Deep Q Learning in Stock Trend Prediction

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Abstract

In my final project, I am going to utilize deep Q-learning with a CNN network to analyze candlestick charts for predicting stock trends. I anticipate that this project will enable me to acquire several skills.

- Develop a CNN network for image analysis.
- Construct a deep Q-learning agent to autonomously learn technical analysis.
- Build an environment from scratch. This environment will provide the agent with essential information such as states, rewards, and next states.

Lo, Mamaysky and Wang [4]

Nevertheless, technical analysis has survived through the years, perhaps because its visual mode of analysis is more conducive to human cognition, and because pattern recognition is one of the few repetitive activities for which computers do not have an absolute advantage (yet).

Introduction

People have tried using stock market data for analyzing future trends. With the advancement of machine learning and deep learning technologies in the modern era, we now have more tools to conduct such research.

- Shen and Zhang [6] used SVM to predict the next day's stock trend.
- Rather [5] attempted to use LSTM for stock price prediction and portfolio optimization.
- Jiang, Kelly and Xiu [1] used CNN to analyze candle charts, classify cross-sectional stocks and obtained alpha that cannot be explained by risk.

Introduction

Also, there are lots of researches on reinforcement learning in finance.

- Jiang, Saunders, and Weng [2] provide a reinforcement learning based Kelly strategy to optimally decide how much money to invest in stocks.
- Moser et al. [7] present a Double Deep Q-learning algorithm for trading on the S&P 500.
- Liang et al. [3] combine an adversarial technique with DDPG and PPO to construct a more robust stocks portfolio.

Data

To expedite the execution of my final project, I am using stock price data provided by yfinance. Additionally, I am converting the data into candle charts, which form the states that the agent will observe. The agent will view charts from the past 40 days and predict the trends for the following 20 days.

- Training period: 2000/01/01 to 2016/12/31
- Tesing period: 2017/01/01 to present
- Training stock tickers: AAPL, INTC, JPM, AEP, NKE, NVDA, MSFT, T, SBUX, GS

Data

- Standardize the volume.
- Set the first close price as 1. Other values are re-scaled according to their ratio with the close price of the first day.

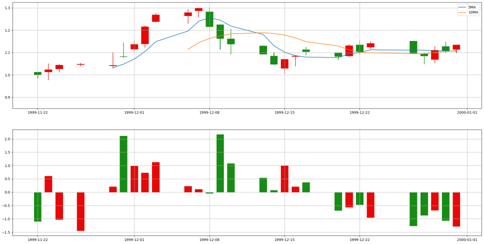


Figure: Training data

Methodology

- State: stock candle chart
- Actions: Bearish, Flat, Bullish
- Rewards:

$$\begin{cases} stock\ return \times 100\ (\%) & \text{if} \quad correct \\ -stock\ return \times 100\ (\%) & \text{if} \quad wrong \\ 5 & \text{if} \quad flat,\ abs(stock\ return) < fee \\ -5 & \text{if} \quad flat,\ abs(stock\ return) > fee \end{cases}$$

Methodology

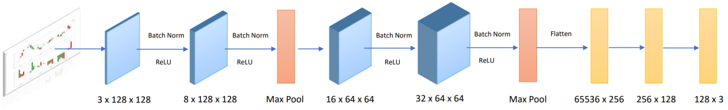


Figure: CNN Network

Methodology

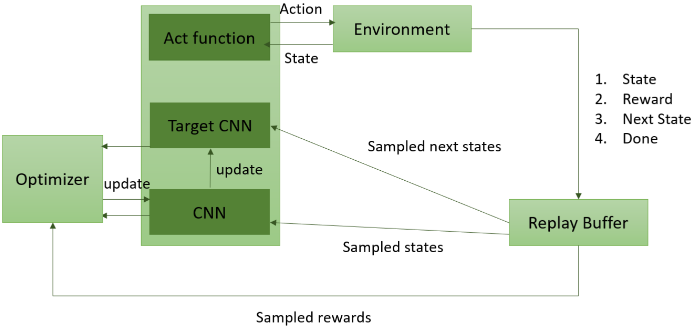


Figure: Deep Q Learning Architecture

Results

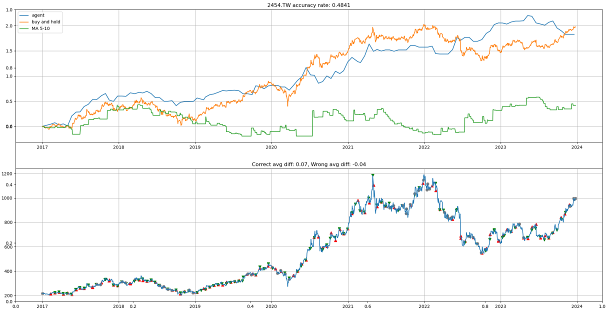


Figure: 2454.TW

Results

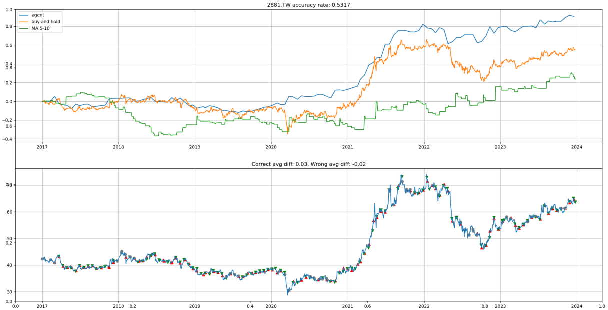


Figure: 2881.TW

Results

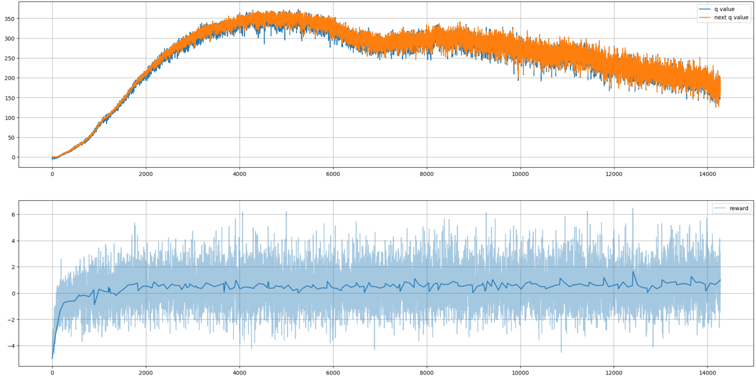


Figure: Reward-Step graph

Discussion

- In Kelly et al. [1], they implemented supervised learning method, extracting factors from cross-sectional stocks' candlestick charts and build a long-short portfolio to obtain significant alpha. However, the concept of my final project is different from what was mentioned above. I trained a deep Q-learning agent to autonomously find patterns based on candlestick charts. Due to computational limits, I only used data from 10 companies for training. According to the efficient market hypothesis, it is very difficult to obtain alpha from past data, especially when making predictions for individual stocks, rather than employing a long-short strategy.

Discussion

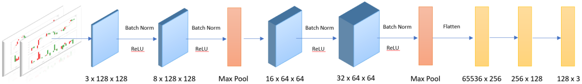
- The reason for utilizing US stocks for training in my project is their availability over a longer training period. If one wishes to apply the agent to the Taiwan stock market, enhancing accuracy might be achieved by using a pre-trained model. This model can then be transferred and further trained on a specific stock, such as 2330.TW, to adapt it more effectively to the characteristics of the Taiwan stock market.

Conclusion

- In this final project, I trained a deep Q-learning agent to analyze candlestick charts and make predictions and trades on stock price trends. The results show that the cumulative returns of the trading strategy predicted by this agent are better than a buy-and-hold approach, and also significantly outperform the MA breakout strategy commonly used in introductory algorithmic trading.
- Most papers on training reinforcement agents for financial trading do not include a reward-step chart, which leads me to doubt the stability of these agents. In this final project, the reward-step chart I provided shows that the reward eventually tends to stabilize and is positive.

Future Work

- Analyzing the reason why the agent can capture stock trends.
- Attempting to optimize pair trading by using a deep Q-learning agent to analyze the relationship between candlestick charts of stock pairs with cointegration.



References I

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[2] R Jiang, D Saunders, and C Weng. "The reinforcement learning Kelly strategy". In: *Quantitative Finance* 22.8 (2022), pp. 1445–1464.

[3] Zhipeng Liang et al. "Adversarial deep reinforcement learning in portfolio management". In: *arXiv preprint arXiv:1808.09940* (2018).

References II

[4] Andrew W Lo, Harry Mamaysky, and Jiang Wang. "Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation". In: *The journal of finance* 55.4 (2000), pp. 1705–1765.

[5] Akhter Mohiuddin Rather. "LSTM-Based deep learning model for stock prediction and predictive optimization model". In: *EURO Journal on Decision Processes* 9 (2021), p. 100001.

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References III

[7] Frensi Zejnullahu, Maurice Moser, and Joerg Osterrieder. "Applications of Reinforcement Learning in Finance–Trading with a Double Deep Q-Network". In: *arXiv preprint arXiv:2206.14267* (2022).