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Innovative Applications of O.R.

A hybrid stock trading system using genetic network programming and mean conditional value-at-risk

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ABSTRACT

This paper describes a hybrid stock trading system based on Genetic Network Programming (GNP) and Mean Conditional Value-at-Risk Model (GNP–CVaR). The proposed method, combining the advantages of evolutionary algorithms and statistical model, has provided useful tools to construct portfolios and generate effective stock trading strategies for investors with different risk-attitudes. Simulation results on five stock indices show that model based on GNP and maximum Sharpe Ratio portfolio performs the best in bull market, and that based on GNP and the global minimum risk portfolio performs the best in bear market. The portfolios constructed by Markowitz's mean–variance model performs the same as mean-CVaR model. It is clarified that the proposed system significantly improves the function and efficiency of original GNP, which can help investors make profitable decisions.

1. Introduction

This paper describes an advanced stock trading strategy using Genetic Network Programming with Mean Conditional Value-at-Risk Model (GNP–CVaR), which combines the advantages of evolutionary algorithms and statistical models, i.e., mean–variance and mean-CVaR models, has made a good performance on the finance market. In the proposed system, technical indices and candlestick charts are used as judgment functions of GNP to decide buying and selling points, while mean-CVaR model is used to distribute the weight of capitals to different stock indices in the portfolio at each time point. Efficient frontier is used to verify the expected return and risk under different distributions of capital. Finally, the performances of the proposed model are compared with original GNP as well as buy-and-hold strategy.

The paper contributes to the existing finance and computing literatures in several ways. First of all, forecasting of stock prices has always been a hot topic, however, the hybrid research of evolutionary computation and statistical model is little. This is the first time to combine GNP with risk measurement models. Secondly, the weight distribution of capital in original GNP model is fixed and takes no consideration of risk, while the mean–variance and mean-CVaR models provide a measurement of risk and construct a variety of portfolios by allocating different capital to each asset. Thus, GNP–CVaR may trade off the expected return and risks in a special way. Thirdly, most methods evaluate the stock prices at one time period in the simple market environment, however, we propose a new method to forecast the stock prices in two opposite environments, i.e., bull market and bear market. At last, sliding window is used in the testing of model performances.

The rest of this paper is organized as follows. Section 2 provides background information and a literature review in this field. In Section 3, we explain the portfolio optimization algorithm and stock trading strategy. Section 4 presents experimental environments, conditions and simulation results. The proposed method is compared with some traditional methods, and its efficiency has been confirmed. Finally, Section 5 concludes this paper.

2. Background

In recent years, stock has been a major investment due to its high returns. Generally speaking, there are two most often used analytical methods when one selects stocks to invest: fundamental analysis and technical analysis. On one hand, fundamental analysis mainly focuses on the listed company operations, conditions and financial status in an effort to determine the intrinsic value of a company's stock and forecast the future profits. Since fundamental analysis can be an useful tool for stock market prediction, one can select stocks accordingly. On the other hand, technical analysis has played an important role in the stock market due to the fact that it

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offers a relative mixture of human, political, and economic events. Technical analysis studies historical data surrounding the price and volume movements of stocks by using charts as the primary tool to forecast future price movements. All these factors make technical analysis an important tool for stock market prediction (Huang, Chen, & Pan, 2011; Achelis, 2001; Samaras, Matsatsinis, & Zopounidis, 2008).

Technical analysis aims at more accurate results, calculations and better performance. The success enjoyed by technical analysis has allowed it to become broadly accepted among financial analysts and brokerage firms. Many major brokerage firms publish technical commentary on the market and individual securities, and various analysts publish newsletters based on technical analysis (Brock, Lakonishok, & LeBaron, 1992). Surveys also show that many investors use technical analysis to make decisions on buying and selling. This paper will focus more on the analytical nature of technical analysis, which was composed of various approaches that could be separated into statistical models and artificial intelligence (AI) models.

The statistical models are widely used to predict the returns of financial instruments based on the past time series data. For example, Box and Pierce (1970) firstly proposed the autoregressive moving average model (ARMA) for time series analysis. Bollerslev (1986); Engle (1982) and Nelson (1991) introduced the ARCH family models, including ARCH, GARCH and EGARCH models. Kung and Yu (2008) adopted the GM(1, 1) model to predict the rates of return of nine major index futures in the American and Eurasian markets, and revealed that the GARCH/TGARCH model performs better than the GM(1, 1), including the optimal α method, in terms of forecasting capabilities. All of these are very useful in capturing the volatility clustering of returns. Traditionally used tool to assess and control market risk is Markowitz's mean–variance model (Markowitz, 1952), which assumes the portfolio returns to be normally distributed, and the mean and variance are used to balance the return and risk.

However, it is widely argued that the variance is not a good measurement for risk, because it cannot define the direction of volatility. Thus, a measure aimed at calculating the downside risk named Value-at-Risk (VaR) became popular and even achieved a high status of being written into the industry regulation (Morgan, 1995; Goh, Lim, Sim, & Zhang, 2012). VaR has been widely used in various applications, but it is inadequate for market risk evaluation since it is non-convex and discontinuous for discrete distributions, and is not a coherent risk measure. When the loss distributions are "sharp and heavy tail", VaR would become unstable and difficult to work with numerically. Moreover, VaR does not account for properties of the distribution beyond the confidence level.

To overcome these shortages, a new model named Conditional Value-at-Risk (CVaR) is proposed by Rockafellar and Uryasev (2002), which is also called Mean Excess Loss, Mean Shortfall, or Tail VaR. CVaR is the expected loss given that the loss is greater than or equal to the VaR at a given confidence level. Pflug (2000) proved that CVaR is a coherent risk measure having the properties of sub-addictive, convex, monotonic w.r.t. stochastic dominance of order 1, and monotonic w.r.t. monotonic dominance of order 2. Furthermore, it may handle a large amount of instruments and scenarios, since it could be optimized using linear programming and non-smoothing optimization algorithms. A simple description of the approach for minimization of CVaR and its optimization problems could be found in the review paper by Rockafellar and Uryasev (2000).

Since econometric tests of the ARCH and GARCH family models clearly reject the hypothesis of constant volatility and find evidence of volatility clustering over time. In the financial literature, stochastic volatility (SV) models have been proposed to model these effects in a continuous-time setting (Hull & White, 1987; Scott, 1987; Wiggins, 1987). Pricing methods for options on a stock with a stochastic volatility process are widely available, both in the discrete-time and the continuous-time framework (Heston, 1993; Finucane & Tomas, 1996; Ritchken & Trevor, 1999). Schweizer (1991, 1995) has proposed methods to minimize the replication error of contingent claims in general incomplete markets, including stochastic volatility as a special case. Schweizer (1995) only considers trading strategies involving the riskless bond and the underlying stock itself. Since the bond and the underlying stock price are insensitive to changes of the volatility, these hedging schemes are considered to be inefficient compared to strategies involving traded option contracts on the underlying stock (Frey & Sin, 1999).

In particular, SV can be seen as an explanation of many well-known empirical findings, for example, the volatility smile and the volatility clustering implied by option prices. To study more practical financial market, Heston (1993) assumed that the volatility of the risky asset was driven by a Cox-Ingersoll-Ross (CIR) process, while this model has some computational and empirical advantages. Since then, numerous scholars have investigated the optimal portfolio choice for investors under Heston's SV model. For instance, Liu and Pan (2003), Chacko and Viceira (2005), Kraft* (2005) and Liu (2007) considered the optimal investment problems under Heston's SV model by adopting the stochastic dynamic programming approach. Viens (2002) and Kim and Viens (2012) focused on portfolio optimization problems under SV models with partially observed information using particle filter theory. Xu, Wu, and Li (2010) considered a robust equilibrium pricing model under Heston's SV model.

On the other hand, Artificial Intelligence (AI) including Support Vector Machine (SVM), Artificial Neural Networks (ANNs), Genetic Algorithms (GA) and Genetic Programming (GP) et al. are widely used in the financial field (Kaucic, 2010). Among them GP has the advantages of systematic random search and derivative-free optimization, which was firstly introduced by Koza (1992). This method is an extension and substitution of GA, and both of them are typical evolutionary algorithms based on the biological evolution. These methods could perform a randomized global search in the solution space, where a candidate of population is associated with a fitness value correspondingly. By using the genetic operations of selection, crossover and mutation, the best candidate was reserved to the next generation and finally translated into the best solution. Kaboudan (2000) has used GA with the aim of stock price forecasting, and he showed that the price were predictable and proposed a profitable trading strategy. Nunez-Letamendia (2007) has studied the problem of how changes in the design of the GA have an effect on the results obtained in real-life applications. However, more common approaches focus on the use of GA or GP to take advantage of the market trends (Allan & Karjalainen, 1999). Researchers have used GP to discover profitable trading rules in different stock markets. El-Telbany (2005) uses GP to forecast the Egyptian Sock Market returns and achieves more accurate results than neural networks. Kaucic (2009) uses GA to select variables and detects outliers simultaneously in a dynamic linear model, so as to pursue excess returns on the MSCI European stock index. Miles and Smith (2010) apply GP to the trading of 24 stocks on the NYSE, and finds the trading rules evolved by GP, which do not outperform the simple buy-and-hold rule. Furthermore, Neely, Weller, and Dittmar (1997) use GP to find trading rules for the foreign exchange market. Using the daily frequency data for four currency pairs, the authors achieve consistent excess returns, even after considering the transaction costs. Sermpinis, Theofilatos, Karathanasopoulos, Georgopoulos, and Dunis (2013) have introduced a hybrid neural network architecture of Particle Swarm Optimization and Adaptive Radial Basis Function (ARBF-PSO), a