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Boosting Trading Strategies performance using VIX indicator together with a dual-objective Evolutionary Computation optimizer

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ABSTRACT

In this study a Multi-Objective Evolutionary System is used to predict the future tendency of assets price. Therefore, a framework using a Multi-Objective Genetic Algorithm (GA) in its core to optimize a set of Trading or Investment Strategies (TSs) was developed. The investigated framework is used to determine potential buy, sell or hold conditions in stock markets, aiming to yield high returns at a minimal risk. The Volatility Index (VIX), indicators based on the VIX and other Technical Indicators (TI) are optimized to find the best investment strategy. Additionally, fair and established metrics are used to evaluate both the return and the linked risk of the optimized TSs. Furthermore, these strategies are evaluated in several markets using data from the main stock indexes of the most developed economies, such as: NASDAQ, S&P 500, FTSE 100, DAX 30, and also NIKKEI 225. The achieved results clearly outperform both the Buy&Hold and Sell&Hold. Additionally, the Pareto-Fronts obtained with the training data during the experiments clearly show the inherent trade-off between risk and return in financial. In this paper the option of using an adaptive approach was chosen, which led to the development of a framework able to operate continuously and with minimal human intervention. To sum up, the developed framework is able to evolve a set of TSs suitable for the diverse profiles of investors from the most risky to the most careful with interesting results, which suggests great potential in the framework generalization capabilities. The use of the VIX enables the system to increase the stock return compared to traditional Technical Indicators by avoiding losses when the stress in the stock market increases. The GA enables the system to adapt to different types of markets. The algorithm achieves a return of higher than 10% annual for the period of 2006–2014 in the NASDAQ and DAX indexes, in a period that includes the stock market crash of 2008.

1. Introduction

Time-ordered sequences of data (time series data) have arisen in a broad range of applications in nearly all domains, spreading from biological to financial and meteorological data; examples include patient's medical observation data, economic indexes in stock markets, or weather forecast. Hence, the relationship analysis and forecasting of tick-by-tick temporarily ordered series of data arises as a fundamental, essential and useful task, thus worth researching. In this study, extensive experiments using real world data obtained from one of the most dynamic environments are used – financial markets. To name, the developed forecasting strategies are evaluated in several financial markets using data from the main stock indexes of the most developed economies: NASDAQ, S&P 500, FTSE 100, DAX 30 and NIKKEI 225.

In artificial intelligence (Whitley, 1994), Genetic Algorithms (GAs) are a family of computational techniques that apply the Darwinian theory of evolution to develop and optimize a possible solution to a given problem. These algorithms encode a probable problem solution on a data structure and apply selection (survival of the fittest) and recombination operators (crossover and mutation) to these data structures. These GA machine-learning techniques begin with a set of potential solutions (population) to the problem and are used to optimize them according to a fitness function that evaluates each solution depending on its ability to perform or solve a specified task. Genetic Algorithms are often viewed as function optimizers although the variety of problems to which Genetic Algorithms can be useful is fairly wide.

Besides some unfavorable judgments (Fama, 1970; Korczak & Roger, 2002), Technical Indicators (TIs) are still widely used as tools to carry out the technical analysis of financial markets, exploiting the existence of trends to establish potential buy, sell or hold conditions. Although (Achelis, 2000) has made a complete reference that fully explains the most important TIs that one can

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identify and use, this study is still very tricky for several reasons. The main difficulty of an indicator usage is deciding its suitable parameter values, as number of days of periods, in order to take advantage of the market and improve your likelihood of success. In financial practice, it is not uncommon to see analysts conducting extensive manual analysis of historically well performing indicators. This search for hidden interactions among variables that perform well in combination is often kept as a private secret when someone finds one of these interactions.

Thus, Evolutionary Computation (Chen, 2002) appear as a highly suitable alternative to extend the technical analysis of financial markets to tune the parameters of some chosen TI or a set of TIs so that the desired goals are achieved to the maximum possible extent. In this environment, what should be done by the system can be viewed as a form of predicting future stock prices. Consequently, Evolutionary Computation emerges as a stochastic search technique able to deal with highly complicated and non-linear search spaces.

In the last decade several financial crises have caused broad consequences on the financial assets valorization, which has warned investors that risk should also be taken into consideration when making any decision. As a result, the main motivation for this study emerged: to tune a set of Investment or Trading Strategies (TSs) able to achieve the highest returns with minimal risk. The simultaneous achievement of both these goals is supposed to lead us to obtain more robust solutions.

The main contributions of the present study are: 1 – The use of clear and transparent metrics to evaluate the dual conflicting goals: return and risk. 2 – The use of the VIX and indicators based on the VIX in conjunction with several other Technical Indicators to decide when to buy or sell. 3 – The use of a Multi-Objective GA adaptive approach able to operate continuously and almost autonomously (that is: with minimal human intervention).

Consequently, in this study, a Multi-Objective Evolutionary Optimization approach will be presented and used to simultaneously optimize two conflicting objectives: the maximization of the Return on Investment (ROI), and the minimization of the related risk. The proposed framework will be tested using data from the main stock indexes of the most developed economies, the results will be presented and some possible conclusions outlined.

The next section will present the related work on the Genetic Algorithms applied to financial markets. Section 3 explains the system architecture, and the roles of the most relevant modules used to build the proposed framework as well the TIs used to build the underlying strategies. Section 4 presents the results and highlights the most relevant outcomes. Finally, the conclusions of this study and the direction of possible future efforts are presented in Section 5.

2. Related work

Stock market analysis has been one of the most attractive and active research fields where many machine learning techniques are adopted. Generally speaking one can distinguish two methods for anticipating future stock prices and the time to buy or sell; one is technical analysis (Murphy, 1999) and the other is Fundamental Analysis (Graham, Zweig, & Buffett, 2003). Fundamental Analysis looks at stock prices using the financial statements of each company, economic trends and so on; it requires a large set of financial and accounting data that is difficult to obtain, released with some delay and often suffers of low consistency. Technical analysis numerically analyzes stock prices' past movement; it is based on the use of technical stock market indicators that work on a series of data, usually stock prices or volume (Achelis, 2000); it is accurate, on time, and relativity easy to obtain. Consequently, this paper will be focused on the use of technical analysis to anticipate future stock price movements.

One of the earliest proposals, in which Genetic Programming was applied to generate technical trading rules in stock market, was published in Allen and Karjalainen (1995) and in Allen and Karjalainen (1999). Later, many approaches based on Evolutionary Computation have been proposed and applied to diverse fields of Financial Computing to predict market trends. Financial markets prediction has been a subject of many studies, and in recent years a combination of algorithms and methods has been extensively used. Table 1 summarizes some of the relatively recent approaches found in the vast available literature.

In Table 1, the term B&H (Buy and Hold strategy) stands for a commonly used TS that simply invests all available cash into the asset at the start of the investment period and keeps it there until the end of the investment period. Conversely a related strategy called S&H (Sell and Hold) can also be used. It does the same but bets on the decline of the market, this means that it sells the assets at the start of the investment period without owning them and repurchases them at the end (of the investment period). In this later case the return is the decline in the price of the assets between the sale and the repurchase. In this later case the return is the decline in the price of the assets between the sale and the repurchase. Note that the B&H strategy achieves a return equal to the difference in the price between the last day of the time interval and the first day. The decade of 1990–2000 is an example of a stable rising period, when the B&H strategy was the simple way to invest in the market. The S&H strategy is used when the stock is decaying over a period.

To summarize, in most of the works (listed in Table 1) the generated returns are exclusively used as the only fitness metric without accounting for the related risk. Some examples are the use of GAs to optimize Technical Indicators (TIs) parameters, such as Fernández-Blanco, Bodas-Sagi, Soltero, and Hidalgo (2008) or to develop Trading Strategies (TSs) based on the use of TIs, for example Bodas-Sagi, Fernández, Hidalgo, Soltero, and Risco-Martín (2009), Gorgulho, Neves, and Horta (2009), Yan and Clack (2007).

According to what was stated for the first time in Markowitz (1952), any TS should have the highest possible profit with the minimal risk. Sadly, these two metrics are intrinsically conflicting due to the risk-return trade-off. Some previous articles proposed the combination of the two conflicting objectives into one single metric, particularly the proposals by Bodas-Sagi et al. (2009) that use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to gauge the risk. Also Schoreels and Garibaldi (2006) propose the use of the Capital Asset Pricing Model (CAPM) (William, 1964) system, based on Markowitz (1952) portfolio theory to reduce risk, through a balanced selection of securities. More recently, Pinto, Neves, and Horta (2011) propose and study several alternatives to the classical fitness evaluation functions.

Using real Multi-Objective Optimization some studies can be found, such as Hassan and Clack (2009) where a Multi-Objective system to maximize return, as the annualized average of the returns, and minimize risk, as the standard deviation of the annualized average of the returns, was presented. Genetic Programming (GP) was used to model equations that combine the time-series input data to score a given stock. Additionally, low-frequency trading was used as the training data consisted of monthly data.

In another paper by Chiam, Tan, and Mamun (2009) a Multi-Objective system to maximize the total returns and minimize risk was used. The proposed framework was tested using data obtained from only one stock market, the Singapore Exchange stock market (Straits Times Index (STI)). In this study, when analyzing the experimental results, the authors suggest that the positive connection between the gains with training data and test data,