Optimizing Portfolio Management and Risk Assessment in Digital Assets Using Deep Learning for Predictive Analysis

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Abstract. Portfolio management issues have been extensively studied in the field of artificial intelligence in recent years, but existing deep learning-based quantitative trading methods have some areas where they could be improved. First of all, the prediction mode of stocks is singular; often, only one trading expert is trained by a model, and the trading decision is solely based on the prediction results of the model. Secondly, the data source used by the model is relatively simple, and only considers the data of the stock itself, ignoring the impact of the whole market risk on the stock. In this paper, the DQN algorithm is introduced into asset management portfolios in a novel and straightforward way, and the performance greatly exceeds the benchmark, which fully proves the effectiveness of the DRL algorithm in portfolio management. This also inspires us to consider the complexity of financial problems, and the use of algorithms should be fully combined with the problems to adapt. Finally, in this paper, the strategy is implemented by selecting the assets and actions with the largest Q value. Since different assets are trained separately as environments, there may be a phenomenon of Q value drift among different assets (different assets have different Q value distribution areas), which may easily lead to incorrect asset selection. Consider adding constraints so that the Q values of different assets share a Q value distribution to improve results.

Keywords: Portfolio management; Stock forecast; DRL algorithm; Deep learning

A. Haldorai et al. (eds.), *Proceedings of the 2024 3rd International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID 2024)*, Atlantis Highlights in Intelligent Systems 11,
https://doi.org/10.2991/978-94-6463-490-7_5

1 INTRODUCTION

With the development of artificial intelligence, much progress has been made in the study of portfolio management problems, aiming to maximize the expected return of multiple risky assets. Simultaneously, China's stock exchange market is gradually evolving towards diversification, convenience, and information, resulting in the generation of vast amounts of data daily. [1]To address the deficiency in traditional transaction analysis methods, which struggle with handling large datasets, and to mitigate the irrational operations of undisciplined human investors, quantitative investment characterized by scientific, systematic, and accurate approaches has gradually become a focal point for institutional investment researchers.

Additionally, the trends of certain individual stocks exhibit a correlation with the overall market trend. This study expands the application of deep reinforcement learning in the field of quantitative investment, offering significant references and practical guidance for the integration of deep reinforcement learning in financial investment, particularly in stock investment.

2 RELATED WORK

2.1 Portfolio management

The portfolio management department, a key component of risk control, handles risk measurement and data analysis, reporting to top executives. This article explores portfolio management's integral role in the product or customer life cycle, emphasizing [2-3]risk management through indicators and discussing monitoring, forecasting, and early warning systems. This cohesive process underscores the department's significance in asset portfolio management. The construction of monitoring forecast and early warning will mainly focus on the prediction methods of common indicators, and how we monitor forecast and early warning, these three blocks are linked together, mainly the construction and combing of a process, asset portfolio management, asset portfolio management.

2.2 Deep learning and Deep Q-learning

Deep Q-Learning algorithm is referred to as DQN. DQN evolved on the basis of Q-Learning. DQN's modification of [4]Q-Learning mainly includes two aspects:

1) DQN uses deep convolutional neural networks to approximate value functions

2) DQN uses experiential replay of the learning process of training reinforcement learning

2.2.1 Introduction to DQN

In Figure 1, the steps of the Q-Learning algorithm are outlined. This algorithm, when integrated with a neural network, forms the basis of the DQN (Deep Q-Network). The

Q-Learning algorithm involves maintaining a Q table, which is updated according to a specific formula.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)] \quad (1)$$

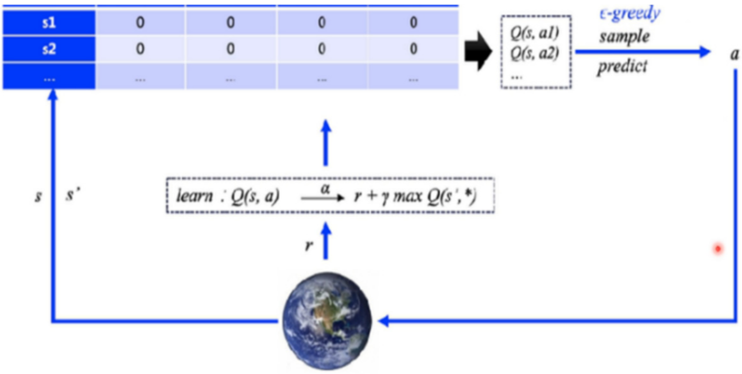

Fig. 1. Q-Learning algorithm steps

DQN is to replace this Q table with a neural network, and the rest are the same, as shown in the figure below:

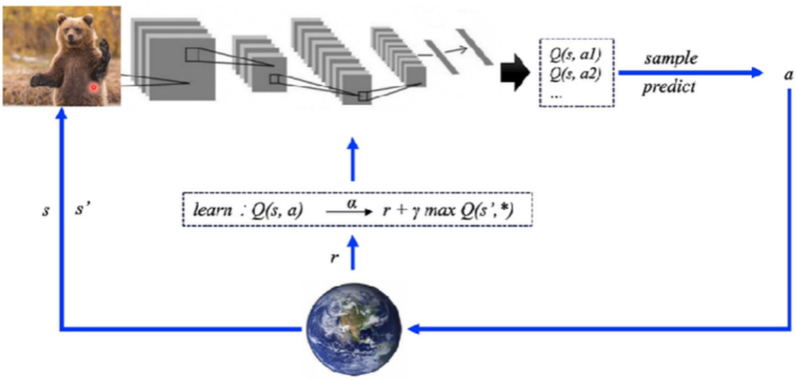

Fig. 2. DQN neural network structure

In Figure 2, the DQN neural network structure is illustrated, showcasing the architecture utilized for stock price prediction. The advantage of employing the DQN (Deep Q Learning) neural network for this task lies in its capacity to autonomously learn and optimize trading strategies. By integrating a deep reinforcement learning algorithm, the model can extract intricate patterns and rules from historical stock price data, thereby adeptly adapting to fluctuations in the market and attaining exceptional performance across diverse trading scenarios. This integration offers an adaptive and remarkably intelligent approach to stock price prediction.

2.2.2 Market volatility and stock price prediction

There is a relationship between fluctuations in stock volume and stock prices, but it cannot directly predict the rise and fall of stock prices. An increase in trading volume usually indicates higher enthusiasm among market participants, while stable or rising investor confidence can trigger an increase in stock prices. However, high volume may cause stock prices to fluctuate more sharply or frequently, increasing the risk for investors.Furthermore, the fluctuation of trading volume is influenced by various factors, including market sentiment, funds, and policy environment. These factors may have a complex relationship with the rise and fall of stock prices. Therefore, when making investment decisions, investors cannot solely rely on volume to determine the trend of stock prices. [6-7]It is essential to consider multiple factors.

In summary, while there is a correlation between trading volume and stock price fluctuations, it is not a completely accurate predictor of stock price movements. Investors should analyze other indicators and market conditions to make more informed investment decisions.

In this study, each asset is treated as an environment, and the strategy is trained by considering the income from holding the asset as its return and the average income from other portfolio assets as the cash return. The goal is to allocate cash to assets with expected performance above the average.

3 METHODOLOGY

The method is applied to 48 US stock portfolios, varying from 10 to 500 stocks, with diverse selection criteria and transaction costs. The algorithm employs a single hyperparameter setting across all portfolios, demonstrating superior performance compared to passive and active benchmark investment strategies.

3.1 Algorithm establishment

The algorithm in this paper mainly needs to be explained:

1. Train each asset separately as an environment, sampling one asset initialization environment at a time[8];

2. Use the Q function of cumulative return evaluation training on the verification data, and record the Q function with the best performance on the verification data;

3. The action space is a two-dimensional discrete action, with 0 representing holding cash and 1 representing holding the asset.

The main algorithm formula is as follows:

$$\nabla\theta_i L_i(\theta_i) = E_{s'\sim\varepsilon}[R_t + \gamma_{a'}^{max} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i)\nabla\theta_i Q(s,a;\theta_{i)} \quad (2)$$

$$R_t = \{r_{t+1,i} - (1 - a_{t-1)}C \ \ if \ a_t = 1 \quad (3)$$

3.2 Test data

The algorithm selected the historical data of 500 US stocks from 2010-01-01 to 2021-06-30 for testing.

Data division:

Training data set period: 2010-01-01 to 2018-12-31

Data set validation period: 2019-01-01 to 2019-31

Test data set period: 2020-01-01 to 2021-06-30

Portfolio grouping: Test 500 stocks by market capitalization as low, mid, and high.

Transaction cost: [9]bps

Test method: Three agents were trained on the training set for model integration and tested on the test set.

Comparison basis:

Buy-and-hold: equal rights to Buy and hold all shares;

Momentum: A strategy of buying stocks that have had a positive average return over the past five trading days;

Reversion: A return strategy to buy stocks that have had negative average returns over the past five trading days.

Table 1. Out-of-sample cumulative returns at the end of the test period for each level of transaction costs and different portfolios

Transaction costs	Portfolio size	Portfolio type	Agent	Buy-and-hold	Momentum	Reversion
1~10 bps	10	big	123.2%	129.5%	76.6%	44.3%
		random	24.2%	56.4%	31.1%	13.1%
		small	173.7%	65.7%	73.6%	81.7%
	25	big	11.6%	66.2%	20.4%	37.1%
		random	38.5%	48.1%	27.4%	19.2%
		small	134.6%	84.0%	79.9%	67.5%
	50	big	76.0%	52.7%	24.7%	38.8%
		random	79.2%	62.5%	0.6%	54.8%
		small	64.3%	66.9%	30.7%	60.2%
	100	big	104.4%	56.3%	32.5%	63.6%
		random	107.3%	67.8%	0.8%	86.5%
		small	204.1%	68.0%	30.9%	48.0%
	200	big	89.0%	58.9%	12.8%	82.0%
		random	103.1%	63.6%	1.3%	77.4%
		small	99.0%	59.4%	21.3%	51.8%
	500	all	100.8%	59.2%	20.8%	63.1%
	Mean		95.8%	66.6%	30.3%	55.6%
	Mean		75.7%	66.6%	8.4%	29.5%

Analysis:

In the Table 1 ,Among 48 groups of experiments, DQN was the best in 36 groups of experiments.

The larger the portfolio, the more stocks to choose from, the better the performance of DQN strategy;

In a small-cap portfolio, the DQN strategy outperforms the benchmark strategy.

Compared with momentum and regression strategies, [10]DQN strategies have better applicability to transaction costs.

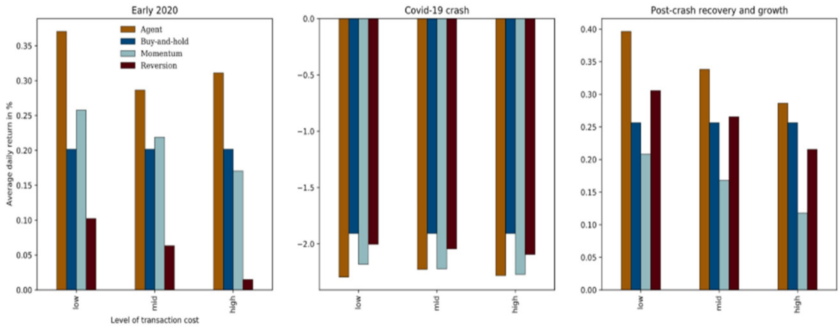

Fig. 3. Out-of-sample trading performa three phases based on market conditions

In Figure 3, the out-of-sample trading performance is depicted across three phases based on market conditions: the normal market stage before the COVID-19 epidemic, the market decline stage when COVID-19 appears, and the market recovery stage after. The performance of the DQN strategy is highlighted, showing optimal performance in both the normal phase and the recovery phase. However, during the market decline phase, DQN performed poorly, potentially due to the absence of similar situations in the training data. This graph visually represents the findings discussed in the text regarding the performance of the DQN strategy in different market conditions.

3.3 Experimental results

In this study, the application of the DQN model in the asset management portfolio showed good adaptability, achieving the best performance in 36 experiments out of 48 experimental groups by randomly selecting a single asset from a group of assets as the trading environment. Through the return calculation of the average return of the asset group, the model shows strong performance in a variety of trading scenarios. However, in emergency situations, the model showed a significant decline, revealing the limitations of its limited ability to generalize.

3.4 Experimental limitations:

While the DQN model generally performs well, experiments have revealed certain limitations. Specifically, the model's performance is significantly reduced under emergency conditions, indicating limited generalization ability for non-extreme cases. Additionally, the experiment did not account for differences in experience and judgement among trading experts, raising the possibility that the model may not capture the diversity of real trading decisions. These limitations indicate areas for improvement in future studies. This could involve increasing the diversity of training data and incorporating more trading expert experience to enhance the model's robustness and adaptability.

4 CONCLUSION

Although the experimental model was successful, it also revealed some limitations. Specifically, in emergency situations, strategies may experience performance degradation. This highlights the need for deeper consideration of algorithmic robustness when dealing with complex financial problems. As for future research directions, it is necessary to address the limitations of the current strategy. Firstly, introducing constraints in the asset selection process should be considered to prevent Q-value drift between different assets, thereby improving the strategy's robustness and accuracy. Secondly, a deeper analysis of the reasons behind the strategy's performance deterioration in emergency market situations is necessary to identify ways to improve. Finally, the application of deep reinforcement learning can be extended to other areas of finance, such as risk management and forecasting, to explore more potential applications.

Although AI has been successful in asset management, its application to portfolio management is still in its infancy and lacks a deep understanding of the complexity and uncertainty of financial markets. Further research is needed to improve the adaptability of algorithms to the financial environment. By continuously improving algorithms and expanding their application areas, we can better leverage the benefits of deep reinforcement learning in asset management and risk assessment, enabling smarter and more accurate financial innovation.

ACKNOWLEDGEMENT

During the completion of this study, I would like to sincerely thank Liu, Bo and others for their outstanding contributions to the academic community. Their journal article "Integration and Performance Analysis of Artificial Intelligence and Computer Vision Based on Deep Learning. Algorithms provides valuable inspiration and enlightenment for my research on financial portfolio management and risk prediction in the field of machine reinforcement learning. This paper deeply discusses the integration and performance analysis of artificial intelligence and computer vision based on deep learning algorithms, providing me with rich theoretical support in experimental design and reinforcement learning application. Some of the core conclusions and methods adopted in my research are derived from this article, which has played an important guiding role for my research.

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