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Financial Market Trend Prediction Based on Big Data and Deep Learning Algorithms

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ABSTRACT
Driven by deep learning technology, the financial market is becoming more and more advanced. Therefore, this study aims to introduce a financial market forecasting algorithm based on deep learning technology to solve the difficulty and unpredictability of dealing with financial data in the financial market. To this end, this paper first obtains a variety of data sources related to the financial market, such as stock prices, trading volume, market index and so on, and data cleaning and feature engineering are carried out. Then, the time series problem is solved by constructing a deep learning model based on GRU. In the model training stage, efficient model storage strategy and extensible distributed model training are adopted, and the model optimization stage begins with cross-validation strategy and early stop method. The analysis part of this paper further verifies the correctness of the model in the analysis of historical data, in which the minimum Mean Squared Error (MSE) is 0.06 in the best case and the maximum determination coefficient is 0.98 in the worst case, which shows that the model has good accuracy and reliability. The part of model sensitivity analysis (parameter sensitivity) also proves that the proposed model has strong stability and robustness at different learning rates. The conclusion part emphasizes once again that the prediction model based on big data and deep learning in this study is effective for experimental data, and provides traders, investors and analysts with a reliable source of further insights.

KEYWORDS
Financial market trend forecasting; Big data; GRU model; Investment strategy

1 Introduction

Predicting market trends from financial markets is a basic task for investors, analysts and policy makers. With the rapid development of big data technology and the maturity of deep learning algorithms, forecasting financial market trends is more accurate and efficient. Big data provides a lot of historical and real-time data, while GRU models the complex patterns and long-term dependence of financial markets.

In this paper, a new approach to analyze and process data and build a GRU model for predicting financial market trends through deep learning algorithms and big data is proposed. The model can utilize the long-range correlation of time series data to provide a deeper understanding of the dynamic process of financial markets.

The first part of the paper is the introduction, which introduces the concept of forecasting

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financial market trends, as well as the progress and significance of big data and deep learning technology. The second part is related work, which introduces the tradition and related research of financial market forecasting. The next part is methodology, which describes the source of data and preprocessing methods, the composition of the model and how to train and test the model. The fourth part is Results and Discussion, which shows the results of model performance analysis, performs parameter sensitivity analysis, and discusses the potential value of the model in practical applications. The fifth part is the conclusion, which summarizes the main findings, contributions and future research directions of this study.

2 Related Work

In the financial field, accurate prediction of market trends is crucial for investors and analysts. Aiming at the problem of large deviation of prediction results of long and short-term trends of financial market by current methods, Gao Xia collected financial data according to a certain time interval, generated time series of financial data, processed the time series of financial data using wavelet analysis, removes the noise in it, and retained the approximate data, and put forward a method of predicting the trend of financial market based on machine learning [1]. Dai Yurui utilized discrete wavelet transform to perform noise reduction on the original financial stock index series, and then used variational modal decomposition to further decompose the noise-reduced data into a number of sub-sequences. Then, he combined the multivariate fundamental features and used the attention-based Conditional Bidirectional Long Short-Term Memory network model to make multi-step predictions for each sub-sequence, and finally added up the prediction results to get the final results, which realized the longer-term financial market trend prediction [2]. Liu Bo collected the historical sample data of financial market trend changes, and pre-processes the sample data to a certain extent. He used the deep neural network model in machine learning algorithm to model the historical data, combined with the artificial immune algorithm to optimize the parameters of the deep neural network prediction model, constructed the financial market trend prediction model, and output the optimal solution [3]. Ma Feng reconstructed several new heterogeneous autoregressive realized volatility models based on a variety of volatility decomposition methods and embedded in combination with Markov mechanism models in the complex and changing financial market environment [4]. Considering that the financial data had asymmetric and spiked thick-tailed characteristics, Chen Zhenlong extended the Burr distribution with spiked thick-tailed characteristics to the bilateral Burr distribution, gave its important numerical characteristics, great likelihood estimation, least-squares estimation, and weighted least-squares estimation, and verified the validity of the three parameter estimation methods through numerical simulation [5].

In addition, Ananthi M used predicted stock prices and datasets collected from various sources about specific stocks to predict the overall trend of stocks [6]. Javed Awan M used big data analytics to process and analyze large amounts of data on social media and explored how social media data can be used as part of big data analytics for predicting trends in the stock market [7]. Wu J M T proposed a new framework structure for the characteristics of financial time series and price forecasting tasks to achieve more accurate forecasting of stock prices [8]. Milana C reviewed and analyzed the existing literature on the application of AI in finance and discussed how these techniques can improve the efficiency and effectiveness of financial activities [9]. Yan X used Long Short-Term Memory to model and predict financial data [10]. The purpose of this paper is to study and propose a financial market trend prediction method based on big data and deep learning algorithms. This study will consider the complexity, variability, and real-time demand of financial market data, and construct a more accurate and efficient prediction model by fusing multiple data sources and employing advanced deep learning techniques.

3 Method

3.1 Data Collection and Preprocessing

When exploring the prediction of financial market trends based on big data and deep learning algorithms, the data collection covers all kinds of financial indicators obtained from diversified channels such as stock exchanges, financial data service providers and public data platforms, which not only include basic data such as stock prices and trading volumes, but also extend to more macroeconomic parameters such as market indices, interest rates, exchange rates, etc. [11-12]. In the face of the huge volume of data in the big data environment, adopting efficient storage and processing strategies can ensure the manageability and analyzability of data. As shown in Table 1, it is the collected financial data:

Table 1 Financial data

Date	Stock Code	Open	Close	Volume	Market Cap. (Billions USD)	VIX (Volatility Index)	CSI 300 Index	1-Year Treasury Rate (%)	Exchange Rate (USD)
2024-05-01	000001.SZ	10.50	10.75	150,000	5.2	15.2	4500	1.50	6.30
2024-05-02	000002.SZ	20.00	19.80	180,000	4.8	14.8	4480	1.51	6.31
2024-05-03	000003.SZ	30.20	30.45	200,000	6.0	14.5	4520	1.52	6.32
2024-05-04	000004.SZ	40.10	40.30	250,000	7.3	14.9	4550	1.53	6.33
2024-05-05	000005.SZ	50.50	51.20	300,000	8.6	15.3	4580	1.54	6.34
2024-05-06	000006.SZ	60.75	60.90	350,000	9.1	15.7	4600	1.55	6.35

Table 1 shows the collected financial data, which provides a multi-dimensional view of the financial market, including the date, stock code, opening price, closing price, trading volume, market capitalization, volatility index, CSI 300 index, one-year treasury bond interest rate, and exchange rate, etc. By analyzing these data, we can better understand the market dynamics, predict the market trend, and formulate the corresponding strategies accordingly.

In terms of data preprocessing, the collected raw data are thoroughly cleaned to remove or correct missing values and outliers in the data in order to improve the data quality. In addition, feature engineering becomes a key step in improving the performance of the model, which involves extracting the most critical features for the prediction task from the raw data and includes the creative generation of new features.

In addition, due to the inherent time series characteristics of financial market data, in order to capture the time correlation, the sliding window technology is applied, and the characteristics reflecting the time dynamics are constructed by using a specific time series analysis method. From data collection and pretreatment to model training, etc., the professionalism and rigor of investment directly determine the effect of subsequent model training and the accuracy of prediction. The stage of data preparation and pretreatment lays the foundation for the model, and then this foundation produces better predictions, which can be more stable in the unstable, fluctuating and complex fields of financial market trend prediction [13-14].

3.2 Deep Learning Model Construction

In the study, GRU is adopted as the model framework [15-16]. GRU can deal with the problem of long-range correlation, control the information flow by introducing update gates, and reduce the number of model parameters while maintaining its effectiveness in time series data. The formula for updating gate z_t is:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{1}$$

σ is the activation function, W_z is the weight matrix, h_{t-1} is the hidden state of the previous time step, x_t is the input of the current time step, and b_z is the bias term.

In designing the model architecture, two GRU layers, each containing 128 units, are used, aiming to capture short-term and long-term dependencies in financial market data, and the GRU layer automatically learns dynamic features in the data, such as price fluctuations trading volume changes. The output layer of the model uses a fully connected layer to map the learned features to the final prediction, and the output layer for stock price prediction contains a node that predicts the price at the next time step using a linear activation function. Among them, the candidate hidden state $\widetilde{h}_t$ is calculated as:

$$\widetilde{h}_t = \tanh(W \cdot [h_{t-1} \odot r_t, x_t] + b) \tag{2}$$

W is the weight matrix of the candidate hidden state, r_t is the reset gate of the current time step, b is the bias term of the candidate hidden state, and $\tanh$ is the hyperbolic tangent activation function for introducing nonlinearity.

The formula for the final hidden state h_t is:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h}_t \tag{3}$$

In terms of parameter setting and optimization strategy, the initial learning rate is set to 0.001. Adam optimizer is used to adjust the learning rate based on the gradient variance and the first moment of adaptive estimation, and large-scale data sets are processed. The batch size is set to 64 to improve the efficiency of memory use and reduce the noise during training. The number of iterations is set to 100 according to the performance of the verification set, but the loss of the verification set is monitored by the early stop method to prevent the model from over-fitting. The loss function adopts mean square error, which is suitable for regression task.

3.3 Model Training and Validation

In order to realize the effectiveness and generalization ability of the financial market trend prediction model, firstly, the data are divided into training set, verification set and test set. After segmentation, the input is normalized to make the training of the model stable and converge quickly. Because financial data depends on its time series data, cross-validation method is applied to its verification. The model evaluates the performance, including MSE, determination coefficient and other evaluation indicators. These indicators can explain the prediction accuracy of the model and the extent to which the model can explain the change of data. The main purpose is to optimize the performance of the model by using the feedback from the model evaluation in the verification set; the performance indexes of the model include learning rate, batch size, number of layers and number of neurons. Techniques such as learning rate attenuation and early stop are used to monitor the training process to ensure that the model will not fall into local optimum and maintain performance improvement.

4 Results and Discussion

4.1 Model Performance Analysis

The data set will be divided into time series, and then the prediction performance of the model will be quantified by the mean square error MSE and the determination coefficient. The lower MSE value and the determination coefficient value close to 1 show that the model has better prediction accuracy.

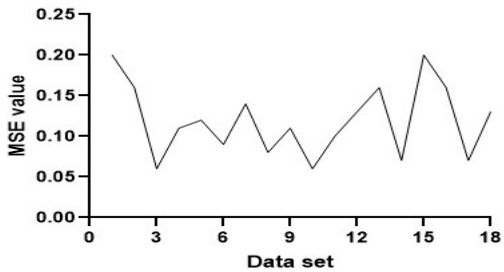

Figure 1 MSE values

According to Figure 1, the MSE values of the GRU model are all kept at a low level, reaching a minimum of 0.06. The low MSE values imply that the differences between the model predicted values and the actual observed values are small, thus verifying that the GRU model shows high accuracy and stability in the time series forecasting task.

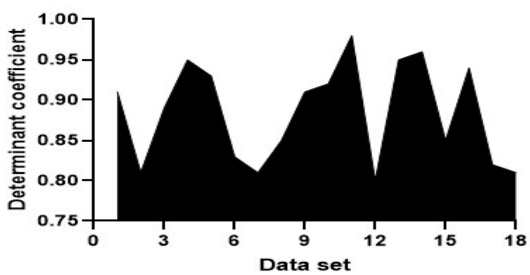

Figure 2 Determination coefficient

The values of the coefficient of determination in Figure 2 are kept at a high level, with the highest reaching 0.98. In financial market trend forecasting, reaching a high value of the coefficient of determination implies that the model is capable of accurately predicting the changes in the market indices or stock prices, and a high value of the R^2 also implies that the model has a more in-depth understanding of the underlying market mechanisms and is capable of revealing the root causes of the price movements.

4.2 Parameter Sensitivity Analysis and Model Robustness Testing

Parameter sensitivity analysis focuses on evaluating the impact of key parameters on model performance, which include learning rate, batch size, number of network layers and neurons, regularization coefficients, and optimizer selection. Adjusting the learning rate observes the convergence speed and stability of the model, while changing the batch size affects the memory usage efficiency and training speed. Increasing the number of network layers and neurons may enhance the learning ability of the model, but it may also lead to overfitting, dropout regularization technique helps to control the model complexity and prevent overfitting, while different optimizers have different impacts on the training efficiency and final performance of the model. As in Figure 3, the values of root mean square error for different learning rates are shown:

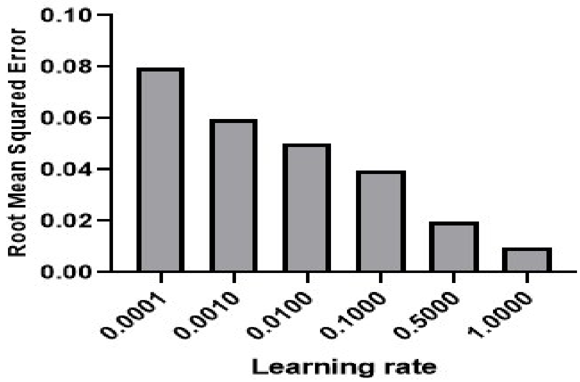

Figure 3 Root Mean Square Error

As can be seen in Figure 3, the root mean square error is at its lowest value of 0.01 when the learning rate is 1. This result indicates that at this particular learning rate, the difference between the predicted and actual values of the model is minimized, and the model exhibits the best prediction performance.

4.3 Practical Application Scenarios

Financial market trend prediction models can provide investors with insights into the future trend of the market, helping to formulate more scientific investment strategies, such as increasing or decreasing investment in an asset based on the model's prediction results, or looking for hedging opportunities when the market is predicted to fall. At the same time, applying the model in the field of risk management is helpful to predict potential market fluctuations and extraordinary events, adjust the investment portfolio in time and reduce potential losses. By accurately predicting market trends, risk managers can better evaluate market risks and formulate appropriate risk response measures. In addition, GRU model can be integrated into quantitative trading system to automatically trade assets. The predictive results of such a model can be utilized as the trade signal to assist in algorithmic trading (buying and selling of assets, and make the trade more efficient and profitable), it can also be combined with a big data analysis to analyze market sentiment, providing some predictions as to how market sentiment and investor behavior may be driving market trends. That is the key to understanding the market dynamics and making decisions on investments. Also, regulators can use this predictive model about market trend to monitor suspicious market trades, prevent market price manipulation and fraudulent market actions, and safeguard the fairness and transparency of market trades.

5 Conclusion

The newly proposed financial market trend prediction method from this study significantly improves the predictive accuracy and efficiency by integrating multiple financial data and utilizing the GRU model. The study highlights the importance of high-quality data in financial market trend prediction. The GRU model experimental data includes diverse time series financial data, such as of stock price, trading volume, market index and are collected and combined from various databases. By designing the GRU with two GRU layers, the long-term data correlation in time series data is effectively handled, and the ability of our model to model the short-term and long-term correlation of financial markets is improved. The study further uses a number of methods, such as data preprocessing, data processing, cross-validation, early stop, and sensitivity analysis to enable that the model can make predictions with high accuracy, robustness under different learning rates, and best performance. Furthermore, this study further explores the actual application scenarios in the financial market predictions of the model, including investment strategy, risk management, quantitative trading systems, and market sentiment analysis to illustrate the prospect of a wide range of model applications. Although the results of this study have been significantly successful, there are inevitably future directions for further research to be explored, including further optimizing the model parameters, exploring more financial data sources, improving the generalization ability of the model, and adapting the financial market that is constantly changing.

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