DATA-DRIVEN CONTROL

Deep Reinforcment Learning vs Classical Control



Classical Control methods such as Proportional Integral Derivative often struggle with complex non-linear systems, leading to suboptimal results.

Objectives

Evaluate the feasibility of DRL for control, comparing the performance of six DRL algorithms against Classical Control and each other

Methodology

Algorithms

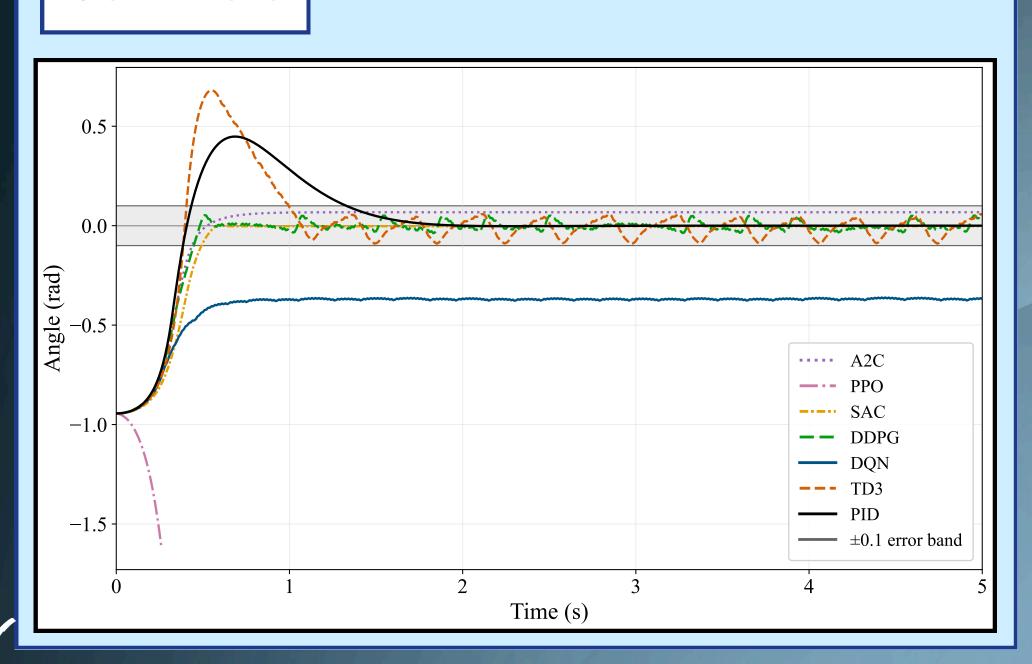
PID, A2C, PPO, DQN, SAC, TD3, DDPG Systems

Inverted Pendulum Cart-Pole

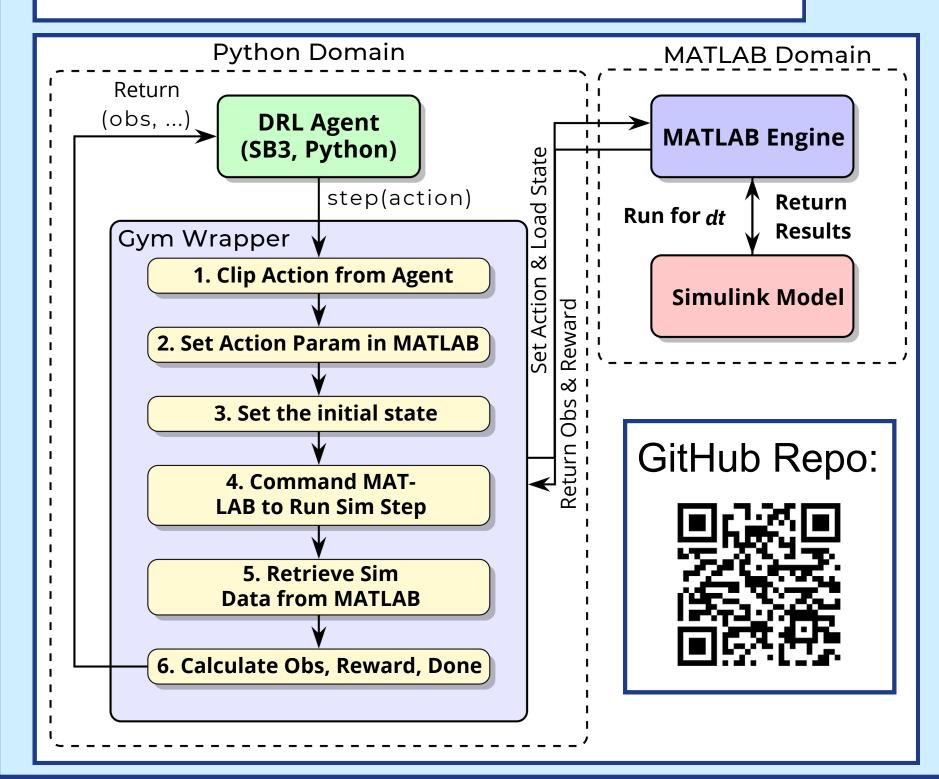
Buck Converter

Buck-boost Converter

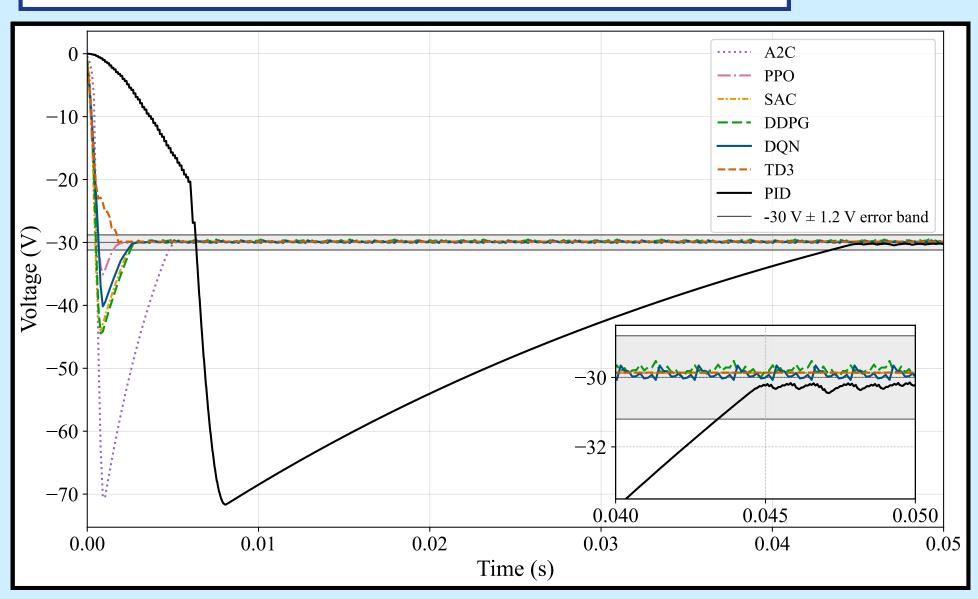
Cart-Pole



MATLAB Gymnasium Wrapper



Inverting Buck Boost Converter



SB3's DRL algorithms were integrated with Optuna for hyperparameter tuning. Custom wrappers and simulation environments, **significantly** reduced training time and **improved** experimental reproducibility.

DRL vs PID

DRL consistently **outperformed PID** across **all** systems, especially as system complexity/noise grew.

DRL vs DRL

- A2C and SAC were the **fastest** and most **stable**.
- PPO was slower but balanced.
- TD3/DDPG were noise-sensitive
- DQN performed **well** despite its discrete nature.

On vs Off Policy

- On-policy had an extremely **fast** computational throughput but exhibited **low sample efficiency**.
- Off-policy exhibited high sample efficiency, but at the cost of longer training times.

Conclusions

The results show that **DRL** algorithms, especially **actor-critic** algorithms, **outperform classical PID controllers** in both **speed** and **precision** across varied continuous control systems. This highlights the potential of DRL to handle complex, nonlinear control tasks that challenge traditional methods.



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