Reinforcement learning

A brief overview through the A3C paper

BACK TO BASICS

1

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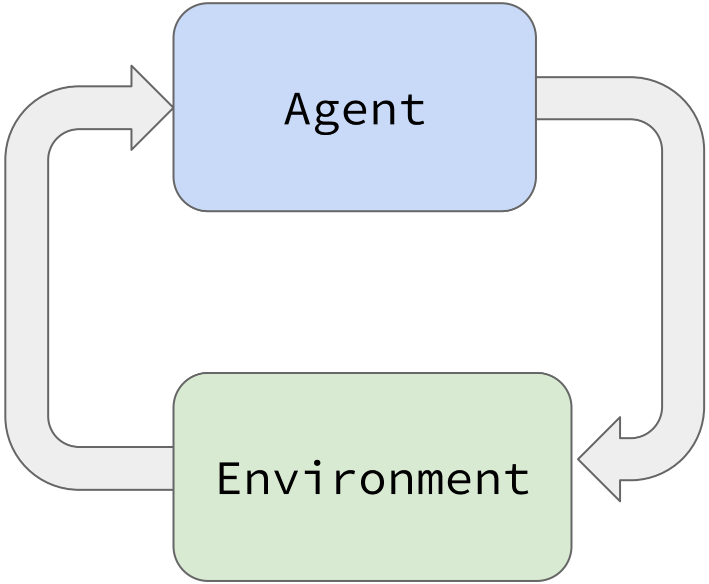
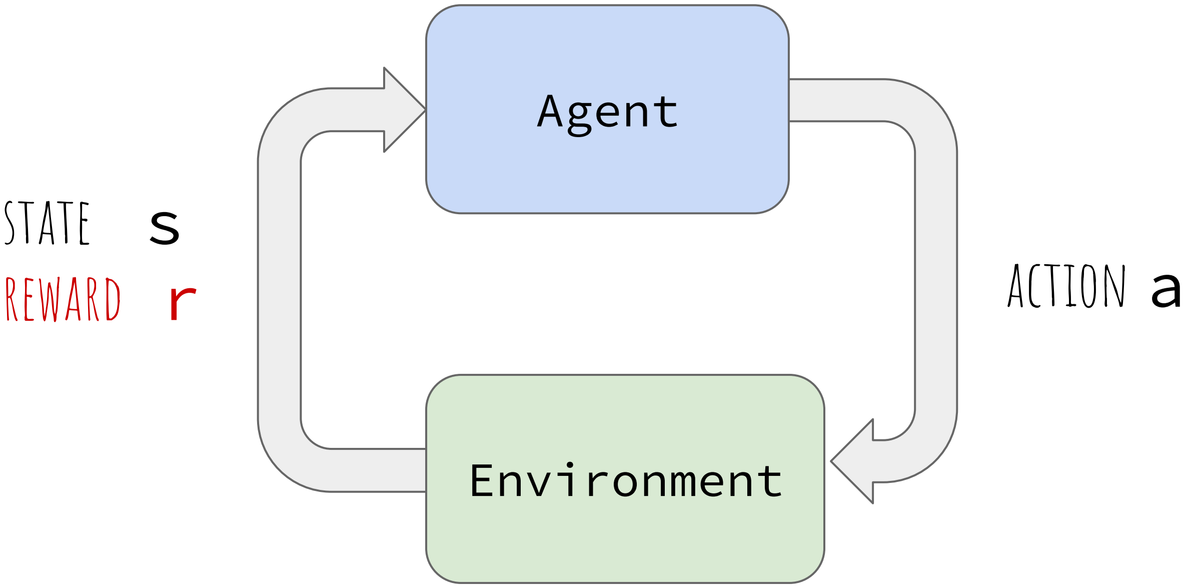
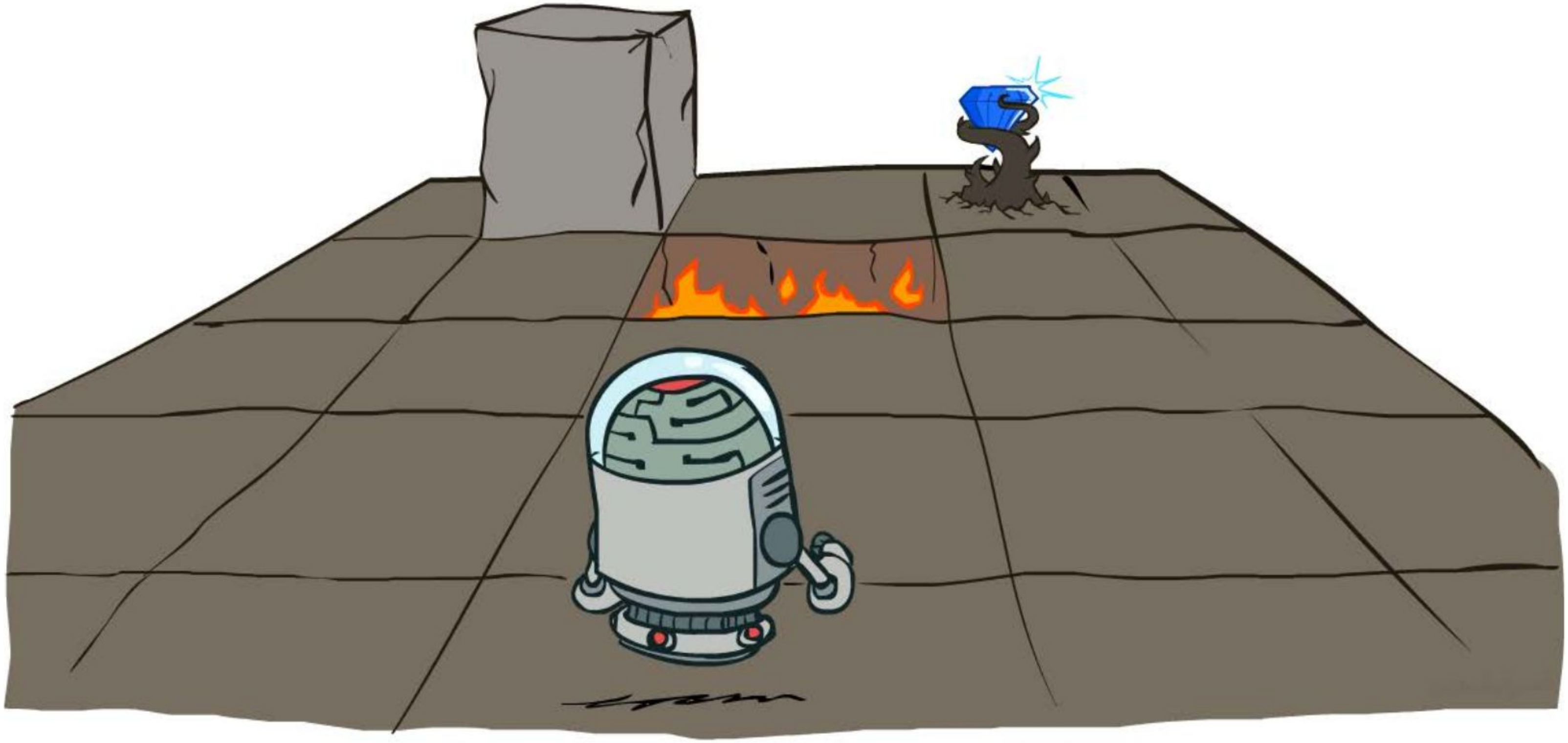


BACK TO BASICS



Markov Decision Processes : Example



Markov Decision Processes

Markov Decision Processes

set of actions $a \in A$

set of states $s \in S$

transition function $T(s, a, s')$

reward function $R(s, a, s')$

start / terminal state

Markov Decision Processes

Andrey Markov
1856 - 1922

Markov Decision Processes

The stochastic process is memoryless

Markov Decision Processes

The stochastic process is memoryless

$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t, \ldots S_0 = s_0)$$

$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t)$$

RL Framework

RL Framework

At each timestep t:

RL Framework

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- The agent receives a **state** s_t from S

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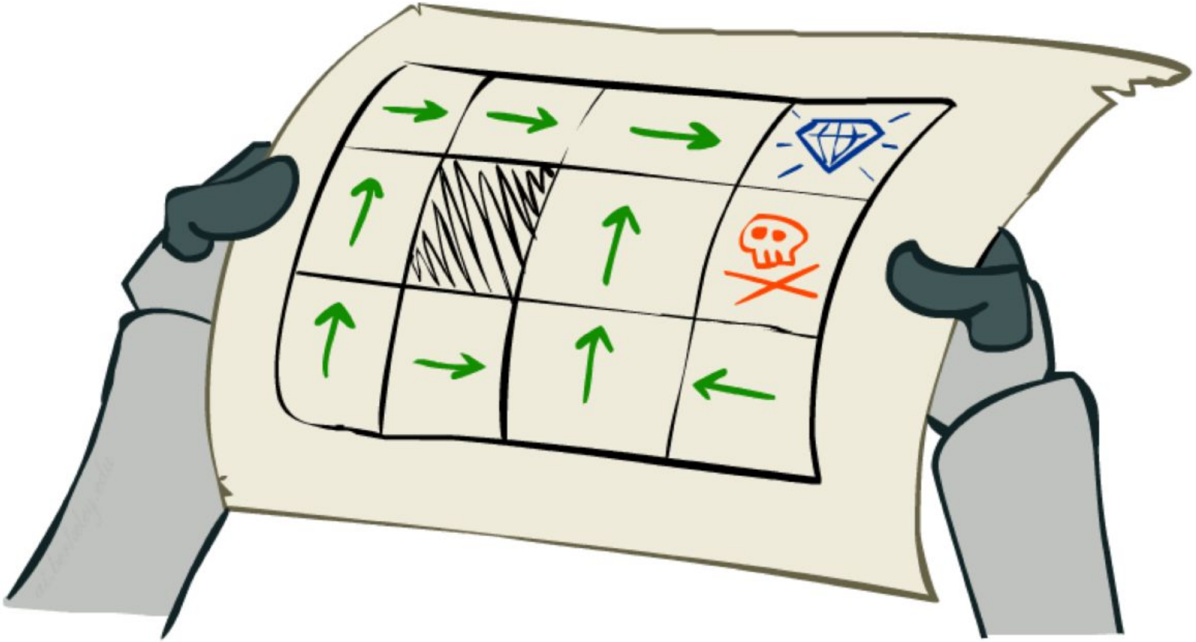
The goal of the agent is to maximize the **expected return** from each state s_t

Goal



Value Methods

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State value

$$V^{\pi}(\boldsymbol{s}) = \mathbb{E}[R_t | \boldsymbol{s}_t = \boldsymbol{s}]$$

Value Methods

State value $V^\pi(s) = \mathbb{E}[R_t | s_t = s]$

Action value $Q^\pi(s, a) = \mathbb{E}[R_t | s_t = s, a_t = a]$

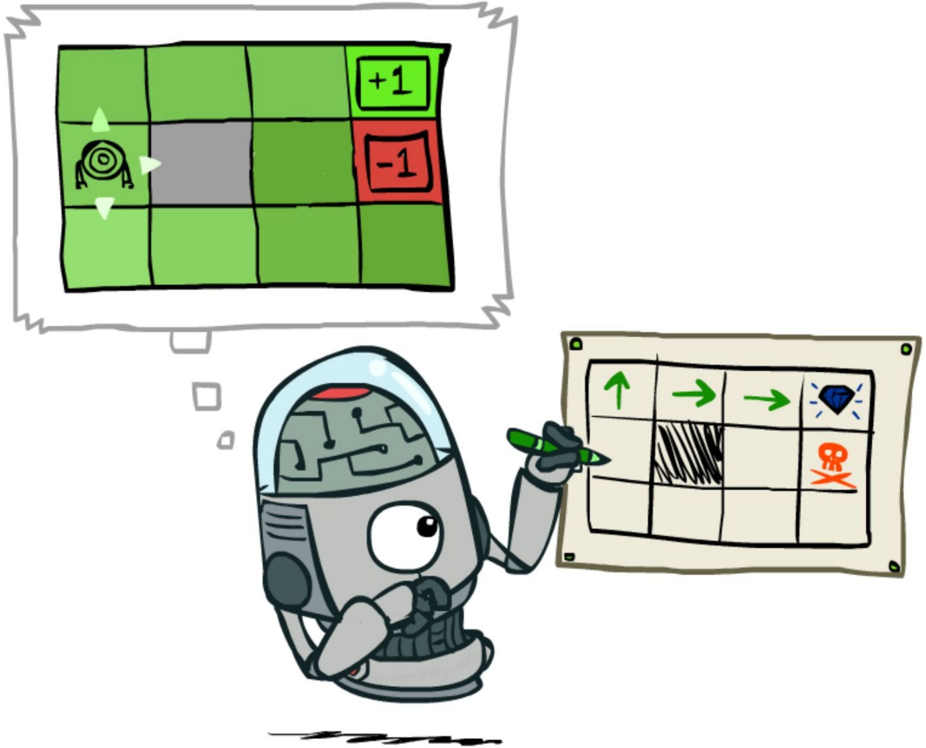
Value Methods

State value $V^\pi(s) = \mathbb{E}[R_t | s_t = s]$

Action value $Q^\pi(s, a) = \mathbb{E}[R_t | s_t = s, a_t = a]$

Optimal value function $Q^*(s, a) = \max_\pi Q^\pi(s, a)$

Value Methods



Q-Learning

Q-Learning

$$Q^{new}(s_t, a_t) \leftarrow (1-\alpha)Q^{old}(s_t, a_t) + \alpha(r_t + \gamma \max_{a'} Q^{old}(s_{t+1}, a'))$$

Approximate setting

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$$Q(s, a; \theta)$$

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$$Q^*(s, a) \approx Q(s, a; \theta)$$

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$$L_i(\theta_i) = \mathbb{E}[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) - Q(s, a; \theta_i)]^2$$

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r directly affects one Q(s,a)

N-step Q-Learning

N-step Q-Learning

Use n-step return instead!

$$R^n = r_t + \gamma r_{t+1} + \ldots + \gamma^{n-1} r_{t+n-1} + \max_a \gamma^n Q(s_{t+n}, a)$$

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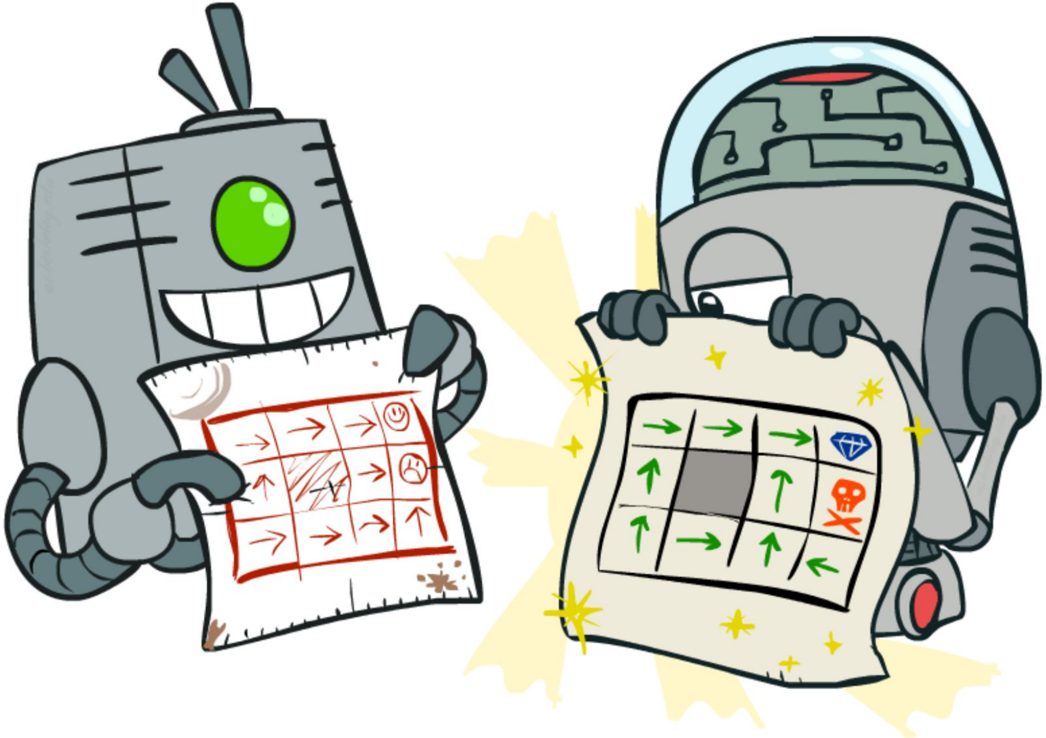
Policy Methods



Policy Methods

Value methods: implicit policy

$$\pi(a|s)$$

Policy Methods

Value methods: implicit policy $\pi(a|s)$

Policy methods: explicit policy $\pi(a|s;\theta)$

Policy Methods

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Gradient ascent on the return $\mathbb{E}[R_t]$

Policy Methods

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Policy methods: explicit policy $\pi(a|s;\theta)$

Gradient ascent on the return $\mathbb{E}[R_t]$

REINFORCE update $\nabla_\theta \log \pi(a_t|s_t;\theta)R_t$

Williams, 1992

Policy Methods

REINFORCE update

$$\nabla_\theta \log \pi(a_t | s_t ; \theta) R_t$$

Policy Methods

REINFORCE update

$$\nabla_\theta \log \pi(a_t | s_t; \theta) R_t$$

Variance problem

Policy Methods

REINFORCE update $\nabla_\theta \log \pi(a_t | s_t ; \theta) R_t$

Variance problem $\nabla_\theta \log \pi(a_t | s_t ; \theta)(R_t - b_t(s_t))$

Policy Methods

REINFORCE update $\nabla_\theta \log \pi(a_t | s_t; \theta) R_t$

Variance problem $\nabla_\theta \log \pi(a_t | s_t; \theta)(R_t - b_t(s_t))$

Common baseline $b_t(s_t) \approx V^\pi(s_t)$

Policy Methods

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Advantage

$$A(a_t, s_t) = Q(a_t, s_t) - V(s_t)$$

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$$A(a_t, s_t) = Q(a_t, s_t) - V(s_t)$$

Sutton & Barto, 1998; Degris *et al*. 2012

ASYNCHRONOUS RL

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Mnih et al, 2016

Asynchronous Methods for Deep Reinforcement Learning

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Abstract

We propose a conceptually simple and lightweight framework for deep reinforcement learning that uses asynchronous gradient descent for optimization of deep neural network controllers. We present asynchronous variants of

line RL updates are strongly correlated. By storing the agent's data in an experience replay memory, the data can be batched (Riedmiller, 2005; Schulman et al., 2015a) or randomly sampled (Mnih et al., 2013; 2015; Van Hasselt et al., 2015) from different time-steps. Aggregating over memory in this way reduces non-stationarity and decorrelates updates, but at the same time limits the methods to

MOTIVATION

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RL + function approximation = ?

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Strongly correlated online RL updates

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Experience replay

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Off-policy only

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Asynchronous RL

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Multiple agents in parallel

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Multiple instances of the environment

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On-policy: Sarsa, n-step methods, actor-critic methods

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GPU -> CPU

Asynchronous RL framework

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1 asynchronous actor-learner = 1 thread

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1 asynchronous actor-learner = 1 different exploration policy

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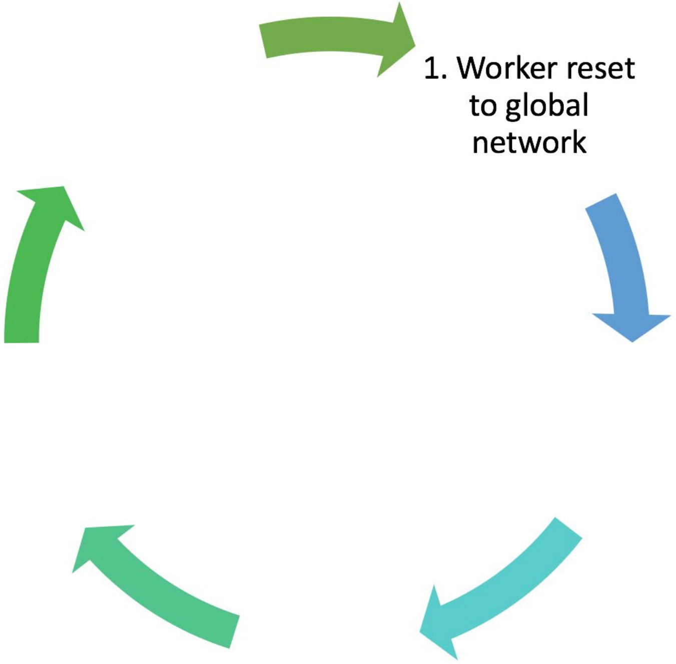
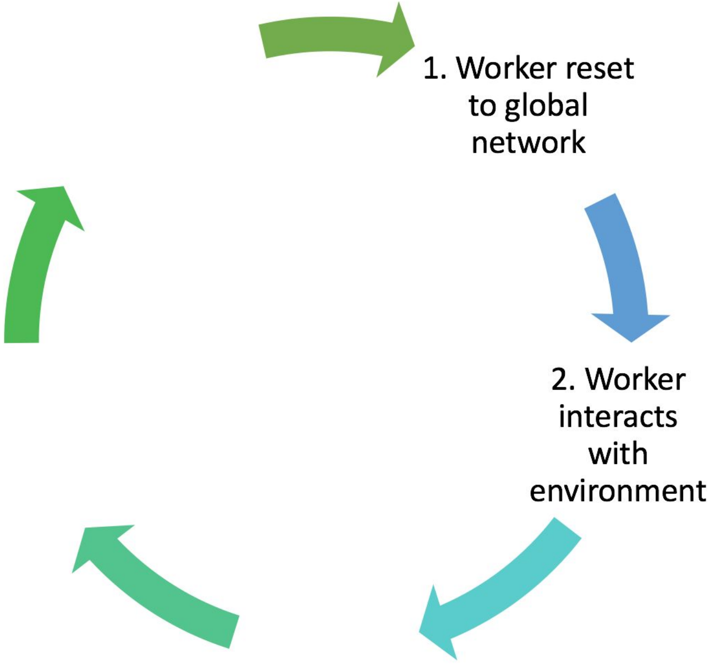
No replay memory

Asynchronous RL framework



Asynchronous RL framework



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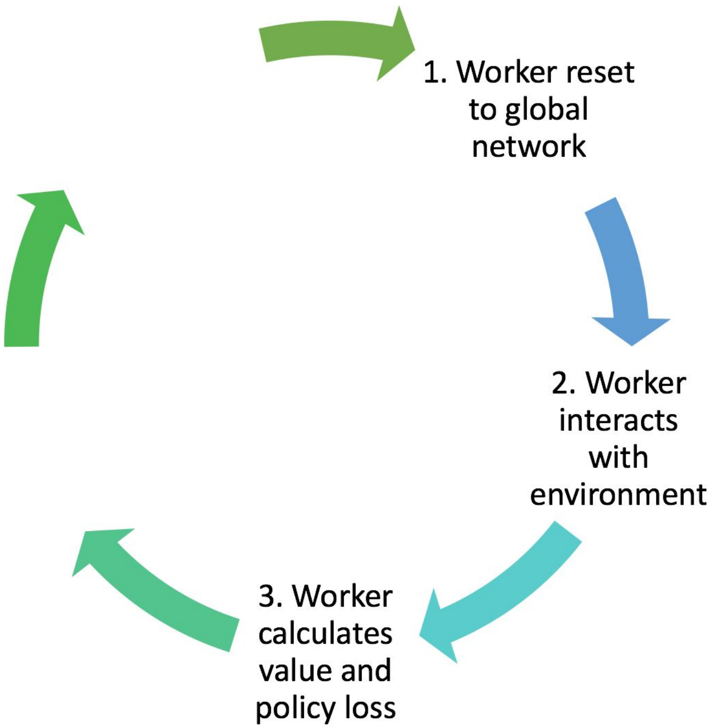

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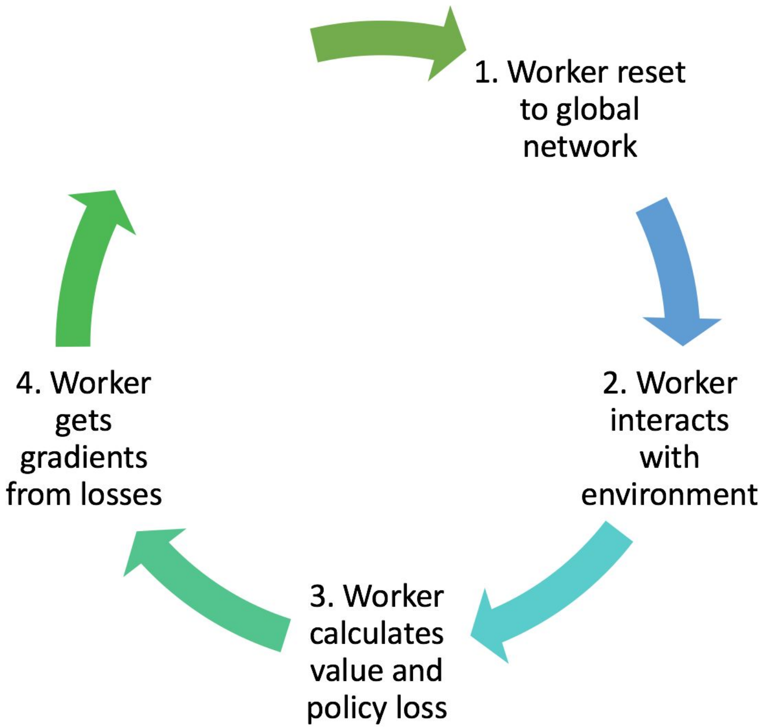

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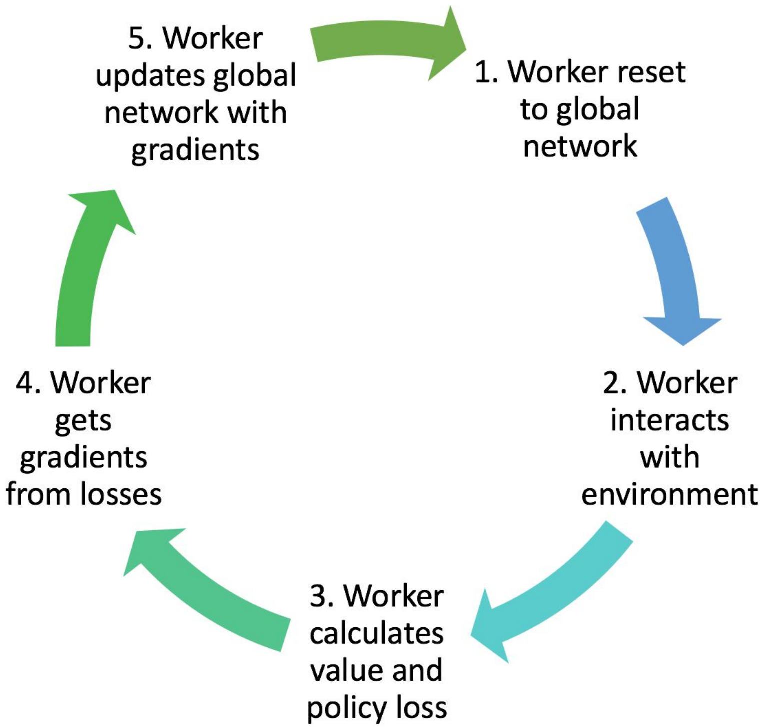

Asynchronous one-step Q-learning

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Accumulate gradients over multiple time steps

Algorithm 1 Asynchronous one-step Q-learning - pseudocode for each actor-learner thread.

// Assume global shared θ, θ^-, and counter $T = 0$.
Initialize thread step counter $t \leftarrow 0$
Initialize target network weights $\theta^- \leftarrow \theta$
Initialize network gradients $d\theta \leftarrow 0$
Get initial state s
repeat
    Take action a with ϵ-greedy policy based on $Q(s, a; \theta)$
    Receive new state s' and reward r
    $y = \begin{cases} r & \text{for terminal } s' \\ r + \gamma \max_{a'} Q(s', a'; \theta^-) & \text{for non-terminal } s' \end{cases}$
    Accumulate gradients wrt θ: $d\theta \leftarrow d\theta + \frac{\partial (y - Q(s,a;\theta))^2}{\partial \theta}$
    $s = s'$
    $T \leftarrow T + 1$ and $t \leftarrow t + 1$
    if $T \mod I_{target} == 0$ **then**
        Update the target network $\theta^- \leftarrow \theta$
    end if
    if $t \mod I_{AsyncUpdate} == 0$ or s is terminal **then**
        Perform asynchronous update of θ using $d\theta$.
        Clear gradients $d\theta \leftarrow 0$.
    end if
until $T > T_{max}$

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Sarsa

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Easier for training NNs with momentum

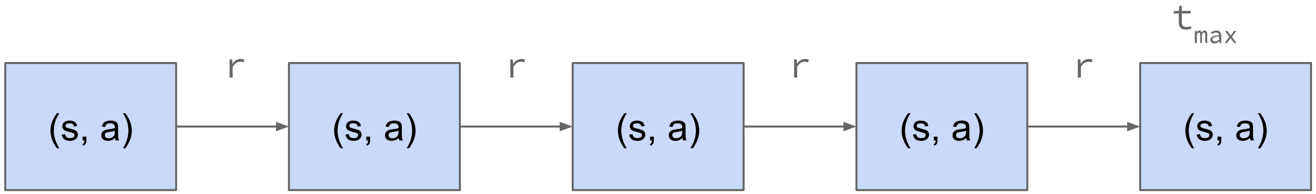
Asynchronous n-step Q-learning

Use forward view instead of backward view

Easier for training NNs with momentum

First select actions up to t_{max} or until terminal state

Asynchronous n-step Q-learning



Asynchronous Advantage Actor Critic (A3C)

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Maintains $\pi(a_t, s_t; \theta)$ and $V(s_t; \theta_v)$

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Also operates in forward view (update after every t_{max})

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Update $\nabla_{\theta'} \log \pi(a_t | s_t; \theta') A(s_t, a_t; \theta, \theta_v)$

Advantage (k up to t_{max}) $\sum_{i=0}^{k-1} \gamma^i r_{t+i} + \gamma^k V(s_{t+k}; \theta_v) - V(s_t; \theta_v)$

A3C details

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θ and θ_v come from the same network with two heads

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θ and θ_v come from the same network with two heads

Add entropy regularization term

Results

3

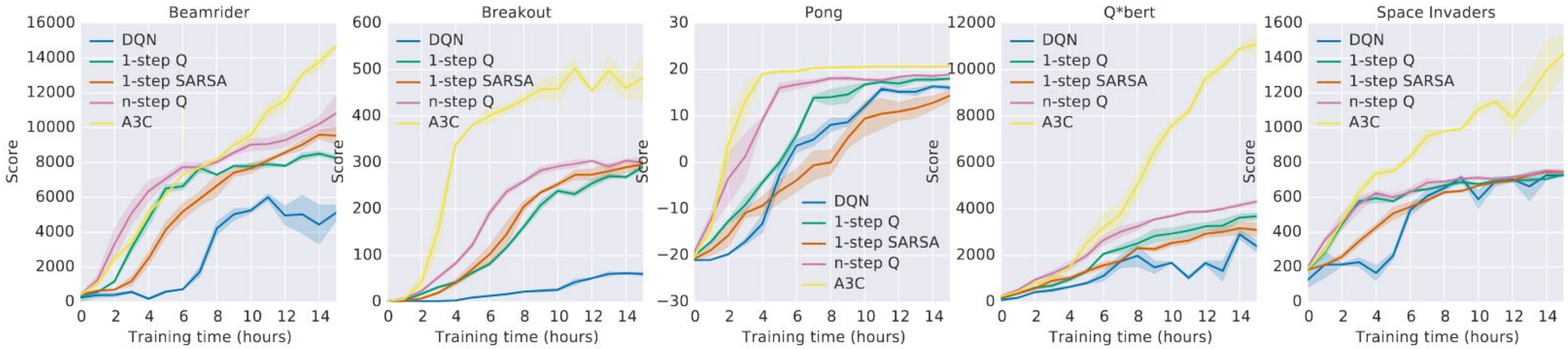
Benchmarks

Arcade Learning Environment (Bellemare et al., 2012)

TORCS 3D Racing simulator (Wyman et al., 2013)

A3C only: MuJoCo (Todorov, 2015)

ATARI 2600



DQN: Nvidia K40 GPU

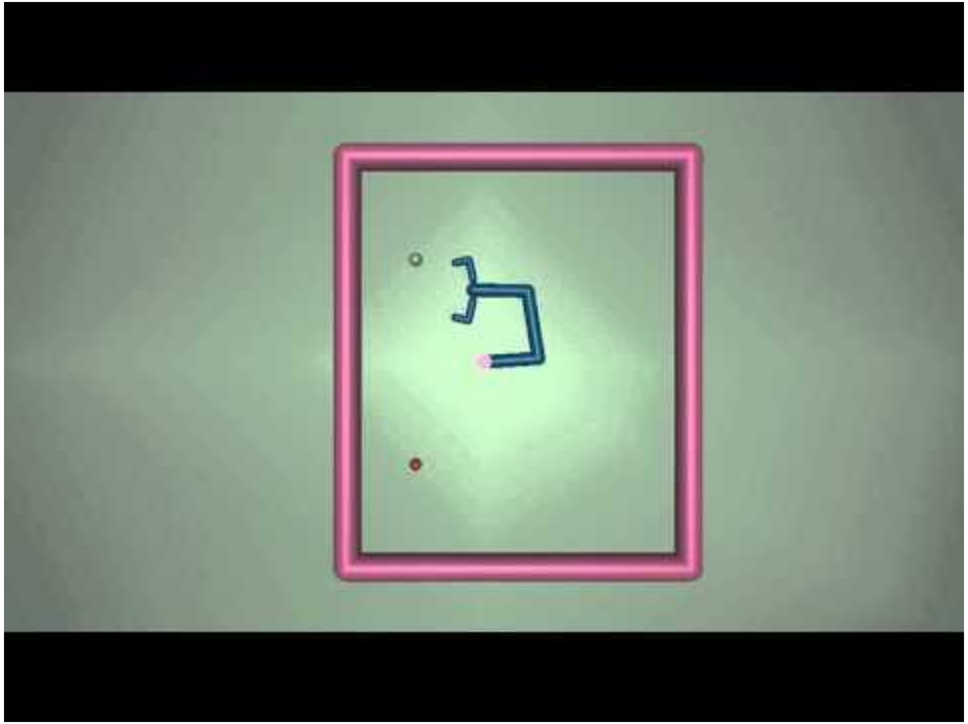
Asynchronous: CPU (16 cores)

ATARI 2600

Method	Training Time	Mean	Median
DQN	8 days on GPU	121.9%	47.5%
Gorila	4 days, 100 machines	215.2%	71.3%
D-DQN	8 days on GPU	332.9%	110.9%
Dueling D-DQN	8 days on GPU	343.8%	117.1%
Prioritized DQN	8 days on GPU	463.6%	127.6%
A3C, FF	1 day on CPU	344.1%	68.2%
A3C, FF	4 days on CPU	496.8%	116.6%
A3C, LSTM	4 days on CPU	623.0%	112.6%

Table 1. Mean and median human-normalized scores on 57 Atari games using the human starts evaluation metric. Supplementary Table SS3 shows the raw scores for all games.

MuJoCo



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Illustrations from Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley http://ai.berkeley.edu

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QUESTIONS

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