Paper Review: Benchmarking Reinforcement Learning Algorithms on Real-World Robots

Summary:

This paper studies the real-world application of several reinforcement learning tasks, including TRPO, PPO, DDPG, and Soft-Q, using three commercially available robots of varying difficulty, setup, and repeatability. The authors test four off-the-shelf reinforcement learning algorithms on these tasks and analyze their sensitivity to hyper-parameters to determine their readiness for various real-world applications. The results show that with careful task setup and computations, some implementations can be readily applicable to physical robots. However, it is discovered that state-of-the-art learning algorithms are highly sensitive to their hyper-parameters, and the best hyper-parameter configuration from one task may not transfer to other tasks with different robots.

Contributions:

The main contributions of this work are introducing benchmark tasks for physical robots, setting up conducive tasks for learning, and providing an extensive empirical study of multiple policy learning algorithms on multiple physical robots. This is a valuable contribution in the space of DRL applications because most benchmark tests are done in virtual environments because of their consistency and reproducibility.

Strengths and Weaknesses:

The main strength of this paper is its practical application to real world DRL algorithms. I believe that most research papers often explore and study the theoretical results of their algorithms and rarely follow it up with how it performs in the real world. However, I believe the one weakness of this paper is that it does not compare its results to theoretical results for each DRL algorithm. Doing so would provide a good reference for each algorithm's performance to what was expected.

Experimental Validity:

In this paper, the experiments were thoroughly investigated, with more than 450 experiments taking over 950 hours to complete. Each hyper-parameter configuration was used to run experiments with different neural network initializations. The experiments concluded that they were highly repeatable, and the hyper-parameters of each algorithm were randomly searched to investigate their sensitivity within and across tasks.

How can this work be extended:

It would be exciting to see these algorithms be applied to more complex real-world games such as Jenga, Soccer, or mazes. The work done in this paper is highly valuable for scoring and evaluating real world applications, so I think evaluating the limitations of their environments would be a great benefit. Overall, this paper does a very good job at extending previous research in a meaningful way that will greatly benefit the future of AI and robotics.