The 2023 International Planning Competition: RL and Stochastic Planning Track Method Abstract Title

Ayal Taitler,[1] Scott Sanner, [1] Mike Gimelfarb [1]

[1] University of Toronto

ayal.taitler@utoronto.ca, ssanner@mie.utoronto.ca, mike.gimelfarb@mail.utoronto.ca

Abstract

Write here a short summary of your method and your key ideas. This part should not exceed 200 works. Please make sure the whole text (without the references) will not exceed two pages. Please write every detail of your method as it will be used later to evaluate and present you method at the final competition presentation at ICAPS 2023.

Introduction

Introduce the context and the background of your approach. E.g., if you are using RL say a few words on RL and the specific algorithms you are using (PPO, DQN, etc.). This is the place to introduce the terminology and reference to the appropriate papers for further reading. Assume the reader does not know what you are using and needs an explicit introduction and references. Here you list everything you need in order to be able to explain your method in the next section. The next paragraph is an example for an introduction for a method that uses DQN.

Control problems are prevalent in various domains, ranging from robotics and autonomous systems to game playing and optimization. The ability to find optimal control policies that maximize long-term rewards in dynamic environments is a fundamental challenge in these domains. In recent years, reinforcement learning (RL) has emerged as a powerful paradigm for addressing such control problems. Among the myriad of RL algorithms, the Deep Q-Network (DQN) (Mnih et al. 2013) algorithm has gained significant attention due to its ability to learn effective control policies directly from raw sensory inputs. In this paper, we present a method for control problems using the DQN algorithm. We delve into the underlying principles of the algorithm, discuss its strengths and limitations, and demonstrate its relevance to the problem presented in the 2023 IPPC. By exploring the capabilities and performance of DQN in different scenarios, this study aims to contribute to the understanding and advancement of RL-based control methods, specifically for the goals set by the 2023 IPPC – continuous problems, indegenous and exogenous noises on states and actions, etc.

method

This is the place to introduce and explain your method. If there is a non standard usage of the simulation infrastructure (Taitler et al. 2022) please deatil it here. Please be specific and explain in detail every aspect of you proposed method. This includes training procedures, heuristics, normalizations, and any ”trick” you have used to make you method work. Don’t be afraid to use figures if it will help to illustrate your approach.

External Libraries

List the modules and external tools you used, that are not original to your solution. This includes non standard python packages.

Conclusion

If you have some concluding remarks, some take home messages this is the place to briefly bring it to the attention of the reader.

References

Mnih, V.; Kavukcuoglu, K.; Silver, D.; Graves, A.; Antonoglou, I.; Wierstra, D.; and Riedmiller, M. 2013. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*.

Taitler, A.; Gimelfarb, M.; Gopalakrishnan, S.; Mladenov, M.; Liu, X.; and Sanner, S. 2022. pyRDDLGym: From RDDL to Gym Environments. *arXiv preprint arXiv:2211.05939*.