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Stock trend prediction method coupled with multilevel indicators

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Abstract: To systematically incorporate multiple influencing factors, the coupled-state frequency memory (Co-SFM) network is proposed. This model integrates Copula estimation with neural networks, fusing multilevel data information, which is then fed into downstream learning modules. Co-SFM employs an upstream fusion module to incorporate multilevel data, thereby constructing a macro-plate-micro data structure. This configuration helps identify and integrate characteristics from different data levels, facilitating a deeper understanding of the internal links within the financial system. In the downstream model, Co-SFM uses a state-frequency memory network to mine hidden frequency information within stock prices, and the multifrequency patterns of sequential data are modeled. Empirical results show that Co-SFM's prediction accuracy for stock price trends is significantly better than that of other models. This is especially evident in multistep medium and long-term trend predictions, where integrating multilevel data results in notably improved accuracy.

Key words: stock trend prediction; multilevel indicators; Copula; state-frequency memory network

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Exploring stock price trends is a key focus in capital market research. However, the high volatility of stock prices makes their trends inherently unstable[1]. Traditionally, linear regression models and autoregressive models have been widely applied to the prediction of stock trends. Researchers have used autoregressive models to predict the stock market prices and provide investment advice[2-3]. Despite their widespread use, these traditional methods often fall short when applied to the complex nature of real-world financial systems. With the rapid development of artificial intelligence, machine learning and deep learning models have increasingly been adopted across various fields owing to their excellent prediction capabilities[4-6]. Machine learning models, such as support vector machines, have shown promising results in financial market prediction[7-8]. With the iteration of models, researchers have developed innovative neural network models to address the learning and prediction tasks of different financial time series. Kim et al.[9] used genetic algorithms to mitigate the instability of neural networks when predicting noisy financial data. Adebiyi et al.[10] proposed a hybrid method that combines technical and fundamental analysis variables to enhance stock market indicators. This data-level supplement can also improve prediction accuracy. Recently, more complex neural network models, such as long short-term memory (LSTM), transformer, and informer, have significantly outperformed earlier recurrent and convolutional neural networks[11-14].

The scale of real-world data is not uniform. For the entire system, there is an interactive effect between these data with different scales. Therefore, multiscale deep learning methods are feasible for certain real-world problems[15-17]. Li et al.[18] proposed a multiscale deep convolutional neural network to better describe complex systems, allowing for the detection of interactions between different levels of data and improving sequence trend predictions. Taking the financial market as an example, multiscale data mining can compensate for the information loss caused by applying single data sources, thereby aiding intelligent investment decisions[19]. Chen et al.[20] proposed a stock price trend prediction model to reduce the impact of high volatility on stock price forecasts, enabling adaptive predictions of stock trends and durations. Additionally, researchers have employed multigranularity market data to improve prediction accuracy of stock trend prediction, proposing frameworks such as the comparative multigranularity learning framework to integrate data from different scales for more comprehensive forecasts[21]. Researchers found that deep learning models can effectively address the highly stochastic nature of time series and the multiscale problem of data in the prediction process[22]. Despite these advancements, challenges remain. Integrating data from different levels and recognizing multifrequency patterns are significant hurdles in predicting sequence data in complex systems. Stock market data in the financial market is a typical example. Stock prices are affected by varied market and macroeconomic data[23] and

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contain inherent information from different transaction frequencies. Mining this implicit information to provide more accurate predictions remains a critical challenge[24].

Based on the above research, it is evident that traditional autoregressive models can predict the general trend of stocks, but their accuracy is diminished by the inherent randomness and nonlinearity of stock prices. While machine learning and deep learning models enhance predictive accuracy, relying solely on historical data may result in merely "repeating history." Therefore, integrating multilevel relevant data becomes essential. However, dealing with multilevel data introduces new uncertainties, especially in complex systems such as financial markets, where general models struggle to systematically predict accurate price trends.

In this paper, we propose a macro-sector-micro data analysis structure that incorporates macroeconomic indicators, sector-specific indicators, and micro-level data at multiple levels. Our study makes several key contributions to the existing literature. First, we introduce a neural network that integrates multilevel financial data. Second, we apply state-frequency memory (SFM) techniques to extract and learn hidden transaction patterns. Third, we explore the intrinsic relationship among macroeconomic indicators, sector-specific indicators, and micro-level data within the financial system.

1 Coupled-State Frequency Memory Network (Co-SFM)

In this section, we introduce the structure of Co-SFM, and we analyze the role of each structure in utilizing stock market data for prediction.

1.1 Macro-sector coupling layer

In the financial system, stock prices are influenced not only by their historical trends but also by the overall trends in their respective industries and macroeconomic indicators. Macroeconomic policies and conditions exert varying degrees of influence on different capital markets through various transmission mechanisms. Inventors adjust their consumption and investment preferences based on these macroeconomic conditions[25]. During periods of rapid economic growth, investments are positively stimulated, whereas during downturns in consumption, capital flows toward various investment markets. Changes in macroeconomic policies also impact enterprise development, thereby influencing capital market performance[26].

To explore the effects of macroeconomic and sector factors, we establish a macro-sector coupling layer through the medium of stock sectors. This involves generating macro-sector information using a multilevel data fusion method inspired by Wang et al. [23]. As shown in Fig. 1, the coupling layer maps each observed sequence to a hidden space and calculates their marginal distributions through this mapping. We then use a Copula function to integrate these marginal distributions, obtaining a joint distribution of the coefficient matrix $\boldsymbol{R}$. Ultimately, a gating function generates specific stock macro-sector context information.

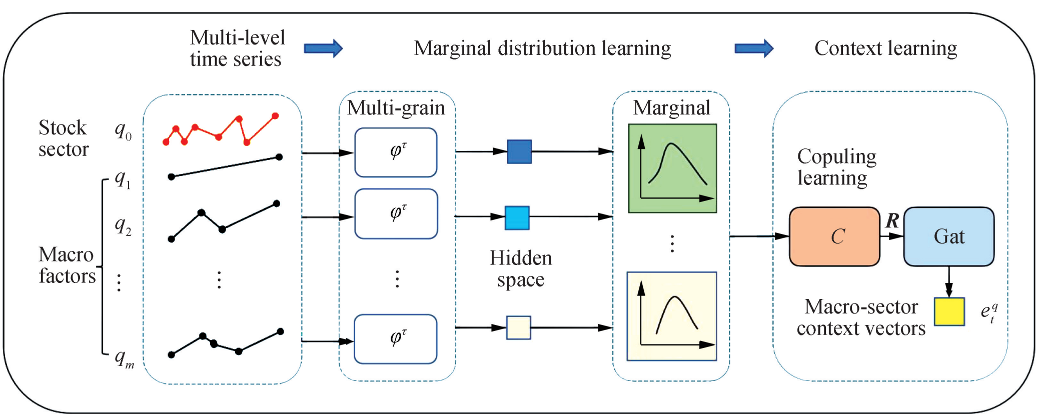

Fig. 1 Generation process of macro-sector context vectors

Sklar's theorem[27] lays the theoretical groundwork for copulas, asserting that any multivariate cumulative distribution function (CDF) can be broken down into its individual marginal distributions F_i and a distinct copula C:

$$F(\boldsymbol{v}) = C(F_1(v_1), F_2(v_2), \dots, F_n(v_n)) \tag{1}$$

The Copula function is suitable for modeling the relationship between heterogeneous macroeconomic variables and specific stock sectors. In our model, we use the Gaussian Copula function to integrate macro and sector data. Given m sequential macroeconomic variables $q_1, q_2, \dots, q_m$ and a sequential stock sector variable, we define the Gaussian Copula function as follows:

$$C(\cdot) = \Phi_R(\Phi^{-1}(F_0(q_0)), \Phi^{-1}(F_1(q_1)), \dots, \Phi^{-1}(F_m(q_m))) \tag{2}$$

where $\Phi^{-1}(\cdot)$ is the inverse CDF of a standard normal distribution; $\Phi_R(\cdot)$ is the joint CDF of a multivariate normal distribution parameterized by mean vector zero and covariance matrix $\boldsymbol{R}$. In general, we use Gaussian distributions to construct the dependence structure of these indicators.

Before employing Copula functions for multilevel information coupling, we utilized a multigranularity marginal distribution estimation method. This method computes the marginal distributions of information sequences, laying the groundwork for the coupling process mentioned above. By using a multigranularity approach, we can discern the states of different indicators over various time spans, effectively exploring their interactions within the broader macro environment. Specifically, in determining parameters, we adopt a nonlinear deterministic state space model. For each time series q_i, its state $h^{\tau}_{i,t}$ evolves independently according to a transition dynamics function φ^{τ}. The specific evolution formula is as follows:

$$\left.\begin{aligned} &h^{\tau}_{i,t} = \varphi^{\tau}(h^{\tau}_{i,t-1}, q_{i,t\tau}, p_t; \theta_h) \qquad i = 0, 1, \ldots, m \\ &p_t = \mathrm{Lookup}(k(t)) \end{aligned}\right\} \tag{3}$$

Here, the transitional dynamics function φ^{τ} includes sequential variables and their specific time labels, where time is represented in a lookup manner embedded within a week or a year to retrieve the value of a particular day (denoted by $k(t)$). The parameterization of this transitional dynamics function is achieved through an LSTM network with multigranularity parameters. This means that time series with the same time interval τ share the same parameters θ_h.

Subsequently, we assume that these observed values follow a Gaussian distribution, with their mean and variance derived from the state $h^{\tau}_{i,t-1}$, thereby preserving their characteristics. The formal expression is as follows:

$$\left.\begin{aligned} \mu_{i,t} &= \boldsymbol{w}^{\mathrm{T}}_{\mu} h^{\tau}_{i,t} \\ \sigma_{i,t} &= \boldsymbol{w}^{\mathrm{T}}_{\sigma} h^{\tau}_{i,t} \end{aligned}\right\} \tag{4}$$

1.2 Macro-sector context information

Based on the learned marginal distribution $\hat{F}$ and parameter $\boldsymbol{\beta} = \{\theta_h, w_{\mu}, w_{\sigma}\}$ for each time series, we can calculate the correlations between different time series using Eq. (4). First, we calculate the rank $\tilde{q}_{i,t}$ of each variable in its sequence. Then, we transform the variables in the sequence using the inverse function Φ^{-1} of the CDF obtained from the learned marginal distribution. The transformed i-th time series is represented as follows:

$$\begin{aligned} \boldsymbol{u}_i = [&\Phi^{-1}(\hat{F}_i(\tilde{q}_{i,1}; \beta_i)), \Phi^{-1}(\hat{F}_i(\tilde{q}_{i,2}; \beta_i)), \ldots, \\ &\Phi^{-1}(\hat{F}_i(\tilde{q}_{i,t\tau}; \beta_i)), \ldots] \end{aligned} \tag{5}$$

Then, the loss for learning the covariance matrix in Eq. (2) can be expressed in the form of a maximum likelihood function. Since the CDF is differentiable, the model can learn the loss using a method based on stochastic gradient descent.

$$L_{\mathrm{C}} = -\sum_{i=0}^{m} \left\{ \log \Phi_{\boldsymbol{R}}(u_0, u_1, \ldots, u_m) + \sum_t \hat{f}_i(\tilde{q}_{i,t}) \right\} \tag{6}$$

where $\hat{f}_i(\cdot)$ is the probability density function of the CDF $\hat{F}_i$. During the training process, the function $\Phi_{\boldsymbol{R}}(\cdot)$ needs to calculate the inverse matrix of the matrix $\boldsymbol{R}$. However, this can lead to unstable numerical values during the training process and render the initialization conditions ineffective. Therefore, we use Cholesky decomposition to decompose the coefficient matrix and parameterize the matrix $\boldsymbol{R}$[28].

$$\alpha = \mathrm{Gat}(\boldsymbol{R}) = \mathrm{Sigmoid}(w_{\boldsymbol{R}}\boldsymbol{R} + b_{\boldsymbol{R}}) \tag{7}$$

The model uses a gating function, Gat, in the macro-sector coupling layer to integrate various influencing factors, thereby forming specific macro-sector contextual information. This gate consists of a linear layer and a sigmoid function. The parameters $w_{\boldsymbol{R}}$, $b_{\boldsymbol{R}}$, and α share the same dimension. The context embedding state of this specific macro-sector contextual information at time t is expressed as e^q_t, obtained from the embedding representation $h^{\tau}_{i,t}$ of the state.

$$e^q_t = \sum_{i=0}^{m} \alpha_i h^{\tau}_{i,t} \tag{8}$$

1.3 Downstream model of Co-SFM

The Co-SFM dynamically inputs time series x_t into the memory layer of the network. Similarly to LSTM, we define the external hidden state output of the memory unit at time t as R. However, unlike LSTM, the Co-SFM is designed to capture cross-frequency trading patterns. To achieve this, the internal hidden state in the memory layer of the Co-SFM is decomposed into two parts. One part contains a set of frequency segments of length K, uniformly distributed between 0 and 2π.

Following Zhang et al.'s research[24], SFM decomposes and reorganizes the internal hidden states based on the LSTM framework. This structure can decompose the information input to the storage layer at both the state and frequency levels. The goal is to capture the contextual vectors of time and frequency for the input time series. Through this decomposition, the internal hidden state of the Co-SFM can be represented as a matrix, where rows correspond to D states and columns correspond to K frequency values. The SFM layer of Co-SFM evolves into a gating mechanism that can obtain the output of the memory layer from previous time steps and the current input. However, unlike LSTM, the memory of Co-SFM is reflected in both the state and frequency components. By applying the Fourier transform, the internal hidden state of the memory layer is updated from both the time domain and the frequency domain. This dual update mechanism supports different goals for long-term and short-term stock price predictions. The rule for updating the state-frequency matrix is as follows:

$$S_t = F_t \odot S_{t-1} + (i_t \odot \tilde{c}_t) \begin{bmatrix} e^{jw_1 t} \\ e^{jw_2 t} \\ \vdots \\ e^{jw_K t} \end{bmatrix}^{\mathrm{T}} \in C^{D \times K} \quad (9)$$

The matrix $[e^{jw_1 t} \quad e^{jw_2 t} \quad \dots \quad e^{jw_K t}]$ is the Fourier basis of K frequency components of the state sequence. Similarly to LSTM, the model uses a gating mechanism inside the memory unit to express the short-term and long-term dependencies in financial time series. The input gate i_t adjusts the amount of new information currently flowing into the memory unit. In addition to the input gate, the model also defines a state-frequency forget gate, which outputs a state-frequency matrix to control how much of the different state and frequency information should be retained in the memory unit.

The candidate state $\tilde{c}_t$ in the memory unit integrates the current input information and then decomposes it into a set of frequency bands. This multifrequency decomposition enables the Co-SFM to identify variations in transaction patterns across different frequencies. The update rule divides the matrix S into real and imaginary parts:

$$\left.\begin{aligned} \mathrm{Re}\, S_t &= F_t \circ \mathrm{Re}\, S_{t-1} + (i_t \circ \tilde{c}_t)[\cos\omega_1 t, \cos\omega_2 t, \dots, \cos\omega_K t] \\ \mathrm{Im}\, S_t &= F_t \circ \mathrm{Im}\, S_{t-1} + (i_t \circ \tilde{c}_t)[\sin\omega_1 t, \sin\omega_2 t, \dots, \sin\omega_K t] \end{aligned}\right\} \quad (10)$$

To control how much past information is retained in the memory unit, the model defines a state forgetting gate and a frequency forgetting gate to regulate the information of multiple states and multiple frequencies, respectively. The formulas for these two gating mechanisms are as follows:

$$\left.\begin{aligned} f_t^{\mathrm{ste}} &= \mathrm{sigmoid}(W_{\mathrm{ste}} x_t + U_{\mathrm{ste}} h_{t-1} + b_{\mathrm{ste}}) \\ f_t^{\mathrm{fre}} &= \mathrm{sigmoid}(W_{\mathrm{fre}} x_t + U_{\mathrm{fre}} h_{t-1} + b_{\mathrm{fre}}) \end{aligned}\right\} \quad (11)$$

As shown in Fig. 2, within the memory unit, Co-SFM decomposes the internal hidden state into frequency and state components, drawing from the LSTM structure. The specific algorithm is detailed in Eq. (10). In addition, outside the memory unit, the context information formed by the coupling layer is fed into the Co-SFM's memory unit. It is important to note that these two parts of the model do not directly interact before time t. This means that the macro-sector information is integrated through the coupling layer prior to time t and is then unified with the internal hidden state generated by the stock price sequence at time t. The model leverages this integration of multilevel and multifrequency information to predict specific stork prince trends from a holistic system perspective.

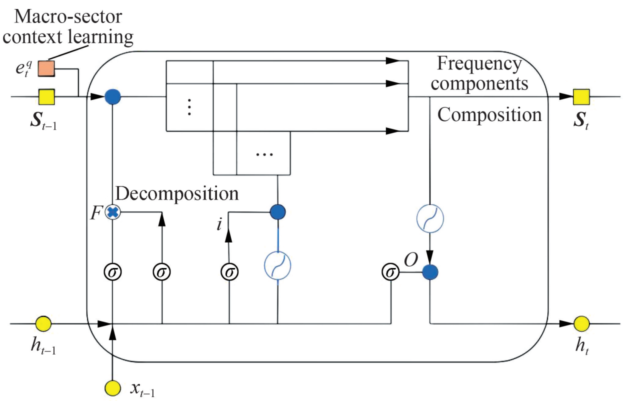

Fig. 2 Co-SFM's downstream structure

2 Experimental and Performance Analysis

In this section, we construct an experiment to verify the efficacy of the proposed Co-SFM. We first introduce a data set derived from the capital market and compare Co-SFM's performance against other time-series prediction methods.

2.1 Data set

To validate the model, we selected price data from several index stocks, including the Shanghai composite index, the Shanghai and Shenzhen 300 Index, the CSI 500 Index, and the Shenzhen Component Stock Index. The time span for this price data spans from 2014 to 2023. Additionally, we included macroeconomic indicators in the financial system, such as CPI, M1, the macroeconomic prosperity index, and Shibor. Ultimately, for sector data, we used the rolling P/E ratio to represent the main sectors within component stocks. This sector data was weighted and averaged according to the components of the different indices. Table 1 shows the details of the data set.

For training the model, we used daily prices from 2014 to 2022, integrating relevant macro- and sector data

Table 1 Macro- and sector data

Indicators	Introduction	Level
Shanghai Interbank Offered Rate (Shibor)	The RMB interbank offered rate independently quoted by banks with high credit ratings	Macroeconomic indicators
Money supply (M1)	The total amount of financial instruments that serve as means of circulation and payment at a certain point in time	Macroeconomic indicators
Consumer price index (CPI)	The number reflecting the trend and degree of price changes in consumer goods and services purchased by urban and rural residents over a certain period of time	Macroeconomic indicators
Rolling P/E ratio (P/E)	Daily updated sector P/E ratio of the sector	Sector indicators

in the upstream fusion module. The fused data was then fed into the downstream model alongside the daily price data. The model uses price data from 2022 to 2023 for verification and testing, allowing us to assess the feasibility of this multilevel stock price prediction model.

2.2 Comparison with the basic model

To verify the feasibility of our proposed Co-SFM model, we conducted a series of comparative experiments to evaluate its performance against LSTM and SFM models. We compared the Co-SFM with LSTM and SFM. LSTM is well known for uncovering long-term internal dependencies in time series through its complex internal network structure. Evaluating Co-SFM against LSTM helps us understand Co-SFM's capability in multilevel data analysis structure and frequency information mining. Meanwhile, SFM is a variant of LSTM that extracts hidden frequency information from time-series data, which is particularly useful for identifying hidden alternating frequency patterns in stock prices. Therefore, using SFM as a standalone model provides a benchmark to further assess the impact of incorporating multilevel data into the Co-SFM.

We used mean squared error as the evaluation metric for model performance. To verify each model's internal dependencies, we set different time steps: one-step for short-term accurate predictions and five-step for longer-term predictions.

The results, summarized in Table 2, show that as the time step increases, the mean square error of each model increases. While long-term predictions are less accurate than short-term ones, they better capture the overall trend of the sequence data as a whole. Notably, Co-SFM consistently outperforms the other models at all time steps. Especially in the 5-step prediction, Co-SFM's error is significantly lower, highlighting its superior capability in long-term predictions. These findings demonstrate Co-SFM's advantage in integrating multilevel data for enhanced performance in predicting stock price trends.

Table 2 Mean square errors for 1-step, 3-step, and 5-step predictions

Model	1-step	3-step	5-step
LSTM	90.731 9	109.194 6	148.324 2
SFM	44.232 6	50.337 2	81.512 1
Co-SFM	18.597 9	32.665 8	46.428 9

We visualized the prediction results of the model to provide a more intuitive comparison. Since the visualization results of SFM and LSTM are almost identical, we present comparative results between LSTM and Co-SFM. In the one-step prediction shown in Fig. 3, Co-SFM's prediction is much more accurate than that of LSTM. Figs. 4 and 5, which show predictions over increasing time steps, demonstrate that Co-SFM maintains consistent and stable prediction accuracy. Compared with the comparison model, Co-SFM's predictions are significantly more accurate

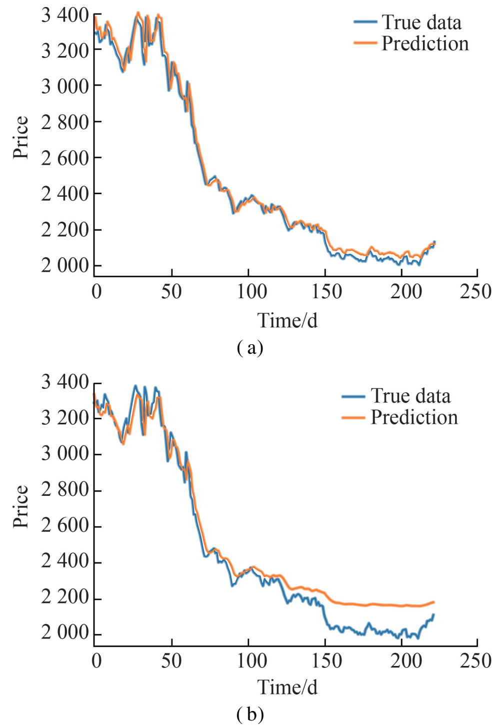

Fig. 3 Prediction results of 1-step prediction. (a) Co-SFM; (b) LSTM

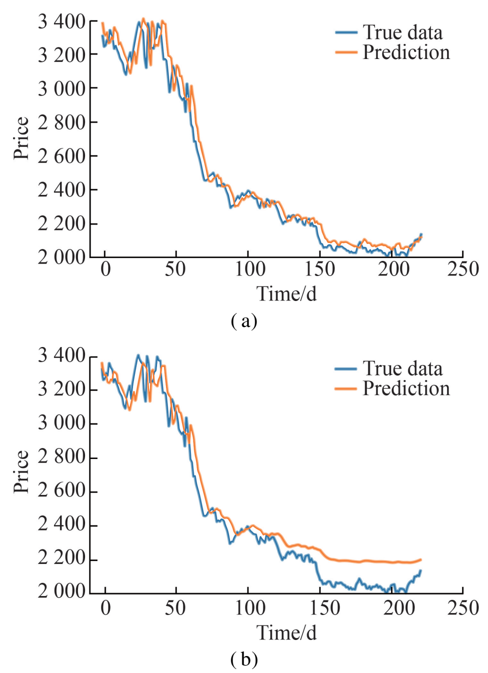

Fig. 4 Prediction results of 3-step predictions. (a) Co-SFM; (b) LSTM

across multiple time steps. This result proves that Co-SFM excels in long-term predictions of financial market trends by integrating multilevel data.

By integrating multilevel data, our model significantly improves its capability to capture comprehensive financial system information, particularly excelling in long-term trend forecasting. The coupling layer combines both economic and industry-related data pertinent to the index, thereby forming tailored integrated information. This com-

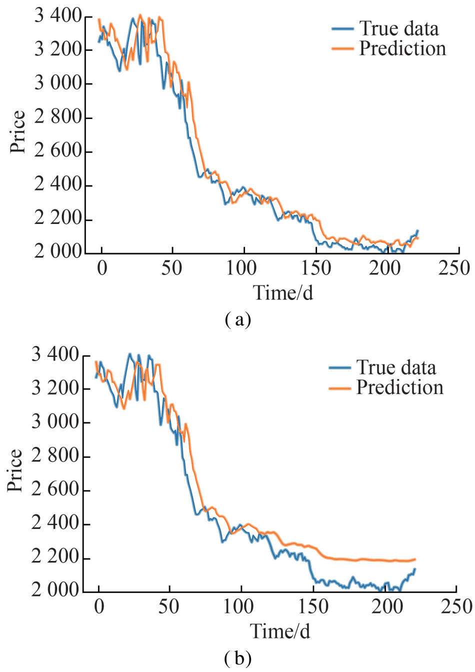

Fig. 5 The prediction results of 5-step. (a) Co-SFM; (b) LSTM

bined data is then fed alongside price sequences into downstream SFM models. This approach for multifrequency, heterogeneous data fusion not only enhances the model's generalization ability but also boosts its predictive performance. Consequently, the model exhibits superior performance in forecasting errors, which is validated through visual comparisons. For short-term single-step predictions, the forecasts are nearly perfect. In long-term forecasts, the model outperforms comparative models, further highlighting its advantage in capturing long-term trends.

3 Conclusions

1) A coupling module is designed to integrate related multilevel data, constructing a macro-sector-micro data hierarchy. This innovation at the data level allows for the integration of relevant multilevel data while retaining the original financial time-series data.

2) Using the SFM network as a predictor enables better identification and learning of hidden frequency information in financial time-series data. Our study found that the model performance significantly improves when using this fused data for classification prediction, resulting in more accurate financial market trend forecasts.

3) The Co-SFM, which incorporates multilevel data, outperforms LSTM and SFM models in both short-term and long-term predictions. Notably, in long-term trend predictions, Co-SFM performs better than other comparative models. This data processing approach can also be applied to other financial time-series forecasting tasks, especially in complex systems where model diversity and integrity are crucial.

4) In the future, we plan to analyze the impact of different levels of data on model performance. We aim to explore the influence of relevant data from a systematic perspective.

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耦合多层次指标的股票走势预测方法

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摘要：为了系统地将多种指标的影响纳入到股票走势研究中，设计了一个耦合多层次数据的状态频率记忆网络(Co-SFM)模型. 该模型将 Copula 估计整合到神经网络中，将各个层次的数据信息进行融合并输入到下游的学习模块. Co-SFM 使用上游的融合模块来纳入多个层次的数据，构建了宏观–板块–微观的数据结构. 这种结构通过多层次的数据指标识别出金融系统中不同层级数据的特征并进行融合，可以更好地挖掘出金融系统中的内在联系. 而在下游的模型中，Co-SFM 模型使用状态频率记忆网络来挖掘价格数据中隐含的频率信息，对价格数据的多频交易模式进行建模. 实证结果表明，Co-SFM 模型在融入多层次数据后对股价走势的预测效果明显优于其他模型，尤其在多步长的中长期走势预测中，其预测的精度得到明显提升.

关键词：股票走势预测；多层次数据；Copula；状态频率记忆网络

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