Indicator Selection for Daily Equity Trading with Recurrent Reinforcement Learning

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ABSTRACT

Recurrent reinforcement learning (RRL), a machine learning technique, is very successful in training high frequency trading systems. When trading analysis of RRL is done with lower frequency financial data, e.g. daily stock prices, the decrease of autocorrelation in prices may lead to a decrease in trading profit. In this paper, we propose a RRL trading system which utilizes the price information, jointly with the indicators from technical analysis, fundamental analysis and econometric analysis, to produce long/short signals for daily trading. In the proposed trading system, we use a genetic algorithm as a pre-screening tool to search suitable indicators for RRL trading. Moreover, we modify the original RRL parameter update scheme in the literature for out-of-sample trading. Empirical studies are conducted based on data sets of 238 S&P stocks. It is found that the trading performance concerning the out-of-sample daily Sharpe ratios turns better: the number of companies with a positive and significant Sharpe ratio increases after feeding the selected indicators jointly with prices information into the RRL system.

Categories and Subject Descriptors

I.2 [**ARTIFICIAL INTELLIGENCE**]: Problem Solving, Control Methods, and Search; J.1 [**Administrative Data Processing**]: Financial—*automated trading system*

General Terms

Algorithms, Economics

Keywords

Recurrent reinforcement learning; Genetic algorithm; Technical analysis; Fundamental analysis; Econometric analysis

1. INTRODUCTION

Recurrent reinforcement learning (RRL) has been used to discover return patterns for online trading [7]. The RRL-type trading systems are designed to maximize an instant reward based on feedbacks from previous long/short positions and a set of inputs, e.g. a series of lagged returns in the conventional ways. In the literature, most discussions about RRL trading have been carried out to study high-frequency FX trading (see [4, 2]), since RRLs are especially good at making profit by capturing the price autocorrelation that tends to be stronger for higher frequency financial data. Only a few papers mention the RRL applications in low frequency trading (see [7, 5]), and these papers have been devoted to trading stock indices rather on-listed stocks. Although it is commonly assumed that stock indices can be traded like stocks, in real world there is no way to make either long or short trades on any stock indices directly. Moreover, variance and autocorrelation of index prices may be different from that of stocks. There is limited research in the literature answering the question whether stocks are still tradable with RRLs at a low frequency.

Various analysis tools have been developed to forecast future trends of stock prices with the use of daily observable information. For example, technical analysis [8] and fundamental analysis [6] are two different stock selection methods. Technical analysts believe there is no needs to analyze financial fundamentals as all the information about a company has been reflected by charts. Fundamental analysts evaluate a company's intrinsic value based on the company's financial statements. Econometric tools which focus on the study of return features also have been used to facilitate price movement analysis in financial industry. Under the efficient market hypothesis [3], both technical analysis and fundamental analysis cannot beat the market by generating abnormal returns. Nevertheless, it has been found that markets are not always efficient and investors are able to make superior returns by exploiting market anomalies. Artificial intelligence (AI) techniques have increased in terms of application to discover the anomalies in the area of technical trading (see [1]). However, most previous studies about AI trading have concentrated on testing/finding technical rules, in isolation of financial fundamentals and other available information.

2. THE INTEGRATED TRADING SYSTEM

Unlike most applications of AI in automated trading, the focus of this paper is on neither trading rules selection nor trading strategies development. Utilizing information from technical analysis, financial fundamentals and econometric analysis to facilitate RRL trading and enhance trading performance is the main contribution of this paper. To reduce noise at the RRL input terminal, we only feed the indicators which help to improve trading performance into the RRL trading system. Our trading system consists of a GA selec-

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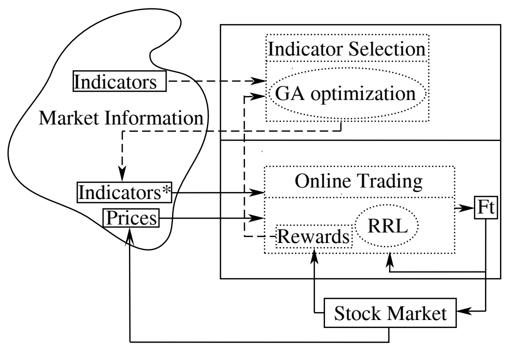

Figure 1: The integrated GA-RRL trading system

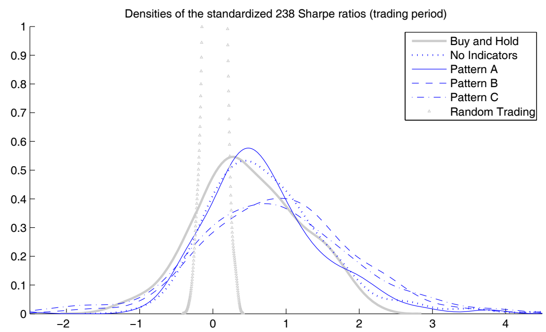

Figure 2: IR densities of the 238 stocks produced by GA-RRL in the out-of-sample period

Table 1: Indicator patterns

	IPVI	IBBI	IPBI	IRSI	DPE	IOBV	CVOL	IVOL
Pattern A					✓	✓		
Pattern B				✓	✓		✓	
Pattern C	✓			✓	✓	✓	✓	

tion system and a RRL trading system: the GA finds combinations of eight boolean numbers indicating the inclusion of eight indicators as a part of RRL inputs; the RRL gives long/short actions to maximize an instant reward based on the selected information and stock returns. Moreover, to reduce the over-fitting impact on the out-of-sample performance, we develop a new approach, namely the 'average elitist' scheme, to update the parameters of RRLs.

Figure 1 presents the integrated trading system which consists of the GA selector and the RRL trader. After determining the optimal combination $\mathcal{C}$, the chosen indicators and prices are exported to the RRL for out-of-sample trading. The two most popular indicator patterns selected by the GA are referred to as Pattern A and B in Table 1. Pattern C shows the individual indicators which receive over 50% of the 238 votes.

The S&P 500 American companies traded on the New York Stock Exchange and Nasdaq were used. We downloaded the daily prices and volume information of the 500 companies from Bloomberg (1st January 2009 – 3rd December 2012, 980 observations for a single series). Some indicators such as the RSI, the implied volatility are also available on Bloomberg. When a company's information is insufficient for analysis, e.g. with an incomplete expected P/E series, we excluded the company from the S&P 500 list, leaving 238 companies. The 980 observations are partitioned into an initial training set consisting of the first 500 samples ($T_{train} = 500$), an evaluation set of the subsequent 250 samples ($T_{eva} = 250$) and a trading set containing the last 230 observations ($T_{trade} = 230$). In the out-of-sample period T_{trade}, we recorded the SRs of the traders which were labeled as 'elitist' from the evaluation period.

3. RESULTS AND CONCLUSIONS

To assess the stability of the integrated trading system, we restarted the GA-RRL trading system (each consists of 100 sim-traders) 100 times, saving the daily SR of the elitist trader (i.e. the one with the highest SR among the 100 sim-traders in the evaluation period) from each trial for each stock. Therefore, there are 100 elitist SRs for each stock. The mean and standard deviation (SD) are calculated based on the 100 elitist SRs. Figure 2 shows probability densities of 'information ratio' (IR) of SR by taking the ratio of the mean to the SD of the out-of-sample Sharpe ratios. In fact, the IR can be interpreted as the Z-score in statistics which helps us to tell the significance of the SR. To benchmark the trading performance of our trading system, IRs produced by using a random trading strategy and a Buy&Hold strategy are also provided in the figure for reference.

It is found that the best strategy among the six is Pattern B in terms of a larger number of significant IRs which are greater than zero. RRL traders shall utilize technical indicators, financial fundamentals and econometric tools jointly with price information to facilitate daily trading.

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