Bridging the Simulation-to-Real Gap in Deep Reinforcement Learning

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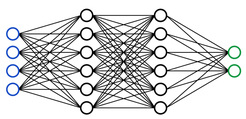
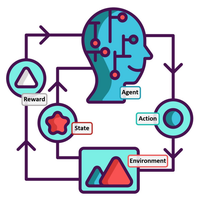
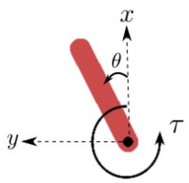
Background

Deep reinforcement learning (RL) is a **powerful control paradigm** which has proven to be a promising alternative to traditional algorithms. For complex environments, deep RL relies on **simulated environments** for training since it can take millions of interactions to learn an optimal policy. However, simulations are **imperfect representations** of real-world systems, so a gap between performance in simulation and performance in the real-world is formed. This performance disparity is known as the **simulation-to-real gap**, and solving it is the focus of this research.







Methods

The current state of the art algorithms, like **Soft Actor-Critic (SAC)** [1] and **Proximal Policy Optimization (PPO)** [2], are model-free meaning they do not learn the dynamics of the system, but rather the actions that are most likely to maximize the reward. This work investigates how using the model-based **Short Horizon Actor-Critic (SHAC)** [3] algorithm with a differentiable simulator compares to these model-free algorithms. To emulate a real-world environment, models were tested for their **robustness to observation noise and system parameter tweaks**. All experiments were averaged over **five different seeds** on the classical **pendulum control** problem.

Acknowledgements

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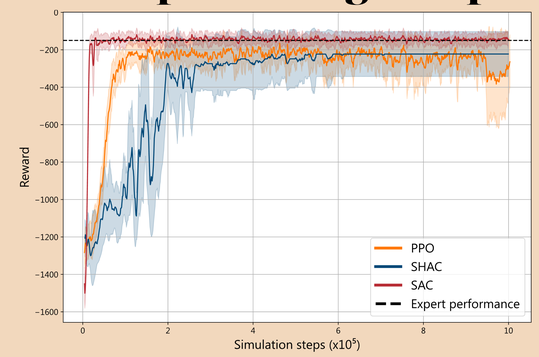
Auxiliary Information

All graphs created from the data, hyperparameters used for the experiments, and references used for this research.

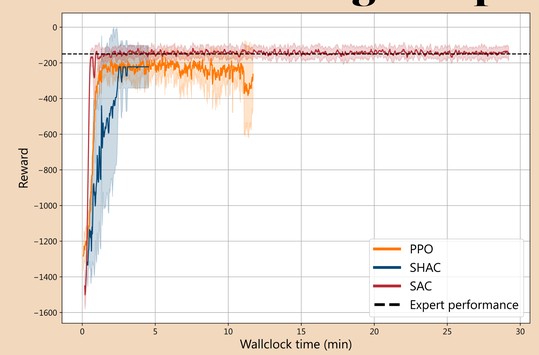
Results

Across every test, **SAC outperformed** both **PPO and SHAC**. It converged to expert level performance with **5x** less timesteps, and its policies were **more robust** to **observation noise and system parameter tweaks** across the board. However, its sample efficiency comes at the cost of **increased training time** relative to PPO and SHAC (as shown in the auxiliary information).

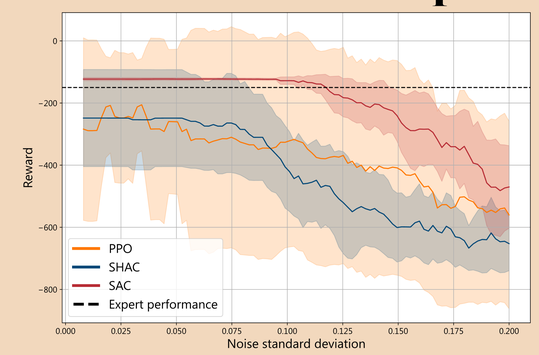
Timestep Learning Comparison



Wallclock Learning Comparison



Noise Robustness Comparison



Conclusions

Why does this matter?

- These results **go against** the findings in the SHAC paper, but this is likely due to **optimizations in their simulator** that were not used for this environment
- SHAC can obtain **expert performance**, but fails with certain seeds likely due to getting stuck in **local minima**
- **Model-free algorithms** are likely more robust and efficient than **model-based algorithms**

Future Work

These findings are **preliminary results** for later experiments which will use the more complex **double pendulum environment**. Similar methods will be used to test the algorithms in simulation, and a **physical system of the environment** will be developed to test the **transferability of each algorithm's policy**. This will give a better representation of how well each model is able to **bridge the simulation-to-real gap**.

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