How to pick the domain randomization parameters for sim-to-real transfer of reinforcement learning policies?

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I. INTRODUCTION

Recently, reinforcement learning (RL) algorithms have demonstrated remarkable success in learning complicated behaviors from minimally processed input ([1], [2], [3], [4], [5], [6]). However, most of this success is limited to simulation. While there are promising successes in applying RL algorithms directly on real systems ([7], [8], [9], [10], [11]), their performance on more complex systems remains bottlenecked by the relative data inefficiency of RL algorithms. Domain randomization is a promising direction of research that has demonstrated impressive results using RL algorithms to control real robots ([12], [13], [14], [15], [16]).

At a high level, domain randomization works by training a policy on a distribution of environmental conditions in simulation. If the environments are diverse enough, then the policy trained on this distribution will plausibly generalize to the real world. A human-specified design choice in domain randomization is the form and parameters of the distribution of simulated environments. It is unclear how to pick the form and parameters of this distribution and prior work uses hand-tuned distributions. This extended abstract demonstrates that the choice of the distribution plays a major role in the performance of the trained policies in the real world.

II. BACKGROUND AND NOTATION

In RL, the robotic learning problem is abstracted as a discrete time sequential decision making problem in a Markov decision process (MDP). An MDP is a tuple \((S, A, r, T, \gamma, \rho)\) with state space \(S\), action space \(A\), reward function \(r: S \times A \rightarrow \mathbb{R}\), state transition function \(T: S \times A \rightarrow S\), a discount factor \(\gamma\) and a distribution over the initial state \(\rho\). Given a state \(s \in S\), a policy \(\pi\) defines a distribution \(\pi(s|a)\) over the action space \(A\). \(\theta\) represents the parameters of the policy, which can be linear operators ([17], [18]) or the weights and biases of a deep neural network. Let \(m\) denote one specific MDP \((S^{(m)}, A^{(m)}, r^{(m)}, T^{(m)}, \gamma, \rho^{(m)})\). The performance of a policy \(\pi_{\theta}\) with respect to the MDP parameterized by \(m\) is evaluated by:

\[
J^{(m)}(\pi_{\theta}) \triangleq \mathbb{E}_{\tau \sim \tau_{\pi_{\theta}}} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]
\]

where \(\tau = (s_0, a_0, r_0, s_1, \ldots)\) is a trajectory generated by using the policy \(\pi_{\theta}\) to interact with the MDP \(m\). Let \(m_{\text{real}}\) denotes the MDP representing the real world. Formally, domain randomization performs the optimization

\[
\theta^* = \arg\max_{\theta} \mathbb{E}_{m \sim p_\phi} \left[ J^{(m)}(\pi_{\theta}) \right]
\]

where \(p_\phi\) is a distribution over MDPs parameterized by \(\phi\). \(\pi_{\theta^*}\) is then used to perform the task of interest in \(m_{\text{real}}\). For example, in [13] where domain randomization was successfully used to transfer a policy trained in simulation to the real world on object pushing tasks, \(\phi\) parameterizes the distribution over the masses and damping coefficients of the robot’s links in addition to other environmental conditions.

III. OPTIMIZATION OF THE DOMAIN RANDOMIZATION PARAMETERS

At a high level, domain randomization is a technique to accomplish the general goal: “Given a simulator, we want to use it such that when we train a policy in the simulator, the policy will perform well in the real world”. We argue that this is an objective that we can optimize for directly. In prior works, the parameter \(\phi\) of the distribution over MDPs is chosen by hand, presumably using domain knowledge and through trial-and-error; it is also kept fixed throughout the training process. Prior works also assume that there is a clear demarcation between training and testing, i.e. during training in simulation, the policy does not have access to the real system. However, in practice, this assumption could be incorrect, as we may have limited or costly access to the real system. In such scenarios, we could use the real system to provide some signal for domain randomization.

With access to the real environment \(m_{\text{real}}\), we can formalize domain randomization as a bilevel optimization problem:

\[
\arg\max_{\phi} \quad J^{(m_{\text{real}})}(\pi_{\theta^*(\phi)})
\]

such that

\[
\theta^*(\phi) = \arg\max_{\theta} \mathbb{E}_{m \sim p_\phi} \left[ J^{(m)}(\pi_{\theta}) \right]
\]

To establish that this is a research direction worth pursuing, we need to demonstrate the following:

- The choice of the parameter \(\phi\) plays a major role in the performance of the policies in the real environment.
• φ can be optimized to increase the performance of the trained policies in the real environment.

We experimentally demonstrate these two points by using Cross Entropy Method (CEM) to approximately solve the outer problem (Equation 1) and Proximal Policy Optimization (PPO) [19] to solve the inner problem (Equation 2). The closest related work to ours is [20], which finds the simulation parameters that bring the state distribution in simulation close to the state distribution in the real world. We argue that this is only a proxy measure of the actual objective we ultimately care about and optimize for directly, i.e. the performance of the trained policy in the real environment. Other than domain randomization, other parallel research directions for sim-to-real transfer exist and have been demonstrated to be promising research areas as well ([21], [22], [23], [24], [11]).

IV. Algorithmic Description

CEM is a simple iterative gradient-free stochastic optimization method. Given the decision variable φ, CEM alternatives between evaluating its current value on the objective function (Equation 1) and updating φ. We refer interested readers to [25] for a more detailed description. We initialize φ with φ0, evaluate φ0 to obtain J(m/sim)(πθ∗(φ0)), use the evaluation result to update φ0 to obtain φ1, and so on.

V. Experimental Settings and Results

To demonstrate the potential of our research direction, we focus on transferring learned policies between two simulators. Specifically, we focus on transferring policies for the environments Hopper and Walker from the Dart simulator [26] to the Mujoco simulator [27]. Thus, m/sim represents the parameters of the MDP in the Mujoco simulator. Transferring between these two simulators has been demonstrated to be a fruitful experimental testbed for sim-to-real studies [14]. In our setting, the MDPs in both simulators are parameterized by the masses, damping coefficients of the robot’s links and the gravity constant (R3 for Hopper and R15 for Walker).

φ represents the parameters of a distribution over m. In our experiments, φ is the mean and variance of a diagonal Gaussian distribution over the simulation parameters. The initial mean φ0 is set to m/sim and initial variance set to 1 for all parameters. These values are reasonable defaults for the domain randomization distribution parameters without domain knowledge or trial-and-error. CEM is then used to optimize for φ.

We replicate our results for each setting over 5 different random seeds. In the Hopper environment, the performance of the policies trained with the optimized φ is on averaged 102% higher than the performance of the policy trained with the initial value φ0 with a standard deviation of 48% and minimum improvement of 28%. In the Walker environment, the performance of the policies trained with the optimized φ is on average 80% higher than the performance of the policy trained with the initial value φ0 with a standard deviation of 53% and minimum improvement of 19%. The existence of a better value for φ than φ0 shows that environment distributions chosen by hand can be improved with optimization. Furthermore, our result is consistent with ongoing research in domain randomization for supervised learning which demonstrated the importance of the sampling distribution for sim-to-real transfer success ([28], [29]).

VI. Future Research Directions

A. Learning complex distributions

We assume a diagonal Gaussian sampling distribution for simplicity, but learning a more complex distribution could result in a better randomized environments. For example, deep generative modeling approaches such as variational autoencoders ([30], [31]) and autoregressive flows ([32], [33]) could be used to model complex dependencies and correlations between simulation parameters.

B. Optimization techniques

CEM was chosen to solve the outer problem (1) due to its simplicity. We are interested in more advanced gradient-free optimization methods, such as CMA [34] or Bayesian optimization [35]. If we assume that the parameter φ is parameterized by a distribution pφ, it can be shown that ∇φ E [J(m/sim)(πθ∗(φ))] = E[φ∼pφ(φ)] ∇φ log pφ(φ)J(m/sim)(πθ∗(φ)) and we could apply stochastic gradient-based techniques to directly optimize for φ. We are also particularly excited about asynchronous evolutionary algorithms (AEA). Whereas previous techniques are synchronous by nature, AEA enables simultaneously training policies in simulation and evaluating in reality, thereby making the best use of the available resources in terms of wall-clock time.

C. Off-policy Reinforcement Learning

PPO, an on-policy RL algorithm, was chosen to solve the inner problem (2) due to its simplicity and speed. However, off-policy training of the policy with real world data has been demonstrated to improve the policy performance ([16], [36]). In our setting, the real world data generated to evaluate the policy at every iteration of solving the outer problem (1) can be used to optimize the next policy in an off-policy fashion. Preferably, the inner problem (2) is solved by an off-policy algorithm to allow for easy fine-tuning of the trained policy on real world data.

D. Transferable Domain Randomization Parameters and Testing On Real Robots

It would be of interest to understand if there exists general principles to determine the value of φ or transferable initial values for φ that works for domain randomization across a wide range of tasks and robots. This is so that the expensive problem (Equation 1 and 2) does not have to be solved from scratch for every problem instance. Ultimately, the goal is to test our approach to domain randomization on real robots.
