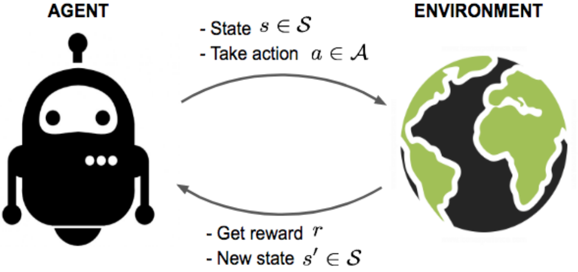

Final Report

Kushagra Chandak
International Institute of Information Technology, Hyderabad (IIIT-H), India

Where do I come from?

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Contents

Introduction

Policy Gradient

- Policy based RL: $\pi_\theta(s, a) = P(a|s, \theta)$

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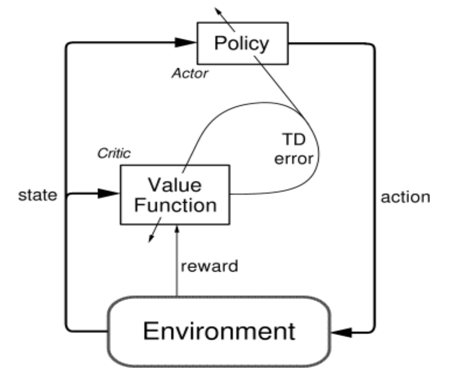
- A lot of problems with vanilla PG (continuous domains, credit assignment, etc.)

Actor-Critic



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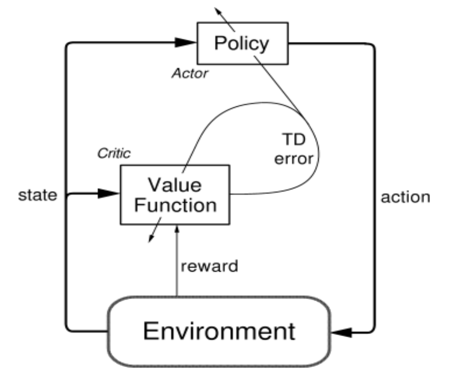

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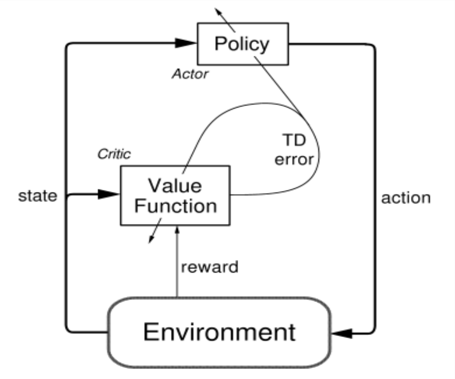

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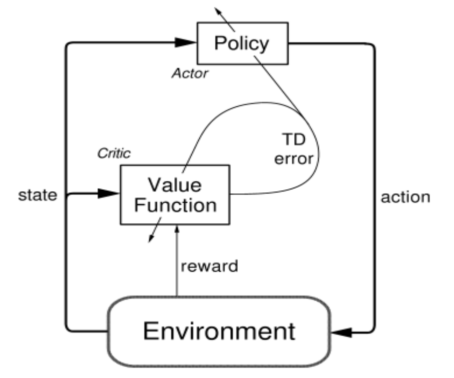

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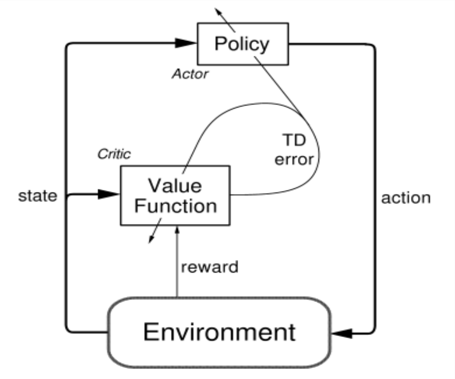

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- Policy: Actor, Value: Critic
- Given current state, actor produces an action.
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- In DRL, neural nets can be used to represent actor and critic.

Baseline Algorithms

Deep Deterministic Policy Gradient (DDPG)[1]

- Motivation: To tackle continuous action spaces.

[1] Lillicrap et al., 2015

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- DQN: Learning is stabilized using experience replay and frozen target network.
- DDPG: Extends DQN to continuous space with actor-critic framework while learning a deterministic policy.

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DDPG: The algorithm

- Choosing action: Get $a = \mu(s)$ from actor. While training, add exploration noise.

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- Better exploration: An exploration policy is $\mu^{'}$ is constructed by adding noise $\mathcal{N}$

$$\mu^{'}(s) = \mu_{\theta}(s) + \mathcal{N}$$

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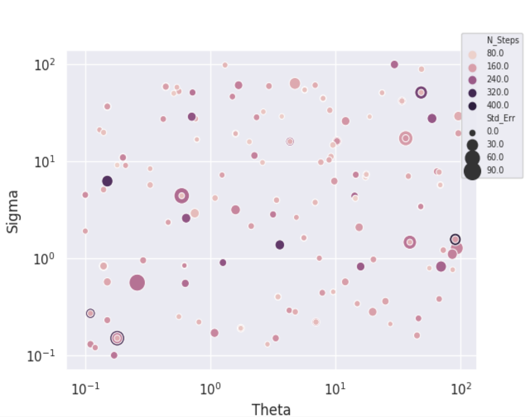
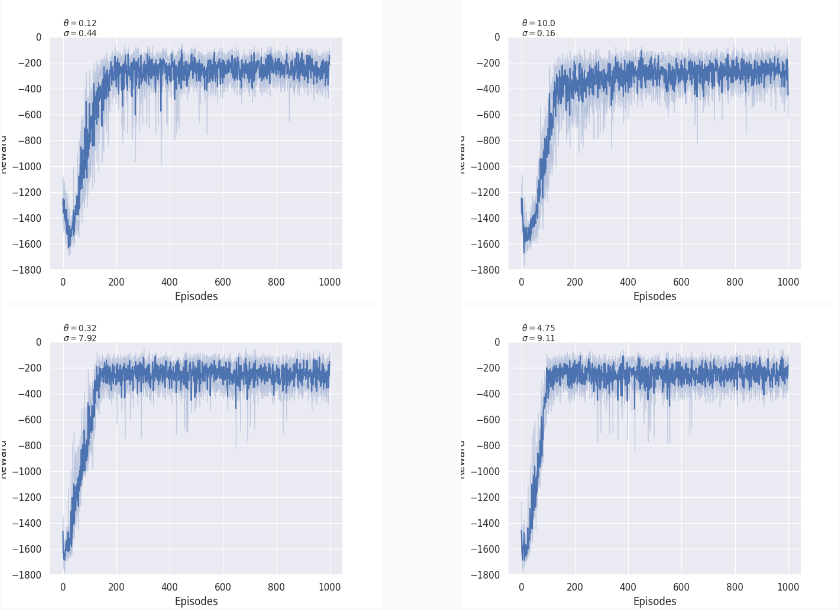
- *Why* in DDPG? It's a diffusion type Markov process (and Normally distributed).

Parameters of OU process



- $\mu(= 0)$ is the long term mean.
- $\theta > 0$ is rate of mean reversion.
- $\sigma > 0$ is the volatility, per square-root t, of the random fluctuations.

DDPG on OpenAI Gym’s Pendulum



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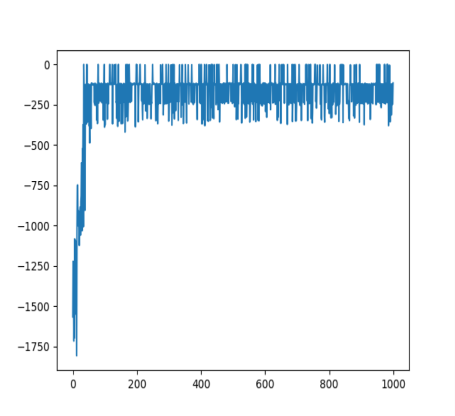
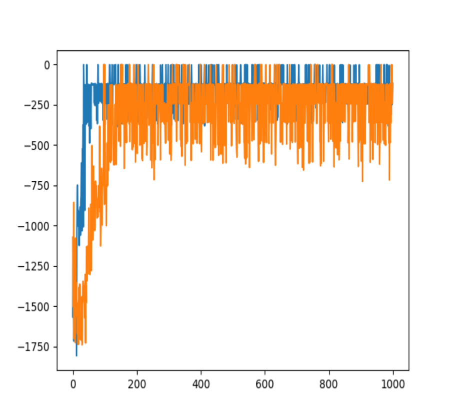
- Can compute unbiased stochastic gradients for both the steps using off policy data.

Results

SAC



SAC vs DDPG



Towards data efficient and stable RL: Conservative Value Iteration

Conservative Value Iteration (CVI)

- Optimizing KL divergence and entropy

$$W_{\tilde{\pi}}^{\pi}(s) = \mathbb{E}^{\pi}\left[\sum_{t\geq 0}^{\infty} \gamma^t \left(R_t - \tau \log \frac{\pi(A_t|S_t)}{\tilde{\pi}(A_t|S_t)} - \sigma \log \pi(A_t|S_t)\right)\middle| S_0 = s\right]$$

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- Analogous to policy iteration.

Arriving at CVI

- CVI computes W_k defined by

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- Find a policy that optimizes the W_k
- Analogous to value iteration.

- Let $\alpha = \tau/(\tau+\sigma)$ and $\beta := 1/(\tau+\sigma)$.[3]. π_k can be analytically obtained as

$$\pi_k(a|s) = \frac{\pi_{k-1}(a|s)^\alpha e^{\beta(r+\gamma\mathbb{P}W_{k-1})(s,a)}}{\sum_b \pi_{k-1}(b|s)^\alpha e^{\beta(r+\gamma\mathbb{P}W_{k-1})(s,b)}}.$$

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- After some *dangerous* algebraic manipulations and defining action-value function as

$$\Psi_k(s,a) = (r+\gamma\mathbb{P}W_{k-1})(s,a) + \frac{\alpha}{\beta}\log\pi_{k-1}(a|s)$$

we get π_k as

$$\pi_k(a|s) = \frac{\exp(\beta\Psi_k(s,a))}{\sum_b \exp(\beta\Psi_k(s,b))}$$

and

$$W_k(s) = \mathbf{m}_\beta\Psi_k(s) = \mathbb{E}^{\pi_k}\left[\Psi_k(s,A) - \frac{1}{\beta}\log\pi_k(A|s)\right],$$

where $\mathbf{m}_\beta\Psi_k(s) := \beta^{-1}\log\sum_a \exp(\beta\Psi_k(s,a))$.

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The final (*not* so dangerous) update rules are:

$$\Psi_k(s,a) = r + \gamma \mathbb{P} W_{k-1}(s,a) + \alpha \left(\Psi_{k-1}(s,a) - W_{k-1}(s) \right)$$

$$\pi_k(a|s) = \frac{\exp\left(\beta \Psi_k(s,a)\right)}{\sum_b \exp\left(\beta \Psi_k(s,b)\right)}$$

$$W_k(s) = \mathbb{E}^{\pi_k}\left[\Psi_k(s,A) - \frac{1}{\beta} \log \pi_k(A|s) \right]$$

Conclusion

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- *List goes on...*

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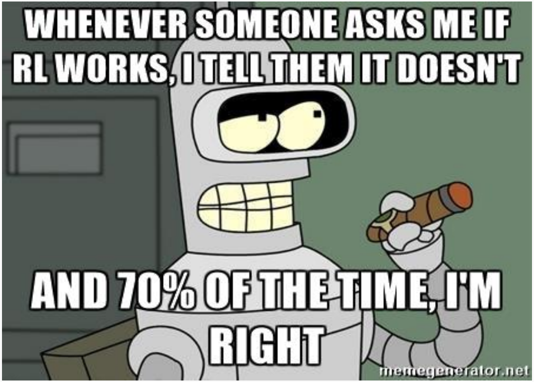
Take Home



Thank You!

Acknowledgements

Arigato Gozaimasu!