Stock Time Series Prediction Based on Deep Learning

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Abstract: With the continuous development of financial markets and the gradual improvement of the financial system, people participate in financial market investment. The interest in capital is also growing, and it is accompanied by a strong demand for accurate and effective financial information services. So how to accurately predict the trend of stocks has become a focus of attention. In this paper, based on the traditional method ARIMA, the corresponding RNN (LSTM) model is proposed for the stock time series prediction problem, and its application situation is further analyzed and optimized, so that it can better explore the change law of stock data. And by setting the corresponding experimental test model method on the stock forecasting task performance. The research and evaluation of the model method demonstrates the good performance of the deep learning model and the ARIMA model in the stock time series forecasting task. The error between the stock forecasting result and the real value of each model method is at a low level. In comparison with the prediction effects of model methods such as Prophet, the RNN model proposed in this paper is closer to the real market performance, and has achieved a significantly better prediction effect than the comparison method.

1. Introduction

Financial markets play a vital role in the country's overall economic system. In recent years, many researchers from different fields have begun to pay attention to financial markets and try to use the latest computer technology to solve some information needs in this field. Among them, predicting the future trend of stocks is one of the most attractive research issues in the current academic world.

Due to the corresponding economic policies of the country, most of the stock information and its historical data are in an open state, and data acquisition is relatively easy. However, the domestic stock market is huge and there are many kinds of stocks. Therefore, this issue builds stocks with certain universality and market representation. The data set is used as the research object, and the model method is studied on the basis of it.

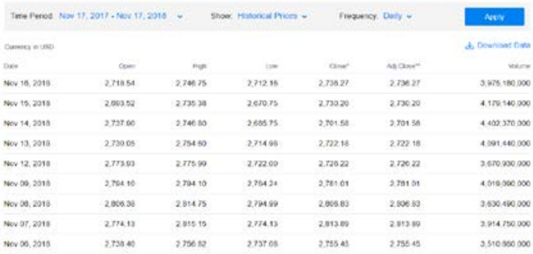
With the development of computer technology, deep learning-based methods and models have been gradually applied to study this problem. Researchers have been proposing some well-performing method models to try to predict stocks or stocks of certain combinations.

In recent years, deep learning methods such as neural networks have been widely used in the classification and regression of financial time series data, and because of their excellent performance in classification problems and regression problems, neural networks have been successfully applied to discover the trend of financial varieties. In the question.

2. Methodology and Experiments

2.1 Stock dataset

This article uses Standard & Poor's 500 data from January 3, 1950 (the longest date that Yahoo Finance can trace back to June 23, 2017). The data set provides several price points per day. The dataset can be downloaded from https://finance.yahoo.com/quote/%5EGSPC/history?p=%5EGSPC.


Time Period: Nov 17, 2017 - Nov 17, 2018 Show: Historical Prices Frequency: Daily Apply

Currency in USD Download Data

Date	Open	High	Low	Close*	Adj Close**	Volume
Nov 16, 2018	2,718.54	2,746.75	2,712.16	2,736.27	2,736.27	3,975,180,000
Nov 15, 2018	2,693.52	2,735.38	2,670.75	2,730.20	2,730.20	4,179,140,000
Nov 14, 2018	2,737.90	2,746.80	2,685.75	2,701.58	2,701.58	4,402,370,000
Nov 13, 2018	2,730.05	2,754.60	2,714.98	2,722.18	2,722.18	4,091,440,000
Nov 12, 2018	2,773.93	2,775.99	2,722.00	2,726.22	2,726.22	3,670,930,000
Nov 09, 2018	2,794.10	2,794.10	2,764.24	2,781.01	2,781.01	4,019,090,000
Nov 08, 2018	2,806.38	2,814.75	2,794.99	2,806.83	2,806.83	3,630,490,000
Nov 07, 2018	2,774.13	2,815.15	2,774.13	2,813.89	2,813.89	3,914,750,000
Nov 06, 2018	2,738.40	2,756.82	2,737.08	2,755.45	2,755.45	3,510,860,000

2.2 Data Preparation

The stock prices is a time series of length N , defined as $p_0, p_1, ..., p_{N-1}$ in which p_i is the close price on day i , $0 \leq i \leq N$. Imagine that we have a sliding window of a fixed size w (later, we refer to this as **input_size**) and every time we move the window to the right by size w , so that there is no overlap between data in all the sliding windows.

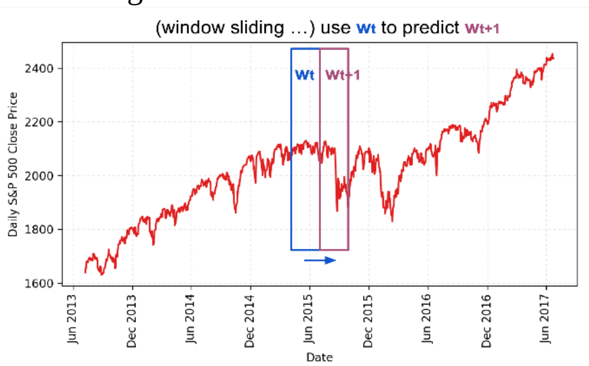


Fig. 1 The S&P 500 prices in time.

We use content in one sliding windows to make prediction for the next, while there is no overlap between two consecutive windows.

2.3 RNN Model

The recurrent neural network (RNN) is a type of artificial neural network with self-loop in its hidden layer(s), which enables RNN to use the previous state of the hidden neuron(s) to learn the current state given the new input. RNN is good at processing sequential data. Long short-term memory (LSTM) cell is a specially designed working unit that helps RNN better memorize the long-term context.

The RNN model we are about to build has LSTM cells as basic hidden units. We use values from the very beginning in the first sliding window W_0 to the window W_t at time t :

$$W_0 = (p_0, p_1, ..., p_{w-1})$$

$$W_1 = (p_w, p_{w+1}, ..., p_{2w-1})$$

$$W_t = (p_{tw}, p_{tw+1}, ..., p_{(t+1)w-1})$$

To predict the prices in the following window W_{t+1} :

$$W_{t+1} = (p_{(t+1)w}, p_{(t+1)w+1}, ..., p_{(t+2)w-1})$$

Essentially we try to learn an approximation function, $f(W_0, W_1, ..., W_t) \approx W_{t+1}$

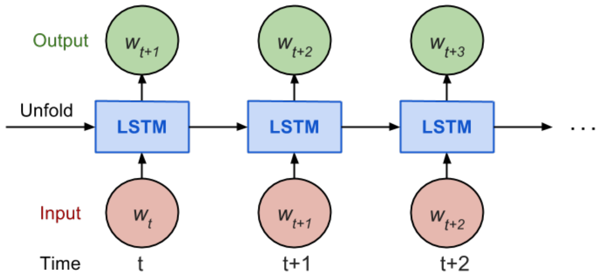


Fig. 2 The unrolled version of RNN.

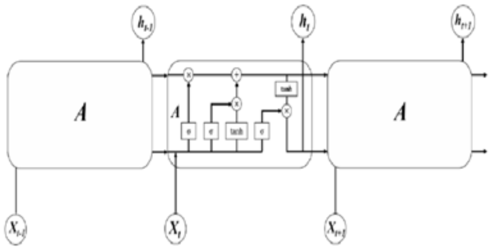


Fig.3 The LSTM structure diagram.

The above structure is not difficult to see that the cyclic neural network is most suitable for processing time series related problems. In practical applications, the data of a certain time sequence can be input sequentially, and the output is the prediction of the next time of the sequence, and the long-term application indicates the cycle. Neural networks can effectively deal with time series data analysis and prediction problems. The state and parameters are shared among the multi-layer neural networks, which avoids a lot of training work and is also a subtle structure.

Considering how back propagation through time (BPTT) works, we usually train RNN in the 'unrolled' version so that we don't have to do propagation computation too far back and save the training complication.

In this paper, a batch gradient descent method is proposed for the problems of large amount of computation and long training time in the gradient descent method. The algorithm divides the data into batches, and only optimizes the loss function of the previous batch at a time, which is divided into batches here. This optimizes the parameters and reduces the number of iterations of the model.

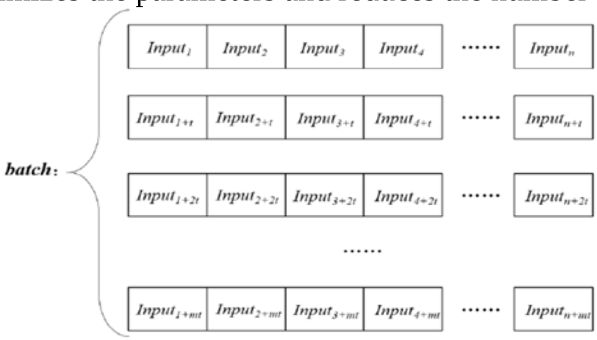


Fig.4 Batch, model training input after batch division

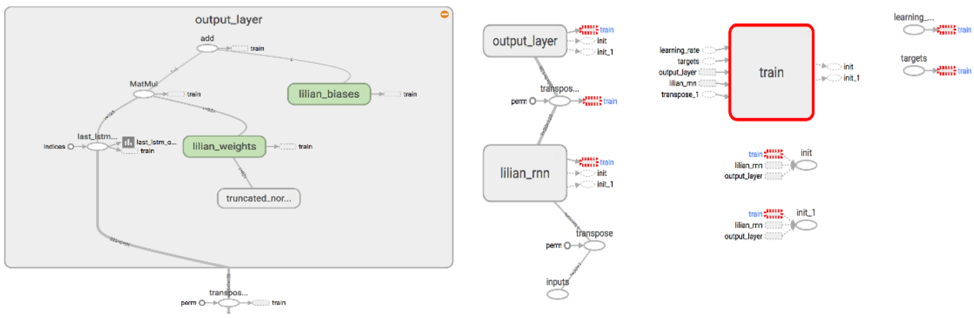


Fig.5 The structure of Model

3. Experiment

3.1 Train / Test Split

Since we always want to predict the future, we take the latest 10% of data as the test data.

3.2 Normalization

The S&P 500 index increases in time, bringing about the problem that most values in the test set are out of the scale of the train set and thus the model has to predict some numbers it has never seen before. Sadly and unsurprisingly, it does a tragic job. See Fig. 6.

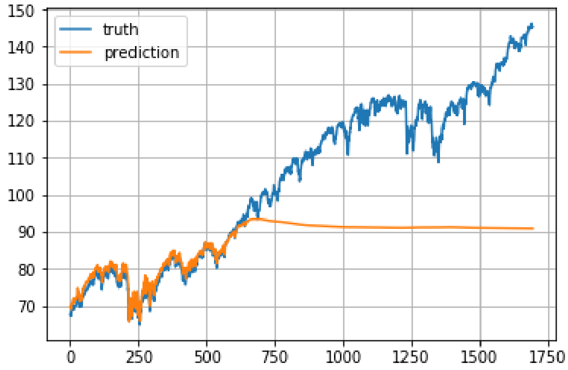


Fig. 6 A very sad example when the RNN model have to predict numbers out of the scale of the training data.

To solve the out-of-scale issue, I normalize the prices in each sliding window. The task becomes predicting the relative change rates instead of the absolute values. In a normalized sliding window W_t' at time t, all the values are divided by the last unknown price—the last price in W_{t-1}:

$$W_t' = \left(\frac{p_{tw}}{p_{tw-1}}, \frac{p_{tw+1}}{p_{tw-1}}, \ldots, \frac{p_{(t+1)w-1}}{p_{tw-1}}\right)$$

3.3 Results

Overall predicting the stock prices is not an easy task. Especially after normalization, the price trends look very noisy.

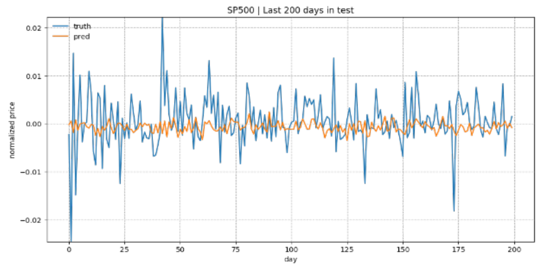


Fig. 7a Predictoin results for the last 200 days in test data. Model is trained with input_size=1 and lstm_size=32.

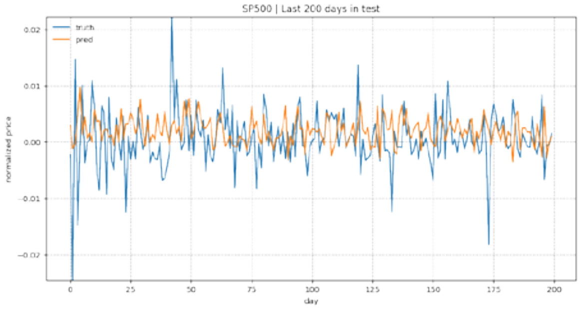


Fig. 7b Predictoin results for the last 200 days in test data. Model is trained with input_size=1 and lstm_size=128.

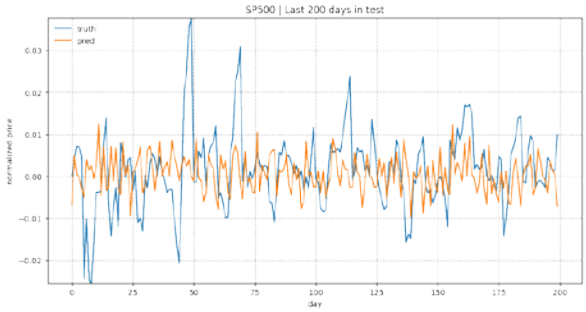


Fig. 7c Predictoin results for the last 200 days in test data. Model is trained with input_size=5, lstm_size=128 and max_epoch=75 (instead of 50).

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