ABSTRACT

Many researchers and developers are exploring for adopting Deep Reinforcement Learning (DRL) techniques in their applications. They however often find such an adoption challenging. Existing DRL libraries provide poor support for prototyping DRL agents (i.e., models), customising the agents, and comparing the performance of DRL agents. As a result, the developers often report low efficiency in developing DRL agents. In this paper, we introduce RLzoo, a new DRL library that aims to make the development of DRL agents efficient. RLzoo provides developers with (i) high-level yet flexible APIs for prototyping DRL agents, and further customising the agents for best performance, (ii) a model zoo where users can import a wide range of DRL agents and easily compare their performance, and (iii) an algorithm that can automatically construct DRL agents with custom components (which are critical to improve agent’s performance in custom applications). Evaluation results show that RLzoo can effectively reduce the development cost of DRL agents, while achieving comparable performance with existing DRL libraries.

Keywords Reinforcement Learning, Programming Abstraction, Hyper-parameters

1 Introduction

In the last few years, we have seen many successful applications of Deep Reinforcement Learning (DRL) technologies, such as computer gaming \cite{1,2}, robotic control \cite{3,4}, self-driving cars \cite{5}, language modeling \cite{6,7} and optimisation \cite{8}. To adopt DRL techniques, developers often need to construct DRL agents. These agents interact with training environments, e.g., OpenAI Gym \cite{9}, RLbench \cite{10}, to collect training samples. Samples are sent to DRL algorithms which learn policies, e.g., on-policy algorithms \cite{11,12} and off-policy algorithms \cite{1}, that can maximise agent’s performance, i.e., rewards, in interacting with the environments.

Developing a DRL agent that can tackle a real-world application is however challenging. There are several phases that are particularly time-consuming in developing a DRL agent: (i) Prototyping phase. A DRL agent contains various components (i.e., environments, DRL algorithms, and training drivers). To create a DRL agent, developers have to spend tremendous time in importing external training environments, modifying the environments to make them compatible with downstream DRL algorithms, and writing training drivers that can iteratively train the agents and distribute the training onto heterogeneous processors \cite{13}. (ii) Customisation phase. The default configuration (e.g., neural network...
architecture) of a DRL algorithm often exhibit sub-optimal performance [10, 16]. Developers thus must customise the DRL algorithm to improve its performance. (iii) Algorithm comparison phase. In tackling a training environment, there are often multiple DRL algorithms available [11, 1, 12, 14]. Developers usually need to implement all these algorithms and compare their performance.

Even though though several DRL libraries have become available recently, developers still find it inefficient in using these libraries to construct DRL agents for custom applications. On the one hand, tutorial-oriented DRL libraries, such as OpenAI Baselines [15], Stable Baselines and Coach [16], provide command-line-based interfaces and they focus on reproducing classical benchmarks. They do not have low-level APIs which are necessary to control how a DRL agent is being trained, and how it is customised. On the other hand, research-oriented DRL libraries, such as Tianshou [17], keras-rl [18], and Tensorforce [19], provide flexible APIs (e.g., defining the reward functions or policy networks), useful for defining custom DRL agents. They, however, fail to provide expressive high-level APIs to help prototype DRL agents, and access commonly used DRL agents.

In this paper, we introduce RLzoo, a DRL library that can enable developers to efficiently prototype, train and evaluate DRL agents. The design of RLzoo makes several contributions:

(i) High-level yet flexible APIs for declaring DRL agents. RLzoo contains high-level APIs for prototyping DRL agents. These APIs contain expressive functions for importing external training environments, declaring DRL algorithms, and launching training drivers which can iteratively train the policies and scale the training to distributed nodes.

Yet, RLzoo’s APIs do not compromise flexibility. They contain flexible functions which allow DRL agents to take custom agent components, e.g., providing a custom neural network for a DRL algorithm or providing a custom communication topology for distributed DRL agents. By consolidating both the high-level and low-level APIs, RLzoo is effective in facilitating both the prototyping phase and the customisation phase in developing DRL agents.

(ii) DRL model zoo. RLzoo provides a DRL model zoo to further facilitate the algorithm comparison phase in developing DRL agents. The model zoo contains many useful pre-defined DRL environments and algorithms. Generally, these algorithms can be classified into those for tutorial purposes (i.e., beginners) and those for research purposes (i.e., professionals). In particular, RLzoo puts a focus on offering support for distributed DRL algorithms [14, 20] and robot-learning-related environments, e.g., RLBench [10].

Further, the RLzoo model zoo contains an easy-to-use agent training notebook. RLzoo users can track the performance (e.g., reward) and configuration (e.g., hyper-parameters) of DRL agents, and evaluate different DRL agents in an intuitive manner.

(iii) Automatic algorithm for constructing DRL agents. RLzoo minimises developer’s effort for integrating custom components into DRL agents, or re-configuring the agents for new scenarios. This is achieved by a novel algorithm that can automatically construct DRL agents with various custom components. Specifically, this algorithm has adaptors for connecting the components (e.g., environments and DRL algorithms) in DRL agents. The adaptors can automatically infer the input/output shapes of agent components. As long as changes in these components are detected, the adaptors can automatically re-configure the DRL agent, which avoids the need for developers to make manual modification as in existing DRL libraries.

RLzoo is implemented as a Python library based on TensorFlow [21], TensorLayer [22] and KungFu [23]. It is open-sourced on Github[1] in December, 2019. It has attracted numerous users from both education and industry. RLzoo has also been used for implementing demonstrations in a multi-lingual DRL textbook [24].

2 RLzoo Design

In this section, the design of RLzoo is introduced in detail. We start with an overview of the workflow, then describe its major APIs with a concrete code example.

2.1 Overview

The workflow of RLzoo is shown in Fig. [1]. Four steps are necessary for training/testing: Step 1. Select the environment and the RL algorithm; Step 2. Pass in or call default hyper-parameters for the algorithm and learning process; Step 3. Start the training or testing. An additional step 4 for re-configuration and iterative learning may be applied when comparisons among different algorithms and settings are required.

[1]https://github.com/tensorlayer/RLzoo
## Building learning environment

DRL environments are often imported from external libraries, e.g., OpenAI Gym. To hide the difference in the APIs of using these libraries, RLzoo provides an abstracted function: `build_env()` for importing environments. This function takes the environment name `env_name` and its type `env_type` (line 6 in Listing 1). The details of building the environments, importing the DRL algorithms, and constructing the DRL agents are hidden by the expressive API calls provided by RLzoo. In the following, we will discuss the details of these API calls.

| Function                                                                 | Description                                                                 |
|--------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| `env = build_env(EnvName, EnvType)`                                       | Return the built environment instantiation with the name and type of it.     |
| `alg_params, learn_params = call_default_params(env, EnvType, AlgName)`   | Return two dictionaries of default hyper-parameters w.r.t. environments and algorithms. |
| `agent = eval(AlgName+'(**alg_params)')`                                 | Instantiate the class of DRL agent.                                          |
| `agent.learn(env, mode='train', render=False, **learn_params)`           | Launch training/testing process with the agent.                             |

### Table 1: RLzoo API

#### 2.2 High-level yet Flexible APIs

The API design of RLzoo has the following goals: (i) We want to enable users to use high-level expressive functions in declaring a DRL agent with custom training environments, DRL algorithms and training drivers; (ii) We want to support users to flexibly customise their DRL agents by plugging different custom objects into DRL implementations.

We introduce the RLzoo APIs using a sample program as shown in Listing 1. To declare a DRL agent, RLzoo users first need to choose an environment (i.e., Pendulum-v0) (line 4–6). Based on the chosen environment, users further decide a DRL algorithm: TD3 (line 8). In order to train this DRL agent, the users obtain its default construction parameters (line 11). The algorithm parameters (`alg_params`) are used for constructing a DRL agent (line 8). This agent then launches its training process (line 12) given the environment and hyper-parameters (`learn_params`). As we can see in this program, a DRL agent can be declared with 3 abstracted steps (9 lines of code). A summary of API functions and descriptions are provided in Table 1. The details of building the environments, importing the DRL algorithms, and constructing the DRL agents are hidden by the expressive API calls provided by RLzoo. In the following, we will discuss the details of these API calls.
Obtaining default agent configuration. Initialising a DRL agent needs massive parameters (e.g., the parameters for instructing the DRL algorithms and those for controlling the training process). Letting RLzoo users decide all these parameters makes RLzoo difficult to adopt among general users. To address this, RLzoo provides default pre-tuned parameters for its DRL agents. These parameters are obtained through the `call_default_params()` function. This function returns the pre-tuned algorithm parameters in the dictionary `alg_params`, and the learning hyper-parameters in the dictionary `learn_params`.

Customising agents. RLzoo allows users to easily customise DRL agents. This is achieved through providing an intuitive manner for configuring the algorithm and learning hyper-parameter dictionaries. For example, to customise the neural networks used within the DRL algorithm, users can access the default neural networks through the key: `net_list`. They can replace the default networks with custom neural networks. These neural networks follow a shared ‘Model’ interface. They can thus be seamlessly integrated within the agent environment. Following the same manner, RLzoo users can customise other algorithm parameters, e.g., optimisers, and learning hyper-parameters like learning rate and batch size.

Constructing and manipulating agents. RLzoo makes the construction and manipulation of DRL agents easy and efficient. All DRL methods in RLzoo can be instantiated to be an agent (line 11 in Listing 1). This allows these agents to be manipulated consistently. All these agents can share utility functions that are pre-implemented within the base agent class, such as the `learn()` function which launches the training process or evaluates the performance of the agents.

2.3 Automatic Agent Construction

Using RLzoo APIs, users can implement a wide range of DRL agents. This however introduces challenges. These agents usually consist of external environments and custom agent’s modules, while those environments and modules may not be compatible with the existing components in the RLzoo library (e.g., some environments might produce image observations while the other produce vectors).

Existing DRL libraries often rely on users to manually resolve this compatibility issue. Figure 2 contains a typical architecture of a DRL agent (ignoring the three adaptors added by RLzoo). In this agent, if a new environment is provided, users would have to manually update the neural networks (e.g., MLP and CNN) to process the new observations. This manual update needs to propagate through the agent, e.g., updating the policies, then the action types. Relying on users to manually make all these updates incurs high development costs. It can also make the expertise of DRL become a prerequisite for using DRL libraries.

RLzoo wants to automate the process of constructing a DRL agent. Our key idea is to embed numerous adaptors between agent components. These adaptors infer the type of the output from upstream agent components and dynamically compute the input for downstream components. The adaptors will be called in sequence and automatically re-configure the entire agent.

Figure 2 illustrates the automatic agent construction algorithm in RLzoo. First of all, this algorithm places an observation adaptor between the observation from the environment and the neural network (see 1). This adaptor infers the type of
observations and produces different types of neural networks, e.g., a MLP for a vector, the CNN for an image, and a multi-head architecture for a hybrid dictionary. The policy adaptor is placed in between the algorithm selection and the policy output (see \(2\)). Based on the stochastic/deterministic nature of the DRL algorithm, this adaptor produces corresponding policy outputs for each selected DRL algorithm. The action adaptor is placed in between the policy (stochastic only) and the environment (see \(3\)): if the environment requires discrete action, this final adaptor will produce a categorical distribution to represent the action; if the action needs to be continuous, the adaptor produces policy output as a diagonal Gaussian distribution.

2.4 Model Zoo

Making RLzoo useful for users introduces unique challenges. First, these users may not have the expertise of DRL to implement agents that are suitable for their applications. Second, training the agents to reach high accuracy often requires extra DRL knowledge in comprehending training results, and tuning hyper-parameters.

To address these challenges, we want to make RLzoo a comprehensive DRL platform. To avoid making DRL expertise a prerequisite, RLzoo provides a large collection of pre-defined DRL environments and algorithms which can be directly leveraged by users. RLzoo makes the tuning of DRL agents easy for non-experts of DRL. This is achieved through an interactive training notebook. This notebook provides useful functionalities for managing DRL agents and tuning their performance.

Pre-defined DRL algorithms and environments. Our choice for pre-defined DRL environments and algorithms is driven by the following observation: many users like to first verify the benefits of DRL technologies by starting with simple DRL algorithms and environments. They will gradually move to advanced DRL algorithms/environments once they realise the need for improving the performance of DRL agents.

RLzoo supports both simple and advanced training environments. Many simple environments have been integrated within the library, including Atari, Box2d, Classic control, MuJoCo, Robotics in OpenAI Gym, and DeepMind Control Suite. These environments cover most of the classical DRL benchmarks we are aware of. In addition, developers can access to more up-to-date environments such as those used for emerging realistic robot learning, e.g., RLBench [10]. These environments produce complex observations represented as compound dictionaries, and they can be used by practitioners to test DRL with robots.

RLzoo provides a large number of DRL algorithms. Classical DRL algorithms, including the Deep Q-Network (DQN) [1] and its variants [25, 26, 27, 28] in the discrete action spaces, are pre-implemented in RLzoo. Many state-of-the-art DRL algorithms, which often achieve better agent performance, are pre-implemented as well. Examples include hindsight experience replay (HER) [29], deep deterministic policy gradient (DDPG) [2], twin delayed deep deterministic policy gradient (TD3) [30], soft actor-critic (SAC) [31], advantage actor-critic (A2C) [32], asynchronous advantage actor-critic (A3C) [32], proximal policy optimisation (PPO) [33], distributed proximal policy optimization (DPPO) [14], trust region policy optimisation (TRPO) [12].

Agent training notebook. RLzoo users can exploit a high-level agent training notebook to manage the configurations of DRL agents, analyse their training performance metrics. This notebook is implemented based on the Jupyter Notebook. It tracks the configurations of being evaluated DRL agents and stores the agents’ traces for performance analysis. Specifically, the notebook displays agent performance metrics, including agent configurations, learning status (e.g., training steps and instant rewards), and training results (e.g., averaged rewards over time and values of loss functions). Based on these metrics, developers can infer the impacts of modification made towards the DRL agents, thus facilitating the tuning of such agents for better performance.

2.5 Distributed Agent Training

DRL agents usually need to accelerate computation using parallel heterogeneous processors. To achieve this, developers often rely on the native multiprocess library in Python. The usage of such a library, however, is generally limited within a single machine. To use distributed machines, developers must use external libraries, such as Ray [34] and Acme [35]. These libraries provide custom Remote-Process-Communication (RPC) programming interfaces. Developers must largely modify existing DRL programs in order to adopt these RPC libraries.

In designing RLzoo, we want to minimise developer’s efforts in modifying existing single-node programs when scaling out DRL agents. Our idea is to ensure RLzoo’s distributed training APIs can follow the convention in the API design of the popular multiprocess library. For each key component in the multiprocess library (e.g., queues and pipes), RLzoo provides equivalent distributed implementations. Hence developers can easily replace single-node communication components with those equivalent in RLzoo. Further, RLzoo extends the APIs of the multiprocess library. It provides
novel collective communication APIs (e.g., all-reduce) to achieve complex communication patterns among DRL agents [23].

Figure 3 shows the distributed architecture of RLzoo DRL agents. In a cluster, RLzoo replicates RLzoo runtime on each machine. This runtime launches RLzoo DRL agents as Python processes, and assigns CPUs and GPUs to the agents. The DRL agents communicate data using expressive communication functions defined in the collective APIs and point-to-point APIs (Figure 3):

**Agent collective APIs:** RLzoo agents are often assigned with different roles (e.g., actors, learners and inference servers as in IMPALA [20]). The agents in the same role can use (i) role_all_reduce to synchronise the gradients among parallel learners, (ii) role_broadcast to broadcast weights to parallel learners (which produce gradients to update DRL models), and (iii) role_barrier to coordinate the synchronous execution of parallel actors (which collect training trajectories from environments).

**Agent point-to-point APIs:** Developers can use (i) save and request to asynchronously push and pull weights among DRL agents, and (ii) queue or queue_pair to exchange data among those agents, similar to the queues in the Python multiprocess library.

### 3 Evaluation

In this section, we compare RLzoo with other DRL libraries in terms of the supported algorithms, supported environments and their API designs. We choose the following popular libraries as baseline: OpenAI Baselines [15], Tianshou [17], Coach [16], ReAgent [36], garage [37], keras-rl [18], MushroomRL [38] and Tensorforce [19].

| Library    | # Algo. | # Env. | Image | Vector | Dict. | LoC    |
|------------|---------|--------|-------|--------|-------|--------|
| RLzoo      | 12      | 7      | ✓     | ✓      | ✓     | 4      |
| Baselines  | 9       | 5      | ✓     | ✓      | ✓     | N/A    |
| Tianshou   | 8       | 5      | ✓     | ✓      | ✓     | 15-20  |
| Coach      | 11      | 8      | ✓     | ✓      | ✓     | N/A    |
| ReAgent    | 4       | 3      | ✓     | ✓      | ✓     | 5      |
| garage     | 9       | 6      | ✓     | ✓      | ✓     | 5-10   |
| keras-rl   | 5       | 3      | ✓     | ✓      | ✓     | 10-15  |
| MushroomRL | 9       | 7      | ✓     | ✓      | ✓     | 5-10   |
| Tensorforce| 8       | 5      | ✓     | ✓      | ✓     | 5-15   |

Table 2: Comparison of different DRL libraries.

**Algorithms.** We first evaluate the algorithm support. All algorithms we considered in this comparison include DQN, HER, Rainbow [39], vanilla policy gradient (VPG) [11], A2C, A3C, actor-critic with experience replay (ACER) [40], actor critic using Kronecker-factored trust region (ACKTR) [41], DDPG, TD3, SAC, PPO, DPPO, TRPO, as well as the variants of DQN like double DQN [25], dueling DQN [26], Retrace [42], noisy DQN [27], distributed DQN [43], prioritized experience replay (PER) [28], quantile regression DQN (QR-DQN) [44], N-step Q-learning [32], normalized advantage functions (NAF) [45] and Rainbow [39]. As we can see from Table 2, RLzoo supports 12 DRL algorithms,
whereas Coach supports 11 algorithms and other libraries support less than 10 algorithms. A key difference between RLzoo and other libraries is its support of distributed DRL algorithms, which makes RLzoo one of the few libraries that support distributed DRL algorithms such as DPO. This type of algorithms is increasingly critical because practitioners have recently achieved great success of training DRL agents using parallel learning framework [14].

**Environments.** We then evaluate the environment support. The environments include: (1) Atari, Box2d, Classic control, Mujoco, Robotics in OpenAI Gym (counted separately); (2) DeepMind Control Suite; (3) RLbench [10]; (4) Roboschool; (5) PyBullet [46]. As shown in Table 2 RLzoo supports 7 environments, making it among those libraries, e.g., Coach and MushroomRL, that provide a large collection of environments. A key feature for RLzoo is its support for all observations types (e.g., Vector, Image, and Dictionary). The Dictionary in this paper indicates either a dictionary or a tuple type in Python, which is literally a collection of sub-data with different shapes. The other library: keras-rl, which can offer the same full support, only provide 3 DRL algorithms, whereas RLzoo can support 12 DRL algorithms. This shows the importance of achieving automatic agent construction in RLzoo: new observations can be automatically supported by all DRL algorithms. In addition, the full observation support also makes RLzoo the only library, as far as we know, that supports an important environment: RLbench. This environment has growing popularity due to the recent booming of robot learning applications. It produces complex observations that contain images, vectors, and dictionaries, making it difficult to be supported by existing libraries.

**API expressiveness.** We evaluate the API design by counting the lines of code (LoC) for declaring DRL agents. We exclude Baselines and Coach because they have only command-line interfaces. The LoCs here only consider necessary code for declaring agents, excluding other lines for importing libraries or assigning values for variables. As we can see in Table 2 RLzoo requires 4 LoCs to declare DRL agent while the ReAgent library comes as the second, costing 5 LoCs on average. Other programmable DRL libraries require users to write around 10 - 20 LoCs. In addition, RLzoo differentiates with other libraries in terms of its support for customising agents. This makes RLzoo an attractive option for robot learning users who often need to (i) deal with RGB-D camera produced by the learning environment RLbench, and (ii) adopt customised network architectures like recurrent layers.

A complete comparison of RLzoo with other popular DRL libraries on (1) supported RL algorithms, (2) supported environments and (3) LoC are provided in Appendix A.

**4 Conclusion**

This paper introduces RLzoo, a novel DRL library that makes the development of DRL agents efficient. RLzoo provides high-level yet flexible APIs for declaring DRL agents. These APIs are particularly efficient in prototyping DRL agents, and scaling out the training of agents to many nodes. RLzoo further comes with a model zoo, enabling developers to easily evaluate different DRL algorithms. In the future, we will consistently improve the API design of RLzoo, e.g., providing better support for implementing emerging multi-agent DRL algorithms. We will also add new DRL algorithms into the model zoo, especially those targeting robot learning.

**5 Acknowledgements**

This project was supported by National Key R&D Program of China: New Generation Artificial Intelligence Open Source Community and Evaluation (No.2020AAA0103500), Topic: New Generation Artificial Intelligence Open Source Community Software and Hardware Infrastructure Support Platform (No.2020AAA0103501).

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## Appendix A  Comparison Table

|                | RLzoo | Baselines | Tianshou | Coach | ReAgent | garage | keras-rl | MushroomRL | Tensorforce |
|----------------|-------|-----------|----------|-------|---------|--------|----------|------------|-------------|
| DQN            | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| DQN variants   | 4     | 4         | 2        | 8     | 4       | 1      | 3        | 4          | 4           |
| HER            | ✓     | ✓         | x        | ✓     | x       | ✓      | x        | ✓          | ✓           |
| Rainbow        | x     | x         | x        | ✓     | x       | ✓      | x        | x          | x           |
| VPG            | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| A2C            | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| A3C            | ✓     | ✓         | x        | ✓     | ✓       | x      | x        | ✓          | ✓           |
| ACER           | x     | ✓         | x        | ✓     | ✓       | x      | x        | x          | x           |
| ACKTR          | x     | ✓         | x        | ✓     | ✓       | x      | x        | x          | x           |
| DDPG           | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| TD3            | ✓     | x         | ✓        | x     | ✓       | ✓      | ✓        | ✓          | ✓           |
| SAC            | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| PPO            | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| DPPO           | ✓     | ✓         | ✓        | ✓     | ✓       | x      | x        | x          | x           |
| TRPO           | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| # of Alg.       | 12    | 9         | 8        | 11    | 4       | 9      | 3        | 9          | 8           |
| Atari          | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| Box2D          | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| Classic        | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| MuJoCo         | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| Robotics       | ✓     | ✓         | ✓        | ✓     | ✓       | ✓      | ✓        | ✓          | ✓           |
| Control Suite  | ✓     | x         | ✓        | ✓     | ✓       | x      | x        | ✓          | ✓           |
| RLbench        | ✓     | x         | ✓        | ✓     | ✓       | ✓      | x        | x          | x           |
| Roboschool     | x     | x         | ✓        | ✓     | ✓       | x      | x        | x          | x           |
| PyBullet       | x     | x         | ✓        | ✓     | ✓       | x      | x        | ✓          | x           |
| # of Env.       | 7     | 5         | 5        | 8     | 3       | 6      | 5        | 7          | 5           |
| LoC            | 4     | N/A       | 15-20    | N/A   | 5       | 5-10   | 10-15    | 5-10       | 5-15        |

Table 3: A complete comparison of RLzoo with other popular DRL libraries on: (1) supported RL algorithms, (2) supported environments, and (3) LoC. In “# of Alg.”, all DQN variants are counted as one type.