Reinforcement Learning

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Can reinforcement learning solve robotics?

Alpha Go Zero (Silver et al, Nature, 2017)

selecting among possible moves for that piece. We represent the policy $\pi(a|s)$ by a $8 \times 8 \times 73$ stack of planes encoding a probability distribution over 4,672 possible moves. Each of the 8×8 positions identifies the square from which to "pick up" a piece. The first 56 planes encode

Dota 5 (OpenAI et al, 2019, https://cdn.openai.com/dota-2.pdf)

floats and categorical values with hundreds of possibilities) each time step. We discretize the action space; on an average timestep our model chooses among 8,000 to 8 pending on hero). For comparison Chess requires around one thousand valu

Alpha Star (Vinyals et al, Nature, 2019)

observe and act next (Fig. 1a). This representation of actio in approximately 10^{26} possible choices at each step. Similar

Extended Data Table 2 | Agent action space

Field	Description
Action type	Which action to execute. Some examples of actions are moving a unit, training a unit from a building, moving the camera, or no-op. See PySC2 for a full list[7]
Selected units	Entities that will execute the action
Target	An entity or location in the map discretised to 256x256 targeted by the action
Queued	Whether to queue this action or execute it immediately
Repeat	Whether or not to issue this action multiple times
Delay	The number of game time-steps to wait until receiving the next observation

DDPG (Lillicrap et al, 2015)

A first “Deep” crack at RL with continuous action spaces

Deterministic Policy Gradient

DPG (Silver et al., 2014)

- Finds deterministic policy
- Applicable to continuous action space

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- Not learning-based, can we do better?

DDPG

DDPG (Deep DPG) in one sentence:

- Extends **DPG** (Deterministic Policy Gradients, Silver et al., '14) using deep learning,

- borrowing tricks from **Deep Q-Learning** (Mnih et al., '13)

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- Extends **DPG** (Deterministic Policy Gradients, Silver et al., ‘14) using deep learning,

- borrowing tricks from **Deep Q-Learning** (Mnih et al., ‘13)

- Contribution: model-free, off-policy, actor-critic approach that allows us to better learn deterministic policies on continuous action space

DDPG

DDPG (Deep DPG) is a model-free, off-policy, actor-critic algorithm that combines:

- **DPG** (Deterministic Policy Gradients, Silver et al., ‘14): works over continuous action domain, not learning-based

- **DQN** (Deep Q-Learning**,** Mnih et al., ‘13): learning-based, doesn’t work over continuous action domain

Background - DPG

In Q-learning, we find deterministic policy by

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Problem: In large discrete action space or continuous action space, we can't plug in every possible action to find the optimal action!

Solution: Learn a function approximator for argmax, via gradient descent

$$\mu^{k+1}(s) = \pi_{\boxed{\theta}}(s)$$

Background - DPG

- Goal:

  Derive a gradient update rule to learn deterministic policy π_θ

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- Idea:

  Adapt the **stochastic policy gradient** formulation for deterministic policies

Background - DPG

- Vanilla Stochastic Policy Gradient:

Source: http://rail.eecs.berkeley.edu/deeprlcourse/static/slides/lec-5.pdf

Background - DPG

- Vanilla Stochastic Policy Gradient:

$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right]}_{J(\theta)}$$

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Background - DPG

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$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right]}_{J(\theta)}$$

$$\nabla_\theta J(\theta) = E_{\tau\sim\pi_\theta(\tau)}\left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)\right)\left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)\right)\right]$$

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$$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$$

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model-free

Not trivial to compute!

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Background - DPG

- Vanilla Stochastic Policy Gradient with Monte-Carlo Sampling:

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

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Problem: Point Estimate - High Variance!

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

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

True value function is still not trivial to compute

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

True value function is still not trivial to compute, but we can approximate it with a parameterized function:

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

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Background - DPG

- Stochastic Policy Gradient (Actor-Critic)

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

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Actor: Policy function π_θ

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Actor: Policy function π_θ

Critic: Value function Q^w, which provides guidance to improve the actor

Background - DPG

- Deterministic Policy Gradient (Actor-Critic)

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Objective:

$$J(\pi_\theta) = \int_S \rho^\pi(s) r(s, \pi_\theta(s)) ds$$
$$= \mathbb{E}_{s \sim \rho^\pi}[r(s, \pi_\theta(s))]$$

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Policy Gradient:

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

Background - DPG

Deterministic Policy Gradient (Actor-Critic)

Objective:

$$J(\pi_\theta) = \int_{\mathcal{S}} \rho^\pi(s) r(s, \pi_\theta(s)) ds$$

$$= \mathbb{E}_{s\sim\rho^\pi}\left[\boxed{r(s, \pi_\theta(s))}\right]$$

Policy Gradient:

$$\nabla_\theta J(\pi_\theta) = \int_{\mathcal{S}} \rho^\pi(s) \nabla_\theta \pi_\theta(s) \nabla_a \boxed{Q^w(s, a)|_{a=\pi_\theta(s)}} ds$$

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

Background - DPG

Stochastic Policy Gradient:

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

Deterministic Policy Gradient:

$$\begin{aligned}\nabla_\theta J(\pi_\theta) &= \int_{\mathcal{S}} \rho^\pi(s) \nabla_\theta \pi_\theta(s) \nabla_a Q^w(s,a)|_{a=\pi_\theta(s)} ds \\ &= \mathbb{E}_{s\sim\rho^\pi}[\nabla_\theta \pi_\theta(s) \nabla_a Q^w(s,a)|_{a=\pi_\theta(s)}]\end{aligned}$$

Background - DPG

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Stochastic Policy Gradient:

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

Deterministic Policy Gradient:

DDPG: Use deep learning to learn both functions!

$$\begin{aligned}\nabla_\theta J(\pi_\theta) &= \int_{\mathcal{S}} \rho^\pi(s) \nabla_\theta \pi_\theta(s) \nabla_a Q^w(s,a)|_{a=\pi_\theta(s)} ds \\ &= \mathbb{E}_{s\sim\rho^\pi}\left[\nabla_\theta \boxed{\pi_\theta(s)} \nabla_a \boxed{Q^w(s,a)}|_{a=\pi_\theta(s)}\right]\end{aligned}$$

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- DPG: Formulates an update rule for deterministic policies, so that we can learn deterministic policy on continuous action domain

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  - Target Network
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  Model-Free, Actor-Critic

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  Model-Free, Actor-Critic

- DQN: Enables learning value functions with neural nets , with two tricks:
  - Target Network
  - Replay Buffer - Off-Policy
- DDPG: Learn both the policy and the value function in DPG with neural networks, with DQN tricks!

Method - DDPG

DDPG Problem Setting

$$\mu(s|\theta^{\mu})$$

Policy (Actor) Network
Deterministic, Continuous Action Space

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$$Q(s, a|\theta^{Q})$$

Value (Critic) Network

DDPG Problem Setting

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Policy (Actor) Network
Deterministic, Continuous Action Space

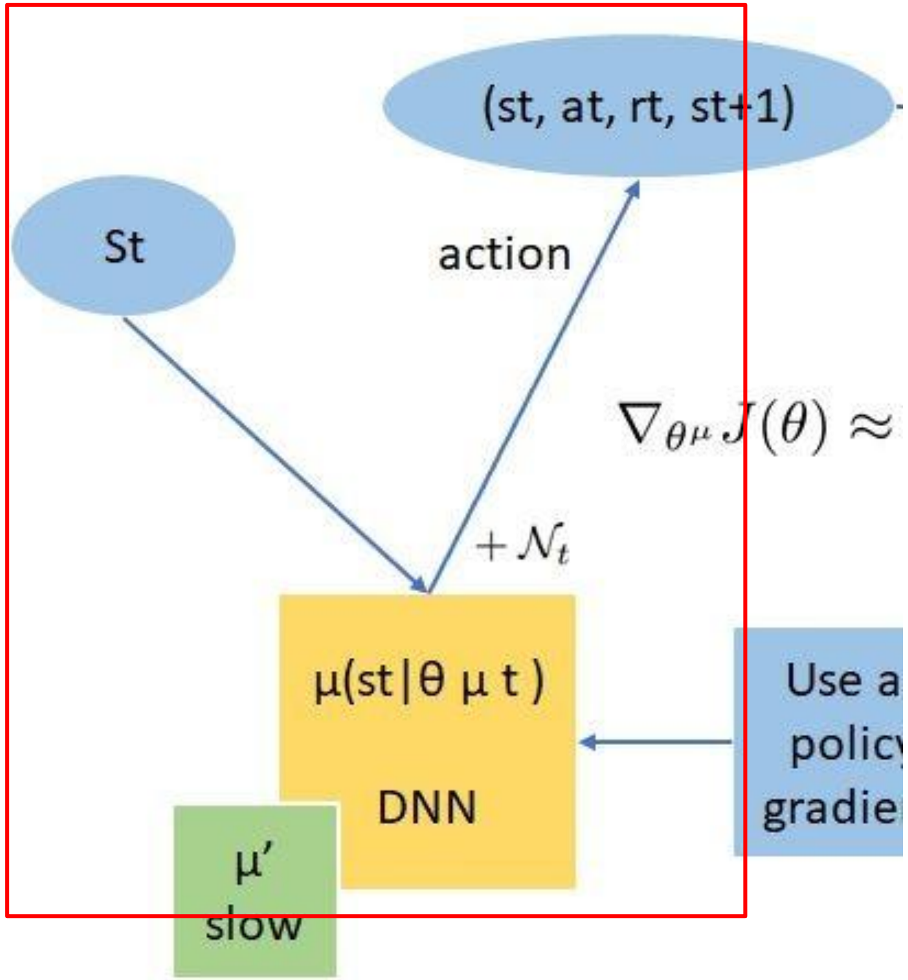
$$Q(s, a|\theta^{Q})$$

Value (Critic) Network

$$\mu'(s|\theta^{\mu'}), Q'(s, a|\theta^{Q'})$$

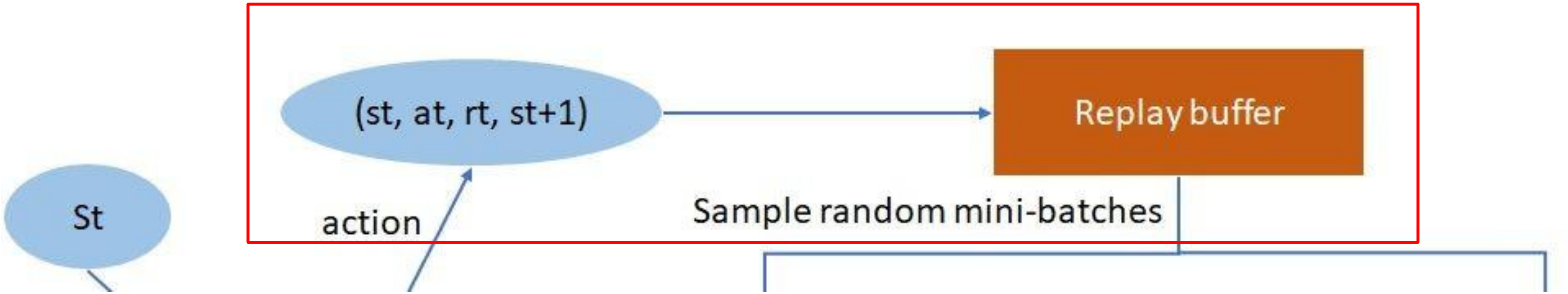
Target Policy and Value Networks

Method



Credit: Professor Animesh Garg

Method



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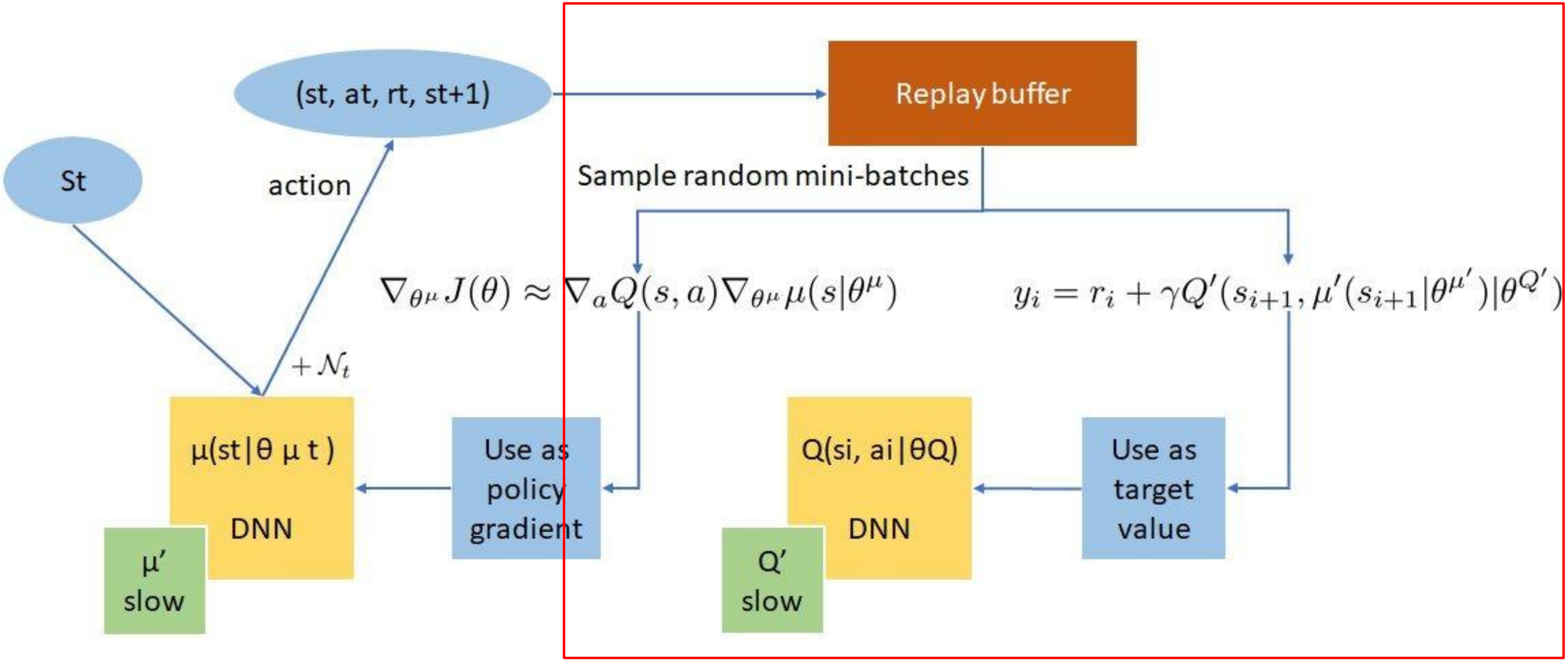

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Method

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:

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

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Method

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Replay buffer

"Soft" target network update

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Add noise for exploration

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Value Network Update

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Policy Network Update

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

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Method

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

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    for $t = 1, T$ **do**

DDPG: Policy Network, learned with Deterministic Policy Gradient

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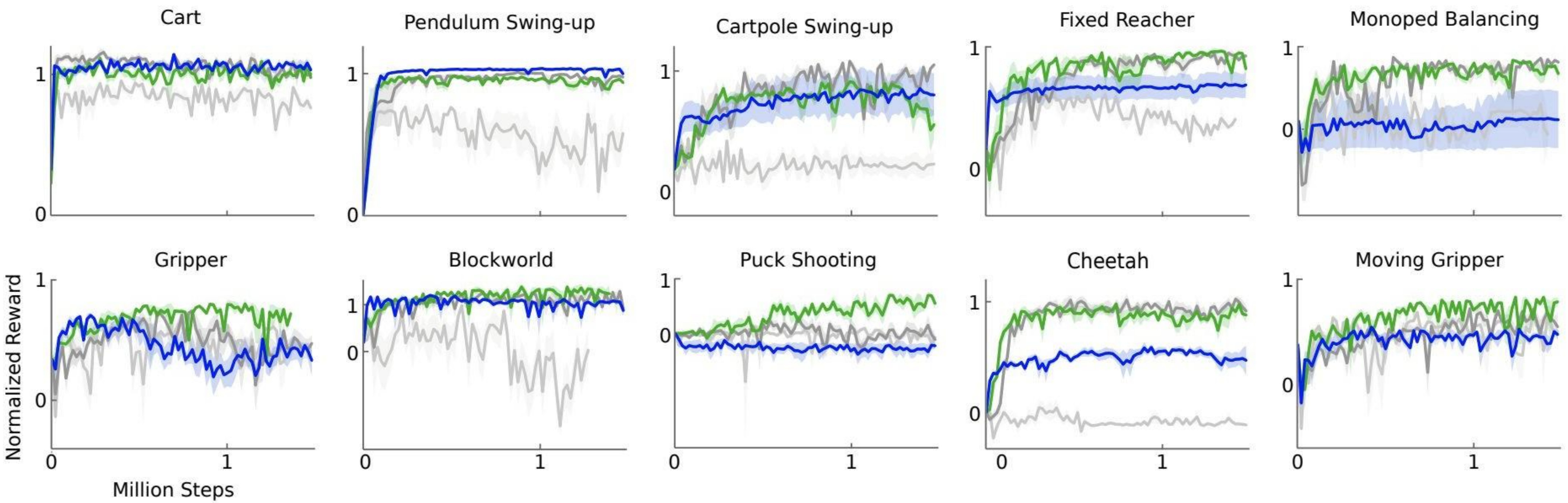
        Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
        Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
        Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
        Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
    end for
end for

Experiments



Light Grey: Original DPG
Dark Grey: Target Network
Green: Target Network + Batch Norm
Blue: Target Network from pixel-only inputs

Experiments

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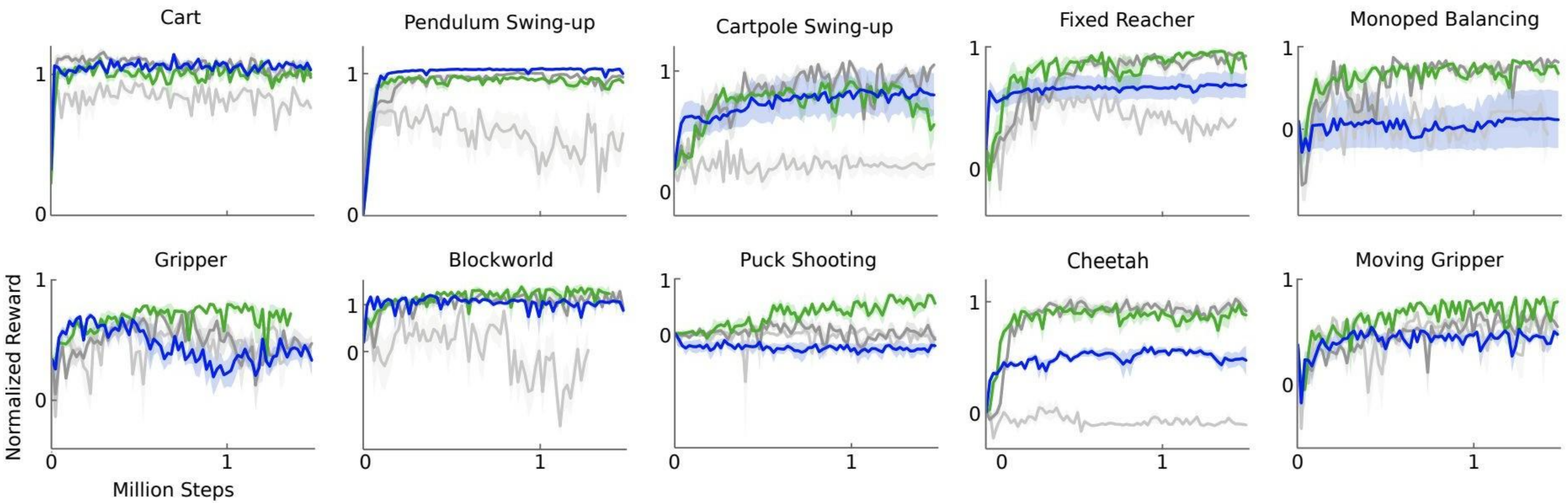
Do target networks and batch norm matter?



Light Grey: Original DPG
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Experiments

DDPG DPG

Is DDPG better than DPG?

environment	$R_{av,lowd}$	$R_{best,lowd}$	$R_{av,pix}$	$R_{best,pix}$	$R_{av,cntrl}$	$R_{best,cntrl}$
blockworld1	1.156	1.511	0.466	1.299	-0.080	1.260
blockworld3da	0.340	0.705	0.889	2.225	-0.139	0.658
canada	0.303	1.735	0.176	0.688	0.125	1.157
canada2d	0.400	0.978	-0.285	0.119	-0.045	0.701
cart	0.938	1.336	1.096	1.258	0.343	1.216
cartpole	0.844	1.115	0.482	1.138	0.244	0.755
cartpoleBalance	0.951	1.000	0.335	0.996	-0.468	0.528
cartpoleParallelDouble	0.549	0.900	0.188	0.323	0.197	0.572
cartpoleSerialDouble	0.272	0.719	0.195	0.642	0.143	0.701
cartpoleSerialTriple	0.736	0.946	0.412	0.427	0.583	0.942
cheetah	0.903	1.206	0.457	0.792	-0.008	0.425
fixedReacher	0.849	1.021	0.693	0.981	0.259	0.927
fixedReacherDouble	0.924	0.996	0.872	0.943	0.290	0.995
fixedReacherSingle	0.954	1.000	0.827	0.995	0.620	0.999
gripper	0.655	0.972	0.406	0.790	0.461	0.816
gripperRandom	0.618	0.937	0.082	0.791	0.557	0.808
hardCheetah	1.311	1.990	1.204	1.431	-0.031	1.411
hopper	0.676	0.936	0.112	0.924	0.078	0.917
hyq	0.416	0.722	0.234	0.672	0.198	0.618
movingGripper	0.474	0.936	0.480	0.644	0.416	0.805
pendulum	0.946	1.021	0.663	1.055	0.099	0.951
reacher	0.720	0.987	0.194	0.878	0.231	0.953
reacher3daFixedTarget	0.585	0.943	0.453	0.922	0.204	0.631
reacher3daRandomTarget	0.467	0.739	0.374	0.735	-0.046	0.158
reacherSingle	0.981	1.102	1.000	1.083	1.010	1.083
walker2d	0.705	1.573	0.944	1.476	0.393	1.397
torcs	-393.385	1840.036	-401.911	1876.284	-911.034	1961.600

Experiments

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DDPG DPG

Is DDPG better than DPG?

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Experiments

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DDPG DPG

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Is DDPG better than DPG?

Experiments

KAUST ACADEMY أكاديمية كاوست

DDPG | DPG

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Is DDPG better than DPG?

Experiments

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DDPG still exhibits high variance

Experiments

How well does Q estimate the true returns?

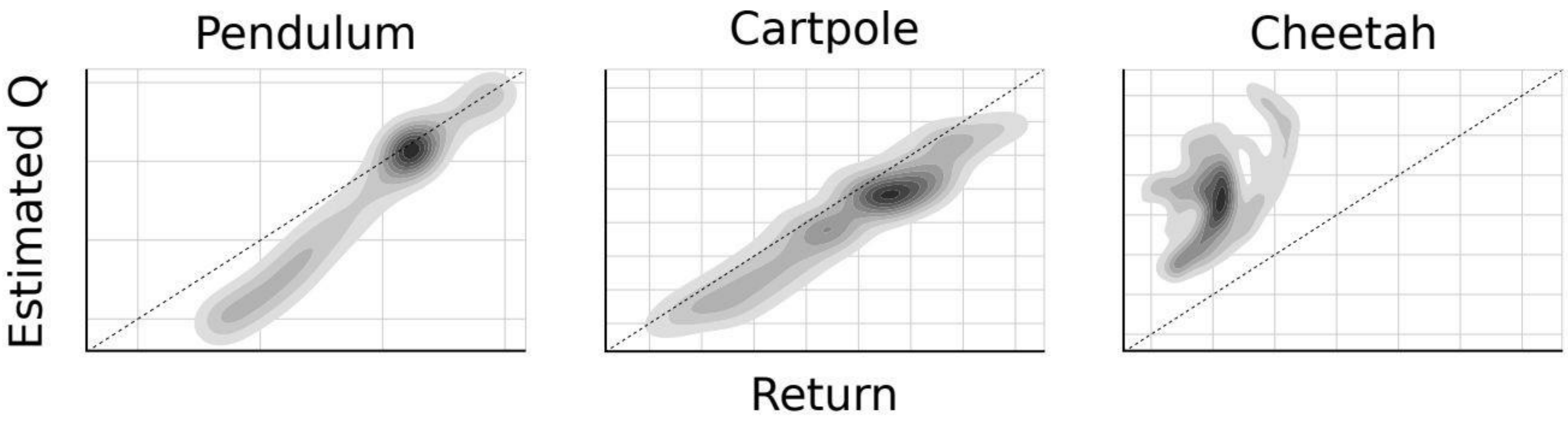

Figure 3: Density plot showing estimated Q values versus observed returns sampled from test episodes on 5 replicas. In simple domains such as pendulum and cartpole the Q values are quite accurate. In more complex tasks, the Q estimates are less accurate, but can still be used to learn competent policies. Dotted line indicates unity, units are arbitrary.

DDPG Follow-up

- Model the actor as the argmax of a convex function
  - Continuous Deep Q-Learning with Model-based Acceleration (Shixiang Gu, Timothy Lillicrap, Ilya Sutskever, Sergey Levine, ICML 2016)
  - Input Convex Neural Networks (Brandon Amos, Lei Xu, J. Zico Kolter, ICML 2017)
- Q-value overestimation
  - Addressing Function Approximation Error in Actor-Critic Methods (TD3) (Scott Fujimoto, Herke van Hoof, David Meger, ICML 2018)
- Stochastic policy search
  - Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor (Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, Sergey Levine, ICML 2018)

often used to perform the maximization in Q-learning. A commonly used algorithm in such settings, deep deterministic policy gradient (DDPG) (Lillicrap et al., 2015), provides for sample-efficient learning but is notoriously challenging to use due to its extreme brittleness and hyperparameter sensitivity (Duan et al., 2016; Henderson et al., 2017).

ily to very complex, high-dimensional tasks, such as the Humanoid benchmark (Duan et al., 2016) with 21 action dimensions, where off-policy methods such as DDPG typically struggle to obtain good results (Gu et al., 2016). SAC also avoids the complexity and potential instability associ-

A cool application of DDPG: Wayve

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Learning to Drive in a Day (Alex Kendall et al, 2018)

We selected a simple continuous action domain model-free reinforcement learning algorithm: deep deterministic policy gradients (DDPG) [8], to show that an off-the-shelf reinforcement learning algorithm with no task-specific adaptation is capable of solving the MDP posed in Section III-A.

DDPG consists of two function approximators: a critic $Q: \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, which estimates the value $Q(s, a)$ of the expected cumulative discounted reward upon using action a in state s, trained to satisfy the Bellman equation

$$Q(s_t, a_t) = r_{t+1} + \gamma(1 - d_t)Q(s_{t+1}, \pi(s_{t+1})),$$

under a policy given by the actor $\pi: \mathcal{S} \to \mathcal{A}$, which attempts to estimate a Q-optimal policy $\pi(s) = \operatorname{argmax}_a Q(s, a)$; here $(s_t, a_t, r_{t+1}, d_{t+1}, s_{t+1})$ is an experience tuple, a transition

Conclusion

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- DDPG = DPG + DQN
- Big Idea is to bypass finding the local max of Q in DQN by jointly training a second neural network (actor) to predict the local max of Q.
- Tricks that made DDPG possible:
  - Replay buffer, target networks (from DQN)
  - Batch normalization, to allow transfer between different RL tasks with different state scales
  - Directly add noise to policy output for exploration, due to continuous action domain
- Despite these tricks, DDPG can still be sensitive to hyperparameters. TD3 and SAC offer better stability.

References

These slides have been adapted from

- Animesh Garg, CSC2621: Reinforcement Learning in Robotics, University of Toronto