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Development and Design of an Intelligent Financial Asset Management System Based on Big Data Analysis and Kubernetes

Yicheng Peng*

Mergers & Acquisitions Practice, West Monroe Partners, New York, 10019, NY, USA

Abstract

The rise of deep learning in the financial field has led to the integration of artificial intelligence and investment, providing users with intelligent investment decisions. However, the data volume of financial market continues to expand, traditional data processing methods can no longer meet the needs of efficiency and accuracy. This article focuses on deep reinforcement learning algorithms and delves into key issues such as stock price prediction, investment portfolios, and algorithmic trading. By comparing and analyzing the experimental results, not only was the performance of the model evaluated, but also the actual effect of the algorithm output was deeply explored. At the same time, drawing on Kubernetes container orchestration and microservice technology, a high concurrency and high-performance distributed financial data analysis system was constructed. This system not only meets the needs of users for real-time data analysis and deep learning, but also provides more reasonable investment suggestions for users. The contribution of this article lies in introducing deep reinforcement learning to solve nonlinear data problems in the financial field, proposing intelligent asset management methods, and designing a feasible intelligent financial asset management system, providing new ideas and practical experience for the further development of financial data analysis platforms.

Keywords: Deep learning, Financial data analysis, Reinforcement learning algorithms, Kubernetes

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: yicheng.peng0329@yahoo.com

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1. Introduction

The rise of financial technology represents a disruptive challenge to traditional financial models. It not only brings innovation at the technical level, but more importantly, it uses big data analysis and artificial intelligence technology to redefine the form of financial services and achieve innovation and optimization of financial products and services. The integration of big data analysis and artificial intelligence technology enables the financial industry to more accurately understand market changes, user needs, and risk situations, thereby providing more personalized and intelligent services. In recent years, the field of financial technology has flourished and become a hot area pursued by global investors and entrepreneurs. Its impact is no longer limited to the financial industry, but gradually permeates all aspects of society, affecting people's production and lifestyle. With the rapid growth of financial market data, traditional data processing methods are no longer applicable, and the processing of high-dimensional data has become a major challenge facing the financial field. However, the emergence of deep learning technology provides a feasible path to solve this problem. By conducting deep learning analysis on financial data, we can more accurately grasp market trends, optimize investment portfolios, and achieve intelligent trading. Therefore, the application of deep learning in the financial field is not only a technological innovation, but also an improvement in the level and efficiency of financial services. We should be keenly aware of the opportunities and challenges brought about by this change. We need to constantly learn and adapt to new technologies, apply them to practical business, in order to improve the level and quality of financial services. Building an intelligent financial asset management system based on big data analysis and Kubernetes is an inevitable choice to keep up with the trend of the times and meet user needs. Such a system can not only optimize the execution efficiency and accuracy of financial services, but also provide users with a more personalized and intelligent financial service experience, thereby better meeting their needs and expectations.

2. Related Research

2.1. Stock trend prediction

Stock trend prediction refers to the use of historical stock prices and trading data, combined with various analytical methods and models, to attempt to predict the direction of future stock price trends. This type of prediction usually involves analyzing various factors such as the historical trend of stock prices, trading volume, market sentiment, financial data, etc., and using techniques such as statistics, machine learning, and deep learning for modeling and analysis. In their article[1], Y Lin and his team have combined traditional candlestick chart patterns with the latest artificial intelligence technology to create an innovative comprehensive machine learning framework for predicting daily stock trends. Multiple machine learning techniques, including deep learning, were utilized to analyze stock data and predict the trend of closing prices.M Sharaf et al. put forward a stock market forecasting system in the article[2], He paid attention to the impact of COVID-19 on the stock market, and used sentiment analysis technology to process stock news headlines to predict the future trend of stocks during the epidemic. The machine learning classifier is also used to analyze the final impact of COVID-19 on some specific stocks (such as TSLA, AMZ and GOOG). In the study, WGZ Chen proposed a new method that utilizes a graph convolutional feature based convolutional neural network (GC-CNN) model to predict the trend of stocks[3], which both the overall information of the stock market and specific information of individual stocks. In the article[4], M Hou and his team have proposed a new method called contrastive multiscale learning framework (CMLF) to address the challenge of a large amount of fine-grained information, including high-frequency data. This framework can provide more detailed investment signals, thereby improving prediction performance.

2.2. Algorithmic trading

Algorithm trading refers to a trading method that utilizes computer programs to execute trading strategies. These programs automatically execute transactions based on pre-set rules and conditions, without the need for manual intervention. In the article[5], N Majidi et al. proposed a method using double delayed DDPG (TD3) and daily closing prices to implement trading strategies in the stock and cryptocurrency markets. Frattini et al.[6]introduced a two-step trading algorithm called TI SiSS in their article. By combining trend indicators with other technical analysis indicators, we determine the automatic rules for buying/selling signals.

2.3. Container based Distributed System Architecture - Kubernetes

Kubernetes, commonly referred to as K8s, is an open-source container orchestration engine dedicated to the autonomous deployment, expansion, and monitoring of containerized applications. It provides a highly scalable platform that can manage containerized applications on multiple hosts, enabling these applications to run efficiently, self repair, and maintain stability. K Leiter discussed in the article how to use Kubernetes Operators to implement Netconf based configuration management, and based on the GitOps principle, demonstrated in detail the significant effects of this network management method[7]. NNC Zhu et al. stated in the article[8] that as one of the widely adopted open-source container orchestration systems, it provides built-in mechanisms such as HPA for dynamically adjusting resource allocation, thereby achieving self-regulation and optimization of the system. M Imran summarized various storage options implemented for the CMSWEB cluster in his paper, and considered different storage solutions in the Kubernetes infrastructure to meet the needs of the cluster[9]. All CMSWEB services require a persistent log storage solution, and some services also require data storage. Prasanna J et al.[10]used the Kubernetes orchestration platform to perform multiple tasks simultaneously and for parallel processing of multiple tasks. This improves the efficiency of the machine and the performance of the system becomes faster.

3. Method

3.1. System Requirements Analysis

In the analysis of system requirements for intelligent asset management systems, we first need to focus on the functional requirements of the system. These requirements include four main functional modules: personal asset management, stock data management, index data management, and fund data management. The personal asset management module, as the core function of the system, should provide users with the ability to manage their personal investment portfolios and have the ability to intelligently analyze, recommend, and support decisions. Other modules also need to provide real-time collection, storage, processing, and analysis functions for various financial data to support the data requirements of the personal asset management module. When designing functions, it is necessary to consider the accuracy, real time execution capability, and processing efficiency of the system. The overall system structure diagram is shown in Figure 1.

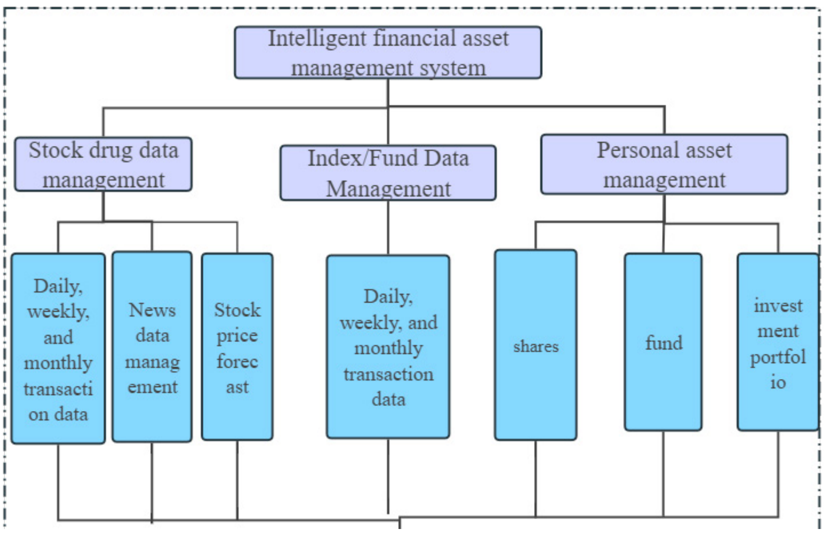

Figure 1. System overall structure diagram

In terms of non functional requirements, the efficiency, reliability, and maintainability of the system are crucial. The system needs to have high data processing and analysis capabilities to ensure stable performance even in high concurrency situations. At the same time, the system must have high availability and data integrity to ensure that users' assets and transaction information are not damaged or tampered with. In addition, the system also needs to have good maintainability, be able to update and expand flexibly to adapt to constantly changing financial markets and user needs. Therefore, in the process of system design and implementation, it is necessary to comprehensively consider various factors to ensure that the system can meet real needs of users and has good performance and availability.

3.2. Architectural design

The system architecture is specifically divided into five design levels, namely the access layer, interface layer, service layer, containerization layer, and data layer. The system architecture diagram is shown in Figure 2.

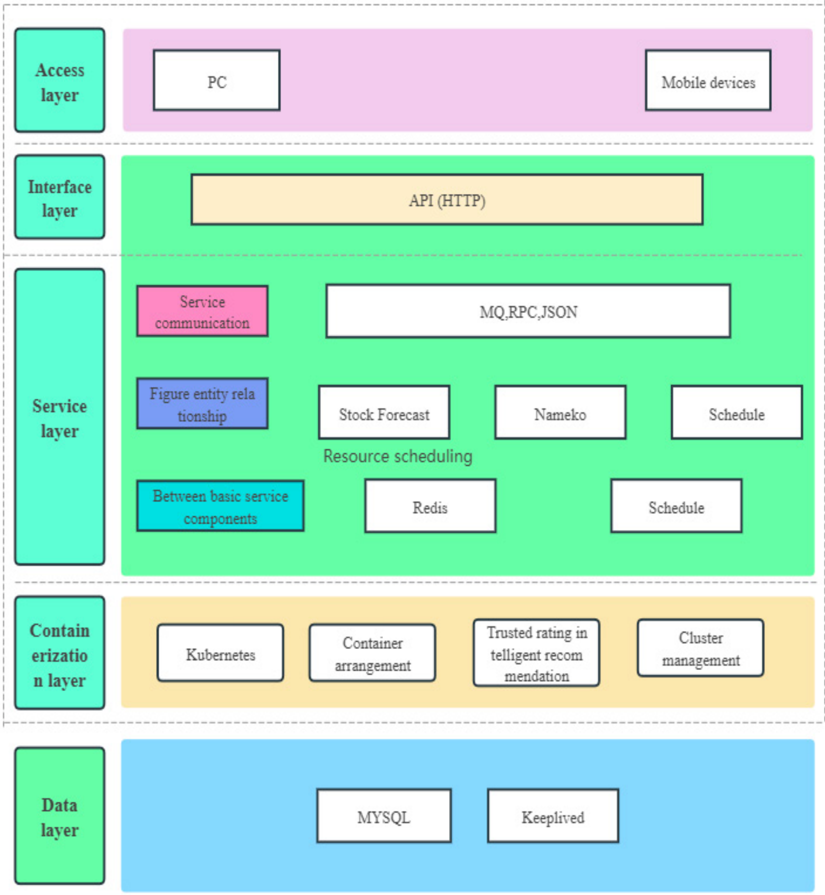

Figure 2. System architecture diagram

3.3. Kubernetes architecture

Kubernetes, as a Docker based distributed architecture, plays a crucial role in modern software development and deployment. Its emergence greatly simplifies the management and operation of applications, without the need to pay too much attention to underlying infrastructure details. Its rapid deployment and automated scalability provide a solid guarantee for the high availability and elasticity of applications. And it has good scalability, which can meet the constantly growing business needs and complexity.

Kubernetes is based on the main database data and effectively virtualizes computing, storage, and network resources through virtualization technology, ensuring the stability and reliability of the system. As a management platform for container applications, Kubernetes has powerful monitoring and scheduling capabilities, which can monitor and adjust the running status of Pods in real time, ensuring the efficient and stable operation of system algorithm modules. In practical applications, the high availability of Kubernetes is mainly reflected in the stability of etcd data storage and Kubernetes master components, providing reliable basic support for the system.

3.4. Functional module design

This system is designed for real-time storage and big data analysis of data in the financial industry, using deep learning methods to establish decision-making and prediction models, and intelligently processing stock price trends and asset management functions. By integrating intelligent algorithms, we have achieved intelligent solutions in various aspects such as price prediction, portfolio management, and algorithmic trading, providing users with comprehensive financial services. The functional module design diagram is shown in Figure 3.

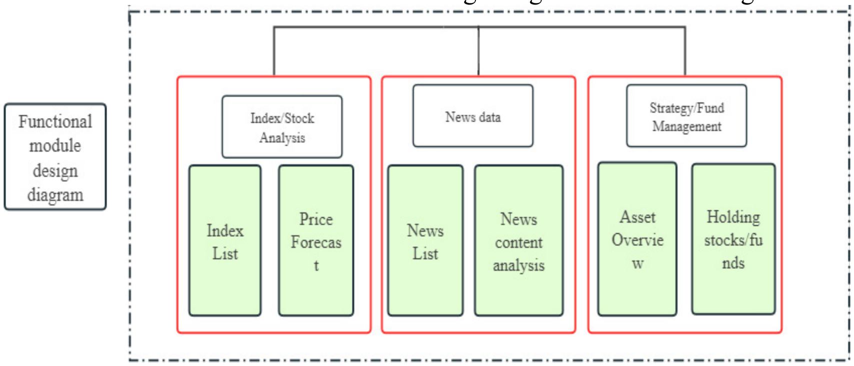

Figure 3. Functional module design diagram

The system integrates major global indices and provides comprehensive analysis of market trends through index analysis modules, providing investors with comprehensive market information. The stock analysis module includes individual stock analysis, rise and fall analysis, and stock price prediction, presenting detailed trading data and news information in the form of charts, providing users with a deeper understanding. The news data analysis module displays the latest stock market trends, which helps users obtain information in a timely manner. The trading strategy module supports users to create and execute trading strategies, and evaluates their effectiveness. The asset management module achieves optimal allocation of funds through portfolio management algorithms.

4. Results and Discussion

The comparison results of the models show that the GRU network based on Attention performs slightly better than the LSTM neural network, mainly in two aspects: fast training speed and small model error. The comparison of GRU prediction performance based on attention mechanism is shown in Figure 4.

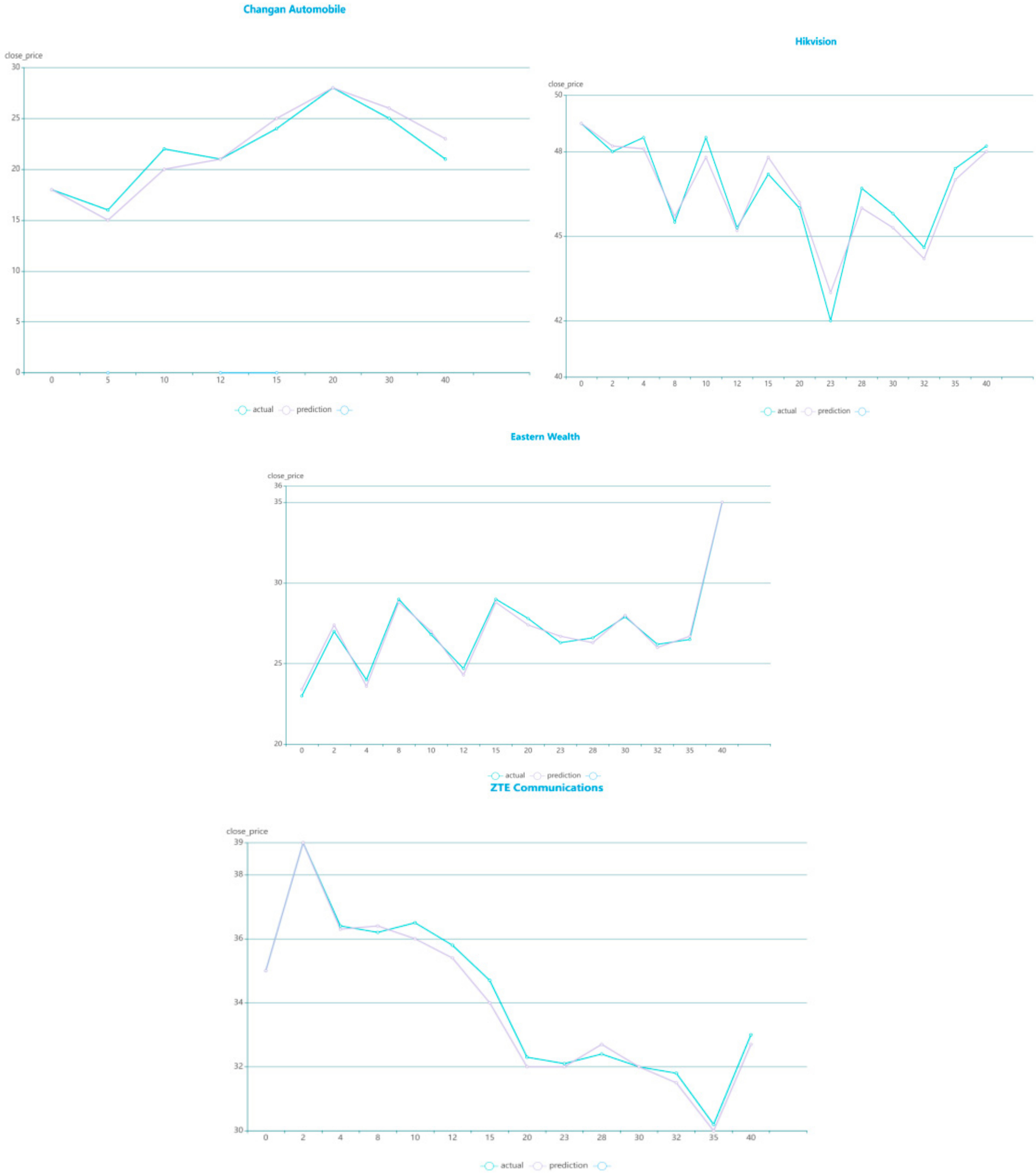

Figure 4. GRU prediction performance based on attention mechanism

This study used a binary classification prediction algorithm to predict the default and non default values of the samples, and evaluated the training effectiveness of the model by comparing it with the actual situation. The results showed that the model performed well in terms of accuracy, precision, recall, and F1 score, with an accuracy of 97.64%, an accuracy of 98.35%, a recall of 98.76%, and an F1 score of 98.55%. This indicates that the model can achieve high accuracy and reliability in predicting default and non default samples. In addition, the AUC value is

0.97 and the KS value is 0.63, indicating that the model has good ability in classifying default and non default samples, and can effectively distinguish between the two types of samples, as shown in Table 1.

Table 1. Functional test results

Number	content	test result	conclusion
1	HA deployment topology	Successfully installed cluster	Infrastructure successfully built
2	Adding/deleting nodes	Successfully added/removed node	Pod management function successful
3	Upgrade/Remove Cluster	Upgrade/deletion successful	Pod management function successful

According to the model we have trained, we have conducted early warning for 81 Internet financial listed companies. Please refer to Table 2 for specific classification results.

Table 2. Performance test results

Number	content	test result	conclusion
1	Starting multiple Pods in a cluster	Utilization rate<75%, startup time is about 2 seconds; Utilization rate>75%, startup time approximately 7 seconds	Can meet daily usage needs
2	Multiple clients accessing simultaneously	Utilization rate>80%, can access 10 clients simultaneously	Can meet daily usage needs

5. Conclusion

This study aims to integrate deep learning technology with financial business to solve complex problems in the financial field. We have designed and implemented an intelligent financial asset management system to meet the growing data processing needs of the financial market. Explored the background and significance of intelligent financial asset management, and examined the research status of deep reinforcement learning technology in the financial field at home and abroad. In terms of algorithms, deep reinforcement learning is applied to the analysis and prediction of financial market volatility trends, and an intelligent asset management method is proposed, which achieves effective asset allocation and trading through intelligent portfolio management. And a highly available and high-performance distributed architecture financial asset management system was designed, fully utilizing Docker containerization virtualization technology and Kubernetes container orchestration technology. We have introduced a continuous integration solution and conducted comprehensive functional and non functional testing to ensure the efficiency and stability of the system. In the future, we will strengthen the comprehensive analysis of factors such as news and public opinion, and further improve the monitoring and management module of the system to adapt to the rapid changing needs of the financial market.

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