Trust Region Policy Optimization

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May 26, 2022

Introduction

We introduce an iterative procedure for optimizing policies, guaranteeing monotonic improvement.
We provide the theoretical framework and by making a series of approximation we develop a practical algorithm.
Trust Region Policy Optimization (TRPO) algorithm is built upon natural policy gradient methods, showing effectiveness in improving nonlinear policies $\pi(a|s)$ such as neural networks.
TRPO comes in two different fashion way:

- *single-path* method, which can be applied in model-free setting
- *vine* method, requiring the system to be restored in particular states, typically applicable only in simulation

Model Description

We can express the expected return of another policy $\tilde{\pi}$ in terms of the expected discounted reward $\eta(\pi)$ of the policy π

$$L_{\pi}(\tilde{\pi}) = \eta(\pi) + \sum_{s} \rho_{\pi}(s) \sum_{a} \tilde{\pi}(a|s) A_{\pi}(s, a) \tag{1}$$

where $\rho(\cdot)$ is the discounted visitation frequencies and $A(\cdot, \cdot)$ is the advantage function.
The result above (i.e. parametrised ρ w.r.t. π) ensure that we have a monotonic increase since ρ ignores changes in state visitation frequencies, i.e. initial state probabilities are fixed w.r.t. the initial policy.
In [Kakade & Langford, 2002] the authors provided a lower bound when considering the new updated policy as a mixture of the previous policy and the new one

$$\eta(\pi_{new}) \geq L_{\pi_{old}}(\pi_{new}) - \frac{2\epsilon\gamma}{(1-\gamma)^2}\alpha^2$$

$$\text{where } \epsilon = \max_{s} \left| \mathbb{E}_{a \sim \pi'(a|s)} \left[A_{\pi}(s, a) \right] \right|$$

Key Catch

One of the key aspects is the following. We extend the previous bound of having a mixture of policies driven by α to general stochastic policies, using a distance measure between the old policy and the new one.

Theorem

The following bound holds

$$\eta(\tilde{\pi}) \geq L_\pi(\tilde{\pi}) - CD_{KL}^{max}(\pi, \tilde{\pi}) \tag{2}$$

where $C = \frac{4\epsilon\gamma}{(1-\gamma)^2}$

which can be proved by showing that it construct a sequence of policies $\tilde{\pi}_i$ improving at each iteration i

Theoretical Algorithm

The theoretical algorithm developed from the previous equation is an algorithm of type minorization-maximization (MM). It is only a theoretical scheme since TRPO applies some approximation to the algorithm below

Initialize π_0
for $i = 0, 1, 2, \dots$ until converge **do**
  Compute all advantage values $A_{\pi_i}(s, a)$
  Solve the constrained optimization problem
  $\pi_{i+1} = \arg\max_\pi \left[L_{\pi_i}(\pi) - CD_{KL}^{max}(\pi_i, \pi)\right]$
  where $C \frac{4\epsilon\gamma}{(1-\gamma)^2}$
  and $L_\pi(\tilde{\pi}) = \eta(\pi) + \sum_s \rho_\pi(s) \sum_a \tilde{\pi}(a|s) A_\pi(s, a)$
end for

TRPO

The policy update above is not suitable in practical application

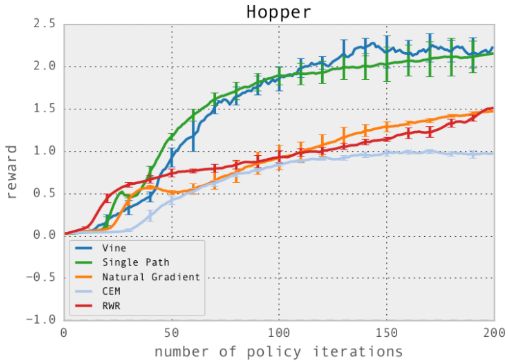
- Using the penalty coefficient C reflects on very small step sizes $\Longrightarrow$ we substitute it with a trust region constraint
- The KL divergence imposes a large number of constraints after applying the change above $\Longrightarrow$ we consider the average KL divergence

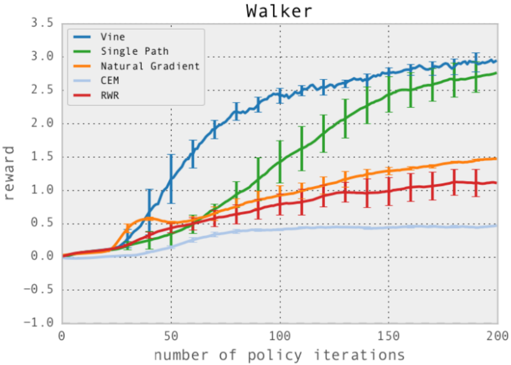
$$\begin{aligned} \underset{\theta}{\text{maximize}} \quad & L_{\theta_{old}}(\theta) \\ \text{subject to} \quad & \bar{D}_{KL}^{\rho_{\theta_{old}}}(\theta_{old}, \theta) \leq \delta \end{aligned} \tag{3}$$

which can be solved by using Monte Carlo simulation

Results

TRPO outperforms different methods in the simulated robotic locomotion environment, in particular when considering the *Hopper* and *Walker* tasks.





Conclusion

To conclude, we can highlight some pros and cons of the described method.

Pros:

- The introduction of the trust region constraint on the KL divergence brings strong improvements in the policy update, allowing for larger step sizes

Cons:

- The *vine* method suffer from less variance but needs to evaluate multiple paths from a fixed state. Doing so is possible mostly only in simulated environments

References

- Schulman, J., Levine, S., Moritz, P., Jordan, M. & Abbeel, P. Trust Region Policy Optimization. (arXiv,2015), https://arxiv.org/abs/1502.05477
- Kakade, S. & Langford, J. Approximately Optimal Approximate Reinforcement Learning. *IN PROC. 19TH INTERNATIONAL CONFERENCE ON MACHINE LEARNING*. pp. 267-274 (2002)