SuperSuit: Simple Microwrappers for Reinforcement Learning Environments

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Abstract

In reinforcement learning, wrappers are universally used to transform the information that passes between a model and an environment. Despite their ubiquity, no library exists with reasonable implementations of all popular preprocessing methods. This leads to unnecessary bugs, code inefficiencies, and wasted developer time. Accordingly we introduce SuperSuit, a Python library that includes all popular wrappers, and wrappers that can easily apply lambda functions to the observations/actions/reward. It’s compatible with the standard Gym environment specification, as well as the PettingZoo specification for multi-agent environments. The library is available at https://github.com/PettingZoo-Team/SuperSuit and can be installed via pip.

1 Introduction

Applying transformations to information passing between a model and an environment in reinforcement learning is an integral part of every major experimental work in the field (Mnih et al., 2013; Vinyals et al., 2019; Silver et al., 2017; Berner et al., 2019). Techniques popular on Atari environments include scaling down observations with image processing methods or making the observation greyscale to reduce processing time with neural networks, “stacking” frames together to help establish velocity, or skipping frames to increase training speed (Mnih et al., 2013).

These “wrappers” are very useful, but using them in practice has pain points. For code modularity, ease of debugging, and ease of hyper-parameter tuning, it’s generally preferable to define the wrapper function(s) outside the environment. Ideally these very commonly used functions would be distributed in a library, so that the implementation used is as fast as possible. This is fairly important considering how many times it would be called in large research projects.

Gym (Brockman et al., 2016) has become the standard API and set of benchmark environments for single-agent reinforcement learning. PettingZoo (Terry et al., 2020a) has recently been released, achieving similar goals for multi-agent reinforcement learning environments. The only existing library with wrappers for reinforcement learning are those included inside Gym, but those are primarily the initially popular wrappers for Atari preprocessing (Mnih et al., 2013). Newer preprocessing methods for Atari (Machado et al., 2018), other types of environments, or multi-agent environments are omitted. Many Gym wrappers are also missing “quality of life” features, like outputting arrays in
a shape compatible with CNNs by default. Accordingly, people typically write their own wrappers themselves. This leads to lower code quality and performance throughout the field for such key functions, and makes the possibility of bugs greater. Accordingly, we’ve released the SuperSuit Python library to include all widely used wrappers for both Gym and PettingZoo environments. Each wrapper is a function that takes an environment object and returns one, and for clarity and modularity, only includes a single function, hence our terming them “microwrappers”.

2 Wrapper Methods

The observation wrappers we include are:

- Agent Indication (Multi-Agent Only) [Gupta et al. 2017]
- Color Reduction (Greyscaling, etc.)
- Flatten Observation
- Frame Skipping [Mnih et al. 2013]
- Frame Stacking [Mnih et al. 2013]
- Observation Delay
- Observation Normalization
- Observation Padding (Multi-Agent Only) [Terry et al. 2020b]
- Recast Observation Type
- Reshape Observation
- Resize 2D/3D Observation

The action wrappers we include are:

- Action Clipping [Fujita and Maeda 2018]
- Action Space Padding (Multi-Agent Only) [Terry et al. 2020b]
- Sticky Actions [Machado et al. 2018]

The only reward wrapper we include is:

- Reward Clipping [Mnih et al. 2013]

Additionally, we introduce lambda wrappers that take an environment and a lambda function as an argument and the lambda function to the environment it, allowing people to easily create custom wrappers. Separate lambda wrappers exist to apply functions to actions, observations, or rewards.

3 Conclusion

We introduce SuperSuit, a Python library that includes reasonable implementations of all popular RL wrappers, for environments of both the Gym and PettingZoo API specification. This will allow researchers to conduct more computationally efficient experiments, to try new RL wrappers much more easily, and to reduce the likelihood of bugs due to one-off implementations. The library is available at [https://github.com/PettingZoo-Team/SuperSuit](https://github.com/PettingZoo-Team/SuperSuit), and can be installed via pip.

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