FinRL Contest Task I

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In this work, we propose a reinforcement learning method based on feature mining and market representation to solve the difficult problem of stock price prediction in financial quantification. The results showed that our strategy paid off significantly, from an initial 1 million dollars to 4.5 million dollars three years later.

Additional Key Words and Phrases: Quantitative financial reinforcement learning , strategy characterization , feature factors

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1 INTRODUCTION

In this article, we describe our quantitative strategy training based on selected features, and the results show that we have achieved good stock price prediction results in various situations.

2 FEATURE EXTRACTION

We first encode the features, including the following features, technical indicator, vix,turbulence,and more than 100 user defined features.

For the training set we used, the time was from '2010-01-01' to '2020-06-30', and the test set was from '2020-07-01' to '2023-10-24'.

Quantitative modeling in finance revolves around the application of mathematical and statistical methods to analyze and predict market behavior. A key aspect is 'market timing' (timing the market), which involves predicting market movements to make buy or sell decisions at the most opportune moments. Another critical element is 'portfolio construction' or 'asset allocation', where models help in selecting a combination of investments that align with specific risk and return objectives. 'Market sentiment encoding' plays a crucial role too, as it involves quantifying investor attitudes and emotions to gauge market directions. Lastly, 'indicator strategies and factor models' are used to identify variables that affect asset prices. These factors can range from macroeconomic indicators to company-specific metrics, providing a multi-dimensional view for informed investment decisions.

Overfitting is a frequent phenomenon in the training process. We reduce overfitting by means of distillation learning, etc. In addition, we have a self-developed DSAC-T algorithm, which can achieve better results than baseline in a large number of RL tasks.

The data is attached to the second page, other information can be found in the code, if you have more questions, please contact me.

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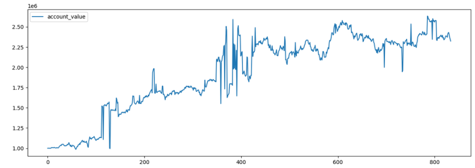

Fig. 1. Backtest Results1

Table 1. Backtest Results1

Metric	Value
Annual return	0.290193
Cumulative returns	1.323882
Annual volatility	0.819415
Sharpe ratio	0.707907
Calmar ratio	0.791926
Stability	0.795008
Max drawdown	-0.366439
Omega ratio	1.277254
Sortino ratio	1.165091
Tail ratio	1.088514
Daily value at risk	-0.100935

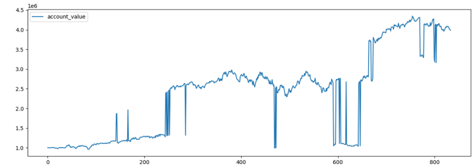

Fig. 2. Backtest Results2

Table 2. Backtest Results2

Metric	Value
Annual return	0.519022
Cumulative returns	2.989246
Annual volatility	2.781321
Sharpe ratio	1.160238
Calmar ratio	0.779210
Stability	0.605838
Max drawdown	-0.666088
Omega ratio	1.940627
Sortino ratio	2.920633
Tail ratio	1.078753
Daily value at risk	-0.337608