Application Of Neural Network To Technical Analysis Of Stock Market Prediction

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Abstract: This paper presents a neural network model for technical analysis of stock market, and its application to a buying and selling timing prediction system for stock index. When the numbers of learning samples are uneven among categories, the neural network with normal learning has the problem that it tries to improve only the prediction accuracy of most dominant category. In this paper, a learning method is proposed for improving prediction accuracy of other categories, controlling the numbers of learning samples by using information about the importance of each category. Experimental simulation using actual price data is carried out to demonstrate the usefulness of the method.

Keywords: stock market prediction, technical analysis, neural network, learning method

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1. Introduction

This paper proposes a neural network model for technical analysis of stock market, and its learning method for improving the prediction capability. In stock market prediction, many methods for technical analysis have been developed and are being used [1]. In technical analysis, technical indexes calculated from price sequence are used to predict the trend of future price changes. Many statistical methods have been proposed, but the results are insufficient in prediction accuracy. In this paper, neural network [2, 3] is applied to technical analysis as a prediction model, and a buying and selling timing prediction system for TOPIX (Tokyo Stock Exchange Prices Index) is presented. TOPIX is a weighted average of prices of all stocks listed on the First Section of Tokyo Stock Exchange.

Several neural network models have already been developed for market prediction. Some are applied to predicting future price or rate of changes [4], and some are applied to recognizing certain price patterns that are characteristic of future price changes [5]. In these models, however, little is considered about the learning method of neural network. In case the numbers of learning samples are uneven among categories, neural network models with normal learning try to improve only the prediction accuracy of the most dominant category which might be less important than others.

This paper proposes a learning method that contributes to improving prediction accuracy of the other categories, which are more important. In the method, the numbers of learning samples are controlled by using information about the importance of each category. Experimental simulation using actual TOPIX price data is carried out to demonstrate the usefulness of the proposed method.

2. TOPIX Prediction System

The overview of the proposed buying and selling timing prediction system for TOPIX is shown in Figure 1. The prediction system classifies the input pattern that consists of several technical indexes of TOPIX, and generates a buying or selling timing signal for notifying users [6]. As shown in the Figure, the system consists of a neural network, a preprocessing unit, and a postprocessing unit. The preprocessing unit normalizes each technical index into an analog value in 0 to 1 to form an input pattern into the neural network. Then the network recognizes the turning point of the TOPIX price curve from the input pattern. Finally, the postprocessing unit converts the result of recognition into a buying and selling timing signal.

3. Neural Network Model

3.1 Network Architecture

As shown in Figure 1, the neural network as prediction model is a hierarchical network that consists of three layers: the input layer, the hidden layer, and the output layer. Each unit in the network is connected to all units in the adjacent layers. Each unit receives outputs of the units in the lower layer and calculates the weighted sum to determine total input. Then the output is determined by applying the logistic function [7] to the total input. As a result, the output ranges in 0 to 1.

3.2 Input Data Selection

Data items to form the input pattern to the system are technical indexes of TOPIX. Typical technical indexes are:

- Moving average

  This is an average of the prices over certain past period, and developed for allowing users to understand the trend without everyday fluctuation. There are several variations according to the period: 6, 10, 25, 75, 100, 150, and 200 days. The direction and position of moving average

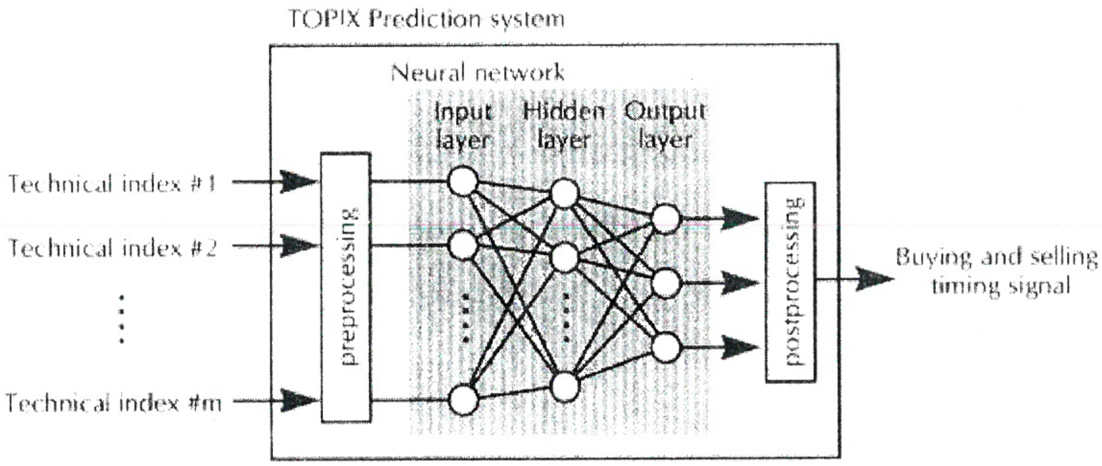


Figure 1. Overview of TOPIX Prediction System

curve are used for predicting the price change.

- Deviation of price from moving average
- This index is used for checking whether the price on each day is too high or too low if compared with the expected price.
- Psychological line
- This index is calculated by dividing the number of days of price ups by certain past period. This is used for predicting the price change from the rhythm of ups and downs.
- Relative strength index
- This index is similar to the psychological line, and is calculated by dividing the sum of price ups by the sum of price ups and downs over certain past period.

Each of these indexes is normalized into 0 to 1 to form an input pattern to the neural network model.

3.3 Output Data Definition

In the neural network model, the output layer has three units. As output patterns of the network, we define three patterns as shown in Table 1. Each corresponds to specific TOPIX curve patterns: buying signal (i.e. current price is at bottom), selling signal (i.e. current price is at top), and no-change (i.e. otherwise), respectively. Bottoms and tops in the price curve are closely related to buying and selling timings. When teaching the neural network model, each correct output pattern of learning sample is calculated from three TOPIX data as described in Table 1: current price, price at five weeks before, and price at five weeks later.

Figure 2 shows an example of computer generated correct buying and selling signals on the TOPIX graph. Buying and selling signals are designated by black circles and white triangles, respectively. These correct signals are calculated from three TOPIX data (i.e. current price, price at five weeks before, and price at five weeks later) as described in Table 1, and are not recognized by human experts. However, an expert analyst comments that these correct signals are almost satisfactory as long as the investment period is supposed to be of three months.

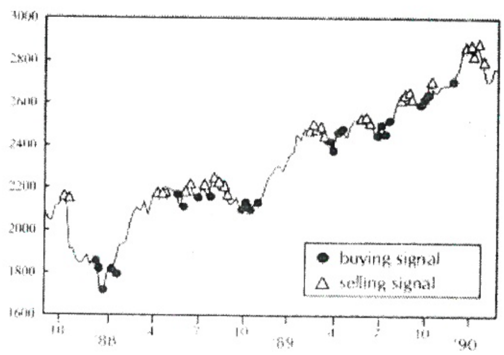


Figure 2. Example of Computer Generated Correct Outputs

Because the output of the units in the output layer ranges in analog of 0 to 1 in a neural network, an actual output pattern may not match with any of the three patterns. In this case, the postprocessing unit converts the analog value to 0 or 1 by using two thresholds. In the experimental simulation further described , 0.4 and 0.6 are used as thresholds. When the output is beneath 0.4, then 0 is selected. In the same way, when the output is more than 0.6, then 1 is selected. If the output is between 0.4 and 0.6, or if the converted pattern still does not match any of the three categories, the system notifies that prediction has failed.

Table 1. Relation Between TOPIX Curve and Correct Output Pattern of Neural Network

TOPIX curve (past)	(current) (future)	neural network correct output pattern
↗	↘	(1, 0, 0) : selling signal
↗	↗	(0, 1, 0): no-change
↘	↘	(0, 1, 0): no-change
↘	↗	(0, 0, 1) : buying signal

4. Equalized Learning Method

In the prediction system, a learning method is developed for improving prediction accuracy. As earlier described , the neural network model tries to generate one of three output patterns for classification.

Learning of the network is done using the back-propagation algorithm [7]. The learning strategy in this algorithm is to modify the weights of connections between units towards decreasing the total sum of prediction errors. However, in case that the deviation of the numbers of learning samples is large among output pattern categories, the following problem arises: the neural network will have the tendency of trying to improve only the prediction accuracy of the most dominant category. As a result, the prediction system generates less buying and selling timing signals than expected. This is because little is considered about the difference of importance among categories. We must teach the neural network that we expect it to generate buying and selling timing signals, and that generating no buying signal or no selling signal makes no sense.

To overcome this problem, we propose the "equalized learning method" [8] as shown in Figure 3. Before learning samples are fed to the neural network, histogram calculation step and sample duplication step are inserted. Equalized learning is carried out in the following way:

1. **Histogram calculation**

   Histogram is calculated by counting the learning samples in each category.

2. **Sample duplication**

   By using information about the importance of categories and the histogram, learning samples in each category are duplicated to modify the histogram

3. **Shuffling new samples**

4. **Feeding to the neural network**

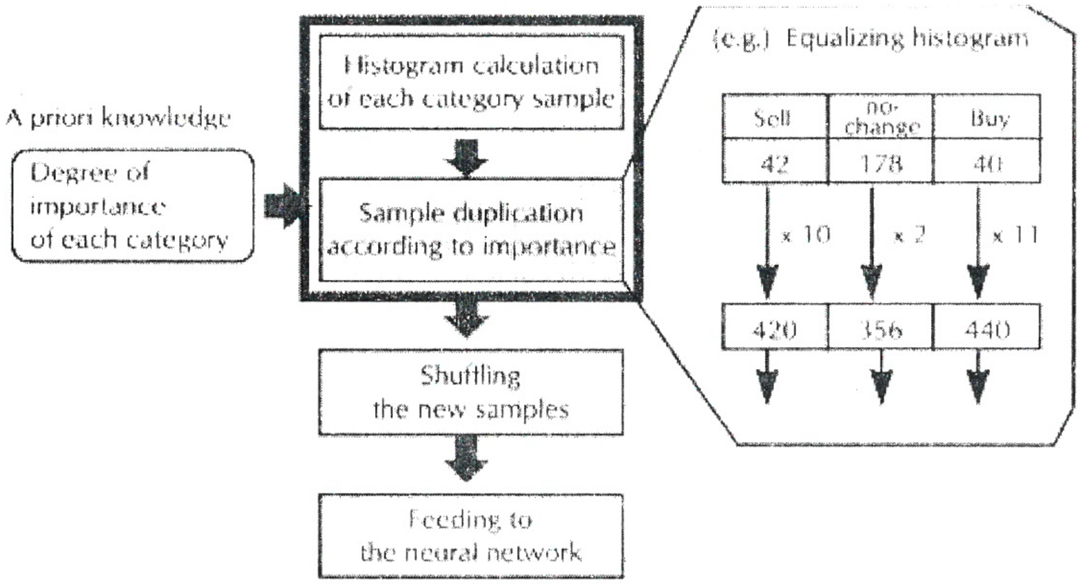


Figure 3. Equalized Learning Procedure

In the sample duplication step, the more important the category is, the larger the coefficient of duplication assigned. In the TOPIX prediction system, learning samples of buying signal and selling signal are less in spite of the fact that these two categories are more important than the no-change category. Therefore, the coefficients of duplication are set to higher values of these categories. However, it is difficult to decide these values for each category, though it is possible to decide their order. In the prediction system, the coefficients are set so that the histogram becomes nearly flat. Consequently the prediction system begins to generate more buying and selling signals at proper timings.

5. Experimental Simulation

5.1 Data and Method

To verify the accuracy of the prediction system, we have carried out an experimental simulation applied to actual weekly TOPIX data. Figure 4 shows the test data. As shown in the Figure, 260 weekly data from September 1982 to August 1987 (five years) have been used as learning samples for making prediction models. Following 119 weekly data from October 1987 to January 1990 (two years) are used as prediction samples for evaluation. For both samples, correct output patterns are calculated according to the definition described in Table 1.

Table 3 shows the details of the computer generated correct output patterns of the test data. As for the learning samples, ratios of the samples in three categories (i.e. selling signal, buying signal, and no-change) are 16 %, 15 %, and 69 %, respectively. As for prediction samples, ratios of samples are 26 %, 24 %, and 50 %, respectively. In both samples, the samples in no-change category are extremely larger than those in the other two categories. This suggests that a neural network with normal learning method may always generate no-change category as its output pattern.

Figure 4 also shows that both the learning period and the simulation period have an increasing trend on the whole. This suggests

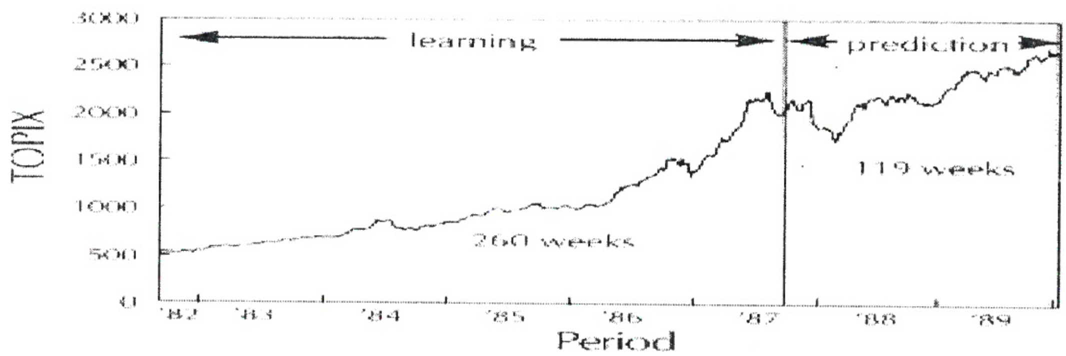


Figure 4. Test Data for Experimental Simulation (TOPIX Weekly Data)

Table 2. Technical Indexes To Form Input Pattern

1. Deviation from 25 days moving average	2. Deviation from 75 days moving average
3. Deviation from 200 days moving average	4. Vector curve of 6 days moving average
5. Vector curve of 25 days moving average	6. Vector curve of 75 days moving average
7. Psychological line in 12 days base	8. Psychological line in 25 days base
9. Relative strength index in 9 days base	10. Relative strength index in 12 days base
11. Volume ratio in 25 days base	—

Eleven technical indexes of TOPIX are selected to form input patterns into the system as listed in Table 2. These indexes are selected by a human expert analyst. Each of these has been commonly used and believed useful in technical analysis.

possible difficulty in predicting selling timings because of the lack of efficient learning samples for selling signals.

Table 3. Details of Correct Output Patterns in the Test Data

output pattern \ samples	learning samples	prediction samples
sell	42 (16%)	31 (26%)
no change	178 (69%)	59 (59%)
buy	40 (15%)	29 (24%)
total	260	119

Table 4. Prediction Result by Neural Network Model with Equalized Learning

(a) Learning

		correct answer			
		sell	no-change	buy	total
result	sell	**41**	8	0	49
	no-change	0	**157**	0	157
	buy	0	4	**40**	44
	invalid	1	9	0	10
	total	**42**	**178**	**40**	

(b) Prediction

		correct answer			
		sell	no-change	buy	total
result	sell	**14**	6	0	20
		13	**39**	3	55
	buy	1	10	**22**	33
	invalid	3	4	4	11
	total	**31**	**59**	**29**	

Table 5. Prediction Result by Neural Network Model with Normal Learning

(a) Learning

		correct answer			
		sell		buy	total
result	sell	35	0	0	35
	no-change	5	**178**	1	134
	buy	0	0	**39**	39
	invalid	2	0	0	2
	total	**42**	**178**	**40**	

(b) Prediction

		correct answer			
		sell	no-change	buy	total
result	sell	**5**	0	0	5
	no-change	23	**49**	5	77
	buy	1	7	**19**	27
	invalid	2	3	5	10
	total	**31**	**59**	**29**	

Table 6. Prediction Result by Statistical Model

(a) Learning

		correct answer			
		sell	no-change	buy	total
result	sell	**26**	24	1	51
	no-change	16	**148**	9	173
	buy	0	6	**30**	36
	invalid	–	–	–	–
	total	**42**	**178**	**40**	

(b) Prediction

		correct answer			
		sell	no-change	buy	total
result	sell	**6**	9	3	18
		25	**48**	20	93
	buy	0	2	**6**	8
	invalid	–	–	–	–
	total	**31**	**59**	**29**	

Table 7. Performance Comparison of Prediction

model	ratio of correctness (%) in learning				ratio of correctness (%) in prediction			
	sell	no-change	buy	overall	sell	no-change	buy	overall
neural network model with equalized learning	**98**	**88**	**100**	**92**	**45**	**66**	**76**	**63**
neural network model with normal learning	83	100	98	97	16	83	66	61
statistical model	62	83	75	78	19	81	21	50
(answering no-change)	0	100	0	68	0	100	0	50

For comparison of prediction performance, three prediction models are applied:

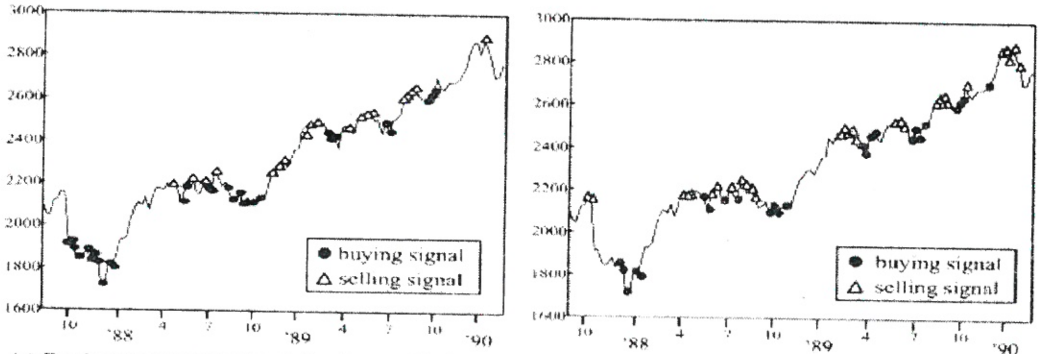
1. **neural network model with the proposed equalized learning**
    - coefficients of duplicating learning samples: 10, 2, and 11
    - 11 units in input layer, 10 units in hidden layer, and 3 units in output layer
    - coefficients for updating weights: 0.1 and 0.9
    - 5,000 iterations
    - thresholds for postprocessing: 0.4 and 0.6
2. **neural network model with normal learning**
    - same parameters as the above model except no duplication of learning samples
    - 20,000 iterations
3. **statistical model based on discriminant analysis** [9, 10]
    - two models are used: one for classifying whether buying signal or not, and one for classifying whether selling signal or not
    - Mahalanobis' generalized distance is used as distance measure

5.2 Result of Prediction

Tables 4, 5, and 6 show the results of learning and prediction by the three prediction models. Table 7 summarizes these results.

As shown in Table 5, the neural network model with normal learning has learned the learning samples in no-change category completely. Total ratio of correctness for learning is 97 % and is sufficient. However, as for learning selling signal samples, the ratio of correctness is 83 % (35/42), lower than the total one. That means that the network learns mainly the samples in no-change category, which is most dominant of the three categories. As for prediction, though the ratio of correctness for predicting no-change is 83 % (49/59), the ratios for predicting buying signals and selling signals are 66 % (19/29) and 16 % (5/31), i.e. much lower. It can be understood that not enough learning has been carried out for the learning samples in these two latter categories.

On the other hand, as shown in Table 4, though the neural network model with the equalized learning method learned the learning samples in no-change category for 88 % (157/178), it learned the selling signals and the buying signals in 98 % (41/42) and 100 % (40/40). These exceed the performance of neural network model with normal learning by 15 % and 2 %, respectively. This indicates that learning was carried out equally over the three categories. As for prediction, though the ratio of correctness for predicting no-change is 66 % (39/59) and lower than the normal learning model, the ratio of correctness for predicting selling signals is 45 % (14/31), which exceeds the normal learning model by 29 %. The ratio of correctness for predicting buying signals is 76 % (22/29) and exceeds the normal learning model by 10 %. The total ratio of correctness is 63 % and there is no significant difference if compared with the normal model. Assuming that the improvement of prediction accuracy for selling and buying signals is more important to users, these results demonstrate that the proposed neural network model shows higher performance of prediction than the normal neural network model does. However, since the



(a) Buying and selling signals by the prediction system (b) Computer generated correct signals

Figure 5. Comparison of Buying and Selling Signals

prediction accuracy for selling signals is still low, further analysis is necessary to improve this.

As shown in Table 6, the performance of the statistical model is much lower than that of the normal neural network model in every aspect except for the prediction accuracy for selling signals.

In Figure 5 (a), the buying and selling timing signals generated by the prediction system are plotted. Comparison with the computer generated correct signals in Figure 5 (b) shows that the signals by the system are similar to the correct ones on the whole. An expert analysis comments that the signals by the system are almost satisfactory except that proper signals do not appear in some situations. This means the selling timing signals by the system are still less satisfactory than expected.

5.3 Result of Buying and Selling Simulation

To verify the usefulness of the proposed prediction system, buying and selling were simulated. For comparison of performance reason, two other cases of simulation have also been carried out using a single technical index: psychological line, and relative strength index (RSI) as listed in Table 8. These indexes have been used everyday in stock market analysis. Buying and selling strategy in each case is also shown in the Table. One more case of buy-and-hold strategy was also taken as a basis. In buy-and-hold, buying is done once at the beginning of the simulation and selling is done at the end of it, that means no active buying and selling. Prediction systems are required to achieve higher performance than this strategy's.

at buying situations:

$$Rate\ of\ profit =$$

$$\prod \left\{ \frac{TOPIX\ at\ settlement - TOPIX\ at\ buying}{TOPIX\ at\ buying} \right\} + 1$$

at selling situations:

$$Rate\ of\ profit =$$

$$\prod \left\{ \frac{TOPIX\ at\ selling - TOPIX\ at\ settlement}{TOPIX\ at\ selling} \right\} + 1$$

The simulation results are summarized in Table 9. From these results, an expert analyst will make the following comments:

- Buying situations:
- Before converting in yearly profit rate, the proposed neural network model scored highest performance (1.51). On the other hand, in yearly profit rate, psychological line and RSI showed better performances. That means the neural network model does not generate proper buying and selling signals at the best timings. However, since it exceeds the performance achieved by the buy-and-hold strategy, the timings of signals by the proposed neural network model are proved to be useful on the whole.
- Selling situations:
- Rate of profit must be higher than one if the selling timing signals are appropriate. How-ever, the performance achieved by the proposed neural network model is 0.99 and slightly under one. That means the model does not generate appropriate selling signals. However, if comparing the result with other cases (0.84 and 0.90), the neural network model minimized the loss. In this sense, the

Table 8. Simulation Models and Buying-and-Selling Strategies

model	buying-and-selling strategy
neural network model	**buy or sell when the timing signal reverses**
psychological line (25 days)	buy when value <= 30 and sell when value >= 75 at weekend
RSI (9 days)	buy when value <= 25 and sell when value >= 75 at weekend
buy-and-hold strategy	buy at the beginning and sell at the end of simulation period

As a measure of performance, rate of profit is used, calculated as follows:

Table 9. Performance Comparison of Buying-and-Selling Simulation

model	rate of profit			rate of profit (yearly)		
	buying	selling	overall	buying	selling	overall
neural network model	**1.51**	**0.99**	**1.50**	**1.34**	**0.99**	**1.20**
psychological line (25 days)	1.20	0.72	0.87	1.70	0.84	0.94
RSI (9 days)	1.32	0.84	1.10	1.64	0.90	1.05
buy-and-hold strategy	1.52	—	1.52	1.21	—	1.21

proposed model is relatively the best of the three cases.

- Overall:
- On the whole, although the neural network model did not make the higher profit in buying situations than in other cases, it made the highest in selling situations in the sense of a minimum loss. Consequently, its overall performance (1.20) was greater than that achieved by single use of the technical index (0.94, 1.05). However, it was still slightly lower than that of buy-and-hold strategy (1.21). This might be because the trend of price change is increasing throughout the learning and prediction period in this simulation.

6. Conclusion

This paper proposed a neural network model for the technical analysis of stock market prediction, and its application to the buying and selling timing prediction system for TOPIX. So far, little has been considered about the learning method of neural network. In case the numbers of learning samples are uneven among categories, neural network models with normal learning try to improve only the prediction accuracy of the most dominant category that may be less important than others. This paper proposed a learning method that contributed to improving prediction accuracy of other, more important categories. In the method, the numbers of learning samples are controlled by using information about the importance of each category. Experimental simulation applied to practical data has demonstrated that the prediction system generates buying and selling signals at more proper timings on the whole, and made higher profit compared with that yielded by a single use of each technical index. As future work, we have to study several problems which will help improve the model. First, we have to study what makes it difficult for the system to generate selling signals at appropriate timings. Second, on analyzing the network, it is necessary to know the effectiveness of each technical index used as input.

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