ON-POLICY REINFORCEMENT LEARNING WITH ENTROPY REGULARIZATION

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ABSTRACT

Entropy regularization is an imported idea in reinforcement learning, with great success in recent algorithms like Soft Actor-Critic and Soft Q Network. In this work, we extend this idea into the on-policy realm. With the soft gradient policy theorem, we construct the maximum entropy reinforcement learning framework for on-policy RL. For policy gradient based on-policy algorithms, the policy network is often represented as Gaussian distribution with the action variance restricted to be global for all the states observed from the environment. We propose an idea called action variance scale for policy network and find it can work collaboratively with the idea of entropy regularization. In this paper, we choose the state-of-the-art on-policy algorithm, Proximal Policy Optimization, as our basal algorithm and present Soft Proximal Policy Optimization (SPPO). PPO is a popular on-policy RL algorithm with great stability and parallelism. But like many on-policy algorithms, PPO can also suffer from low sample efficiency and local optimum problem. In the entropy-regularized framework, SPPO can guide the agent to succeed at the task while maintaining exploration by acting as randomly as possible. Our method outperforms prior works on a range of continuous control benchmark tasks, Furthermore, our method can be easily extended to large scale experiment and achieve stable learning at high throughput.

Keywords RL · Entropy · On-policy · Stable

1 INTRODUCTION

Model-free deep reinforcement learning algorithms show the power in many challenge domains, from tradition game "go" to moderate robotic control tasks [Henderson et al., 2018]. The combination of reinforcement learning and high-capacity function approximators such as neural networks hold the promise of learning on a lot of decision making and control tasks, but when it comes to real-world application, most of these methods have been hindered by three larger challenges [Ha and Schmidhuber, 2018].

First of all, most of the current method is easily suffer from the local optimal, they find a solution looks good a in shorter view, but often sacrifice the performance in the long run, for example, maybe the agent learns to stay still to avoid death, it’s not something we want. Second, the model-free method has a bad name for its low sample efficiency, even some simple tasks need millions of interval with the environment when it comes to complex decision-making problem, the total interval step could easily come to $10^{10}$ [Kapturowski et al., 2018], which is inaccessible for most domain except in some really fast simulator, more and more parallel technique is used to speed up the wall-time [Horgan et al., 2018] [Espeholt et al., 2018], but the limit of computing resource lag the use of these methods.

Meanwhile, current methods are often extremely brittle with respect to their hyper-parameters and they often have so much hyper-parameters that need to be tuned. It means we need carefully tuning the parameters, most important, they often suck to local optimal. In many cases they fail to find a reward signal, even when the reward signal is relatively

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dense, they still fail to find the optimal solution, some researchers design such a complex reward function for each environment they want to solve [Guo, 2017].

In this paper, we propose a different approach to deal with complex tasks with deep reinforcement learning. We investigate an entropy regularization approach to learning a good policy under the PPO framework. Extensive experiments on continuous control tasks demonstrate the effectiveness and advantages of the proposed approach, which performs the best among a set of previous state-of-the-art methods.

2 BACKGROUND

2.1 MDP

Our problem is searching an optimal policy which maximize our accumulate future reward in Markov Decision Process (MDP) defined by the tuple \((S, A, P, R)\) [Hafner et al., 2018].

- \(S\) represent a set of states
- \(A\) represent a set of actions,
- \(P: S \times A \rightarrow \mathcal{P}(S)\) stand for the transition function which maps state-actions to probability distributions over next states \(P(s'|s, a)\)
- \(R: S \times A \times S \rightarrow \mathbb{R}\) correspond to the reward function, with \(r_t = R(s_t, a_t, s_{t+1})\)

Within this framework, the agent acting in the environment according to \(a \in A\). the environment changes to a new state following \(s' \sim P(\cdot|s, a)\). Next, an state \(s \in S\) and reward \(r \sim R(s, a)\) are received by the agent. Although there are many approaches suitable for the MDP process, we focus on using the policy gradient method with an entropy bonus. The Deep Q-Network agent (DQN) [Mnih et al., 2015] learns to play games from the Atari-57 benchmark by using frame-stacking of 4 consecutive frames as observations, and training a convolutional network to represent a value function with Q-learning, from data continuously collected in a replay buffer. Other algorithms like the A3C, use an LSTM and are trained directly on the online stream of experience without using a replay buffer. In paper [Song et al., 2018] combined DDPG with an LSTM by storing sequences in the replay and initializing the recurrent state to zero during training.

2.2 ENTROPY-REGULARIZED REINFORCEMENT LEARNING

The key idea in reinforcement learning is finding a policy which can maximizes expected future return which we can purposed as in Equation 2

\[
P(\tau|\pi) = \rho_0(s_0) \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t)\pi(a_t|s_t)
\]

\[
J(\pi) = \int_{\tau} P(\tau|\pi)R(\tau) = E_{\tau \sim \pi}[R(\tau)]
\]

Instead of maximize \(J(\pi)\) directly, we will use a maximum entropy objective [Ziebart, 2010], which is more preferred with stochastic policies by strengthening the objective. Within the entropy-regularized framework, along with environment reward our agent gets a bonus reward proportional to the entropy of the policy at each time-step as well. This changes the RL problem to:

\[
\pi^* = \arg \max_{\pi} E_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( r(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \right]
\]

The temperature parameter \(\alpha\) making trade-off between the importance of the entropy term against the environment’s reward. When \(\alpha\) is large, the entropy bonuses play an important role in reward, so the policy will tend to have larger entropy, which means the policy will be more stochastic, on the contrary, if \(\alpha\) become smaller, the policy will become more deterministic. We should define a slightly-different value function in this setting. Now \(V^\pi\) should be changed to include the entropy bonuses as below:
With equation (4) (5), we can draw the connection between \( v_\pi \) which have the form:

\[
v_\pi(s) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( r(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \right] \bigg| s_0 = s
\]

(4)

And \( q_\pi \) has to be modified to contain the entropy bonuses as well:

\[
q_\pi(s, a) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left[ r(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right] \right] \bigg| s_0 = s, a_0 = a
\]

(5)

With equation (4) (5), we can draw the connection between \( v_\pi \) and \( q_\pi \) as:

\[
v_\pi(s) = \mathbb{E}_{a \sim \pi} [q_\pi(s, a)] + \alpha H(\pi(\cdot|s))]
\]

(6)

Meanwhile, the Bellman equation for \( q_\pi \) is changing to:

\[
q_\pi(s, a) = \mathbb{E}_{s' \sim \pi} \left[ r(s, a, s') + \gamma (q_\pi(s', a') + \alpha H(\pi(\cdot|s'))) \right]
\]

(7)

\[
= \mathbb{E}_{s' \sim \pi} r(s, a, s') + \gamma v_\pi(s')
\]

(8)

### 2.3 Policy Gradient

Policy gradient methods maximize the expected return by computing an estimate of the gradient of policy parameters using stochastic gradient descent. With the help of deep neural networks, the policy gradient has become an important model-free reinforcement learning algorithm. The value of the reward (objective) function depends on this policy and then various algorithms can be applied to optimize parameters for the best reward. These methods are behind much of the recent success in using deep neural networks for control ([Mnih et al., 2015] [Schulman et al., 2015a] [Henderson et al., 2018]). Such methods are also attractive because they don’t require an explicit model of the world. Let \( \pi_\theta \) denote a policy with parameters \( \theta \) and \( J(\pi_\theta) \) denote the expected return, we can derive the gradient of \( J(\pi_\theta) \) as:

\[
\nabla_\theta J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[ \sum_{t=0}^{\infty} \gamma^t \log \pi_\theta(a_t|s_t) A_{\pi_\theta}(s_t, a_t) \right]
\]

There are several different expressions for the policy gradient estimator which have the form different choices of \( A \) lead to different algorithms, for example taking the sample return of a trajectory, or use a baseline, such as a value function baseline, to ameliorate the high variance. Generalized advantage estimation ([Schulman et al., 2015b]) takes this approach of using a learned value function to reduce variance at the cost of some bias and using an exponentially weighted estimator of the advantage function.

### 2.4 Proximal Policy Optimization

How can we make the biggest possible improvement step on a policy using the data we currently have, without stepping so far that we accidentally cause performance collapse? That is the problem for many on-policy algorithms, TRPO ([Schulman et al., 2015a]) updates policies by taking the largest step possible to improve performance while satisfying a special constraint on how close the new and old policies are allowed to be. But TRPO tends to be inefficient because it tries to solve this problem with a complex second-order method. PPO ([Schulman et al., 2017]) is a family of first-order methods that use a few other tricks to keep new policies close to old. PPO methods are significantly simpler to implement. The key idea behind PPO is using a surrogate objective which is maximized while penalizing large changes to the policy, which lead to objective as:

\[
L(s, a, \theta_k, \theta) = \min \left( \pi_\theta(a|s) \frac{\pi_{\theta_k}(a|s)}{\pi_{\theta_k}(a|s)} A_{\pi_\theta}(s, a), g(\epsilon, A_{\pi_\theta}(s, a)) \right)
\]

(9)

The algorithm alternates between sampling multiple trajectories from the policy and performing several epochs of SGD on the sampled dataset to optimize this surrogate objective. Since the state value function is also simultaneously approximated, the error for the value function approximation is also added to the surrogate objective to compute the complete objective function.
3 The Soft Policy Gradient Theorem

To keep the notation simple, we leave it implicit in all cases that \( \pi \) is a function of \( \theta \), and all gradients are also implicitly concerning \( \theta \). First note that the gradient of the state-value function can be written in terms of the action-value function as

\[
\nabla v_\pi(s) = \nabla \left[ \sum_a \pi(a|s)q_\pi(s,a) \right] = \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \pi(a|s) \nabla q_\pi(s,a) \right]
\]

(10)

\[
= \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \pi(a|s) \nabla \sum_{s'} p(s'|s,a)(r_\pi(s,a) + v_\pi(s')) \right]
\]

(11)

(\text{where } r_\pi(s,a) = r + \alpha H(\pi(\cdot|s)))

\[
= \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \pi(a|s) \nabla H(\pi(\cdot|s)) + \pi(a|s) \sum_{s'} p(s'|s,a) \nabla v_\pi(s') \right]
\]

(12)

\[
\sum_{a} \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) + \pi(a|s) \sum_{s'} p(s'|s,a) \nabla v_\pi(s') \right]
\]

(13)

\[
= \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) + \pi(a|s) \sum_{s'} p(s'|s,a) \nabla v_\pi(s') \right]
\]

(14)

\[
= \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) + \pi(a|s) \sum_{s'} p(s'|s,a) \pi(a'|s') \sum_{s''} p(s''|s',a') \nabla v_\pi(s'') \right]
\]

(15)

\[
\cdots \text{(unrolling)}
\]

\[
= \sum_{x \in S} \sum_{k=0}^{\infty} \Pr(s \rightarrow x, k, \pi) \sum_a \left[ q_\pi(x,a) \nabla \pi(a|x) + \alpha \nabla H(\pi(\cdot|x)) \right],
\]

(16)

where \( \Pr(s \rightarrow x, k, \pi) \) is the probability of transitioning from state \( s \) to state \( x \) in \( k \) steps under policy \( \pi \). It is then immediate that

\[
\nabla J(\theta) = \nabla v_\pi(s_0)
\]

(17)

\[
= \sum_{s} \left( \sum_{R=0}^{\infty} \Pr(s_0 \rightarrow s, k, \pi) \right) \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) \right]
\]

(18)

\[
= \sum_s \eta(s) \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) \right]
\]

(19)

\[
= \sum_s \eta(s') \sum_s \sum_{\eta(s')} \eta(s) \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) \right]
\]

(20)

\[
\propto \sum_s \mu(s) \sum_a \left[ q_\pi(s,a) \nabla \pi(a|s) + \alpha \nabla H(\pi(\cdot|s)) \right]
\]

(21)

where \( \mu(s) = \sum_s \sum_{s'} \eta(s') \)

\[
= \sum_s \mu(s) \sum_a \left[ q_\pi(s,a) - \alpha \log \pi(a|s) \right] \nabla \pi(a|s)
\]

(22)

For now, we have the soft policy gradient theorem as below:

\[
\nabla J(\theta) \propto \sum_s \mu(s) \sum_a \left[ q_\pi(s,a) - \alpha \log \pi(a|s) \right] \nabla \pi(a|s)
\]

(23)
It seems crucial for the derivation that the entropy is with \( s \) instead of \( s' \), i.e. \( H(\pi(\cdot|s)) \). If we use the definition \( H(\pi(\cdot|s')) \) for the entropy regularization, \( H(\pi(\cdot|s')) \) should be the expectation of \( \pi(a|s) \sum_{a'} p(s'|s,a) \), but the formula don’t change. In order to construct the SPPO algorithm, we should first define the policy gradient loss and value loss. In the framework of maximum entropy reinforcement learning, the reward have two components \( r = r^{\text{ext}} + r^{\text{int}} \): the external reward given by the environment \( r^{\text{ext}} \) and the internal \( r^{\text{int}} \) defined according to the action entropy. The objective for the value part is to minimize a square-error loss for value estimation:

\[
L^v_\theta(\phi) = (V_\phi(s_t) - V^\text{targ}_t)^2 = (V_\phi(s_t) - \hat{R}_t)^2
\]  

The advantage estimator that look within \( T \) timesteps can be written as:

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

where \( t \) specifies the time index in \([0, T]\), within a given T-timestep truncated trajectory. Generalized Advantage Estimation (GAE) is the generalized version of the normal advantage estimation. GAE can reduce to the above equation when \( \lambda = 1 \):

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

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

With the advantage estimation, the policy gradient loss of the SPPO algorithm can be written as:

\[
L^\pi_\theta(\phi) = \min \left( \frac{\pi_\theta(a_t|s_t)}{\pi_\theta'(a_t|s_t)} A^\pi'(s_t, a_t), g(\epsilon, A^\pi'(s_t, a_t)) \right)
\]  

where

\[
A^\pi'(s_t, a_t) = \hat{A}^\pi'(s_t, a_t) = -\alpha \log \pi_\theta'(a_t|s_t),
\]

\[
g(\epsilon, A) = (1 + \epsilon)A \text{ if } A > 0 \text{ else } (1 - \epsilon)A.
\]

We can also construct the policy gradient loss according to Equation \(21\), which can reduce the sample variance in the training procedure. We summarize the complete algorithm in Algorithm 1.

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**Algorithm 1: SPPO**

**Input**

- Initial policy parameters \( \theta \)
- Value-function parameters \( \phi \)
- Temperature \( \alpha \)

1. while not converge do
2.   for each step do
3.     \( a_t \sim \pi_\theta(a_t|s_t) \) // Sample action from the policy
4.     \( s_{t+1} \sim p(s_{t+1}|s_t, a_t) \) // Sample transition from the environment
5.     \( \mathcal{D} \leftarrow \cup \{(o_t, s_t, a_t, r(s_t, a_t), o_{t+1}, s_{t+1})\} \) // collect set of trajectories
6.     Compute rewards-to-go \( \hat{R}_t \)
7.     Compute advantage estimates, \( \hat{A}_t \) (using and method of advantage estimate based on the current value function )
8.     Compute policy gradient \( L^\pi_\theta(\phi) \) from equation \(28\)
9.     \( \theta \leftarrow \theta - \lambda_\theta \nabla_\theta L^\pi_\theta(\phi) \) // Update policy parameter
10.    Compute value gradient from equation \(24\)
11.   \( \phi \leftarrow \phi - \lambda_\phi \nabla_\phi L^v_\phi(\phi) \) // Update value parameter
12.  end
13. end
Figure 1: (a) to (e) are the training curves on continuous control benchmarks, SPPO agent performs consistently across all tasks and outperforming PPO methods in the most challenging tasks. (f) shows the discrete case for training on LunarLander-v2, where SPPO achieves a significant improvement over PPO.

4 EXPERIMENT

To test our agent, we designed our experiments for answering the following questions:

1. Can SPPO be used to solve challenging continuous control problems? How does our agent compare with other methods when applied to these problems, with regard to the final performance, computation time, and sample complexity?
2. What is the impact of different reward scale, and how different hyper-parameter influence the stability of our agent?
3. We add entropy bonus on our agent, does this parts give us a more powerful agent?

To answer (1) we compare the performance of our agent with other methods in session 4.1. Concerning (2)(3), we addressed the ablation study on our algorithm in session 4.2, testing how does different settings and network design influence the performance?

The results show overall our agent outperforms baseline with a large margin, both in terms of learning speed and the final performance. The quantitative results attained by our agent in our experiments also compare very favorably to results reported by other methods in prior work, indicating that both the sample efficiency and the final performance of our agent on these benchmark tasks exceeds the state of the art.

4.1 MUJOCO

The goal of this experimental evaluation is to understand how the sample complexity and stability of our method compares with prior on-policy deep reinforcement learning algorithms. We compare our method to prior techniques on a range of challenging continuous control tasks from the OpenAI gym benchmark suite. Although easier tasks can be solved by a wide range of different algorithms, the more complex benchmarks, such as the 21-dimensional Humanoid, are exceptionally difficult to solve with standard PPO algorithms. The stability of the algorithm also plays a large role in performance: easier tasks make it more practical to tune hyper-parameters to achieve good results, while the already narrow basins of effective hyper-parameters become prohibitively small for the more sensitive algorithms on the hardest benchmarks, leading to poor performance [Gu et al., 2016].
We compare our method to proximal policy optimization (PPO) [Schulman et al., 2017], a stable and effective on-policy policy gradient algorithm.

We conducted the robotic locomotion experiments using the MuJoCo simulator [Todorov et al., 2012] The states of the robots are their generalized positions and velocities, and the controls are joint torques. Under actuation, high dimensionality, and non-smooth dynamics due to contacts make these tasks very challenging. To allow for a reproducible and fair comparison, we evaluate all the algorithm with a similar network structure, for the on-policy algorithm, we use a two-layer feed-forward neural network of 300 and 300 hidden nodes respectively, with rectified linear units (ReLU) between each layer for both the actor and critic, we use the parameters with is shown superior in prior work [Henderson et al., 2018] as the comparison of our agent. Both network parameters are updated using Adam [Kingma and Ba, 2014] with the learning rate of $10^{-4}$, with no modifications to the environment or reward function.

Figure 1 compares five individual runs with both variants, initialized with different random seeds. SPPO performs much better, shows that our agent significantly outperforms the baseline, indicating substantially better stability and stability. As evident from the figure, with an entropy bonus, we can achieve stable training. This becomes especially important with harder tasks, where tuning hyperparameters is challenging.

It shows our agent outperforms other baseline methods with a large marginal, indicating both the efficiency and stability of our method is superior.

### 4.2 ABLATION STUDY

#### 4.2.1 THE IMPACT OF REWARD SCALE

Reward scale play an important role in many algorithms, here the reward scale and $\alpha$ balance each other, large reward scale means we need larger $\alpha$, so we can adjust only one of them to get similar result. Here we discuss the impact of different scale of entropy bonus. As the results show, the entropy stimulus go down as the reward increase. It suggests that we may need to increase $\alpha$ according to the increasing return, which we shall delve into in our future work.

#### 4.2.2 THE IMPACT OF DIFFERENT METHOD

In standard policy gradient algorithms like PPO, a global action variance $\sigma$ is used. While in SPPO, we try to break this constraint and endow policy networks with more representation capacity. It is a naive way to let the policy network output a local $\sigma$ for every state. This is problematic due to the high update variance of policy gradient. Instead, we maintain the global action variance $\sigma$ as the main source of action variance, but in the meanwhile, we introduce a local variance scale $\sigma_s$ for each state. Furthermore, In order to reduce the effect of encouraging the agent to seek an undesired large local variance scale, we propose a new scheme that clips the local variance scale to be logarithmic negative. As shown in Table 1, we list the four kinds of schemes. Figure 1 shows how learning performance changes according to different schemes. For scheme 2, the policy becomes nearly random and consequently fails to exploit the reward signal, resulting in substantial degradation of performance. For scheme 1, the policy has limited capability then becomes nearly deterministic, leading to a poor local minimum due to the lack of adequate exploration. As for scheme 3, although the policy network capability becomes larger due to a large range of $\sigma_s$, still it can not achieve favorable performance. With scheme 4, by balancing exploration and exploitation, the model achieves fast and stable learning.

| scheme | $\mu$     | $\sigma$       |
|--------|-----------|----------------|
| 1      | MLP       | Global $\sigma$ |
| 2      | MLP       | Local $\sigma$ |
| 3      | MLP       | Global $\sigma + Local \sigma_s$ |
| 4      | MLP       | Global $\sigma + Local clip(\sigma_s)$ |

5 CONCLUSION

We found that the impact of entropy bonuses goes beyond providing the agent with extra motivation to explore more. Instead, also serves a more stable training process by avoiding collapsing. Empirically results show that SPPO outperforms state-of-the-art on-policy algorithm by a substantial margin, providing a promising avenue for reinforcement learning with improved robustness and stability, meanwhile can be easily parallelism which shed light on real-world applications.
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