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Enhancing High-Frequency Trading Strategies with Edge Computing and Deep Learning

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Abstract: As financial markets continue to evolve, high-frequency trading (HFT) has become an important force in the market, which involves the execution of large numbers of orders at extremely fast speeds. These strategies rely on the ability to process large amounts of real-time data in order to make split-second decisions using small price differences between various trading venues. However, the efficiency and effectiveness of HFT strategies are largely affected by delays in data processing and order execution. In order to overcome data processing and execution delays, edge computing technology has gradually emerged. Edge computing allows real-time data processing closer to the data source, reducing data transfer times and improving response speed. In high-frequency trading, this means faster decision making and order execution, allowing traders to better take advantage of price movements in the market. This paper introduces data privacy and security through edge computing, as data does not have to travel long distances over the network, but can be processed locally. This is particularly important for high-frequency trading, where leakage or tampering of trading data can lead to significant risks and losses. In conclusion, the application of edge computing technology in high-frequency trading is expected to improve the efficiency and reliability of strategies and enhance traders' competitiveness in a rapidly changing market environment. This development reflects the ongoing exploration of emerging technologies in the financial sector to improve the competitive advantage of trading strategies and highlights the potential applications of edge computing in financial markets.

Keywords: High-Frequency Trading, Data Processing Latency, Edge Computing, Rading Strategy Efficiency

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1 Introduction

High frequency trading is a computerised trading strategy that seeks to profit from extremely small price changes in the market. These small price changes can include small fluctuations in the spread between the bid and ask price of a security, or the small spread between the price of a stock on different exchanges. High-frequency trading is characterised by extreme speed, so much so that trading firms set up their own server farms very close to the exchanges to reduce the time it takes to transmit trading orders, taking advantage of optical cables that travel at the speed of light. High-frequency trading has also been affected by several regulatory changes, some of which have facilitated its development. For example, the US Securities and Exchange Commission's Alternative Trading Systems Regulations, enacted in 1998, gave electronic trading platforms the opportunity to compete with the major exchanges. This led exchanges to start quoting prices in units as close as a penny rather than a sixteenth of a dollar, further narrowing the spread between bids and offers and forcing traders to look for other ways to trade.

The rise of edge computing technology has attracted much attention in the financial sector, supporting business transformation and bringing computing closer to the user. Organisations across industries are considering edge computing solutions to automate real-time business processes and gain critical insights to improve business operations. Edge computing provides organisations with real-time or near real-time interactive insights, which for the financial industry means faster data processing and faster decision making. In finance, edge computing is already being used to monitor sensors and devices, analyse data and support automated decision making. The banking industry is also actively exploring the potential of edge computing to improve customer experience and predict market behaviour. The application of this technology is expected to provide the financial sector with more tools and insights to improve trading strategies and business operations.

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2 Related Work

2.1 High-frequency Trading

High-frequency trading is the field of quantitative investment, a bright star of the financial market, is the product of the development of financial technology to a certain extent. It is also a financial tool commonly used by international financial speculators. The European Commission of Securities Regulators defines high-frequency trading as a form of automated trading, known for its speed, which uses sophisticated computer technology and systems to execute trades in milliseconds and hold short positions throughout the day. Now add an AI approach to create a reasonable high-frequency trading model.

What are the key characteristics of high-frequency trading:

1. Processing fractional transaction data and algorithmic transactions

Processing transaction data and algorithmic trading is an important process of high-frequency trading. High-frequency trading collects and processes market transaction data to analyze potential trading opportunities in the micro level of the market. Once the trading opportunity is confirmed, it is a trading strategy to place orders in time through algorithmic trading and quickly close positions after making profits.

2. High capital turnover and day trading

High capital turnover and day trading are also characteristics of high-frequency trading, the trading process, the rapid entry of funds, a second can occur several orders, withdrawals action. Funds circulate at high speed throughout the trading process, improving market liquidity. At the same time, day trading also avoids overnight risk.

2.2 There are the following mature trading strategies in the international financial market

1. Market microstructure trading strategy

The market microstructure trading strategy is mainly a strategy of trading the selected trading pair in a short period of time according to the imbalance principle of the trading order flow by analyzing the real-time trading data in the market. For example, EOS rose 12% on the day, ETH rose 3%, such a strategy has a large arbitrage space in a short time. There are many trading opportunities in the instant buy and sell order flow in the market. Through the system statistics of visible trade orders and other parameter changes, we can analyze whether the sell order flow dominates or the buy order flow dominates in the very short time in the future. In a market dominated by sell orders, prices will fall; In a market dominated by buying streams, prices will rise. Operate according to market changes.

2, the use of market microstructure trading strategy, the system through comparative analysis of the volume of trading orders, trading first, and quickly closed positions. The prerequisite is to obtain real trade order data to prevent interference with data. Therefore, this trading strategy also needs to be analyzed together with other trading strategies and trading parameters to make correct analytical judgments.

This trading strategy is widely used in the futures trading market. By observing the trading information, looking for opportunities, placing orders quickly, closing positions quickly, and high-frequency trading, the profit is not small.

The quest for precise robot positioning within logistics automation has been a focal point in recent research endeavors. A multitude of techniques and methodologies have been explored to address this critical challenge.

2.3 Edge Computing

Edge computing refers to the processing and analysis of data at the edge nodes of the network. Here, we give the definition of edge node, which refers to any node with computing resources and network resources between the data generation source and the cloud center. For example, the mobile phone is the edge node between people and the cloud center, and the gateway is the edge node between the smart home and the cloud center. In an ideal environment, edge computing refers to the analysis and processing of data near the source of data generation, without the flow of data, thereby reducing network traffic and response time.

Why do you need edge computing

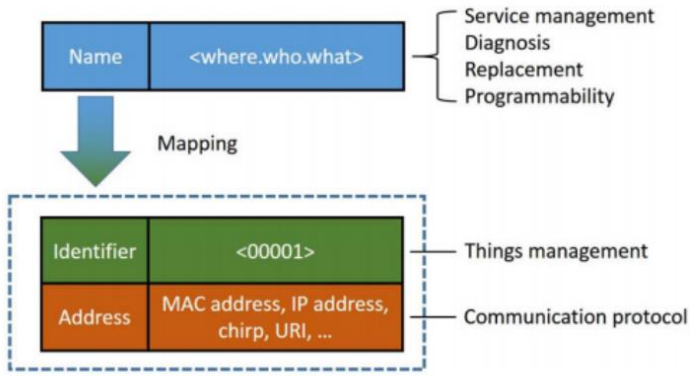

Figure 1: Edge computing naming mechanism

The promotion of cloud services: The cloud center has strong processing performance and can handle huge amounts of data. But moving massive amounts of data to cloud centers has become a challenge. The system performance bottleneck of the cloud computing model lies in the limited network bandwidth, which takes a certain amount of time to transmit massive data and takes a certain amount of time for the cloud center to process data, which will increase the request response time and lead to poor user experience. The push for the Internet of Things: Almost all

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electronic devices can now be connected to the Internet, and these electronic devices generate huge amounts of data. The traditional cloud computing model can not process these data in a timely and effective manner, and processing these data at the edge nodes will bring a very small response time, reduce the network load, and ensure the privacy of user data.

2.4 Edge computing is applied to high-frequency trading strategies

Edge computing and deep learning technologies have led to improvements in HFT strategies. Edge computing pushes data processing and decision making closer to the market, allowing traders to catch small price movements faster by reducing data transmission latency. At the same time, the application of deep learning models in high-frequency trading has also made significant progress. These models automatically analyze large amounts of market data, identify potential trading signals, and adjust trading strategies in real time. By combining the real-time data processing of edge computing with the intelligent decision-making capabilities of deep learning, traders are able to better grasp market opportunities and improve the efficiency and accuracy of their strategies.

$$R_i = \frac{(M_1 - M_3 + M_4 - M_2) - tax_1(M_2 + M_4) - (tax_1 + tax_2)(M_1 + M_3) - \frac{M_1 tax_3 t_i}{365}}{M_2} \#(3.2)$$

$$Final\ Returns_p = \sum R_i \#(3.3) \quad (1)$$

The strategy return formula is often used to evaluate the benefits of a trading strategy, and it relates to the cost, risk, and return of the strategy. The relationship between the edge computing trading strategy and the strategy return formula is that edge computing technology can significantly reduce the delay of data processing and trading decisions, thus helping to improve the execution speed and accuracy of the strategy. This can be achieved by reducing costs, reducing risk, and increasing the return of the strategy, thus making the various elements of the strategy's return formula more conducive to the success of the strategy. As a result, edge computing provides a powerful tool for HFT strategies to improve their performance and increase strategy returns in the actual market.

In summary, the data is transmitted from the exchange to the edge computing device, which is processed in real time to generate trading signals and execute orders. As shown in Figure 2, the deep learning model can identify potential trading opportunities through feature extraction and prediction of market data. These models can be continually learned and optimized to adapt to changing market conditions. Taken together, the combination of edge computing and deep learning provides a faster, smarter and more adaptable solution for HFT strategies, giving traders a better competitive advantage.

3 Methodology

3.1 Model Architecture

Reinforcement learning is used in most cases in the edge computing process of high-frequency trading, where the agent's goal is to maximize the cumulative return Rt:

$$R_t = r_t + \gamma \cdot r_{t+1} + \gamma^2 \cdot r_{t+2} + \gamma^3 \cdot r_{t+3} + \cdots$$

$$R_t = \sum_{k=0}^{\infty} \gamma^k \cdot r_{t+k} \quad (2)$$

Next, the model assumes that in the real market, the operation situation is complex and changeable, such as the large amount of trading capital may have instantaneous and permanent impact on the market, and investors cannot trade stocks at the closing price. In order to establish an effective market transaction model, it is necessary to appropriately simplify the transaction problem, and the following assumptions are made in this paper:

Hypothesis 1: The amount of money traded is small enough to have a shock effect on the market price.

Assume 2 that the transaction can be completed at the closing price at the closing time.

Hypothesis 3 The market does not allow short selling.

3.2 Trading model trend tracking

Trend following is a trading strategy that makes trading decisions based on changes in stock price trends. Once the trend is confirmed, the trade is carried out according to the predefined strategy, and it can be seen that trend tracking directly affects the behavior. In this paper, the trend improves the agent's behavior by adjusting the reward function, and the trend and the agent's behavior jointly decide to encourage or inhibit the trading behavior under certain conditions.

Trends are calculated using technical analysis indicators, such as Relative Strength Index (RSI), Commodity Channel Index (CCI), etc. If the trend is upward, the stock price is estimated to rise, and you should hold a long position; on the contrary, if the trend is downward, the stock price is estimated to fall, and you should close the previous long position. Since short selling is not allowed in the Chinese stock market, short positions are not considered here. In this paper, the trend is determined using the relative strength coefficient (RSI), a momentum indicator that provides an overbought or oversold signal. The value of this indicator ranges from 0 to 100, with a value below 30 indicating oversold and a value above 70 indicating overbought. The relative strength coefficient is calculated based on the stock's volatility over the previous 14 trading days.

$$\mathrm{RSI} = 100 - \frac{100}{1 + \frac{\text{average-gain}}{\text{average-loss}}} \quad (3)$$

Among them, average-gain is the average sum of the increase in the closing price within 14 days, and average-loss is the average sum of the decline in the closing price within 14 days. In order to avoid risks, when the market is overbought, the stock price is very likely to reverse down. At this time, the buying and holding behavior of the agent should be inhibited, and the selling behavior should be encouraged. The more the closing price falls on the next day, the higher the encouragement for selling behavior. On the contrary, when the market is oversold, the stock price is very likely to reverse the rise, at this time should inhibit the agent's selling and holding behavior, encourage buying behavior, and the more the closing price rises on the next day, the higher the encouragement for buying behavior.

In the transaction prediction, the value range is extended by the reward function adjusted by the trend indicator, and the agent's behavior can be feedbacks more effectively, so as to update the network. Compared with the model without adjusting the reward function, the adjusted model can identify the downside risk faster, seize the upside opportunity, and achieve the goal of maximizing profit and minimizing risk.

3.3 Analysis and comparison of experimental results

In this paper, the actions are discretized into 21 values, the action space is limited, and it is feasible to use deep Q-learning algorithm, which is composed of two neural networks with the same structure, namely, Q network and Q-Target network. The neural network is composed of three fully connected network layers, and the activation function of the fully connected layer adopts ReLU function. In the network input state, the argmax function is used to get the action from the output of the final layer. Since the network output is positive, the number of unilateral actions is subtracted from the output to get the final number of transactions. In the training stage, the ε-greedy strategy is used to select the action, that is, the agent chooses the optimal action with the probability of ε at any time, and randomly chooses the action with the probability of 1−ε. In the test stage, the current optimal action is selected completely according to the network.

In the experiment, the initial capital was set at 100,000 yuan. According to market regulations, the maximum commission for stock trading is 0.3% of the transaction amount, and the minimum commission for each transaction starts from 5 yuan. In addition, the seller needs to charge a stamp duty of 0.1% of the transaction amount. Each transaction is closed at the closing price prior to closing.

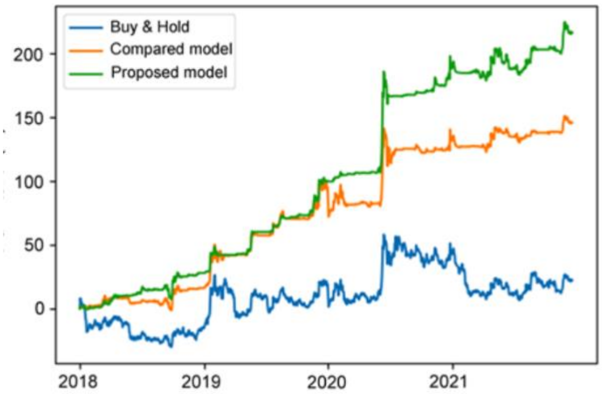

Figure 2: Cumulative returns of three investment models on 600030

The model presented in this paper will be compared with the following benchmarks. Buy & Hold, where the initial funds are invested in stocks until the end; The other is a reinforcement learning model that uses the traditional profit function as the reward function, which is different from the model proposed in this paper only in the setting of the reward function. The performance of the three investment models is reflected by the average annual return, annual volatility and Sharpe ratio during the test period.

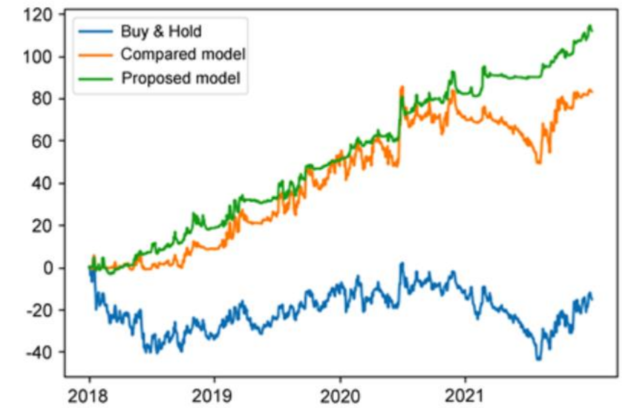

Figure 3: Cumulative returns of three investment models on 600048

Figure 2, Figure 3 and Figure 4 show the cumulative yield comparison of the three investment models in CITIC Securities, Poly Development and Conch Cement. The corresponding curve of Buy & Hold is the income generated by the Buy & Hold investment model. The curve corresponding to the Proposed model is the income generated by the reinforcement learning investment model that uses the traditional profit function as the reward function, while the curve corresponding to the proposed model is the income generated by the investment model constructed in this paper. As can be seen from the figure, the return rate of the investment model constructed in this paper is higher than that of other models, but there is no significant difference between it and the traditional model in the initial stage of the test. When the stock price fluctuates violently, the investment model in this paper can effectively deal with it, and the return curve does not produce violent fluctuations, and the return increases steadily. Then the experimental data were further analyzed.

In this paper, the stock price trend is combined with the reward function in reinforcement learning method, and the reward function is adjusted by the influence coefficient of model action and stock price under different conditions, so as to build a new deep reinforcement learning stock trading model and apply it to stock trading. In this paper, three stocks are selected in the Chinese stock market for investment experiment. The experimental results show that the model in this paper performs better than other control groups, with higher average annual return, lower annual volatility and better Sharpe ratio during the experiment period, indicating its effectiveness in stock trading and good application value. However, the model in this paper is based on some assumptions, which does not accord with the investment mode of actual investors in the market. For example, when the large trading volume has an impact on the stock price, the model in this paper is not applicable, so it needs to be further studied and explored.

4 Conclusion

This study examines the importance of High Frequency Trading (HFT) in the financial markets and the significant impact that data processing and trade execution delays have on its efficiency and effectiveness. As edge computing technology comes to the fore, we see a potential solution that can significantly reduce data processing and decision latency, thereby improving the execution speed and accuracy of HFT strategies. By moving data processing closer to the data source, edge computing technology reduces data transfer times and speeds up response times. In high-frequency trading, this means faster decision making and order execution, allowing traders to take greater advantage of small fluctuations in market prices. In addition, edge computing offers data privacy and security because data does not have to travel over a long-distance network but can be processed locally, which is particularly important in high-frequency trading where the loss or manipulation of transaction data can lead to significant risks and losses.

The ultimate goal of this research is to explore the potential applications of edge computing and deep learning in improving HFT strategies, as well as the future impact of artificial intelligence on the financial industry. By combining the real-time data processing of edge computing with the intelligent decision-making capabilities of deep learning, we are delivering faster, smarter and more adaptable solutions to HFT strategies, giving traders a stronger competitive advantage. This development represents the ongoing exploration of emerging technologies in the financial sector to improve the competitive advantage of trading strategies, and highlights the potential applications of edge computing in financial markets.

In summary, this study provides promising directions for the future development of high-frequency trading and explores the potential application of edge computing and deep learning in the financial industry to continuously improve the efficiency and reliability of trading strategies. This will have a profound impact on financial markets and traders, and open up more opportunities for future innovation in the financial industry.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Author Contributions

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