SOFT ACTOR-CRITIC

Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

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OUTLINE

Introduction

Related work

Soft Actor-Critic

New objective

Policy update rule

Cost functions and gradients

Algorithm

Experiments

INTRODUCTION

Model-Free Reinforcement Learning

- In combination with high-capacity function approximators such as neural networks

INTRODUCTION

Model-Free Reinforcement Learning Challenges

- Very High Sample Complexity
  - Requires millions of steps
- brittle with respect to their hyperparameters
  - Learning rate, exploration constants and …
- Continuous state and action spaces

RELATED WORK

Off-policy

- E.g. DDPG
- Improve Sample Complexity
- Extremely difficult to stabilize and brittle to hyperparameter settings
  - difficult to extend to complex, high-dimensional tasks
- Continuous state and action spaces

On-policy

- E.g. PPO
- Improve Stability
- Good for continuous state and action spaces
- Poor sample complexity

SOFT ACTOR-CRITIC

an actor-critic architecture with separate policy and value function networks

an off-policy formulation that enables reuse of previously collected data for efficiency

entropy maximization to enable stability and exploration

NEW OBJECTIVE

$$J(\pi) = \sum_{t=0}^{T} \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \rho_\pi} \left[r(\mathbf{s}_t, \mathbf{a}_t) + \alpha \mathcal{H}(\pi(\,\cdot\,|\mathbf{s}_t)) \right]$$

$$J(\pi) = \sum_{t=0}^{\infty} \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \rho_\pi} \left[\sum_{l=t}^{\infty} \gamma^{l-t} \, \mathbb{E}_{\mathbf{s}_l \sim p, \mathbf{a}_l \sim \pi} \left[r(\mathbf{s}_t, \mathbf{a}_t) + \alpha \mathcal{H}(\pi(\,\cdot\,|\mathbf{s}_t)) | \mathbf{s}_t, \mathbf{a}_t \right] \right]$$

α: The temperature parameter

$$\mathrm{H}(X) = -\sum_{i=1}^{n} \mathrm{P}(x_i) \log_b \mathrm{P}(x_i)$$

POLICY UPDATE RULE

$$\pi_{\text{new}} = \arg\min_{\pi' \in \Pi} \mathrm{D}_{\mathrm{KL}} \left(\pi'(\,\cdot\,|\mathbf{s}_t) \,\middle\|\, \frac{\exp\left(Q^{\pi_{\text{old}}}(\mathbf{s}_t,\,\cdot\,)\right)}{Z^{\pi_{\text{old}}}(\mathbf{s}_t)} \right)$$

Lemma 2 (Soft Policy Improvement)**.** *Let* $\pi_{\text{old}} \in \Pi$ *and let* π_{new} *be the optimizer of the minimization problem defined in Equation 4. Then* $Q^{\pi_{\text{new}}}(\mathbf{s}_t, \mathbf{a}_t) \geq Q^{\pi_{\text{old}}}(\mathbf{s}_t, \mathbf{a}_t)$ *for all* $(\mathbf{s}_t, \mathbf{a}_t) \in \mathcal{S} \times \mathcal{A}$ *with* $|\mathcal{A}| < \infty$.

COST FUNCTIONS & GRADIENTS

$$J_V(\psi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[\frac{1}{2} \left(V_\psi(\mathbf{s}_t) - \mathbb{E}_{\mathbf{a}_t \sim \pi_\phi} \left[Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \log \pi_\phi(\mathbf{a}_t | \mathbf{s}_t) \right] \right)^2 \right]$$

$$\hat{\nabla}_\psi J_V(\psi) = \nabla_\psi V_\psi(\mathbf{s}_t) \left(V_\psi(\mathbf{s}_t) - Q_\theta(\mathbf{s}_t, \mathbf{a}_t) + \log \pi_\phi(\mathbf{a}_t | \mathbf{s}_t) \right)$$

$$J_Q(\theta) = \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \mathcal{D}} \left[\frac{1}{2} \left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \hat{Q}(\mathbf{s}_t, \mathbf{a}_t) \right)^2 \right]$$

$$\hat{Q}(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \gamma \, \mathbb{E}_{\mathbf{s}_{t+1} \sim p} \left[V_{\bar{\psi}}(\mathbf{s}_{t+1}) \right]$$

$$\hat{\nabla}_\theta J_Q(\theta) = \nabla_\theta Q_\theta(\mathbf{a}_t, \mathbf{s}_t) \left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - r(\mathbf{s}_t, \mathbf{a}_t) - \gamma V_{\bar{\psi}}(\mathbf{s}_{t+1}) \right)$$

$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[\mathrm{D}_{\mathrm{KL}} \left(\pi_\phi(\cdot | \mathbf{s}_t) \,\middle\|\, \frac{\exp\left(Q_\theta(\mathbf{s}_t, \cdot)\right)}{Z_\theta(\mathbf{s}_t)} \right) \right]$$

$\mathbf{a}_t = f_\phi(\epsilon_t; \mathbf{s}_t)$ reparameterization trick

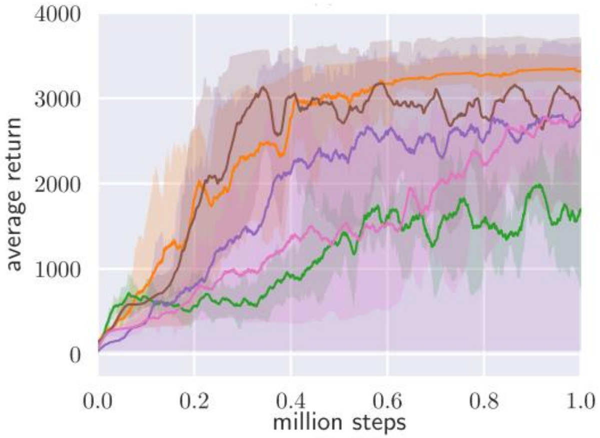
$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}, \epsilon_t \sim \mathcal{N}} \left[\log \pi_\phi(f_\phi(\epsilon_t; \mathbf{s}_t) | \mathbf{s}_t) - Q_\theta(\mathbf{s}_t, f_\phi(\epsilon_t; \mathbf{s}_t)) \right]$$

$$\begin{aligned} \hat{\nabla}_\phi J_\pi(\phi) = & \nabla_\phi \log \pi_\phi(\mathbf{a}_t | \mathbf{s}_t) \\ & + (\nabla_{\mathbf{a}_t} \log \pi_\phi(\mathbf{a}_t | \mathbf{s}_t) - \nabla_{\mathbf{a}_t} Q(\mathbf{s}_t, \mathbf{a}_t)) \nabla_\phi f_\phi(\epsilon_t; \mathbf{s}_t) \end{aligned}$$

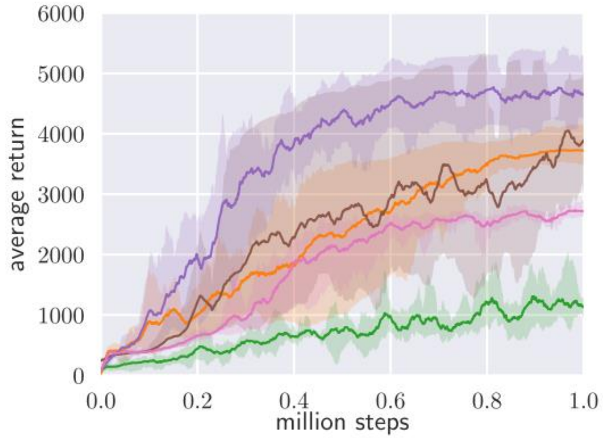
ALGORITHM

Initialize parameter vectors ψ, $\bar{\psi}$, θ, ϕ.
for each iteration **do**
  for each environment step **do**
    $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$
    $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$
  end for
  for each gradient step **do**
    $\psi \leftarrow \psi - \lambda_V \hat{\nabla}_\psi J_V(\psi)$
    $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$
    $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$
    $\bar{\psi} \leftarrow \tau\psi + (1 - \tau)\bar{\psi}$
  end for
end for

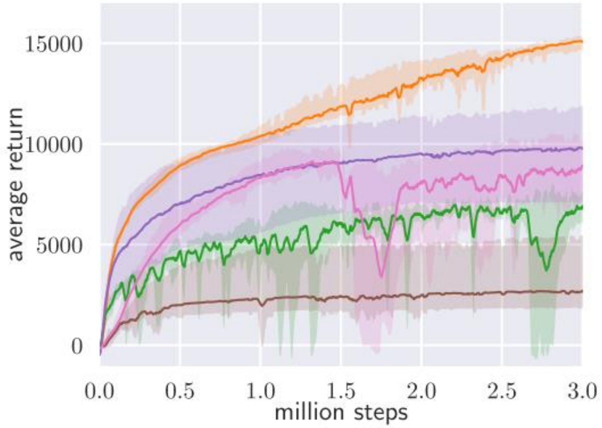
EXPERIMENTS



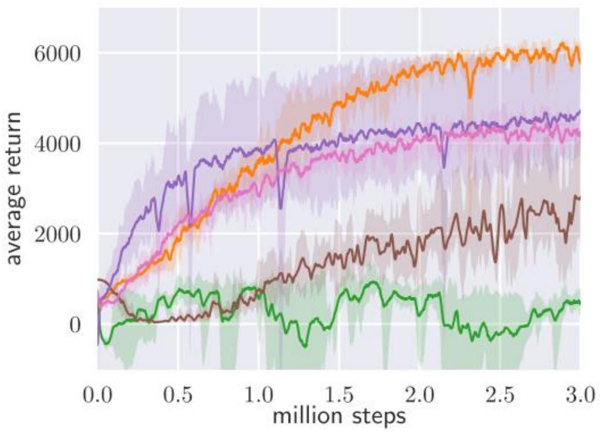
(a) Hopper-v1



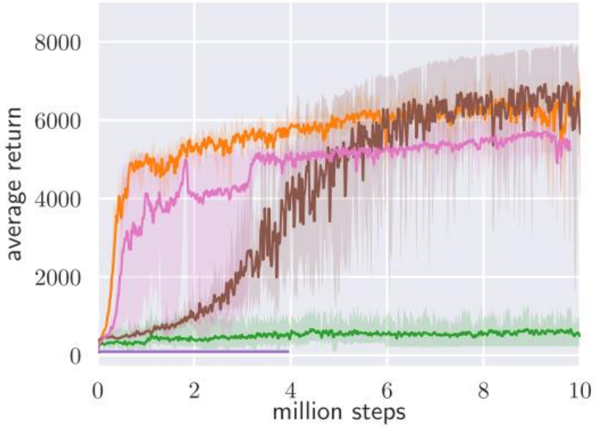
(b) Walker2d-v1



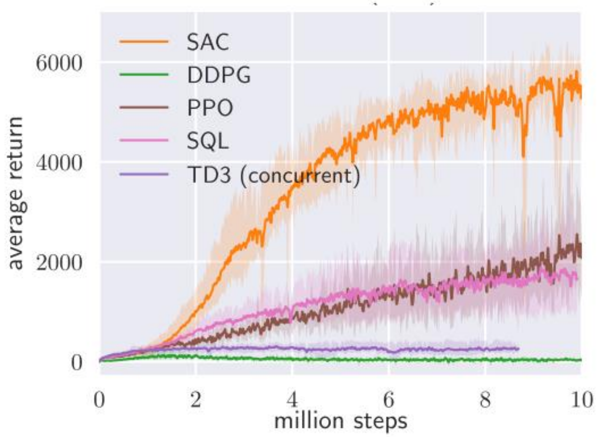
(c) HalfCheetah-v1



(d) Ant-v1

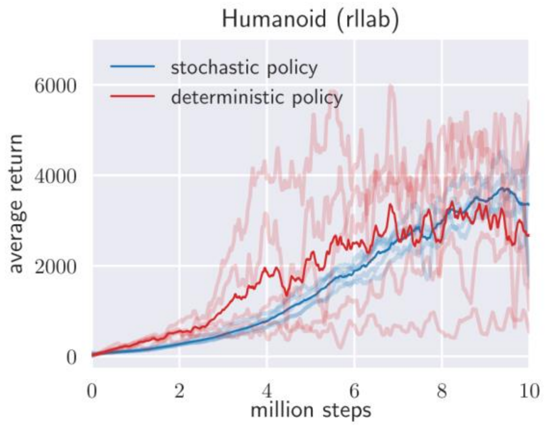


(e) Humanoid-v1

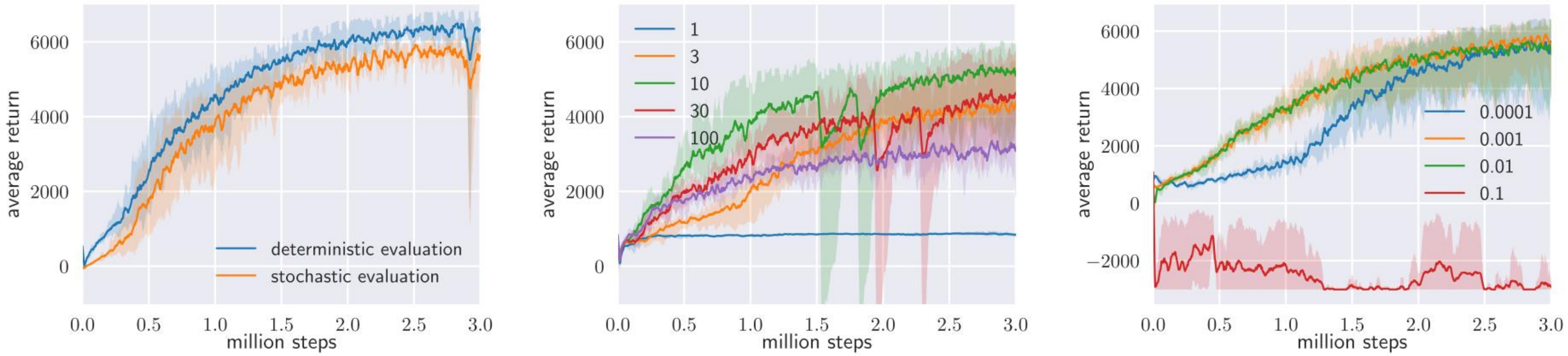


(f) Humanoid (rllab)

EXPERIMENTS



learning a stochastic policy with entropy maximization can drastically stabilize training



(a) Evaluation (b) Reward Scale (c) Target Smoothing Coefficient (τ)

THANK YOU

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