RLLTE: Long-Term Evolution Project of Reinforcement Learning

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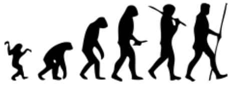
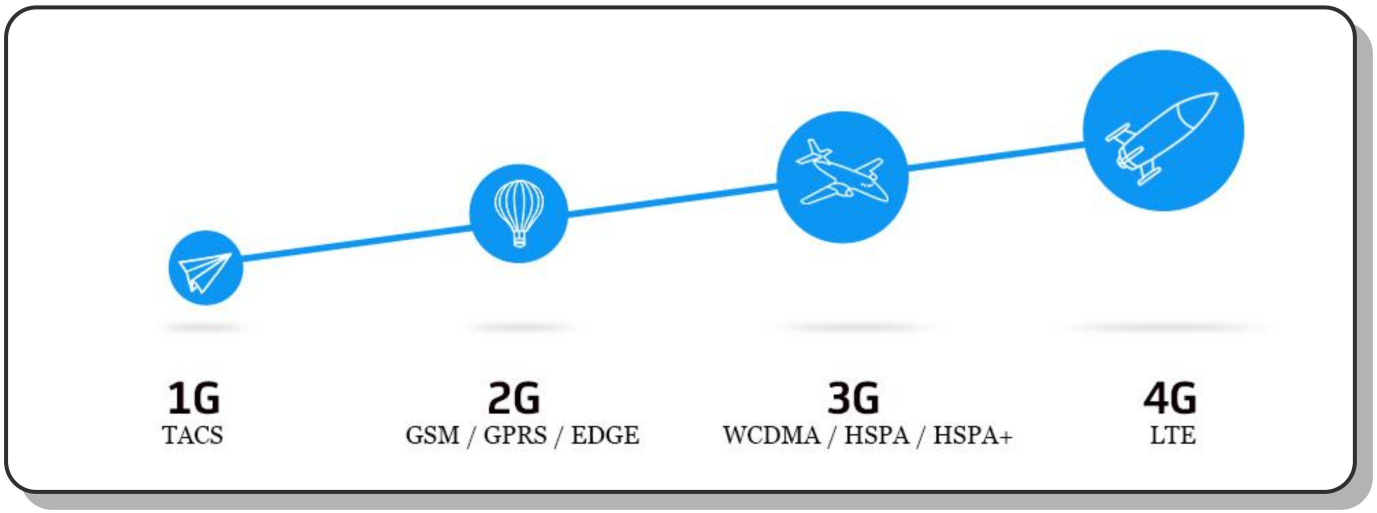
Background

- Volatile performance of different implementations;
- Algorithm updates are very complex and miscellaneous;
- Unfriendly support for the latest tricks;
- Incomplete benchmark testing;
- Expensive computational cost of algorithm reproduction;
- Few active repositories;
- High learning costs for developers.

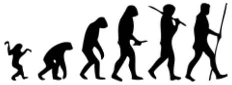


What is RLLTE?

- ❑ A novel reinforcement learning (RL) library inspired by the long-term evolution (LTE) standard project in telecommunications.



- ❑ GitHub Link: https://github.com/RLE-Foundation/rllte



What is RLLTE for?

For Academia:

- ❑ Accelerating algorithm development;
- ❑ Tracking the latest research progress;
- ❑ Reusable and reliable baselines;

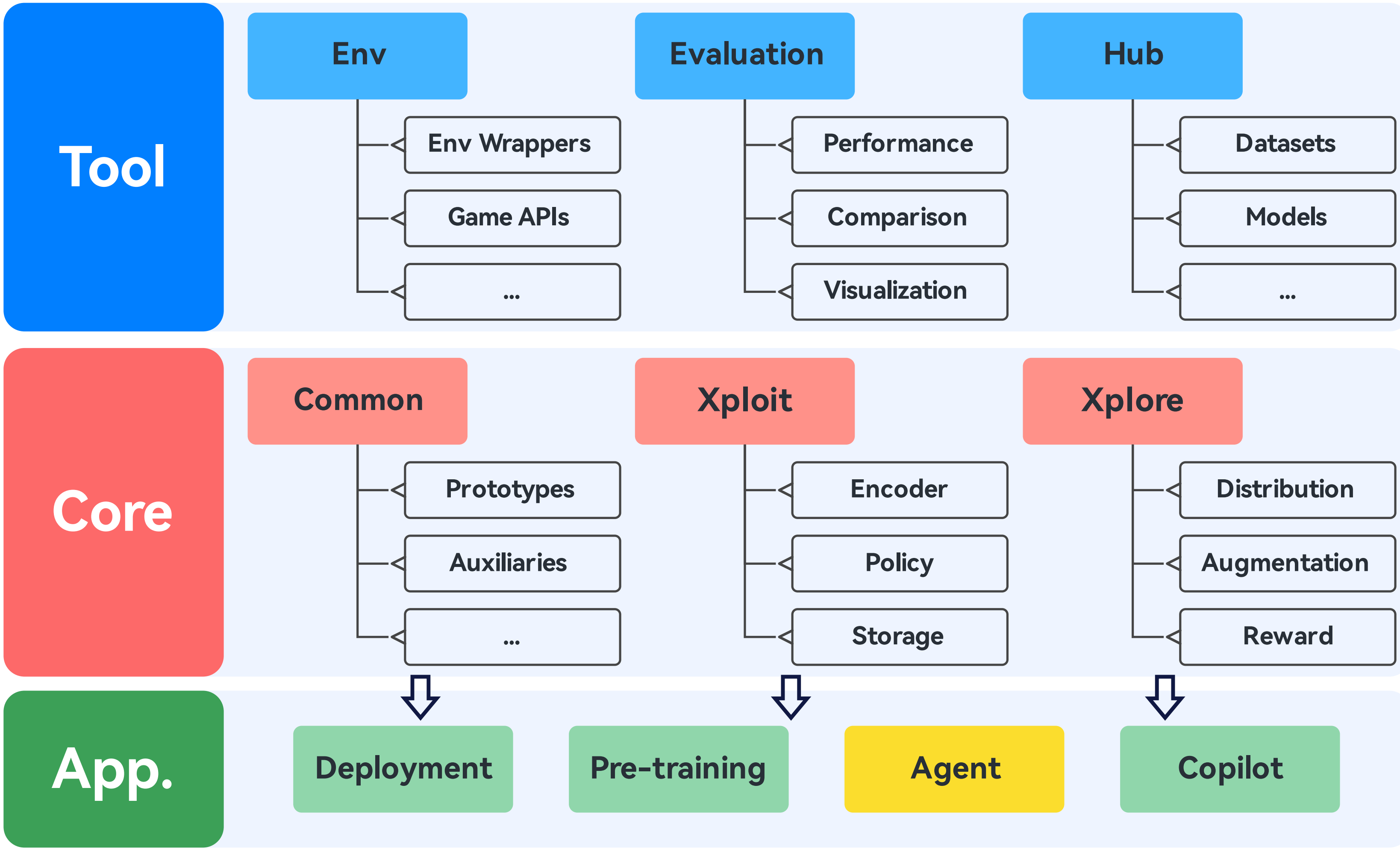
For Industry:

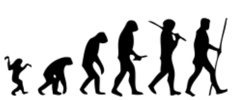
- ❑ Ultrafast application construction;
- ❑ High scalability and friendly interface;
- ❑ Convenient model deployment.

Highlight Features

- ❑ Long-term evolution for providing latest algorithms and tricks;
- ❑ Complete ecosystem for task design, model training, evaluation, and deployment (TensorRT, CANN, ...);
- ❑ Module-oriented design for complete decoupling of RL algorithms;
- ❑ Optimized workflow for full hardware acceleration;
- ❑ Support custom environments and modules;
- ❑ Support multiple computing devices like GPU and NPU;
- ❑ Large number of reusable benchmarks (rllte-hub);
- ❑ Large language model-empowered copilot.

Architecture (Overview)





Architecture

- **Common**: Prototypes and auxiliary modules.

- **Xploit**: Modules that focus on exploitation in RL.
  - **Encoder**: feature extraction;
  - **Policy**: interaction and learning;
  - **Storage**: experience storage and sampling.

- **Xplore**: Modules that focus on exploration in RL.
  - **Distribution**: action sampling;
  - **Augmentation**: observation data augmentation;
  - **Reward**: intrinsic reward modules.

Architecture

- ❑ **Agent**: Implemented RL Agents using RLLTE building blocks.
- ❑ **Pre-Training**: Methods of pre-training in RL.
- ❑ **Deployment**: Methods of model deployment in RL.
- ❑ **Copilot**: LLM-based copilot that helps developer build RL applications;
- ❑ **Hub**: Fast training API and reusable benchmarks.
- ❑ **Evaluation**: Reasonable and reliable metrics for algorithm evaluation.
- ❑ **Env**: Packaged environments (e.g., Atari games) for fast invocation.

Fast Algorithm Development

- Three steps to implement an agent:

Prototype Selection

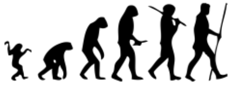
```python
from rllte.common.prototype import OnPolicyAgent
```

Modules Selection

```python
from rllte.common.prototype import OnPolicyAgent
from rllte.xploit.encoder import MnihCnnEncoder
from rllte.xploit.policy import OnPolicySharedActorCritic
from rllte.xploit.storage import VanillaRolloutStorage
from rllte.xplore.distribution import Categorical
```

Update Function

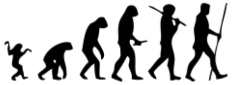
```python
def update(self) -> Dict[str, float]:
```



Training with Implemented Agents

- RLLTE provides implementations for well-recognized RL algorithms, and provides simple interface for building applications:

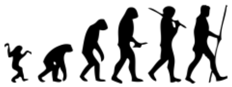
```python
# import `env` and `agent` api
from rllte.env import make_dmc_env
from rllte.agent import DrQv2

if __name__ == "__main__":
    device = "cuda:0"
    # create env, `eval_env` is optional
    env = make_dmc_env(env_id="cartpole_balance", device=device)
    # create agent
    agent = DrQv2(env=env, device=device, tag="drqv2_dmc_pixel")
    # start training
    agent.train(num_train_steps=500000)
```



Training with Implemented Agents

❑ Training Example:

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

(rllte) yuanmingqi@YUAN-WS:/export/yuanmingqi/code/rllte$ python test.py
pygame 2.4.0 (SDL 2.26.4, Python 3.8.16)
Hello from the pygame community. https://www.pygame.org/contribute.html
[08/03/2023 07:11:28 PM] - [INFO.] - Invoking RLLTE Engine...
[08/03/2023 07:11:28 PM] - [INFO.] - ================================================================================
[08/03/2023 07:11:28 PM] - [INFO.] - Tag                : drqv2_dmc_pixel
[08/03/2023 07:11:28 PM] - [INFO.] - Device             : NVIDIA GeForce RTX 3090
[08/03/2023 07:11:29 PM] - [DEBUG] - Agent              : DrQv2
[08/03/2023 07:11:29 PM] - [DEBUG] - Encoder            : TassaCnnEncoder
[08/03/2023 07:11:29 PM] - [DEBUG] - Policy             : OffPolicyDetActorDoubleCritic
[08/03/2023 07:11:29 PM] - [DEBUG] - Storage            : NStepReplayStorage
[08/03/2023 07:11:29 PM] - [DEBUG] - Distribution       : TruncatedNormalNoise
[08/03/2023 07:11:29 PM] - [DEBUG] - Augmentation       : True, RandomShift
[08/03/2023 07:11:29 PM] - [DEBUG] - Intrinsic Reward   : False
[08/03/2023 07:11:29 PM] - [DEBUG] - ================================================================================
[08/03/2023 07:11:31 PM] - [TRAIN] - S: 1000        | E: 2          | L: 500        | R: 277.332     | FPS: 297.322    | T: 0:00:03
```



Module Replacement

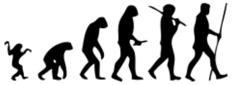
- The module-oriented design allows developers to perform module replacement to make model comparison and improvement:

```python
# compare the performance of different encoders
from rllte.agent import DrQv2
from rllte.xploit.encoder import MnihCnnEncoder, TassaCnnEncoder

if __name__ == "__main__":
    agent = DrQv2(...)

    encoder1 = MnihCnnEncoder(...)
    encoder2 = TassaCnnEncoder(...)

    agent.set(encoder=encoder1)
    agent.train(...)

    agent.set(encoder=encoder2)
    agent.train(...)
```

RLLTE Pre-training

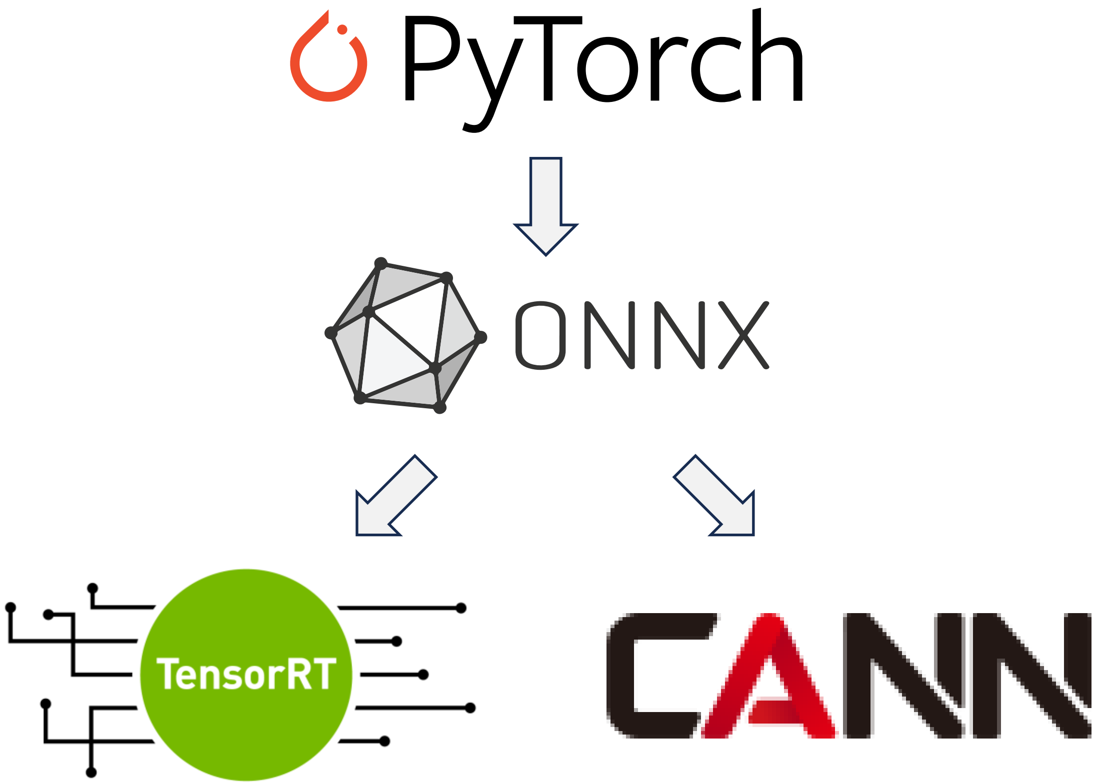
❑ Pre-training Based on Intrinsic Rewards

```python
from rllte.agent import PPO
from rllte.env import make_atari_env
from rllte.xplore.reward import RE3

if __name__ == "__main__":
    # env setup
    device = "cuda:0"
    env = make_atari_env(device=device)
    # create agent and turn on pre-training mode
    agent = PPO(env=env,
                device=device,
                tag="ppo_atari",
                pretraining=True)
    # create intrinsic reward
    re3 = RE3(observation_space=env.observation_space,
              action_space=env.action_space,
              device=device)
    # set the intrinsic reward module
    agent.set(reward=re3)
    # start training
    agent.train(num_train_steps=25000000)
```



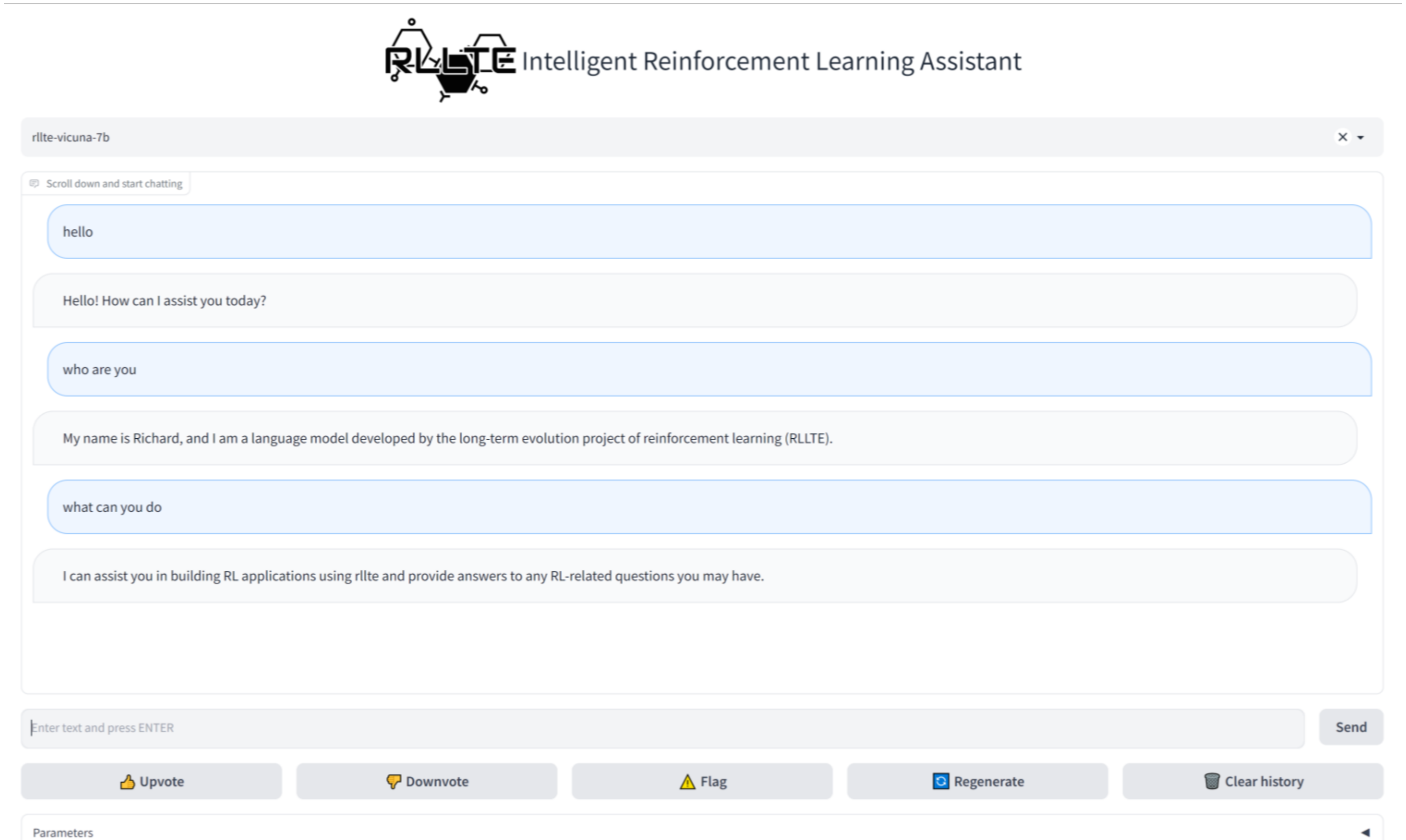
RLLTE Deployment

- Model Deployment Based-on TensorRT and CANN



RLLTE Copilot

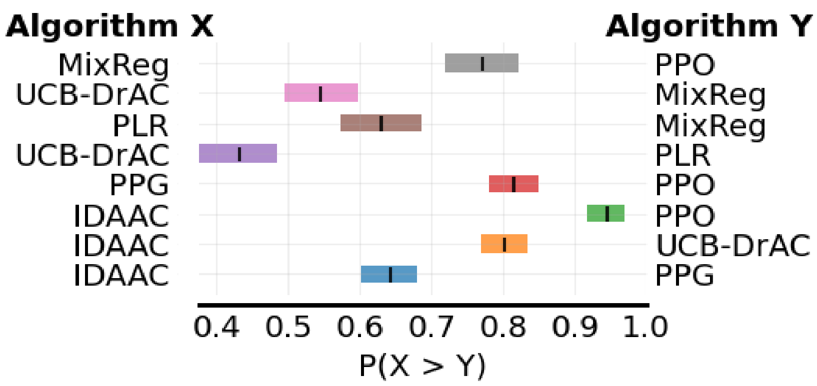
❑ LLM-Based Copilot: An attempt

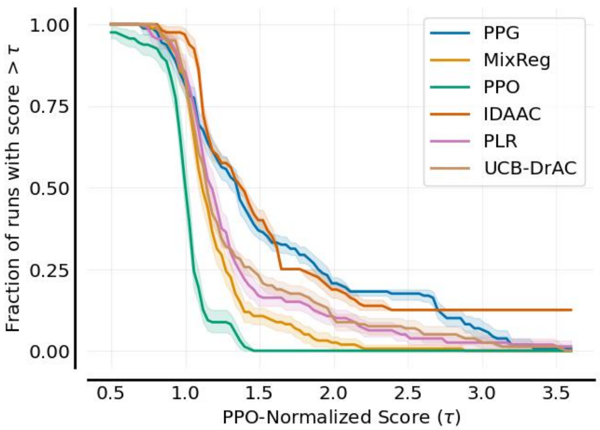


RLLTE Evaluation Toolbox

- RLLTE provides evaluation methods based on:

Agarwal R, Schwarzer M, Castro P S, et al. Deep reinforcement learning at the edge of the statistical precipice[J]. Advances in neural information processing systems, 2021, 34: 29304-29320.





RLLTE Hub

- **Hub**: Fast training API and reusable benchmarks.
  - **Datasets**: test scores and learning cures of various RL algorithms on different benchmarks.

```
from rllte.hub.datasets import Procgen
```

  - **Models**: trained models of various RL algorithms on different benchmarks.

```
from rllte.hub.models import Procgen
```

  - **Applications**: fast-API for training RL agents with one-line command.

```
python -m rllte.hub.apps.ppo_procgen --env_id bigfish
```

RLLTE Env

❑ Packaged environments (Part)

Function	Name	Remark
`make_atari_env`	Atari Games	Discrete control
`make_bullet_env`	PyBullet Robotics Environments	Continuous control
`make_dmc_env`	DeepMind Control Suite	Continuous control
`make_minigrid_env`	MiniGrid Games	Discrete control
`make_procgen_env`	Procgen Games	Discrete control
`make_robosuite_env`	Robosuite Robotics Environments	Continuous control

Project Evolution

- RL Algorithm and Module Selection Tenet
  - Excellent performance on recognized benchmarks;
  - Improvements in generalization ability;
  - Improvements in sample efficiency;
  - Great compatibility for redevelopment;

Future Work

- Advanced LLM-Based Copilot;
- Support Multi-Agent Reinforcement Learning;
- Support Offline Reinforcement Learning;
- Hardware-Level Code Acceleration;
- More Convenient Interface for Everyone;
- General Reinforcement Learning Model.

Contact Us

- GitHub Link: https://github.com/RLE-Foundation/rllte
- E-mail: friedrichyuan19990827@gmail.com
- Documentation: https://docs.rllte.dev/
- Benchmarks: https://hub.rllte.dev/
- Discussions: https://github.com/RLE-Foundation/rllte/discussions

Thanks!