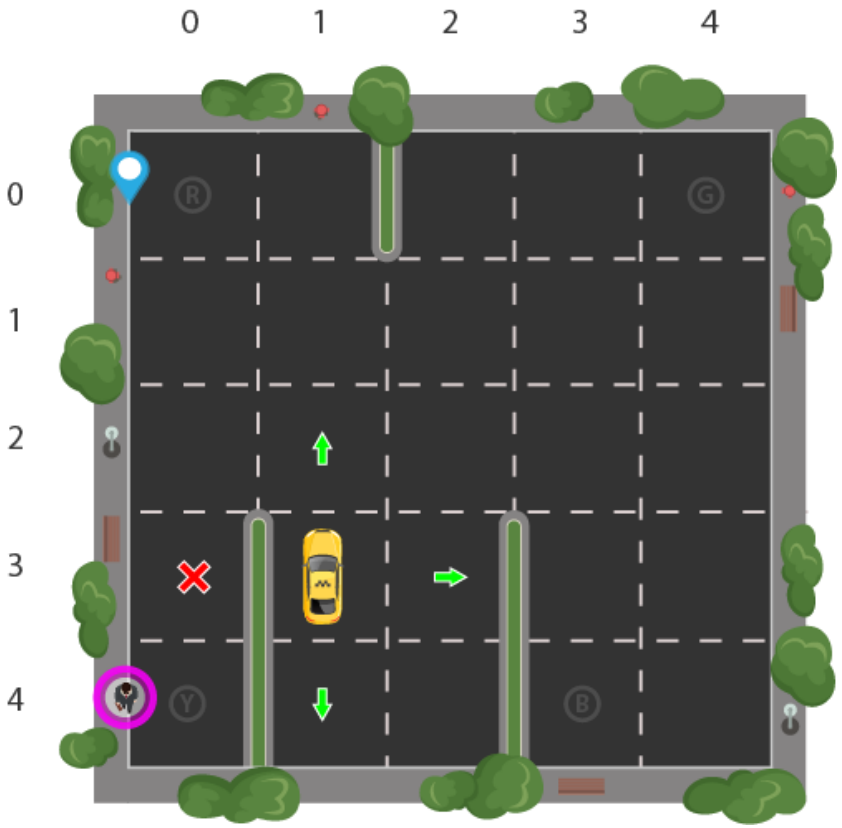
rewards

rewards

- a high positive reward for a successful dropoff
- a high negative reward for a wrong dropoff
- a slight negative reward for every time-step
- reward table: *State Space* X *Action Space* matrix
- reward table[state] returns a dictionary…

  {action: [(probability, nextstate, reward, done)]}
- rewards at state (row, entry) 328

  { 0: [(1.0, 428, -1, False)],
  1: [(1.0, 228, -1, False)],
  2: [(1.0, 348, -1, False)],
  3: [(1.0, 328, -1, False)],
  4: [(1.0, 328, -10, False)],
  5: [(1.0, 328, -10, False)]}



Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

a self-driving cab

Q-learning

Initialized

Q-Table		Actions					
		South (0)	North (1)	East (2)	West (3)	Pickup (4)	Dropoff (5)
States	0	0	0	0	0	0	0
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	327	0	0	0	0	0	0
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	499	0	0	0	0	0	0

Training

Q-Table		Actions					
		South (0)	North (1)	East (2)	West (3)	Pickup (4)	Dropoff (5)
States	0	0	0	0	0	0	0
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	328	-2.30108105	-1.97092096	-2.30357004	-2.20591839	-10.3607344	-8.5583017
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	499	9.96984239	4.02706992	12.96022777	29	3.32877873	3.38230603

Source: Satwik Kansal, Brendan Martin. Reinforcement Q-Learning from Scratch in Python with OpenAI Gym. LearnDataSci, 2023.

RL paradigms

tabular solutions: the action-value function is represented as an array or a table

approximate, gradient-descent, solutions: the state-action spaces involve continuous domains or complex representations (e.g. an image)

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

approximate solutions
motivation

- continuous, infinite state/action spaces: it requires generalization from previously experienced states to ones that have never been seen.

- online function approximation

  - it takes earlier examples from previous interactions between the agent and the environment (bootstrap)

  - it learns by bootstrapping from current estimates of the value function

  - generalization from selected examples as in supervised learning (by comparing current function outputs against expectations)

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

approximate solutions
introduction

learning problem (the usual one)

on policy learning

- to learn a policy π based on a state-value function $v_\pi(s)$

novelty

- the unknown state-value function $v_\pi(s)$ is approximated by a parameterized function $\hat{v}_w(s)$ with a parameter vector $w \in \mathbb{R}^n$
- $\hat{v}_w(s)$ can be a deep artificial neural network, with w being the vector of connection weights (deep reinforcement learning)

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

approximate solutions

state value function approximation

assumption: there exist $v_\pi(s_t)$ that computes the *true value* from a state s_t at time step t under de policy π, $\forall t = 1,2,3, \ldots$

goal: to find w such that $\hat{v}_w(s_t)$ best approximates $v_\pi(s_t)$

gradient-descent method:

the change is proportional to the negative gradient of the example's squared error

$$w_{t+1} = w_t - \frac{1}{2}\alpha\nabla\left[v_\pi(s_t) - \hat{v}_{w_t}(s_t)\right]^2$$

$$= w_t + \alpha\left[v_\pi(s_t) - \hat{v}_{w_t}(s_t)\right]\nabla\hat{v}_{w_t}(s_t)$$

learning rate
step-size param.

$$\left(\frac{\partial\hat{v}_{w_t}(s_t)}{\partial w_{t,1}}, \frac{\partial\hat{v}_{w_t}(s_t)}{\partial w_{t,2}}, \ldots, \frac{\partial\hat{v}_{w_t}(s_t)}{\partial w_{t,n}}\right)$$

under certain conditions, the method converges to a local minimum

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

approximate solutions

state value function approximation

what if $v_\pi(s_t)$ is unknown? the *true value* does not exist

alternative: a rough/noisy approximation v_t of $v_\pi(s_t)$; for example:

$$v_t = r_{t+1} + \gamma \hat{v}_{w_t}(s_{t+1})$$

$$s_{t+1}, r_{t+1} \leftarrow env\big(s_t, \pi(s_t)\big)$$

gradient-descent method:

$$w_{t+1} = w_t + \alpha\big[v_t - \hat{v}_{w_t}(s_t)\big]\nabla \hat{v}_{w_t}(s_t)$$

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

approximate solutions

neural networks are function approximators

neural networks are particularly useful in RL when

the state space or action space are too large

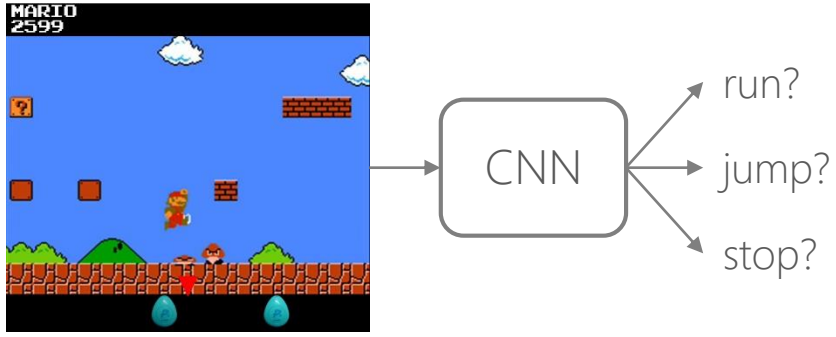
to be completely known

Source: Chris V. Nicholson. A Beginner's Guide to Deep Reinforcement Learning. Pathmind Inc., 2023.

approximate solutions

neural networks are function approximators

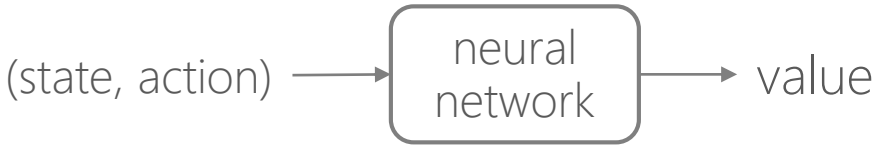
policy $a = \hat{\pi}_w(s)$



source: flickr.com

value function $v = \hat{v}_w(s)$

Q-value function $v = \hat{v}_w(s, a)$



approximate solutions

actor-critic methods

previous methods

have policy implementations that directly use the value function of states or state-action pairs in choosing an action (e.g. ε-greedy)

actor-critic methods

have a separate memory structure to explicitly represent the policy independent of the value function

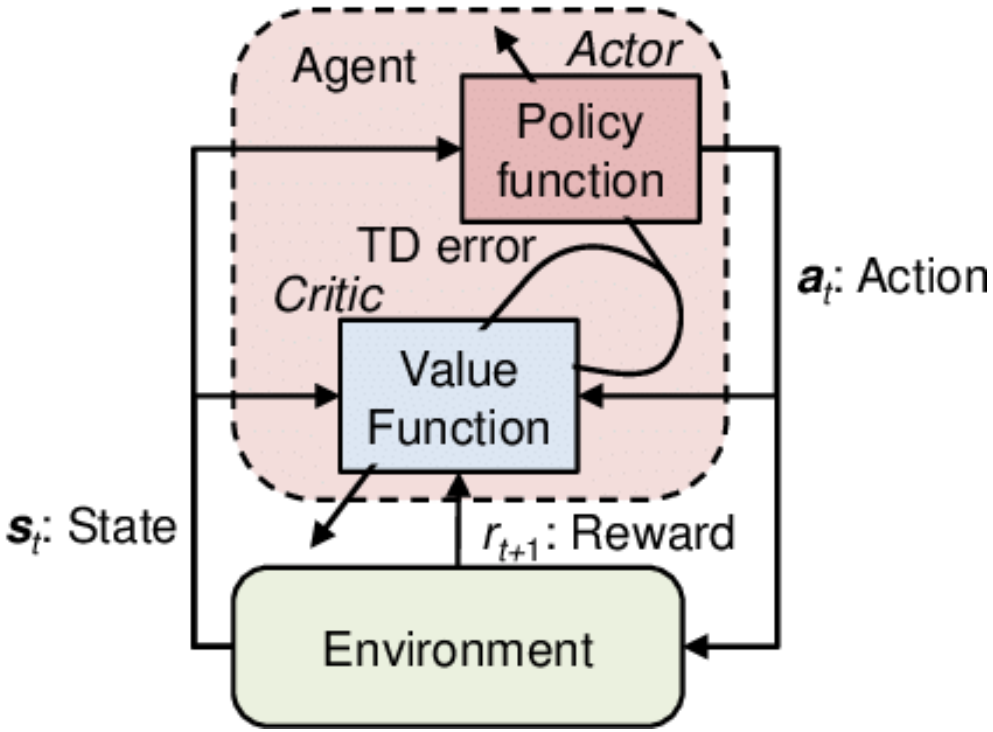
Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

actor-critic methods

architecture

actor (policy): select actions

critic (value): criticizes the actions made by the actor



Source: Fuji, Taiki & Ito, Kiyoto & Matsumoto, Kohsei & Yano, Kazuo. (2018). Deep Multi-Agent Reinforcement Learning using DNN-Weight Evolution to Optimize Supply Chain Performance. 10.24251/HICSS.2018.157.

Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

actor-critic methods

architecture

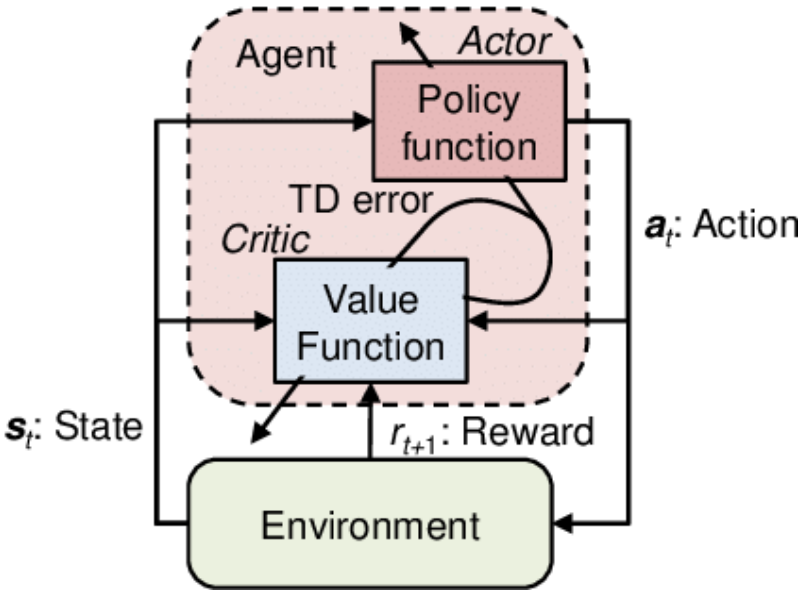
- the critique error (a scalar) drives learning in both actor and critic
- after each action a_t, the critic evaluates the new state s_t to determine whether things have gone better or worse than expected.
- critique error:

  $\delta_t = r_{t+1} + \gamma v_t(s_{t+1}) - v(s_t)$

- where…

  v_t is the critique value at time t

  v is an expected state value



Source: SUTTON, Richard S.; BARTO, Andrew G. Reinforcement learning: An introduction. MIT press, 2018.

Deep Deterministic Policy Gradient (DDPG)

an actor-critic method

learning overview

- Q-function (critic) and a policy μ (actor) are learned iteratively and alternately
- Q-function learning involves off-policy data (a policy different from the agent's)
- policy learning is based on the Q-function
- Q-function and policy μ are deep neural networks

scope overview

- DDPG is an actor-critic method
- DDPG is an off-policy algorithm
- DDPG can only be used for environments with continuous action spaces
- DDPG can be understood as a deep Q-learning for continuous action spaces

Source: Deep Deterministic Policy Gradient. Copyright 2018, OpenAI. Link.

Deep Deterministic Policy Gradient (DDPG)

two key tricks

experience replay buffer

- the replay buffer ($\mathcal{R}$) is the set of previous experiences $(s_t, a_t, r_{t+1}, s_{t+1})$
- $\mathcal{R}$ should be as large and diverse as possible (useful for learning)
- a random minibatch $\mathcal{B}_t$ of N transitions is sampled from $\mathcal{R}$ at each learning step t
- $\mathcal{B}_t$ is used to update both the Q-function and the policy networks

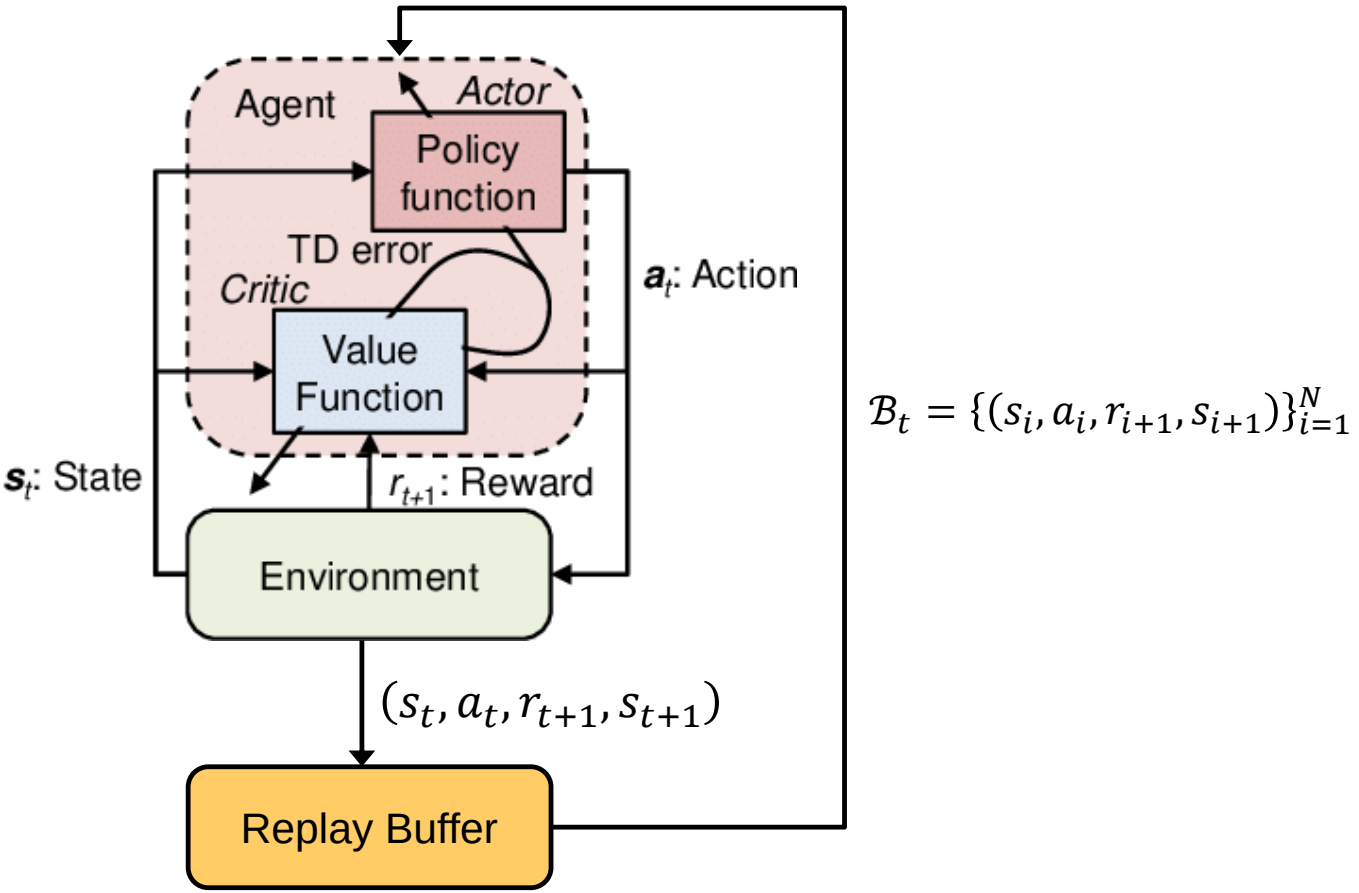
target networks (intended to make the loss minimization stable)

- lagging versions of the Q-function and the policy (main) networks
- target networks do not change when main networks are being updated
- target networks provide more stable expectations for main networks updates
- target network are updated once after main network update by Polyak averaging (+)

Source: Deep Deterministic Policy Gradient. Copyright 2018, OpenAI. Link.

Deep Deterministic Policy Gradient (DDPG)

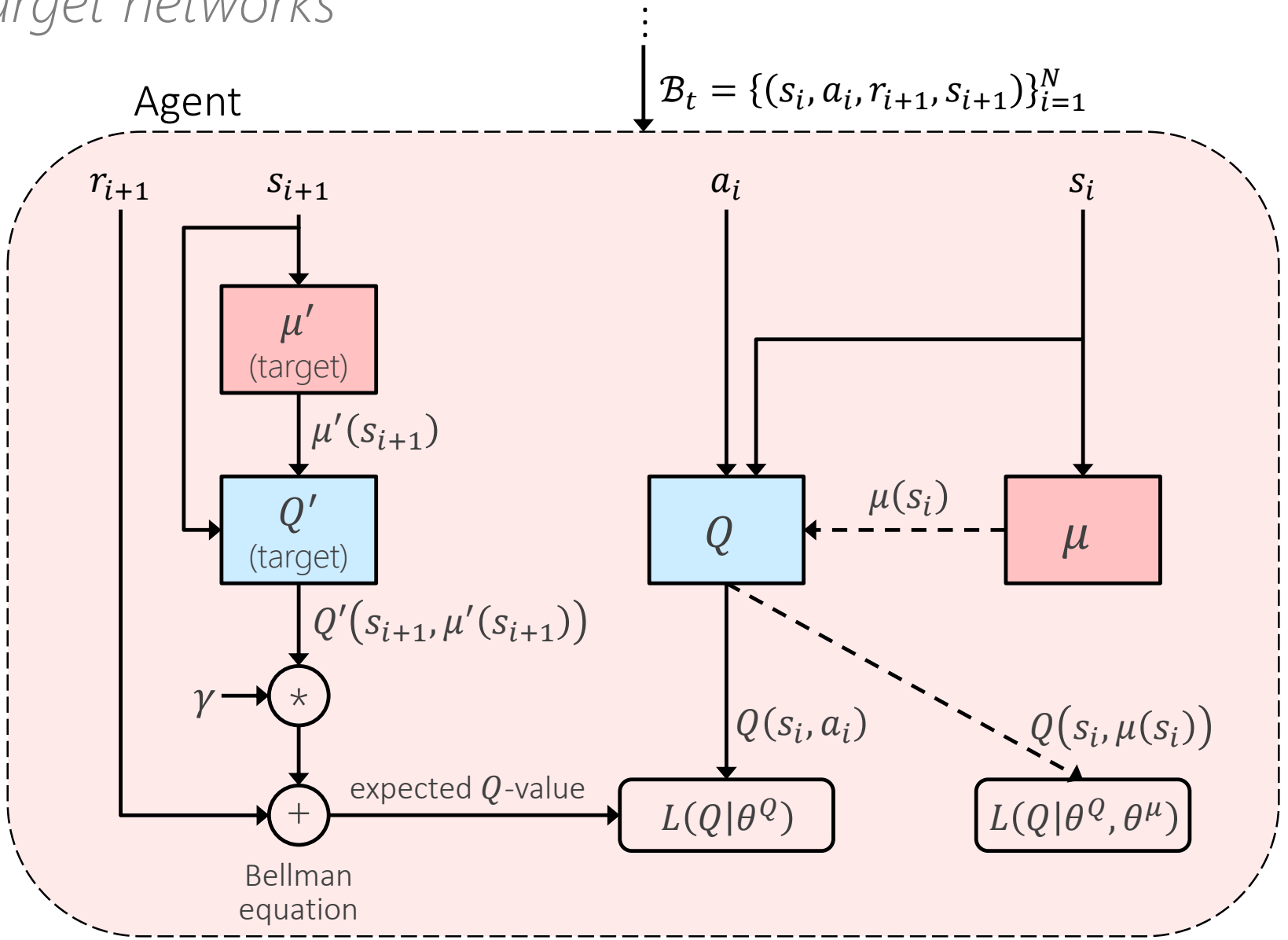
experience replay buffer



Source: Deep Deterministic Policy Gradient. Copyright 2018, OpenAI. Link.

Deep Deterministic Policy Gradient (DDPG)

target networks



Deep Deterministic Policy Gradient

algorithm

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Source: LILLICRAP, Timothy P., et al. Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971, 2015.

bootstrapping

overview

- bootstrap method: statistical technique for estimating quantities about a population by averaging estimates from multiple small data samples (sets).
- a data sample is constructed by drawing individual observations from a large data sample with replacement
- an observation can thus be included in a given sample more than once
- bootstrapping usually perform better than nonbootstrapping methods
- bootstrapping methods are of great interest to RL

Source: Jason Brownlee. Gentle Introduction to the Bootstrap Method. machinelearningmastery.com, 2019 (link).

bootstrapping

algorithm

1. Choose a number of bootstrap samples (iterations) to perform
2. Choose a bootstrap sample size
3. For each bootstrap sample
    a. Draw a sample with replacement with the chosen size
    b. Calculate the statistic on the sample
4. Calculate the mean of the sample statistics

Source: Jason Brownlee. Gentle Introduction to the Bootstrap Method. machinelearningmastery.com, 2019 (link).

summary

- RL goal: to learn how to map each state to the most promising action
- exploitation/exploration dilemma: exploit known actions or explore new actions
- RL elements: a policy π, a reward signal, a value function, an environment model
- tabular solutions: suitable for finite and small spaces of state and action
- gradient-descent solutions: suitable for continuous and infinite spaces of st & act
- off-policy learning: Q's update does not depend on the agent policy π
- on-policy learning: Q's update does depend on the agent policy π
- Deep Deterministic Policy Gradient (DDPG) is an actor-critic method
- actor-critic method: the policy function is fully independent of the value function