PAPER • **OPEN ACCESS**

Boosting Learning Algorithm for Stock Price Forecasting

To cite this article: Chengzhang Wang and Xiaoming Bai 2018 *IOP Conf. Ser.: Mater. Sci. Eng.* **322** 052053

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Chengzhang Wang[1], Xiaoming Bai[2,*]

[1]School of Statistics and Mathematics, Central University of Finance and Economics, Beijing, China
[2]Information School, Capital University of Economics and Business, Beijing, China

*Corresponding author e-mail: xmbaiczwang@163.com

Abstract. To tackle complexity and uncertainty of stock market behavior, more studies have introduced machine learning algorithms to forecast stock price. ANN (artificial neural network) is one of the most successful and promising applications. We propose a boosting-ANN model in this paper to predict the stock close price. On the basis of boosting theory, multiple weak predicting machines, i.e. ANNs, are assembled to build a stronger predictor, i.e. boosting-ANN model. New error criteria of the weak studying machine and rules of weights updating are adopted in this study. We select technical factors from financial markets as forecasting input variables. Final results demonstrate the boosting-ANN model works better than other ones for stock price forecasting.

1. Introduction

Stock price forecasting is an important element to make decision. Errors in statistical approaches are assumed to subject to Gaussian distribution. However, it is believed stock market is complicated and nonlinear, it changes discontinuously and high-frequently[1]. Too many assumptions narrow statistical model's applications. Machine learning approaches are adopted in recent works for doing financial forecasting, such as SVM, CART, ANNs[2]. ANNs, with ability to model nonlinearity, were widely exploited in different financial research disciplines, such as costs monitoring, decision support, financial analysis[3].

ANN shows prominent superiority for stock market predicting. Along boosting theory, one can build a highly accurate combined classifiers by assembling rules of thumb. And weak-learners can be employed to discover these simple rules[4]. Boosting predictor, the set of multiple weak ones, can promote accuracy of forecasting and obtain better results than the single one. In this paper, we attempt to construct a boosting predictor for stock price forecasting. ANNs are employed as the weak predictors to form a stronger one. Different from binary classification, we elaborately design the boosting rules and propose a boosting-ANN model for stock price forecasting. Our work mainly focuses on constructing a stronger predictor using multiple simple ANN models, which is different from most of previous works for stock market forecasting concentrating on optimizing parameters and architecture of one single ANN.

2. Literature Survey

There are two different classes of research schemes for stock price forecasting[5]. The first one is based on fundamental analysis. Researchers try to forecast stock price through analyzing domestic stocks worth and taking effective factors into consideration. Value of stock is estimated by analysis and compared with market price to determine purchasing or selling the stock. The second one is based on technical factors analysis. Premise of it is stock's behavior could be predicted on the basis of its performance in past and all effective factors are reflected by its price. By analyzing technical factors of previous price, one could obtain important information which could be explored to forecast the following price[6].

Performance of ANN and SVM were tested to forecast stock price index movement's direction on ISE[7]. Findings showed ANN was superior to SVM. In study of [8], they employed ANN to predict stock market index movement. Effectiveness of prediction was tested in different period of duration. Findings showed ANN could provide high ratio of correctly predicted signs. In study of [9], researchers combined ANN with metaheuristics for the task of stock price predicting. They used 45 technical factors, such as the close, highest and lowest price, MACD, as the input to ANN. Results proved HS-ANN model did better than its rivals. Researchers tested ANN and PCA approaches for the task of forecasting price on TSE market[10]. Findings showed ANN model got better results than other methods. In study of [11], researchers tested effectiveness of forecasting algorithm ARIMA and ANN. Experiments were conducted on the stock data including open, low, high and close price from New York Stock Exchange. Results verified that ANN model outperformed ARIMA model. Researchers forecasted the Brazilian power distribution companies' maximum and minimum day stock prices using ANN model[12]. They used many different ANN frameworks. As for input data, they performed selection on the basis of correlation analysis. Their experimental results showed ANN model having 1 hidden layer and 5 hidden neurons was the best one.

3. Proposed Method

In this work, we select stock market data from Shanghai Stock Exchange over a period from January 2011 to March 2016. In addition, we also combined stock data of international markets, including S&P 500, NSADAQ, and DJIA, and foreign exchange rates to US dollar under the same duration.

3.1. Technical factors

Technical factors can give more useful information than pure price for stock market prediction[9]. Property of one stock market is different from the other ones. And economic globalization enhanced interaction between different financial markets. Therefore, we select 38 technical factors as the independent input variables. Domestic and international factors include open price of current and previous day; highest, lowest and close price of last day; open price of current and last day, close price of last day in S&P500, NSADAQ, DJIA market; exchange ratio to US dollar; momentum of close price; fast and slow stochastic %D and %K; %R of William; middle, higher and lower band of Bollinger; 5-day, 6-day, 10-day, 20-day simple, exponential and triangular moving average of close price; close price moving average convergence/divergence; accumulation/distribution oscillator.

3.2. Boosting-ANN predicting algorithm

PAC learning model is the basis of boosting[4]. A series of weak learning algorithms can be combined into a stronger one. As to binary classification problem, one can get that response variable $Y \in \{-1, 1\}$. In the architecture of boosting method, one will invoke the weak learning algorithms recursively.

During each loop, hard samples would get more attention by the latter weak learner. One can get the best "weak hypothesis" which can be denoted as $h_t : X \to Y$ with respect to sample distribution D_t. The weak learning algorithm's error, represented by ε_t, is defined by:

$$\varepsilon_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i] = \sum_{i:h_t \neq y_i} D_t(i)$$

After getting the weak hypothesis, we can obtain the final one $H(x)$ which is denoted by:

$$H(x) = \mathrm{sign}(\sum_{t=1}^{T} \alpha_t h_t(x))$$

Whereas, for task of stock price forecasting, one can get $Y \propto R$. The error of weak hypothesis and the rule of updating weight of sample will be different from traditional ones. In this work, we adopt the error of weak hypothesis as:

$$\varepsilon_t = \Pr_{i\sim D_t}[|h_t(x_i) - y_i| > E] = \sum_{i:|h_t(x_i)-y_i|>E} D_t(i)$$

Where E is a given threshold. Actually, in traditional boosting architecture, the criteria $h_t(x_i) \neq y_i$ can be formulated equivalently as $|h_t(x_i) - y_i| > 0$. Along with this, the rule of updating weights of samples is then modified into:

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{\alpha_t}, & \text{if } |h_t(x_i) - y_i| > E; \\ e^{-\alpha_t}, & \text{else.} \end{cases}$$

Accordingly, the final result in the paper is formulated as:

$$H(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$$

In this work, we use ANN algorithms to construct the stronger boosting learning model, because ANNs reveal prominent effectiveness for stock price forecasting. In detail, the multilayer perceptions (MLPs)[11] are assembled to form the boosting-ANN model.

4. Experimental Results

In this study, data recorded during interval of time from 01/10/2011 to 03/02/2016 is used for experiment. Sample size of the total data set is 1247. Data during interval of time from 01/10/2011 to 08/04/2015 is used as the training set. The rest is used as the testing set. In our boosting-ANN model, hidden layer size of MLPs is set to 25. 10 weak learners is used to form the stronger learner. To verify the performance of the proposed model and ANN, 9 different error criteria are calculated and reported. Errors under the same conditions are shown in Table 1.

Table.1 Error comparison.

Error criteria	boosting-ANN	ANN
MAE	99.9720	117.6427
MSE	18279.32	25086.48
RMSE	135.2010	158.3871
MARE	0.030516	0.035832
MSRE	0.001720	0.002356
RMSRE	0.041472	0.045533
MAPE	3.051657	3.583225
MSPE	0.172000	0.235605
RMSPE	0.414729	0.455334

Experimental results show that our boosting-ANN forecasting model is superior to the single ANN predicting model in terms of all statistical error criteria. In addition, we also test these two forecasting models on the same testing data set. Indictors of the predicting performance can be denoted by the statistical results. Note that, our boosting-ANN model produces the best MAPE error with 3.05%, while the best result reported in similar work of [10] is 3.38%. Our model has got lower error rate.

Stock prices can be considered as the time series, they contained in the testing dataset and the corresponding forecasted ones with the hidden layer size been set to 25 are demonstrated in Fig.1. Actual stock prices and the results forecasted by the boosting-ANN forecasting model is shown in Fig.1(a). Fig.1(b) depicts the actual prices and the ones forecasted by the single ANN.

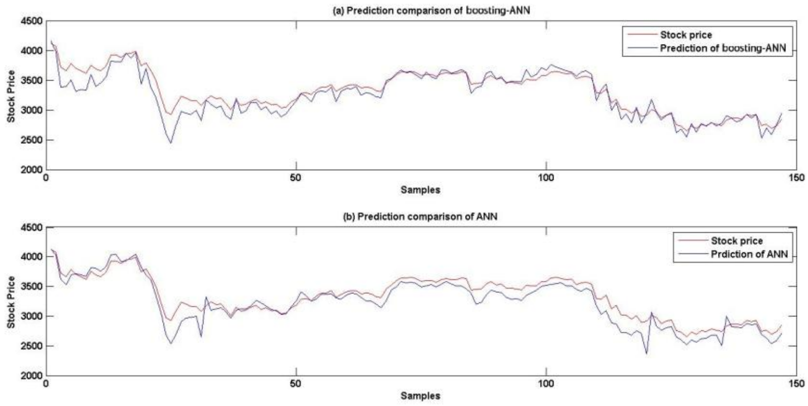

Fig.1 Stock prices and the forecasted ones

5. Conclusion

A novel predicting model along with the idea of boosting is proposed in this paper. We construct a stronger forecaster by multiple three-layer feed-forward ANNs which are used as the weak learners. New criteria for determining the mis-predicting samples is adopted in our new model. The rule of updating weights of samples is also designed accordingly. To verify the effectiveness and performance of the boosting-ANN model, experiments are carried out under the same conditions. Statistical experimental results show the boosting-ANN model has superiority over its rivals. It can improve the accuracy of prediction effectively.

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