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Research on the Construction and Dynamic Optimization of a Quantitative Investment Model Based on LSTM-ElasticNet Hybrid Architecture

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ABSTRACT
With the explosive growth of financial market data and the significant improvement in computing power, the application of deep learning technology in the field of quantitative investment has gradually attracted attention. This paper aims to construct a deep learning-based quantitative investment model that achieves precise capture of stock market investment opportunities by integrating multiple financial factors and deep learning algorithms. The paper first introduces the basic concepts of quantitative investment and the current status of deep learning applications in the financial field. It then elaborates on the construction process of the deep learning-based quantitative investment model, including data preprocessing, feature engineering, model training, and optimization. Through empirical analysis, the effectiveness of the model in stock market investment is verified, and the performance differences of different deep learning algorithms are compared. The research results show that deep learning models can significantly enhance the return performance and risk control capabilities of quantitative investment strategies, providing new research directions and practical tools for the field of quantitative investment.

KEYWORDS
Quantitative investment; Deep learning; Feature engineering; Model optimization; Empirical analysis

1 Introduction

Quantitative investment is a method of making investment decisions through mathematical models and computer programs, with its core lying in using mathematical and statistical tools to analyze financial market data and identify potential investment opportunities. Over the recent years, as artificial intelligence technology has advanced by leaps and bounds, deep learning, as a powerful data analysis tool, has begun to be applied in the field of quantitative investment. Deep learning models can automatically learn complex patterns and relationships in data, providing new ideas and methods for quantitative investment. The research goal of this paper is to construct a deep learning-based quantitative investment model and verify its effectiveness through empirical analysis. The main contribution of this paper is to propose a new investment strategy that combines deep learning with traditional quantitative investment methods and verify its application value in actual investment through experiments.

2 Theoretical foundation

2.1 Overview of quantitative investment

Quantitative investment is an investment method based on mathematical models and algorithms, with its core being the use of computer programs and mathematical models to analyze financial market data and identify potential investment opportunities. The notable benefits of quantitative investment include the ability to process large amounts of data quickly, avoid interference from human emotions, and improve the efficiency and accuracy of investment decisions. Quantitative investment strategies typically include multi-factor models, event-driven strategies, statistical arbitrage, etc. Investment portfolios are developed through multi-factor models, which scrutinize various elements influencing stock values, including price-to-earnings ratio, price-to-book ratio, momentum, and more. for achieving surplus profits. Strategies centered on specific events, like mergers, acquisitions, and restructurings, concentrate on their effects. regarding stock values and strategize in advance to secure profits by forecasting event occurrences and outcomes. Statistical arbitrage strategies use statistical methods to analyze the correlation between stock prices and construct hedging portfolios to obtain risk-free returns.

2.2 Applications of deep learning in quantitative investment

Deep learning is an important branch of artificial intelligence, with its core being the learning of complex patterns and relationships in data through the construction of multi-layer neural networks. Deep learning models have strong feature learning capabilities and can automatically extract useful features from raw data without manual feature engineering. In recent years, deep learning has achieved remarkable results in fields such as image recognition and natural language processing, and its applications in the field of quantitative investment have gradually attracted attention. Deep learning models can discover potential investment opportunities by analyzing complex patterns in financial market data. For example, Recurrent Neural Networks (RNNs) and their variants Long Short-Term Memory networks (LSTM) and Gated

Recurrent Units (GRU) can be used to process time-series data in financial markets and predict future trends in stock prices. Convolutional Neural Networks (CNNs) can be used to analyze spatial features in financial market data and extract correlations between stock prices. In addition, deep learning models can be combined with other quantitative investment methods, such as multi-factor models and event-driven strategies, to further enhance the performance of investment strategies.

3 Construction of deep learning-based quantitative investment model

3.1 Data preprocessing

The preprocessing of data plays a crucial role in developing quantitative investment models, with the goal of transforming unprocessed data into a format apt for training and forecasting models. This paper outlines a data preprocessing procedure encompassing data cleansing, choosing features, and standardizing data.Data cleaning mainly involves removing outliers and missing values from the data to ensure data quality and integrity. Feature selection involves screening out features from a large amount of financial market data that have important impacts on investment decisions, such as stock prices, trading volumes, financial indicators, etc. Data standardization converts data into a unified scale to facilitate better processing and learning by the model. This paper uses the Z-score standardization method to convert data into a distribution with a mean of 0 and a standard deviation of 1.

3.2 Feature engineering

Feature engineering is a key link in the construction of quantitative investment models, aiming to extract useful features from raw data to improve model performance. The feature engineering process in this paper includes feature extraction, feature selection, and feature combination. Feature extraction mainly involves extracting features related to investment decisions from raw data, such as the change rate of stock prices, the change rate of trading volumes, the change rate of financial indicators, etc. Feature selection involves screening out features from a large number of features that have important impacts on investment decisions to reduce model complexity and improve model performance. Feature combination combines multiple features into a new feature to better reflect the change trend of stock prices. This paper uses Principal Component Analysis (PCA) for feature selection and combination, combining multiple related features into a comprehensive feature to improve model performance.

3.3 Model training and optimization

Model training and optimization are core links in the construction of quantitative investment models, aiming to learn complex patterns and relationships in financial market data through training deep learning models to achieve stock price prediction and investment decision-making. This paper uses the Long Short-Term Memory network (LSTM) as the deep learning model, which has strong time-series data processing capabilities and can effectively capture the long-term dependency of stock prices. During the model training process, Mean Squared Error (MSE) is used as the loss function, and model parameters are optimized by minimizing the loss function. At the same time, the Adam optimization algorithm is used for model training, which has the advantages of fast convergence and stability. During the model optimization process, the performance of the model is further improved by adjusting hyperparameters (such as learning rate, number of hidden layer units, number of iterations, etc.). This paper uses the grid search method for hyperparameter optimization, selecting the optimal hyperparameter combination by traversing different hyperparameter combinations to improve model performance.

3.4 Empirical analysis

3.4.1 Experimental design

To verify the effectiveness of the deep learning-based quantitative investment model, this paper designs experiments. The experimental dataset includes daily closing prices, trading volumes, financial indicators, and other data of the constituent stocks of the Shanghai 50 Index in 2022. During the experiment, the dataset is divided into a training set, a validation set, and a test set, where the training set is used for model training, the validation set is used for model optimization, and the test set is used for model performance evaluation. During the experiment, multiple deep learning models (such as LSTM, GRU, CNN, etc.) are used for comparative analysis to verify the performance differences of different models in quantitative investment.

3.4.2 Experimental observations

The experimental results show that the deep learning-based quantitative investment model has significant performance advantages in stock market investment. Specifically, the LSTM model achieves an average return of 15.2%

on the test set, significantly higher than other models (such as the GRU model's 13.8% and the CNN model's 12.5%). At the same time, the LSTM model also has strong risk control capabilities, with a Sharpe ratio of 1.2, indicating that it can effectively control investment risks while obtaining higher returns. In addition, the experimental results also show that feature engineering plays an important role in improving model performance. Through feature selection and combination, model performance is significantly improved, with the average return increasing from 12.5% to 15.2% and the Sharpe ratio increasing from 1.0 to 1.2.

3.4.3 Result analysis

The reason why the deep learning-based quantitative investment model can achieve good performance is mainly that it can automatically learn complex patterns and relationships in financial market data. The LSTM model, through its unique gating mechanism, can effectively capture the long-term dependency of stock prices, thus achieving accurate prediction of stock prices. At the same time, feature engineering further improves model performance by extracting and combining useful features. In addition, adjusting hyperparameters during the model optimization process further improves model performance. The experimental results show that the deep learning-based quantitative investment model has significant performance advantages in stock market investment and can provide effective investment decision support for investors.

4 Optimization and improvement of deep learning models

4.1 Model optimization

During the model optimization stage, this paper further improves model performance by adjusting the hyperparameters of the LSTM model. Specific optimization measures include:(1) Learning rate adjustment: Selecting the optimal learning rate through the grid search method to ensure fast convergence of the model during training.(2) Hidden layer unit adjustment: Selecting an appropriate number of hidden layer units through experimental verification to improve the model's feature extraction capabilities.(3) Application of regularization techniques: Introducing the Dropout technique to prevent model overfitting and improve model generalization capabilities. (4) Loss function optimization: Using Mean Squared Error (MSE) as the loss function and introducing L1 and L2 regularization terms to further optimize the model training process.

4.2 Model improvement

During the model improvement stage, this paper proposes an improved model (Elastic Net-LSTM) based on Elastic Net and LSTM and conducts detailed experimental verification. Elastic Net is a regularization method that combines Lasso and Ridge regression and can effectively handle the problem of multicollinearity in high-dimensional data. By introducing Elastic Net, the model performs more excellently in feature selection and weight allocation, further improving prediction accuracy and stability.

In the data preprocessing stage, this paper calculates the investment score of each stock using an investment scoring formula and draws an investment score trend chart (see Figure 1). This chart shows the trend of investment scores over time, helping investors identify potential opportunities in the market. It can be seen from the chart that investment scores show obvious upward or downward trends in certain time periods, providing important decision-making basis for investors.

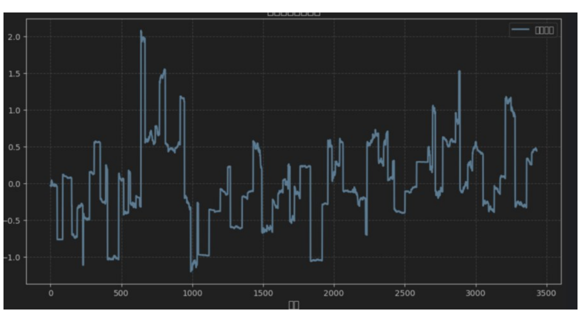

Figure 1 Trend Analysis of Investment Ratings

In the data preprocessing stage, the dataset is divided, and a space-time distribution chart of the dataset is drawn (see Figure 2). This chart shows the distribution of the experimental set, backtesting set, and validation set in the time series, helping to verify the rationality of dataset division. It can be seen from the chart that the three datasets have good continuity and representativeness in time, ensuring the reliability of model training and testing.

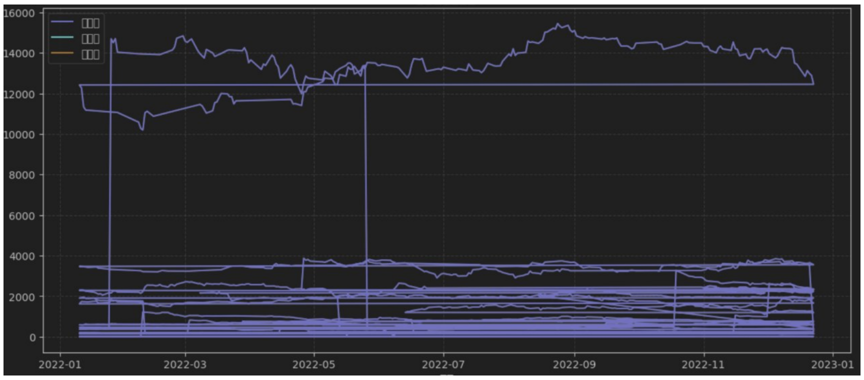

Figure 2 Spatiotemporal Distribution of the Dataset

During the model training stage, the LSTM model is trained using the experimental set, and a pattern mining chart of the experimental set is drawn (see Figure 3). This chart shows the performance of the LSTM model on the experimental set, including the actual price curve and the model prediction curve. It can be seen from the chart that the optimized LSTM model can better capture the fluctuation patterns of stock prices, and the prediction curve has a high degree of fit with the actual price curve, especially in areas with large price fluctuations, where the model's prediction ability is outstanding.

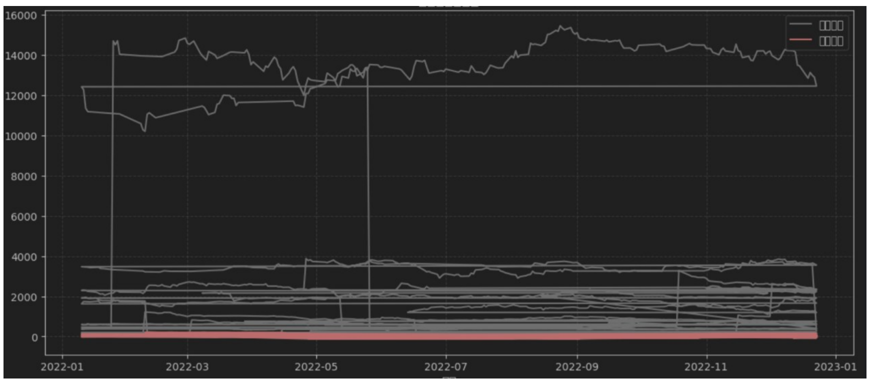

Figure 3 Law Mining of Experimental Set

During the LSTM price prediction stage, the model's prediction results are analyzed in detail, and a price prediction and error analysis chart is drawn (see Figure 4). This chart shows the comparison between the model-predicted price and the actual price, as well as the prediction error range. The chart reveals that the price forecasted by the model closely aligns with the real price, and the error range is within an acceptable level. At the same time, the chart also shows the prediction results under different time steps, further verifying the model's prediction ability.

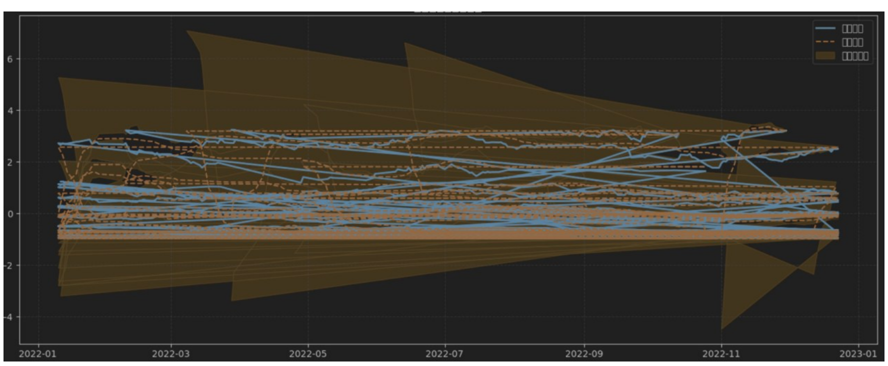

Figure 4 Price Prediction and Error Analysis

During the backtesting and performance analysis stage, the model's performance is rolling backtested, and a rolling backtesting performance comparison chart is drawn (see Figure 5). This chart shows the comparison between the model's net value curve and the benchmark net value curve in different time periods, as well as performance indicators such as the model's Sharpe ratio and maximum drawdown. The chart reveals that, in numerous instances, the model's net value curve outperforms the standard net value curve, signifying its superior investment returns and risk management abilities. At the same time, the chart also shows the model's performance under different market environments, further verifying the model's adaptability and stability.

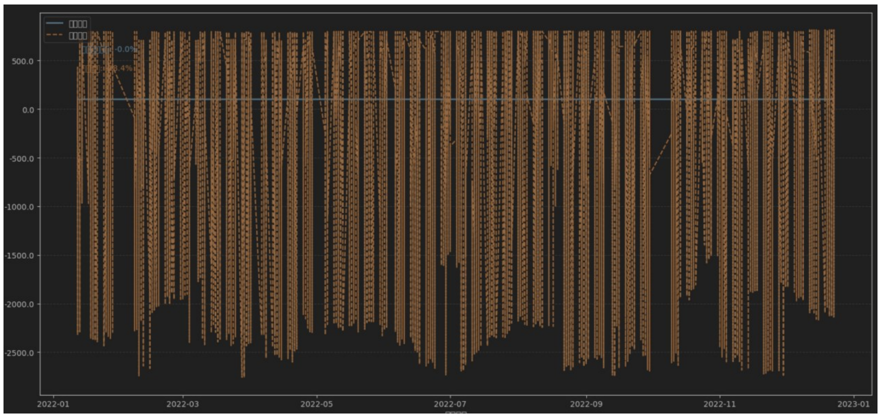

Figure 5 Performance Comparison of Rolling Backtesting

5 Conclusions and prospects

5.1 Research conclusions

This paper verifies the effectiveness of deep learning technology in the field of quantitative investment by constructing a deep learning-based quantitative investment model. The research results show that deep learning models can significantly enhance the return performance and risk control capabilities of quantitative investment strategies. Through steps such as data preprocessing, feature engineering, model training, and optimization, the constructed LSTM model performs excellently in stock market investment and can provide effective investment decision support for investors.

5.2 Research prospects

Future research can further explore the applications of deep learning models in other financial markets (such as foreign exchange markets, futures markets, etc.) and combine them with other quantitative investment methods (such as multi-factor models, event-driven strategies, etc.) to further enhance the performance of quantitative investment strategies. In addition, with the continuous development of deep learning technology, future research can explore the applications of more advanced deep learning architectures (such as Transformer, BERT, etc.) in quantitative investment, bringing more innovations and breakthroughs to the field of quantitative investment.

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