Generalized Deep Neural Network and its Application in Financial Time Series Forecasting

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Abstract: Generalized representation is a very important concept in deep learning, which can treat multiple data as random sequences. The different types and parameters are somehow intrinsically related to each other and independent of each other. The generalized representation model has a very important role in financial time series, and the generalized analysis method is a kind of deep learning based on data mining, which can solve a large number of complex problems encountered in financial time series forecasting. Since traditional neural networks have the advantages of high complexity, real-time and good stability, their applications have a wide development prospect in many fields, but the current research hotspots mainly focus on how to improve the quality and accuracy of the model, and the research on generalized deep neural networks is still relatively small. Therefore, this paper investigates the modeling and prediction performance of generalized deep neural network models based on the generalized analysis method.

Keywords: Generalized deep neural networks, Financial time series, Forecasting research

1 Introduction

Financial time series networks are used to study and analyze the correlation between investors and securities markets. In the Internet era, more and more scholars in the financial field are focusing on deep neural networks and their development. The generalization algorithm (CNNTS) is a proposed method based on knowledge learning, modeling and classification with high generalization ability, and the method does not need to pre-train the original samples when processing data, so this is good for the correlation between financial time series networks and deep neural structures. The technique has the following features: First, the depth approximation is fast, and it can approximate arbitrary time intervals [1]. Second, the generalized search performance is good. There are many uncertainties and shortcomings of deep neural networks in processing data, such as: too fast training speed, improper parameter selection, etc., which leads to its inability to solve these nonlinear models and non-smooth characteristics well [2]. Thirdly, the effective information processing capability is strong and has high fault tolerance. The algorithm maps the original samples into the deep neural network by preprocessing the data, so that the generalized model can obtain a time series prediction result that approximates the real world. Fourthly, it is highly sensitive to parameters and has a large margin of parameter

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selection. The algorithm needs to use its spatial distribution property to map the data space into the deep neural network when processing the data, and it is implemented by the generalized algorithm [3].

For the prediction of complex time series data such as financial time series, the traditional method is shallow neural network model, mainly including GRNN network, NARX network, etc. GRNN network is formed by interconnecting multiple layers of neurons. Deep neural network is composed of a large number of complex samples, which has good fault tolerance and robustness, and it can process the data quickly and give prediction results [4]. Compared with other methods, it has obvious advantages: The model can well solve the problem of redundant information in traditional research, and the algorithm has the characteristics of higher complexity in the learning process, slower computation speed and not easy to fall into local optimum or local minimal value. NARX network can well solve the problems that are difficult to be handled by traditional model algorithms, and NARX network has strong fault tolerance, which can make fast, effective and accurate prediction of data [5]. When facing the financial data with high noise, high intensity and strong interference, the traditional methods are difficult to achieve the desired effect, and the deep neural network can effectively use these complex data to predict the financial time series, which has greatly improved than the GRN network in the accuracy of processing data, and it can effectively solve the problems encountered by the traditional methods [6].Based on the above description, neural networks in forecasting can innovatively propose an intelligent hybrid forecasting method based on deep learning as well as locally homogenized indicators. This method firstly improves the model of deep neural networks by adopting the noise reduction self-coding (dSAE) algorithm in deep learning, secondly selects the locally homogenized indicator (Zipzap/PI) indicator as the output layer indicator, and finally focus on predicting the trend and direction of the price series and compare it with the prediction results of the deep neural network [7].

2 Generalized function noise reduction self-coding network (FdAE)

A functional map is defined as a stochastic system consisting of two or more continuous functions. FdAE is a neural network-based method that can directly process input signals and noisy data. Its stability and effectiveness are trained by studying the process of calculating and analyzing its parameters to determine the best algorithm (e.g., minimum mean square error distribution) and the optimal routing protocol. It can also be used for the optimal design of predictive models to improve the accuracy and reliability of generalized depth data processing performance, and these methods should be used in combination in other fields in practical applications.

Deep learning is a network technology with rich theoretical and practical foundation, as well as high depth information processing ability, strong comprehensive application development ability and strong innovation consciousness and learning interest. It is a new type of network based on data mining, and its research mainly includes deep neural network and generalized function theory, which is of great significance in financial time series. Traditional deep learning methods can only transform continuous time function relationships into spatial relationships, while deep neural networks can transform continuous time function relationships into spatial trajectory variables, and we need to use generalized function theory to construct a generalized function model when conducting in-depth research. In this paper, we mainly draw on the theoretical knowledge related to time-frequency analysis and wavelet analysis, and combine with stacked self-coding neural network to propose a new deep learning algorithm - generalized function noise reduction self-coding network (FdAE).In the generalized deep neural network, the training of time series data is completed by a depth mapping to gradient BP neurons to achieve the parameter selection ability of the deep neural network, and then the data is mapped to a generalized model. The input and output variables need to be trained separately in this process [8].

The original noise reduction self-coding network (dAENN) is a method that introduces a deep neural network on top of the self-coding network. When dealing with high-dimensional data, the steps are as follows:

Step1: the algorithm firstly starts from the original non-complete sample, and then maps it to the generalized sequence after pre-training it;

Step2: the initialization parameters are obtained through the adaptive knowledge base;

Step3: the gradient descent method is used to achieve the effective noise reduction effect and the back propagation speed, so that the fast noise reduction of the generalized deep neural network is achieved.

The original noise-reducing self-coding network enables the self-encoder to learn more robust features, and it also enables the generalized deep neural network to better adapt to various complex environments. Based on this, the numerical structure is extended to the generalized structure (the topology of the self-coding network for the numerical case is shown in Figure 1), which is a statistical-based probability distribution model with a wide range of applications in financial time series forecasting.

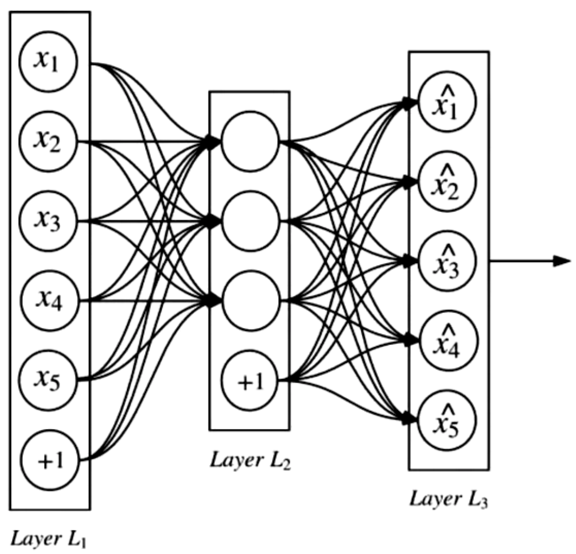

Figure 1. Self-coding network topology

Specifically, let x be the input vector, f(-) be the transfer function, Wi be the summation weight, and b be the offset term, then the output of the hidden layer, hw, b(x), is shown in Equation (1). Summing up the weights of the network, we can get that in that time period, as the weights and offset terms increase mapping to the next moment, it is improved: using the weighted deep neural algorithm to deal with the generalized space PMM problem, the output of the two generalized self-coding function can be expressed as shown in Equation (2).

$$h_{W \cdot b}(x) = f(W^T x) = f(\sum_{i=1}^{3}(W_i x_i + b)) \tag{1}$$

$$\hat{x}_j(\cdot) = b_{2j} + \sum_{i=1}^{m} W_{ij}^{(2)} f(b_{1i} + \sum_{l=1}^{n} \int x_l(\cdot) W_{ij}^{(1)}(\cdot) dt) \tag{2}$$

where m<n, plays the role of extracting high-level features. Considering the case of multiple samples, let k learning sample functions are given as shown in Equation (3), and the coefficient vector of its expansion is shown in Equation (4).

$$\begin{gathered} (x_{11}(t), x_{12}(t), \cdots, x_{1n}(t)), \\ (x_{21}(t), x_{22}(t), \cdots, x_{2n}(t)), \\ \vdots \\ (x_{k1}(t), x_{k2}(t), \cdots, x_{kn}(t)), \end{gathered} \tag{3}$$

$$C_{ki} = (c_{ki \cdot 1}, c_{ki \cdot 2}, \cdots, \quad c_{ki \cdot L}) \tag{4}$$

The weight function is then expressed as a basis function expansion form as shown in Equation (5).

$$W_{i,j}^{(l)}(t) = \sum_{s=1}^{L} \omega_{ij}^{(l,s)} b_l(t) \tag{5}$$

3 Local normalized metrics

Local normalized metrics are built on the basis of deep learning, which is extracted from the original data set after processing, and its performance metrics are reflected in the deep neural network, so it is important to study the generalized exponential and threshold function for a deeper understanding of financial time series theory. Its function is to use the unimportant and unused feature points or representative (such as wavelet transform, support vector machine, etc.) in the original sample as the training set to construct the weight matrix, and introduce the weight calculation function to form a new sample subset. The local normalization method is a good solution to the problem of determining global variables by the properties of the parameters themselves, and it has been widely applied to statistical learning theory and techniques in practical applications.

The local normalization metric is performed spatially and reflects the topological relationships between each node in the entire network, rather than making local improvements to the overall model. Both global variable-weight and speed-free optimization algorithms can be implemented, and they have their different advantages and disadvantages for traditional methods. Firstly, the global clustering problem has the principle of adaptivity, and the local optimal solution also has the principle of adaptivity. Secondly, good convergence, high accuracy, and also not easy to fall into local optimum or over-prematurity, etc., so it is often used in neural network-based generalized analysis to solve this difficult problem.

In high-frequency financial time series forecasting problems, the commonly used output indicators are peal indicators, i.e., exponential smoothing coefficients and altitude angles of latitude α. In traditional financial time series forecasting problems, two methods are mainly used for analysis: one is based on statistical models, which derive generalized exponential smoothing coefficients by analyzing the models. This method has some limitations when dealing with data in deep neural networks. The other is to use the weighted average algorithm to realize the processing and calculation of the data set by the deep neural network [9]. The method is realized by using the weighted average, which not only can guarantee the accuracy of the deep neural network model in processing, but also can avoid the impact of the generalized exponential smoothing coefficients on the data set. However, in the traditional financial time series forecasting problem, limited by the weighted average algorithm, and for the exponential smoothing coefficients to be studied usually need to use non-parametric methods to deal with. Therefore, the researchers proposed a locally normalized position indicator (PI) as the output indicator. The main idea of the indicator is to introduce the position indicator in a deep neural network so that the error of the generalized exponential is minimized, and then the nonparametric data is processed by interpolating and locally normalizing the data between two adjacent reversal points. The index is taken as 0 on all local maxima and 0 on all local minima, while it is filled with 3 interpolations between inversion points to ensure certain continuity, and the position index (PI) 3 interpolations are shown in Figure 2.

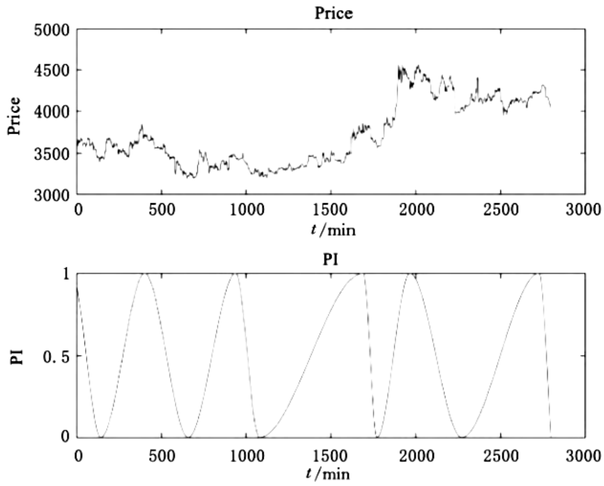

Figure 2. Position Indicator (PI) 3 times interpolation

4 Experimental effects of financial time prediction error and prediction direction based on generalized deep neural network

4.1 Comparison of the Degree of Fluctuation of Neural Networks Over the Original Time Series

Artificial neural network is a kind of model obtained by a large number of calculations, which can be used for prediction and control without using any known information in the research process. However, because the input vector has self-organization, many parameters and hidden layer activation, which leads to its limitation in practical applications, we will use the weight comparison method and BP algorithm to process the data samples, and then use the weights to approximate the artificial neural network model to get a fluctuation degree much smaller than the original time series, so it is very necessary to use it to predict the rate of change of the generalized exponential. Since the large amount of noise contained in the real market price is unpredictable, it is also best to use the BP network to predict the generalized index, which can estimate the real market price volatility more accurately, using the relative standard deviation (RSD) and the standard deviation of the return to express the volatility, that is, as shown in Equation (6).

$$RSD = \frac{\sigma_p}{p} \tag{6}$$

where: op is the standard deviation of the price series and p is the mean of the price series. The statistics of the estimated series obtained from the NAR model, the obtained indicators are shown in Table 1.

Table 1. statistical indicators of the estimated series of the NAR model

Type	RSD	σ_r
Original sequence	0.2944	0.0070
NAR model	0.2946	0.0069

Through Table 1, it is found that the degree of volatility of the series predicted by NAR can be measured by the exponential function, and in the prediction of financial time series, the NS distribution is obtained by analyzing the data. From this test result, it can be seen that the NAR network actually lacks the effective discovery of the true value, and the denoising ability is weak and cannot reflect the true value [10]. The data obtained through the analysis shows that NS network has a strong advantage in time series forecasting.

4.2 Comparison of the Degree of Error of Neural Network Prediction Compared to "Random" Prediction

In generalized theory, the error is a random variable whose magnitude depends on the relationship between the input and output. If the input signal is transmitted from the middle node to each node of the network, the error will be larger. The "stochastic" prediction model is a prediction method built on the basis of a data set, which uses knowledge of the network structure to convert the error into a valid value. Only when the error level MSE and the statistical goodness-of-fit RR of the NAR network can be much better than the "random" model, the prediction of the NAR network can be proved to be meaningful, and the experimental results are shown in Table 2.

Table 2. Prediction results for the accuracy of NAR network trends

Type	MSE	R^2
"Stochastic" model	0.0043	0.9991
NAR network	0.0046	0.9991

Table 2 shows that the MSE of the NAR network is slightly higher than that of the "random" model, but smaller than that of the "depth model". The NAR network is more commonly used in financial time series forecasting for generalized mapping, and its superiority makes it well suited for financial time data. However, the error after training with the neural network is similar to the R effect of the "random" model, which reflects that the neural network is not very effective in time series forecasting and its forecasting effect is doubtful.

4.3 Matching the Low Error Level of the Prediction Size of the Neural Network with the High Accuracy of the Prediction Direction

In generalized theory, for a data prediction, if it is the effective value will be large compared with the threshold score, and vice versa for low error. But when the generalized model reaches a certain level it is possible to achieve high accuracy prediction because in this case the original samples are trained and found to have good enough information to support the use of the network and calculate their propagation in the time series, so it is a very accurate and fast data set. The NARX network and the "stochastic" forecasting model were tested by testing the neural network with respect to the accuracy of the forecasting trend, using the SR indicator as a basis for judgement and the raw price data normalized to the output and input data for effective comparison. The results are shown in Table 3.

Table 3. statistical indicators of the estimated series of the NAR model

Type	MSE	R^2	SR
"Stochastic" model	625.7726	0.9991	0.4869
NAR network	618.5152	0.9991	0.4704

Table 3 shows that the error level of NAR network is still high on the whole data set after the training convergence, and it is not significantly different from the random model. Meanwhile, its directional accuracy SR<50% indicates that it has good prediction ability for the generalized exponential model, but still cannot improve its classification performance well when the time series data have not yet reached the optimum, resulting in the low prediction accuracy of the generalized exponential model.

5 Conclusion

The application of generalized function analysis in financial time series forecasting provides a new method for investors and financial institutions, which is based on deep neural network approach. Deep neural network is a multi-layer feed-forward compensation model without tutor learning, and its basic idea is to adjust the number of layers by calculating the expected error between the weights and the threshold rate of change to obtain the expected weights. When processing time series data, the multilayer feedforward compensation model is used for calculation rather than based on deep neural networks. A generalized model is obtained by classifying the data after processing, training and comparing steps, which is then used to predict the generalized model and obtain a function. According to this function to analyze parameters such as eigenvalues, threshold changes and weight coefficients of the data, and compare the prediction results with the actual data to finally obtain a generalized deep neural network model. The research direction of this paper is to classify different types of functions on the basis of deep neural networks, and then apply them to financial time series data forecasting. In the future, deep neural networks will be used more and more in financial time series forecasting, and their research will be more and more in-depth.

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