Proximal Policy Optimization Algorithms, Schulman et al, 2017

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Introduction

Proximal Policy Optimization Algorithms, Schulman et al, 2017

- In recent years, several different approaches have been proposed for reinforcement learning with neural network function approximators. The leading contenders are deep Q-learning, "vanilla" policy gradient methods, and trust region / natural policy gradient methods.
- However, there is room for improvement in developing a method that is **scalable** (to large models and parallel implementations), **data efficient**, and **robust** (i.e., successful on a variety of problems without hyperparameter tuning).

Introduction

- DQN
  - fails on many simple problems and is poorly understood
- A3C – "Vanilla" policy gradient methods
  - have poor data efficiency and robustness
- TRPO
  - relatively complicated
  - is not compatible with architectures that include noise (such as dropout) or parameter sharing (between the policy and value function, or with auxiliary tasks)

Introduction

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- We propose a novel objective with **clipped probability ratios**, which forms a pessimistic estimate (i.e., lower bound) of the performance of the policy.
- This paper seeks to improve the current state of affairs by introducing an algorithm that attains the data efficiency and reliable performance of TRPO, while using only first-order optimization.

Introduction

- To optimize policies, we alternate between sampling data from the policy and performing several epochs of optimization on the sampled data.

Introduction

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- Our experiments compare the performance of various different versions of the surrogate objective, and find that the version with the **<u>clipped probability ratios performs best</u>**.
- We also compare PPO to several previous algorithms from the literature.
  - On continuous control tasks, <u>it performs better than the algorithms we compare against</u>.
  - On Atari, <u>it performs significantly better (in terms of sample complexity) than A2C and similarly to ACER though it is much simpler</u>.

Background: Policy Optimization

PPO, Schulman et al, 2017

- Policy gradient methods work by computing an estimator of the policy gradient and plugging it into a stochastic gradient ascent algorithm. The most commonly used gradient estimator has the form

$$\hat{g} = \hat{\mathbb{E}}_t\left[\nabla_\theta \log \pi_\theta\left(a_t|s_t\right)\hat{A}_t\right]$$

  - where π_θ is a stochastic policy and $\hat{A}_t$ is an estimator of the advantage function at timestep t. Here, the expectation $\hat{\mathbb{E}}_t[\ldots]$ indicates the empirical average over a finite batch of samples, in an algorithm that alternates between sampling and optimization.

Background: Policy Optimization

PPO, Schulman et al, 2017

- Implementations that use automatic differentiation software work by constructing an objective function whose gradient is the policy gradient estimator; the estimator $\hat{g}$ is obtained by differentiating the objective

$$L^{PG}(\theta) = \hat{\mathbb{E}}_t\left[\log \pi_\theta (a_t|s_t)\hat{A}_t\right]$$

Background: Policy Optimization

PPO, Schulman et al, 2017

- While it is appealing to perform multiple steps of optimization on this loss L^{PG} using the same trajectory, doing so is not well-justified, and empirically it often leads to **destructively large policy updates**.

Background: Policy Optimization

PPO, Schulman et al, 2017

- In TRPO, an objective function (the "surrogate" objective) is **<u>maximized subject to a constraint on the size of the policy update</u>**. Specifically,

$$\underset{\theta}{\text{maximize}}\ \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t\right]$$

$$\text{subject to}\ \hat{\mathbb{E}}_t\left[KL[\pi_{\theta_{\text{old}}}(\cdot\,|s_t),\pi_\theta(\cdot\,|s_t)]\right]\le\delta$$

  - Here, θ_{old} is the vector of policy parameters before the update.

Background: Policy Optimization

PPO, Schulman et al, 2017

- This problem can efficiently be approximately solved using the conjugate gradient algorithm, after making a linear approximation to the objective and a quadratic approximation to the constraint.

Background: Policy Optimization

PPO, Schulman et al, 2017

- The theory justifying TRPO actually suggests **using a penalty instead of a constraint**, i.e., solving the unconstrained optimization problem for some coefficient β.

$$\underset{\theta}{\text{maximize}}\ \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t - \beta KL[\pi_{\theta_{\text{old}}}(\cdot\,|s_t), \pi_\theta(\cdot\,|s_t)]\right]$$

Background: Policy Optimization

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- This follows from the fact that a certain surrogate objective (which computes the max KL over states instead of the mean) forms a lower bound (i.e., a pessimistic bound) on the performance of the policy π.
- TRPO uses a hard constraint rather than a penalty because **it is hard to choose a single value of β that performs well across different problems**—or even within a single problem, where the characteristics change over the course of learning.

Clipped Surrogate Objective

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- Let $r_t(\theta)$ denote the probability ratio $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$, so $r_t(\theta_{\text{old}}) = 1$. TRPO maximizes a "surrogate" objective

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

- The superscript CPI refers to conservative policy iteration, where this objective was proposed.

Clipped Surrogate Objective

PPO, Schulman et al, 2017

- Without a constraint, maximization of L^{CPI} would lead to **an excessively large policy update**; hence, we now consider how to modify the objective, to penalize changes to the policy that move $r_t(\theta)$ away from 1.
- The main objective we propose is the following:

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

  - where epsilon is a hyperparameter, say, $\epsilon = 0.2$.

Clipped Surrogate Objective

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- The motivation for this objective is as follows.
  - The first term inside the min is $L^{CPI}(\theta)$.
  - The second term, $\text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t$, modifies the surrogate objective by **clipping the probability ratio**, which removes the incentive for moving $r_t(\theta)$ outside of the interval $[1-\epsilon, 1+\epsilon]$.
  - Finally, we take the minimum of the clipped and unclipped objective, so the final objective is **a lower bound (i.e., a pessimistic bound) on the unclipped objective**.

Clipped Surrogate Objective

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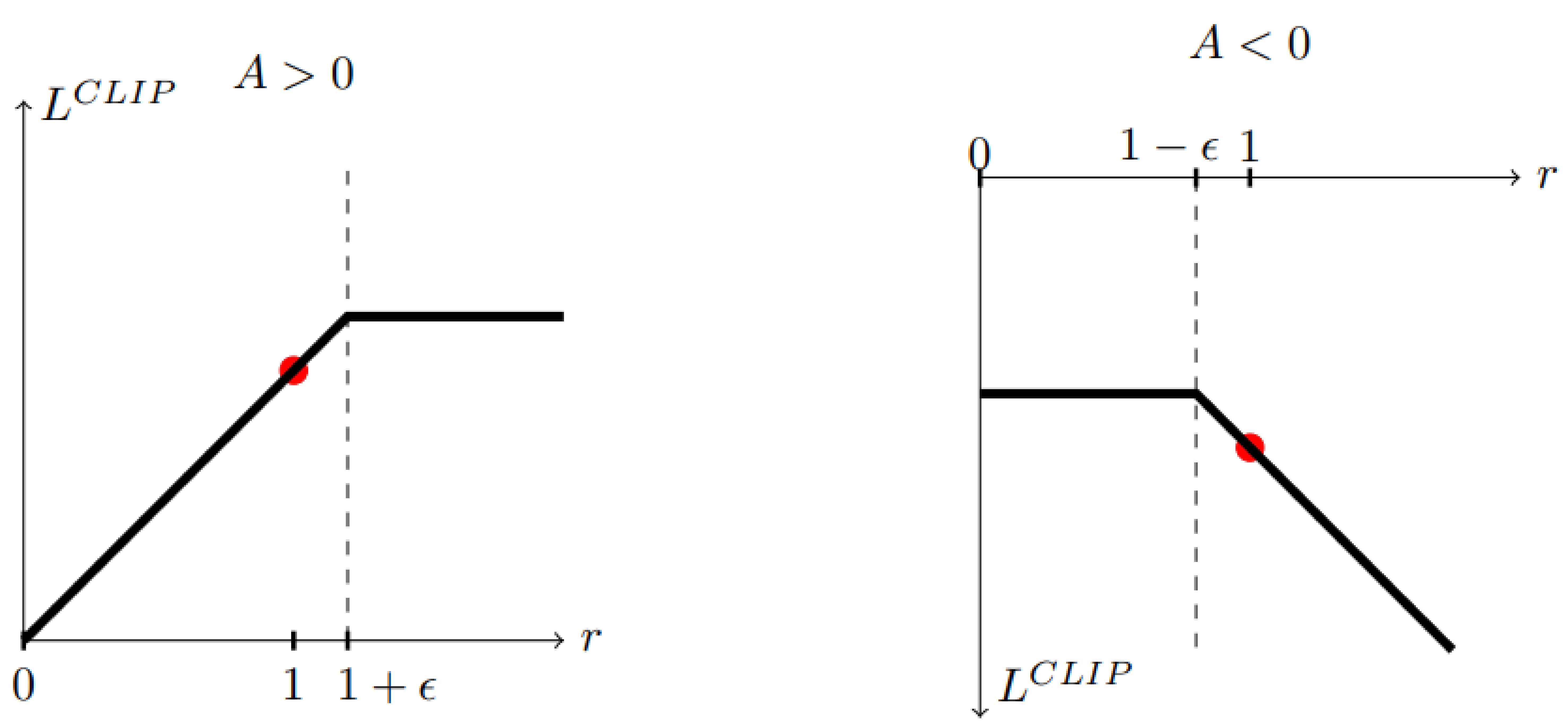

Figure 1: Plots showing one term (i.e., a single timestep) of the surrogate function L^{CLIP} as a function of the probability ratio r, for positive advantages (left) and negative advantages (right). The red circle on each plot shows the starting point for the optimization, i.e., $r = 1$. Note that L^{CLIP} sums many of these terms.

Clipped Surrogate Objective

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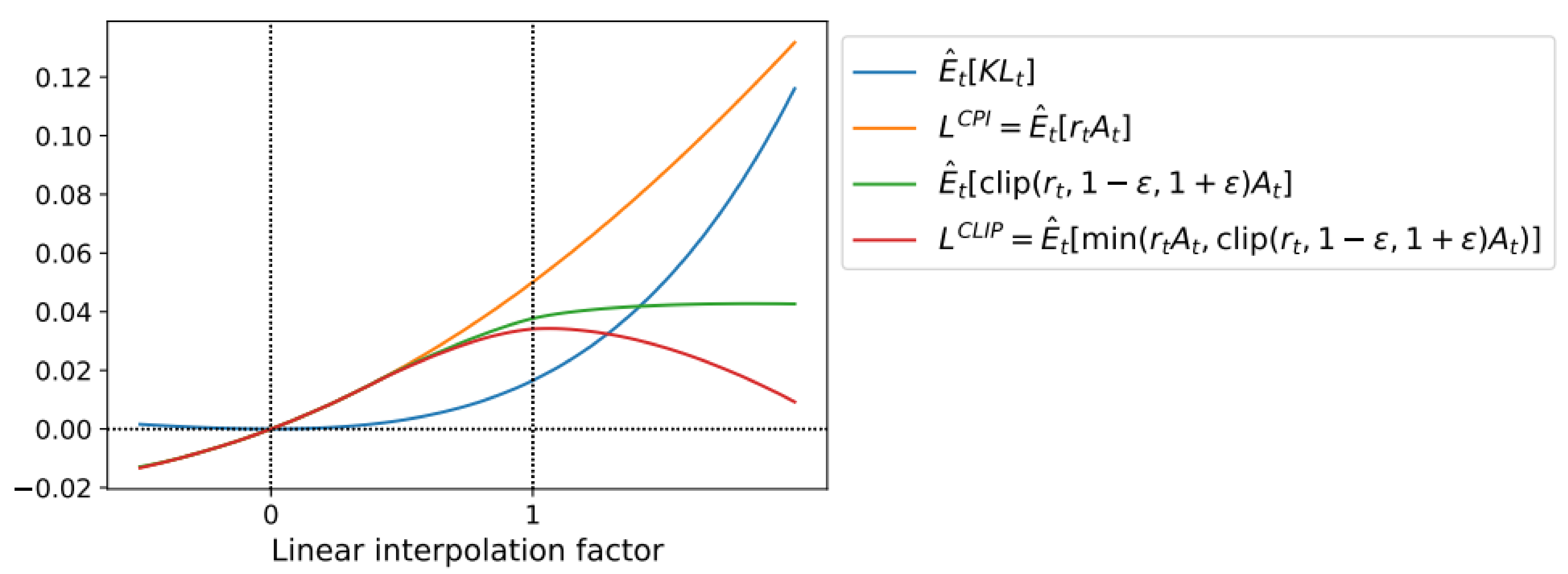

Figure 2: Surrogate objectives, as we interpolate between the initial policy parameter θ_{old}, and the updated policy parameter, which we compute after one iteration of PPO. The updated policy has a KL divergence of about 0.02 from the initial policy, and this is the point at which L^{CLIP} is maximal.

Adaptive KL Penalty Coefficient

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- Another approach, which can be used as an alternative to the clipped surrogate objective, or in addition to it, is to use a penalty on KL divergence, and to **adapt the penalty coefficient** so that we achieve some target value of the KL divergence d_{targ} each policy update.
  - In our experiments, we found that the KL penalty performed worse than the clipped surrogate objective, however, we've included it here because it's an important baseline.

Adaptive KL Penalty Coefficient

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- In the simplest instantiation of this algorithm, we perform the following steps in each policy update:
  - Using several epochs of minibatch SGD, <u>**optimize the KL-penalized objective**</u>

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

  - <u>**Compute $\boldsymbol{d} = \hat{\mathbb{E}}_t\left[\boldsymbol{KL}[\boldsymbol{\pi_{\theta_{old}}}(\cdot\,|\boldsymbol{s_t}), \boldsymbol{\pi_\theta}(\cdot\,|\boldsymbol{s_t})]\right]$**</u>
    - If $d < d_{targ}/1.5$, $\beta \leftarrow \beta/2$
    - If $d > d_{targ} \times 1.5, \beta \leftarrow \beta \times 2$
    - The updated β is used for the next policy update.

Algorithm

- Most techniques for computing variance-reduced advantage-function estimators make use a **learned state-value function** $V(s)$
  - Generalized advantage estimation
  - The finite-horizon estimators

Algorithm

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- If using a neural network architecture that shares parameters between the policy and value function, we must use a loss function that combines the policy surrogate and a value function error term.
- This objective can further be augmented by adding an entropy bonus to ensure sufficient exploration, as suggested in past work (A3C).

Algorithm

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- Combining these terms, we obtain the following objective, which is (approximately) maximized each iteration:

$$L_t^{CLIP+VF+S}(\theta) = \hat{\mathbb{E}}_t[L_t^{CLIP}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t)]$$

  - where c_1, c_2 are coefficients, and S denotes an entropy bonus, and L_t^{VF} is a squared-error loss $\left(V_\theta(s_t) - V_t^{\text{targ}}\right)^2$.

Algorithm

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- One style of policy gradient implementation, popularized in A3C and well-suited for use with recurrent neural networks, **runs the policy for T timesteps (where T is much less than the episode length), and uses the collected samples for an update**.

Algorithm

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- This style **requires an advantage estimator that does not look beyond timestep T**. The estimator used by A3C is

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

  - where t specifies the time index in $[0, T]$,
    within a given length-T trajectory segment.

Algorithm

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- Generalizing this choice, we can use a truncated version of **generalized advantage estimation**, which reduces to previous equation when $\lambda = 1$:

$$\hat{A}_t = \delta_t + (\gamma\lambda)\delta_{t+1} + \cdots + \cdots + (\gamma\lambda)^{T-t+1}\delta_{T-1}$$

$$\text{where } \delta_t = r_t + \gamma V(s_{t+1}) - V(s_t)$$

Algorithm

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- A proximal policy optimization (PPO) algorithm that uses fixed-length trajectory segments is shown below.
  - Each iteration, each of N (parallel) actors collect T timesteps of data.
  - Then we construct the surrogate loss on these NT timesteps of data, and optimize it with minibatch SGD (or usually for better performance, Adam), for K epochs.

Algorithm 1 PPO, Actor-Critic Style

for iteration$=1,2,\ldots$ **do**
  for actor$=1,2,\ldots,N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ in environment for T timesteps
    Compute advantage estimates $\hat{A}_1,\ldots,\hat{A}_T$
  end for
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$
  $\theta_{\text{old}} \leftarrow \theta$
end for

Experiments

- First, we compare several different surrogate objectives under different hyperparameters. Here, we compare the surrogate objective L^{CLIP} to several natural variations and ablated versions.
  - No clipping or penalty: $L_t(\theta) = r_t(\theta)\hat{A}_t$
  - Clipping: $L_t(\theta) = \min(r_t(\theta)\,\hat{A}_t, \mathrm{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)$
  - KL penalty (fixed or adaptive): $L_t(\theta) = r_t(\theta)\hat{A}_t - \beta KL[\pi_{\theta_{\mathrm{old}}}, \pi_\theta]$

Experiments

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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

Experiments

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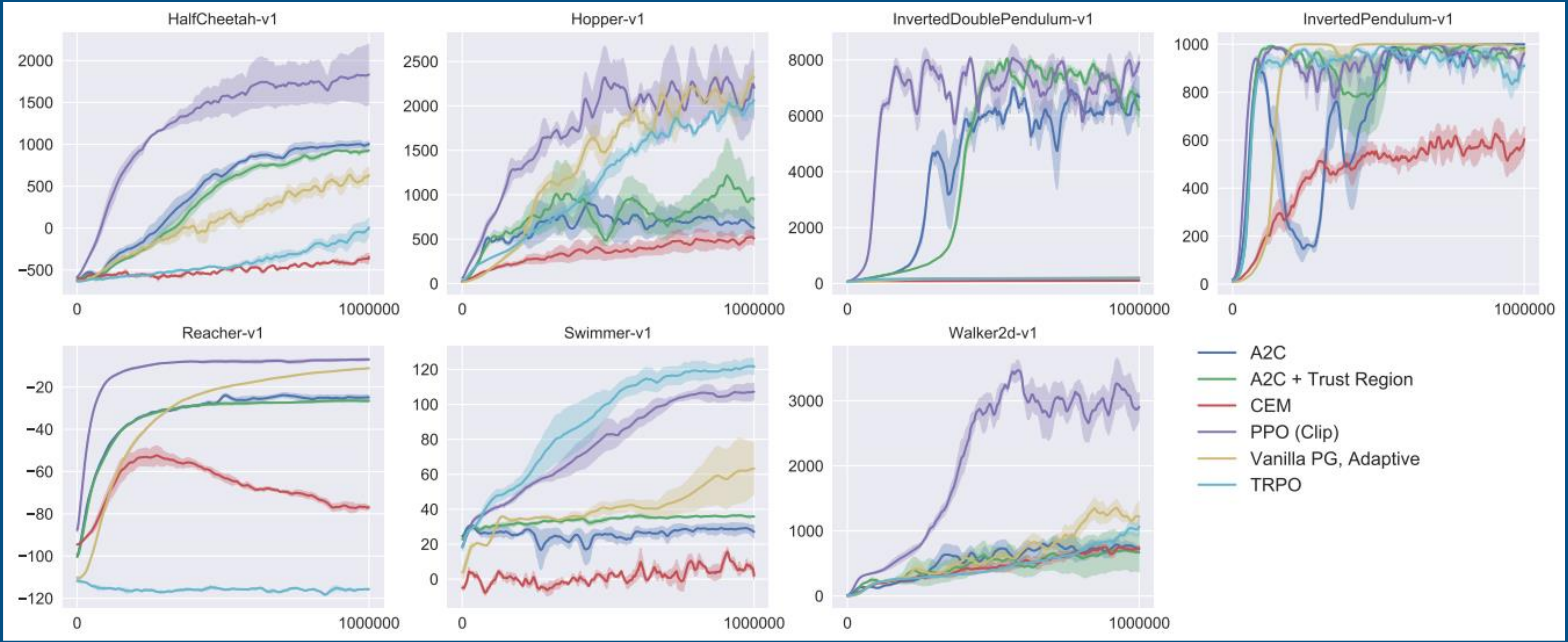

Experiments

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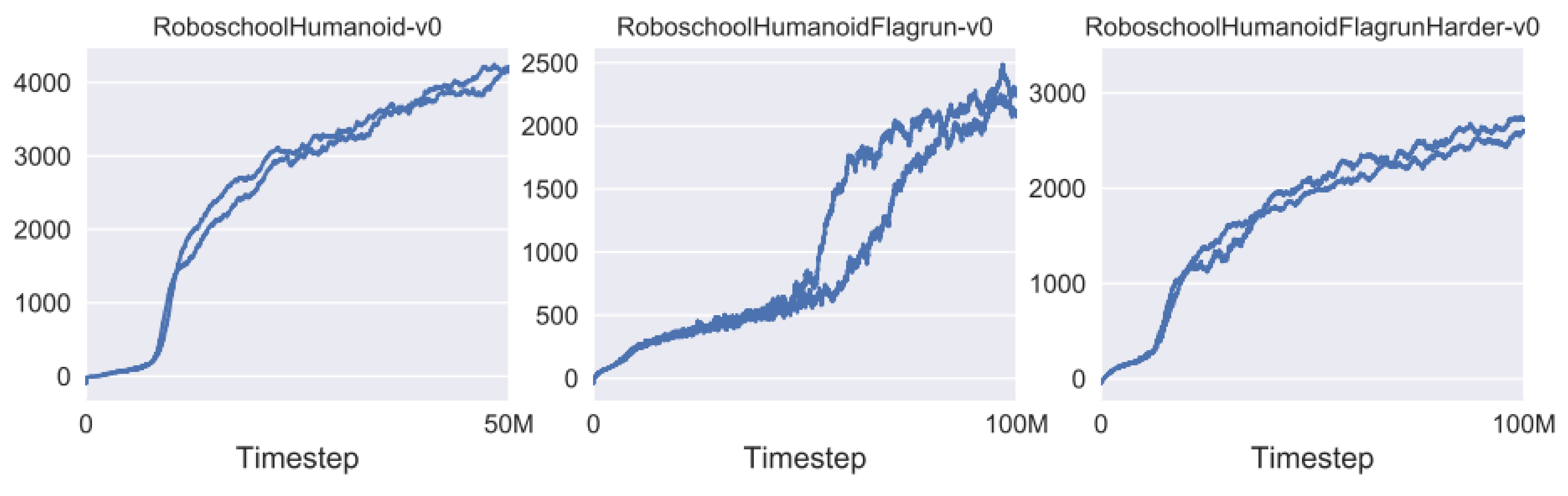

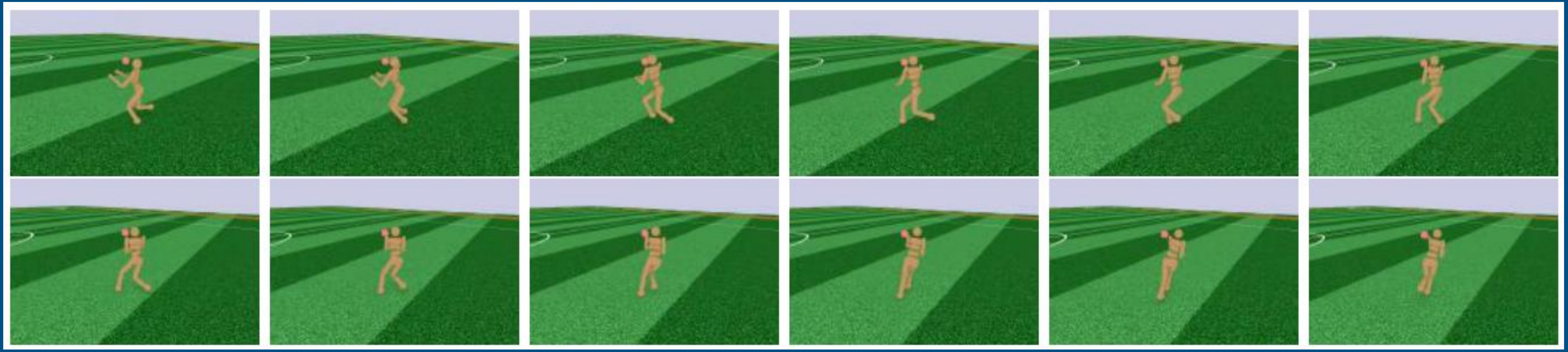

Experiments

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	A2C	ACER	PPO	Tie
(1) avg. episode reward over all of training	1	18	**30**	0
(2) avg. episode reward over last 100 episodes	1	**28**	19	1

Conclusion

- We have introduced **proximal policy optimization**, a family of policy optimization methods that **use multiple epochs of stochastic gradient ascent** to perform each policy update.

Conclusion

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- These methods have **the stability and reliability of trust-region methods** but are much simpler to implement, requiring only few lines of code change to a vanilla policy gradient (A3C) implementation, applicable in more general settings (for example, when using a joint architecture for the policy and value function), and have better overall performance.

References

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Thank you!