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PREDICTION ALGORITHM OF INDUSTRY ROTATION BASED ON ATTENTION LSTM MODEL

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Abstract. *Industry rotation has gradually become a hot topic in academic research. Analyzing the laws of industry rotation and predicting industry trends are of great guiding significance for funds and stock investment. Existing industry research mostly uses macroeconomic characteristics to conduct qualitative analysis on it, and has achieved good results. However, the analysis results are different due to the subjective experience of the analyst, and it is difficult to quantify and reproduce. In addition, some scholars use industry-related data for quantitative analysis, such as price fluctuations, market data and fundamental data. Although the use of industry data has eliminated the influence of human factors in qualitative analysis and achieved good results, the analysis perspective is relatively single. In response to the above problems, this paper constructs a multi-dimensional factor data set from the perspective of industry momentum effect, industry component stock behavior characteristics, industry profitability and Hong Kong capital flow, and uses the attention LSTM (Long Short-Term Memory Networks) model to learn and predict industry rotation and obtains about 77% accuracy rate. The results show that the multi-factor data set proposed in this paper can well show the industry rotation law, and the attention LSTM model can focus on key information and obtain better prediction results.*

Keywords: Industry rotation, Multi-factor data set, LSTM, Attention mechanism

1. **Introduction.** When most of the funds in the market flow into different industries, most investors will follow the shift of the focus of funds to change their investment strategies, which will make each industry sector show a state of rising and falling one after another. This phenomenon is called industry rotation [1]. If investors can grasp the development law of the industry rotation, they will be able to obtain excess returns in each round of the market.

Industry rotation has become an investment strategy and has been widely used in investment practice. Sassetti and Tani conducted a research on 41 funds that adopt industry rotation strategies, and the results show that industry rotation strategies can obtain excess returns [2]. Chisholm et al.'s research shows the important impact of industry configuration on revenue [3]. Sarwar et al. used alpha analysis to study the risk adjustment performance and industry rotation strategy of the US sector investment portfolio, and the Alpha benefit was significant [4]. Wu used Merrill Lynch's clock theory to study the A-share stock market and found that industry fluctuations will affect market returns [5]. Alexiou and Tyagi studied the industry rotation strategies in the European and American markets from 1999 to 2019, and found that industry rotation strategies can achieve excess

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returns [6]. The above research results show that industry rotation is one of the factors affecting stock market changes. By studying the changing laws of industry rotation, we can capture the hot industries in the current stock market in time, which plays a guiding role in stock investment and fund trading.

In addition, many scholars distinguished the economic cycle through macroeconomic factors, and designed the corresponding industry rotation model [7,8]. Rapach et al. demonstrated the predictability of industry rotation income through empirical evidence of the lagging returns of the financial industry, consumer industry and materials industry [9]. Huang used Merrill Lynch's clock investment theory to divide the Shenwan Tier 1 Industry Index, and obtain excess returns [10].

Some scholars have obtained excess returns through quantitative analysis of industries and design of corresponding industry rotation models. Peng and Liu used the association rule algorithm to mine the industry rotation rules in different time periods, and proposed an asset allocation strategy, and found that this strategy can significantly outperform the market benchmark [11]. Xu used the construction of basic multi-factor models and other models to compare the returns of different models to verify the effectiveness of the industry's rotating stock selection strategy [12]. Jin et al. used the Markov state transition model to capture changes in the sequence of financial asset returns, and constructed a cross-regional and cross-industry asset allocation model [13]. Huang used the industry's rise and fall data and LSTM to study the industry rotation, and the experimental results were better than the CSI 300 benchmark [14]. Zhang studied the index data from 2008 to 2018. Through the Granger causality test, he concluded that consumer industries such as agriculture, feeding and fishing are more affected by macroeconomic policies, and medicine and biology are less affected [15].

As mentioned above, both qualitative analysis and quantitative analysis of the industry have achieved good results. However, the empirical results of qualitative analysis are often affected by subjective factors and are difficult to quantify and replicate. The existing quantitative analysis uses relatively single data. In response to the above problems, this article attempts to construct a multi-dimensional factor data set from the perspective of industry momentum effect, behavior characteristics of industry component stocks, industry profitability, and Hong Kong capital flow, and uses the attention LSTM model to learn and analyze the laws of industry rotation, which have important guiding significance for funds trading and stock investment.

The rest of our paper is structured as follows: Section 2 discusses the construction of the industry multi-factor data set, Section 3 describes the model construction in detail, Section 4 provides experiments to demonstrate the effectiveness of the attention LSTM model, and Section 5 summarizes this work and future directions.

2. **Construction of Multi-Dimensional Factor Data Set.** In addition to the macro economy, the formation of industry rotation is also affected by the behavior of investors, their own development cycle [16], the behavioral characteristics of the industry's constituent stocks, and the direction of capital flows. Now, this section attempts to construct a multi-dimensional factor data set from the perspective of the above influencing factors.

2.1. **Split momentum factor.** Due to the convergence of investment behavior of general investors, some trading institutions and rational investors will use information and capital advantages to create "hot spots" to attract general investors to follow. In this process, some popular industries have shown a trend of continuous rise due to the continuous inflow of capital. With the limited amount of funds, other poorly performing industries will continue to fall due to the continuous outflow of funds. The industry index maintains the previous movement direction is the industry momentum effect. Conversely, if the industry index trend reverses, this is the industry reversal effect. The momentum effect and reversal effect of multiple industries alternately appear, forming the phenomenon of industry rotation. Research has found that industry momentum is more significant in terms of daily and weekly cycles [17]. Therefore, this article attempts to divide the industry momentum at the daily cycle level into intra-day momentum and inter-day momentum. Observe whether the momentum effect is formed from the intra-day momentum factor. And observe whether the momentum of the previous trading day continues to the current trading day from the inter-day momentum factor, so as to carefully observe the influence of the industry momentum effect on the industry rotation. The specific calculation method is as follows:

$$intra_m = \frac{tclose - topen}{topen} \tag{1}$$

$$inter_m = \frac{topen - yclose}{yclose} \tag{2}$$

Among them, *topen*, *tclose* are the opening and closing prices of the industry index on the current trading day, and *yclose* is the closing price of the previous trading day.

2.2. **Industry synergy factor.** The price changes of the constituent stocks within the industry will directly affect the trend of the index. Historical data shows that when the market appears, the leading stocks in the industry will try to lead the relatively flat common stocks to rise together. If they can successfully lead, then the entire industry index will show an upward trend; if not, the downturn continues. Therefore, this article attempts to divide industry constituent stocks into leading stocks and common stocks according to market value, and calculates the traction of leading stocks on common stocks, so as to obtain the potential of the entire industry index to rise. The calculation method of the industry synergy factor is as follows:

$$S = l_{chg} - c_{chg} \tag{3}$$

l_{chg} is the rise and fall of leading stocks, and c_{chg} is the rise and fall of common stocks.

2.3. **Prosperity factor.** Industries in different development cycles have different profitability. The fast-developing industry has become a star industry for investors due to strong market demand and rising profits. The stagnant industries are often not favored by investors due to stagnant industry development and declining profits. The profitability of the industry can directly reflect the development cycle of the industry. Therefore, construct the prosperity factor to predict the industry trend from the perspective of changes in the industry's own profitability. There are 16 factors in total, which are obtained from GuoRen.com, and some of the data obtained are shown in Table 1.

TABLE 1. Prosperity factors of the communication industry

index_code	date	pe	Wpe_subpoints	...	Float_mv
801770	2016/7/05	50.82	0.64691	...	6795.96
801770	2016/7/06	50.77	0.64611	...	6796.72
...	...	...	...	...	...
801770	2020/12/31	40.08	0.72137	...	9347.7

2.4. **Hong Kong capital flow factor.** The direction of capital flow affects the industry rotation to a certain extent. The difference between capital inflow and capital outflow is the net force left after the confrontation between the buyers and sellers to push the index up. It reflects the strength of the force that promotes the rise and fall of the industry index. Since the flow of funds of retail investors and institutions is difficult to obtain, and the data of Hong Kong capital is open and transparent, this article conducts research on the flow of Hong Kong capital.

By the end of 2020, the market value of Hong Kong-owned shares in A-shares has reached nearly 2.3 trillion RMB, and Hong Kong capital is having an increasing influence on the A-share market. As the largest incremental capital in the A-share market, Hong Kong capital plays a very important guiding role in selecting industries and investment opportunities [18]. As a result, the impact of Hong Kong capital inflows into individual stocks can be mapped to the industry level, and the changes in the driving force of funds on the rise and fall of the industry can be observed. The calculation method is as follows:

$$con_{inflow} = hk_{hold} \times con_{ave} \tag{4}$$

$$sector_{inflow} = \sum_{i=1}^{n} con_{inflow} \tag{5}$$

con_{inflow} is the Hong Kong capital flow factor of the constituent stocks, hk_{hold} is the daily increment of Hong Kong capital's holdings of the constituent stocks, and con_{ave} is the average price of the constituent stocks. $sector_{inflow}$ is the Hong Kong capital flow factor of the industry, which is the sum of the Hong Kong capital inflows of all its constituent stocks.

3. **Model Overview.** This paper proposes a model for industry multi-factor data, called attention LSTM model, which is used to mine effective information from industry multi-factor data. The model architecture is shown in Figure 1.

The model is mainly composed of LSTM model and self-attention mechanism, through their mutual cooperation to mine the effective information in the industry data, so that the model can get good prediction accuracy. After obtaining the industry multi-factor data set, feed it into the model as input data. The data first goes through a feature extraction layer that projects the input features into a latent representation. Then, the data is input into the LSTM layer, and the effective information in the data is extracted through the LSTM layer, and the output values of different neurons in the hidden layer are obtained. The similarity calculation is then performed on this output, and the weight vector is obtained after normalization by the softmax function. Finally, the weight vector is input into the fully connected layer to obtain the predicted value.

3.1. **LSTM.** Considering the machine learning model comprehensively, the LSTM model performs well in the prediction of time series data and can solve the long-term dependency problem of Recurrent Neural Network (RNN), and is widely used in quantitative investment [19,20]. This article attempts to use LSTM to mine the time series characteristics of industry multi-factor data set. Due to the large randomness of forecasting the rise and fall of the industry over a period of time, model training has been transformed into a classification problem. Compared with RNN, LSTM uses a "gating device" to selectively store information, which solves the problem of gradient disappearance and long-term storage of information in traditional recurrent neural networks [21]. The structure of LSTM neuron is shown in Figure 2.

Each memory block in the LSTM model receives the information from the previous moment, and uses the output at that moment as part of the input at the next moment.

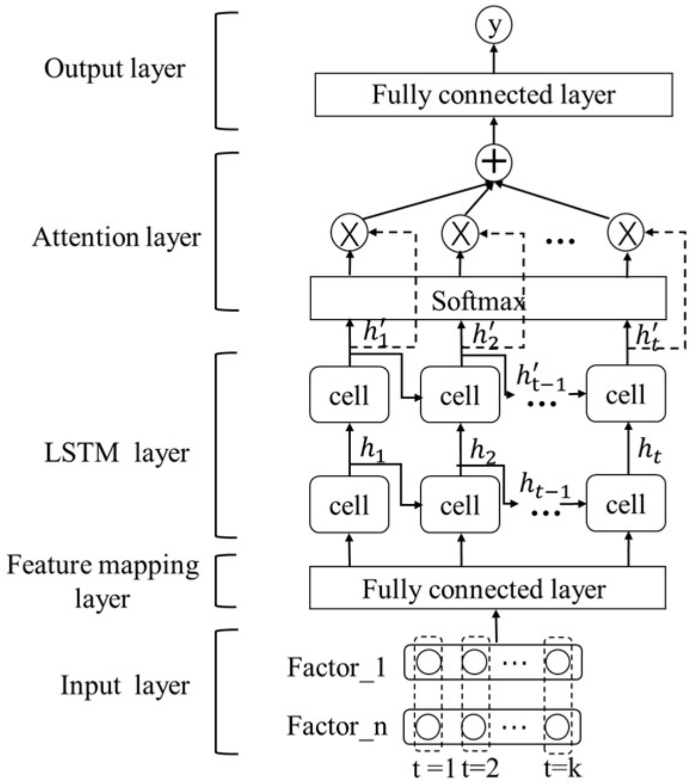

FIGURE 1. Model architecture

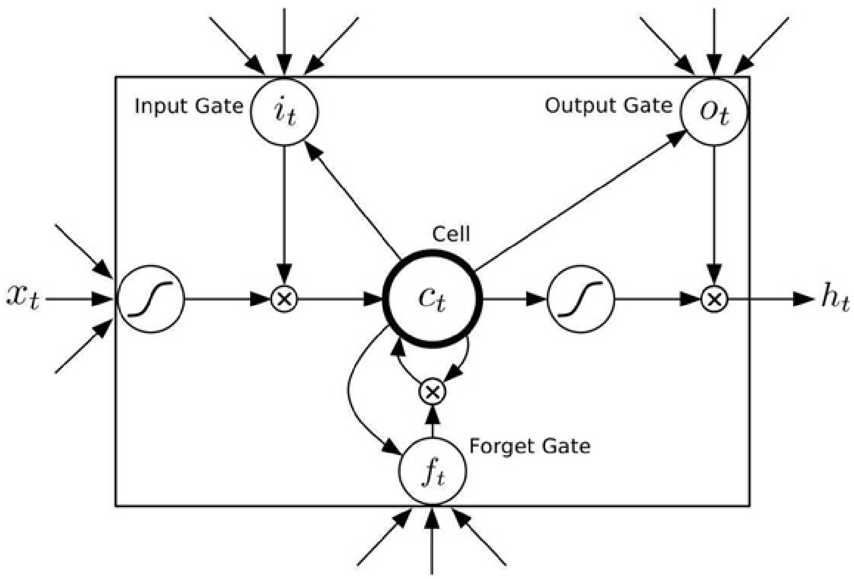

FIGURE 2. LSTM neuron structure

In this way, the LSTM model can correlate useful information in the industry's multi-factor data with long intervals and mine the correlation of multi-factor data set.

3.2. **Self-attention mechanism.** When the LSTM model processes multi-factor data, it considers the input factor data to be equally important, but this does not match the actual situation. With the changes in the economic situation and the development of the industry itself, the degree of influence of different factors on the industry index is also constantly changing. The self-attention mechanism can distinguish the importance of different information to the prediction, so as to improve the interpretability and prediction accuracy of the network model [22]. Therefore, try to introduce self-attention mechanism into the model to make the model focus on the key information that has a greater impact on the industry index, while ignoring the information with less impact. The self-attention mechanism is a variant of the attention mechanism, which reduces the dependence on external information, but instead captures the internal correlation of data or features.

4. **Experiment.** This article uses industry multi-factor data set to predict industry trends. If machine learning methods are used to learn a single industry index, it is easy to over-fit and fail to obtain ideal results. Therefore, this article classifies industries again. After that, use appropriate machine learning methods to study and predict each industry category. This section will take the electronic components, communication, computer, and media industries as examples to conduct experiments. The model experiment parameters are shown in Table 2.

Table 2. Multi-factor attention LSTM model related parameters

LSTM layers	Batch size	Dropout	Hidden layer neurons	Classification function	Categories
2	64	0.2	128	Softmax	3

In order to test the effectiveness of the factor set proposed in this article, the experiment uses the following three data sets as input: a) Industry rise and fall data set, b) Industry fundamental data set (price-earnings ratio, price-to-book ratio and market value), c) The multi-factor data set proposed in this article. The experimental results are shown in Table 3.

Table 3. The comparison experiment results of different input data sets

Data set Model	Rise and fall data set Attention LSTM	Fundamental data set Attention LSTM	Multi-factor data set Attention LSTM
Accuracy	0.6624	0.7127	0.7768
Precision	0.6135	0.6776	0.7557
Recall	0.6070	0.6521	0.7491
F1_macro	0.6094	0.6587	0.7521
F1_micro	0.6624	0.7127	0.7768
Kappa	0.2198	0.3226	0.5043
Ham_distance	0.3376	0.2873	0.2232

In this experiment, the accuracy rate, precision rate, recall rate, F1, kappa coefficient and Hamming distance are used to evaluate the predictive ability of the model. The accuracy rate refers to the proportion of correctly predicted samples in the total samples. The precision rate is the average of the precision rates of each label, representing the average accuracy of the classification sample prediction. The recall rate is the proportion of correct predictions among the actual positive samples. F1 is calculated from a combination of precision and recall, which objectively demonstrates the overall accuracy of the model. The kappa coefficient is used to measure the classification accuracy. The Hamming distance is used to measure the distance between the predicted label and the real label.

It can be seen from the results that the multi-factor data set constructed in this paper has obtained good results. Compared with the use of the rise and fall data set and the fundamental data set, the accuracy rate has increased by about 11.44% and 6.41% respectively, and the precision rate, recall rate and F1 value have also been correspondingly improved. The kappa coefficient of using the multi-factor data set is 0.5043, which indicates that when using the multi-factor data set, the model has a medium classification level (0.4∼0.6), which is higher than the use of the former two data sets. When using a multi-factor data set, the Hamming distance is 0.2232, which is the lowest value among the three. The experimental results show that multi-factor data can provide more effective information, and help the model better learn the changing laws of the industry index.

LSTM is the original model; therefore, comparing the LSTM with the attention LSTM proves the effectiveness of the self-attention algorithm. Since SVM is a machine learning method, compared with the previous traditional machine learning algorithm, it can better handle high-dimensional data and can solve the prediction problem of nonlinear financial data. As an emerging ensemble algorithm model, XGBoost is efficient. Compared with other traditional machine learning algorithms, XGBoost has achieved good results in the financial field. The industry multi-factor data is also input into the SVM model and XGBoost model. The experimental results are shown in Table 4.

Table 4. Comparison results of different models

Model	SVM	XGBoost	LSTM	Attention LSTM
Accuracy	0.4156	0.7330	0.6834	0.7768
Precision	0.4034	0.7342	0.6921	0.7557
Recall	0.3742	0.7419	0.6870	0.7491
F1_macro	0.3556	0.7374	0.6893	0.7521
F1_micro	0.4056	0.7330	0.6834	0.7768
Kappa	0.0680	0.5232	0.4545	0.5043
Ham_distance	0.5944	0.2670	0.3166	0.2232

From the above experimental results, it can be seen that the attention LSTM model has achieved good results. Compared with SVM model, XGBoost model and LSTM model, the accuracy rate is improved by about 36.12%, 4.38% and 9.34%, respectively, and the precision rate, recall rate and F1 value are also improved accordingly. In addition, the kappa coefficient of the attention LSTM model is 0.5043, which indicates that the model has a medium classification level (0.4∼0.6), which is higher than that of SVM, XGBoost and LSTM model. When using attention LSTM model, Hamming distance is 0.2232, which is the lowest of the four, which shows that this model can dig out more effective information and has better accuracy than the former three models. The experimental results prove the effectiveness of the attention LSTM model. Compared with SVM model, XGBoost model and LSTM model, attention LSTM model gives different weights to input factors to distinguish the importance of input information, thus further improving the reliability of the model.

5. **Conclusions.** This paper constructs a multi-factor industry data set from the perspective of industry momentum, behavior characteristics of industry constituent stocks, industry profitability and Hong Kong capital flow. On this basis, the attention LSTM model is constructed for experiments. The experimental results show that the multi-factor data set proposed in this paper can well show the law of industry rotation, and the attention LSTM model can focus on the key information and get good prediction results.

Compared with other research methods of industry rotation, this paper has the following advantages.

1) Compared with the previous methods of using single data such as industry fluctuations data, this paper constructs a data set from multiple perspectives to quantify the factors that affect industry rotation and make analysis perspectives diverse.

2) Compared with qualitative analysis methods such as Merrill Lynch clock, this paper re-clusters the industries and uses different machine learning models to make predictions, thus avoiding the different analysis results caused by subjective experience, cognitive bias and other factors.

Although preliminary results have been obtained, there is still room for improvement.

1) Macroeconomics, monetary policy also affects industry rotation and it can be considered to be quantified.

2) It is also necessary to construct suitable models for other different types of industries.

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