强化学习
第8节

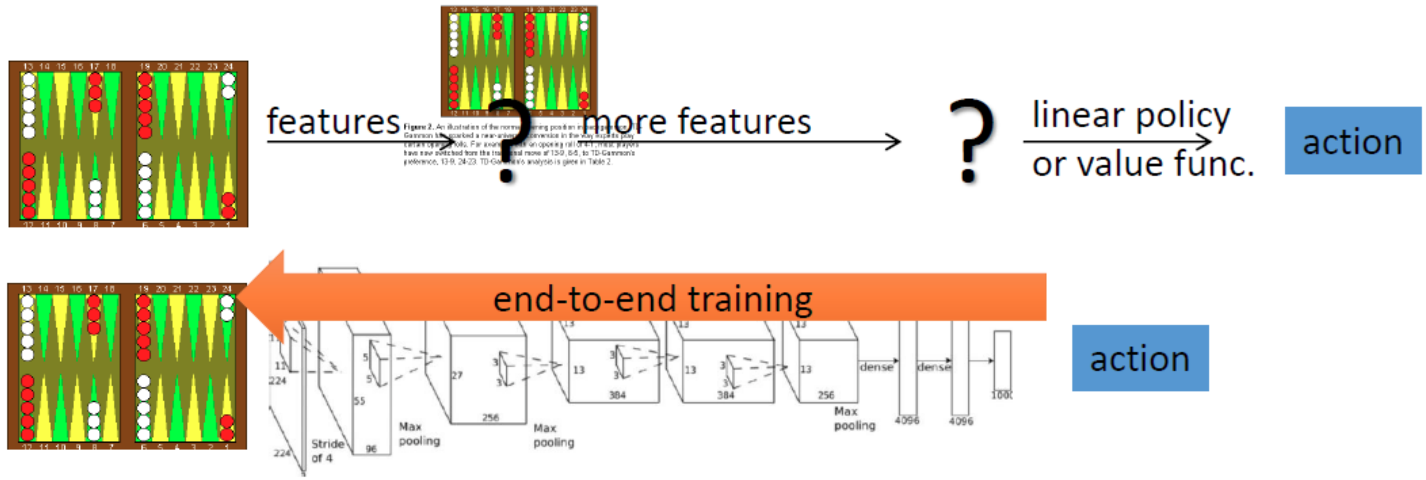
涉及知识点：
基于神经网络的策略梯度、A3C、确定性梯度策略、深度确定性策略梯度、TRPO、PPO

深度策略梯度

深度强化学习

标准（传统）
强化学习

深度强化学习



- 直面理解：深度学习+强化学习
- 深度强化学习使强化学习算法能够以端到端的方式解决复杂问题
- 真正让强化学习有能力完成实际决策任务
- 比强化学习和深度学习各自都更加难以驯化
- 基于价值函数的深度强化学习
  - DQN：一次输入多个行动Q值输出、目标网络、随机采样经验
  - Double DQN：解耦合行动选择和价值估计、解决DQN过高估计问题
  - Dueling DQN：精细捕捉价值和行动的细微关联、多种advantage函数建模

深度强化学习的分类

- 基于价值的方法
  - 深度Q网络及其扩展
- 基于随机策略的方法
  - 基于神经网络的策略梯度，信任区域策略优化（TRPO），近端策略优化（PPO），A3C
- 基于确定性策略的方法
  - 确定性策略梯度（DPG），DDPG

基于神经网络的策略梯度

复习：策略梯度定理

- 策略梯度定理把似然比的推导过程泛化到多步马尔可夫决策过程
  - 用长期的价值函数 $Q^{\pi_\theta}(s,a)$代替前面的瞬时奖励 r_{sa}
- 策略梯度定理涉及
  - 起始状态目标函数 J_1，平均奖励目标函数 J_{avR}，和平均价值目标函数 J_{avV}
- 定理
  - 对任意可微的策略 $\pi_\theta(a|s)$，任意策略的目标函数 $J = J_1, J_{avR}, J_{avV}$，其策略梯度是

$$\frac{\partial J(\theta)}{\partial \theta} = \mathbb{E}_{\pi_\theta}\left[\frac{\partial \log \pi_\theta(a|s)}{\partial \theta} Q^{\pi_\theta}(s,a)\right]$$

详细证明过程请参考Rich Sutton’s Reinforcement Learning: An Introduction (2nd Edition)第13章

策略网络的梯度

- 对于随机策略，一般采样到每一个行动的概率由Softmax实现

$$\pi_\theta(a|s) = \frac{e^{f_\theta(s,a)}}{\sum_{a'} e^{f_\theta(s,a')}}$$

  - 其中$f_\theta(s,a)$是对状态-行动队的打分函数，由θ参数化，这可以通过一个神经网络来实现

- 其log形式的梯度为

$$\begin{aligned}\frac{\partial \log \pi_\theta(a|s)}{\partial \theta} &= \frac{\partial f_\theta(s,a)}{\partial \theta} - \frac{1}{\sum_{a'} e^{f_\theta(s,a')}} \sum_{a''} e^{f_\theta(s,a'')} \frac{\partial f_\theta(s,a'')}{\partial \theta} \\ &= \frac{\partial f_\theta(s,a)}{\partial \theta} - \mathbb{E}_{a' \sim \pi_\theta(a'|s)}\left[\frac{\partial f_\theta(s,a')}{\partial \theta}\right]\end{aligned}$$

策略网络的梯度

- 其log梯度形式

$$\frac{\partial \log \pi_\theta(a|s)}{\partial \theta} = \frac{\partial f_\theta(s,a)}{\partial \theta} - \mathbb{E}_{a' \sim \pi_\theta(a'|s)}\left[\frac{\partial f_\theta(s,a')}{\partial \theta}\right]$$

- 策略网络的梯度为

$$\begin{aligned}\frac{\partial J(\theta)}{\partial \theta} &= \mathbb{E}_{\pi_\theta}\left[\frac{\partial \log \pi_\theta(a|s)}{\partial \theta} Q^{\pi_\theta}(s,a)\right] \\ &= \mathbb{E}_{\pi_\theta}\left[\left(\underbrace{\frac{\partial f_\theta(s,a)}{\partial \theta}}_{\text{反向梯度传播}} - \mathbb{E}_{a' \sim \pi_\theta(a'|s)}\underbrace{\left[\frac{\partial f_\theta(s,a')}{\partial \theta}\right]}_{\text{反向梯度传播}}\right) Q^{\pi_\theta}(s,a)\right]\end{aligned}$$

策略梯度和Q学习的对比

- Q 学习算法学习一个由 θ 作为参数的函数 $Q_\theta(s,a)$
  - 优化目标为最小化TD error
$$J(\theta)=\mathbb{E}_{\pi'}\left[\frac{1}{2}\left(r_t+\gamma\max_{a'}Q_{\theta'}(s_{t+1},a')-Q_\theta(s_t,a_t)\right)^2\right]$$
  - 更新方程
$$\begin{aligned}\theta &\leftarrow \theta-\alpha\frac{\partial J(\theta)}{\partial\theta}\\ &=\theta+\alpha\mathbb{E}_{\pi'}\left[\left(r_t+\gamma\max_{a'}Q_{\theta'}(s_{t+1},a')-Q_\theta(s_t,a_t)\right)\frac{\partial Q_\theta(s,a)}{\partial\theta}\right]\end{aligned}$$

- 策略梯度学习一个由 θ 作为参数的策略$\pi_\theta(a|s)$
  - 优化目标直接为策略的价值（比Q学习更加直接）
$$\max_\theta J(\theta)=\mathbb{E}_{\pi_\theta}[\pi_\theta(a|s)\,A^{\pi_\theta}(s,a)]$$
  - 更新方程
$$\theta\leftarrow\theta+\alpha\frac{\partial J(\theta)}{\partial\theta}=\theta+\alpha\mathbb{E}_{\pi_\theta}\left[\frac{\partial\log\pi_\theta(a|s)}{\partial\theta}A^{\pi_\theta}(s,a)\right]$$

A3C

复习：Actor-Critic

- Actor-Critic的思想
  - REINFORCE策略梯度方法：使用蒙特卡罗采样直接估计(s_t, a_t)的值G_t
  - 为什么不建立一个可训练的值函数Q_Φ来完成这个估计过程?
- 演员（Actor）和评论家（Critic）

演员 $\pi_\theta(a|s)$

采取动作使评论家满意的策略

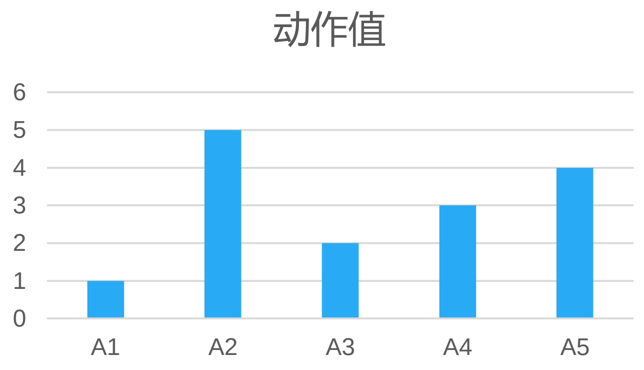
评论家 $Q_\Phi(s,a)$

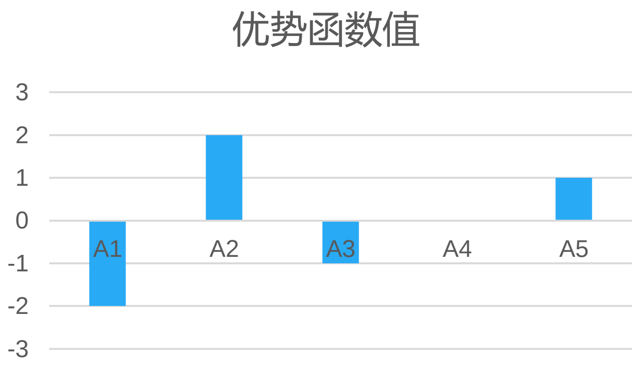
学会准确估计演员策略所采取动作价值的值函数

复习A2C：优势Actor-Critic

- 思想：通过减去一个基线函数来标准化评论家的打分
  - 更多信息指导：降低较差动作概率，提高较优动作概率
  - 进一步降低方差
- 优势函数（Advantage Function）

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$





A3C: 异步A2C方法

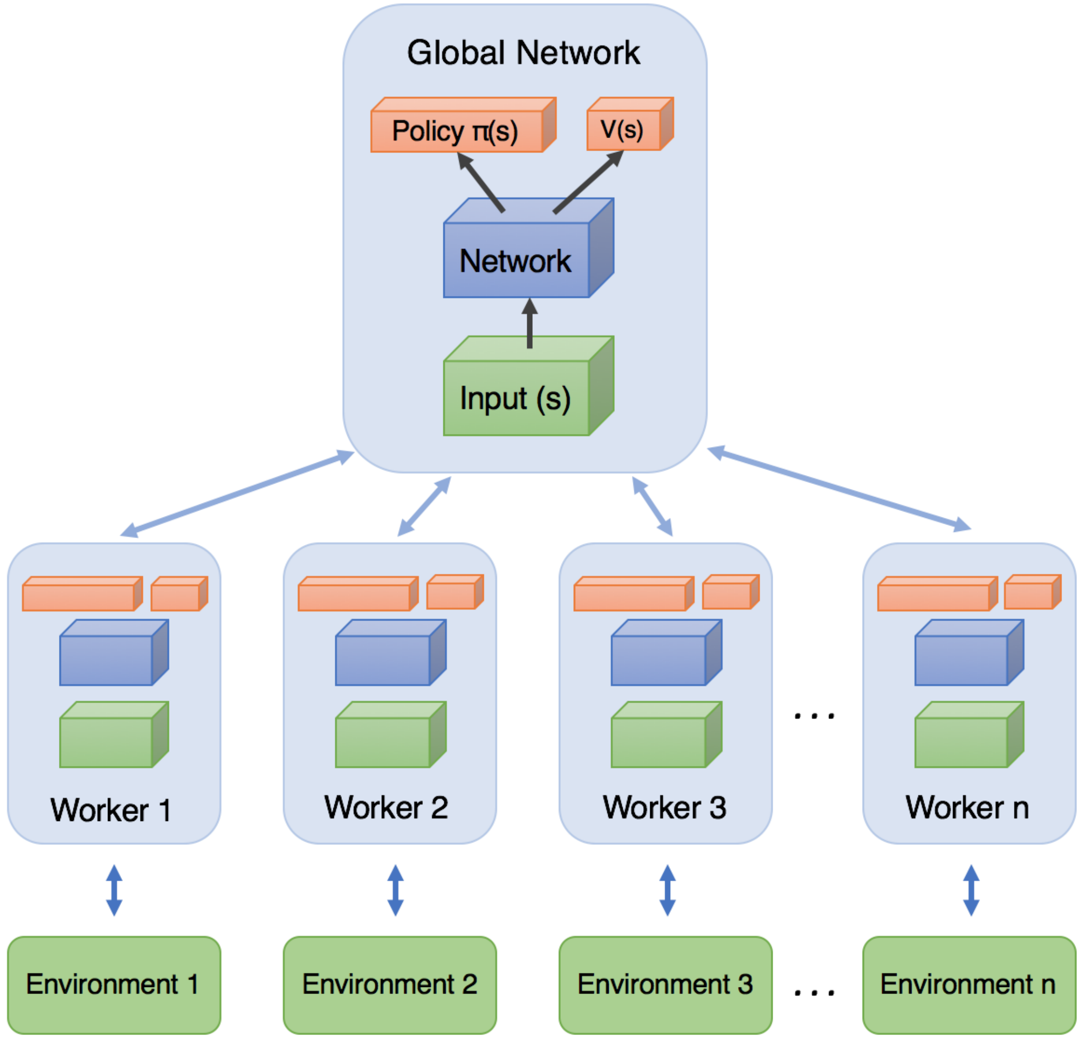
- A3C代表了异步优势动作评价（Asynchronous Advantage Actor Critic）
  - 异步（Asynchronous）：因为算法涉及并行执行一组环境
  - 优势（Advantage）：因为策略梯度的更新使用优势函数
  - 动作评价（Actor Critic）：因为这是一种动作评价（actor-critic）方法，它涉及一个在学得的状态值函数帮助下进行更新的策略

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

$$A(s_t,a_t;\theta_v) = \sum_{i=0}^{k-1} \gamma^i r_{t+i} + \gamma^k V(s_{t+k};\theta_v) - V(s_t;\theta_v)$$

https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2

A3C: 异步A2C方法



https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2

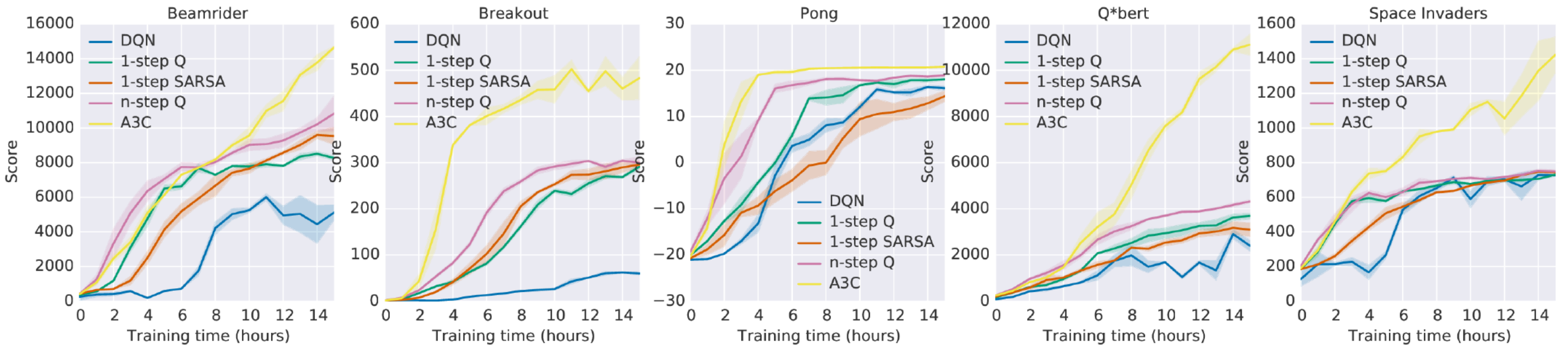
A3C算法

Algorithm S3 Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

// Assume global shared parameter vectors θ *and* θ_v *and global shared counter* $T = 0$
// Assume thread-specific parameter vectors θ' *and* θ'_v
Initialize thread step counter $t \leftarrow 1$
repeat
    Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
    Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$ 初始化局部参数
    $t_{start} = t$
    Get state s_t
    repeat
        Perform a_t according to policy $\pi(a_t|s_t;\theta')$
        Receive reward r_t and new state s_{t+1}
        $t \leftarrow t + 1$
        $T \leftarrow T + 1$
    until terminal s_t **or** $t - t_{start} == t_{max}$
    $R = \begin{cases} 0 & \text{for terminal } s_t \\ V(s_t, \theta'_v) & \text{for non-terminal } s_t \text{// Bootstrap from last state} \end{cases}$
    for $i \in \{t-1, \ldots, t_{start}\}$ **do**
        $R \leftarrow r_i + \gamma R$
        Accumulate gradients wrt θ': $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i|s_i;\theta')(R - V(s_i;\theta'_v))$ actor
        Accumulate gradients wrt θ'_v: $d\theta_v \leftarrow d\theta_v + \partial\left(R - V(s_i;\theta'_v)\right)^2 / \partial\theta'_v$ critic
    end for
    Perform asynchronous update of θ using $d\theta$ and of θ_v using $d\theta_v$. 只更新全局参数
until $T > T_{max}$

Volodymyr Mnih et al. Asynchronous Methods for Deep Reinforcement Learning. NIPS 2016.

A3C对比实验



a single Nvidia K40 GPU while the asynchronous methods were trained using 16 CPU cores

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%

Nvidia K40 GPUs

16 CPU cores and no GPU

Mean and median human-normalized scores on 57 Atari games

Volodymyr Mnih et al. Asynchronous Methods for Deep Reinforcement Learning. NIPS 2016.

确定性策略梯度

深度强化学习的分类

- 基于价值的方法
    - 深度Q网络及其扩展
- 基于随机策略的方法
    - 使用神经网络的策略梯度，自然策略梯度，信任区域策略优化（TRPO），近端策略优化（PPO），A3C
- 基于确定性策略的方法
    - 确定性策略梯度（DPG），DDPG

随机策略与确定性策略

随机策略

对于离散动作 $$\pi(a|s;\theta)=\frac{\exp\{Q_\theta(s,a)\}}{\sum_{a'}\exp\{Q_\theta(s,a')\}}$$

对于连续动作 $$\pi(a|s;\theta)\propto\exp\left\{\left(a-\mu_\theta(s)\right)^2\right\}$$

确定性策略

对于离散动作 $$\pi(s;\theta)=\arg\max_a Q_\theta(s,a)$$ 不可微

对于连续动作 $$a=\pi(s;\theta)$$ 可微

确定性策略梯度

- 用于估计状态-动作值的评论家（critic）模块

$$Q^w(s,a) \simeq Q^\pi(s,a)$$

$$L(w) = \mathbb{E}_{s\sim\rho^\pi, a\sim\pi_\theta}\left[\left(Q^w(s,a) - Q^\pi(s,a)\right)^2\right]$$

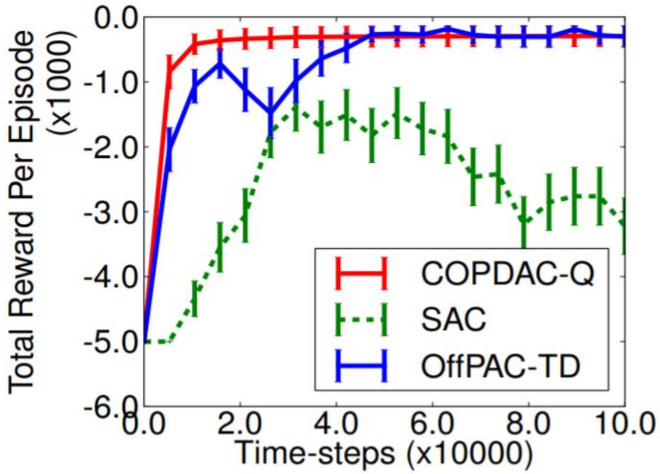
- 确定性策略
  - 确定性策略梯度定理

$$J(\pi_\theta) = \mathbb{E}_{s\sim\rho^\pi}[Q^w(s,a)]$$

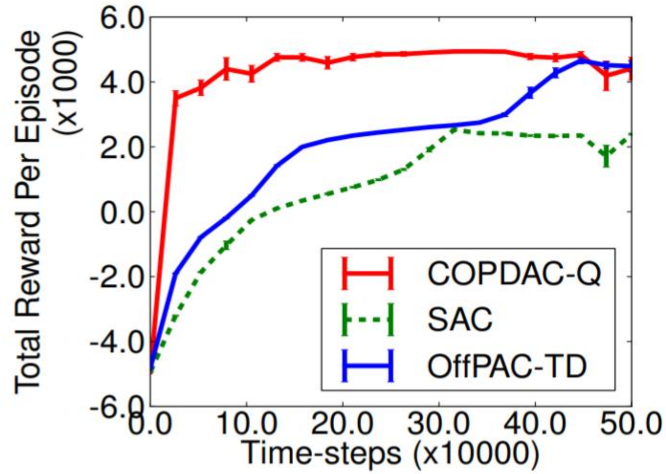
$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{s\sim\rho^\pi}[\underbrace{\nabla_\theta \pi_\theta(s)}_{\text{在线策略}} \cdot \underbrace{\nabla_a Q^w(s,a)|_{a=\pi_\theta(s)}}_{\text{链式法则}}]$$

D. Silver et al. Deterministic Policy Gradient Algorithms. ICML 2014.

确定性策略梯度实验效果

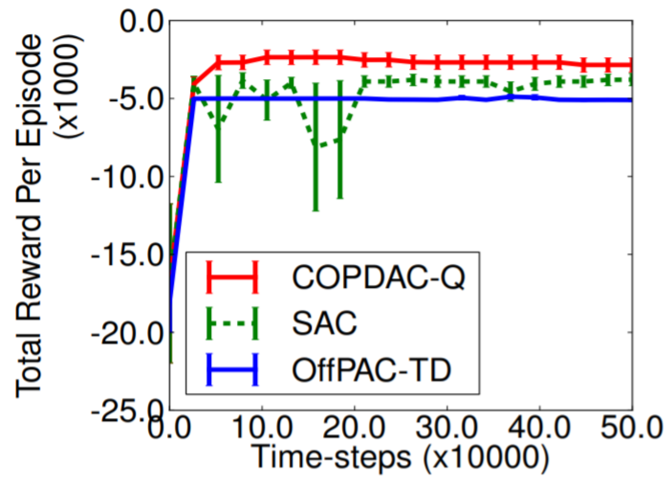


(a) Mountain Car



(b) Pendulum

- COPDAC-Q: 当时论文提出的确定性策略梯度（off-policy）
- SAC：随机梯度策略（off-policy）
- OffPAC-TD：随机梯度策略（off-policy）



(c) 2D Puddle World

D. Silver et al. Deterministic Policy Gradient Algorithms. ICML 2014.

深度确定性策略梯度

DDPG：深度确定性策略梯度

- 对于确定性策略的梯度

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{s\sim\rho^\pi}[\nabla_\theta \pi_\theta(s) \cdot \nabla_a Q^w(s,a)|_{a=\pi_\theta(s)}]$$

- 在实际应用中，这种带有神经函数近似器的actor-critic方法在面对有挑战性的问题时是不稳定的
- 深度确定性策略梯度（DDPG）给出了在确定性策略梯度（DPG）基础上的解决方法
  - 经验重放（离线策略）
  - 目标网络
  - 在动作输入前批标准化Q网络
  - 添加连续噪声

Lillicrap et al. Continuous control with deep reinforcement learning. ICLR 2016.

DDPG：深度确定性策略梯度

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**

动作上的噪声

    Select action $\boxed{a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t}$ 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 $\boxed{(s_i, a_i, r_i, s_{i+1}) \text{ from } R}$ Replay Buffer
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$ 更新critic网络（a_i带有噪声）
    Update the actor policy using the sampled gradient:

目标critic网络

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

目标actor网络

更新actor网络

    Update the target networks:

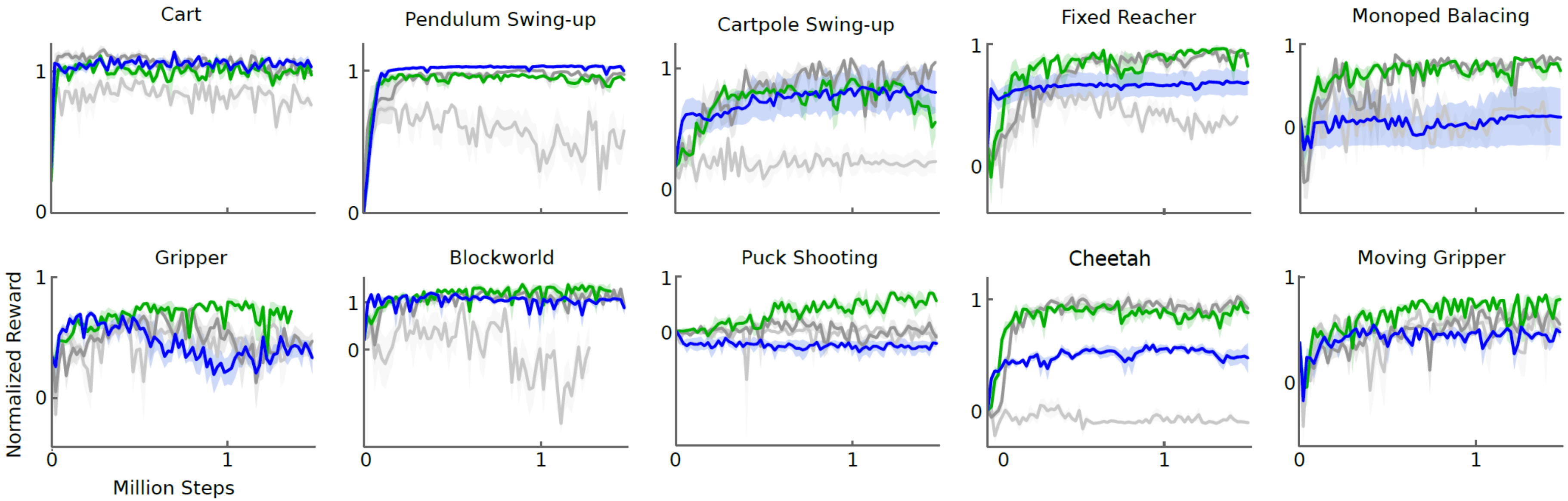
$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$

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

  end for
end for

Lillicrap et al. Continuous control with deep reinforcement learning. ICLR 2016.

深度确定性策略梯度实验



- 确定性策略梯度（DPG）及其变种在一系列经典强化学习任务中的表现曲线
  - 浅灰色：使用批标准化的原始DPG算法
  - 暗灰色：使用目标网络的原始DPG算法
  - 绿色：同时使用目标网络和批标准化
  - 蓝色：使用仅像素作为输入的目标网络
- 目标网络至关重要

Lillicrap et al. Continuous control with deep reinforcement learning. ICLR 2016.

信任区域策略优化
TRPO

目录

Contents

01

策略梯度的缺点

策略梯度算法回顾

- 蒙特卡洛策略梯度（REINFORCE）算法

initialize θ arbitrarily

for each episode $\{s_1, a_1, r(s_1, a_1), \dots, s_T, a_T, r(s_T, a_T)\} \sim \pi_\theta$ do

for $t = 1$ to T do

$$\theta \leftarrow \theta + \alpha \frac{\partial}{\partial \theta} \log \pi_\theta(a_t | s_t) G_t$$

end for

end for

return θ

相关定义

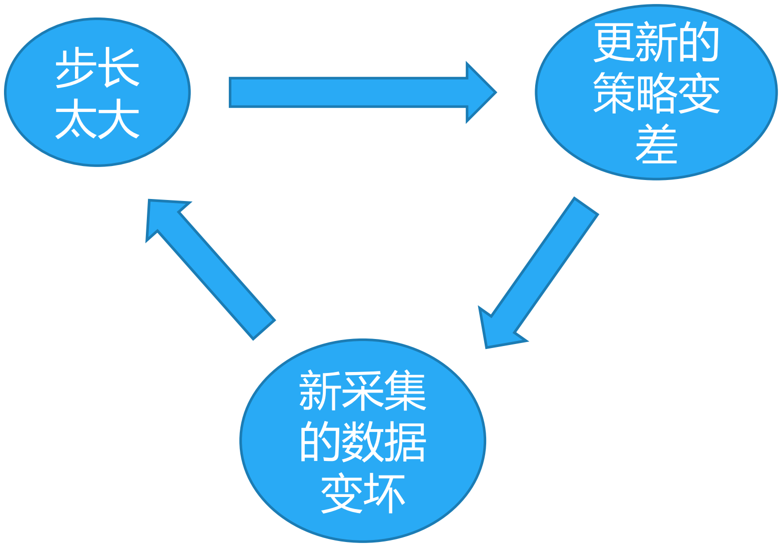
- s_t， a_t， $r(s_t, a_t)$： t 时刻的状态，动作和奖励
- π_θ， θ：使用的策略，表示策略所使用的参数
- G_t：累计奖励
- α：步长

“OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS”， John Schulman. (2016)

策略梯度的缺点

步长

- 步长难以确定
  - 采集到的数据的分布会随策略的更新而变化。
  - 较差的步长产生的影响大。



“OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS”， John Schulman. (2016)

02

TRPO

策略梯度的优化目标

- 优化目标的两种形式
  - 第一种：$J(\theta)=\mathbb{E}_{\tau\sim p_\theta(\tau)}[\sum_t \gamma^t r(s_t,a_t)]$
  - 因为 $V^{\pi_\theta}(s)=\mathbb{E}_{a\sim\pi_\theta(s)}[Q^{\pi_\theta}(s,a)]=\mathbb{E}_{a\sim\pi_\theta(s)}\left[\mathbb{E}_{\tau\sim p_\theta(\tau)}[\sum_{s_k=s,a_k=a}\sum_{t=k}^{\infty}\gamma^{t-k}r(s_t,a_t)]\right]$
  - 所以优化目标的第二种形式是：$J(\theta)=\mathbb{E}_{s_0\sim p_\theta(s_0)}[V^{\pi_\theta}(s_0)]$

相关定义

- τ：轨迹
- s_0：初始状态
- s_t，a_t，$r(s_t,a_t)$：t 时刻的状态，动作和奖励
- π_θ：使用的策略
- θ：表示策略所使用的参数
- Q^{π_θ} 和 V^{π_θ}：策略 π_θ 下的 Q 值与状态值函数

“OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS”，John Schulman. (2016)

优化目标的优化量

$$J(\theta) = \mathbb{E}_{\tau\sim p_\theta(\tau)}[\textstyle\sum_t \gamma^t r(s_t, a_t)]$$
$$J(\theta) = \mathbb{E}_{s_0\sim p_\theta(s_0)}[V^{\pi_\theta}(s_0)]$$

$$\begin{aligned}
J(\theta') - J(\theta) &= J(\theta') - \mathbb{E}_{s_0\sim p(s_0)}[\mathrm{V}^{\pi_\theta}(s_0)] \\
&= J(\theta') - \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}[\mathrm{V}^{\pi_\theta}(s_0)] \\
&= J(\theta') - \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t \mathrm{V}^{\pi_\theta}(s_t) - \sum_{t=1}^{\infty}\gamma^t \mathrm{V}^{\pi_\theta}(s_t)\right] \\
&= J(\theta') + \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t (\gamma \mathrm{V}^{\pi_\theta}(s_{t+1}) - \mathrm{V}^{\pi_\theta}(s_t))\right] \\
&= \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t r(s_t, a_t)\right] + \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t (\gamma \mathrm{V}^{\pi_\theta}(s_{t+1}) - \mathrm{V}^{\pi_\theta}(s_t))\right] \\
&= \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t (r(s_t, a_t) + \gamma \mathrm{V}^{\pi_\theta}(s_{t+1}) - \mathrm{V}^{\pi_\theta}(s_t))\right] \\
&= \mathbb{E}_{\tau\sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty}\gamma^t A^{\pi_\theta}(s_t, a_t)\right]
\end{aligned}$$

初始状态的分布与θ无关

$J(\theta')$的定义

$Q^{\pi_\theta}(s_t, a_t)$

$A^{\pi_\theta}(s_t, a_t)$
$= Q^{\pi_\theta}(s_t, a_t) - \mathrm{V}^{\pi_\theta}(s_t)$

不方便采样

“OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS”，John Schulman. (2016)

使用重要性采样

- 使用重要性采样（Importance Sampling）

$$A^{\pi_\theta}(s_t, a_t) = Q^{\pi_\theta}(s_t, a_t) - V^{\pi_\theta}(s_t)$$

$$\begin{aligned}
&J(\theta') - J(\theta) \\
&= \mathbb{E}_{\tau \sim p_{\theta'}(\tau)}\left[\sum_{t=0}^{\infty} \gamma^t A^{\pi_\theta}(s_t, a_t)\right] \\
&= \sum_t \mathbb{E}_{s_t \sim p_{\theta'}(s_t)}[\mathbb{E}_{a_t \sim \pi_{\theta'}(a_t|s_t)}[\gamma^t A^{\pi_\theta}(s_t, a_t)]] \\
&= \sum_t \mathbb{E}_{s_t \sim p_{\theta'}(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]
\end{aligned}$$

仍然是 $p_{\theta'}$
(近似操作)

重要性采样

“OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS”，John Schulman. (2016)

忽略状态分布的差异

- 当策略更新前后的变化较小时，可以令 $p_\theta(s_t) \approx p_{\theta'}(s_t)$。
  - 假设使用确定性策略，当 $\pi_{\theta'}(s_t) \neq \pi_\theta\ (s_t)$ 的概率小于ϵ时
  - 或者假设使用随机策略，当$a' \sim \pi_{\theta'}(\cdot\ |s_t) \neq a \sim\ \pi_\theta(\cdot\ |s_t)$的概率小于$\epsilon$时
  - $p_{\theta'}(s_t) = (1-\epsilon)^t p_\theta(s_t) + (1-(1-\epsilon)^t) p_{mistake}(s_t)$
  - $|p_{\theta'}(s_t) - p_\theta(s_t)| = (1-(1-\epsilon)^t)|p_{mistake}(s_t) - p_\theta(s_t)| \leq 2(1-(1-\epsilon)^t) \leq 2\epsilon t$

$(1-\epsilon)^t \geq 1-\epsilon t\ for\ \epsilon \in [0,1]$

$$J(\theta') - J(\theta) \approx \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]$$

"OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS" , John Schulman. (2016)

约束策略的变化

- 使用KL散度约束策略更新的幅度

$$\theta' \leftarrow \arg\max_{\theta'} \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]$$

$$s.t. \quad \mathbb{E}_{s_t \sim p(s_t)}[D_{KL}\left(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)\right)] \le \epsilon$$

- 实际多使用constraint violate as penalty

$$\theta' \leftarrow \arg\max_{\theta'} \quad \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]$$

$$-\lambda(D_{KL}(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)) - \epsilon)$$

1. 优化上式，更新θ'
2. 更新 $\lambda \leftarrow \lambda + \alpha(D_{KL}(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)) - \epsilon)$

"OPTIMIZING EXPECTATIONS: FROM DEEP REINFORCEMENT LEARNING TO STOCHASTIC COMPUTATION GRAPHS" , John Schulman. (2016)
http://rail.eecs.berkeley.edu/deeprlcourse/static/slides/lec-9.pdf

Natural Policy Gradient

schemes. The natural policy gradient (Kakade, 2002) can be obtained as a special case of the update in Equation (12) by using a linear approximation to L and a quadratic approximation to the $\overline{D}_{\mathrm{KL}}$ constraint, resulting in the following problem:

$$\underset{\theta}{\text{maximize}} \left[\nabla_\theta L_{\theta_{\text{old}}}(\theta) \big|_{\theta=\theta_{\text{old}}} \cdot (\theta - \theta_{\text{old}}) \right] \tag{17}$$

$$\text{subject to } \frac{1}{2}(\theta_{\text{old}} - \theta)^T A(\theta_{\text{old}})(\theta_{\text{old}} - \theta) \leq \delta,$$

$$\text{where } A(\theta_{\text{old}})_{ij} =$$

$$\frac{\partial}{\partial \theta_i} \frac{\partial}{\partial \theta_j} \mathbb{E}_{s \sim \rho_\pi} \left[D_{\mathrm{KL}}(\pi(\cdot|s, \theta_{\text{old}}) \,\|\, \pi(\cdot|s, \theta)) \right] \big|_{\theta=\theta_{\text{old}}}.$$

The update is $\theta_{\text{new}} = \theta_{\text{old}} + \frac{1}{\lambda} A(\theta_{\text{old}})^{-1} \nabla_\theta L(\theta) \big|_{\theta=\theta_{\text{old}}}$,

TRPO的原理

Line search
(like gradient ascent)

Optimization in Trust Region

https://medium.com/@jonathan_hui/rl-trust-region-policy-optimization-trpo-explained-a6ee04eeeee9

03

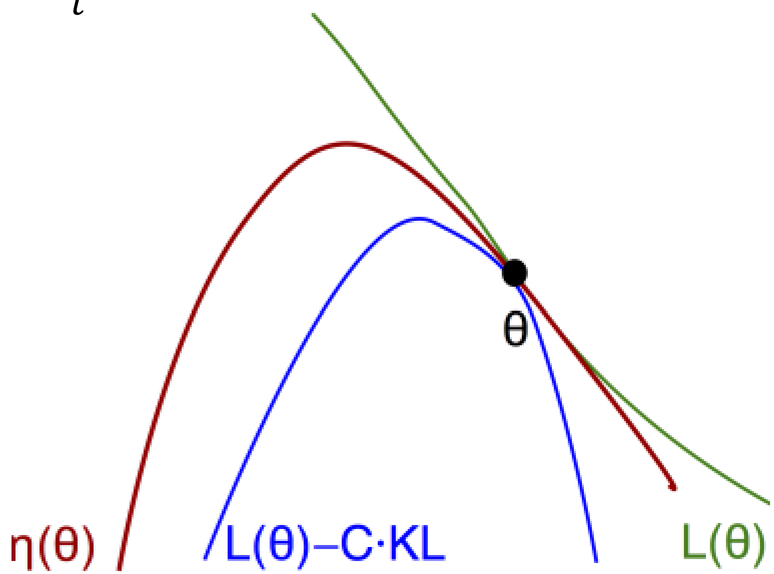
策略改进的单调性保证

策略改进的单调性保证

$$J(\theta') \geq L_\theta(\theta') - C \cdot D_{KL}^{max}(\theta, \theta'), where\ C = \frac{4\epsilon\gamma}{(1-\gamma)^2}, \epsilon = \max_{s,a} |A_\pi(s,a)|$$

$$L_\theta(\theta') = J(\theta) + \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]$$

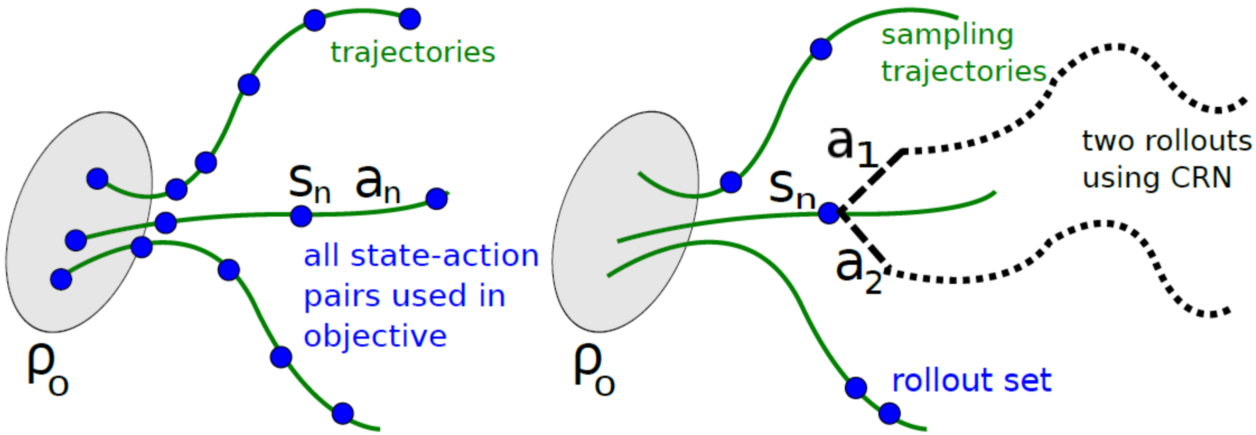
$J(\theta')$



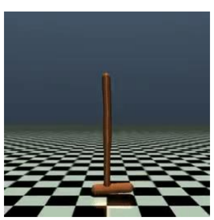
04

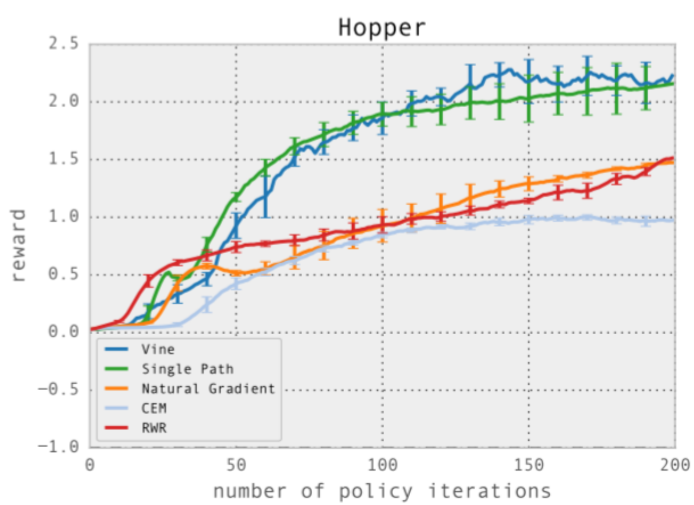
实验结果

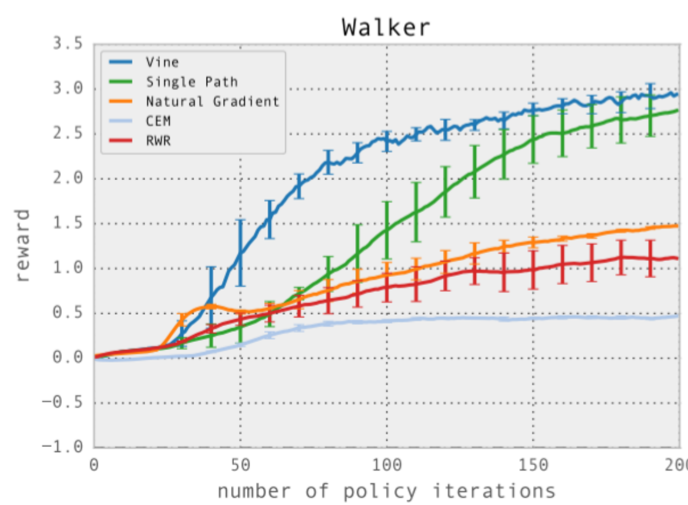
训练曲线

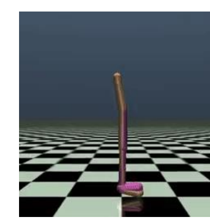


Single path | Vine









“Trust Region Policy Optimization”，John Schulman, et al. (2017)

结果比较

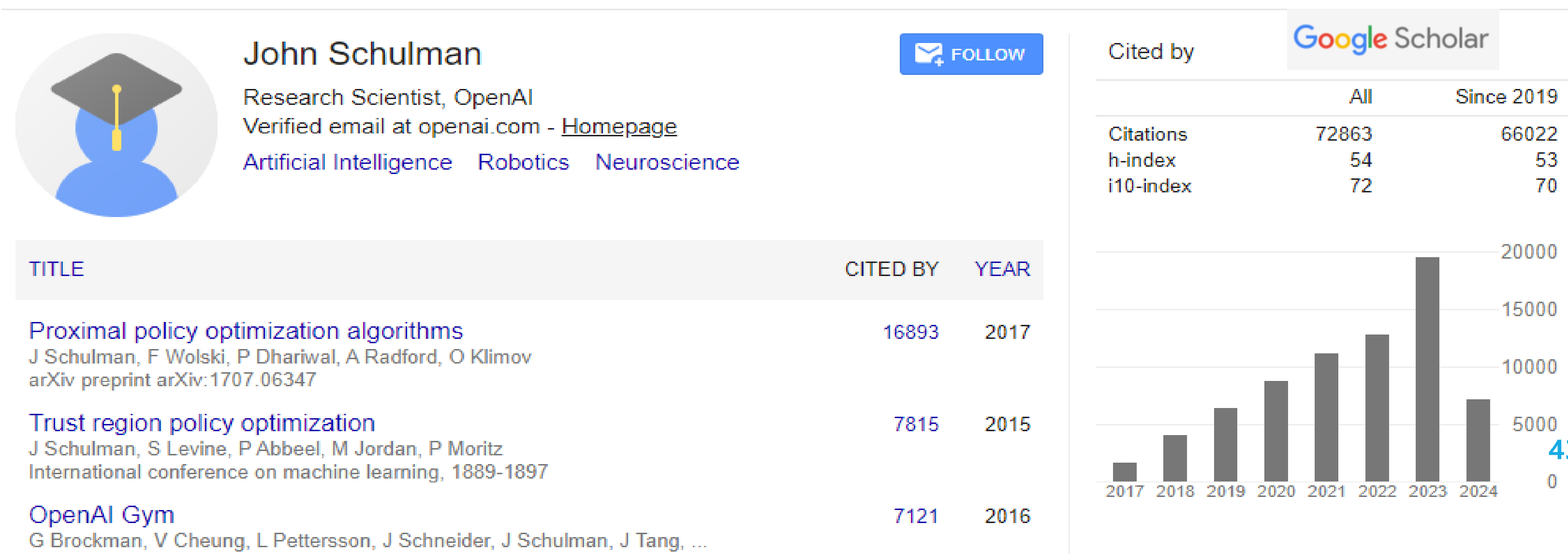
	B. Rider	*Breakout*	*Enduro*	*Pong*	*Q*bert*	*Seaquest*	*S. Invaders*
Random	354	1.2	0	−20.4	157	110	179
Human (Mnih et al., 2013)	7456	31.0	368	−3.0	18900	28010	3690
Deep Q Learning (Mnih et al., 2013)	4092	168.0	470	20.0	1952	1705	581
UCC-I (Guo et al., 2014)	5702	380	741	21	20025	2995	692
TRPO - single path	1425.2	10.8	534.6	20.9	1973.5	1908.6	568.4
TRPO - vine	859.5	34.2	430.8	20.9	7732.5	788.4	450.2

"Trust Region Policy Optimization", John Schulman, et al. (2017)

推荐阅读

PPO

- TRPO的不足
  - 近似带来误差
  - 求解约束优化问题的困难
- PPO算法
  - 理论更简洁，操作更简单，实验效果更好
  - 推荐阅读 Proximal Policy Optimization Algorithms, John Schulman, et al. (2017)



近端策略优化
Proximal Policy Optimization

回顾TRPO

- TRPO使用KL散度约束策略更新的幅度

$$\theta' \leftarrow \arg\max_{\theta'} \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]]$$

$$such\ that\ D_{KL}(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)) \le \epsilon$$

  - 使用constraint violate as penalty

$$\theta' \leftarrow \arg\max_{\theta'} \sum_t \mathbb{E}_{s_t \sim p_\theta(s_t)}[\mathbb{E}_{a_t \sim \pi_\theta(a_t|s_t)}[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \gamma^t A^{\pi_\theta}(s_t, a_t)]] - \lambda(D_{KL}(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)) - \epsilon)$$

1. 优化上式，更新θ'
2. 更新 $\lambda \leftarrow \lambda + \alpha(D_{KL}(\pi_{\theta'}(a_t|s_t) \parallel \pi_\theta(a_t|s_t)) - \epsilon)$

TRPO的不足

- 重要性比例带来的大方差
- 求解约束优化问题的困难

PPO: Proximal Policy Optimization

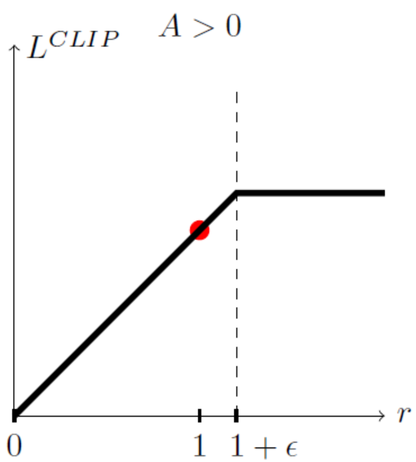
PPO在TRPO基础上的改进

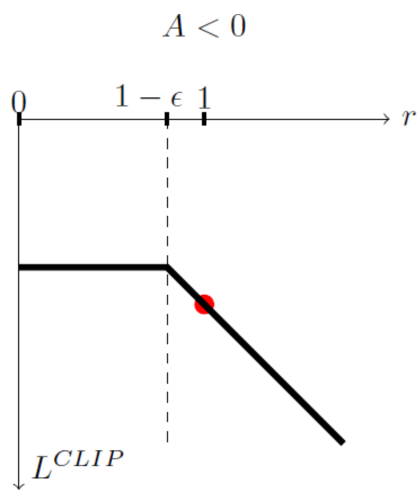
1. 截断式优化目标

conservative policy iteration

$$L^{CPI}(\theta) = \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t\right] = \hat{\mathbb{E}}_t\left[r_t(\theta)\hat{A}_t\right]$$

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t\left[\min(r_t(\theta), \mathrm{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon))\hat{A}_t\right]$$





构建下界

$$L^{CLIP}(\theta) \leq L^{CPI}(\theta)$$

在$r = 1$附近相等

$$L^{CLIP}(\theta) = L^{CPI}(\theta)$$

PPO: Proximal Policy Optimization

PPO在TRPO基础上的改进

1. 截断式优化目标

conservative policy iteration

$$L^{CPI}(\theta)=\hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t\right]=\hat{\mathbb{E}}_t\left[r_t(\theta)\hat{A}_t\right]$$

$$L^{CLIP}(\theta)=\hat{\mathbb{E}}_t\left[\min\left(r_t(\theta)\hat{A}_t,\operatorname{clip}(r_t(\theta),1-\epsilon,1+\epsilon)\hat{A}_t\right)\right]$$

2. 优势函数$\hat{A}_t$选用多步时序差分

$$\hat{A}_t=-V(s_t)+r_t+\gamma r_{t+1}+\cdots+\gamma^{T-t+1}r_{T-1}+\gamma^{T-t}V(s_T)$$

- 在每次迭代中，并行N个actor收集T步经验数据
- 计算每步的$\hat{A}_t$ 和$L^{CLIP}(\theta)$，构成mini-batch
- 更新参数θ，并更新$\theta_{\text{old}}\leftarrow\theta$

PPO: Proximal Policy Optimization

PPO在TRPO基础上的改进

3. 自适应的KL惩罚项参数

$$L^{KLPEN}(\theta) = \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t - \beta\ \mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot\ |s_t)|\pi_\theta(\cdot\ |s_t)]\right]$$

动态调整β方法

- 计算KL值 $d = \hat{\mathbb{E}}_t\left[\mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot\ |s_t)|\pi_\theta(\cdot\ |s_t)]\right]$
  a) 如果$d < d_{\text{targ}}/1.5$，更新$\beta \leftarrow \beta/2$
  b) 如果$d > d_{\text{targ}} \times 1.5$，更新$\beta \leftarrow \beta \times 2$

注：这里1.5和2是经验参数，算法效能和它们并不是很敏感

PPO实验对比

No clipping or penalty: $L_t(\theta) = r_t(\theta)\hat{A}_t$

Clipping: $L_t(\theta) = \min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta)), 1-\epsilon, 1+\epsilon)\hat{A}_t$

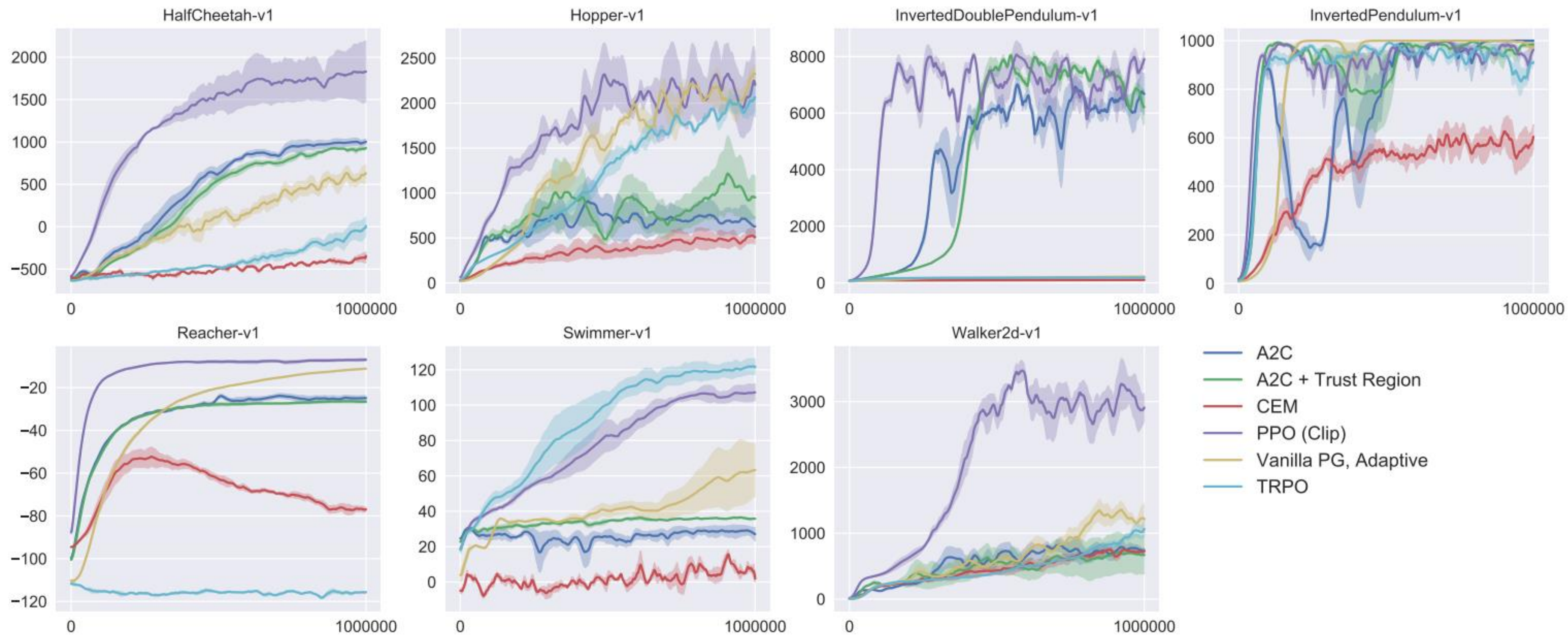
KL penalty (fixed or adaptive) $L_t(\theta) = r_t(\theta)\hat{A}_t - \beta\,\text{KL}[\pi_{\theta_{\text{old}}}, \pi_\theta]$

- 7个连续控制的环境
- 3个random seed
- 每个算法跑100个episode，跑21遍，做平均值计算
- 最佳score归一化为1

algorithm	avg. normalized score
No clipping or penalty	-0.39
Clipping, $\epsilon = 0.1$	0.76
Clipping, $\epsilon = 0.2$	**0.82**
Clipping, $\epsilon = 0.3$	0.70
Adaptive KL $d_{\text{targ}} = 0.003$	0.68
Adaptive KL $d_{\text{targ}} = 0.01$	0.74
Adaptive KL $d_{\text{targ}} = 0.03$	0.71
Fixed KL, $\beta = 0.3$	0.62
Fixed KL, $\beta = 1.$	0.71
Fixed KL, $\beta = 3.$	0.72
Fixed KL, $\beta = 10.$	0.69

Proximal Policy Optimization Algorithms, John Schulman, et al. (2017)

PPO实验对比



Proximal Policy Optimization Algorithms, John Schulman, et al. (2017)

总结深度策略梯度方法

- 相比价值函数学习最小化TD误差的目标，策略梯度方法直接优化策略价值的目标更加贴合强化学习本质目标
- 基于神经网络的策略在优化时容易因为一步走得太大而变得很差，进而下一轮产生很低质量的经验数据，进一步无法学习好
- Trust Region一类方法限制一步更新前后策略的差距（用KL散度），进而对策略价值做稳步地提升
- PPO在TRPO的基础上进一步通过限制importance ratio的range，构建优化目标的下界，进一步保证优化的稳定效果，是目前最常用的深度策略梯度算法
- 针对连续动作的决定性策略，可以从构建的critic中直接回传梯度到动作上，然后通过链式法则进一步将梯度回传到策略网络中
- 分布式的actor-critic算法能够充分利用多核CPU资源采样环境的经验数据，利用GPU资源异步地更新网络，这有效提升了DRL的训练效率

THANK YOU