Financial Time Series Prediction Using Deep Learning

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Outline

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Introduction

❖ Backgrounds

- Time series analysis is important in lots of research topics, such as quantitative finance, econometrics.

- Statistical methods

A large number of statistical methods have been applied in this field, such as Auto-Regressive (AR) model, Auto-Regressive Integrated Moving Average (ARIMA) model, ARCH model, GARCH model et al.

- Machine learning methods

Since it could be transferred into a classification problem, machine learning algorithm may provide helps. Lots of basic ML algorithms have been used to solve predicting issues, such as k-nearest neighbors (kNN) model, where the main idea is that it assumes a similarity between time series sequences that occurred in the past, to future sequences, and as a result, the nearest-neighbors are used to yield the forecasts of the kNN model.

Introduction

❖ Brief description

- This project aims to apply deep neural network to predict the trend of financial time series, to be more specific, utilizes raw financial data inputs (1-minute resolution) to predict the temporal trend of China CSI 300 Index in Chinese A-Share Market and derives a trend-following investment strategy, comparing its performance with benchmarks along two-years back-testing.

- Our work mainly based on the paper *"Financial Time Series Prediction using Deep Learning"* (Ariel et al. 2017), but we also make some different application details comparing with the original method in that paper, mainly in two aspect, classification and trading strategy, which would be explained later.

Deep learning prediction of index Trend

❖ **Classification specification**

Given $x(n)$ $n \in Z$ and the time interval T, the difference between future price and current price is $y(n) = x(n+T) - x(n)$.

For Ariel's case

The author set the difference into two states, going up or going down, which means as following:

$$y(n) = \begin{cases} 1, & x(n+T) - x(n) \geq 0 \\ -1, & x(n+T) - x(n) < 0 \end{cases}$$

For our case:

However, under this classification, the model has a flaw that when the absolute value of $x(n+T) - x(n)$ is small, it is impossible to make profits even when the model is completely accurate in real investment market which charges for trading fares. To overcome this flaw, in our experiments, we set the difference into three states, increasing dramatically, decreasing dramatically or others, which means as following:

$$y(n) = \begin{cases} 1, & x(n+T) - x(n) \geq \alpha \\ -1, & x(n+T) - x(n) \leq \beta \\ 0, & others \end{cases}$$

DNN structure

❖ **Prediction system overview**

In order to predict the future index price trend $\hat{y}(n)$, we apply a classification neural network trained using the raw prices data of the previous M minutes.

$$\hat{y}(n) = \hat{y}(n|x^{n-M+1}, \dots, x^{n})$$

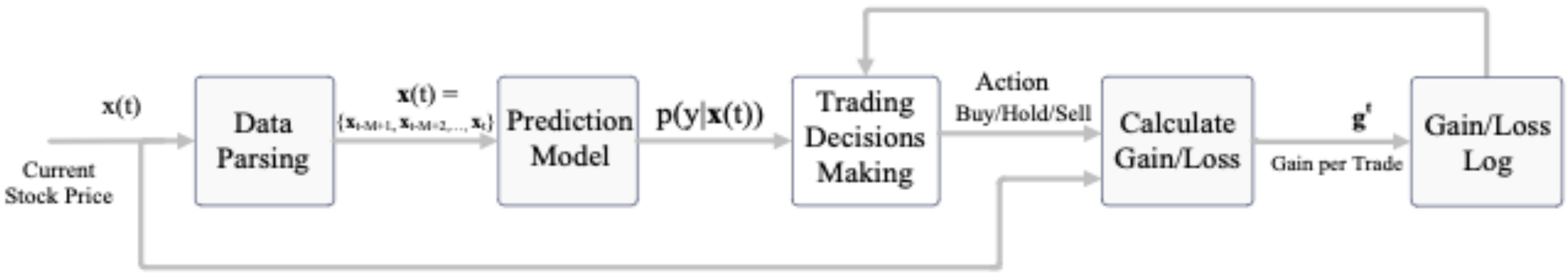

Figure1: Schematic Illustration of our Deep-Learning based financial trends prediction system. (Ariel et al. 2017)

DNN structure

❖ **DNN structure details**

Since the author has tried out a large number of structures of neural networks, containing convolutional layers (however it did not yield significant accuracy improvement), we assume the structure of neural net implemented in the paper is optimal one which is shown as Fig. 2, and also Layer 5 should be changed into 20×3 FC and corresponding output is 3×1 because we set the difference as three states which is different with the paper.

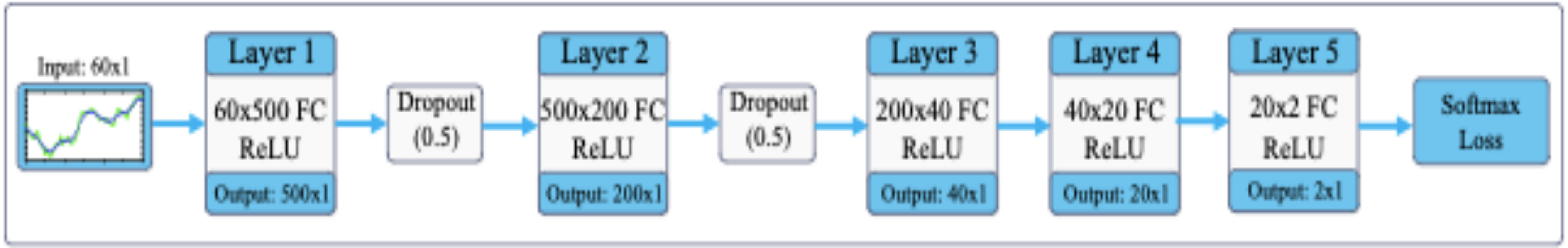

Figure2: The neural network applied to predict the price trends. (Ariel et al. 2017)

Trend-following strategy

❖ Benchmark illustration

- In order to evaluate the performance of our trend-following strategy derived from DNN methodology, we develop a long and holding strategy as the benchmark to comparing the performance of both strategies over the two-years beck-testing period.

- Besides, I want to make an explanation about some finance terminology, long trade and short trade. While long trading means that buying a financial asset and hold it until you want to sell it (closing your position), short trading, a more complicated one, represents that firstly you borrow a financial asset from others and sell it in the market and then you must buy it back to return it to the lender.

Trend-following strategy

❖ **Trade opening using soft-information**

The outputs of softmax layer of the DNN represent the probabilities of future trend belonging to respective classes. In order to use soft-information $p(y|x)$ provided by the DNN model to derive trend-following investment strategy,

- for Ariel's case, since the author set the future difference into two states, it opens trade in the following method. Let $O(n)\ \ n \in Z$ represents whether opening a new position or not at time n.

$$O(n) = \begin{cases} 1, & |p(y(n) = 2|x^{n-M+1}, \dots, x^n) - p(y(n) = 1|x^{n-M+1}, \dots, x^n)| \geq T_H \\ 0, & |p(y(n) = 2|x^{n-M+1}, \dots, x^n) - p(y(n) = 1|x^{n-M+1}, \dots, x^n)| < T_H \end{cases}$$

- for our case, since we set the future difference into three states, it would open trade in a similar method.

$$O(n) = \begin{cases} long, & \hat{y}(n) = 1 \text{ and } p(y(n) = 1|x^{n-M+1}, \dots, x^n) \geq T_H \\ short, & \hat{y}(n) = -1 \text{ and } p(y(n) = -1|x^{n-M+1}, \dots, x^n) \geq T_H \\ none, & other \end{cases}$$

where T_H could help to control opening trade times.

Trend-following strategy

❖ Trade closing rules

Since it is an intra-day trading strategy, the strategy follows these rules to close its position.

- Rule1: After T minutes, if the DNN model's prediction result is different from the signal when we opened the position, we choose to close it and wait to the next signal.
- Rule 2: After T minutes, if the DNN model's prediction result is same as the signal when we opened the position, we keep to hold the position.
- Rule3: During T minutes, if the loss rate of the trade exceeds a certain threshold θ, we choose to close it and wait for the next signal.
- Rule 4: When it is one minute before the closing time of the market, we choose to close our position since it is an intra-day trading and we do not want to take over-night risks.

Notes:

✓ Intra-day trading means that the position should be opened and closed during one trading day.

✓ Over-night risk means the probability of asset price going down due to news of the night.

Trend-following strategy

- **Strategy structure overview**

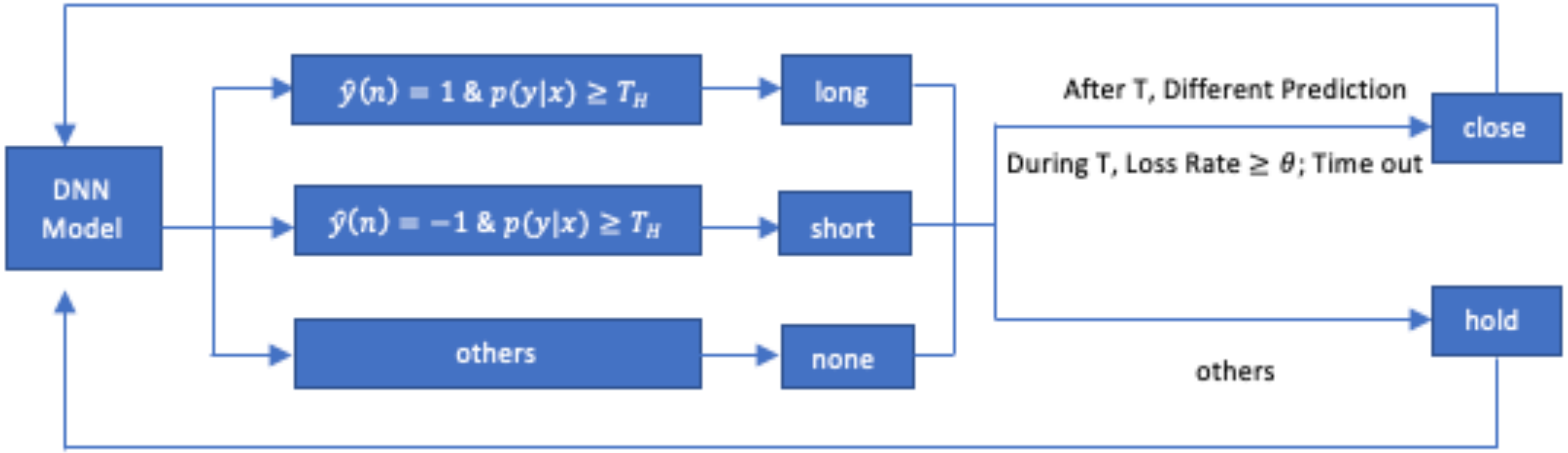

Figure 3: The proposed soft-threshold based trade opening and closing approaches.

Experiments and results

❖ Data collection & pre-processing

The proposed schemes were experimentally verified by using the market data of the CSI index given in one-minute resolution, purchased from Tong Hua Shun which is a major financial information and data supplier in China. Based on regular trading hours (9:30AM-11:30AM & 1:00PM-3:00PM), we eliminated days with partial trading hours. For the whole dataset, it starts from 4th January, 2010 and ends 19th November, 2019.

Notes:

For Tong Hua Shun, its website address: www.51ifind.com

Experiments and results

❖ Data collection & pre-processing (cont'd)

- As we study intra-day trading, we divided the data into different trading days, and extracted all training instance and validation instance during one certain day. For a certain day, we could derive about 200 different data samples, to be more specific, the number of samples derived within a certain day is $60\times4-M-T$, where M is the length of previous prices vector and T is the prediction time interval.
- We use the data after 4th January, 2018 to act as back-testing original data and the data between 4th January, 2016 and 31st December, 2017 to act as validation data and others as training data.
- To make the number of instances of each class to be same, we resampled the training dataset and it is not needed for validation dataset.
- Besides, we also standardized our inputs by subtracting mean value and divided by standard deviation.

Experiments and results

❖ Data collection & pre-processing (cont'd)

In light of labeling, for a certain day during the training time period, we choose a continuous prices series that having length of M which make a vector $(x^{n-M+1}, \dots, x^{n})$ and calculate the difference of $x^{n+T} - x^{n}$, using the formula in section 3.2 to determine the class label.

$$y(n) = \begin{cases} 1, & x(n+T) - x(n) \geq \alpha \\ -1, & x(n+T) - x(n) \leq \beta \\ 0, & others \end{cases}$$

Experiments and results

❖ **Parameter determination**

- For parameter M, the length of previous index prices, in the paper, the author implemented validation method to determine the optimal value, which was set 60 and we also use that value.

- For parameter T, the prediction time interval, in the paper, the author also implemented validation method to determine the optimal value, which was set 28 and we also use that value.

- For parameter T_H, controlling the times of opening a new position, given that μ and σ are the mean value and standard deviation value of probabilities provided by the DNN model on validation dataset, we set it to be $\mu + \sigma$.

Experiments and results

❖ **Parameter determination (cont'd)**

For parameter α and β, we determined their value by exploring the distribution of the prices change over T minutes, as shown in Figure 4 below. It is clear that the distribution is symmetrical and in hence, we set α to be the 75% quantile value and β to be the 25% quantile value, which is 6 and -6 respectively.

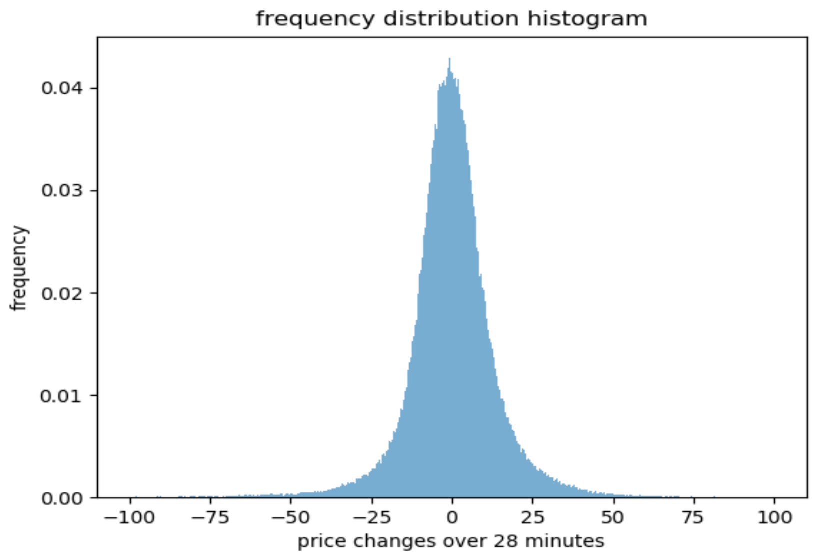

Figure4: Price changes over T (set to be 28) minutes distribution.

Experiments and results

- **Training DNN process and results**

The neural network is built using Keras package and we choose Adam algorithm to minimize the model loss, where mini-batches of size is 100, the learning rate is 0.0001, beta_1 is 0.9 and beta_2 is 0.99. The training accuracy and validation accuracy is shown in Figure 5.

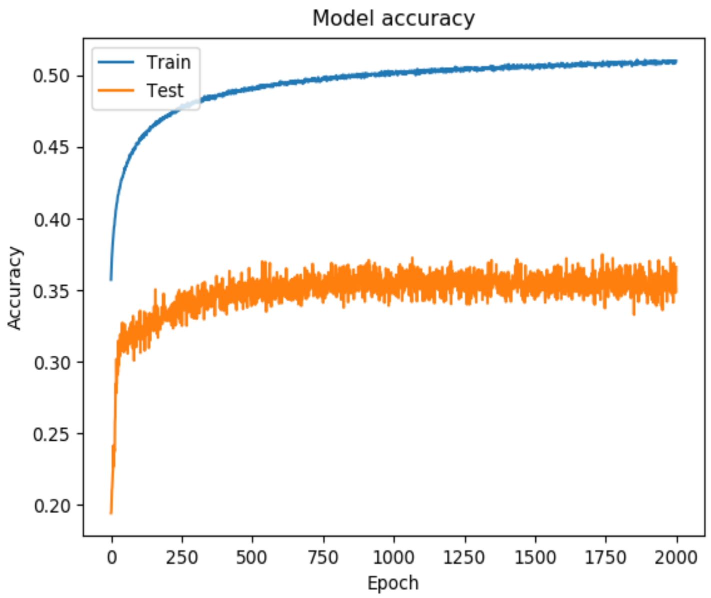

Figure5: Training and validation accuracy versus epoch.

Experiments and results

- **Back-testing process and results**

We implemented back-testing process based on the trade opening rules and closing rules in section 3 over the time period of 4th January, 2018 to 19th November, 2019. The cumulative profits of our trend-following strategy based on DNN model which achieved over 12% return rate is shown in Figure 6.

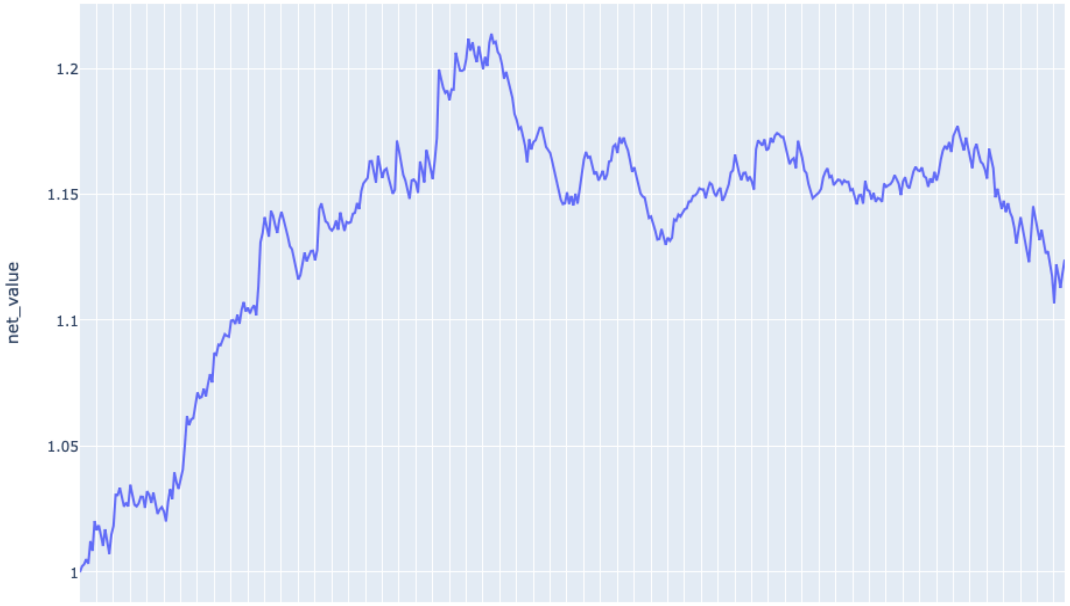

Figure6: Cumulative profits of trend-following & benchmark strategy over back-testing period.

Conclusions

- During this project, we proposed two main improvements based on the works of Ariel et al. (2017), setting the trend into three states instead of two and adding stop loss method to the trend-following intra-day trading strategy.

- We also completely built and trained a DNN model using Keras package, developed a trend-following investment strategy using soft-information provided by the DNN model, and implemented a back-testing process to evaluate a trading strategy quantitatively, which outperformed to the benchmarks.

Future works

- As pointed by Ariel et al. (2017), since the market's characteristics changes period by period, in practical world, it is needed to dynamically train the deep neural networks to adapt to the new market's pattern, otherwise, the profit of the strategy derived by the DNN model would be continuable.

- Besides, when we built and trained the DNN model, we found the accuracy of the model is not high enough. We guess the probable reasons may be the trained epochs are not enough or the DNN structure needs to be modified. Due to the limit of time and computing power, we did not implement these works and we want to focus on these issues in the future.

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To know more:

- https://github.com/Yanjing-PENG/index_prediction
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Many Thanks !