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Predicting CSI 300 Index and NASDAQ Index by Simple RNN and LSTM

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Abstract: Stocks are an important part of the financial market, and their prices can reflect the economic level of a country. It is significant to predict the trends of stocks. With high noise, non-linearity and other complex features, stock systems are hard to be predicted accurately by traditional statistics models and deep learning methods are suitable to be used for stock predictions. In this study, CSI 300 index and NASDAQ index are selected as research targets in this study. Considering one model cannot fit all of the stocks, Simple Recurrent Neural Networks (RNNs) model and its variant model, Long-Short Term Memory (LSTM) model are chosen as two main methods for forecasting these data, and their prediction results will be compared to determine which model fits better. For assessment indicators, graphs and root mean square error (RMSE) can evaluate the accuracy both visually and numerically of prediction results. Experimental results show that simple RNN and LTSM predicts better for CSI 300 index than NASDAQ index. Both simple RNN and LSTM cannot perform well in the test set of NASDAQ index. High discreteness and sudden changes of NASDAQ index may be potential reasons.

Keywords: Stocks predictions, RNN, LSTM.

1. Introduction

Stock companies issue stocks to gather funds, and investors buy stocks to earn returns. It is significant for investors and governments to predict the trends of stock prices to forecast economic trends and changes. Statistical methods like Vector Autoregression (VAR) [1] or ARIMA [2] can be used to analyze the laws and characteristics of stock price trends. However, stock markets are complex and chaotic, statistical methods cannot get good results. At the same time, advances in machine learning enable the data-processing methods to be applied to stock data [3]. Nowadays there are a lot of deep learning models on financial time series forecasting [4]. RNN, (Convolutional Neural Network) CNN and LSTM [5] are common models used for prediction. Besides, a bidirectional long short-term memory neural network (BiLSTM) model, which consists of two layers of LSTMS in opposite directions, was proposed by Graves et al. [6]. Stock price can also be predicted by combined models like CNN-GRU model or CNN-LSTM model to get higher accuracy [7-8]. However, there are still a lack of applied research of complex prediction methods. China and the US are the world's two largest economies. Considering the interactivity [9] and differentiation of stock market between China and USA, CSI 300 index and NASDAQ index are selected as research objects. They are predicted by simple RNN and LSTM in this study to find out which model can fit them better.

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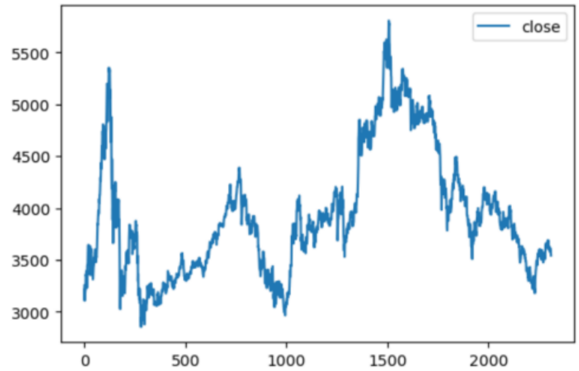
2. Data and Methods

2.1. Data

This study chooses CSI 300 index and NASDAQ index from 12/08/2014 to 06/11/2024 as datasets and forecasts their closing price. Additionally, CSI 300 index comes from JoinQuant and NASDAQ index comes from MSN. Figure 1 shows the trends of CSI 300 index and NASDAQ index. The CSI 300 index is in a state of fluctuation, while the NASDAQ index is generally on an upward trend. And their descriptive statistics are displayed in Table 1.



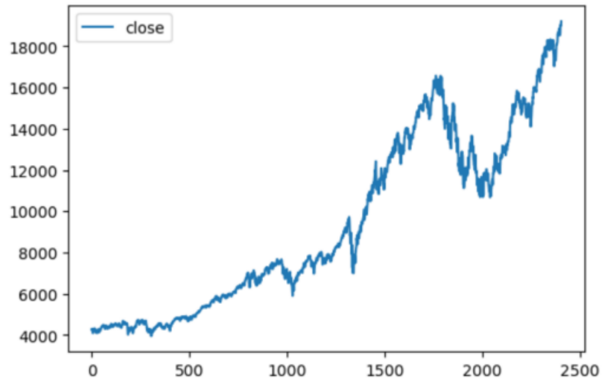


Figure 1: Data Frame of CSI 300 Index(left) and NASDAQ Index(right)

Table 1: Descriptive Statistics of CSI 300 Index and NASDAQ Index

index(close)	count	mean	std	min	max
CSI 300	2311.00	3933.56	599.43	2853.76	5807.72
NASDAQ	2403.00	9368.18	4271.92	3947.80	19210.18

Each data is divided into 2 parts, the first part (1200) is used as training set while the subsequent data is the test set.

2.2. Data Normalization

In this study, normalization is used to bring both the phase space domain dataset and the original chaotic time series dataset to the range of (0, 1). On the one hand, normalization can make the data the same scale to reduce the impact of data on prediction. On the other hand, it can improve prediction accuracy and enhance the convergence speed. The normalization function:

$$x' = \frac{x - min}{max - min} \tag{1}$$

2.3. RNN

Recurrent Neural Networks (RNNs) are a common type of neural network, which can identify patterns in data sequences, time series for example. Different from these traditional neural networks, whose inputs and outputs are assumed to be independent of each other, RNNs leverage their internal states (memories) to process series of inputs. There is a type of RNN operation principle shown in Figure 2 [10].

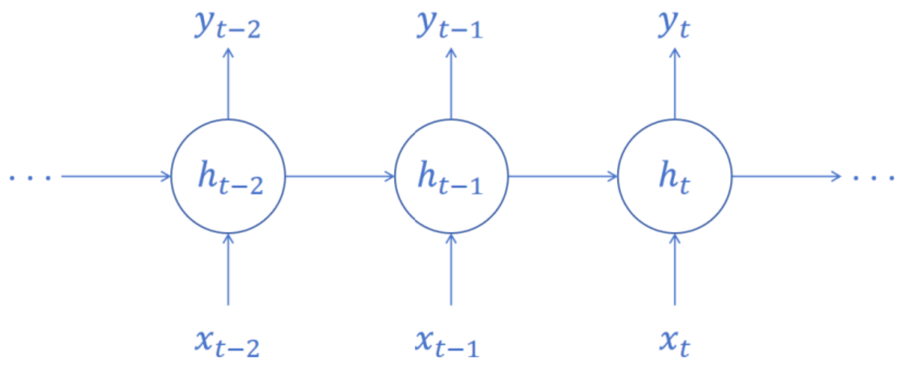


Figure 2: Operation Principle of RNN

Ability to keep a hidden state that catches information from previous time steps is the most outstanding feature of RNNs. This hidden state is updated along the time steps according to hidden state stored in previous cells and the input at present. At time step t, hidden state h_t is:

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \tag{2}$$

Here, x_t is the input, $h_{t-1}$is the hidden state from the previous time step, W_h and U_h are weight matrices, b_h is a bias term, and σ is the activation function (typically tanh or ReLU). And output y_t is:

$$y_t = \sigma\left(W_y h_t + b_y\right) \tag{3}$$

Here, W_y is the weight matrix of the output layer, and b_y is a bias term.

2.4. LSTM

As a variant type of RNN architectures, LSTM is without the defect of long-term dependencies, which is a limitation found in the traditional RNN. LSTMs store information in memory cells which enables them to maintain long-term states and control the changes of information. LSTMs are effective in data-processing. Besides, LSTMs include 3 types of gates, Forget Gate, Input Gate and Output Gate (See Figure 3). This mechanism helps the network handle more complex patterns and structures. The details of gates' functions are as follows.

Forget Gate $\boldsymbol{f_t}$: Select useless information and discard it from the cell state.

Input Gate $\boldsymbol{i_t}$: Determines what new information will be reserved in the cell state.

Output Gate $\boldsymbol{o_t}$: Determines the next hidden state, which contains information that will be passed to the next time step.

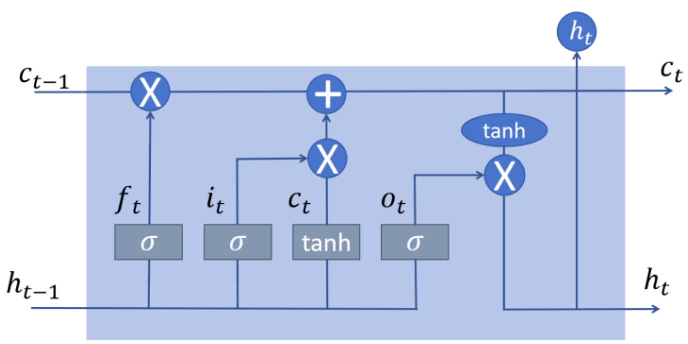


Figure 3: Operation Principle of LSTM

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Where:

$$f_t = \sigma_g\left(U_f h_{t-1} + W_f x_t + b_f\right) \quad (4)$$

$$i_t = \sigma_g(U_i h_{t-1} + W_i x_t + b_i) \quad (5)$$

$$\mathrm{o}_t = \sigma_g(U_o h_{t-1} + W_o x_t + b_o) \quad (6)$$

$$\mathrm{c}_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (7)$$

$$\tilde{\mathrm{c}}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \quad (8)$$

$$h_t = o_t \odot \sigma_h(\mathrm{C}_t) \quad (9)$$

Here, $x_t \in \mathbb{R}^d$ is input vector, f_t is the activation vector of the forget gate, i_t is the activation vector of the input or update gate, o_t is activation vector of output gate, h_t means hidden state, it is LSTM unit's output vector, $\tilde{c}_t$ is the activation vector of the cell input, $c_t \in \mathbb{R}^h$ is a vector containing information in cell state, $W \in \mathbb{R}^{h\times d}, U \in \mathbb{R}^{h\times h}$ are weight matrices and $b \in \mathbb{R}^h$ is bias vector parameters. Additionally, σ_g and σ_c are sigmoid function and hyperbolic tangent function.

2.5. RMSE

For a statistical model, RMSE shows the average difference between its predicted values and actual observed values. RMSE is used to assess the amount of deviation in regression analysis or other statistical models. In this study, RMSE is a standard of models' quality levels. The smaller RMSE means better prediction. Fora sample with N observations, its RSME is as follows:

$$RSME = \sqrt{\frac{\sum(\mathrm{y}_i - \hat{\mathrm{y}}_i)^2}{N}} \quad (10)$$

3. Result

This study predicts CSI 300 index and NASDAQ index (12/08/2024 to 06/11/2024) by simple RNN and LSTM to find out which model fits index better. Each data is divided into 2 parts, the first 1200 data of the index is seen as training set while the subsequent data is the test set. The result of prediction will be presented in both image and RMSE. The better one will be chosen by their comparison. Here the neural network models utilize the stock price from the previous day to forecast the stock price for the following day, leveraging patterns and trends identified in historical data. MSE and ADAM are chosen as loss function and optimizer.

3.1. Simple RNN

Simple RNN model is built to predict CSI 300 index and NASDAQ index separately. As Figure 4 shows, simple RNN predicts really well both for CSI 300 and NASDAQ. However, when it comes to RMSE, their differences are apparent (See Table 2).

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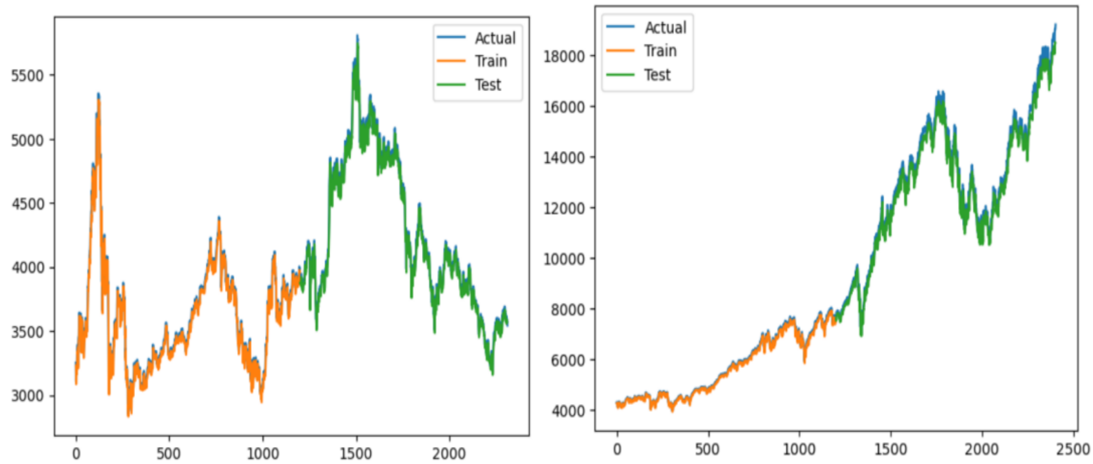

Figure 4: Simple RNN Predicts CSI 300 Index(left) and NASDAQ Index(right)

Table 2: Comparison Results (Simple RNN)

index	Training score (RMSE)	Test score (RMSE)
CSI 300	64.52	60.01
NASDAQ	93.10	341.43

It is clear that simple RNN predicts better for CSI300 index than NASDAQ index. Their training scores are close but test scores are not as that close. At the same time, NASDAQ' test score is much bigger than its training score, which means simple RNN can't predict NASDAQ index well. It may because there is a sudden downward trend after a continuous upward trend for NADAQ index, simple RNN did not anticipate this situation. And there is a relatively obvious rule for CSI 300 index, so this model can fit better.

3.2. LSTM

Then LSTM model is used to forecast both CSI300 index and NASDAQ index. Similar to RNN, LSTM also performs well in prediction (See Figure 5 and Table 3).

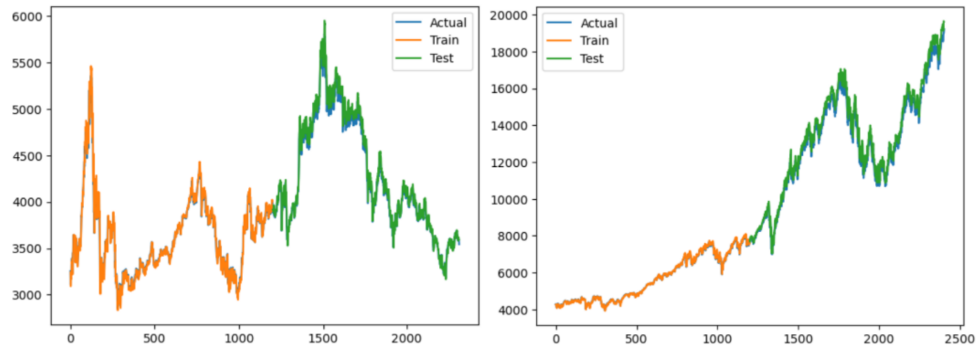

Figure 5: LSTM Predicts CSI300 index(left) and NASDAQ index(right)

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Table 3: Comparison Results (LSTM)

index	Training score (RMSE)	Test score (RMSE)
CSI 300	63.94	72.91
NASDAQ	72.42	377.58

Like simple RNN, LSTM predicts CSI300 index better than NASDAQ. For both CSI 300 index and NASDAQ index, simple RNN predicts better in test set and LSTM is a little better in train set.

4. Conclusion

Though simple RNN and LSTM are good models for prediction, it can be found that both simple RNN and LSTM are better at forecasting CSI300 index than NASDAQ index. This study still has some disadvantages. The models cannot predict sudden changes in data. To handle this problem, it may be effective to try to make models more complex to deal with the changes of data. For example, attention mechanisms can be introduced attention mechanisms in the LSTM model, allowing the network to focus on different degrees of input information at different time steps. Models can also be combined with others to get more precise predictions.

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