Trust Region Policy Optimization - Implementation

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1 Introduction

Trust Region Policy Optimization is an algorithm that make several approximations to a theoretical iterative procedure for optimizing policies with guaranteed monotonic improvement. Despite its approximations that deviate from the theory, TRPO tends to give monotonic improvement, while little tuning of hyperparameters. This algorithm is effective for optimizing large nonlinear policies such as neural networks. The algorithm has been tested on two different openAI gym environments. Gym library is a collection of test problems that can be used to test reinforcement learning algorithms.

2 Environments

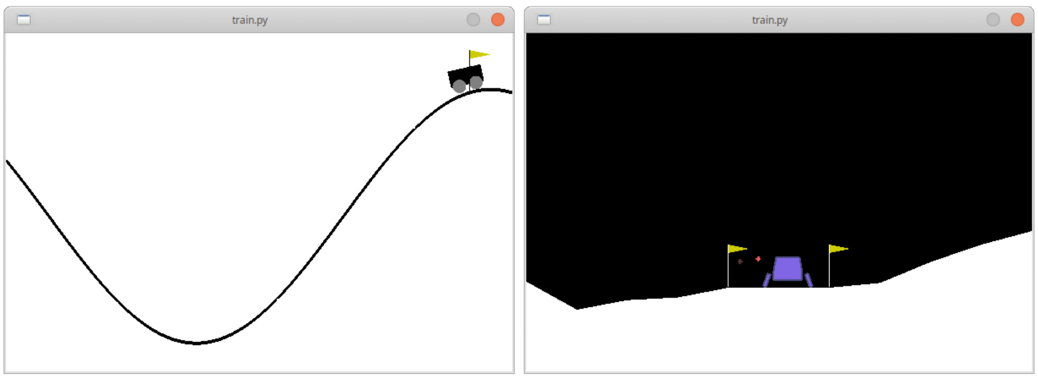
2.1 MountainCarContinuous-v0

An underpowered car must climb a one-dimensional hill to reach a target. The action (engine force applied) is allowed to be a continuous value. The target is on top of a hill on the right-hand side of the car. If the car reaches it or goes beyond, the episode terminates.
On the left-hand side, there is another hill. Climbing this hill can be used to gain potential energy and accelerate towards the target. On top of this second hill, the car cannot go further than a position equal to -1, as if there was a wall. Hitting this limit does not generate a penalty.
The observations are CarPosition and CarVelocity and the only action permits to push the car on the left (negative values) or on the right (negative values).
Reward is 100 for reaching the target of the hill on the right hand side, minus the squared sum of actions from start to goal.

This reward function raises an **exploration challenge**, because if the agent does not reach the target soon enough, it will figure out that it is better not to move, and won't find the target anymore. To consider the problem solved, the reward should be over 90.

2.2 LunarLanderContinuous-v0

A lunar lander is a spacecraft designed to land on the Moon. Landing pad is always at coordinates (0,0). Reward for moving from the top of the screen to landing pad and zero speed is about 100-140 points. If lander moves away from landing pad it loses reward back. Episode finishes if the lander crashes or comes to rest, receiving additional -100 or +100 points. Each leg ground contact is +10. Firing main engine is -0.3 points each frame (fuel is infinite). Solved is 200 points. Action is two real values vector from -1 to +1. First controls main engine, [-1,0] off, [0,1] throttle from 50% to 100% power, Second value [-1.0,-0.5] fire left engine, [0.5,1.0] fire right engine, [0.5,0.5] off.



(a) (b)

Figure 1: Both the environments just described. (a) MountainCarContinuous-v0 when reaching the goal position.(b) LunarLanderContinuous-v2 when reaching the landing pad.

3 TRPO algorithm

TRPO Trust Region Policy Optimization is based on the Minorize-Maximization (MM) algorithm. The MM algorithm can guarantee that any policy updates always improve the expected rewards. This is achived iteratively by maximizing a lower bound function approximating the expected reward locally, as we can see in figure 2, (with π denote a stochastic policy and $\eta(\pi)$ denote its expected discounted reward). After each iteration of the MM algorithm the policy keeps improving. Since there is only finite possible policy, our current policy will eventually converge to the local or the global optimal.

The evolution of this kind of algorithm is called Trust Region Policy Optimization (TRPO), which uses a constraint on the Kullback–Leibler (KL) divergence rather than a penalty to robustly allow large updates. The KL divergence is a measure of how one probability distribution P is different from a second probability distribution Q that is a reference for the first one: $D_{KL}(P||Q)$.

In fact, supposing that we used a penalty coefficient C (that is recommended by theory), the step sizes would be very small (fig. 3). One way to take larger steps in a robust way is to use a constraint

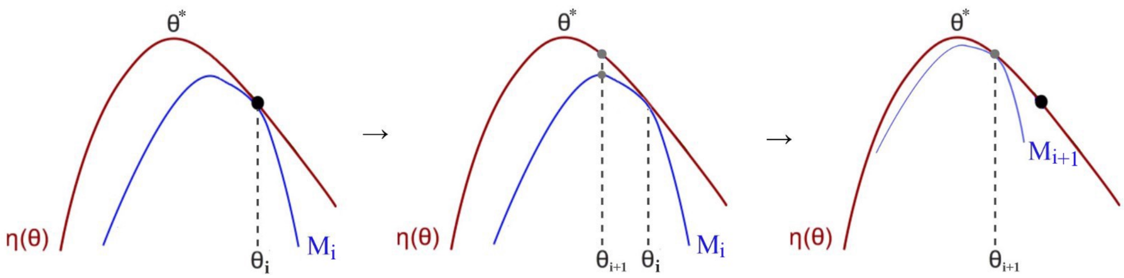


Figure 2: Minorization-Maximization algorithm where M is a lower bound for η (surrogate function). Eventually our guess will converge to the optimal policy but to make this work M should be easier to optimize than η (in fact M is usually approximating to a quadratic equation that is a convex function).

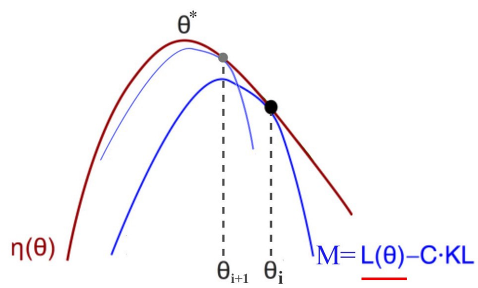


Figure 3: In practice, if penalty coefficient is included in the objective function, the step size will be very small, leading to long training time. Consequently, a constraint on the KL divergence is used to allow a larger step size while guarantee robust performance.

on the KL divergence between new policy and old policy (trust region constraint):

$$\begin{aligned} &maximize_\theta \ L_{\theta_{old}}(\theta) \\ &subject \ to \ D_{KL_{max}}(\theta_{old}, \theta) \leq \delta \end{aligned} \tag{1}$$

Since η is hard to optimized, L is a local approximation to η. While it's motivated by the theory, this problem is impractical to solve due to large number of constraints. Unfortunately, it is not solvable as there are a infinitely large number of states: we can use a heuristic approximation which considers the avarage KL divergence $\bar{D_{KL}}$. Our optimization problem in equation (1) is exactly equivalent to the following one (written in terms of expectations, replacing some terms, under the assumption that $D_{KL}(\theta||\tilde{\theta}) := D_{KL}(\pi_\theta||\pi_{\tilde{\theta}})$):

$$\begin{aligned} &maximize_\theta \ E_t\Big[\frac{\pi_\theta(a_t, s_t)}{\pi_{\theta_{old}}(a_t, s_t)} A_t\Big] \\ &subject \ to \ D_{KL_{max}}(\theta_{old}, \theta) \leq \delta \end{aligned} \tag{2}$$

The advantage function $A_\pi = Q_\pi(s, a) - V_\pi(s)$ is the difference between state-action value function and value function. We can prove that any policy update $\pi \to \tilde{\pi}$ that has a nonnegative expected

advantage at every states is guaranteeed to increase the policy performance η, or leave it constant in the case that the expected advantage is zero everywhere. Intuitively, we can think of it as measuring how good the new policy is with regard to the average performance of the old policy. However, in the approximate setting, it will typically be unavoidable, due to estimation and approximation error, that there will be some state s for which the expected advantage is negative. The objective function is also called a **surrogate objective function** as it contains a probability ratio between current policy and the next policy. The subset of region lies within the constraint is called **trust region**. As long as the policy change is reasonably small, the approximation is not much different from the true objective function By choosing the new policy parameters which maximizes the expectation subject to the KL divergence constraint, a lower bound of the expected long-term reward η is guaranteed. In the trust region, we limit our search within a region controlled by δ.
A practical algorithm could be:

1. Use a procedure to collect a set of state-action pairs.
2. By averaging over samples, construct the estimated objective and constraint in equation 2.
3. Approximately solve this contrained optimization problem to update the policy's parameter vector θ.

The third point has been developed by the author with a conjugate gradient algorithm followed by a line search, or in other words, compute a search direction and perform a line search in that direction. The search direction is computed by approximately solve the equation $Ax = g$ where A is the Fisher information matrix (part of the KL divergence). Given that this matrix is costly in large-scale problems, the conjugate gradient allows us to approximately solve this equation without forming the matrix itself. Having computed the search direction, it's necessary to use a line search to ensure improvement of the surrogate objective and satisfaction of the KL divergence constraint.
The real difference between gradient descent and conjugate gradient is that the latter finds a search direction every time that is A-orthogonal (conjugate) to all previous directions, so it would not undo part of the movement done previously (as we can see in fig. 4). As far as the author specifies that this is an efficient method to solve the problem, it's really hard to implement practically. Given this difficulties in the implementation, I've decided to solve the constraint optimization problem (eq. 2), using an handcrafted solution which uses gradient descent, even if it is not the most efficient solution. The next section will explain the implementation choices for the algorithm.

4 Implementation

The algorithm as described in figure 5 has been developed using Python 3 and TensorFlow 2 as framework.

It has been used the single-path method in which a set of trajectories is generated via simulation of the policy from s_0 for some number of timesteps.

The advantage requires the value function that is approximated through a neural network. The inputs of this neural network are the observations and the estimation has been made with Mean Squared Error (MSE). Another fundamental neural network that has to be implemented is the policy. Given a particular observation the policy neural network will returns the means and log variance, composing a Gaussian distribution from which we can sample the right action to choose. Anyway, to permits to the agent to make exploration (as well as exploitation) ϵ-greedy method has been implemented: the action to choose at each state can be randomly selected with a probability $\epsilon = 0.2$

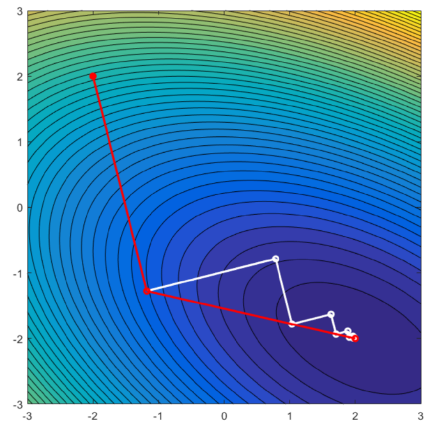


Figure 4: Difference between conjugate gradient (red line) and gradient descent (white line). Conjugate gradient can reach the minimum point of the function in less steps.

The policy network has been optimized with gradient descent on a loss function that is the negate of our objective function from the equation (2). For each iteration, the policy has to be trained (updated) for several epochs and for each epoch it's necessary to check if $D_{KL} \leq \delta$. If this condition is not respected, then the constraint is not either: the previous state (weights) of the neural network would be loaded in order to respect the contraint. As we said in the previous section, this handcrafted method has been made to find a trade-off between complexity and efficiency for the TRPO algorithm. Altough theorically the constraint is respected, given the approximation of the value function, it's not possible to obtain a positive advantage everytime. For this reason, as we will see in the plots in the next paragraph, the policy will have monotonic improvement overall only.

The training of the policy has to be done each time over all the trajectories of a batch. The batch size bs has been set to 5 for memory reason. Among the most important implementation choices, besides those already mentioned, there are:

- Discount factor γ: is a value between 0 and 1 that tells how important future rewards are to the current state. This is set to 0.995.
- D-KL target value δ: this is the upper value of the constraint.
- Policy learning rate lr: this is the learning rate of the policy neural network. This has to be chosen carefully otherwise the convergence would never be obtained. Empirically we can chose this value as the one that allow the policy to train for at least (on avarage) 10 epochs.

for iteration$=1, 2, \ldots$ **do**
Run policy for T timesteps or N trajectories
Estimate advantage function at all timesteps

$$\begin{aligned} &\underset{\theta}{\text{maximize}} && \sum_{n=1}^{N} \frac{\pi_\theta(a_n \mid s_n)}{\pi_{\theta_{\mathrm{old}}}(a_n \mid s_n)} \hat{A}_n \\ &\text{subject to} && \overline{\mathrm{KL}}_{\pi_{\theta_{\mathrm{old}}}}(\pi_\theta) \leq \delta \end{aligned}$$

end for

Figure 5: Pseudocode for TRPO algorithm.

5 Results

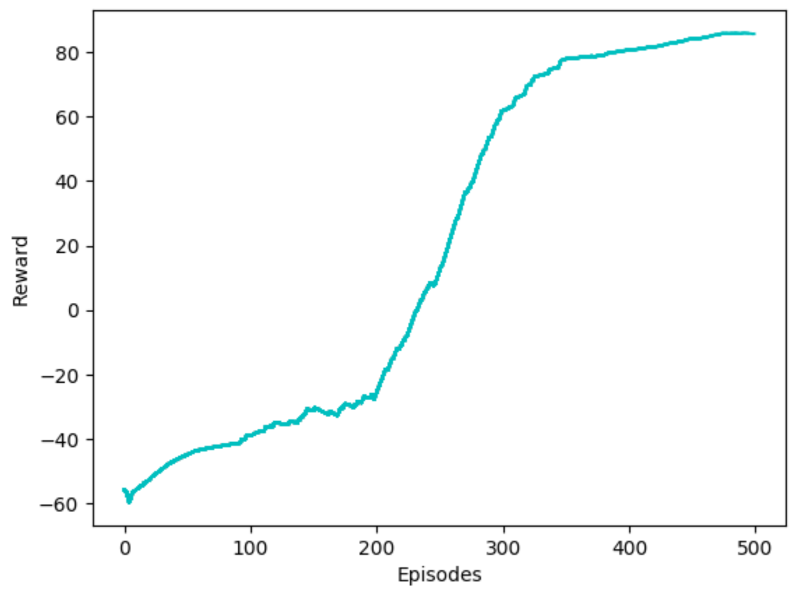
Various tests have been made, tuning the parameters of the algorithm. All the previous results for the most important parameters are valid in both the environment. Subsequent to the completion of tuning, the results have been obtained training each agent for a sufficient quantity of episodes.

5.1 MountainCarContinuous-v0

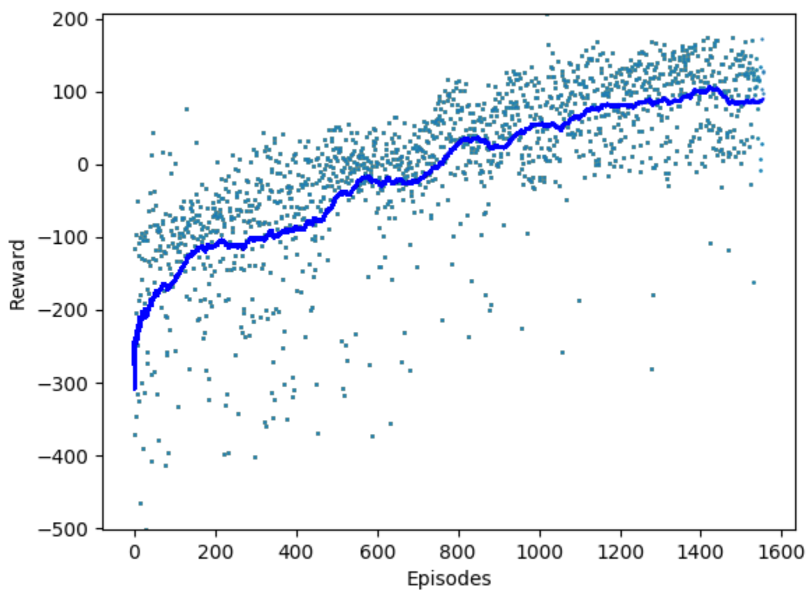
For the mountain car environment is necessary to use $lr = 3 \cdot 10^{-4}$. This permits to solve the problem (90 score) in about 500 episodes. As we can see in fig 6a the agent for at least 200 episodes is training its policy to increase rewards but without the exploration provided with ϵ-greedy parameter, it wouldn't be easy to reach the flag. After its positive reward, the agent obtain an exponentially increase in rewards until it's near to solve the problem. It's possible to test this agent on its environment with the saved model in *"models/mountain.tf"* using the script *test.py*.

5.2 LunarLanderContinuous-v2

For the lunar lander environment an improvement is possible with $lr = 5 \cdot 10^{-5}$ while keeping all the parameters set for the previous environment. As we can see in 6b, the agent will increase generally its performance but it requires more than double of the episodes to reach a good behaviour, respect to mountain car environment. Further improvements can be probably done to this problem tuning other parameters in addition to lr. It's possible to test this agent on its environment with the saved model in *"models/lunar.tf"* using the script *test.py*.



(a)



(b)

Figure 6: Learning curves avaraged across five runs. The environments in which the agent operates are (a) MountainCarContinuous-v0 and (b) LunarLanderContinuous-v2. In the last environment it has been shown also (as a scatter plot) the score for each episode