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Comparison of LSTM and ARIMA in Price Forecasting: Evidence from Five Indexes

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Abstract. The financial industry has been increasingly researching and applying artificial intelligence in both academia and industry. The classical deep learning model, I.E., long-short term memory (LSTM) neural network model, has great advantages in predicting financial time series. This study uses data such as daily opening, closing, high and low prices of five representative global stock indices from 2015 to 2022 to predict stock prices using the LSTM neural network model and the linear autoregressive moving average model (ARIMA). The predicted results are compared with the actual stock prices, and the study findings demonstrate that the LSTM model outperforms the ARIMA in predicting stock index prices. Thus, incorporating deep learning models in a reasonable way can not only improve the accuracy of investment decision-making, but also enrich the methods for processing and analyzing financial time series data, so as to enhance the ability to monitor and warn of financial market risks.

Keywords: Stock price prediction, LSTM neural network model, ARIMA model, deep learning

1 Introduction

In recent years, conventional techniques for machine learning such as Support Vector Machine (SVM) [1] and random forests have gradually shifted to deep learning methods such as multi-layer BP neural networks, recurrent neural networks, and convolutional neural networks [2].

Many research results have shown that deep learning can achieve better predictive effects on financial time series data, and the predictive results have been compared with traditional methods. Fischer and Krauss found that the LSTM model in recurrent neural networks has better adaptability to financial time series data and higher predictive accuracy than random forests and feedforward neural networks [3]. Yang and Wang applied the LSTM model to 30 kinds of stock indexes all over the world and found that it had higher average predictive accuracy and more stable results than support vector machines, multi-layer perceptron and ARIMA models [4]. Ouyang combined wavelet analysis with the LSTM to forecast the closing quotation and found that it had higher predictive accuracy than four other models including multi-layer perceptron, support

F. Balli et al. (eds.), *Proceedings of the 2023 2nd International Conference on Economics, Smart Finance and Contemporary Trade (ESFCT 2023)*, Advances in Economics, Business and Management Research 261,
https://doi.org/10.2991/978-94-6463-268-2_6

vector machines, k-nearest neighbor and GARCH models [5]. Di Persio and Honchar used RNN, LSTM and GRU to calculate Google's stock price trends, showing that the LSTM neural network had an advantage in financial sequence prediction [6].

Based on the literature review, this paper selects five representative global stock indices as research objects, and uses nearly 8 years of stock trading data to compare the accuracy of LSTM model and Arima model in stock price prediction. The rest part of the paper will be organized as follows. The Sec. 2 introduces the data used in this paper and construct research models. The Sec. 3 respectively presents the fitting results of LSTM and Arima models, and compare and analyze their predictive accuracy. The Sec. 4 describes the shortcomings and outlook. Eventually, a brief summary will be given in Sec. 5.

2 Methodology

2.1 Data

Data for the study comes from investing.com, and selects five representative indices: DJIA, S&P 500, NASDAQ Composite, HK Hang Seng Index and UK FTSE 100 Index. The opening quotation, closing quotation, maximum and bottom price of each day from 2015 to 2022 were chosen as research data.

2.2 ARIMA

Auto-Regressive Integrated Moving Average (ARIMA) is a model for making predictions based on time series historical values and prediction errors on historical values. ARIMA integrates the Auto-Regressive (AR) and Moving Average (MA) terms [7]. The mathematical expression of the ARIMA model is as follows:

$$X_t = c + U_t + \sum_{i=1}^{p} \alpha_i X_{t-i} - \sum_{i=1}^{q} \beta_i \, \varepsilon_{t-q} \tag{1}$$

For the prediction of financial time series, the steps to construct the ARIMA model in this article are as follows: Firstly, stationarity test. Test whether the original data is stationary. Secondly, model parameter determination. In the main parameters of the ARIMA (p, d, q) model, d shows the number of differential operations. The determination of p and q mainly relies on observing the auto-correlation function and partial auto-correlation function images and selecting based on AIC criteria. Finally, residual test. Test whether the residual of the model fitting results conforms to a white noise sequence.

2.3 LSTM

Hochreiter and Schmidhuber first proposed the LSTM model [8]. The model controls the information flow and the amount of forgotten information by introducing three concepts called "gates": input gate, forget gate, and output gate. It represents a selective control structure that can control the passing of information. It is implemented through sigmoid function and dot product. LSTM uses the internal memory unit, the cell state, to save historical information and dynamically allows the network to learn to forget historical information based on different "gates," update the cell state based on new information, and thus find the solution of Gradient Vanishing and Gradient Explosion in RNN [9]. The three "gates" work together to process information and complete the prediction of the time series ht [10].

3 Results & Discussion

3.1 ARIMA

Python was used as the programming tool in this article. The opening prices of five indices were used as model variables for prediction. All data were arranged in chronological order and divided equally into five parts. The first four parts of the data were added to the training set (blue line), while the remaining data were used as the testing set. The testing set was subjected to ARIMA prediction (green line) and compared to the original data (orange line), with the results shown in the Fig. 1.

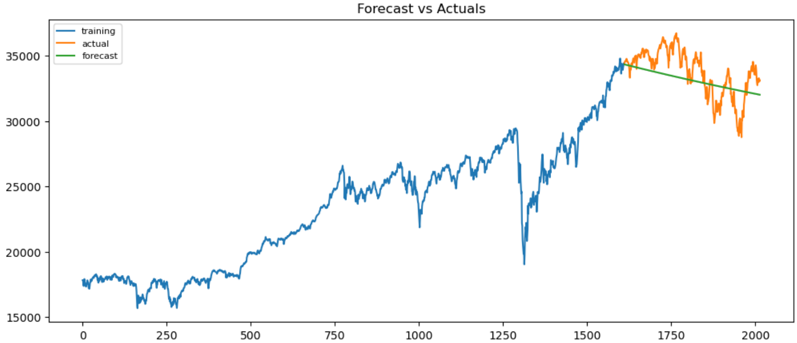

Fig. 1. ARIMA Prediction of Dow Jones Industrial Average.

Table 1. SARIMAX Results

	DJI	SPX	IXIC	HSI	FTSE
ARIMA Model	(1,0,0)	(1,1,0)	(2,0,0)	(1,2,0)	(1,1,1)
AIC	28144.392	19676.109	25472.420	29224.552	22825.202
BIC	28161.215	19687.324	25494.851	29235.726	22842.034

According to the Table 1, the Arima model (1,0,0) fits well with the Dow Jones Industrial Average. Based on the SARIMA test results, the P-values for each variable are less than 0.001, hence the null hypothesis should be rejected. This indicates that in the fitted model, each variable's coefficient has passed the significance test. This indicates that the residuals do not have autocorrelation, and the residual sequence is a white noise sequence. Similarly, it can be concluded that the optimal fitted model for the US Standard & Poor's 500 index is Arima (1,1,0), model for the NASDAQ index is Arima (1,1,1), model for the Hang Seng Index is Arima (1,2,0), model for the FTSE index is

Arima (1,1,1). The significance of the SARIMA test results shows that the p-values are less than 0.001, indicating a good fit for the model. The predicted line for the index is the optimal linear combination.

3.2 LSTM

In this study, Python was used as the programming tool to predict the opening prices of five indices as model variables. The trading days are divided into five parts equally with four parts used as a training set and the rest as a testing set. After computation, a total of 1611 trading days from January 2, 2015 to May 26, 2021 were placed in the training set, 403 trading days from May 27, 2021 to December 30, 2022 were selected as the test set. The LSTM was used to forecast the last one-fifth of the data, and the experimental findings were contrasted with the original data. Observing the data, there are significant differences of five indexes. The study uses MinMaxScaler to scale the data and reduce experimental errors, ensuring the accuracy of the results. The specific prediction method used the past 30 values to predict the 31st target value. In the process of training the model, the girdsearchCV was used for some hyperparameter adjustments to find the basic model.

Fig. 2 shows Hang Seng Index fitted by the optimal parameters. The blue curve shows the forecast opening prices, and the red curve shows the original prices. It is clearly that the prediction results of the model in the test set are very close to the actual results, indicating that the fitting effect is good.

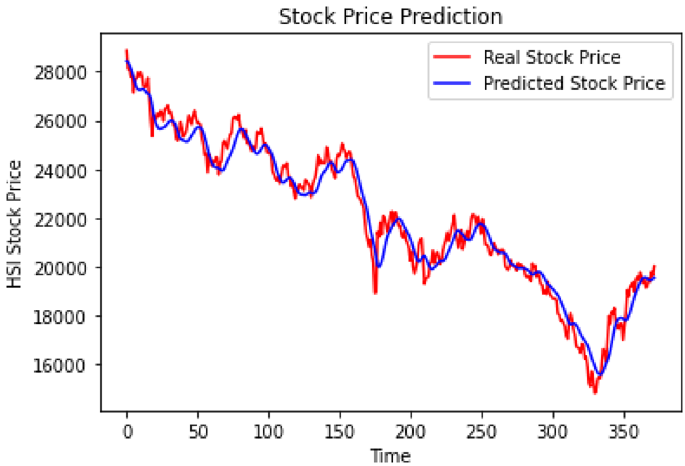

Fig. 2. LSTM Prediction.

3.3 Comparison

This study empirically verifies the preciseness of the LSTM and ARIMA for stock price prediction through the results of Mean Square Error (MSE) and Root Mean Square Error (RMSE). Seen from Table 2, after predicting the prices of the selected five stock indexes, the MSE and RMSE results of LSTM are significantly lower than the results of ARIMA, indicating the deviation between the forecast price and the original price of LSTM is smaller than ARIMA.

Table 2. MSE and RMSE Results

	MSE		RMSE	
	LSTM	ARIMA	LSTM	ARIMA
DJI	361942.33	725905.54	601.62	852.00
SPX	12460.12	18075.73	111.62	134.45
IXIC	141004.38	450319.21	375.51	671.06
HSI	690501.64	2143523.52	830.96	1464.08
FTSE	4911.07	6823.39	70.08	82.60

Based on the above comparison of ARIMA and LSTM models for stock index opening price prediction, LSTM is significantly better than ARIMA in terms of fitting results. The main reason is that when using the ARIMA model to predict time series data, the data must be stable in order to capture the pattern. Unstable data is difficult to capture. During the data fitting process, the ARIMA model is easily affected by the abnormal fluctuations of data, resulting in poor performance in data fitting. However, due to the special model structure of LSTM model, it can selectively forget the adverse effects of abnormal data fluctuations, and then use the memory gate to extract the general rules in the data. So the performance in data fitting is better. Since machine learning is good at mining non-linear relationships between variables, it can be used to make up for the shortcomings of linear relationships between variables in the ARIMA model. With the increase in data volume and types, deep learning models represented by LSTM will have more advantages. Therefore, based on the comparison of the above models, the LSTM model can be considered as one of the best alternatives to the ARIMA model. Based on the experimental results, in practical applications, data modeling should be based on the LSTM model to extract the general rules contained in the data set, simulate, and predict the price changes of stocks. Finally, the extracted rules can be used to predict future data.

4 Limitations & Prospects

There are some limitations to this paper. Firstly, the diversity of data is lacking. Only five representative global stock indexes were chosen as the research objects, which may not represent the prediction results of all stock markets around the world. Secondly, this paper only used ARIMA linear model and LSTM neural network model to predict stock prices, without using the Fama-French multi-factor model for nonlinear prediction. Therefore, the results cannot prove that machine learning is superior to traditional linear and nonlinear models, and there is still some room for optimization in this paper.

In the research on financial time series prediction, this paper combines cutting-edge deep learning technologies and compares the results of traditional linear models to explore better methods and models. Neural network models have good generalization ability and high adjustability in the field of financial time series prediction, and can continue to explore the expansion of application scenarios and the improvement of technical levels in the future.

5 Conclusion

In summary, this study uses daily opening, closing, highest and lowest prices of the DJIA, the S&P 500, the NASDAQ, the Hang Seng Index and the FTSE 100 Index from 2015 to 2022 to use the LSTM neural network model and the linear auto-regressive moving average model (ARIMA) for stock prices prediction, and compares the predicted results with the actual stock prices. Comparing the two models, it is obvious that LSTM outperforms ARIMA in predicting stock prices. Machine learning is good at exploring nonlinear relationships between variables, which can be used to make up for the lack of linear relationships between variables in the ARIMA model. In practical applications, data modeling should be based on the LSTM model to extract the general rules contained in the data set and simulate the predicted changes in stock prices. This research still has certain shortcomings in data diversity and data richness. Moreover, further research is needed on the comparison of the accuracy of stock price prediction between the LSTM neural network model and the nonlinear auto-regressive model. The global stock market price prediction is expanded in this paper by applying both the ARIMA model and the LSTM method in deep learning. It provides practical experience for the widespread application of artificial intelligence technology in the field of quantitative investment, and serves as a useful reference for researchers conducting modeling studies on complex financial time series, while also contributing to the practicality of quantitative research methods.

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