

DATA-DRIVEN CONTROL

Deep Reinforcement Learning vs Classical Control

The Problem

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

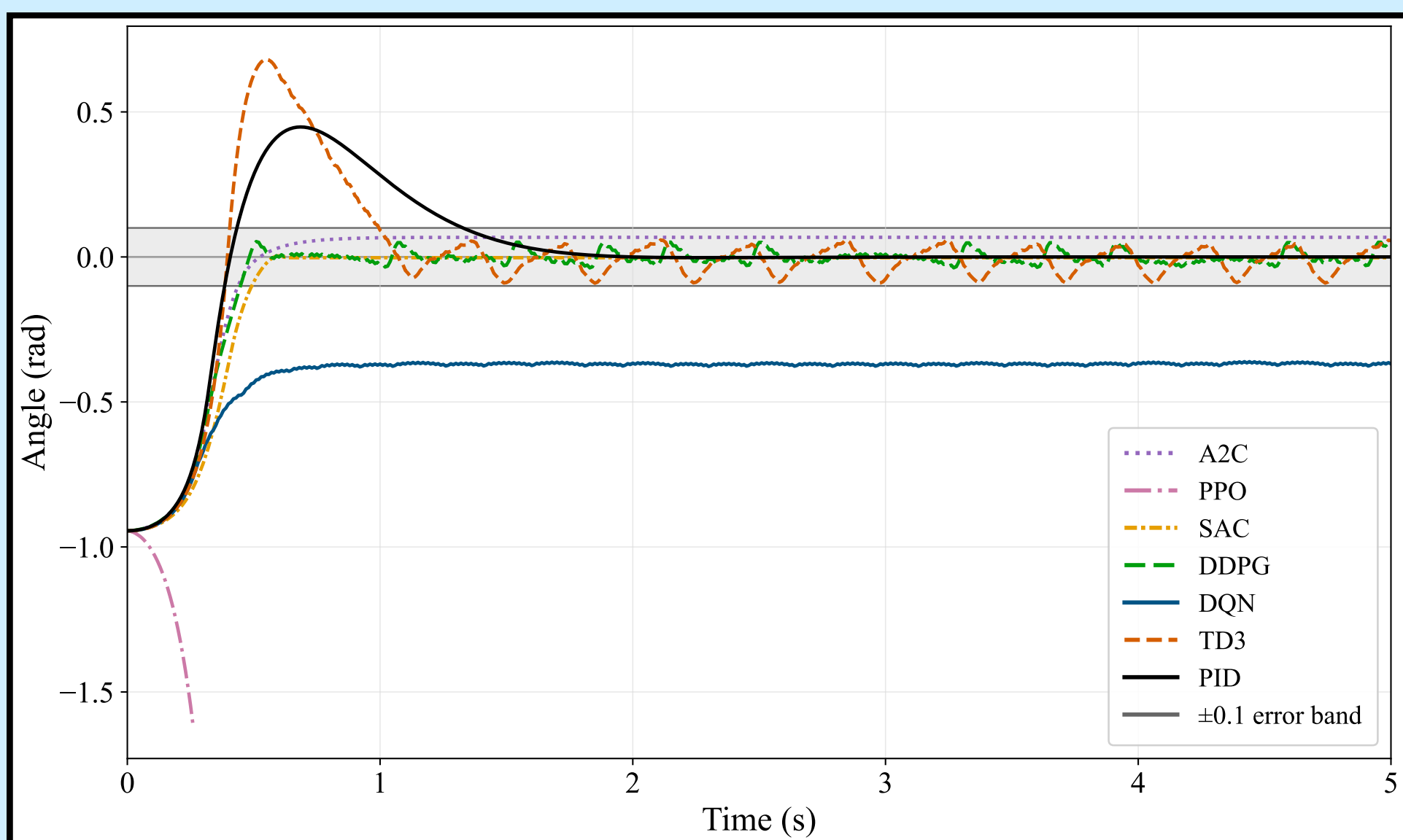
Algorithms

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

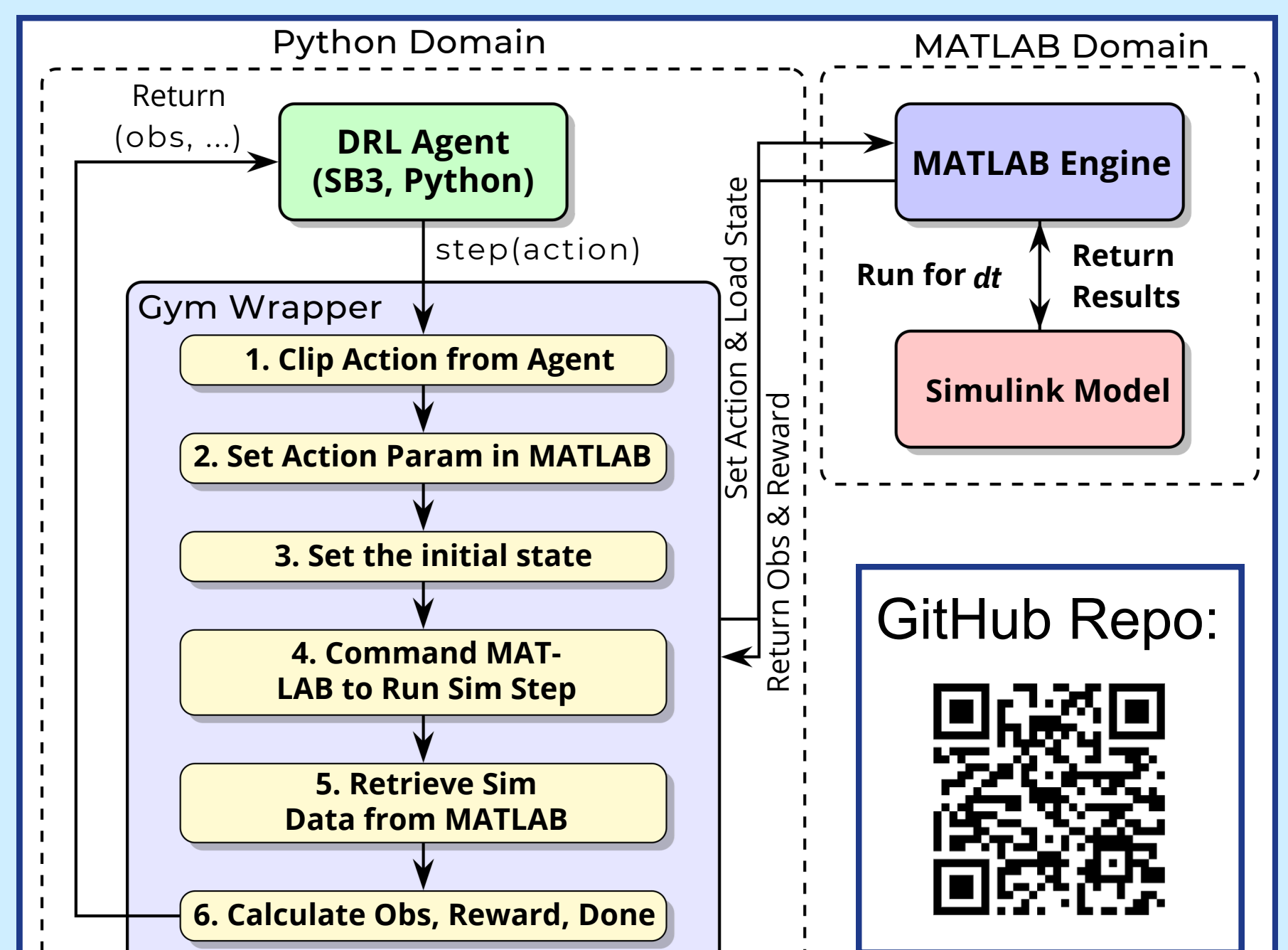
Systems

Inverted Pendulum
Cart-Pole
Buck Converter
Buck-boost Converter

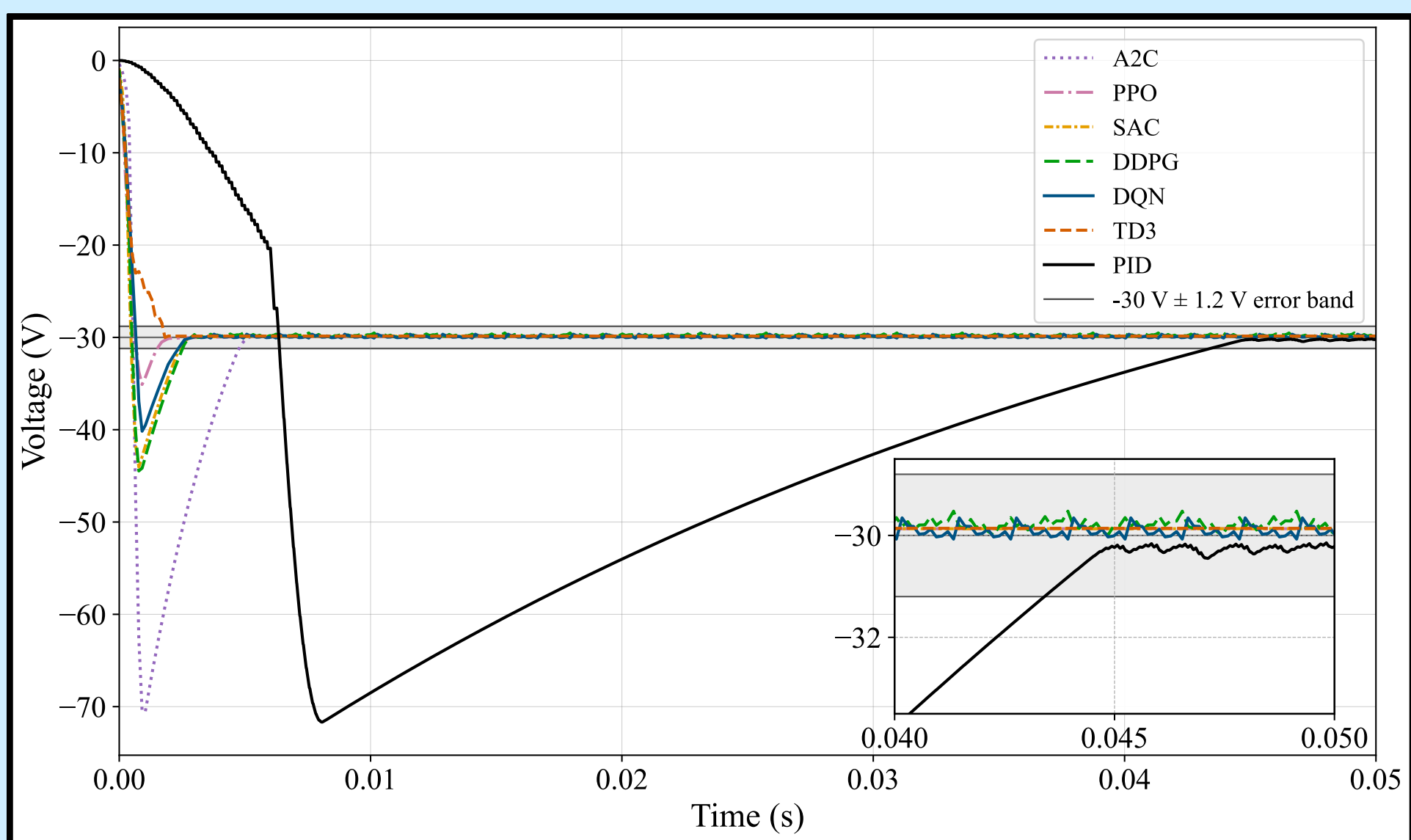
Cart-Pole



MATLAB Gymnasium Wrapper



Inverting Buck Boost Converter



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.

