Expert Systems with Applications 42 (2015) 212–222

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Stock trading rule discovery with an evolutionary trend following model

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A R T I C L E I N F O

Article history:
Available online 8 August 2014

Keywords:
Evolutionary trend following algorithm (eTrend)
eXtended Classifier System (XCS)
Trading rule discovery
Concept drift

A B S T R A C T

Evolutionary learning is one of the most popular techniques for designing quantitative investment (QI) products. Trend following (TF) strategies, owing to their briefness and efficiency, are widely accepted by investors. Surprisingly, to the best of our knowledge, no related research has investigated TF investment strategies within an evolutionary learning model. This paper proposes a hybrid long-term and short-term evolutionary trend following algorithm (eTrend) that combines TF investment strategies with the eXtended Classifier Systems (XCS). The proposed eTrend algorithm has two advantages: (1) the combination of stock investment strategies (i.e., TF) and evolutionary learning (i.e., XCS) can significantly improve computation effectiveness and model practicability, and (2) XCS can automatically adapt to market directions and uncover reasonable and understandable trading rules for further analysis, which can help avoid the irrational trading behaviors of common investors. To evaluate eTrend, experiments are carried out using the daily trading data stream of three famous indexes in the Shanghai Stock Exchange. Experimental results indicate that eTrend outperforms the buy-and-hold strategy with high Sortino ratio after the transaction cost. Its performance is also superior to the decision tree and artificial neural network trading models. Furthermore, as the concept drift phenomenon is common in the stock market, an exploratory concept drift analysis is conducted on the trading rules discovered in bear and bull market phases. The analysis revealed interesting and rational results. In conclusion, this paper presents convincing evidence that the proposed hybrid trend following model can indeed generate effective trading guidance for investors.

1. Introduction

Quantitative investment (QI) has become a hot topic in the field of finance, and numerous QI products (models/tools/systems) have been developed. One of the most popular methods for designing new QI products is evolutionary learning. This method can effectively and robustly handle optimization problems with a huge search space, which make it suitable for mining knowledge from huge, complex, and nonlinear data sets, such as stock market data.

Evolutionary learning techniques were first applied to trading rule discovery in (Allen & Karjalainen, 1999). However, their research demonstrated that there is no excess return on the S&P 500 after transaction cost. Many studies on trading rule discovery have been carried out since then. For example, based on the S&P 500 from 2000 to 2006, Kaucic (2010) found that her/his trading model can achieve excess return in the bull market, but can only reduce loss in the bear market. These studies have two distinct limitations: (1) stock investment theory is not incorporated for heuristic optimization, and (2) underlying decision-making/prediction algorithm is designed to handle one-step problems rather than multi-step ones (this issue is definitely distinguished in the area of reinforcement learning research) and is incapable of adapting automatically to market directions.

Trend following (TF) is a widely accepted investment strategy because of its simple principle, considering the difficulty of accurate stock prediction. To decide when to buy and when to sell a stock, TF adopts a rule-based trading mechanism based on (long-term and/or short term) market trends rather than on any price forecasting or information gathering (Fong, Tai, & Si, 2011). The

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http://dx.doi.org/10.1016/j.eswa.2014.07.059
0957-4174/

underlying assumption of TF is that someone has obtained the market information prior to us, and we can follow the person with considerably less cost for information collection (Covel, 2009). The stock industry has numerous successful TF-based QI products, e.g., the Turtle Trader (Fong, Si, & Tai, 2012). As demonstrated in (James, 2003), TF is a valid trading strategy in currency market, where the simple moving average indicator can gain excess return with adequate information ratio. Meanwhile, Szakmary, Shen, and Sharma (2010) examined the performance of TF trading strategies in commodity futures markets using a monthly dataset spanning over 48 years and 28 markets. Their method yielded positive mean excess returns after transaction costs in 22 markets. Despite the importance and effectiveness of TF, relatively few academic works have investigated the application of machine learning (ML) techniques to enhance TF strategy. The first attempt was carried out by Fong et al. (2012), who applied fuzzy logic to construct a dynamic model for long-term trend trading. The selected TF indicators, however, were hardly optimal ones because no feature selection or equivalent mechanism (e.g., evolutionary learning) was considered.

To solve the above mentioned problems, this paper proposes a hybrid long-term and short-term evolutionary TF algorithm (eTrend). Specifically, eXtended Classifier Systems (XCS) and TF investment strategies are combined in eTrend in a way that the identified long-term and short-term trends are integrated to evolve the XCS, thus achieving a novel constraint learning paradigm. The eTrend is designed in this way for several reasons: (1) long-term trend can reduce volatility whereas short-term trend enables rapid response, (2) XCS acts similarly to a group of robot investors by continuously and automatically adapting to the current stock environment, and (3) XCS can uncover explicit trading rules rather than black-box relationships.

In conclusion, the eTrend model has two distinguished advantages. First, the combination of stock investment strategies and evolutionary learning can significantly reduce computation effort for feature selection and improve model practicability. Second, and more importantly, eTrend can automatically adapt to market directions and the discovered trading rules are reasonable and understandable, further analysis on which can prevent average investors from irrational trading.

As the stock environment changes frequently, the underlying data distribution may change as well over time, making it difficult for any ML model that was built on old data to perform well on the new data. This problem is called concept drift (Tsymbal, 2004), which commonly exists in the stock market, especially between different market phases such as the bull and bear phases. However, few studies have been conducted on concept drift analysis. Thus, in the present paper, we analyze the concept drift problem of the Chinese stock market based on rules discovered through eTrend.

The rest of the paper is organized as follows. A brief survey on related works is presented in Section 2. The research methodology is depicted in Section 3, which describes the design of the quantitative trading model. The experiment results are presented in Section 4. A summary and conclusions are provided in Section 5.

2. Related works

The academe has had a long-standing discussion on the effectiveness of technical analysis in stock trading. Some argued that stock prices are not predictable because all relevant public information is already reflected in the prices. However, recent studies such as those by Brock, Lakonishok, and LeBaron (1992) and Blume, Easley, and O'Hara (1994) have presented positive empirical evidence on the effectiveness of technical analysis (Kaucic, 2010).

Various ML algorithms have been adopted for technical analysis, among which the most popular ones are Artificial Neural Network (ANN) (Cao, Leggio, & Schniederjans, 2005) and Support Vector Machine (SVM) (Huang, Nakamori, & Wang, 2005). However, ANN and SVM are both black-box models, which can hardly provide any insight into the nature of interactions between technical indicators and stock market fluctuations (Lai, Fan, Huang, & Chang, 2009). Michael W. Covel, one of the most famous fund managers in the US, stressed that "black-box makes me uncomfortable, in these trading, the situation which I cope with is the indigestion algorithm."(Covel, 2009). This opinion implies that a trading model should only be put into practice when it is understandable by investors (John, Miller, & Kerber, 1996); otherwise, the risk is unlimited.

Thus, many studies have been carried out to uncover intelligible stock trading rules. Allen and Karjalainen (1999) were the first to implement the generation of automatic trading rules by applying genetic programming (GP). Soon afterward, numerous other researchers recognized the importance of intelligible rule discovery. Table 1 lists several representative studies.

Genetic algorithm (GA) and GP are widely used for rule discovery, such as those in (Allen & Karjalainen, 1999; Esfahanipour & Mousavi, 2011; Gorgulho, Neves, & Horta, 2011; How, Ling, & Verhoeven, 2009; Kaucic, 2010; Mehta & Bhattacharyya, 2004; Núñez-Letamendia, 2007; Tsang, Yung, & Li, 2004). The process of rule construction is based on evolutionary learning, which aims to adapt the rules to the current environment and searches for the global optimum rules in the huge search space. Other popular ML methods include decision tree (DT) (Wu, Lin, & Lin, 2006), fuzzy logic (Bekiros, 2010; Chiung-Hon, Liu, & Wen-Sung, 2006), rough set (Shen & Loh, 2004), and grid search (Chong & Lam, 2010). In particular, explicit rules can be extracted from the black-box model. For example, Lam (2004) proposed a novel rule extraction method called GLARE to reveal the prediction logic and procedure of a black-box ANN.

Most of the above studies adopted different algorithms to perform statistical deduction. For example, DT represents the highest entropy, and ANN converges to the minimal mean squared error. However, these methods lack rigorous economic and financial interpretability; in other words, they are not suitable for guiding actual investment behaviors.

XCS is a special method for discovering automatic trading rules. GA and reinforcement learning are embedded in XCS, enabling XCS with the potential to act like a robot investor. Although there exist several studies on the application of XCS in trading rule discovery, such as those in (Hsu, Chen, & Chang, 2011), the research direction is still at its preliminary stage.

3. Methodology

3.1. XCS

Fig. 1 shows a brief development history of XCS from the original idea of Holland's learning classifier system (LCS) (Holland, 1976) to Wilson's XCS (Wilson, 1995). Many aspects of XCS are derived from ZCS, a "zeroth-level" classifier system intended to simplify Holland's canonical framework while retaining the essence of the classifier system idea. The main differences between XCS and ZCS are derived from the definitions of classifier fitness function, GA mechanism, and the more sophisticated action selection in XCS. XCS was designed to solve complex problems that have numerous optimal solutions and are difficult to choose with only a few attempts. It has demonstrated promising performance in maze and multiplexing problems (Wilson, 1995).