



# FinRL-Meta: Market Environments and Benchmarks for Data-Driven Financial Reinforcement Learning

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July. 03, 2022



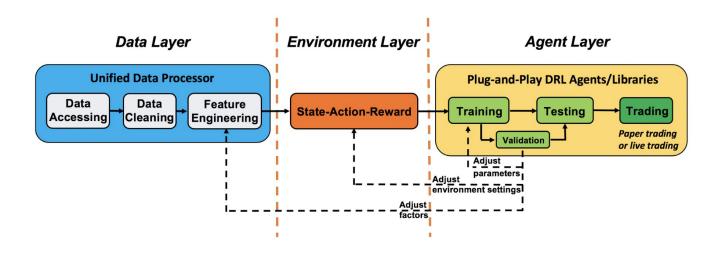
## Overview

- Finance is a particularly difficult playground for deep reinforcement learning (DRL).
- Open-source **FinRL-Meta** library:
  - Build hundreds of market environments.
  - Benchmark popular papers as stepping stones for users.
  - Tens of demos organized in a curriculum, with clean documentation.
- Features:
  - Layered structure
  - Extensibility.
  - "Training-testing-trading" pipeline.
  - Plug-and-play.



## Layered Structure

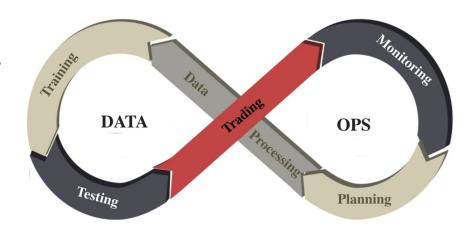
- Three layers: data layer, environment layer, and agent layer.
  - Transparency: layers interact through end-to-end interfaces
  - Modularity: easy extension of user-defined functions



# DataOps Paradigm

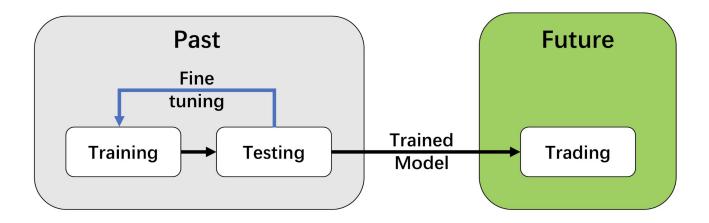
- Automated data engineering and agile development.
- Reduces the cycle time of data engineering and improves data quality.
- To deal with **financial big data**, we implement an **automatic pipeline**:
  - a. Task planning
  - b. Data processing
  - c. Training-testing-trading
  - d. Performance monitoring

We continuously produce dynamic market datasets.



# Training-testing-trading Pipeline

- Training-testing-trading pipeline:
  - First, a DRL agent is **trained** in a training dataset and **fined-tuned** (adjusting hyperparameters) in a testing dataset.
  - Then, backtest the agent (on historical dataset), or deploy in a **paper/live trading** market.



# Plug-and-Play

- A DRL agent can be directly plugged in: training-testing-trading.
- Following DRL libraries are supported:
  - **ElegantRL**: Lightweight, efficient and stable DRL implementation using PyTorch.
  - Stable-Baselines3: Improved DRL algorithms based on OpenAl Baselines.
  - RLlib: An open-source DRL library that offers high scalability and unified APIs.







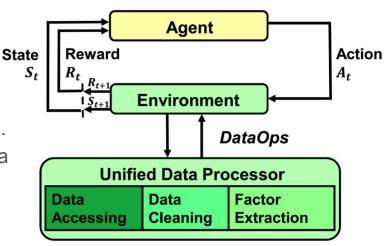
## Data Layer

#### Data Accessing:

- Connect APIs of different platforms via unified interface.
- Access data by specifying the start date, end date, stock list, time interval, and other parameters.
- Support more than 30 data sources, e.g. stocks, cryptocurrencies, ETFs, forex, etc.

#### Data Cleaning:

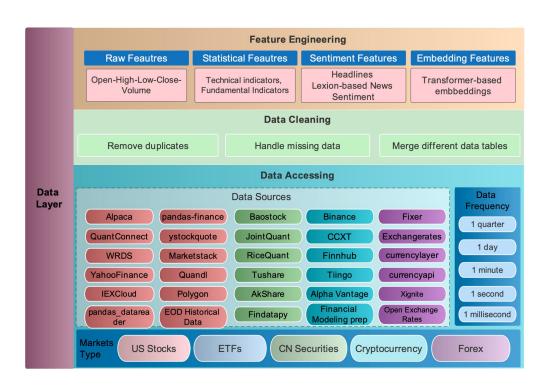
- Raw data are unstructured: erroneous or missing data.
- Automate the data cleaning process with a unified data processor.



## Data Layer

#### Feature engineering:

- Automatically calculate technical indicators, e.g., Stockstats, TA-lib
- Add user-defined features



## **Environment Layer**

- Incorporate common market frictions and portfolio restrictions.
  - Flexible account settings
  - Transaction cost
  - Risk-control for market crash
- Multiprocessing training via vector environment:
  - To utilize GPUs for multiprocessing training to accelerates the training process.
  - To achieve multiprocessing simulation of hundreds of market environments on large datasets.



## Tutorials and Benchmarks

- For education, >100 Jupyter notebooks as tutorials:
  - Stock trading
  - Portfolio allocation
  - Cryptocurrency trading
  - MARL for liquidation strategy analysis
  - Ensemble strategy for stock trading
  - Paper trading demo
  - China A-share demo
  - Hyperparameter tuning
  - 0
- For demo, reproduce papers as benchmarks:
  - Stock trading task
  - Liquidation analysis
  - Explainable financial RL
  - Podracer on the cloud
  - Ensemble strategy



## Conclusion

- Follow the DataOps paradigm and develop FinRL-Meta library
  - provide openly accessible dynamic financial datasets and reproducible benchmarks.

- Future work:
  - FinRL-Meta aims to build a universe of financial market environments.
  - o To improve the performance for the large-scale markets, we are exploiting GPU-based massive parallel simulation such as Isaac Gym.
  - We believe that FinRL-Meta may help provide insights into complex market phenomena and offer guidance for financial regulations.

## Collaboration and Support

Thanks for the collaboration and support of the following institutions:







