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FinRL Ecosystem: Deep Reinforcement Learning to Automate Trading in Quantitative Finance

Wolfe Research 5th Annual QES Global Quantitative and Macro Investing Conference

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Thanks to AI4Finance community

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Open-Source AI4Finance Community

- **Our Mission**: "*Efficiently automate trading. We continuously develop and share codes for finance.*"

- **Our Vision**: "*AI community has accumulated an open-source code ocean over the past decade. We believe proper usages of these intellectual and engineering properties will initiate a paradigm shift from the conventional trading routine to an automated machine learning approach.*"

AI4Finance

Outline

- ➢ FinRL Ecosystem
  - ○ FinRL: full pipeline
  - ○ FinRL-ElegantRL: DRL algorithm library
  - ○ FinRL-Podracer: cloud-native solution
  - ○ FinRL-Meta: universe of market environments
  - ○ … …

FinRL Public

Deep Reinforcement Learning Framework to Automate Trading in Quantitative Finance. NeurIPS 2020 & ICAIF 2021. 🔥

Jupyter Notebook ☆ 2.8k 761

ElegantRL Public

Lightweight and scalable deep reinforcement learning using PyTorch. 🔥

Python ☆ 1.3k 263

Deep-Reinforcement-Learning-for-Automated-Stock-Trading-Ensemble-Strategy-ICAIF-2020 Public

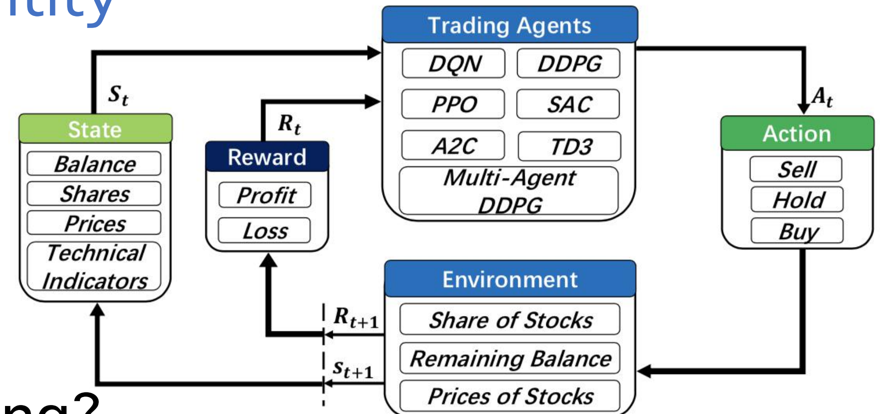
Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy. ICAIF 2020. Please star.

Jupyter Notebook ☆ 890 361

Background

Algorithmic trading in quantitative finance

- Make dynamic decisions
- Decide where to trade, at what price and what quantity
- Trade in a highly stochastic and dynamic market



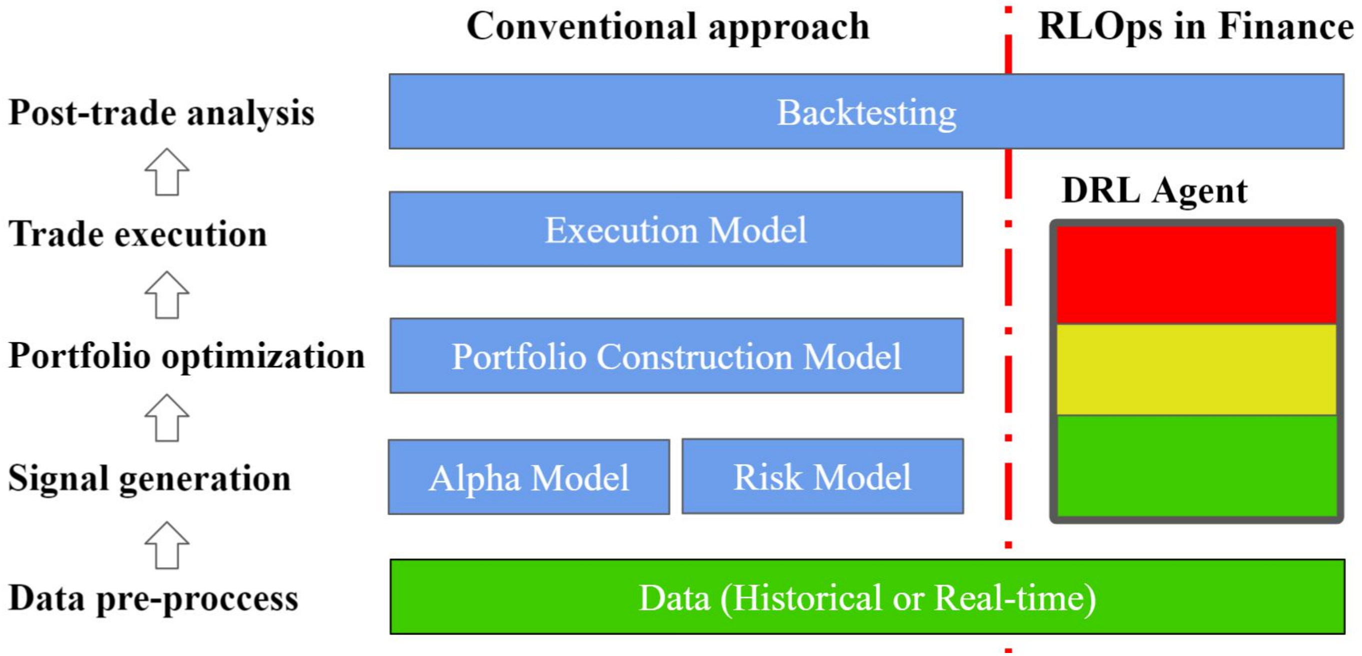
Why Deep Reinforcement Learning (DRL) in quant trading?

- Solves dynamic decision making problems
- Builds a multi-factor model to trade automatically
- Offers portfolio scalability and market model independer

Motivation

To automate the design pipeline of a DRL trading strategy

- Preprocess market data
- Build a training environment
- Manage trading states
- Backtest trading performance



Challenges, Goals and Design Principles

Challenges:

- ❑ **Error-prone programming**
- ❑ **Tedious debugging**
- ❑ **Comprehensive pipeline**

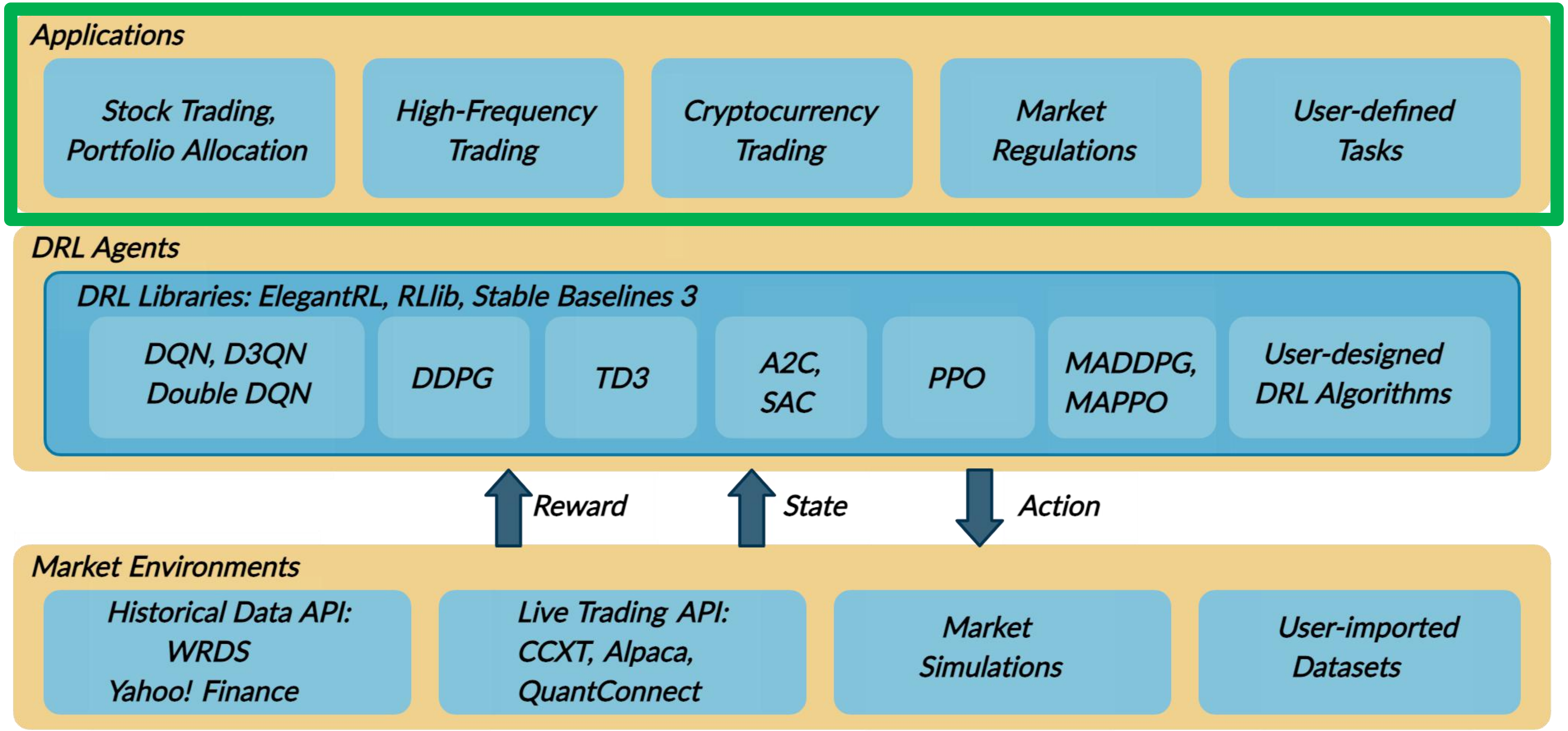
FinRL's Goals:

- ❑ **Overcome the steep learning curve**
- ❑ **Alleviate the debugging workloads**
- ❑ **Iterate the strategy at a high turnover rate**

FinRL has been developed under three primary principles:

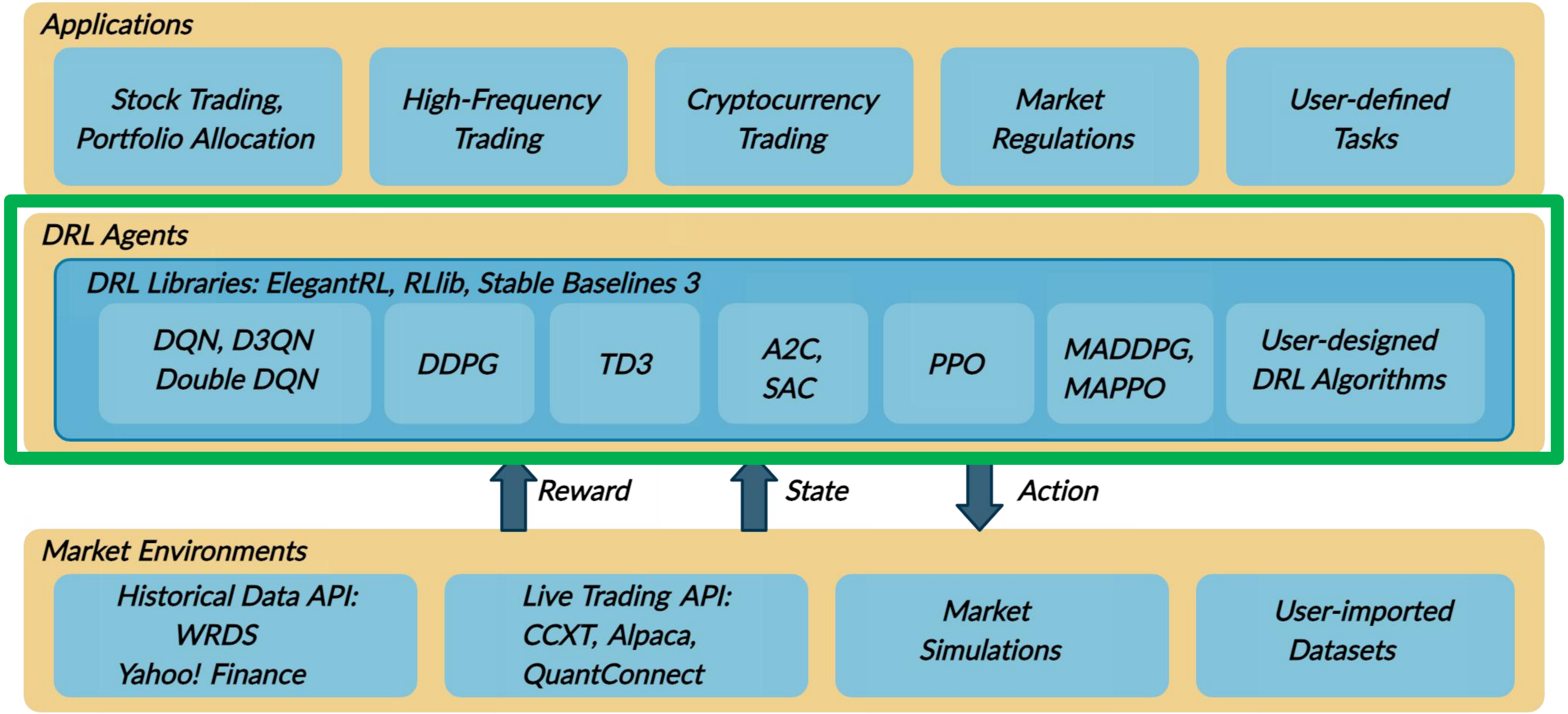
- ❑ **Full-stack framework:** full-stack DRL framework
- ❑ **Customization:** modularity and extensibility
- ❑ **Reproducibility and hands-on tutoring:** tutorials and reproduce the use cases

FinRL: Application Layer



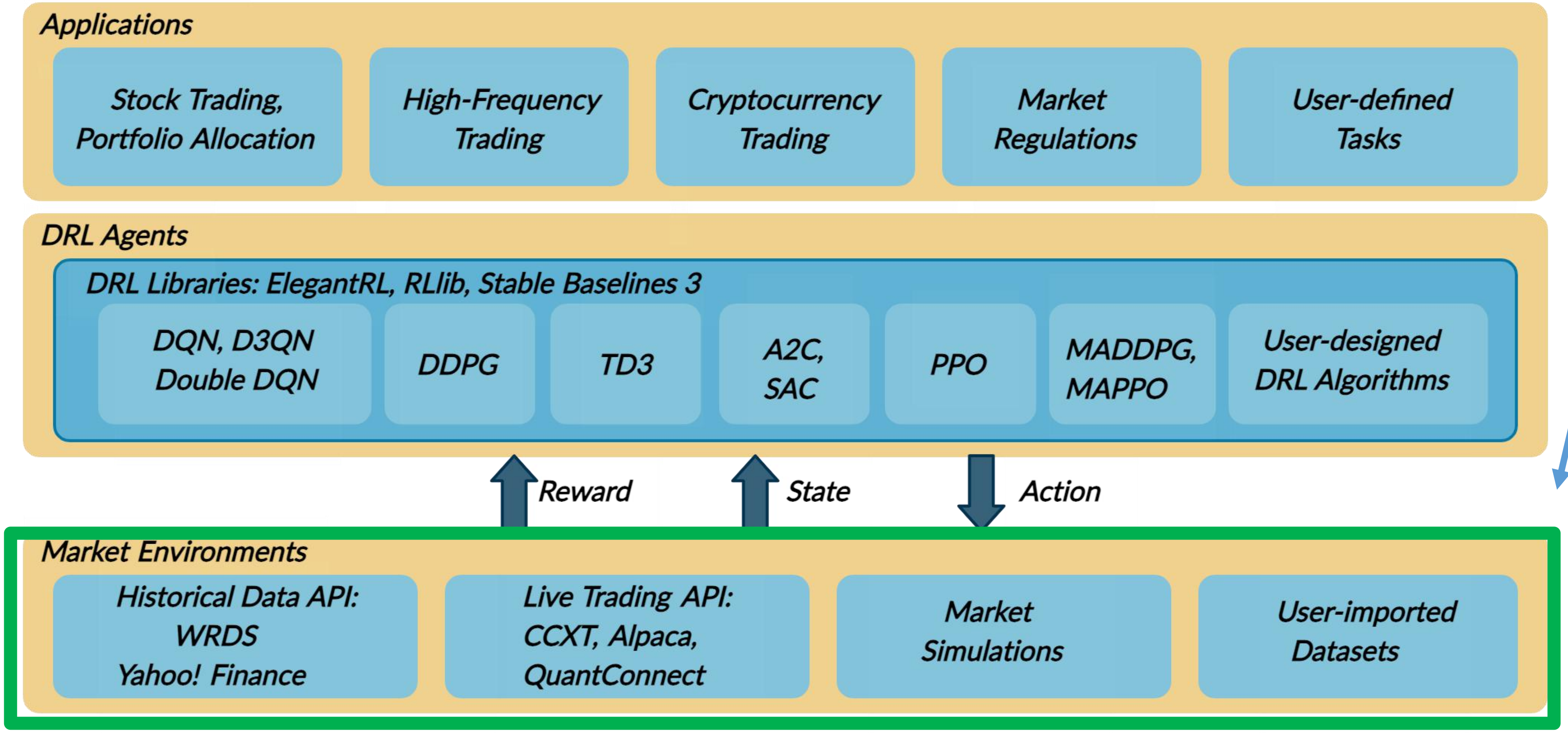
On the application layer, FinRL aims to provide hundreds of **demonstrative trading tasks**, serving as stepping stones.

FinRL: Agent Layer



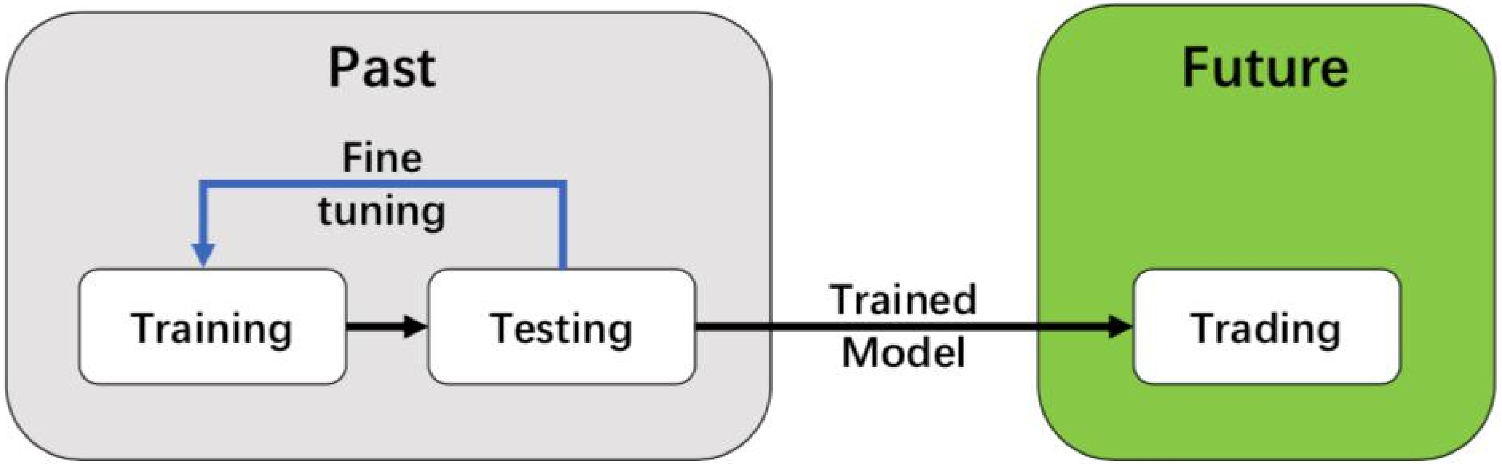
On the agent layer, FinRL supports **fine-tuned DRL algorithms** from DRL libraries in a **plug-and-play** manner.

FinRL: Environment Layer



On the environment layer, FinRL aims to wrap **historical data and live trading APIs** of hundreds of markets into training environments

Training-Testing-Trading Pipeline



The training-testing-trading pipeline:

Step 1: a training window to retrain on agent

Step 2: a testing window to evaluate the trained agent, while hyperparameters can be tuned iteratively

Step 3: use the trained agent to trade in a trading window

FinRL directly connects with live trading APIs:

Step 1: download live data

Step 2: feed data to the trained DRL model and obtain the trading positions

Step 3: allow users to place trades

Hands-on Tutorials and Benchmarks

Cumulative returns (5-minute interval) of trading top 10 market cap cryptocurrencies using FinR

The top 10 market cap cryptocurrencies as of Oct 2021 are: Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Binance Coin (BNB), Ripple (XRP), Solana (SOL), Polkadot (DOT), Dogecoin (DOGE), Avalanche (AVAX), Uniswap (UNI).

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FinRL-Meta: A Universe of Market Environments for Financial Reinforcement Learning

Data-Centric AI Workshop, NeuIPS 2021

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Motivation

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- **Increasing Demand for Market Environments for Financial RL**

Our Goals

- Reduce data processing burden
- Reduce simulation-to-reality gap
- Provide benchmark performance

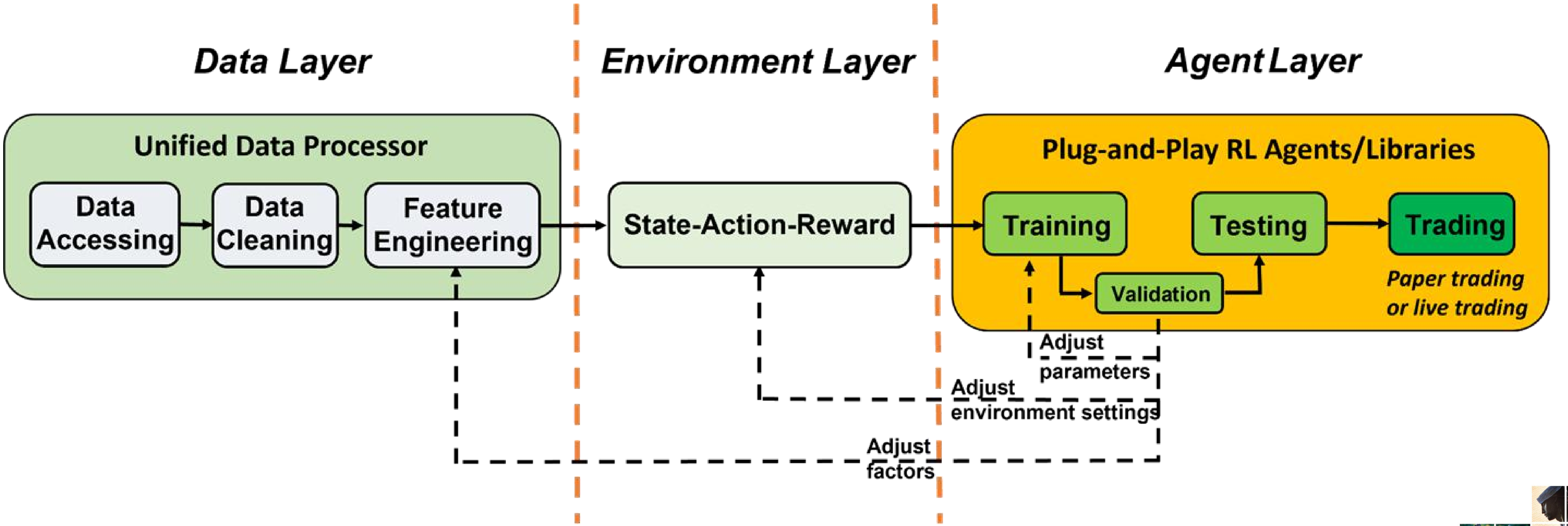
- **FinRL-Meta**

An open-source library that provides

Hundreds of Market Environments for Financial Reinforcement Learning

Architecture

Three-Layered Structure: Data Layer, Environment Layer and Agent Layer



Supported Functions

Data Sources

- Yahoo! Finance
- Alpaca
- Trade and Quote Data
- CCXT
- JoinQuant
- QuantConnect

DRL Libraries

- Stable-baselines3
- Rllib
- ElegantRL

Algorithms:

DQN, DDPG, SAC,

TD3, A2C, PPO…

Trading Tasks

- Stock trading
- Portfolio Allocation
- Cryptocurrency trading
- Forex trading
- Future/Option

Performance Evaluation

Trade Dow Jones 30 stocks

Data split:

- Training:

06/01/2021 to 08/15/2021

- Backtesting:

08/15/2021 to 08/31/2021

- Paper trading:

09/03 to 09/16/2021

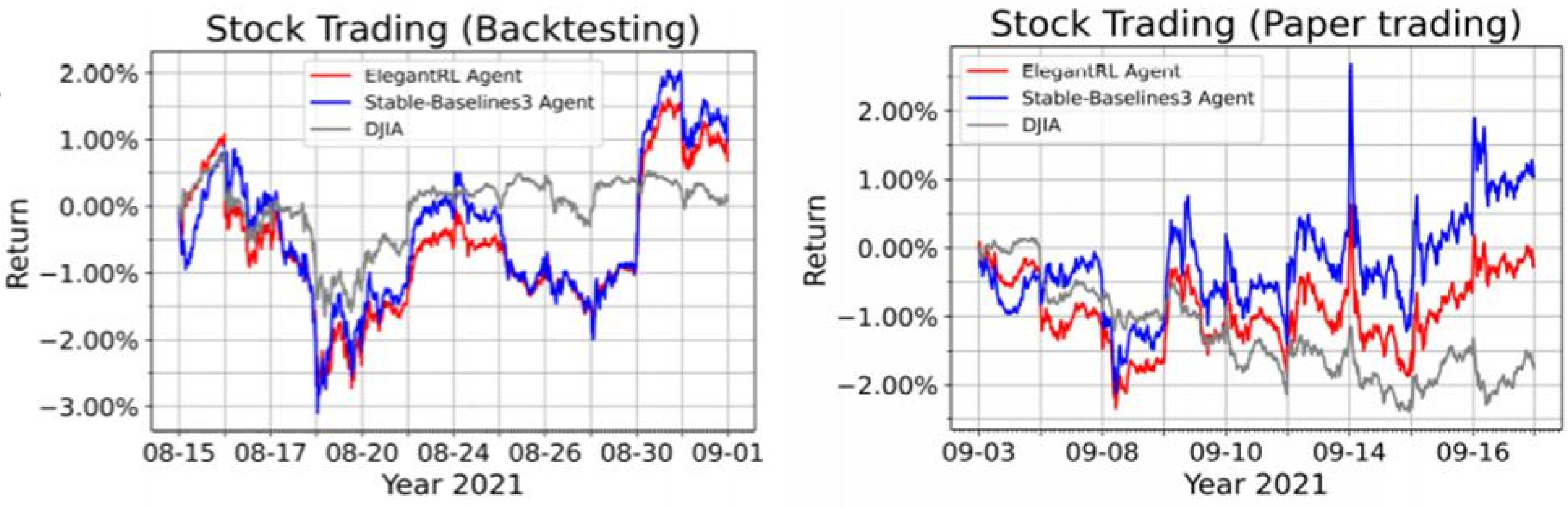


Figure 3: Cumulative returns (5-minute) of stock trading in backtesting and paper trading.

	ElegantRL	Stable-baselines	DJIA
Cumul. return	0.968% / -0.652%	1.335% / 0.191%	0.099% / -1.56%
Annual return	22.425% / -16.746%	32.106% / 5.492%	2.108% / -35.522%
Annual volatility	15.951% / 14.113%	19.871% / 15.953%	9.196% / 9.989%
Sharpe ratio	1.457 / -1.399	1.621 / 0.447	0.289 / -4.894
Max drawdown	-2.657% / -1.871%	-2.932% / -1.404%	-1.438% / -2.220%

Table 2: Performance of backtesting (red) and paper trading (blue) for stock trading.

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FinRL-Podracer: High Performance and Scalable Deep Reinforcement Learning for Quantitative Finance

ACM International Conference on AI in Finance (ICAIF), 2021

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Background

- Recently, deep reinforcement learning (DRL) has been recognized as a promising alternative for quantitative finance.
- However, we are still looking forward to having a wider DRL adoption in real-world (production-level) financial tasks.
- Major challenges:
  - **data collection with large-scale financial data** can lift the trading horizon to a new dimension.
  - **training efficiency** allows traders to continuously update trading strategies, which equips traders with an edge in a highly volatile market.

Motivation

Existing works are not satisfied:

- **Usage of large-scale financial data**: studied algorithmic trading on a daily time-frame or hourly time-frame.
- **Efficiency of agent training**: not be able to meet the intensive computing requirement.

	Sharpe ratio	Max dropdown	Training time
RLlib [19]	1.67	**-23.248%**	**110 min**
SB3 [13]	**1.82**	-23.750%	150 min
FinRL [44]	1.35	-27.267%	345 min
QQQ	1.25	-28.559%	–

Approaches

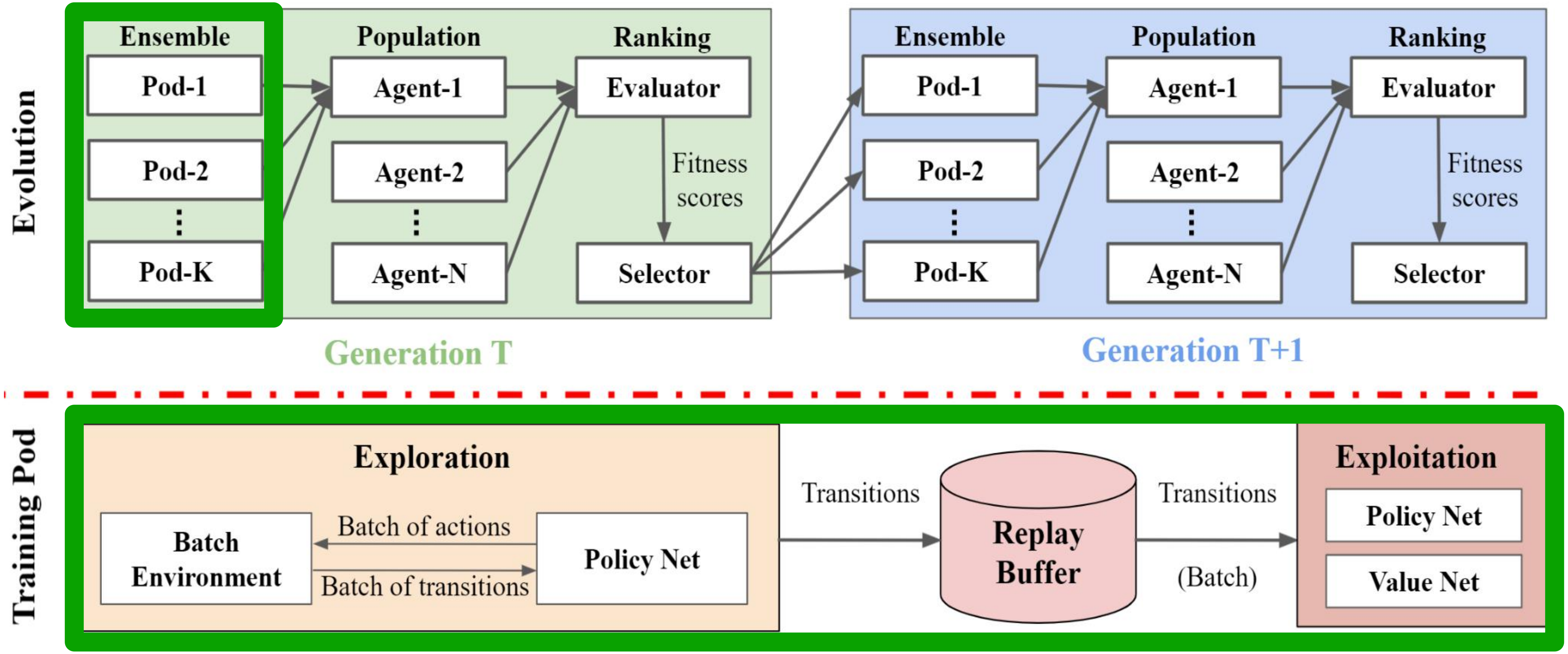
FinRL-Podracer is a high-performance and scalable solution:

- **Evolution layer** (high-level scheduling): employs a multi-level mapping and a generational evolution with an ensemble strategy, to guarantee scalability on cloud platforms.
- **Training layer** (low-level optimization): realizes parallelism encapsulation, GPU acceleration, storage optimization, and efficient parameter fusion, thus achieving high performance.

As a result, FinRL-Podracer can obtain a profitable trading agent in **10 minutes** on an NVIDIA DGX SuperPOD cloud with **80 A100 GPUs**, for a stock trend prediction task on **NASDAQ-100** constituent stocks with **minute-level** data over **5 years**.

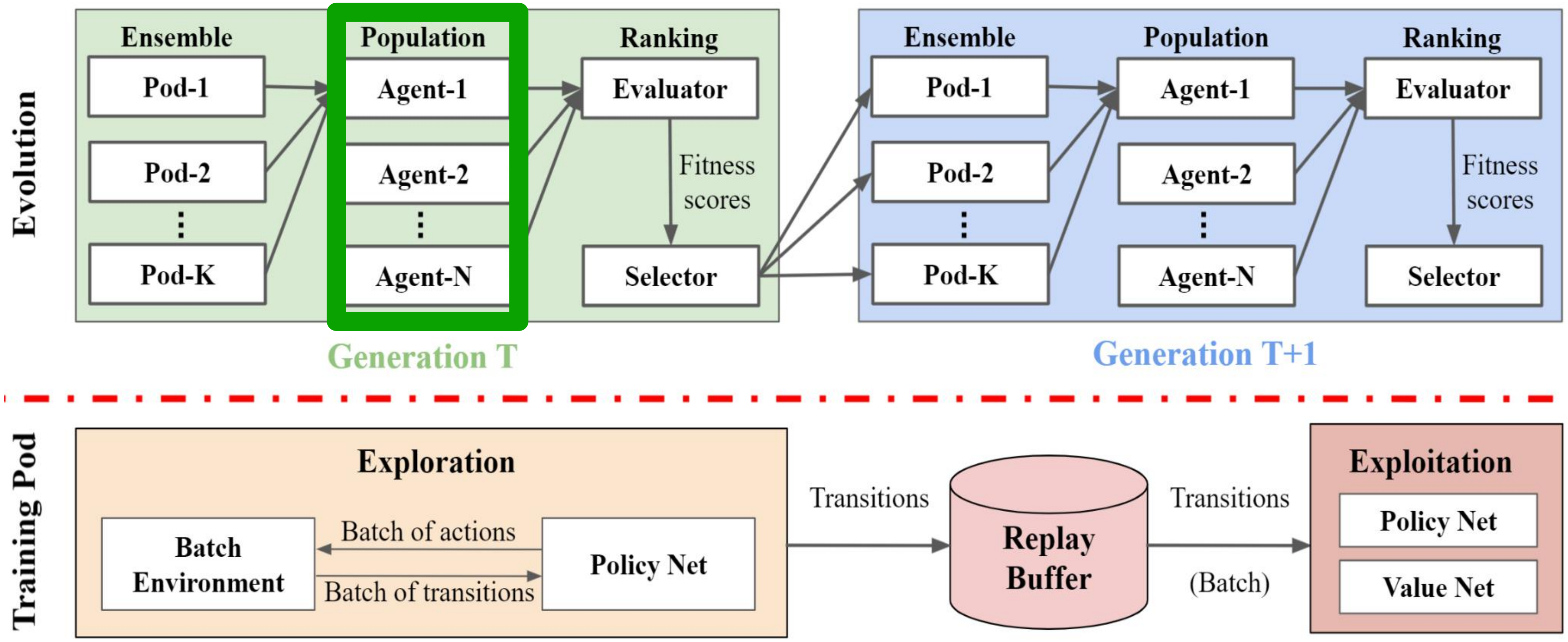
Evolution Layer

K models are trained in parallel and fused at the end of each epoch to obtain a single agent.



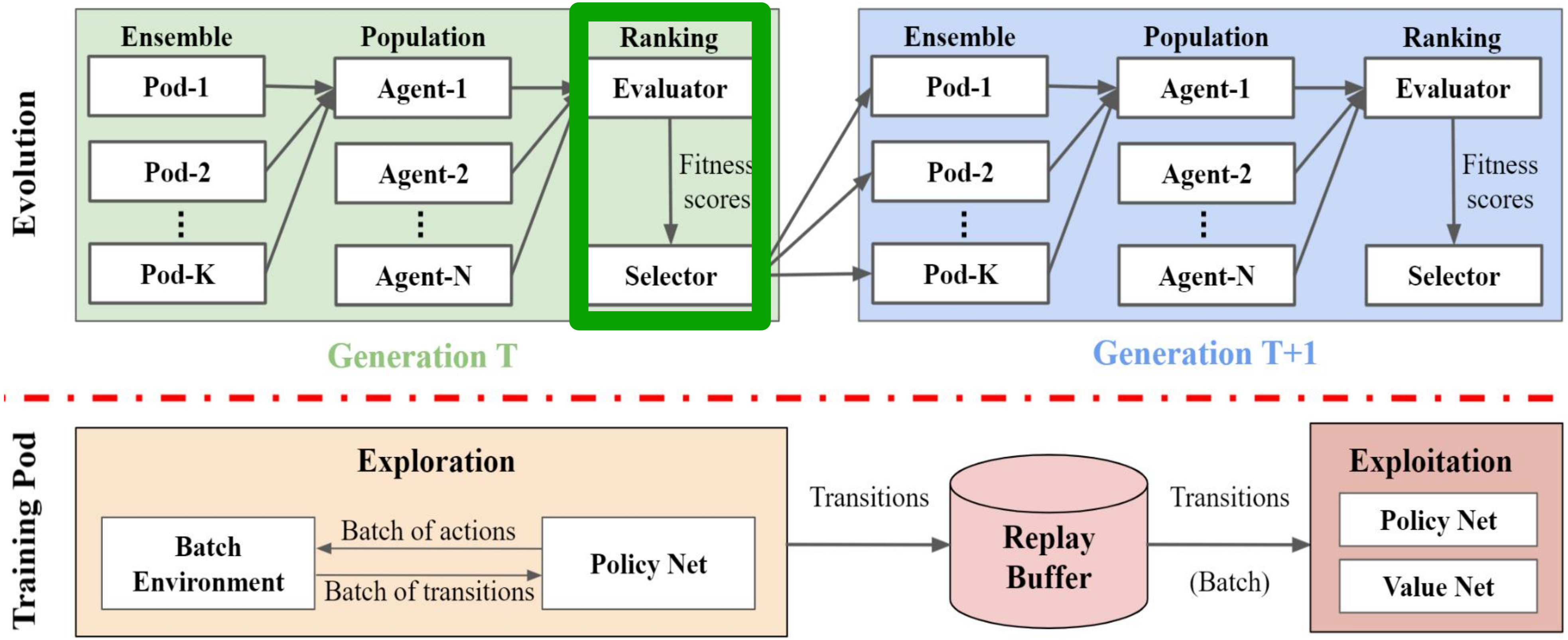
Evolution Layer

N agents form a population, where the generational evolution happens.



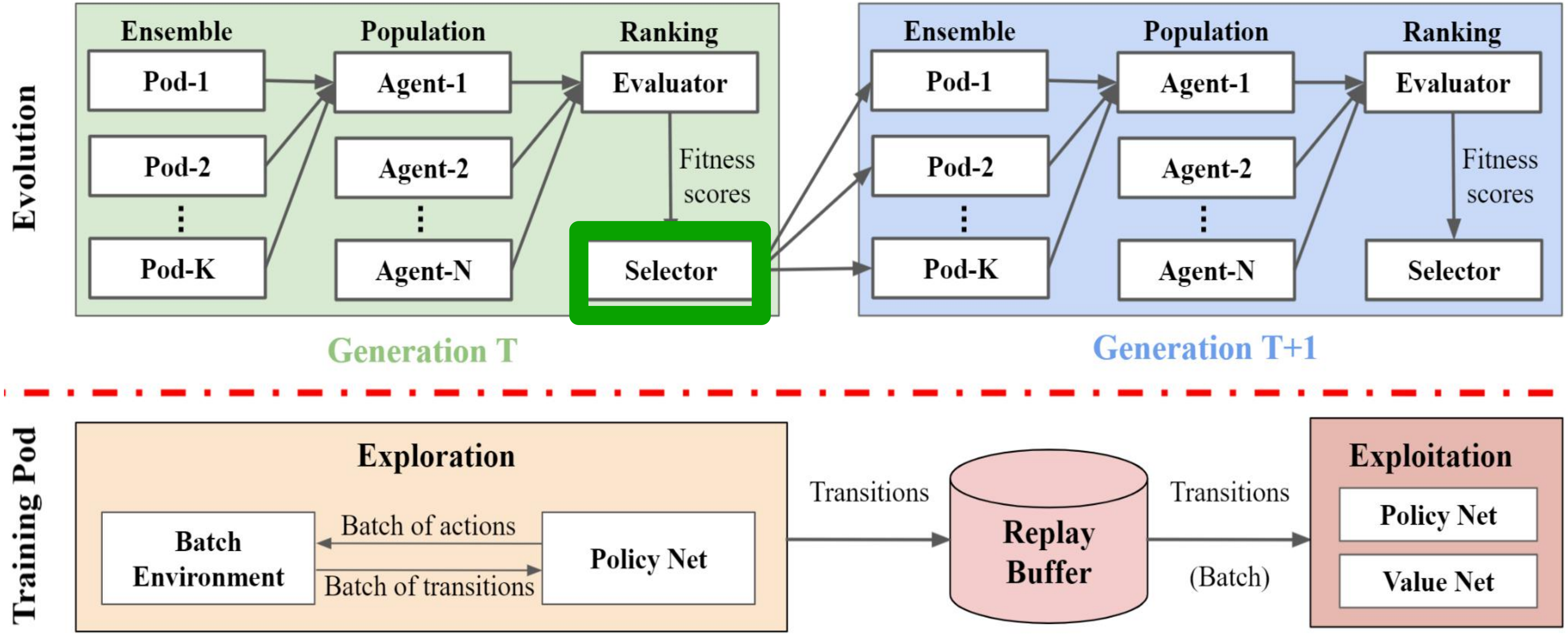
Evolution Layer

The evaluator evaluates N agents and sends their fitness scores as the metric for the future ranking.



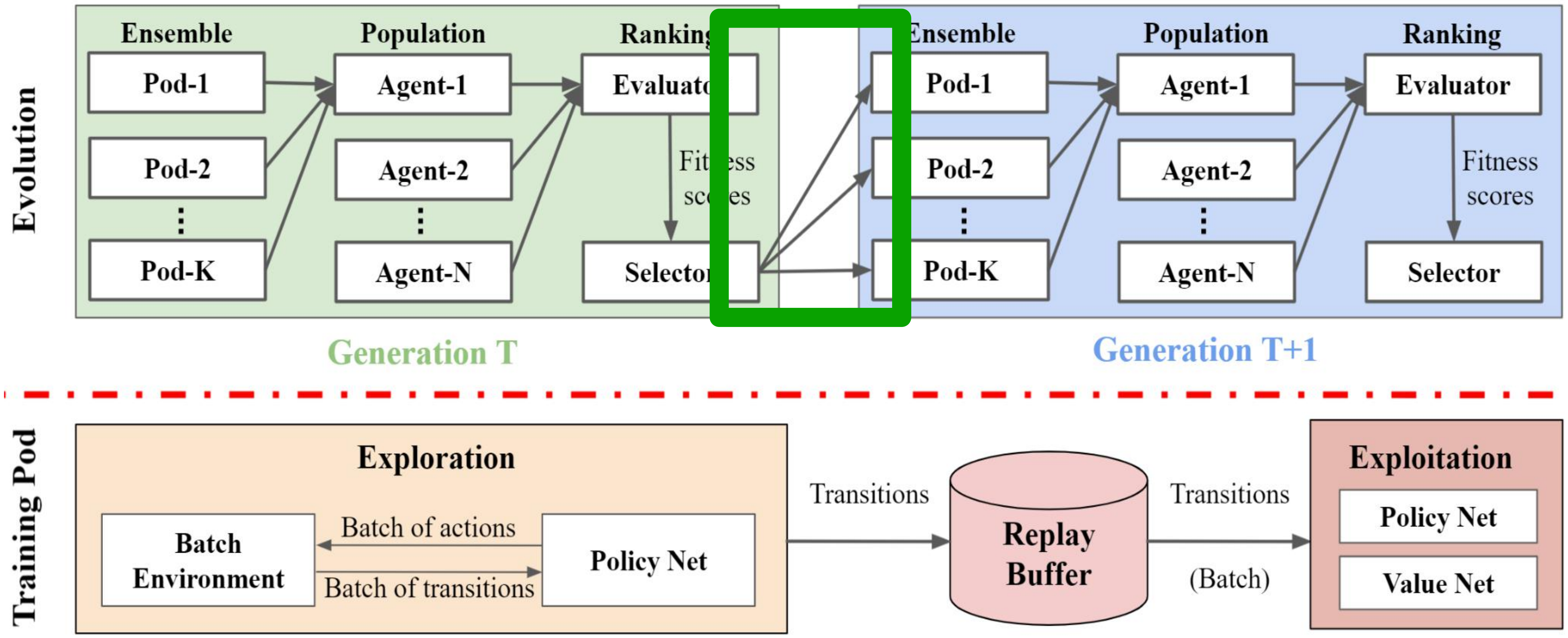
Evolution Layer

The selector chooses the well-evolved agents from the ranking of scores.



Evolution Layer

Replicate the well-evolved agents multiple times, and form a new population.



Data Pre-processing

We select the NASDAQ-100 constituent stocks as our stock pool, accessed at 05/13/2019 (the starting time of our testing period), and use the datasets with two time granularities:

- **Daily dataset**: directly downloaded from Yahoo!Finance.
- **Minute dataset**: first downloaded as raw data from WRDS and then pre-processed to an OHLCV format.

We backtest on the same period from 05/13/2019 to 05/26/2021.

Metrics and Baselines

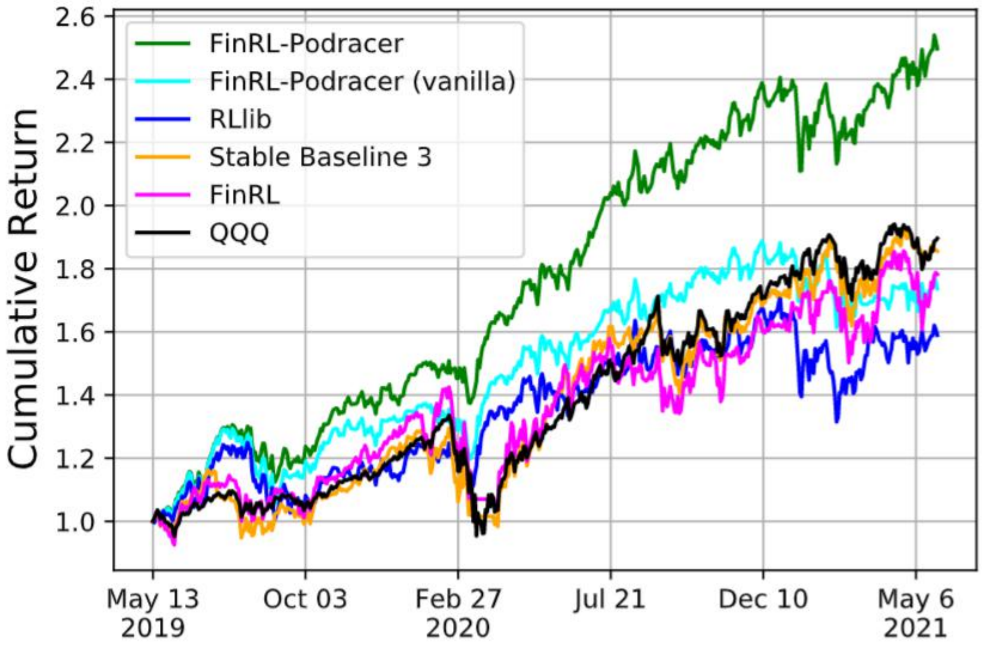
Evaluation metrics:

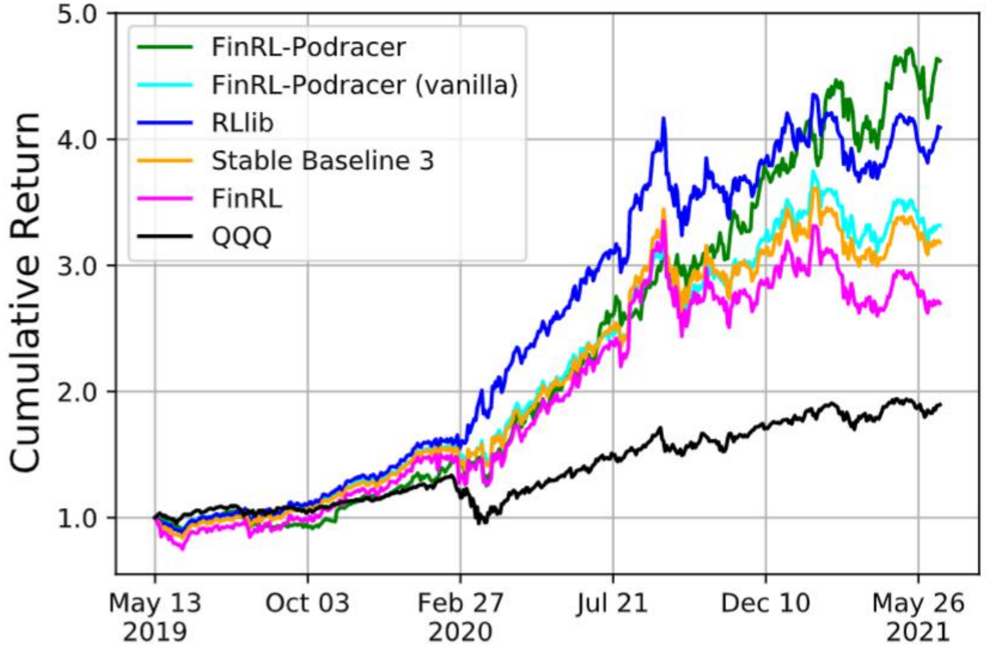
- Cumulative return
- Annual return and volatility
- Cumulative return vs. training time
- Sharpe ratio
- Max drawdown

Baselines:

- FinRL
- RLlib
- Stable Baseline 3
- Invesco QQQ ETF

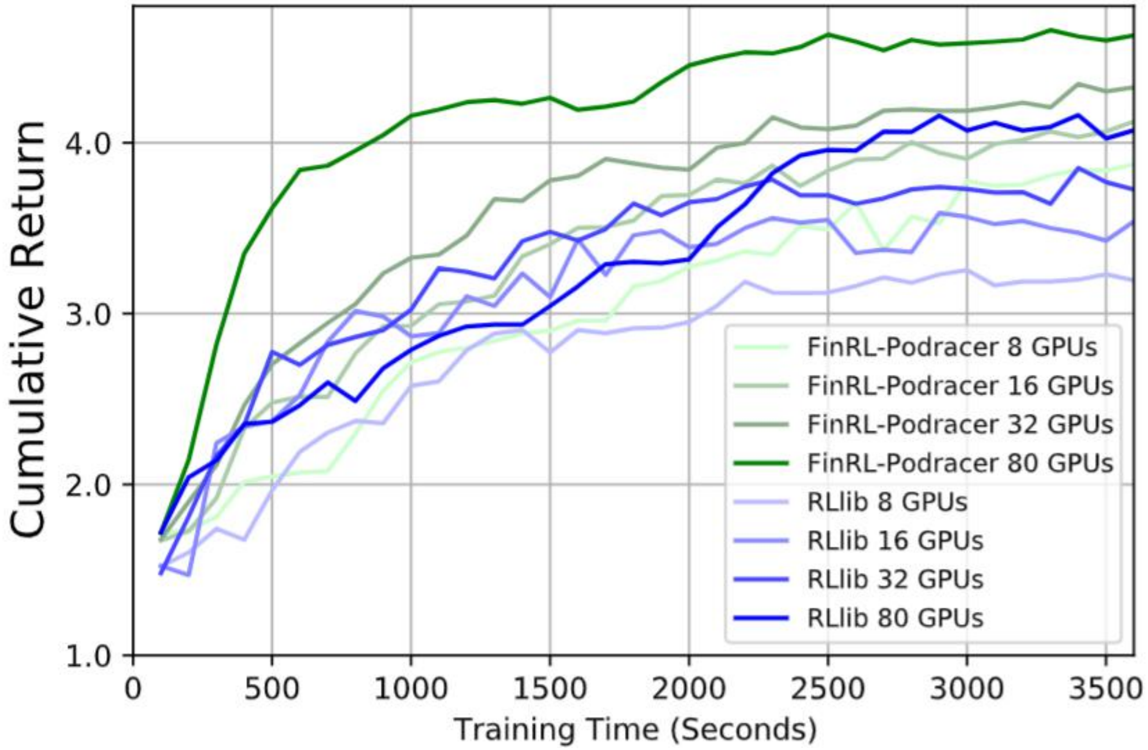
Trading Performance

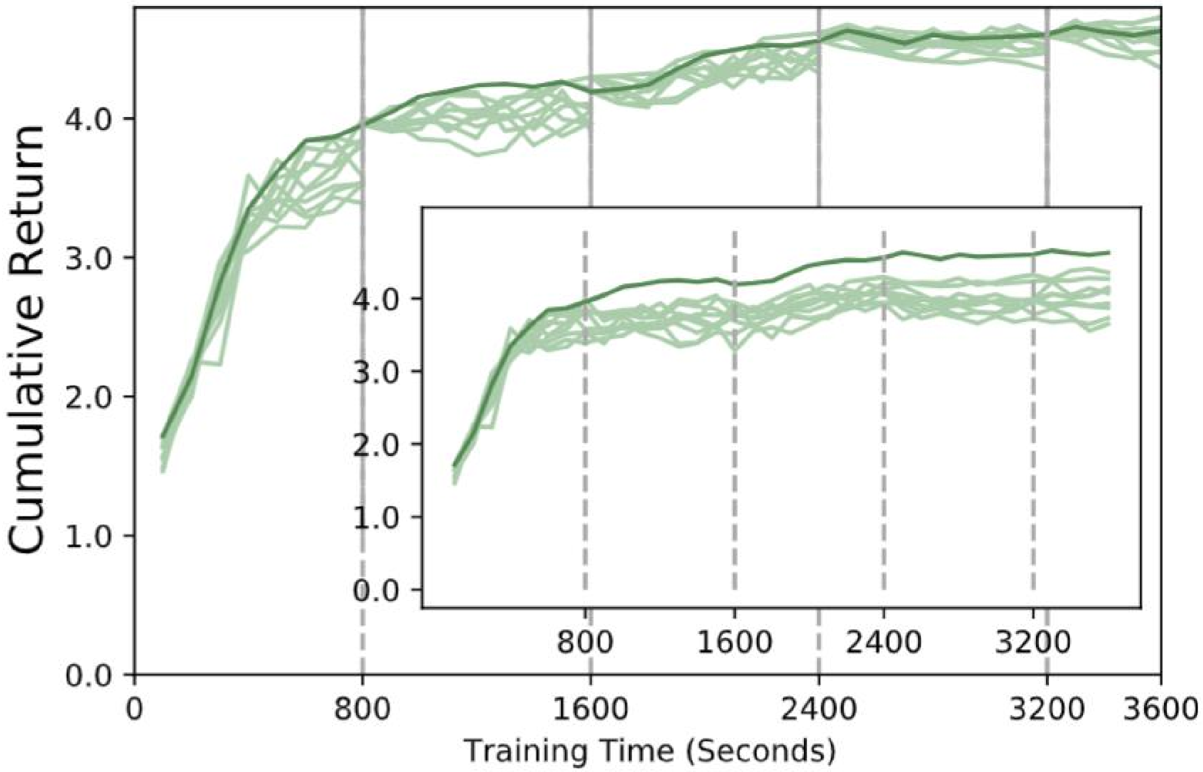




	Cumul. return	Annual return	Annual volatility	Max drawdown	Sharpe ratio
FinRL-Podracer (**Ours**)	**149.553%/362.408%**	**56.431%/111.549%**	**22.331%**/33.427%	**-13.834%/-15.874%**	**2.12/2.42**
FinRL-Podracer (vanilla)	73.546%/231.747%	30.964%/79.821%	23.561%/31.024%	-18.428%/-21.002%	1.27/2.05
RLlib [19]	58.926%/309.54%	25.444%/99.347%	30.009%/31.893%	-23.248%/-22.292%	0.91/2.33
Stable Baseline3 [13]	85.539%/218.531%	35.316%/76.28%	31.592%/34.595%	-24.056%/-23.75%	1.12/1.82
FinRL [25]	78.255%/169.975%	32.691%/62.576%	37.641%/42.908%	-26.774%/-27.267%	0.94/1.35
Invesco QQQ ETF	89.614%	36.763%	28.256%	-28.559%	1.25

Training Efficiency





Conclusion and Discussion

- A high-performance and scalable deep reinforcement learning framework, FinRL-Podracer.
- Two lessons: *the virtues of nested hierarchies* and *getting smart from dumb things*.
- Critical for the FinRL ecosystem:
  - provides a way to take advantage of large-scale financial data (market data, alternative data, indexes and labels).
  - possibly adapts to much more complex neural networks architectures and financial simulations.
  - through GPU-acceleration techniques, reduces latency for future financial simulations.

Publications

- [8] **FinRL-Meta**: Data-driven deep reinforcement learning in quantitative finance, Deep RL Workshop, NeurIPS 2021.
- [7] Explainable deep reinforcement learning for portfolio management: An empirical approach, ACM International Conference on AI in Finance, ICAIF 2021.
- [6] **FinRL-Podracer**: High performance and scalable deep reinforcement learning for quantitative finance. ACM International Conference on AI in Finance, ICAIF 2021.
- [5] **FinRL**: Deep reinforcement learning framework to automate trading in quantitative finance, ACM International Conference on AI in Finance, ICAIF 2021.
- [4] **FinRL**: A deep reinforcement learning library for automated stock trading in quantitative finance, Deep RL Workshop, NeurIPS 2020.
- [3] Deep reinforcement learning for automated stock trading: An ensemble strategy, ACM International Conference on AI in Finance, ICAIF 2020.
- [2] Multi-agent reinforcement learning for liquidation strategy analysis, Workshop on Applications and Infrastructure for Multi-Agent Learning, ICML 2019.
- [1] Practical deep reinforcement learning approach for stock rrading, Workshop on Challenges and Opportunities for AI in Financial Services, NeurIPS 2018.

Thank you!

https://github.com/AI4Finance-Foundation