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Analysis of Stock Price Forecasting Methods based on LSTM Models

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Abstract

In the context of today's global economic integration and the dynamic changes in the financial market, the volatility and uncertainty of the stock market have profound impacts on investors, businesses, and policymakers. Traditional technical analysis and fundamental analysis are no longer sufficient to meet the demand for an in-depth understanding of market dynamics. Therefore, exploring more scientific and precise forecasting methods is particularly important. This study focuses on stock price prediction research based on the Long Short-Term Memory (LSTM) machine learning model and optimizes the LSTM model by constructing and analyzing complex networks in the stock market to obtain trait data of the main net inflow complex network. This study constructs a traditional LSTM model to predict historical price data of individual stocks. The model employs a two-layer Long Short-Term Memory (LSTM) network architecture and uses the Adam optimization algorithm along with Mean Squared Error (MSE) as the loss function for training, to measure the model's accuracy in predicting stock prices. Subsequently, this study constructs a complex network of the stock market. Pearson correlation coefficients are obtained from the main force purchase data to build an unweighted correlation network, and key features of the network, such as node degree and betweenness centrality, are extracted. These features, after normalization, form a new set of input features. The study then incorporates the extracted complex network feature data as variables into the traditional LSTM model. The new model structure includes the input layer, hidden layers, output layer, and adapted feature set. During the model training process, batch normalization and Dropout techniques are used to enhance the model's generalization ability. Experimental results show that the improved model has significantly reduced prediction errors in multiple time windows. The innovation of this study lies in combining complex network analysis data with the LSTM model, focusing on the internal structural characteristics of the stock market while emphasizing the dynamics and real-time nature of market forecasting. Additionally, Independent Component Analysis (ICA) is used for preprocessing market data, reducing noise interference, and improving the accuracy of the prediction model.

Keywords

LSTM Model; Complex Network Theory; Stock Market Prediction; Independent Component Analysis (ICA).

1. Introduction

Financial markets are dynamic systems where changes can have profound impacts on investors, businesses, and policymakers. Traditional analytical methods often fall short in capturing the complexity of these markets. This paper explores an advanced method combining LSTM neural networks with complex network theory to predict stock prices more accurately. By focusing on the internal structure and dynamics of the market, this research contributes new insights into

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financial forecasting. Specifically, we aim to explore the complex network structures within the stock market, construct a more accurate stock price prediction model, analyze information transmission mechanisms, optimize risk management and asset allocation, and ultimately improve prediction accuracy.

By incorporating complex network data, the model can capture the interdependencies among stocks and the overall dynamics of the market, thereby providing richer feature information. These features include the degree of nodes, betweenness centrality, closeness centrality, and clustering coefficients, which reflect the interactions among stocks and the mechanisms of information transmission. They enable the model to more comprehensively understand market dynamics. The additional information provided by complex network data allows the model to learn more about the market structure, rather than relying solely on the historical data of individual stocks, thereby enhancing the model's generalization ability.

By constructing complex networks using net buying data of major players, the model incorporates sentiment and behavioral patterns of market participants. Net buying data not only contain historical price information of stocks but also reflect the main capital flows and changes in investor sentiment. Integrating these sentiment features into the LSTM model enables it to more comprehensively understand market sentiment, thereby improving prediction.

To adapt to the integrated feature set, the structure of the LSTM model has been adjusted, including an expanded input layer, modified hidden layers, and an improved output layer. These adjustments enable the model to better process and utilize complex network data, enhancing prediction performance. During model training, techniques such as Batch Normalization and Dropout have been introduced to improve the model's generalization and robustness. These techniques are particularly effective in handling sentiment features, which are often highly volatile and uncertain.

2. Methodology

2.1. Data Preprocessing

We selected stocks from the CSI 300 Index covering the period from April 2020 to April 2024. To ensure data stability and consistency, we excluded suspended stocks and ensured all chosen stocks remained part of the CSI 300 throughout the study period. Preprocessing steps included handling missing values, outliers, and normalization to scale data between [0, 1], improving model convergence speed. We utilized Wind's stock data interface to crawl relevant stock information and prepared modules for data reading, preprocessing, model building, and plotting.

Table 1. Partially Selected Stocks

000001.SZ	002236.SZ	300661.SZ	600372.SH
000002.SZ	002241.SZ	300750.SZ	600406.SH
000063.SZ	002252.SZ	300751.SZ	600426.SH

2.2. Construction of Complex Networks

For each trading day within our dataset, we constructed a complex network based on the previous year's principal net buying data. A Pearson correlation coefficient matrix was calculated for pairs of stocks over the preceding year. Using a threshold value of 0.5, we connected stock pairs with correlations exceeding this threshold, forming unweighted edges in the network. Key topological features extracted include node degree, closeness centrality, betweenness centrality, and clustering coefficient, which serve as inputs to the LSTM model.

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These features provide rich information about the interactions and information flow among stocks, enhancing the model's feature representation capability.

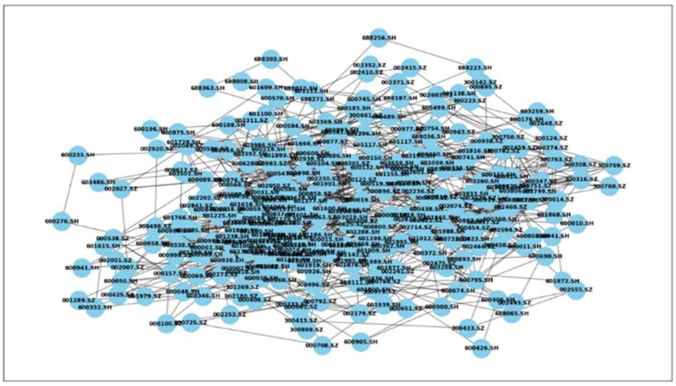

Figure 1. Unweighted complex network graph with a threshold of 0.5

2.3. Model Building

The extracted complex network features were fused with preprocessed stock time series data to form a new input feature set. This fusion enables the model to learn not only individual stock behaviors but also their collective patterns, thereby enhancing predictive power.

Traditional LSTM Model: A two-layer LSTM architecture was used to predict single-stock historical price trends. The model employed Adam optimization algorithm and MSE as the loss function for training.

Enhanced LSTM Model: In addition to the traditional LSTM model, we incorporated complex network features into the input layer, adjusted the hidden layers, and improved the output layer. Batch Normalization and Dropout techniques were introduced to boost generalization and robustness.

Data were divided into training and testing sets at an 80:20 ratio. Initial learning rate was set to 0.001, with momentum decay rates of 0.9 and 0.999 for first and second moments, respectively. Mini-Batch training combined with Adam optimizer was applied to update parameters iteratively. Gradient calculations through backpropagation minimized the MSE loss function.

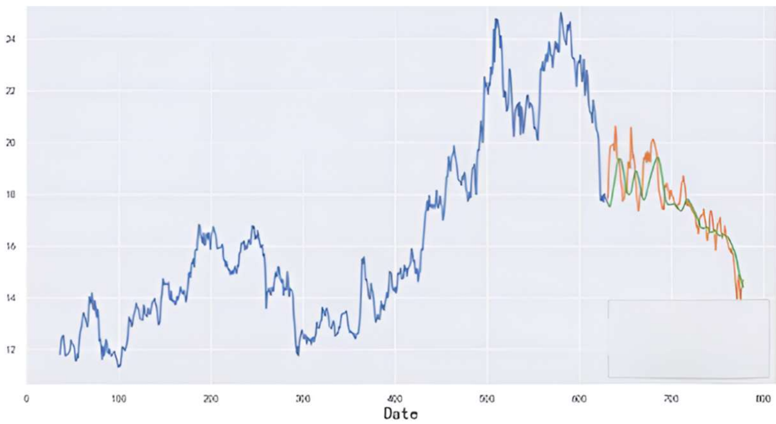

Figure 2. Comparison of Training Results of the Traditional LSTM Model with Actual Values

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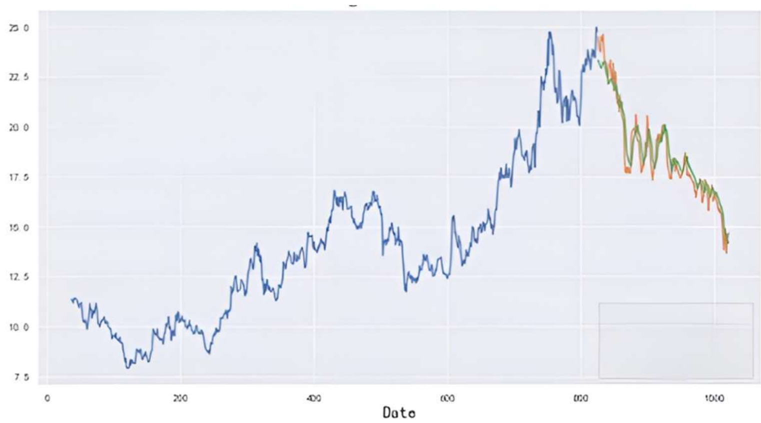

Figure 3. Comparison of Training Results of the LSTM Model with Integrated Complex Network Data and Actual Values

In the figure, the blue line represents the training data, the orange line represents the actual data, and the green line represents the model's predicted data.

2.4. Acknowledgment

I would like to express my sincere gratitude to my mentor, Professor Yuan, for his invaluable guidance and support throughout the research process. His expertise and encouragement have been instrumental in shaping this work. I am also deeply thankful to my alma mater, Hangzhou Dianzi University, for providing an excellent academic environment and resources that have nurtured my growth.

3. Literature References

In recent years, machine learning technologies have made significant progress in the field of stock price prediction, enhancing the accuracy of predictions and the understanding of market fluctuations. Chen L [1] et al. constructed a stock price prediction model using BP neural networks and validated the model's effectiveness through experiments, demonstrating that neural networks can predict stock prices relatively well. Wavelet analysis, which refines and decomposes data through scaling and translation functions, can effectively process and model data in both high-frequency and low-frequency ranges. Du G and Hu Z [2] combined neural network systems with wavelet analysis methods by embedding wavelet analysis into relevant network models, creating a wavelet neural network model. This method, which integrates the strengths of wavelet analysis and neural networks, has achieved high prediction accuracy and has been recognized by the academic community.

In recent years, Lai Y and Hu Y [3] and his team have developed a deep learning-based multi-task model for stock price prediction. Using this model, they constructed a corporate knowledge graph and event database with financial entity recognition methods and other techniques, and proposed an event-driven stock price prediction model. The study revealed the impact of favorable information on stock prices, and the results showed that the model can effectively predict stock prices and demonstrated excellent performance in multi-task prediction

4. Conclusion

T This study has shown that integrating LSTM networks with complex network analysis can significantly improve stock price prediction. Such advancements offer valuable guidance for investors seeking more reliable investment strategies. Moreover, they contribute to the broader field of financial modeling by introducing novel approaches that account for both temporal and structural aspects of the market. The improved prediction accuracy and

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robustness of the model provide a solid foundation for further research and practical applications in financial technology and artificial intelligence.

In order to improve the accuracy of the model, this study adopted a manual parameter tuning strategy. Although this approach avoided the potential imprecision of parameters that may arise from traditional grid search methods, it also increased the workload of the research. This indicates that significant improvements were not achieved in the method of model parameter selection in this study. Future research could consider introducing more advanced automated parameter tuning techniques, such as Bayesian optimization, to reduce the workload and potentially discover better parameter combinations.

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