LETTER

A New Method for Futures Price Trends Forecasting Based on BPNN and Structuring Data

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SUMMARY Forecasting commodity futures price is a challenging task. We present an algorithm to predict the trend of commodity futures price based on a type of structuring data and back propagation neural network. The random volatility of futures can be filtered out in the structuring data. Moreover, it is not restricted by the type of futures contract. Experiments show the algorithm can achieve 80% accuracy in predicting price trends.

key words: *commodity futures price, structuring data, back propagation neural network*

1. Introduction

Due to the following characteristics: high noise, nonlinearity, unstable nature and hidden correlation [1], financial time series prediction is a very challenging task. As an important part of time series, commodity futures have developed very rapidly in recent years, and the futures market has received widespread attention from investors. Unfortunately, there is much noise and strong random volatility in futures market. Mastering the changing rules of futures prices and forecasting the trend of futures prices is a difficult task, which has been the focus of researchers.

Traditional econometrics and statistical models have been used to predict financial time series, such as autoregressive integrated moving average model [2], vector autoregressive model [3], Markov mechanism switching model [4]. The futures market is non-linear, while those traditional approach has linear limitations, hence the prediction effect is not ideal. In recent years, prediction methods based on machine learning have been extensively studied. Compared with traditional model, prediction methods based on machine learning improve the performance on nonlinear problems. For example, support vector machine algorithms are used to predict stock index futures [5]. The artificial neural network also shines with the improvement of stochastic computing power, such as the artificial neural network-GARCH model prediction method proposed by Kristjanpoller W [6] and the enhanced radial basis function network constructed by Lin WM [7]. BPNN (Back Propagation Neural Network) is one of the most powerful tools for predicting financial sequence [8]–[11]. There are also many researchers using two or more machine learning methods to construct hybrid models to predict futures prices. For example, Jinliang Zhang used the EEMD method combined with the LSSVM PSO and GARCH models to predict crude oil prices [12], Dingxian Wang combined decision trees and support vector machines to predict futures price trends [13]. Those models have achieved good results in prediction accuracy. However, given the high noise characteristics of the futures market and the different characteristics of different types of futures contracts, these models can only perform well on specific futures contracts or trading period.

The key to improve the accuracy and stability of model prediction is to filter the noise effectively in futures data and find common law for different contract types. In Teach You to Trade Stocks [14], a method of structuring K-line data is proposed to filter out futures market noise, which is conducive to exploring the law of futures market and predicting the trend of futures prices. Combined with BP neural network and structuring K-line data, this paper proposes a new algorithm to predict the trend of futures prices. The algorithm is not subject to the type of futures contract and trading period. Moreover, the algorithm is not sensitive to changes in parameters of BPNN. Experiments show that the algorithm can achieve 80% accuracy in predicting price trends.

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2. Tables, Figures and Equations

2.1 Tables and Figures

Table 1 Comparison with other algorithms.

Algorithm	BPNN-SD	BPNN	DT-SVM	Bootstrap-SVM
Accuracy	80.6%	59.4%	66.5%	56.7%
Clear trading point	Yes	No	No	No

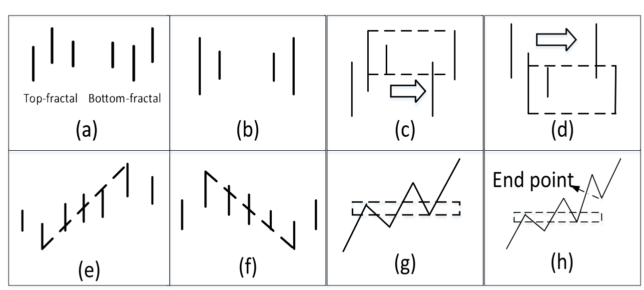

Fig. 1 K lines processing.

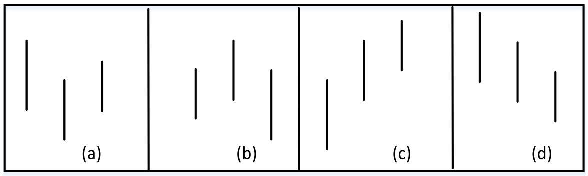

Fig. 2 Complete classification of 3 k lines.

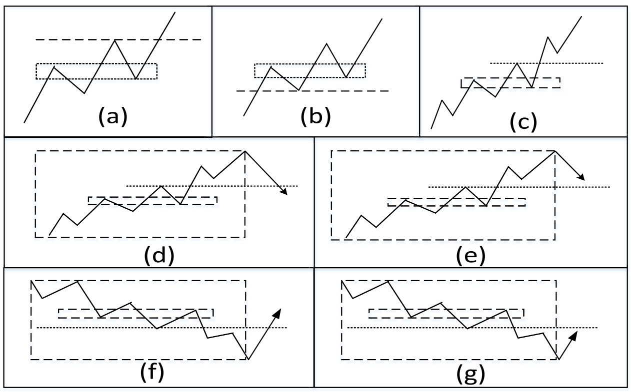

Fig. 3 Centrum and Structure.

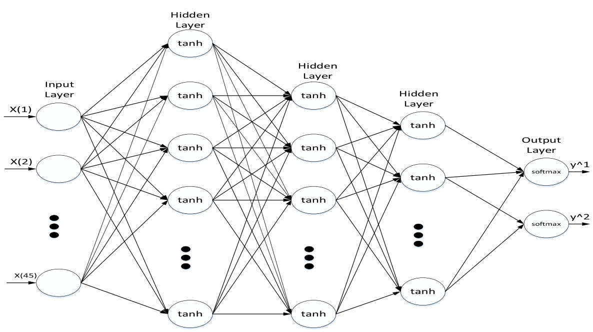

Fig. 4 Neural network structure.

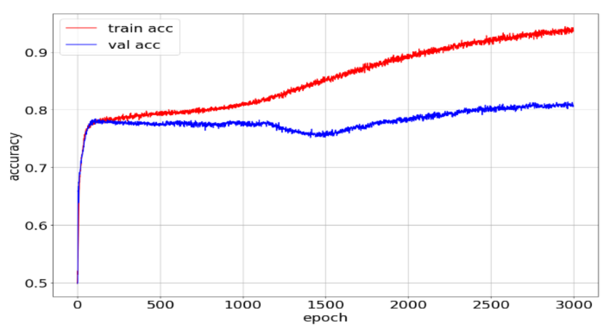

Fig. 5 Accuracy of training and validation sets during the uptrend.

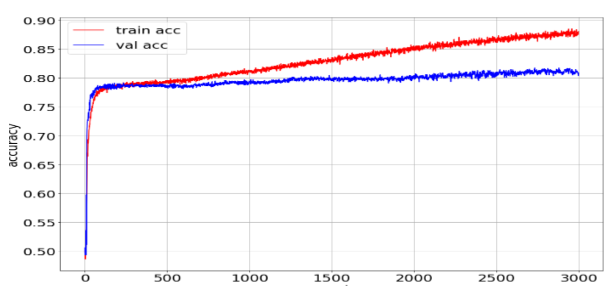

Fig. 6 Accuracy of training and validation sets during the downtrend.

2.2 Equations

$$\begin{cases} h_i = (max_p)_i - (min_p)_i \quad (i = 1, \ldots, 6) \\ \sum_{j=1}^{3} h_j time_j^{1/2} > \sum_{k=4}^{6} h_k time_k^{1/2} \end{cases} \tag{1}$$

$$PRICE_i := \frac{PRICE_i - Mean(PRICE)}{Max(PRICE) - Min(PRICE)} \tag{2}$$

$$TR_i := \frac{TR_i - Mean(TR)}{Max(TR) - Min(TR)} \tag{3}$$

$$DUR_i := \frac{DUR_i - Mean(DUR)}{Max(DUR) - Min(DUR)} \tag{4}$$

$$SLO_i := \frac{SLO_i - Mean(SLO)}{Max(SLO) - Min(SLO)} \tag{5}$$

3. Structuring Data Model

In order to filter out the random noise of the futures market and solve the problem that prediction models are subject to the type of futures contract, we structure the raw K-line data. The method of structuring K-line data is as follows.

3.1 Fractal

We define that the fractal is divided into TF (the top-fractal) and BF (the bottom-fractal). As shown in Fig. 1 (a), among the three K lines, if both the highest and lowest price of the second K line is the highest, we define these three K lines as the TF; if both the highest and lowest price of the second K line is the lowest, we define these three K lines as BF. In addition, we define the highest point of TF as TTF and the lowest point of BF as BBF.

The specific steps to obtain the fractals from the raw K-line data are as follows:

The specific steps to obtain the fractals from the raw K-line data are as follows:

Step 1: Clear useless data. Delete the opening and closing prices in the raw data.

Step 2: Make time difference Continuous. Because trading time is not continuous, we change the time difference between adjacent K lines to one minute.

Step 3: Processing Inclusion relationship. As shown in Fig. 1 (b), we define that there is inclusion relationship between K lines when a K line is completely contained by the adjacent K line. The inclusion relationship between K lines influences the search for segments, which need to be processed before the search for segments. The steps to deal with inclusion relationship are as follows:

1) As shown in Fig. 1 (c), when the trend is upward, the highest point of the two K lines is regarded as the high point, and the higher among the low points is considered as the low point. Then, the two K lines are merged into a new one.

2) As shown in Fig. 1 (d), when the trend is downward,

the lowest point of the two K lines is regarded as the low point, and the lower among the high points is considered as the high point. Then, the two K lines are merged into a new one.

Step 4: Obtain the fractals. After step 1, step 2 and step 3, as shown in Fig. 2, we can get a complete classification of 3 K lines. Further, fractals can be obtained.

3.2 Segment

We define that one segment is composed of adjacent TF and BF. As shown in Fig. 1 (e) and Fig. 1 (f), connected TTF and BBF forms segment, and there is at least one K line between the TF and BF. Moreover, the segment is divided into UWS (upward segment) and DWS (downward segment). Segment has the following attributes: prices, transaction ratio, duration, and slope expressed in terms of PRICE, TR, DUR, and SLO, respectively. Specially, prices include both the highest and lowest prices.

The highest price of a segment refers to the highest point of the segment, and the lowest price refers to the lowest point of the segment. The difference between the highest price and the lowest price reflects the difference of the futures price. Trading volume refers the sum of the trading volume of the K lines that constitute this segment; open interest refers the mean of open interest of the K lines that constitute this segment; transaction ratio refers ratio of trading volume to open interest, which can reflect the purchasing power of the market during the time comprehensively. Slope is the ratio of the price difference to the duration, which reflects the speed of price increase or decline during this time.

3.3 Centrum and Structure

Exchange rate change, economic situation, national policy and people's game are all the reasons for the change of futures prices. The trend of segments evolved from K lines can reflect the change of resultant force effectively. When at least three segments form overlap, we define this overlapping part as the centrum. As shown in Fig. 1 (g), the portion in the dashed box is regarded as centrum. The formation of the centrum indicates that the combined force that drives the rise in futures prices and what causes futures prices to fall are at a deadlock during this period.

As shown in Fig. 1 (h), the centrum breaks up when the segment leaves it. When the condition of formula (1) is met, the departure occurs. In formula (1), h_1, h_2, h_3 are the height difference (price difference) of the first three segments before the centrum, $time_1, time_2, time_3$ are the durations of the first three segments before the centrum; similarly, h_4, h_5, h_6 are the height difference of the first three segments after the centrum, $time_1, time_2, time_3$ are the durations of the first three segments after the centrum. Specially, neither the first three segments before the centrum or the first three segments after the centrum don't form a centrum.

The reason why departure happens is that the combined force, which pushes price up or down, begins to weaken. It can be deduced from this that there is a high probability that the next segment will reach TS (the top swing) or BS (the bottom swing). As shown in Fig. 3 (a) and Fig. 3 (b), TS refers to the highest price of the segments constituting the centrum, and BS refers to the lowest price of the segments constituting the centrum.

As shown in Fig. 3 (c), the first three segments before the centrum, the centrum and the first three segments after the centrum constitute a typical structure that can be predicted when the departure occurs. The structure can filter out random fluctuations in prices during this period and increase the stability of the predictive model.

4. BP Neural Network Model

4.1 Classification

When the trend is upward, as shown in Fig. 3 (d) and Fig. 3 (e), the next segment after the end of the structure is marked as a positive example if it reaches TS of the centrum; otherwise, it is marked as a negative example.

When the trend is downward, as shown in Fig. 3 (f) and Fig. 3 (g), the next segment after the end of the structure is marked as a positive example if it reaches BS of the centrum; otherwise, it is marked as a negative example.

4.2 Data Normalization

The data normalization needs to be performed before entering the bp neural network model for training. This paper improves the existing data normalization method. Rather than to normalize on the entire data set, this paper performs data normalization in units of one structure, which ensures that the algorithm proposed in this paper is not subject to the types of futures contracts. The standardized formula for price, trading ratio, duration and slope is shown in (2)(3)(4)(5). Mean, Max and Min were respectively used to calculate the average, maximum and minimum values for the current attribute, and all attribute values were restricted between -1 and 1.

4.3 Neural Network Structure

The attributes of a structure are as input to the neural network. One structure that meets the requirements consists of 9 segments. Further, each segment has 5 attributes, which are PRICE, TR, DUR, and SLO. Therefore, the number of input nodes is 45. Because this is a two-category forecasting task, we set 2 output nodes which adopt the Softmax function. The entire neural network is provided with three hidden layers, and the number of hidden layer nodes is respectively 100/50/20. Moreover, to prevent overfitting, the Dropout technique is used in the hidden layer of the neural network, and the parameters of the dropout layer are set to 0.5. After data normalization the data attribute values are between -1 and 1, hence the hidden layer uses "tanh" as the activation function. The ADAM optimization algorithm is used to accelerate and optimize the training process, where learning rate is set to Learning rate is set to 0.00001 and the remaining parameters remain at their default values. The neural network diagram is shown as Fig. 4.

5. Numerical Validation

This paper selects the 1-minute data for more than 400 Chinese commodity futures contracts from 2011 to 2016, for a total of 74181098 1-minute data. The raw data file contains the opening price, closing price, highest price, lowest price, trading volume, open interest and trading time. We perform experimental operations in accordance with the model algorithm proposed in this paper.

Step 1: Find all the TF and BF.

Step 2: Find all segments and centrums.

Step 3: Find all the structures that can be used for prediction according to Eq. (1).

Step 4: Classify data. Classify the next segment after the end of the structure, with the positive class labeled $[1, 0]$ and the negative class labeled $[0, 1]$. In the case of upward trend, a total of 10081 structures are obtained, of which 6163 are positive and 3918 are negative. And in the case of downward trend, a total of 10074 structures are obtained, of which 6291 are positive and 3783 are negative.

Step 5: Normalize data values according to Eqs. (2)(3)(4)(5).

Step 6: Avoid the data imbalance problem. Without loss of generality, we take the case of upward trend as an example. 3000 positive examples and 3000 negative examples are used, and a total of 6000 samples constitute a training set; 500 positive examples and 500 negative examples, a total of 1000 samples constitute a verification set; the remaining samples are used for testing set.

Step 7: Build BP neural network.

Step 8: Train neural network in the case of uptrend and downtrend, respectively.

Step 9: Use the test set evaluate the neural model after the training.

6. Result

In this section, the performance of the algorithm proposed in this paper will be evaluated.

The accuracy of the training set and the validation set, in the case of upward trend, is shown in Fig. 5, and the result of training, in the case of downward trend, is shown in Fig. 6. The red line and blue line indicate the change in the accuracy of the test set and validation set during training, respectively. After the training is completed, both the accuracy of the validation set and the test set can achieve 80%, which proves that the variance is small; the accuracy of the test set is above 80%, which proves that the model performs well.

In order to compare the performance of the proposed algorithm, BPNN, Bootstrap-SVM and DT-SVM algorithm were tested on the same dataset, in which the method of structuring data is not used. In the algorithm proposed in this paper, the average time of one segment is 29.89 minutes and BPNN-SD (BPNN and structuring data) is similar to predicting the futures price trend in the next 30 minutes. Therefore, 30 minutes time span are adopted to segment the data. And we use the 3 algorithms above to predict the futures price trend in the next 30 minutes. As shown in Table 1, the prediction accuracy of these algorithms is less than 70%. In summary, the method of structuring data proposed in this paper can make the forecast of futures price trend more accurate. Moreover, possessing a clear trading point is a huge advantage for BPNN-SD.

7. Conclusion

Combined with BP neural network and structuring data, this paper proposes a new algorithm to predict the trends of futures price. The method of structuring data can filter out the random volatility of futures market and it is not restricted by the type of futures contract. Experiments show that based on the combination of BP neural network and the method of structuring data, the accuracy of the model's forecast results in futures price trends can reach more than 80%. In the algorithm there is a relatively clear trading point, which can play a certain role in the actual futures price trend forecasting. Moreover, the algorithm is not sensitive to changes in parameters of BPNN. In addition, statistical results reveal the price change law to a certain extent.

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