Proximal Policy Optimization Algorithm on Open-AI gym Humanoid Enviroment

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Contents

1 Introduction

The goal of this project was to implement the Proximal Policy Algorithm (PPO) [1], and train it on the OpenAI Humanoid enviroment. The Humanoid-v2 enviroment which runs on a physics engine provided by Mujoco, has 27 degrees of freedom.

According the authors of PPO, the algorithm "perform comparably or better than state-of-the-art approaches while being much simpler to implement and tune." [1]. Policy gradients have a convergence problem which is addressed by the natural policy gradient (NPG) [3]. However, NPG in practice uses a second-order derivative matrix which is hard to scale for large problems, and is computationally unfeasible. PPO on the other hand, instead of imposing a hard constraint, it formalizes the constraint as a penalty in the "surrogate" objective function [4]. Hence, PPO may use a first-order optimizer like Gradient Descent (GD) to optimize the objective. Moreover, PPO uses multiple epochs mini-batch updates instead of performing only one gradient update per data sample like PG methods. Another method which PPO outperforms is the Trust Region Policy Objective, which is very efficient but much more complicated and and not compatible with certain architectures.

2 State of the Art

2.1 Policy gradient Methods

The objective function or Policy loss of PG Methods is defined as:

$$L^{PG}(\theta) = \hat{E}_t[\log \pi_\theta(a_t|s_t) \times \hat{A}_t] \tag{1}$$

where:

- $\hat{E}_t$ is the expectation which indicates the empirical average over a finite batch of samples.
- $\log \pi_\theta(a_t|s_t$ is the log probability of taking that action at that state
- $\hat{A}_t$ is an estimator of the advantage function, if > 0, then this action is better than the other action possible at that state.

Through differentiating 2.1, we obtain the policy gradient estimator which is then plugged into the Stochastic GD algorithm. Hence, pushing the agent to take actions that lead to higher rewards and avoid bad actions. However, there is a problem arising from the step size as if its too small, then the training process will be too slow. On other hand, if its too high, then there will be too much variability in the training between epochs. Whereas PPO improves the stability of the Actor training by limiting the policy update at each training step. This is done through the Clipped Surrogate Function, which constrains the policy change in a desired range.

2.2 Clipped Surrogate Objective

Instead of using $\log \pi$ as in 2.1 to trace the impacts of actions, the authors introduce the following probability ratio:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \tag{2}$$

which define the the probability of action under current policy divided by the probability of the action under previous policy. Hence $r_t(\theta_{old}) = 1$.
If $r_t(\theta) > 1$, then action is more probable in the current policy than the old policy. However, if $0 < r_t(\theta) < 1$, then the action is less probable for current policy than for the old one.

The resulting objective function presented in the PPO paper is:

$$L^{CPI}(\theta) = \hat{E}_t[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}\hat{A}_t] = \hat{E}_t[r_t(\theta)\hat{A}_t] \tag{3}$$

In a situation where the action taken is much more probable in our current policy than in the old one, the lack of a constraint, leads to a large policy gradient step, and a resulting excessive policy update. Hence, there is a need to introduce a constraint which will penalize changes that lead to a ratio that will away from 1, which will ensure relatively small policy updates as the new policy can't be too different from the old one.

We could use PRO, which utilizes KL divergence constrains outside of the objective function to constraint the policy update. However, this is as previously stated in the introduction, much more complex and computationally expensive. As a consequence, the author's of PPO introduce a clip probability ratio directly in the objective function, with its clipped surrogate objective function.

$$L^{CLIP}(\theta) = \hat{E}_t[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t] \tag{4}$$

where epsilon is a hyperparameter,and according to the paper $\epsilon = 0.2$.

Hence, we obtain two probability rations: the first being one non-clipped, and the other clipped in the ϵ ranges. Next, we take the minimum of both of these objectives, so the final objective is a lower bound of the unclipped objective.

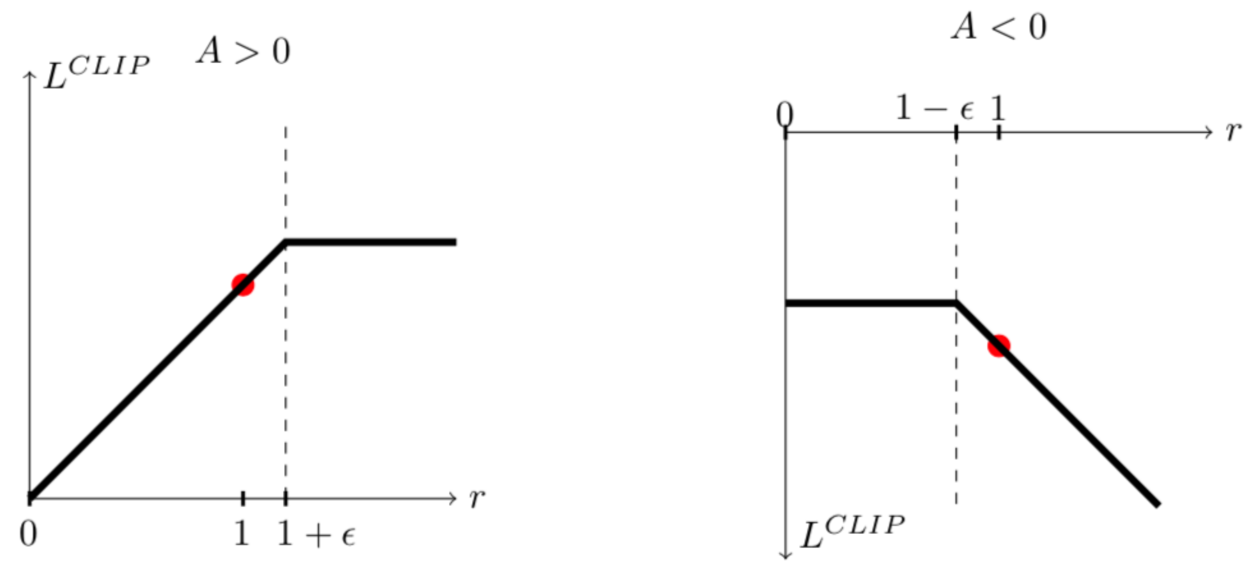

Figure 1: Plots showing one term, of the surrogate function L^{CLIP} as a function of the probability ratio r, for positive advantages (left) and negative advantages (right). The red circle on each plot shows the starting point for the optimization [1].

Figure 1 presents plots of a single term in L^{CLIP}.
In the first case when $A > 0$, we want to increase the probability of taking that action at that step but not too much. However, when $A < 0$, the action should be discouraged because negative effect of the outcome. Effectively, this discourages large policy change if it is outside our comfortable zone.

When using a neural network architecture that shares parameters between the policy and value function, then there is a must to use a loss function that combines the policy surrogate and a value function error term. The addition of an entropy bonus ensures sufficient exploration.

3 Methodology

3.1 Approach

The goals of PPO can be summarised to the following:

- Simple and easy to implement

- Sample efficiency
- Minimal hyperparameter tuning

PPO includes several upgrades built on top of the Actor-Critic Algorithm. They both seek to to maintain smooth gradient updates to get continuous improvement and avoid unrecoverable crashes.

1. Generalized Advantage Estimation (GAE)− a way to calculate returns which reduces variance, through a smoothing factor $0 < \lambda < 1$. The PPO paper suggests $\lambda = 0.95$.
2. Surrogate Policy loss
3. Mini-batch updates (random mini batches, and the network is gradually updated over a fixed number of epochs)

Algorithm 1 depicts the overall procedure of training.

Algorithm 1 PPO with Clipped Objective

Collect a batch of N (multiple of the mini-batch size) transitions from parallel environments (state, action, log-probabilities,a reward, done-mask (0 if terminal), V(s) (value of the state for each state).
Calculate the returns for the batch using GAE
Calculate: advantage = returns - values
For e epochs: *loop*:
    Sample through enough random mini-batches to cover all data.
    Pass state into network, obtain action, value of state', entropy and new-log-probabilities.
    Calculate the surrogate policy loss and MSE value loss.
    Backpropagate the loss through the network using SGD.
5. Repeat above until converged.

3.2 Implementation

The base structure of the code, I borrowed from demo's of the School of AI's Move37 Course [6]. I made a few alterations which included the following:

- changed the code work with mujoco-py instead of roboschool and the humanoid-v2 enviroment
- added several plots which will be shown in the next section containing results of the training.
- Reimplemented the code in Tensorflow from PyTorch to gain a better understanding of the inner workings.

4 Results

Since I did not have access to a dedicated GPU, I trained the model 3 times for 30 minutes, without reallly changing the hyperparameters. The results seemed constant across three runs, however, the test rewards have been increasing so I took that as a positive. The key problem with training is that the humanoid enviroment a huge observation space (376) and action space (17), resulting in slower training and more network parameters.

The results are show in Figure 2 below.

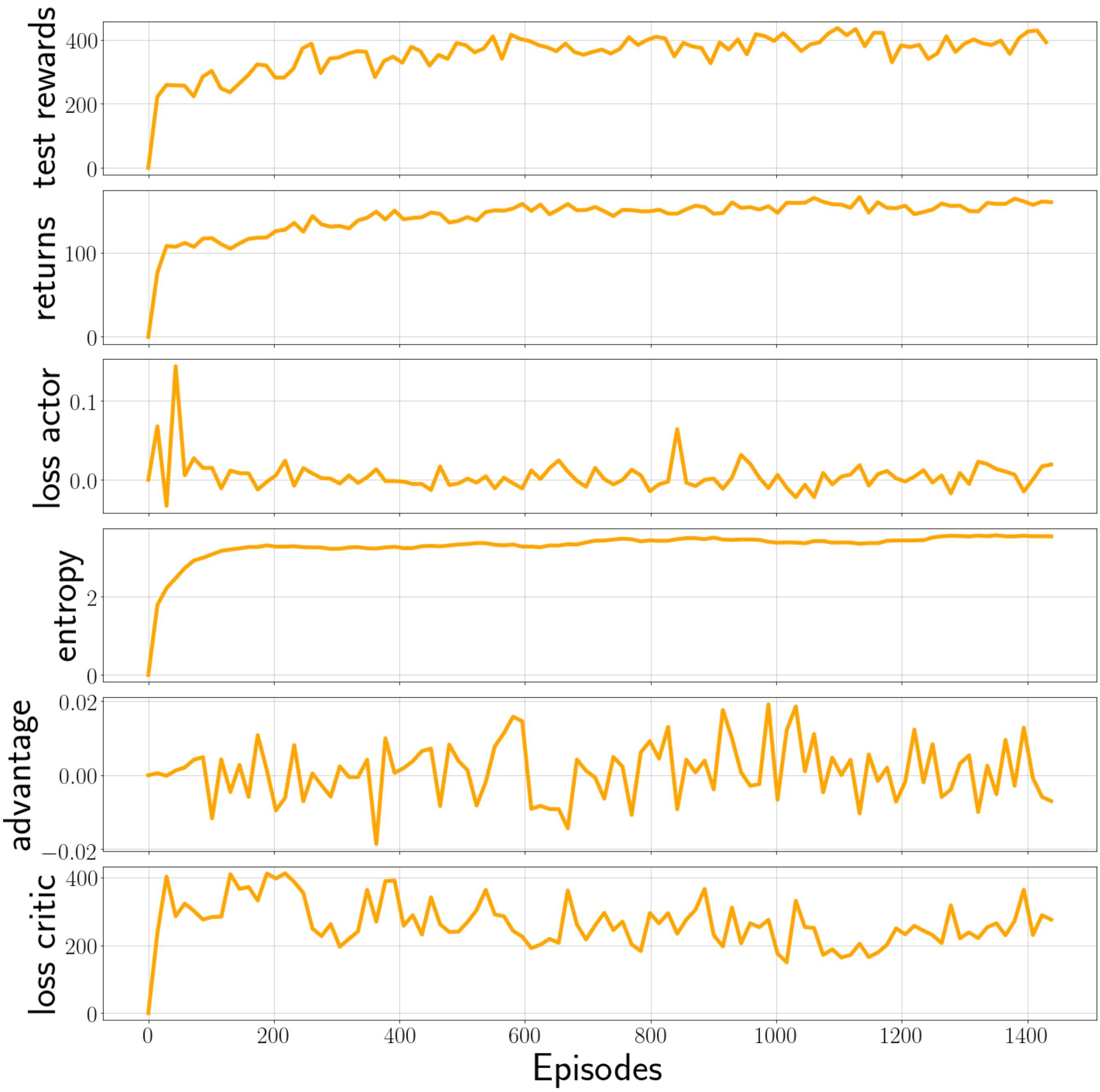

Figure 2: PPO with Clipped Objective results [2]

5 Conclusions

Nice results,
not too bad
better with more training

References

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