Actor-Critic

Hung-yi Lee

Asynchronous Advantage Actor-Critic (A3C)

Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, Koray Kavukcuoglu, “Asynchronous Methods for Deep Reinforcement Learning”, ICML, 2016

Review – Policy Gradient

baseline

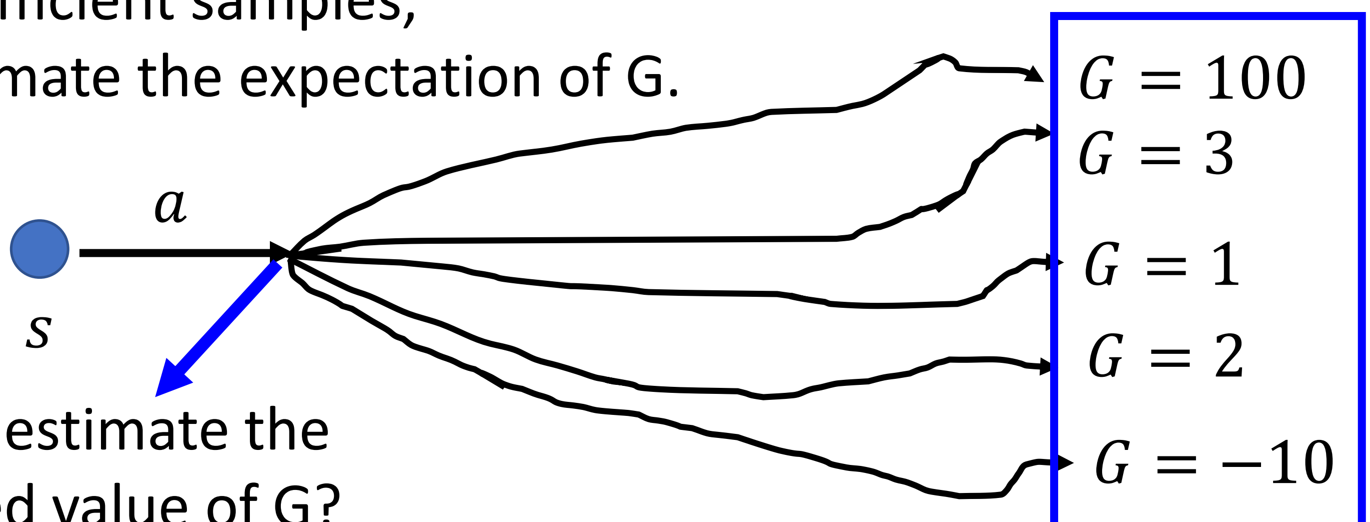
discount factor

$$\nabla \bar{R}_\theta \approx \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n}\left(\underbrace{\sum_{t'=t}^{T_n} \boxed{\gamma^{t'}}^{-t} r_{t'}^{n}}_{G_t^n} - b\right)\nabla \log p_\theta(a_t^n|s_t^n)$$

G_t^n : obtained via interaction

Very unstable

With sufficient samples,
approximate the expectation of G.

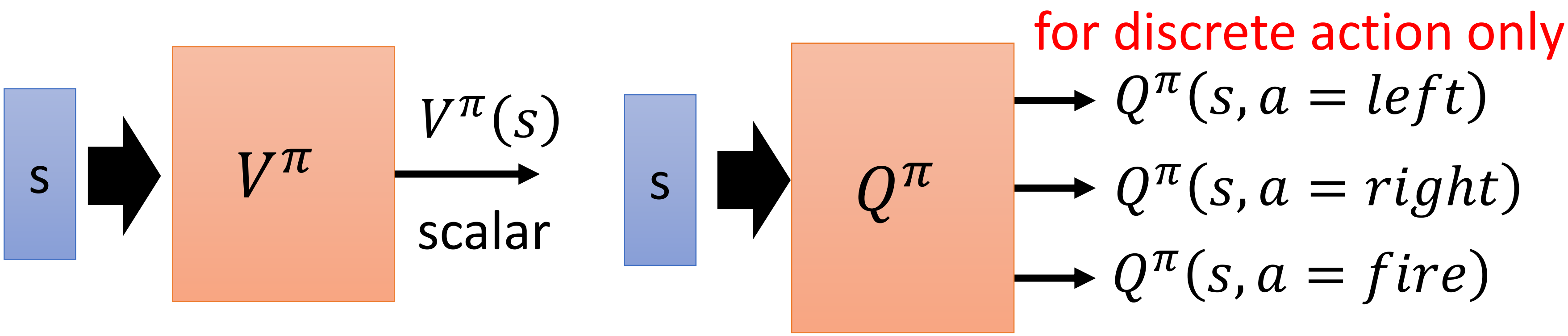


Can we estimate the
expected value of G?

G是random variable，因為遊戲的隨機性
因此train這個G是很不穩定的

Review – Q-Learning

- State value function $V^{\pi}(s)$
  - When using actor π, the *cumulated* reward expects to be obtained after visiting state s
- State-action value function $Q^{\pi}(s, a)$
  - When using actor π, the *cumulated* reward expects to be obtained after taking a at state s



Estimated by TD or MC

Actor-Critic

缺點 estimate兩個network

$$\boxed{Q^{\pi_\theta}(s_t^n, a_t^n) - V^{\pi_\theta}(s_t^n)}$$

value function

$$V^{\pi_\theta}(s_t^n)$$

baseline

$$\nabla \bar{R}_\theta \approx \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n}\boxed{\left(\underline{\sum_{t'=t}^{T_n}\gamma^{t'-t}r_{t'}^n} - \underline{b}\right)}\nabla \log p_\theta(a_t^n|s_t^n)$$

G_t^n : obtained via interaction

$$E[G_t^n] = Q^{\pi_\theta}(s_t^n, a_t^n)$$

accumulative reward的期望值

Advantage Actor-Critic

$$Q^{\pi}(s_t^n, a_t^n) - V^{\pi}(s_t^n)$$

$$\Downarrow$$

$$r_t^n + V^{\pi}(s_{t+1}^n) - V^{\pi}(s_t^n)$$

Estimate two networks? We can only estimate one.

好處

Only estimate state value

A little bit variance

$$Q^{\pi}(s_t^n, a_t^n) = E[r_t^n + V^{\pi}(s_{t+1}^n)]$$

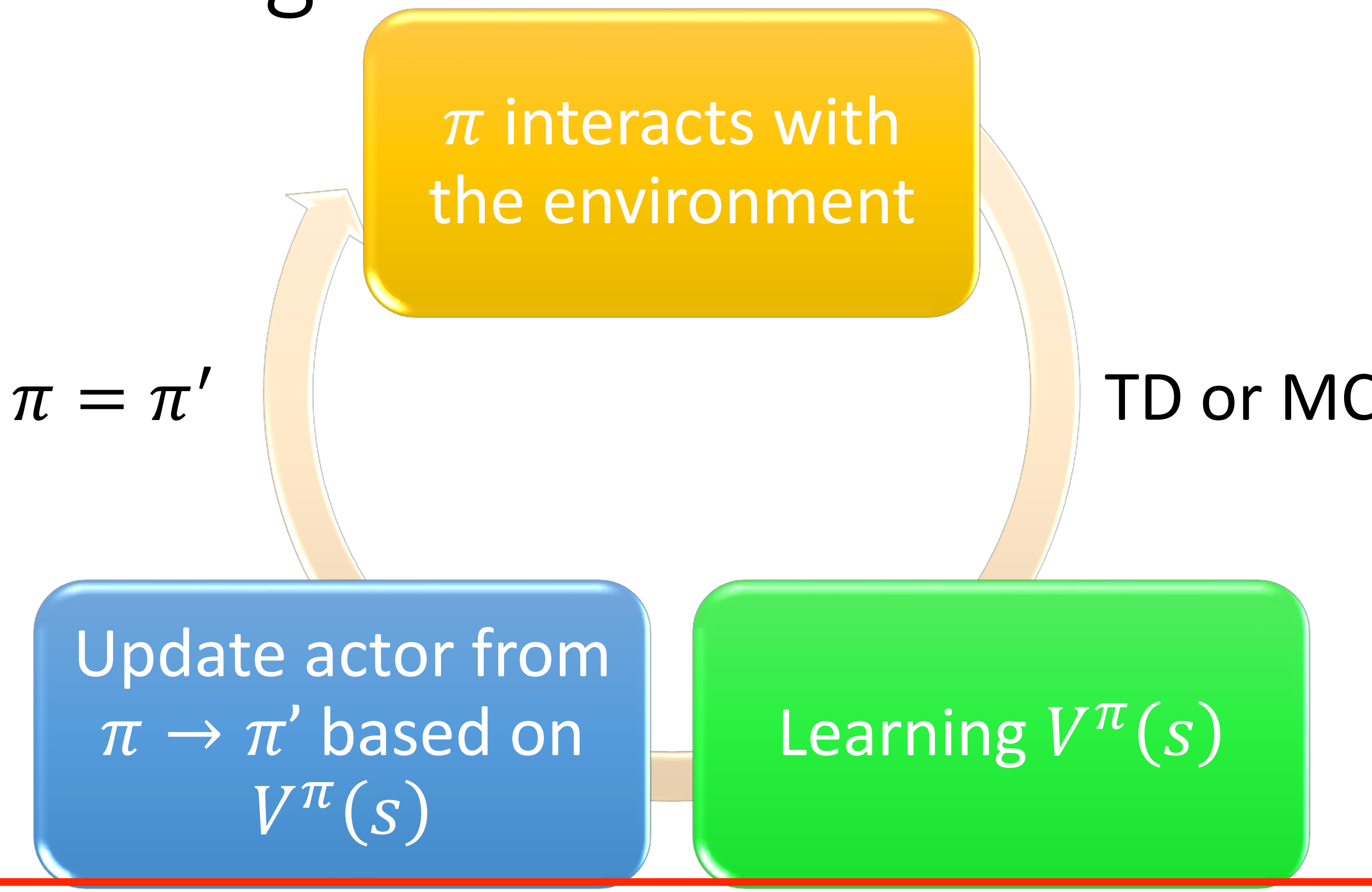
缺點是r具有隨機性

$$Q^{\pi}(s_t^n, a_t^n) = r_t^n + V^{\pi}(s_{t+1}^n)$$

在state s 採取action a，得到reward r，跳到state s t+1

但是這邊故意拿掉期望值

Advantage Actor-Critic



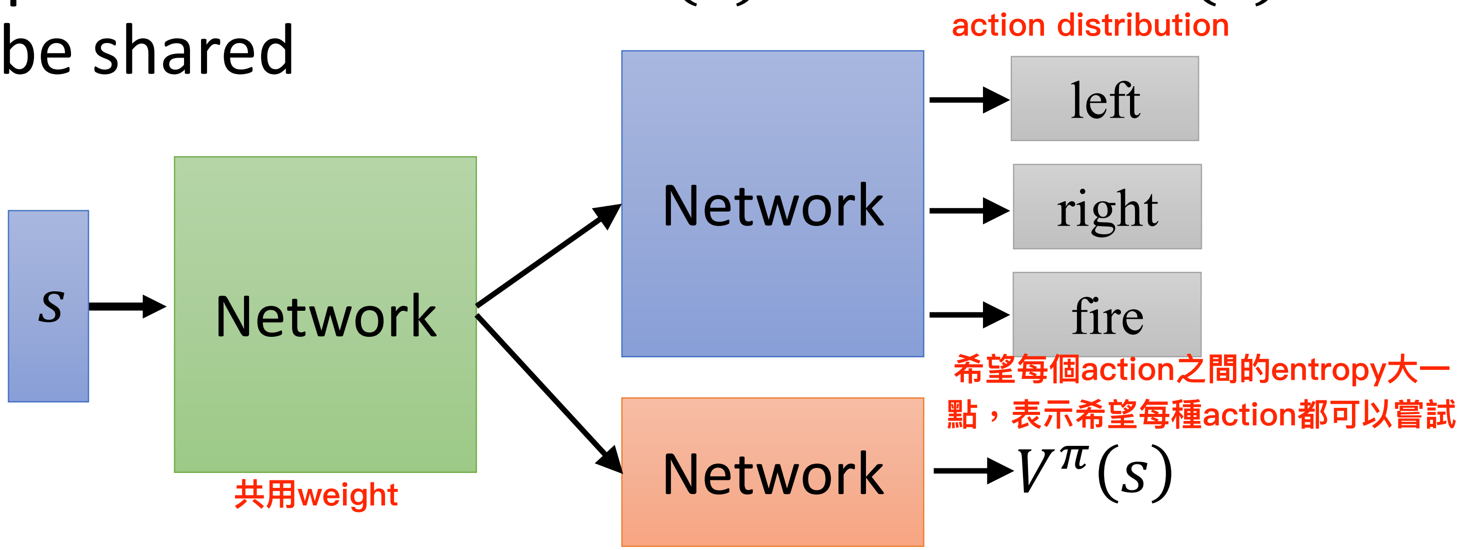
update pi的objective function

$$\nabla \bar{R}_{\theta} \approx \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T_n} \left(r_t^n + V^{\pi}(s_{t+1}^n) - V^{\pi}(s_t^n) \right) \nabla log p_{\theta}(a_t^n | s_t^n)$$

A2C

Advantage Actor-Critic

- Tips
  - The parameters of actor $\pi(s)$ and critic $V^{\pi}(s)$ can be shared



- Use output entropy as regularization for $\pi(s)$
  - Larger entropy is preferred → exploration

Asynchronous Advantage Actor-Critic (A3C)

A2C要train太久，同時間增加worker加快train速度

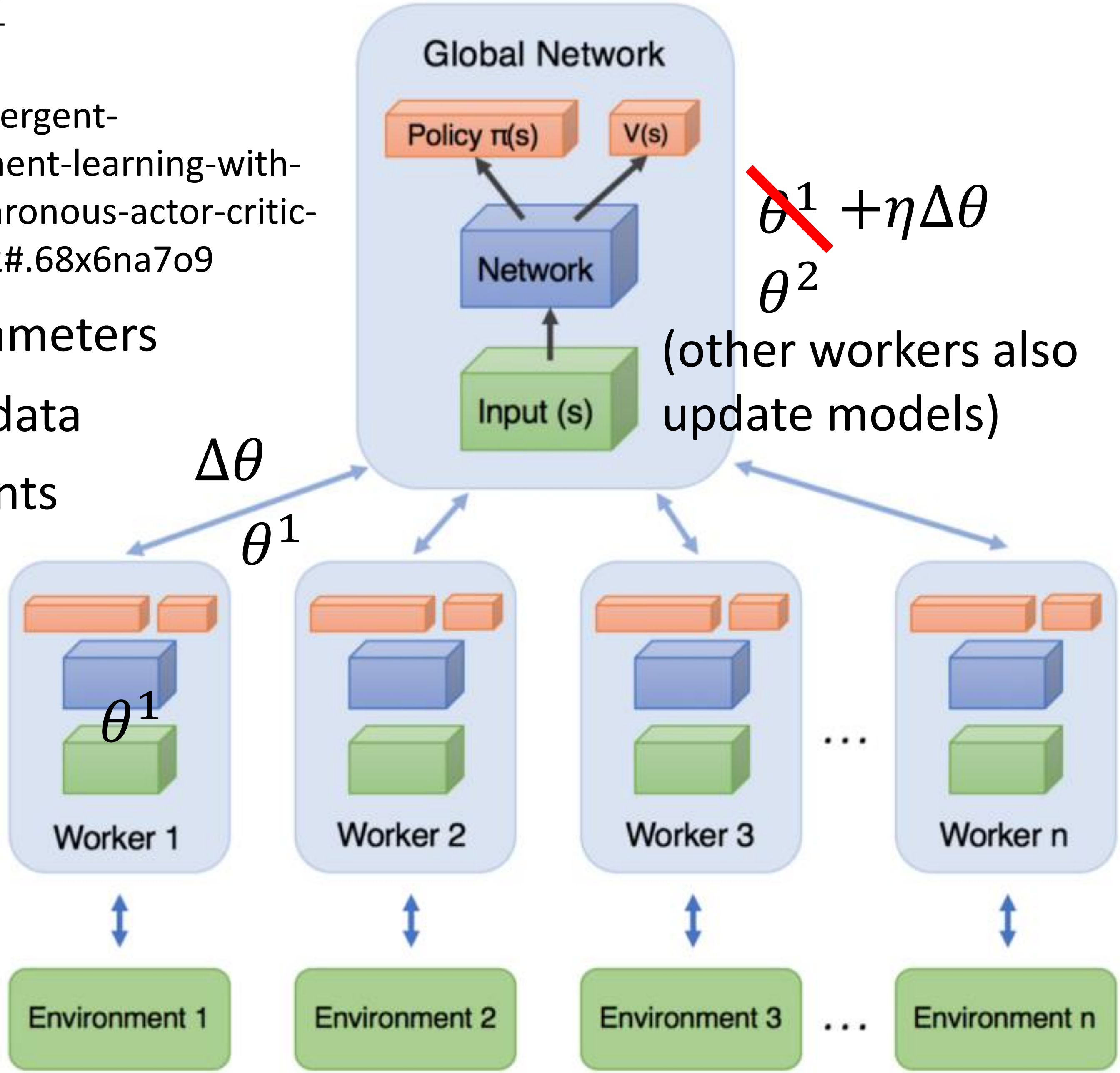
The idea is from 李思叡

Asynchronous

gradient descent跑在主要的worker

Source of image: https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2#.68x6na7o9

1. Copy global parameters
2. Sampling some data
3. Compute gradients
4. Update global models



$\cancel{\theta^1} + \eta \Delta\theta$

θ^2

(other workers also update models)

$\Delta\theta$

θ^1

θ^1

$\Delta\theta$

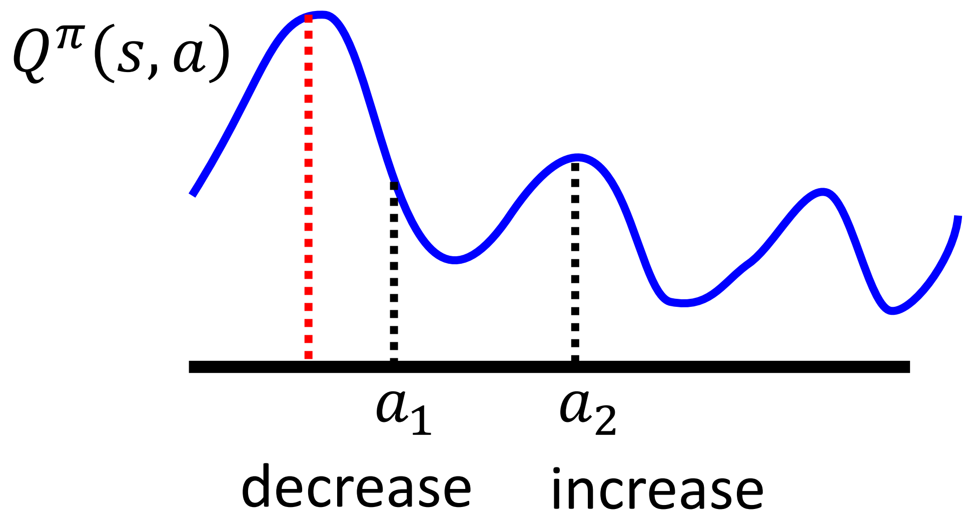
Pathwise Derivative Policy Gradient

David Silver, Guy Lever, Nicolas Heess, Thomas Degris, Daan Wierstra, Martin Riedmiller, "Deterministic Policy Gradient Algorithms", ICML, 2014

Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, Daan Wierstra, "CONTINUOUS CONTROL WITH DEEP REINFORCEMENT LEARNING", ICLR, 2016

Another Way to use Critic

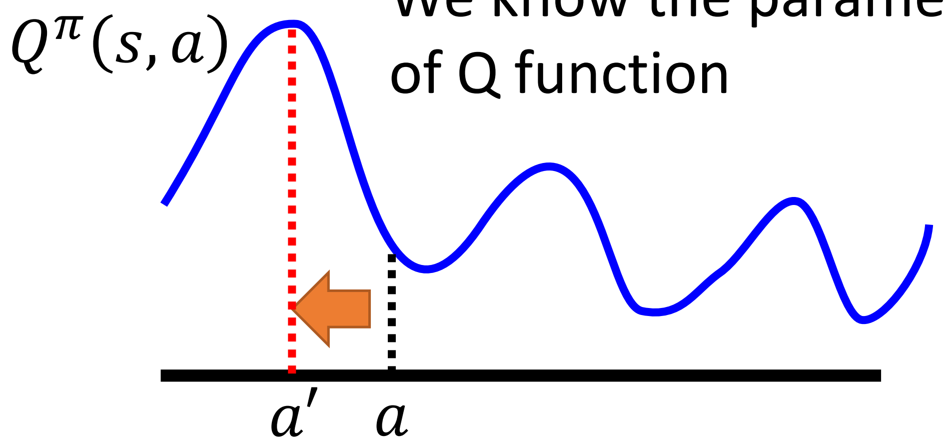
Original Actor-critic



Pathwise derivative policy gradient

From Q function we know that taking a' at state s is better than a

We know the parameters of Q function



Actor

Critic

Pathwise derivative policy gradient

Original Actor-critic

http://www.cartomad.com/comic/1090000811040l1.html

原來的Q function很難解argmax 問題，因此這邊多train一個NN解這個問題

Action a is a *continuous vector*

$$a = arg \max_{a} Q(s,a)$$

$s \rightarrow$ Actor π $\rightarrow a$

Actor as the solver of this optimization problem

Pathwise Derivative Policy Gradient

$$\pi'(s) = arg \max_{a} Q^{\pi}(s,a)$$

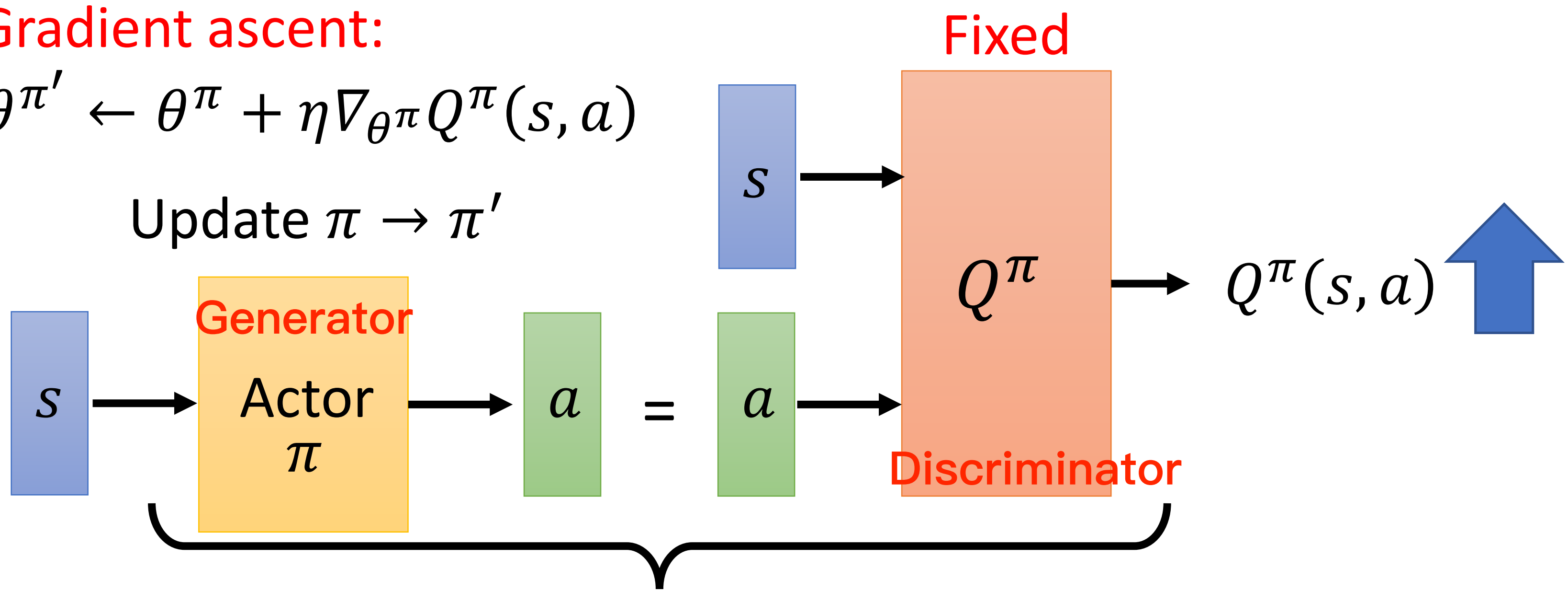
a is the output of an actor

GAN!!!

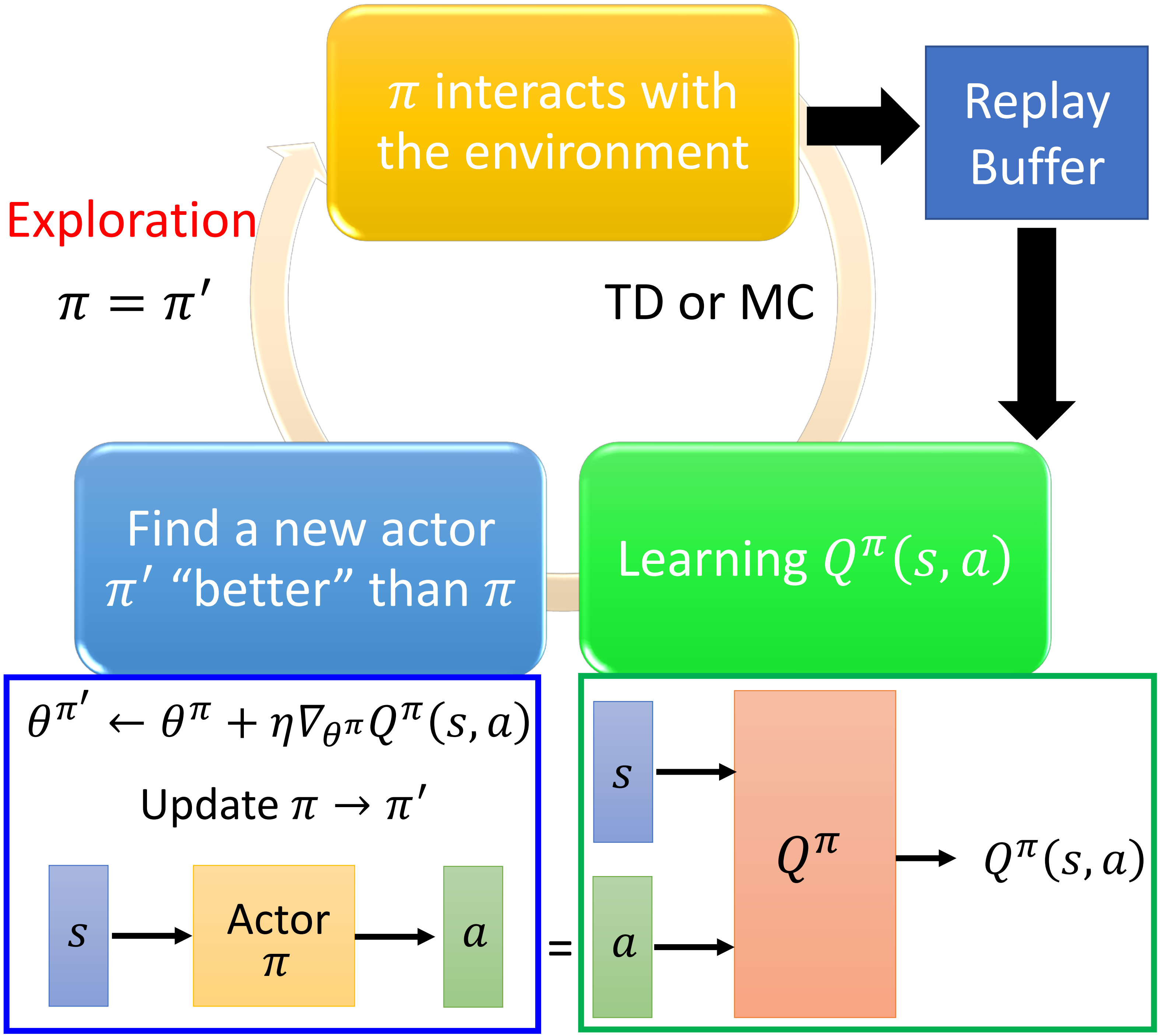
Gradient ascent:

$$\theta^{\pi'} \leftarrow \theta^{\pi} + \eta \nabla_{\theta^{\pi}} Q^{\pi}(s,a)$$

Update $\pi \rightarrow \pi'$



This is a large network


π interacts with the environment
Replay Buffer
Exploration
$\pi = \pi'$
TD or MC
Find a new actor π' "better" than π
Learning $Q^\pi(s,a)$
$\theta^{\pi'} \leftarrow \theta^\pi + \eta \nabla_{\theta^\pi} Q^\pi(s,a)$
Update $\pi \rightarrow \pi'$
s
Actor π
a
=
s
a
Q^π
$Q^\pi(s,a)$

Q-Learning Algorithm

- Initialize Q-function Q, target Q-function $\hat{Q} = Q$

- In each episode
  - For each time step t
    - Given state s_t, take action a_t based on Q (exploration)
    - Obtain reward r_t, and reach new state s_{t+1}
    - Store (s_t, a_t, r_t, s_{t+1}) into buffer
    - Sample (s_i, a_i, r_i, s_{i+1}) from buffer (usually a batch)
    - Target $y = r_i + \max_a \hat{Q}(s_{i+1}, a)$
    - Update the parameters of Q to make $Q(s_i, a_i)$ close to y (regression)

    - Every C steps reset $\hat{Q} = Q$

Q-Learning Algorithm → *Pathwise Derivative Policy Gradient*

- Initialize Q-function Q, target Q-function $\hat{Q} = Q$, actor π, target actor $\hat{\pi} = \pi$
- In each episode
  - For each time step t

learn一個actor,
input st output at

  1
    - Given state s_t, take action a_t based on ~~Q~~ π (exploration)
    - Obtain reward r_t, and reach new state s_{t+1}
    - Store (s_t, a_t, r_t, s_{t+1}) into buffer
    - Sample (s_i, a_i, r_i, s_{i+1}) from buffer (usually a batch)

哪一個action a 最大，直接由actor pi決定

  2
    - Target $y = r_i + \cancel{\max_a \hat{Q}(s_{i+1}, a)}\ \hat{Q}\left(s_{i+1}, \hat{\pi}(s_{i+1})\right)$

要注意的是原本我們只有target network Q head，這邊多了一個target pi，原理一樣，不希望變動太快

    - Update the parameters of Q to make $Q(s_i, a_i)$ close to y (regression)

  3
    - Update the parameters of π to maximize $Q\left(s_i, \pi(s_i)\right)$
    - Every C steps reset $\hat{Q} = Q$

  4
    - Every C steps reset $\hat{\pi} = \pi$

Connection with GAN

Method	GANs	AC
Freezing learning	yes	yes
Label smoothing	yes	no
Historical averaging	yes	no
Minibatch discrimination	yes	no
Batch normalization	yes	yes
Target networks	n/a	yes
Replay buffers	no	yes
Entropy regularization	no	yes
Compatibility	no	yes

David Pfau, Oriol Vinyals, “Connecting Generative Adversarial Networks and Actor-Critic Methods”, arXiv preprint, 2016