FURTHER STUDY OF ADAPTIVE SUPERVISED LEARNING DECISION (ASLD) NETWORK IN STOCK MARKET

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ABSTRACT

This paper further studies the recently proposed Adaptive Supervised Learning Decision (ASLD) network for trading and portfolio management [5] in two sets of stock market data. One is the Hang Seng index in Hong Kong markets. The other is a portfolio of indexes from six major markets in the world. Being different from the study on foreign exchange rates [5], we find that in generating the trading signals for training the neural network used in the ASLD system, the issue of volatility should be considered important in handling stock market data. Several heuristic strategies are investigated for taking volatility into the consideration in training the ASLD trading and portfolio system. Empirical results are given to show how well these strategies work.

1. INTRODUCTION

One widely used type of trading systems consists of two modules: prediction module followed by trading module. First, a prediction is given by the Prediction Module, which have been trained in advance under some prediction criterion such as minimization of mean square error (MSE) and etc. Then, the trading module will output a trading signal based on the prediction and some investment strategies. Since this type of trading system is optimized to some prediction criterion which is not the ultimate goal of financial investment, it usually leads to sub-optimal performance on the profit obtained. To solve this problem, an alternative type of trading systems is recently proposed by Bengio [1], Kang et al. [2] and Moody et al. [3], in which the prediction module and the trading module are merged into one single system that optimizes the returns instead of the prediction criterion. Preliminary experiments in [1] [2] [3] have shown that such a trading system outperforms those based on the best forecasting. Another choice is the Adaptive Supervised Learning Decision (ASLD) network suggested by [5], in which an Extended Normalized Radial Basis Function (ENRBF) network is built to learn the desired past investment decision using an EM-like learning algorithm called Coordinated Competitive Learning (CCL) [4] [6]. The desired past investment decision for a day is obtained right after that day passed, and used as a teaching signal for the network to adaptively learn what decision should be made upon the market input environment.

This paper further studies the ASLD on stock market data, instead of on foreign exchange rates as did in [5]. In Sec. 2, we investigate the original ASLD and several heuristic strategies on Hang Seng index in Hong Kong market. In Sec. 3, a portfolio of indexes from six major markets in the world is considered in the same way. Moreover, in Sec. 4, a further improvement is proposed by considering the variance of the obtained returns. Sec. 5 concludes this paper.

2. INVESTMENT ON HONG KONG HANG SENG INDEX

2.1. Performance of the Original Adaptive ASLD

The Hang Seng Index data we used are from January 1, 1987 to September 24, 1997, totally 2,800 data. The first 1,000 data points are used in our training phase while the rest 1,800 data points are used in our testing phase.

We apply the ASLD network proposed in [6] directly, with the detailed description of the approach omitted for simplicity. For the detail of the ASLD's algorithm, please refer to [6].

In our experiments, we make the following assumptions:

1. The transaction cost rate is assumed to be 3% of the amount of dollars involved in the transaction.
2. For all buying or selling process, we will make use of the whole amount of cash held in our hand to buy shares, or sell all the shares to get back cash.
3. Initially, the amount of money in our hand is \$40,000 for all of our experiments.

Shown in figure 1 is the profit gained by Adaptive CCL-ENRBF ASLD. We got nearly 30% profit gain by making investments following the trading signal generated by it.

Figure 1: The profit gain of investment in Hang Seng Index by the original adaptive ASLD.

2.2. Performances After Adding Several Heuristic Strategies

We have tried totally four different strategies for generating the desired trading signals, given as follows:

1. Strategy 0:

$$\begin{array}{l} \text{Buy when} \begin{cases} price_{t+2} > price_{t+1} \\ \quad > price_t \\ \text{and} \\ (price_{t+2} - price_t) \\ \quad > price_t * 0.03 \end{cases} \\ \text{Sell when} \begin{cases} price_{t+2} < price_{t+1} \\ \quad < price_t \\ \text{and} \\ (price_t - price_{t+2}) \\ \quad > price_t * 0.03 \end{cases} \end{array} \tag{1}$$

For strategy 0, we will buy the share when we predict that the Hang Seng Index will keep increasing in the next two days and the total increment will be larger than the transaction cost for buying it. On the other hand, we will sell the share when we predict that the Hang Seng Index will keep decreasing in the next two days and the total decrement will be larger than the transaction cost for selling it.

2. Strategy 1:

$$\begin{array}{l} \text{Buy when} \begin{cases} price_{t+2} > price_{t+1} \\ \quad > price_t \\ \text{and} \\ (price_{t+2} - price_t) \\ \quad > price_t * 0.03 * 1.5 \end{cases} \\ \text{Sell when} \begin{cases} price_{t+2} < price_{t+1} \\ \quad < price_t \\ \text{and} \\ (price_t - price_{t+2}) \\ \quad > price_t * 0.03 * 1.5 \end{cases} \end{array} \tag{2}$$

For strategy 1, we will buy the share when we predict that the Hang Seng Index will keep increasing in the next two days and the total increment will be larger than 1.5 times of the transaction cost for buying it. On the other hand, we will sell the share when we predict that the Hang Seng Index will keep decreasing in the next two days and the total decrement will be larger than 1.5 times of the transaction cost for selling it.

3. Strategy 2:

$$\begin{array}{l} \text{Buy when} \begin{cases} price_{t+3} > price_{t+2} \\ \quad > price_{t+1} > price_t \\ \text{and} \\ (price_{t+3} - price_t) \\ \quad > price_t * 0.03 * 2 \end{cases} \\ \text{Sell when} \begin{cases} price_{t+3} < price_{t+2} \\ \quad < price_{t+1} < price_t \\ \text{and} \\ (price_t - price_{t+3}) \\ \quad > price_t * 0.03 * 2 \end{cases} \end{array} \tag{3}$$

For strategy 2, we will buy the share when we predict that the Hang Seng Index will keep increasing in the next three days and the total increment will be larger than 2 times of the transaction cost for buying it. On the other hand, we will sell the share when we predict that the Hang Seng Index will keep decreasing in the next three days and the total decrement will be larger than 2 times of the transaction cost for selling it.

4. Strategy 3:

$$\text{Buy when} \begin{cases} price_{t+4} > price_{t+3} > price_{t+2} \\ \quad > price_{t+1} > price_t \\ \text{and} \\ (price_{t+4} - price_t) \\ \quad > price_t * 0.03 * 2 \end{cases}$$

$$\text{Sell when} \begin{cases} price_{t+4} < price_{t+3} < price_{t+2} \\ \quad < price_{t+1} < price_t \\ \text{and} \\ (price_t - price_{t+4}) \\ \quad > price_t * 0.03 * 2 \end{cases} \quad (4)$$

For strategy 3, we will buy the share when we predict that the Hang Seng Index will keep increasing in the next four days and the total increment will be larger than 2 times of the transaction cost for buying it. On the other hand, we will sell the share when we predict that the Hang Seng Index will keep decreasing in the next four days and the total decrement will be larger than 2 times of the transaction cost for selling it.

Shown in figure 2 is the profit gain by ASLD generating the desired trading signal with different strategies.

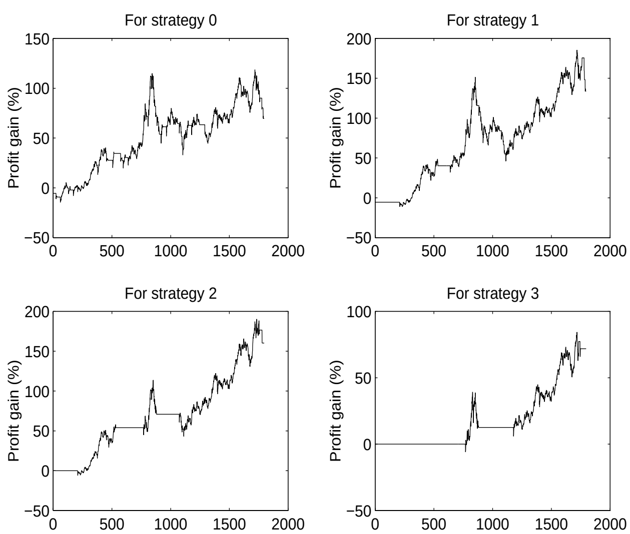

Figure 2: Profit gain of applying strategies 0 to 3.

The profit gain increases when more longer preiod ahead predicted price (strategies 0 to 2) are included in the strategy of generating desired trading signals, as shown in figure 2. However, the performance starts to drop (strategy 3) if too many predicted prices are included in it. Therefore, for optimizing the profit gain, the strategy 2 is suggested to be used in generating the desired trading signals.

The reason for the above interesting fact may be that when more predict price are included in the strategy of generating desired trading signals, our system will avoid generating the signals that will buy or sell with too little expected profit or loss. On the other side of the coin, if too many predicted price are included in the strategy, the signals generated cannot react to the increase or decrease of the market quickly. As a result, a suitable number of predicted price should be included in the strategy only.

3. INVESTMENT ON SIX DIFFERENT STOCK INDEXES

This section tries to make use of our system to generate trading signals for investment on a portfolio of six different stock indexes:

- S&P 500 Composite - price index (USA)
- Hang Seng index (Hong Kong)
- NIKKEI 225 Stock Average (Japan)
- Shanghai SE Composite - price index (China)
- CAC 40 - price index (France)
- Australia SE All Ordinary - price index (Australia)

The assumptions we made in the experiment are the same as the assumptions in the previous section, with two additional assumptions that:

1. The profit gain is calculated in US dollar only.
2. At any instance, we can hold only one index or hold cash money only. Therefore for each transactions, we will make use the whole money to buy one index or sell the whole index.

Suppose we apply the following strategy for our ASLD system:

$$\text{Buy when} \begin{cases} price_{t+x} > price_{t+x-1} > \dots \\ \quad > price_{t+1} > price_t \\ \text{and} \\ (price_{t+x} - price_t) \\ \quad > price_t * 0.03 * y \end{cases}$$

$$\text{Sell when} \begin{cases} price_{t+x} < price_{t+x-1} < \dots \\ \quad < price_{t+1} < price_t \\ \text{and} \\ (price_t - price_{t+x}) \\ \quad > price_t * 0.03 * y \end{cases} \quad (5)$$

where x and y are constant

Then, the strategy for our system to generate the trading signal is shown in the figure 3. The system will follow the

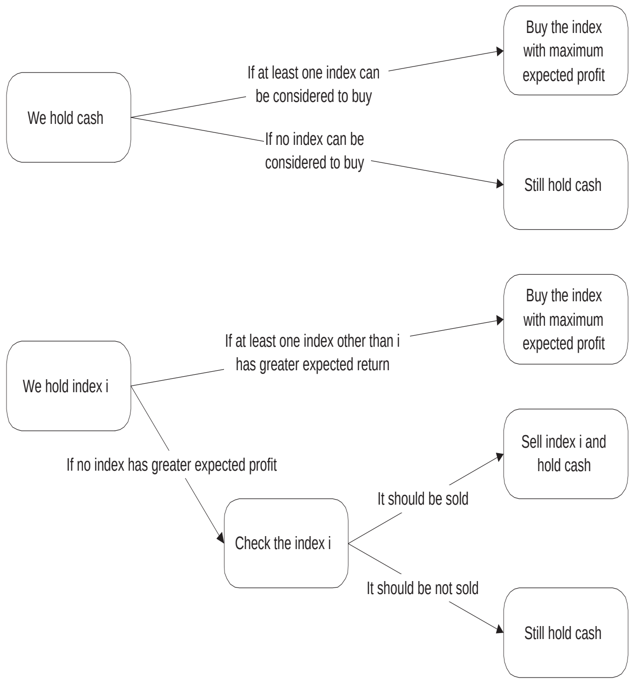

Figure 3: State diagram for generating the trading signal

upper state route if no index is held at the instance. Otherwise, it will follow the lower state route if the index t is held at the instance.

The data we used for testing and training are from May 11, 1992 to February 6, 1998. The first 1000 data points (i.e. from May 11, 1992 to March 10, 1996) are used as training data set while the remaining 500 data points (i.e. from March 11, 1996 to February) are used in testing stage.

Similar to the previous section, we have tried many different strategies for our ASLD system and we find that the following strategy is the best one for our ASLD system in doing investment among these indexes.

$$\begin{array}{l} \text{Buy when} \begin{cases} price_{t+3} > price_{t+2} \\ \quad > price_{t+1} > price_t \\ \text{and} \\ (price_{t+3} - price_t) \\ \quad > price_t * 0.03 * 2.5 \end{cases} \\ \text{Sell when} \begin{cases} price_{t+3} < price_{t+2} \\ \quad < price_{t+1} < price_t \\ \text{and} \\ (price_t - price_{t+3}) \\ \quad > price_t * 0.03 * 2.5 \end{cases} \end{array} \tag{6}$$

Figure 4 shows the profit gain we obtained in our experiment. At the time period of 300, we got nearly 100% profit gain by making investment following the trading signal generated by it. However, we suffer a great drop in the profit gain and at the end of the testing period, we obtain more than 20% profit gain.

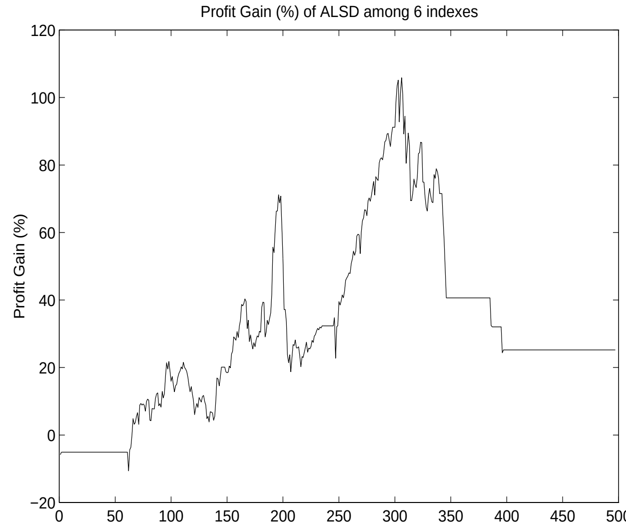

Figure 4: Profit gain of applying our ASLD system in investment among six indexes for different countries.

4. EMBEDDING VARIANCE CONSIDERATION

It is well known that the risk for investment is high when the variation of market prices are large, specially when the market price is dropping. To further improve the strategy used in previous section for generating the desired trading signal, we decided that when certain index's variance is too large and the index is dropping, we should sell it to avoid the risk of it. Therefore, in the selling part, we add a rule that when the index's value is decreasing and its predicted variance is too large, we should sell it even we predict that the amount of drops is not too large, that is,

$$\begin{array}{l} \text{Buy when} \begin{cases} price_{t+3} > price_{t+2} > price_{t+1} > price_t \\ (price_{t+3} - price_t) > price_t * 0.03 * 2.5 \end{cases} \\ \text{Sell when} \begin{cases} \quad price_{t+3} < price_{t+2} < price_{t+1} < price_t \\ \quad (price_t - price_{t+3}) > price_t * 0.03 * 2.5 \\ \text{OR} \\ \quad price_{t+1} < price_t \\ \quad var_t > meanvar * 3 \end{cases} \\ \text{where} \begin{cases} var_t = \sum_{i=0}^{8} \frac{(price_{t+i} - \frac{1}{n}\sum_{j=0}^{8} price_{t+j})^2}{n} \\ \text{meanvar is the mean value of } var_t \text{ among} \\ \text{the whole training data set} \end{cases} \end{array} \tag{7}$$

With the above modified strategy, our ASLD system can obtain a better result with nearly 95% profit gain as shown in figure 5. At the time period of 300, our system can avoid the great drop which is encountered in the previous section.

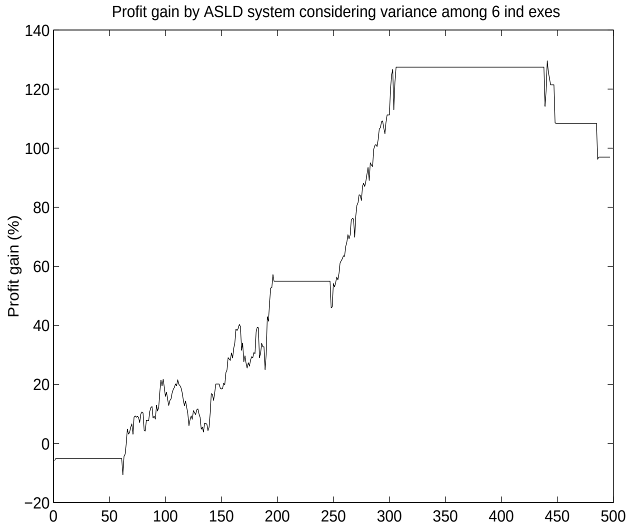

Figure 5: Profit gain of applying our ASLD system by considering variance in investment among six indexes for different countries.

5. CONCLUSIONS

The ASLD system has been further demonstrated to be a decision tool for portfolio management that can bring considerable profit in not only the foreign exchange market as shown in [6], but also in stock index market with modified trading strategy shown in section 2. Moreover, in generating the trading signals for training the ASLD system, the effects of several heuristic strategies have been investigated. We find that including a suitable number of predicted price in the strategy can help in improving the ASLD system's performance. Moreover, by generating a portfolio of indexes from six major markets in the world, the ASLD system can also bring considerable profit, as shown in the experiment in section 3. Lastly, experiments in section 4 have shown that the consideration of variance in strategy is helpful for our trading system.

6. REFERENCES

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