Parallel Stock Price Prediction Using Deep Learning

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1. Introduction

In recent years, quantitative investment research has become a hot spot in the field of finance. In many cases, it involves deep learning and huge datasets (several Terabytes). In this situation, running parallel jobs in CHTC is definitely an efficient way.

2. Dataset

The 13 GB dataset describes data of 100 stocks (Nifty 100 stocks) of the Indian stock market from Jan 2015 to Feb 2022 (Data for each stock is in a separate CSV file). It consists of data samples of 5-minute intervals, and 2 indices (Nifty 50 and Nifty Bank indices). Along with OHLCV (Open, High, Low, Close, and Volume) data, it contains 55 technical indicators like moving average, rate of change, etc.

Since our dataset is clean and there is no NA in it, we only delete 11 datasets whose start dates are too late to provide enough information we need. After that, we unify the start and end time of the dataset as 2015/02//02 14:30 - 2022/02/18 15:25.

3. LSTM Model

- Basic Model

We use the LSTM model, which is designed to model the time series data and enable us to predict stock closing prices. LSTM is a deep learning-based model that evolved from the RNN model in order to solve the vanishing gradient and exploding gradient problem. The LSTM model separates the information flow into long-term memory and short-term memory, and also adds a mechanism to forget past information, which enables the model to overcome the challenge.

- Basic Setting

In order to stabilize the data, we apply MinMax transformation to the data before feeding them to the model and applied a reverse transformation to get the original scale back after getting our prediction from the model. We use 95% of the data as a training set and the rest as a testing set. Specifically, we consider each training unit as a series of closing prices with a length of 60. We will use the first 59 closing prices to predict the 60th closing price. After training is complete, we calculate the RMSE to evaluate the performance of our model.

- Parameter Tuning

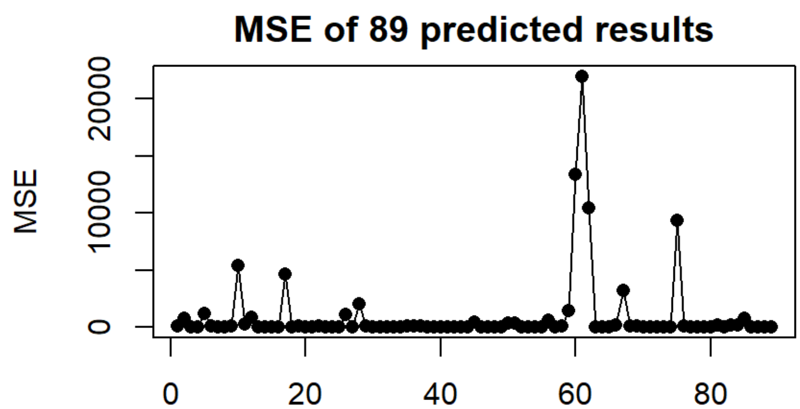
The main parameter to adjust is the batch size, which determines how many training samples we will consider at once to update our model. Basically, a large batch size means that we update the model less frequently, and thus can train fast, however, it could hurt the performance at cost. Following the common practice, we have tested several different batch size options such as 8, 16, 32, 64, and 128. It turns out that batch size 64 gives us the best result. Training time for each stock is reduced to 20 minutes due to the increasing batch size, and the performance is not hurt. We have also tested the effect of different sizes for hidden layers. We end up using two LSTM layers with hidden sizes 128 and 64.

4. Computational Steps

We use miniconda3 to build and manage our environment. We first process the raw data outside of the CHTC and then upload them to the CHTC. In order to run all jobs in one submission, we upload a list containing the names of each stock, then we use queue to read from the list iteratively. Finally, we run the LSTM model and get the prediction for each stock, then we process them outside of the CHTC for downstream analysis afterward.

- Result Evaluation

We use Mean Squared Error and Correlation coefficient between the prediction and actual data to evaluate the result of the prediction. By iterating 89 files of predicted results, we calculated the MSE of each predicted stock, which is shown below. Most MSEs are very small and there are only a few extreme numbers. It indicates that most predictions are pretty accurate and some need further analysis. Then we checked their correlations. Surprisingly, we found the lowest correlation is 0.992, which shows a high correlation between our predicted data and real data.

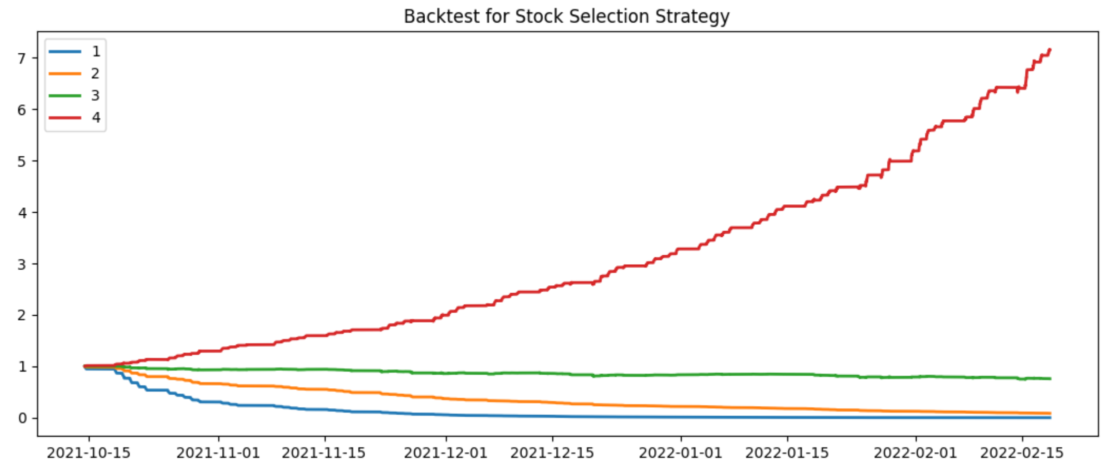


5. Stock Selection Strategy

Firstly, calculate the predicted return for each period as a factor. The 89 stocks are divided into 4 groups as 4 portfolios. They are equally weighted in each group. The strategies are all 5-minutes frequency positions, and the order of stocks selected is their forecast factor values in the LSTM model for the current period. Since it is just a simple practice, we did not consider trading fees and slippage.

6. Backtest Analysis

The figure below shows the cumulative return for the 4 portfolios. We can notice that the red line (group 4) is significantly higher than the other three lines. The stratification phenomenon is very obvious, which means the strategy is effective.



GitHub repository

Contributions

Member	Proposal	CHTC Coding	Downstream Analysis	Report	Presentation
Ziao Zhang	**1**	**1**		**1**	**1**
Yunqing Shao	**1**	**1**		**1**	**1**
Yixuan Xie	**1**	**1**		**1**	**1**
Ran Zhao	**1**		**1**	**1**	**1**
Zixuan Zhao	**1**		**1**	**1**	**1**