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Design and System Implementation of Financial Market Volatility Prediction Model Based on Reinforcement Learning and Swarm Optimization

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Keywords: Financial high-frequency trading data; Volatility prediction; Reinforcement Learning - Swarm Optimization; Noise reduction autoencoder; Unstable attention mechanism

Abstract： Financial market volatility, as a core indicator for measuring asset price fluctuations, directly affects risk appetite, product pricing, and market stability. Its accurate prediction is the key to financial risk management. With the popularity of electronic trading platforms, high-frequency financial trading data provides richer information for volatility research, but also brings challenges such as high-dimensional sparsity, nonlinearity, high autocorrelation, and non stationarity. Traditional statistical methods and existing technologies are difficult to effectively cope with, while existing deep learning models are susceptible to noise and non-stationary interference, which limits prediction accuracy.In response to the above issues, this paper proposes a feature selection method based on reinforcement learning and bee colony optimization algorithm, as well as a volatility prediction model combining denoising autoencoder (DAE) and unstable attention mechanism. The feature selection method generates candidate feature subsets through the distributed search characteristics of the bee colony optimization algorithm, and dynamically optimizes the search direction using the adaptive adjustment mechanism of reinforcement learning, effectively solving the problems of high-frequency factors, high-dimensional sparsity, nonlinearity, and high autocorrelation; The prediction model utilizes the encoding decoding structure of DAE to filter data noise, and combines mixed convolution to enhance the spatiotemporal information learning ability of unstable attention mechanism, alleviating the impact of non stationarity on model performance. We ultimately designed and implemented a volatility prediction system based on the Django framework, integrating user management, data visualization, position simulation, and real-time prediction functions to provide investors with market analysis and decision support. The experimental results show that this method can select more representative feature subsets and verify its ability to handle noise and non stationarity in real high-frequency trading datasets, significantly improving the accuracy of volatility prediction. The system implementation provides effective tools for practical applications. Future research will incorporate external information such as market sentiment and major events to enrich the feature set, explore model lightweighting techniques to improve real-time response efficiency, and combine interpretability methods (such as local sensitivity analysis) to enhance model decision transparency, promoting the wider application of volatility prediction in practical financial scenarios.

1. Introduction

Financial market volatility, as a core indicator for measuring asset price volatility, directly affects investors' risk preferences, financial product pricing, and market stability. Accurate measurement and prediction of financial market volatility are crucial for financial risk management and market stability. With the development of electronic trading platforms, financial high-frequency trading data (full sample, unequal interval, including order and trading information) provides richer market information for volatility research. However, it also brings significant challenges: high-frequency factors have high dimensionality, strong sparsity, and non-linear and high autocorrelation. Traditional statistical feature selection methods and machine learning/reinforcement learning methods are difficult to effectively process due to their tendency to fall into local optima and large computational complexity; High frequency data contains a large amount of noise and non stationarity. Traditional noise reduction techniques (such as pre averaging and wavelet analysis) rely on model assumptions (stationarity, linearity) or smoothing processing, which can easily lose key information. Non stationarity processing (such as moving average and differencing) may excessively smooth and reduce model discrimination; In addition, existing deep learning models are susceptible to noise and non-stationary interference in high-frequency volatility prediction, which limits their prediction accuracy. This paper proposes a complete solution to the challenges of high-dimensional sparse feature selection, noise interference, and non stationarity in predicting the volatility of high-frequency trading data in financial markets. Firstly, a feature selection method that integrates reinforcement learning and bee colony optimization algorithm was designed. This method utilizes the distributed search characteristics of bee colony optimization algorithm to generate candidate feature subsets, and dynamically adjusts the search direction through the adaptive learning strategy of reinforcement learning, effectively solving the sparsity, nonlinear correlation, and high autocorrelation problems of high-dimensional financial factors, and selecting more representative feature sets. Secondly, a deep learning prediction model combining denoising autoencoder (DAE) and unstable attention mechanism was constructed: DAE filters data noise through encoding decoding structure, and unstable attention mechanism combines with mixed convolutional layer to dynamically capture non-stationary features of time series, enhancing the model's ability to learn spatiotemporal information and thus improving prediction accuracy. Finally, a financial high-frequency trading data volatility prediction system was designed and implemented based on the Django framework, integrating user management, data visualization, position simulation, and real-time volatility prediction functions, providing investors with market analysis and decision support. The performance of the model was validated on high-frequency trading datasets in real financial markets, such as ETF and multi class stock data. The experimental results showed that the method outperformed traditional benchmark models in terms of prediction accuracy. The core contributions of this article include: proposing a reinforcement learning driven bee colony optimization feature selection method; Constructing a volatility prediction model that integrates DAE and unstable attention mechanism; Implement a Django prediction system that integrates models.

2. Correlation theory

The research in the field of reinforcement learning and optimization algorithms focuses on method innovation and application expansion. In terms of distributed reinforcement learning, Dong et al. proposed a distributed neural strategy gradient algorithm, which verified global convergence for networked multi-agent systems and provided theoretical support for multi-agent collaborative decision-making; Dai Peng et al. combined neural strategy gradients with networked multi-agent frameworks to further enhance the practicality of distributed reinforcement learning. The bee colony optimization algorithm is widely used in various scenarios due to its global search ability and ability to avoid local optima. Moayedikia A applied it to dynamic payment optimization on micro task platforms, improving task allocation efficiency by dynamically adjusting payment strategies; Amador Angulo et al. combined fuzzy logic in mobile robot control to enhance the stability and adaptability of the controller; Khamsen W has improved the economic efficiency of resource allocation in the field of economic dispatch by enhancing local search mechanisms to process smooth cost functions. In terms of volatility prediction, various hybrid models have been proposed: Liu et al. proposed the AO-GARCH-MIDAS model, which combines heterogeneous data sources to improve the accuracy of stock volatility prediction; Liu Wei et al.'s Transformer model based on mixed frequency data effectively processes multi-scale financial time series; Liao Cong et al. enhanced prediction robustness through ensemble learning using a robust GBM-GRU model; Bedoya Valencia D uses the ANFIS model to evaluate financial time series volatility through adaptive fuzzy inference; Yuan Hua et al. developed a network structure volatility model based on high-frequency data, optimizing volatility modeling by capturing market microstructure characteristics. The advantages of these methods include improving prediction accuracy, handling complex data characteristics, enhancing model robustness and adaptability; The limitations are mainly reflected in the high computational complexity of some models, strong dependence on data quality, or the existence of local optimal risks.

3. Research method

3.1. Introduction and Factor Analysis of Financial High Frequency Trading Dataset

Financial high-frequency trading data refers to order and trading information generated at a frequency of seconds or milliseconds, including details such as price, quantity, buying and selling direction, and time, reflecting the instantaneous trading dynamics of the market. It is widely used in strategy formulation, trend prediction, and risk management. This article focuses on the high-frequency trading dataset of the SSE 50 ETF, which tracks the SSE 50 Index (covering leading listed companies in multiple industries such as finance and energy) and includes two types of variables: order book and trading data. The order book data dynamically records unexecuted orders, such as buy price/volume and sell price/volume, reflecting market supply and demand as well as price trends; Static recording of transaction data for completed orders, such as transaction price, trading volume, etc., providing real-time price and trading volume information. To extract effective features, statistical and technical factors need to be calculated from high-frequency data, resulting in 124 financial factors, including weighted average price, logarithmic return, realized volatility, bid ask spread, cumulative trading volume, etc., and further calculating their statistical features such as sum, standard deviation, maximum spread, etc. Financial high-frequency factors have characteristics such as high-dimensional sparsity, nonlinearity, and high autocorrelation. Traditional feature selection methods suffer from problems such as mutual information ignoring feature interaction, high computational complexity of RFE, overfitting of random forests, and interference from noise/multiple correlations in SHAP. Therefore, this article proposes a bee colony optimization feature selection method based on reinforcement learning, which uses the bee colony algorithm to search the feature subspace in a distributed manner, and combines reinforcement learning adaptive adjustment strategy (with prediction loss as a reward and experience buffer optimization decision) to solve high-dimensional sparsity, non-linearity, and high autocorrelation problems, and improve the efficiency and accuracy of feature selection.

3.2. Overview of Volatility Theory and Q-Learning Algorithm

Volatility theory is one of the core tools for financial market analysis, used to quantify the intensity and uncertainty of asset price changes, and is an important indicator for evaluating market risks. Its core is divided into two categories: historical volatility and realized volatility.

Historical volatility measures the level of volatility by analyzing the changes in asset prices over a certain period of time. Specifically, first calculate the daily price change rate (i.e. the relative change between the closing price of the current day and the closing price of the previous day, Among them, is the closing price on the t-th day), as shown in formula 1

$$S_t = \frac{Q_t - Q_{t-1}}{Q_{t-1}} \quad \text{(Formula 1)}$$

Then calculate the average of these rates of change, and finally represent the volatility in the form of standard deviation (as shown in formula 2)

$$\sigma = \sqrt{\frac{\sum_{j=1}^{o}(S_J - \bar{S})^2}{\sigma - 1}} \quad \text{(Formula 2)}$$

Where o is the total number of trading days. This indicator reflects the volatility characteristics of asset prices in the past. The higher the historical volatility, the more drastic the price changes and the greater the risk. For high-frequency trading data, such as minute or second level price fluctuations, volatility has been captured through finer time windows to capture instantaneous fluctuations. Its calculation is based on the sum of squares of logarithmic rates of return. On the other hand, Q-Learning is a classic value function based method in the field of reinforcement learning, used to solve the optimal decision problem in Markov decision processes (MDP). Its core is that the agent learns the state action value function (Q function) through interaction with the environment, and estimates the expected cumulative benefit of taking actions in a specific state. The algorithm originates from Watkins' value iteration idea, which maintains a Q-table to record the expected returns of each state action pair. It uses a greedy strategy to select the action with the highest current Q-value and updates the Q-value based on the actual return obtained (the update rule is based on the Bellman equation). Through iteration, the Q-value gradually converges to the optimal state action value function, thus obtaining the optimal decision strategy. This algorithm has convergence guarantee and wide applicability, especially suitable for discrete action space and large-scale state space scenarios; Subsequent improvements such as Double Q-Learning effectively solve the problem of overestimation of Q values in traditional Q-Learning by introducing two independent Q functions and taking the average of their smaller values. The Deep Q-Network (DQN) combined with deep neural networks further extends the algorithm to continuous or high-dimensional state spaces, significantly improving its practicality.

3.3. Overview of Evolutionary Algorithms and Attention Mechanisms

Evolutionary Algorithm is a type of optimization algorithm based on the principles of biological evolution, which searches for the optimal solution in the solution space by simulating natural selection and genetic mechanisms. The core process includes initializing a random population, evaluating individual strengths and weaknesses through fitness functions, retaining high-quality individuals through selection operations generating new offspring through crossover (recombination) and mutation operations, and finally iteratively updating the population until convergence. Typical branches include genetic algorithms (GA, binary/real number encoding, balancing global and local search), evolutionary strategies (ES, emphasizing real number parameter optimization and adaptive step size), differential evolution algorithms (DE, generating candidate solutions through differential vector perturbation), and bee colony optimization algorithms (such as ABC, simulating bee foraging behavior) (as shown in Figure 1,

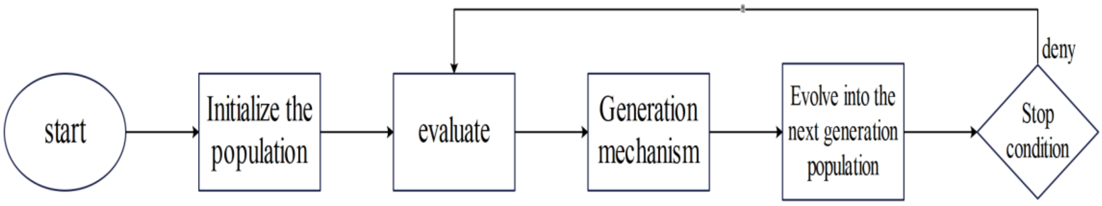

Figure 1. Structure of attention mechanism

which intuitively presents the typical form of evolutionary algorithms and their core mechanism associations.This type of algorithm does not rely on the specific mathematical properties of the problem, and has strong generality and adaptability. It is widely used in engineering optimization, machine learning , and financial fields

The core process is to first randomly initialize the population (generate initial solutions from the solution space), and then evaluate the quality of each solution by calculating its fitness; Then use crossover, mutation and other operations to generate new solutions, form a new generation population, and re evaluate fitness; Finally, excellent individuals are retained for the next round of evolution until the preset evolutionary generation is reached or the population fitness tends to stabilize, and the optimal solution is returned. In response to the characteristics of high-frequency financial trading data, this article uses the bee colony optimization algorithm for feature selection, as it improves search efficiency through multi solution cross updating and is suitable for handling high-dimensional problems; At the same time, its global search capability can avoid local optima and effectively deal with complex nonlinear relationships in financial data. Attention mechanism is a widely used mechanism in deep learning, with the core idea of calculating the correlation between elements in the input sequence and focusing on the most relevant parts to improve model performance. Its typical implementation is based on the Encoder Decoder framework: the Encoder encodes the input sequence into Key Value pairs, and the Decoder generates a Query when generating the output; By calculating the similarity between the Query and all keys (such as dot product), attention scores are obtained, which are then transformed into probability distributions using softmax and weighted with corresponding values. Finally, a weighted sum is generated as contextual information for the Decoder to use. This mechanism dynamically adjusts the weights of input elements to help the model capture key information more accurately.

4. Results and discussion

4.1. Analysis of the problem of predicting the volatility of financial high-frequency trading data

This chapter proposes a volatility prediction model that combines denoising autoencoder (DAE) and unstable attention mechanism to address the issues of noise and non stationarity in high-frequency financial trading data, such as rapid price fluctuations, decreased data quality due to market sentiment and external event interference. The model effectively mitigates the impact of noise and non stationarity on model performance, and its predictive generalization ability for multi class stock volatility after clustering is verified through experiments. Specific issues include: in terms of noise, the high-frequency execution of high-frequency trading algorithms leads to sudden changes in order books and trading data, the complexity of market microstructure further exacerbates noise, time series decomposition shows that the data contains a large number of random residuals (random fluctuations that cannot be explained by trends and seasonality), masking the true volatility signal; In terms of non stationarity, the statistical characteristics of the data (such as mean and variance) change over time. The ADF unit root test p-value is 0.767326 (>0.05), which does not reject the null hypothesis and confirms the non stationarity of the data. This makes it difficult for traditional models to capture long-term trends and may result in spurious correlations. To this end, the model denoises high-frequency data through DAE and extracts robust features; Dynamically adjust feature weights and focus on key fluctuation signals by combining unstable attention mechanisms. The experiment shows that the model has a significant effect on predicting the volatility of non-stationary high-frequency data, and has good generalization ability for predicting the volatility of multi class stocks after clustering.

4.2. Overall network structure of the model

The financial high-frequency trading data volatility prediction model proposed in this article is based on denoising autoencoder (DAE) and unstable attention mechanism. Its overall framework integrates key modules such as denoising, feature extraction, non-stationary modeling, and scale restoration. Firstly, the original high-frequency factor feature vector sequence is constructed with Gaussian noise to create noisy data, which is then input into the DAE module. The encoder maps the noisy data to low dimensional feature vectors, and the decoder extracts denoised low dimensional feature representations by minimizing the Euclidean distance error between the original and reconstructed data. The noise is filtered while preserving key information. Subsequently, the normalization module uses sliding windows to calculate the mean and standard deviation of data within each time window, normalizes low dimensional features, and eliminates time scale differences. Next, the unstable attention mechanism inputs the mean and variance of the current window through a multi-layer perceptron (MLP), calculates the learnable control variables τ and shift vector Δ, dynamically adjusts the Key vector in the attention mechanism, and adaptively allocates attention weights with changes in the time window, capturing the trends and periodic features of non-stationary sequences; After attention output, a mixed convolutional layer is applied, combining 1D convolution and point by point convolution to capture spatiotemporal relationships, and enhancing model stability through residual connections and normalization. Finally, the de normalization module utilizes the mean and standard deviation of the sliding window to invert the processed features into the original data scale, restoring the volatility prediction results and improving accuracy. This model effectively solves the problem of financial high-frequency data noise interference and non-stationary prediction by adapting non-stationary features through DAE denoising, dynamic attention mechanism, and mixed convolution enhancement feature expression.

4.3. Comparative analysis of evaluation effects

This article designs and implements a financial high-frequency trading data volatility prediction system based on Django, using a front-end and back-end separation architecture (Vue3 front-end, Django back-end), with functions covering user management (registration, login, and personal information editing), stock market, position management (simulating stock buying and selling, real-time calculation of floating profits and losses and generating trend charts), and volatility prediction module. The system database design includes 6 tables: User Information Table, Stock Basic Information Table, Order/Trading Data Table, Position Information Table, and Model Prediction Information Table

The model performance was verified through two aspects: on the one hand, using the real high-frequency trading dataset of Shanghai Stock Exchange 50ETF (September 2021 to April 2022), benchmark models such as LGBM, Random Forest, LSTM, CNN, DAE-LSTM, DAE-CNN, ns_Transformer were compared. The experimental environment was Python 3.7, PyTorch framework, Linux system, and the hardware configuration included Intel i7-1270KF CPU, Nvidia Tesla K80 * 2 GPU, and 128GB memory. The evaluation indicators were R^2, MAE, RMSPE, and hyperparameters were set to 8 attention heads, 0.001 learning rate, 32 batch sizes, 100 iterations, and Gelu activation function. The results showed that our model achieved an R^2 of 0.9147 on the 50ETF dataset, with RMSPE and MAE of 0.1571 and $3.302e^{-4}$, respectively, outperforming all benchmark models, such as LSTM with an R^2 of 0.8628 and DAE-LSTM with 0.8891. On the other hand, using 126 stocks from foreign financial markets (divided into two categories A and B) to test robustness, the comparison results in Table 1 are as follows:

Table 1. Comparison of Prediction Results between Class 1A and Class B Stock Models

Stock Category	Model	R^2	RMSPE	MAE
Class A	DAE_LSTM	0.9215	0.1527	3.259e□□
Class A	DAE_CNN	0.9002	0.1819	3.551e□□
Class A	ns_Transformer	0.8581	0.2255	4.621e□□
Class A	Ours	0.9235	0.1478	3.122e□□
Class B	DAE_LSTM	0.7721	0.3363	6.537e□□
Class B	DAE_CNN	0.7905	0.3015	6.201e□□
Class B	ns_Transformer	0.7487	0.4409	7.105e□□
Class B	Ours	0.8747	0.2071	4.202e□□

This model achieved an R^2 of 0.9235 in Class A stocks (better than DAE-LSTM's 0.9215) and 0.8747 in Class B stocks (significantly better than DAE-LSTM's 0.7721 and ns_Transformer's 0.7487), indicating its ability to dynamically adapt to non-stationary data through DAE denoising and unstable attention mechanisms, effectively improving prediction accuracy. The core contributions of the research include: proposing a bee colony optimization feature selection method based on reinforcement learning to solve the problem of high-dimensional sparse financial factor selection; Build DAE unstable attention model, combined with mixed convolution to capture spatiotemporal relationships; Ultimately, the model will be integrated into the system to achieve full process application, assisting investors in understanding market trends and avoiding risks. Future directions for scalability include incorporating external factors such as market sentiment, optimizing model lightweighting to improve real-time performance, and introducing interpretability techniques such as sensitivity analysis to enhance model decision transparency.d.

5. Conclusion

This article proposes a complete solution to the challenges of high-dimensional sparsity, nonlinearity, high autocorrelation, noise interference, and non stationarity in predicting the volatility of financial high-frequency trading data. Based on the reinforcement learning framework, a bee colony optimization feature selection method is designed. By integrating the distributed search capability of the bee colony algorithm with the adaptive adjustment mechanism of reinforcement learning, it effectively solves the high-dimensional sparsity, nonlinearity, and high autocorrelation problems of high-frequency factor features, and selects more representative feature subsets. Constructing a deep learning prediction model that combines denoising autoencoder (DAE) and unstable attention mechanism, using the encoding decoding structure of DAE to filter data noise, and dynamically capturing non-stationary features of time series through unstable attention mechanism combined with mixed convolutional layer, enhancing the model's ability to learn spatiotemporal information, thereby improving prediction accuracy; Design and implement a financial high-frequency trading data volatility prediction system based on the Django framework, integrating user management, data visualization, position simulation, and real-time volatility prediction functions to provide investors with market analysis and decision support. Future research will further incorporate external information such as market sentiment and major events to enrich the feature set, explore model lightweighting techniques to improve real-time response efficiency, and combine interpretability methods to enhance model decision transparency, promoting the wider application of volatility prediction in practical financial scenarios.

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