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A Hybrid Approach of Combining BP Neural Network and GARCH Model for Forecasting Stock Price

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Abstract. In this paper, we first construct a three-layer (one hidden layer) multilayer back propagation neural network (BPNN) model to forecast daily closing prices of stocks, but there are considerable errors between the actual values and predicted values. Then, to get better prediction results with higher accuracy, we fit the tendency of the errors by modeling a generalized autoregressive conditional heteroscedasticity (GARCH) model. Since it can better deal with the non-linearity and other characteristics of financial data, so the predictive effect of our method is better than that of the hybrid approach of BPNN and autoregressive integrated moving average (ARIMA) model. Finally, we verify this assertion through experimental results.

Keywords: BP neural network, Stock price prediction, Nonlinear, ARIMA, GARCH.

1. Introduction

Stock price prediction attracts the attention of many scholars, and a lot of stock price forecasting methods have been put forward. Stock price forecasting methods mainly contain the following two kinds, one is statistical analysis method, and the other is machine learning approach.

In all statistical analysis methods, the prediction method with more frequency is autoregressive integrated moving average (ARIMA) model used in [1]. It is worth mentioning that ARIMA model is suitable for data modeling of stationary and linear time series. However, literature [2] points out that the time series consisting of the stock market data are highly nonlinear and complex. This means that ARIMA model likely prevents jailbreaking to show changing properties of the time series in this case. Thus, machine learning approaches have been widely used to deal with chaotic nature of financial time series, such as back propagation neural network (BPNN) [3], support vector machines (SVMs) [4], and so on. Moreover, literature [4] not only indicates that BPNN and SVMs can be well applied to make the financial time series prediction, but also explores the applicability of BP neural network and SVMs to the problem of financial prediction. Additionally, literature [5] reveals that the stock price prediction effect of BPNN model is better than that of ARIMA model through experimental results.

We consider using the BPNN model to forecast stock price in this paper. However, BPNN is easy to trap in local minimum, which seriously affects prediction performance of the network. For improving the prediction accuracy, scholars have thought of combining statistical analysis with machine learning. For instance, a hybrid approach of BPNN and ARIMA is proposed to forecast stock trend in [6,7], and a hybrid approach of BPNN and GARCH model is proposed to forecast price volatility [8,9], Meanwhile, they also verify the validity of the hybrid approach through experimental results in [6,7,8,9]. Furthermore, literature [6] shows that compared with using the ARIMA model to predict the stock price first and then the BPNN to model the prediction error, using the neural network to forecast the stock price first and building ARIMA model of the prediction error can obtain better prediction effect. Literature [7] uses BPNN, ARIMA model and exponential smoothing model to make stock price prediction simultaneously, and it takes the weighted average of the three model predictions as the final predicted values. Literature [8] and [9] use the GARCH model to forecast the stock price first and then the BPNN to model the output of the GARCH model and other indexes.

In this paper, we first construct a three-layer (one hidden layer) multilayer neural network model trained with back propagational algorithm to forecast the closing prices of stocks, but there are considerable errors between the actual values and predicted values. Then, to getter better prediction accuracy, we next consider to fit the tendency of the errors by modeling affective GARCH model, this is different from the ARIMA model used in [6]. Moreover, differing from the price volatility forecasting [8, 9], we consider predicting stock price. Finally, we make a comparative analysis between our method and the method proposed in [6] through experimental results.

The content of this paper can be listed as follows. In section 2, we describe the methodology used in this paper. In section 3, we give the experimental results. In section 4, we present some concluding remarks.

2. Methodology

2.1 Back Propagation Neural Network (BPNN).

The typical three-layer multilayer BPNN successively is composed of the input layer, one hidden layer and the output layer [3]. Each layer is comprised of multiple nodes, and the number of nodes can be chosen according to design needs. Let us assume that input nodes are x_i, $i\in\{1,2,\ldots,m\}$, hidden nodes are h_j, $j\in\{1,2,\ldots,s\}$, and output nodes are y_k, $k\in\{1,2,\ldots,n\}$. Then, when the actual outputs are z_k, $k\in\{1,2,\ldots,n\}$, the BP algorithm can be formulated as

the output of j_{th} node in the hidden layer:

$$h_j=f(net_j),\ net_j=\sum_{i=1}^{m}\omega_{ij}x_i\text{-}a_j \tag{1}$$

the output of k_{th} node in the output layer:

$$y_k=f(net_k),\ net_k=\sum_{j=1}^{s}\upsilon_{jk}h_j\text{-}b_k \tag{2}$$

the mean square errors:

$$E=\frac{1}{n}\sum_{k=1}^{n}(z_k\text{-}y_k)^2 \tag{3}$$

weights updating:

$$\omega_{ij}(t+1)=\omega_{ij}(t)\text{-}\lambda\partial E/\partial\omega_{ij},\ a_j(t+1)=a_j(t)\text{-}\lambda\,\partial E/\partial a_j \tag{4}$$

$$\upsilon_{jk}(t+1)=\upsilon_{jk}(t)\text{-}\lambda\partial E/\partial\upsilon_{jk},\ b_k(t+1)=b_k(t)\text{-}\lambda\,\partial E/\partial b_k \tag{5}$$

where the arguments t+1 and t are on behalf of the next and the current training step, ω_{ij} and ν_{jk} are connection weights, a_j and b_k are the threshold values for $i\in\{1,2,\ldots,m\}$, $j\in\{1,2,\ldots,s\}$, $k\in\{1,2,\ldots,n\}$, and λ is the learning rate, which is a constant. In this paper, we adopt Sigmoid function as the activation function $f(\cdot)$.

2.2 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA (p, d, q) model can be effectively built by determining the autoregressive (p), the difference (d) and moving average (q) parameters [7], where the difference (d) is determined by the order of difference needed for time series stabilization, the autoregressive (p) and moving average (q) are respectively determined truncated orders of partial autocorrelation coefficient and autocorrelation coefficient of stationary time series. Let $\{e_t\}$ denote stationary time series, the ARIMA (p, 0, q) has the following form:

$$e_t=\phi_0+\phi_1 e_{t\text{-}1}+\phi_2 e_{t\text{-}2}+\cdots+\phi_2 e_{t\text{-}p}+\mu+\varepsilon_t\text{-}\theta_1\varepsilon_{t\text{-}1}\text{-}\theta_2\varepsilon_{t\text{-}2}\text{-}\cdots\text{-}\theta_q\varepsilon_{t\text{-}q} \tag{6}$$

where ϕ_i, θ_j and μ are parameters to be evaluated for $i\in\{0,1,2,\ldots,p\}$, $j\in\{0,1,2,\ldots,q\}$, and $\{\varepsilon_t\}$ are independent identically distributed random errors with the mean equaling to zero. We determine a better model by choosing relatively small Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), relatively high adjusted R square (R^2).

2.3 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Let $\{e_t\}$ denote the time series with ARCH effect. As shown in [8] and [9], the GARCH (p, q) model has been widely used to model financial time series, and it has the following form:

$$e_t=\mu+\varepsilon_t\sigma_t \tag{7}$$

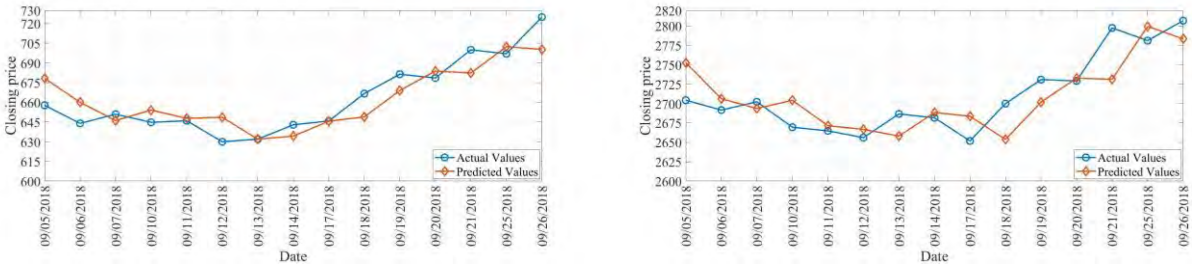
$$\sigma_t^2=\alpha_0+\sum_{i=1}^{q}\alpha_i\varepsilon_{t\text{-}i}+\sum_{j=1}^{p}\beta_j\sigma_{t\text{-}j}^2 \tag{8}$$

where q, p, μ, α_0, α_I and β_j are parameters to be evaluated for $i\in\{0,1,2,\ldots,q\}$, $j\in\{0,1,2,\ldots,p\}$. Generally, α_i, $\beta_j>0$ and $\sum_{i=1}^{q}\alpha_i+\sum_{j=1}^{p}\beta_j<1$ are needed to ensure the stability in the GARCH model.

3. Experimental Results

The daily trading data (from September 2, 2016 to September 26, 2018) of Kweichow Moutai (600519) and Shanghai Stock Price Index (999999) are obtained by using Tushare, which is a Python package specially providing financial data. The training dataset consists of data from September 2, 2016 to September 4, 2018, and the test dataset consists of data from September 5, 2018 to September 26, 2018. In our model, we use the trading data as the input vector, consisting of the opening price, highest price, lowest price, closing price and trading volume of each stock, and the closing price of following day is taken as the output.

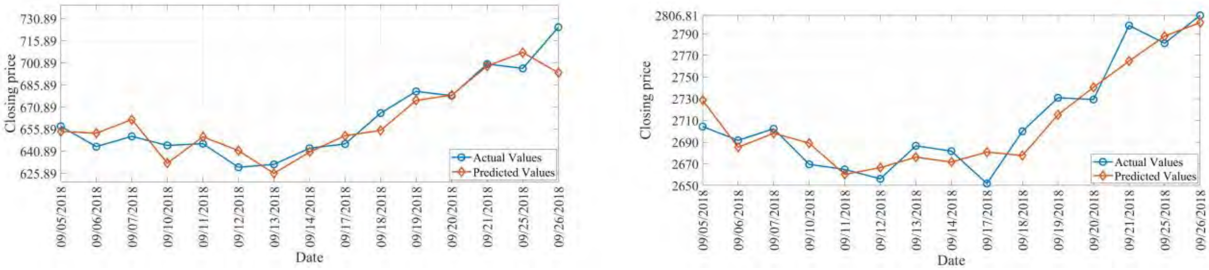
We firstly take the logarithm of the ratio of two adjacent days (eg. $r_t=\ln(p_t/p_{t-1})$) to eliminate the impact of units of measurement and trends embedded in the data. Then, the training parameters were set as follows: $\lambda=0.16$ and epoch size=4000. Meanwhile, the numbers of nodes in the hidden layer are 12 and 9 for Kweichow Moutai (600519) and Shanghai Stock Price Index (999999) after many experiments, respectively. Finally, the network was tested with the data set to estimate its prediction performance by using mean absolute error (i.e. $MAE=\sum_{k=1}^{n}|z_k-y_k|/n$), and the predicted results are shown in the Fig. 1.



(a) Kweichow Moutai (600519) (b) Shanghai Stock Price Index (999999)

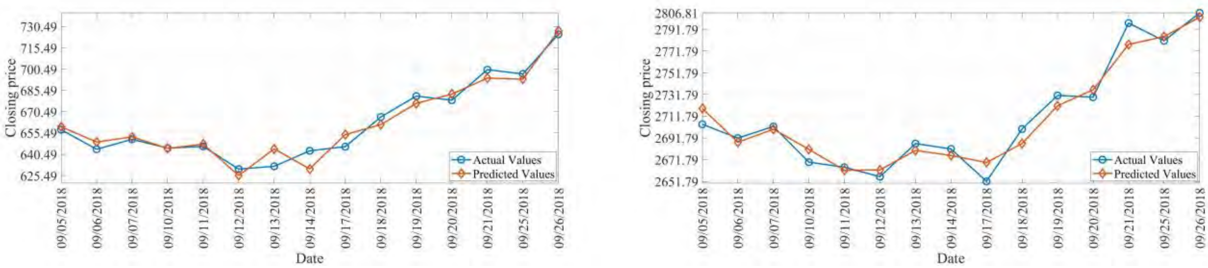
Fig. 1 The comparison between actual values and predicted values of BPNN

As shown in Fig. 1, we can see that there exists a certain error between actual values and predicted values. Then, we respectively adopt ARIMA model and GARCH model to fit the trend of forecasting errors for improving the accuracy of closing prices prediction, and the corresponding models are named as BPNN-ARIMA and BPNN-GARCH. After many experiments, we construct both the ARIMA (0, 2, 2) model and GRACH (1, 1) model for the error data of Kweichow Moutai (600519) and Shanghai Stock Price Index (999999), respectively. Moreover, the predicted results of BPNN-ARIMA and BPNN-GARCH are respectively shown in the Fig. 2 and Fig. 3.



(a) Kweichow Moutai (600519) (b) Shanghai Stock Price Index (999999)

Fig. 2 The comparison between actual values and predicted values of BPNN-ARIMA



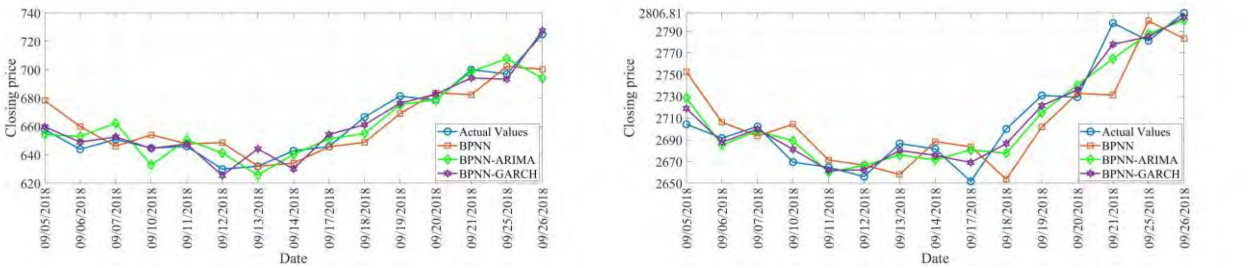
(a) Kweichow Moutai (600519) (b) Shanghai Stock Price Index (999999)

Fig. 3 The comparison between actual values and predicted values of BPNN-GARCH

By comparing Fig. 2 and Fig. 3, we can find that the prediction effect of BPNN-GARCH is better than that of BPNN-ARIMA. In order to compare the prediction performance of these three models, we show the experimental results in Table 1 and Fig. 4.

Table 1 Three Models comparing

Date	Kweichow Moutai (600519)				Shanghai Stock Price Index (999999)			
	Actual Values	Predicted Values			Actual Values	Predicted values		
		BPNN	BPNN-ARIMA	BPNN-GARCH		BPNN	BPNN-ARIMA	BPNN-GARCH
09/05/2018	657.79	678.27	654.38	659.82	2704.34	2752.55	2728.63	2718.91
09/06/2018	644.00	660.02	653.06	649.05	2691.59	2706.28	2685.23	2687.77
09/07/2018	650.97	646.14	662.35	652.68	2702.30	2693.62	2698.14	2699.81
09/10/2018	644.80	654.14	632.81	644.60	2669.48	2704.24	2689.06	2681.23
09/11/2018	646.00	647.79	650.63	647.59	2664.80	2671.43	2660.21	2662.05
09/12/2018	630.00	648.62	641.29	625.49	2656.11	2666.79	2666.43	2662.30
09/13/2018	631.98	631.98	625.89	644.26	2686.58	2658.09	2676.07	2680.27
09/14/2018	642.90	634.27	640.28	630.13	2681.64	2688.48	2671.60	2675.62
09/17/2018	645.81	645.65	651.40	654.33	2651.79	2683.60	2680.76	2669.17
09/18/2018	666.70	648.91	654.97	661.32	2699.95	2653.79	2677.63	2686.56
09/19/2018	681.42	669.05	675.34	676.33	2730.85	2701.89	2715.14	2721.42
09/20/2018	678.55	683.86	678.89	682.79	2729.24	2732.73	2740.55	2736.03
09/21/2018	700.01	682.33	698.65	694.13	2797.48	2731.30	2764.72	2777.83
09/25/2018	697.02	702.36	707.84	693.33	2781.14	2799.46	2787.66	2785.05
09/26/2018	724.93	700.33	694.11	727.37	2806.81	2783.29	2800.20	2802.85



(a) Kweichow Moutai (600519) (b) Shanghai Stock Price Index (999999)

Fig. 4 The comparison between actual values and predicted values of these three models

From the empirical results presented in Table 1 and Fig. 4, all three models can achieve good forecasting effect by judging from the prediction error of these models, but we can observe that the forecasting accuracy level of the BPNN-GARCH model compared with that of both BPNN model and BPNN-ARIMA model is more effective. Meanwhile, the performance of BPNN-GARCH model is better than both BPNN model and BPNN-ARIMA model in terms of forecasting accuracy on many occasions from the test data.

4. Conclusions

In this paper, we construct a BPNN-GARCH model for predicting the daily closing prices of Kweichow Moutai (600519) and Shanghai Stock Price Index (999999). The BPNN-GARCH model is first constructing a three-layer (one hidden layer) multilayer neural network model trained with back propagational algorithm and then building a generalized autoregressive conditional heteroscedasticity (GARCH) model to fit the tendency of the forecasting error between the actual values and predicted values. Trough experimental results, we find that the predictive effect of our hybrid model is superior to that of the typical BP neural network. Meanwhile, compared with using the ARIMA model to fit the forecasting error [6], our hybrid model has better predictive effect. The reason is that the GARCH model can better deal with the non-linearity and other characteristics of financial data, and we verify this assertion by using experimental results.

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