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SSTP: Stock Sector Trend Prediction with Temporal-Spatial Network

Shuo Yin

School of Computer Science and Engineering, Central South University, Changsha, China

Youwei Gao

School of Finance and Economics, Jimei University, 361021 Xiamen Fujian Province, China

Shuai Nie

School of Business Administration, Zhejiang Gongshang University, 310018 Hangzhou, Zhejiang, China

Junbao Li

Institute of Law, Sichuan Academy of Social Sciences, 610500 Chengdu, Sichuan, China

Corresponding author: ys_email@csu.edu.cn

In financial big data field, most existing work of stock prediction has focused on the prediction of a single stock trend. However, it is challenging to predict a stock price series due to its drastic volatility. While the stock sector is a group of stocks belonging to the same sector, and the stock sector index is the weighted sum of the prices of all the stocks in the sector. Therefore the trend of stock sector is more stable and more feasible to predict than that of a single stock to improve the returns on stock prediction. In this paper, we propose a new method named Stock Sector Trend Prediction (SSTP) to solve the problem of predicting stock sector trend. In SSTP method, we adopt the Relative Price Strength (RPS) time series to describe the trend of the stock sector, which is the relative rank of stock sector trend. In order to learn the intrinsic probability distribution of the stock sector index series, we construct the multi-scale RPS time series and build multiple independent fully-connected stock sector relation graphs based on the real relationship among stock sectors. Then, we propose a Temporal-spatial Network (TSN) to extract the temporal features from the multi-scale RPS time series and the spatial features from the stock sector relation graphs. Finally, the TSN predicts and ranks the trends of the stock sector trend with the temporal-spatial features. The experimental results on the real-world dataset validate the effectiveness of the proposed SSTP method for the returns on stock prediction.

KEYWORDS: Stock Sector Trend Prediction; Relative Price Strength (RPS); Multi-scale Feature; Stock Sector Relation Graph.

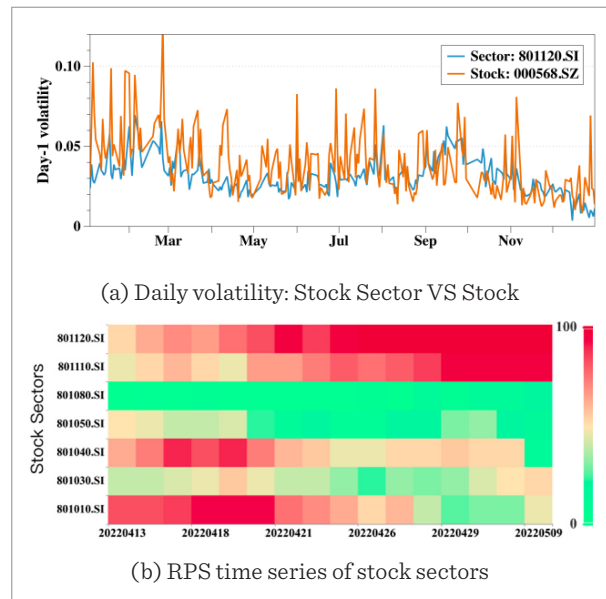
1. Introduction

In fintech, the stock market has developed rapidly and stock trading has become one of the most important financial instruments, and stock prediction is an important manner for investors to participate in stock trading [24]. Stock prediction aims to predict the future trends of a stock in order to help investors make good investment decisions. If stock predictions are accurate, investors can more accurately determine when to buy and sell stocks to maximize profits. Additionally, the accuracy of stock predictions can also help businesses make better business decisions to better meet shareholder needs and increase enterprise value. The purpose of stock forecasting is to predict the future trend of stocks and help investors make correct investment decisions. Traditional stock trend forecasting methods are based on time series analysis, most of them use machine learning algorithms such as the Hidden Markov Model (HMM), support vector machine (SVM), and Kalman Filters [4, 10, 15]. These methods use the technical indicators and financial new articles of the stock as input and the price of the stock as label to train the model, then predict the trend of the stock price [22]. However, the machine learning model can not extract the features from the original stock time series, which limits the performance of its stock trend prediction. With the success of deep learning in modeling sequence data in recent years, it has become a promising option for stock forecasting [6]. Nelson et al. [16] employed LSTM networks on stock time series data to uncover dependencies between features for stock trend prediction. The results demonstrate improved prediction performance compared to traditional machine learning methods. Feng et al. [7] provide a new deep learning solution called Relational Stock Ranking (RSR) for stock forecasting, achieving a return of 0.68 and 0.56 on NASDAQ and NYSE, respectively, over 237 trading days. Ying et al. [25] improved on the basis of RSR and proposed a graph-based stock recommendation model, which improved the stock return and finally achieved a return rate of 0.92 and 1.38 on NASDAQ and NYSE, respectively.

However, the stock price time series has sharp volatility, which hinders the generalization of modeling on stock trend prediction using deep learning. The stock sector is a combination of stocks in the same industry,

and the trend of the stock sector index is the weighted price sum of all the stocks in the sector. As shown in Figure 1(a), the Daily volatility (dv) of a stock trend is stronger than the stock sector trend, and the definition of Daily volatility (dv) is shown as Definition 1 in Section 3. Compared with the stock trend, the deep learning model can obtain better generalization of the stock sector trend and improve the prediction performance of the model. The RPS time series measures the relative trend among stock sectors, and the strict definition of the RPS is shown as Definition 2 in Section 3. From Figure 1(b), the horizontal axis represents the date, and the vertical axis represents different stock sectors. The deeper color means the

Figure 1
Stock trend and stock sector trend



Note: (a) Stock sector is more stable than that of a single stock. In this example, Stock sector 801120.SI is a group of stocks belonging to the same sector, including Stock 000568.SZ. (The detail definition of Daily-1 volatility (dv) is shown as Definition 1 in Section 3). (b) The trend of different stock sector indices from April 13, 2022 to May 9, 2022. We describe RPS time series in shades of color (from 0 to 100). The deeper color means the higher RPS rank of the stock sector. We can clearly find that the RPS time series of different stock sectors have stable and continuous trend, which is beneficial to deep learning to fit its distribution (the detailed definition of RPS is shown as Definition 2 in Section 3.)

higher RPS rank of the stock sector. We can clearly find that the RPS time series of different stock sectors have stable and continuous trend, which is beneficial to deep learning to fit its distribution.

To reduce investment risk in the stock market and improve the prediction performance of the model, we use the stock sectors instead of stocks as the trend prediction object. We propose a novel Temporal Spatial Network (TSN) based on RPS time series to predict the stock sector trend. To better mine the RPS time series for stock sector trend prediction, we construct multi-scale RPS time series and design the temporal extractor to mine the temporal features. According to the efficient market hypothesis, there is a correlation between stock sector trends. We build multiple independent fully-connected graphs called the stock sector relation graphs based on different stock sectors to construct correlations between stock sector trends. Then, TSN extracts the spatial features from the stock sector relation graphs using the spatial extractor. Finally, TSN merges the temporal and spatial features to predict the stock sector trend. The main contributions of this paper are summarized as follows:

- The performance of stock trend-based prediction methods is limited due to the highly volatile characteristic of stock trends. We find that the stock sector trend has the characteristics of stability and continuity, which is beneficial for deep learning to fit its data distribution to improve the returns on stock prediction.
- We propose a Temporal-spatial Network (TSN) to extract the temporal features based on multi-scale RPS time series of stock sectors and mine the spatial features using stock sector relation graphs to predict the stock sector trend.
- The experimental results show that this method can predict the trend of stock market effectively.

2. Related work

Stock Prediction based on Machine Learning. Traditional financial models focus on technical analysis, extracting price-quantity indicators from historical transaction data and using machine learning algorithms. Kavitha et al. [10] give the idea of using Hidden Markov Model (HMM) to analyze stock mar-

ket behavior trend. The trend once followed over a particular period will sure repeat in future. The support vector machine (SVM) and K-nearest neighbor (KNN) algorithm were used to study the stock price forecasting problem, select the transaction data reflecting the stock trend and its technical indicators, forecast the ups and downs and the closing price of the Shanghai Composite Index [15]. In order to reduce the risk of stock investment, Khaidem et al. [11] propose a new method to predict stock returns by using a powerful machine learning algorithm called ensemble learning.

Stock Prediction based on Deep Learning. Establishing effective technical characteristics usually requires considerable expertise, and the assumed stochastic process may not be the best way to simulate highly non-linear and non-stationary fluctuations in the stock market. In recent years, deep learning models have played an important role in prediction tasks [2, 13], especially recurrent neural networks (RNNs) [18, 23, 26]. Chen et al. [1] study LSTM-based method for stock return prediction. In addition to adding historical price series to improve forecasting accuracy, stock forecasting also needs to consider external information, such as news, media and various other information. For example, Deng et al. [5] propose a novel Knowledge-Driven Temporal Convolutional Network to predict the trend of stock. Some recent scientific advances attempt to model how stocks affect each other by learning the characteristics of the relationship between stocks. Given a set of pre-defined stock relationship graphs, extract graph-based stock interaction features using temporal graph convolutional networks [3, 12, 14]. However, a stock (company) is widely related to some other stocks through various relationships, so how to express the relationship between stocks is still a challenging problem. Hsu et al. [9] designed the FinGAT model, which is a multi-task graph neural network-based model that can learn the hierarchical influence between stocks and generate the most profitable stocks. Recently, some studies have begun to consider how to predict the most promising stocks in the financial market [7, 25]. This approach is easier than attempting to predict the stock price of each individual stock, as ranking only requires comparing the relative performance among companies, without the need to accurately forecast the future value of each company.

However, most of the current financial forecasting methods are based on stock forecasting. Stock trends are highly volatile and are easily affected by irrational factors in the financial market, such as market sentiment, investor sentiment and behavior. These factors are not easy to predict through data analysis, and will affect the accuracy of stock forecasting.

3. Preliminaries

3.1. Definition

We define the Daily volatility (dv) and RPS_m^t as follows:

DEFINITION 1: Daily volatility (dv).

The dv is a measure of the daily volatility range of a stock or stock sector and is used to measure risk in this paper. We define the highest index, lowest index, and closing index of the stock sector on day t as P_{high} , P_{low} , P_{close} , the final representation of dv :

$$dv = \sqrt{\left(\frac{P_{high} - P_{close}}{P_{close}}\right)^2 + \left(\frac{P_{low} - P_{close}}{P_{close}}\right)^2}. \quad (1)$$

DEFINITION 2: RPS_m^t .

RPS_m^t is defined as the ranking of the relative change value of each stock sector index in all stock sectors within a period of m . Let $S = \{s_1, s_2, \dots, s_i, \dots, s_n\}$ denote the set of n stock sectors; i is the index value of stock sector i at day t . We calculate the change of the stock sector index i in m days as follows:

$$C_m^t = \frac{(z_t - z_{t-m})}{z_{t-m}}, \quad (2)$$

where $C_m^t \in \mathbb{R}$. Then we sort the in descending order by the ranking algorithm rank, and we get the ranking value of stock sector i in m days: $r_m^t = \text{rank}(C_m^t)$, $r_m^t \in \mathbb{N}^*$, $r_m^t \in \mathbb{N}^*$, and n is the number of stock sectors; Finally, RPS_m^t of stock sector i in m days is defined as follows:

$$RPS_m^t = \left(1 - \frac{r_m^t}{n}\right) * 100, \quad (3)$$

where $RPS_m^t \in \mathbb{R}$ and $RPS_m^t \in [0, 100)$. For example, in a financial market with a total of 100 stock sectors. On day t , the 3-day return of a stock sector i is C_3^t , which ranks 10th among

all 100 stock sectors ($r_3^t = \text{rank}(C_3^t) = 10$). Then the RPS_3^t value of the stock sector is 90 at day t , where $RPS_3^t = (1 - 10/100) * 100 = 90$.

3.2. Problem Formulation

We formulate stock sector trend prediction as a ranking task f , to learn the intrinsic probability distribution of the stock sector index time series. Let $S = \{s_1, s_2, \dots, s_i, \dots, s_n\}$ denote the set of n stock sectors, and we define the set of stock sector RPS time series at day t $\Psi_t = \{X_t^1, \dots, X_t^S\} \in \mathbb{R}^{S * T * U}$, where t is the length of RPS time series, and U is the dimension of features, among which features include RPS_1^t , RPS_3^t , RPS_5^t , RPS_{10}^t , RPS_{15}^t , and RPS_{20}^t . To better predict the future trend, we build multiple independent fully-connected stock sector relation graphs relying on real stock sector internal information. The topological graph is represented as $G = \{V, E\}$, where V is a set of stock sectors; E is a set of sector adjacency relations, indicating the correlated intensity between and. Then, we get the ranking list $Y_{t+1} = \{\hat{y}_{t+1}^1, \dots, \hat{y}_{t+1}^i, \dots, \hat{y}_{t+1}^S\}$ for all stock sectors S by regressing task f , the represented as follows:

$$[G, \Psi_t] \xrightarrow{f} Y_{t+1}, \quad (4)$$

where $\hat{y}_{t+1}^i \in \mathbb{R}$, $\hat{y}_{t+1}^i \in [0, 100)$, $\hat{y}_{t+1}^i = RPS_1^{t+1}$ and \hat{y}_{t+1}^i is the prediction value of stock sector i at day $t+1$. Finally, we recommend that investors buy funds corresponding to the predicted *Top5* stock sectors on each trading day.

4. Methodology

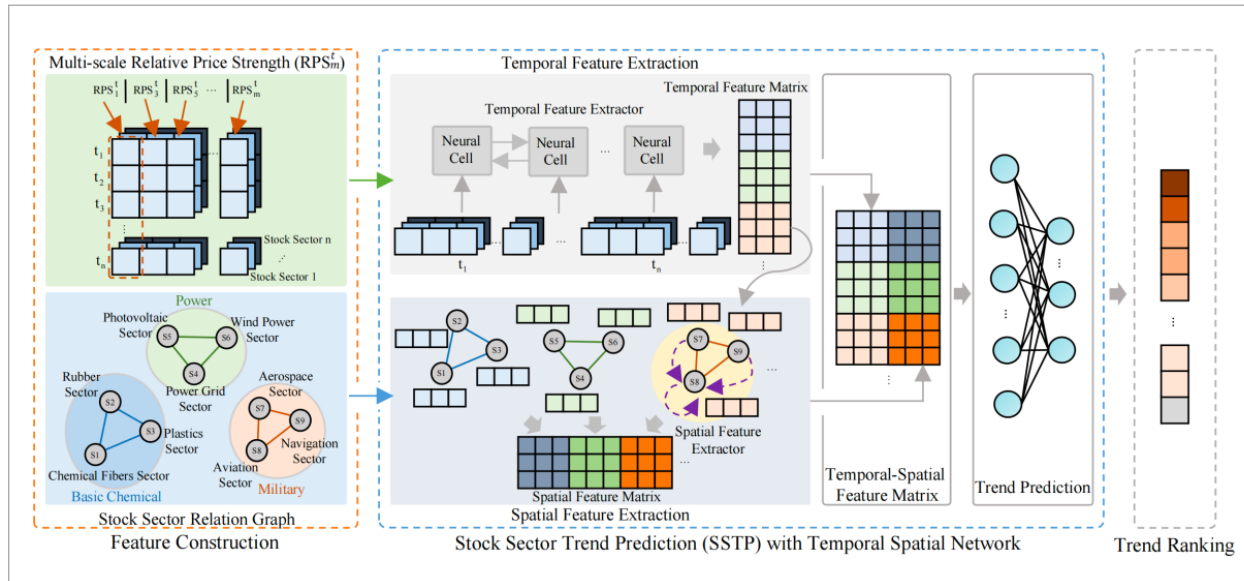
To better understand the process of the stock sector trend prediction, we introduce our method in detail in this section. As shown in Figure 2, there are three main processes in our method, namely feature construction, stock sector trend prediction (SSTP) with temporal-spatial network, and trend ranking.

4.1. Feature Construction

Multi-scale Time Series. To better describe the stock sector index by RPS time series, we construct the multi-scale RPS_m^t time series. The multi-scale RPS_m^t contains the trend characteristics of stock sectors at different time scales, it can add more additional useful information to help improve the performance of deep learning models.

Figure 2

The architecture of stock sector trend prediction with temporal-spatial network based on multi-scale RPS time series and stock sector relation graphs



Note: There are three main processes in our method, namely feature construction, stock sector trend prediction (SSTP) with temporal-spatial network, and trend ranking. (a) Feature construction module builds the input data set of the model, including Multi-scale time series and Stock Sector Relation Graph. (b) Stock sector trend prediction (SSTP) with temporal-spatial network module extracts temporal and spatial features, and fuses the temporal feature and spatial feature to get a new vector, which is then used as the input of the full connection layer to get the predicted value. (c) Trend ranking module calculates the ranking list for all stock sectors.

Stock Sector Relation Graph. In order to build the correlation between stock sectors within the same industry, we construct multiple independent fully-connected graphs based on stock sectors called the stock sector relation graphs. Such as, Wind Power Sector, Power Grid Sector, and Photovoltaic all belong to the Power Industry. In our stock sector relation graph, the stock sectors are nodes, and there is an undirected edge between any two nodes. The TSN extracts the spatial features from the stock sector relation graph for the fusion of features.

4.2. SSTP with Temporal-spatial Network

Temporal Feature Extraction. To better obtain the temporal features from the multi-scale RPS_m^t , the TSN uses the *Bi-LSTM* as the temporal extractor. *Bi-LSTM* can perform bidirectional encoding of time series, which can better capture the local features of time series. Given the RPS_m^t time series of stock sector i , $X_t^i = \{x_{t-T+1}^i, \dots, x_t^i\}$, and the RPS_m^t time series as the input of the *Bi-LSTM* to get the temporal features. It's formulated as follows:

$$e_t^{ij} = Att \left(WH_t^i, WH_t^j \right), \tag{5}$$

where $h_t^i \in \mathbb{R}^U$ and $h_t^{i'} \in \mathbb{R}^U$ denotes the output of *LSTM* unit of forward layer and backward layer. H_t^i is the concatenated vector of the outputs of forwarding and backward processes by *CONCAT* operation and U is the dimension of the hidden layer. The W_n are weight matrices for the input part.

Spatial Feature Extraction. To extract spatial features from stock sector relation graphs, the TSN constructs the graph attention network (*GAT*) as the extractor of spatial features. *GAT* can calculate the correlation coefficient according to the different contributions of the neighbor node features to the central node. Then it can aggregate the features of the neighbor nodes based on the attention coefficient, which can effectively improve the representation ability of the central node. Firstly, *GAT* performs a self-attention *Att* operation on the nodes to compute attention coefficients:

$$e_t^{ij} = \text{Att} \left(W H_t^i, W H_t^j \right), \quad (6)$$

where indicates the importance of sector node j 's features to sector node i at day t and $W \in \mathbb{R}^{2U}$. Then, we normalize them across all choices of j using the softmax function:

$$\alpha_t^{ij} = \text{softmax}_j \left(e_t^{ij} \right) = \frac{\exp \left(e_t^{ij} \right)}{\sum_{k \in \mathcal{N}_i} \exp \left(e_t^{ik} \right)}, \quad (7)$$

where $j \in \mathcal{N}_i$ and \mathcal{N}_i is some neighborhood of stock node i in the graph. For stock sector i , we aggregate the characteristics of all adjacent stock nodes to get the relational feature representation $H_t^{i'}$. It's formulated as follows:

$$H_t^{i'} = \sigma \left(\sum_{j \in \mathcal{N}_i} \alpha_t^{ij} H_t^j \right), \quad (8)$$

where σ is an activation function.

Temporal-Spatial Feature Matrix. In order to get more effective representation, TSN uses the CONCAT operation to fuse the temporal features produced by *Bi-LSTM* and spatial features built by the GAT.

The $H_t^{i'}$ represents the representation of the spatial features. TSN concatenates $H_t^{i'}$ with the temporal feature H_t^i as the final feature representation of stock sector i , and $Q_t^i = \text{CONCAT}(H_t^i, H_t^{i'})$, where $Q_t^i \in \mathbb{R}^{2U}$.

Trend Prediction. When we get the final feature representation, it is used as input of the full connection layer to calculate the \hat{y}_{t+1}^i , and $\hat{y}_{t+1}^i = \text{LeakyReLU}(W Q_t^i + b_p)$, where $RPS_1^{t+1} = \hat{y}_{t+1}^i$, $W \in \mathbb{R}^{2U}$ and U is the dimension of the hidden layer. In order to achieve the best model fitting effect, we use MAE as a loss function:

$$L(\hat{\mathbf{y}}_{t+1}, \mathbf{y}_{t+1}) = |\hat{\mathbf{y}}_{t+1} - \mathbf{y}_{t+1}|. \quad (9)$$

4.3. Trend Ranking

Then, TSN ranks the values in descending order, and by this means, we get the ranking list for all stock sectors S . $Y_{t+1} = \{\hat{y}_{t+1}^1, \dots, \hat{y}_{t+1}^s\} \in \mathbb{R}^S$. Finally, we recommend investors buy funds corresponding to the predicted *Top5* stock sectors on each trading day.

5. Experiments

5.1. Datasets

Stock Sector Indices. We get the stock sector indices in the Chinese A-share market from Tushare [21] which has time series between 11/02/2021 and 08/12/2022, including 124 stock sectors. Table 1 shows the detailed statistics.

RPS Time Series. RPS time series is transformed through Stock Sector Indices as the model's initial input. In detailed, the entire dataset is divided into the training set, validation set and testing set, and their lengths are shown in Table 1.

Table 1

Statistics of the datasets in the Chinese A-share market

Datasets		A-share market
Stock Sector Indices	#Initial data Days	190
	#Training Days	80
	#Validation Days	40
RPS Time Series	#Testing Days	50
	#Nodes	124
Stock Sector Relation Graph	#Relations	31
	#Edges	228

Stock Sector Relation Graph. We have obtained 31 types of stock sector relations, which were then utilized to construct the stock sector relationship graph. In this graph, each "Node" represents a distinct stock sector. The "Relations" category indicates the number of independent fully-connected graphs within the stock sectors, with each graph representing a specific industry. The "Edges" represent the connections between nodes, signifying the relationship between two stock sectors belonging to the same industry. Table 1 shows the summary statistics for stock relation graph.

5.2. Experimental Setup

Learning from the method, we employ a market simulation strategy to assess performance by calculating cumulative returns over the testing period [7, 25]. First, we assume that the financial market operates normally, and each sector has its corresponding funds. Thus the market can meet all the trading needs of investors.

The following assumption is that investors will buy the funds corresponding to the predicted *Top5* stock sectors on each trading day, and the money amount for purchasing each fund is the same and fixed. The funds will be bought on trade day t and sold on trade day $t+1$.

Evaluation Metrics. We use three indicators to evaluate the predictive performance of the model: Mean Absolute Error (MAE), Mean Reciprocal Rank (MRR), and Investment Return Ratio (IRR).

- **Mean Absolute Error (MAE):** MAE is a measure of the error between the true value and the predicted value. MAE is defined as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_{t+1} - y_{t+1}|. \tag{10}$$

- **Mean Reciprocal Rank (MRR) [7]:** MRR is an international mechanism for evaluating search algorithms. MRR is defined as:

$$MRR = \frac{1}{N} \sum_{i=1}^N \frac{1}{rank_i}, \tag{11}$$

where is the rank of the predicted *Top1* stock sector on the i th testing day.

- **Investment Return Ratio (IRR) [25]:** IRR is the cumulative rate of return. IRR is defined as:

$$IRR = \prod_{i=1}^N (1 + R_i) - 1, \tag{12}$$

where is the average rate of return of the predicted *Top5* stock sectors on the i th testing day.

The better the performance, the smaller the MAE value (≥ 0), the larger the MRR value ($0,1$] and the larger the IRR value ($\in \mathbb{R}$). To avoid the influence of accidental factors and hyperparameters, we repeated all experiments 10 times.

Table 2

Performance Comparison With Different Input Features

Methods	MRR	IRR
Rank_LSTM (stock)	1.71e-03±3.44e-04	0.034±0.001
Rank_LSTM (sector)	4.08e-02±1.62e-03	0.079±0.007
Rank_LSTM (RPS)	4.20e-02±1.00e-03	0.089±0.006

Table 3

Performance Comparison With Baseline Models

Methods	MAE	MRR	IRR
RNN [19]	2.67e+01±3.11e-01	3.40e-02±3.00e-03	0.035±0.005
LSTM [17]	2.59e+01±6.92e-01	3.35e-02±1.50e-03	0.042±0.005
GRU [8]	2.54e+01±1.50e-02	4.10e-02±2.00e-03	0.045±0.008
Rank_LSTM [7]	2.53e+01±5.50e-02	4.20e-02±1.00e-03	0.089±0.006
RSR_E [7]	2.53e+01±3.69e-02	4.85e-02±2.25e-03	0.104±0.003
RSR_I [7]	2.53e+01±1.12e-02	5.10e-02±1.00e-03	0.124±0.003
TRAN [25]	2.53e+01±2.42e-02	4.95e-02±1.50e-03	0.112±0.004
TSN	2.52e+01±4.15e-03	5.45e-02±6.35e-03	0.147±0.003

Table 4

Ablation Study

Methods	MAE	MRR	IRR
TSN (w/o T)	2.57e+01±1.32e-01	4.75e-02±1.50e-03	0.083±0.024
TSN (w/o S)	2.52e+01±5.50e-03	4.05e-02±1.35e-02	0.085±0.012
TSN	2.52e+01±4.15e-03	5.45e-02±6.35e-03	0.147±0.003

Table 5

Performance of TSN as compared to six market indices (SSE, SZ, DJI, IXIC, N225 and HSI) and two ideal portfolios (Market and Selected) from June 6, 2022 to August 12. We assume that each index or stock sector has a corresponding fund that can be purchased

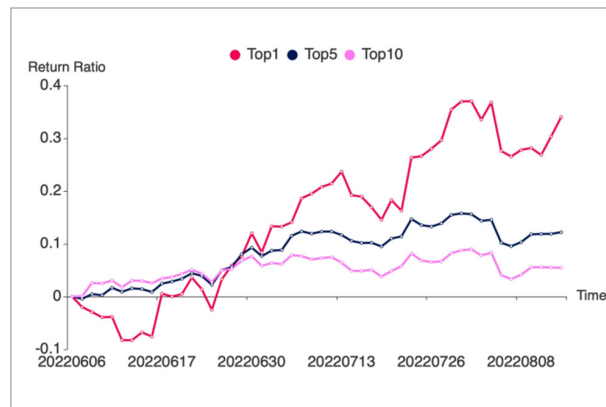
Market Indices	IRR		
SSE	0.040		
SZ	0.012		
DJI	0.025		
IXIC	0.059		
N225	0.041		
HSI	-0.043		
Ideal Portfolios	TOP1-IRR	TOP5-IRR	TOP10-IRR
Market	0.393	0.351	0.330
Selected	0.498	0.270	0.226
TSN	0.340	0.122	0.071

5.3. Baselines

- RNN [19]: We replace TSN with a common RNN layer.
- LSTM [17]: We replace TSN with a common LSTM layer.
- GRU [8]: A common RNN-based model to learn sequential features.

Figure 3

Comparison of market simulation strategies (*Top1*, *Top5*, *Top10*) on the IRR metric

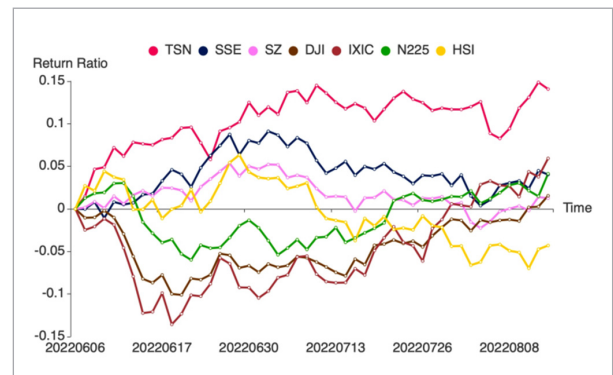


Note: For example, in the *Top5* market simulation strategy, we evenly allocate funds to trade the *Top5* stock sectors and calculate the IRR value by cumulating the mean return ratio of the 5 selected stock sectors

- Rank_LSTM [7]: In this work, a new deep learning solution called Rank_LSTM is contributed to the financial rank prediction problem.
- RSR_E [7]: RSR_E is a model for predicting stock rankings that utilizes stock relations. It incorporates a relational embedding layer into Rank_LSTM, which explicitly models the relationships between stocks.
- RSR_I [7]: RSR_I and RSR_E are related, but differ in the way they model relations. Specifically, RSR_I uses implicit modeling instead of explicit modeling in the relational embedding layer.

Figure 4

Performance of TSN as compared to six market indices (SSE, SZ, DJI, IXIC, N225 and HSI)



- TRAN [25]: The authors of this study introduce a Time-aware Relational Attention Network (TRAN) for graph-based stock recommendation based on ranking stocks according to their return ratios.

5.4. Experimental Results

Performance Comparison with Different Input Features: In order to prove that the deep learning model based on stock sector features can obtain better generalization to predict the future trend in the stock market, we use the Rank_LSTM to model and test three different input features respectively. The experimental results are shown in Table 2, the Rank_LSTM (stock) represents the input of features are the stock time series, the Rank_LSTM (sector) stands for the input of features are the stock sector index time series, the Rank_LSTM (RPS) indicates that the input of features is the multi-scale time series. As the trend of the stock sector index is the weighted sum of the trends of all the stocks in the sector, the stock sector has a more stable trend than the trend of stocks. It is beneficial to deep learning to fit its distribution to improve the generalization. Therefore, the Rank_LSTM (sector) can get better performance than the Rank_LSTM (stock) on the MRR and IRR metrics.

This fully shows that the stock sector trend prediction (SSTP) can better avoid investment risks than the stock trend prediction. Better avoid investment risks than the stock trend prediction. Since our constructed multi-scale time series can better describe the stock sector index, Rank_LSTM (RPS) gets the best results on the MRR and IRR metrics in Table 2. It fully demonstrates the effectiveness of our construction of multi-scale features for stock sector trend prediction.

Performance Comparison with Baseline Models: We can observe from Table 3, our model (TSN) achieves the best performance in the Chinese A-share market, compared to other models, including traditional models (RNN, GRU and LSTM) and ranking-based models (Rank_LSTM, RSR_E, RSR_I and TRAN). We can observe that ranking-based models are greatly improved compared with traditional models. IRR is considered to be the most critical indicator in predicting stock market trends. Compared with other IRR based models, our model achieves the best performance. Specifically, the IRR value is 0.147

in our method and the results validate the superiority and practicality of the proposed trend prediction model. Additionally, the stability is also verified by the MAE and MRR metrics. Both the values of MAE and MRR of TSN achieve the best results among all the baselines.

Ablation Study: As observed from Table 4, since both temporal feature extraction and spatial feature extraction components play an important role in our model TSN, TSN outperforms TSN (w/o T) and TSN (w/o S). Temporal feature extraction can better obtain the temporal features from the multi-scale RPS time series, and the TSN uses the *Bi-LSTM* as the temporal extractor. *Bi-LSTM* can perform bidirectional encoding of time series, which can better extract the local features of time series. Spatial feature extraction can extract spatial features from stock sector relation graphs, and the TSN uses the GAT as the spatial extractor. GAT can calculate the correlation coefficient according to the different contributions of the neighbor node features to the central node. Then it can aggregate the features of the neighbor nodes based on the attention coefficient, which can effectively improve the representation ability of the central node.

- 1 TSN (w/o T): TSN does not rely temporal feature extraction.
- 2 TSN (w/o S): TSN does not rely spatial feature extraction.

Study Simulation Strategies: In order to reduce investment risk, most investors will always choose a variety of different stocks as investment options. Therefore, we study the performance of our proposed TSN under different market simulation strategies (*Top1*, *Top5*, and *Top10*), buying stock sectors with *Top1*, *Top5*, and *Top10* highest expected return ratio, respectively. For example, in the *Top10* market simulation strategy, we allocate the budget equally, trade the *Top10* stock sectors, and calculate the IRR value by accumulating the average returns of the selected 10 stock sectors on each test day. Comparison of market simulation strategies (*Top1*, *Top5*, *Top10*) on the IRR metric is shown in Figure 3. From the figure, the following phenomena can be observed:

- **PHENOMENON 1.** In general, the highest return ratios should be obtained by selecting the most top stock sectors. Therefore, *Top1* strategy has achieved the highest return ratio within the nearly two-month range, but strategy *Top1* is more volatile than strat-

egy *Top5* and strategy *Top10*. There are reasons to think that picking only the *Top1* of more than 100 stock sectors is a risky strategy. From another perspective, *Top10* strategy reduces the return rate because the portfolio is too diversified. Comprehensive consideration, the *Top5* strategy is the recommended investment strategy for most investors.

- **PHENOMENON 2.** In most cases, the IRR performance of our prediction model in most test days follows the ranking of *Top1*>*Top5*>*Top10*. The reason may be that TSN can accurately predict the relative ranking of future returns. Once the predicted stock sector ranking is accurate, we can purchase the funds corresponding to the top *n* sectors with higher expected returns under the previously defined market simulation strategy to achieve a higher cumulative return rate.

Taking into account the strategy's performance across the market, we further compared our approach to six market indices, SSE Composite Index (SSE 000001.SH), Shenzhen Component Index (SZ 399001.SZ), Dow Jones Industrial Average (DJI), NASDAQ Composite Index (IXIC), Nikkei 225 Index (N225), Hang Seng Index (HSI), Figure 4 shows the comparison of TSN with SSE, SZ, DJI, IXIC, N225 and HSI. Furthermore, in order to better judge the performance achieved, we compared two more desirable investment strategies: a) Market: We pick the funds with the highest return ratios (*Top1*, *Top5* and *Top10*) from Eastmoney [20]; b) Selected: During the testing period, we buy the funds associated with highest return ratios (*Top1*, *Top5* and *Top10*) from the dataset of our model. From Table 5, we have the following observations:

- **OBSERVATION 1.** There is a gap between the performance of the proposed method and the ideal investment strategy when trading the same number of stock sectors (*Top1*, *Top5* and *Top10*). Since it is difficult to pinpoint the stock sector with the highest return ratio in a nearly two-month range, this result is acceptable. At the same time,

it can also reflect that the stock recommendation task still has great potential for improvement.

- **OBSERVATION 2.** Our method, trading the *Top1* ranked stock sector on each trading day, achieves best result than the *Top5* and *Top10* of the investment strategy Selected. These results demonstrate the competitiveness of our model and further demonstrate the effectiveness of TSN on the task of stock prediction.

6. Conclusions

In this work, we propose a Temporal-spatial Network (TSN) based method for Stock Sector Trend Prediction (SSTP), which can extract the temporal features based on multi-scale RPS time series of stock sectors and the spatial features with stock sector relation graphs to predict the stock sector trend. The experimental results on real data sets verify the effectiveness of this method for stock market trend prediction. In the future, in order to balance the benefits and risks, we plan to add a market scoring unit study inspired by human investment behavior. It takes the market sentiment indicator as the input, the dynamic adjustment of capital allocation.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Conflicting Interests

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