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CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator

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ABSTRACT

Stock price predictions have been a field of study from several points of view including, among others, artificial intelligence and expert systems. For short-term predictions, the technical indicator relative strength indicator (RSI) has been published in many papers and used worldwide.

CAST is presented in this paper. CAST can be seen as a set of solutions for calculating the RSI using artificial intelligence techniques. The improvement is based on the use of feedforward neural networks to calculate the RSI in a more accurate way, which we call the iRSI. This new tool will be used in two scenarios. In the first, it will predict a market – in our case, the Spanish IBEX 35 stock market. In the second, it will predict single-company values pertaining to the IBEX 35. The results are very encouraging and reveal that the CAST can predict the given market as a whole along with individual stock pertaining to the IBEX 35 index.

1. Introduction

There has been growing interest in decision support trading systems in recent years. Forecasting price movements in stock markets has been a major challenge for common investors, businesses, brokers and speculators (Majhi, Panda, & Sahoo, 2009). The stock market is considered a highly complex and dynamic system with noisy, non-stationary and chaotic data series (Wen, Yang, Song, & Jia, 2010), and hence, difficult to forecast (Oh & Kim, 2002; Wang, 2003). However, in spite of its volatility, it is not entirely random (Chiu & Chen, 2009). Instead, it is non-linear and dynamic (Abhyankar, Copeland, & Wong, 1997; Hiemstra & Jones, 1994) or highly complicated and volatile (Black & Mcmillan, 2004). Stock movement is affected by the mixture of two types of factors (Bao & Yang, 2008): determinant (e.g., gradual strength change between buying side and selling sides) and random (e.g., emergent affairs or daily operation variations).

According to Wen et al. (2010), the study of the stock market is a hot topic, because if successful, the result will transfer to fruitful rewards. Thus, it is obvious that predicting the stock market's movement is the long-cherished desire of investors, speculators, and industries (Kim, 2004). However, this market is extremely hard to model with any reasonable accuracy (Wang, 2003). Prediction of stock price variation is a very difficult task and price movement behaves more like a random walk and time varying (Chang & Liu, 2008).

However, in spite of this complexity, many factors, including macroeconomic variables and stock market technical indicators, have been proven to have a certain level of forecast capability in the stock market during a certain period of time (Lo, Mamaysky, & Wang, 2000). One of the tools for this financial practice is technical analysis, also known as "charting". According to Leigh, Modani, Purvis, and Roberts (2002), Charles Dow developed the original Dow Theory for technical analysis in 1884 revisited by Edwards and Magee (1997) more than a century earlier. Technical analysis studies historical data surrounding price and volume movements of the stock by using charts as the primary tool to forecast future price movements (Murphy, 1999). In recent years, and in spite of several critics (e.g., Malkiel, 1995), technical analysis has proven to be powerful for evaluating stock prices and is widely accepted among financial economists and brokerage firms (Chavarnakul & Enke, 2008).

Due to this importance, a lot of research has gone into the development of models based on a range of intelligent soft computing techniques over the last two decades (Majhi et al., 2009). Most of the work is the combination of soft computing technology and technical analysis in stock analysis (Chen, Mabu, Shimada, & Hirasawa, 2009; Wen et al., 2010).

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Following this research trend, in this paper, CAST is presented. CAST is a tool designed to improve the investment techniques used in trading systems, applied to the Spanish stock market, based on a new way to calculate the relative strength index (RSI) by Wilder (1978). This improvement is based on the use of feedforward neural networks to calculate RSI in a more accurate way, which we call iRSI.

The paper consists of five sections and is structured as follows. Section 2 reviews the relevant literature about technical analysis and its intersection with soft computing. Section 3 discusses the main features of CAST, including the conceptual model, algorithm and architecture. Section 4 describes the evaluation of the tool's performance including a description of the sample, the method, results and discussion. Finally, the paper ends with a discussion of research findings, limitations and concluding remarks.

2. Background

Stock price prediction using soft intelligence methods is not new. To solve the non-linear problem and improve stock price evaluation, many researchers have focused on technical analysis and used advanced maths and science (Wang & Chan, 2006). Along with the development of artificial intelligence, more and more researchers try to build automatic decision-making systems to predict the stock market (Kovalerchuk & Vityaev, 2000). Soft computing techniques such as fuzzy logic, neural networks, and probabilistic reasoning draw most attention because of their abilities to handle uncertainty and noise in the stock market (Vanstone & Tan, 2005). However, though soft computing can somewhat reduce the impact of random factors, low-level data are so uncertain that they even behave purely randomly at some time (Peters, 1994). More in depth, neural networks have also become an important method for stock market prediction because of their ability to deal with uncertain, fuzzy, or insufficient data that fluctuate rapidly in very short periods of time (Schoeneburg, 1990). Furthermore, neural networks are able to decode nonlinear time series data that adequately describe the characteristics of the stock markets (Yao, Tan, & Poh, 1999), and can be applied to various complex financial markets directly (Roh, 2007). Thus, banks and financial institutions are investing heavily in the development of neural network models and have started to deploy them in the financial trading arena. Their ability to 'learn' from the past and produce a generalized model to forecast future prices, freedom to incorporate fundamental and technical analysis into a forecasting model and ability to adapt according to market conditions are some of the main reasons for their popularity (Majhi et al., 2009).

White (1988) was the first to use neural networks for market forecasting in the late 1980s. In the early 1990s, Kimoto, Asakawa, Yoda, and Takeoka (1990) used several learning algorithms and prediction methods to develop a prediction system for the Tokyo Stock Exchange Prices Index. Trippi and DeSieno (1992) combined the outputs of individual networks using Boolean operators to produce a set of composite rules. Other artificial neural network approaches can be found in various papers from that decade (e.g., Aiken & Bsat, 1994; Austin & Looney, 1997; Brownstone, 1996; Chenoweth, Obradovic, & Stephenlee, 1996; Grudnitski & Osburn, 1993; Saad, Prokhorov, & Wunsch, 1998; Thammano, 1999; Yoon & Swales, 1991). According to Chang and Liu (2008), however, these models have their limitations owing to the tremendous noise and complex dimensionality of stock price data, and besides, the quantity of data itself and the input variables may also interfere with each other.

Recently, in the first decade of the 21st century, various studies using ANN have been developed in the fields of forecasting stock indexes (Chang, Liu, Lin, Fan, & Ng, 2009; Chavarnakul & Enke, 2008; Chen & Leung, 2004; Chen, Leung, & Daouk, 2003; Enke & Thawornwong, 2005; Lam, 2004; Lee & Chen, 2002; Lee & Chiu, 2002; Leigh, Hightower, & Modani, 2005; Thawornwong & Enke, 2004; Yao, Li, & Tan, 2000). The importance of further developments in soft computing led to several papers devoted to forecasting stock indexes using techniques such as support vector machines (e.g., Chiu & Chen, 2009; Huang, Nakamori, & Wang, 2005; Kim, 2003; Pai & Lin, 2005; Wen et al., 2010), fuzzy systems (e.g., Chang & Liu, 2008; Chang, Wang, & Liu, 2007; Huang & Yu, 2005; Wang, 2003), genetic algorithms (e.g., Chen et al., 2009; Oh, Kim, & Min, 2005; Oh, Kim, Min, & Lee, 2006; Potvin, Soriano, & Vallee, 2004) and mixed methods (e.g., Armano, Marchesi, & Murru, 2005; Armano, Murru, & Roli, 2002; Hassan, Nath, & Kirley, 2007; Kwon & Moon, 2007; Leigh, Purvis, & Ragusa, 2002).

As stated before, the CAST (Chartist Analysis System for Trading) is based on the use of an improved version of the RSI, one of the leading technical analysis indexes. The RSI as a part of diverse calculations and formulas is commonly present in soft computing research (e.g., Chang & Liu, 2008; Chang et al., 2009; Chiam, Tan, & Al Mamun, 2009; Chiu & Chen, 2009; Kim, 2004; Lai, Fan, Huang, & Chang, 2009; Lu, Lee, & Chiu, 2009; Majhi et al., 2009; Tan, Quek, & Yow, 2008; Yao & Herbert, 2009). However, using soft computing methods in getting iRSI calculations is a research task with no presence in the literature. In this paper is proposed CAST, a system that uses a generalized feedforward neural network to perform improved RSI calculations.

3. System core

The idea of the system developed in the CAST is to create a trading system based on fundamental or chartist analysis. Concretely, the main idea is to use one of the most used financial indicators, namely, the RSI. As described before, the RSI is a financial technical analysis momentum oscillator measuring the velocity and magnitude of directional price movement by comparing upward and downward close-to-close movements. Momentum measures the rate of the rise or fall in stock prices. Is the momentum increasing in the "up" direction, or is the momentum increasing in the "down" direction.

There are several ways to calculate this indicator, and it depends on whether you want to calculate a "normal RSI" or gentler RSI formulas. The calculation of the RSI is described as follows:

For each day, an upward change (U) or downward change (D) is calculated. "Up" days are characterized by the daily close being higher than yesterday's daily close, i.e.:

$$U = close_{today} - close_{yesterday},$$
$$D = 0.$$

Conversely, a down day is characterized by the close being lower than the previous day's (note that D is nonetheless a positive number)

$$U = 0,$$
$$D = close_{yesterday} - close_{today}.$$

If today's close is the same as yesterday's, both U and D are zero. An average for U is calculated with an exponential moving average (EMA) using a given N-days smoothing factor, and likewise for D. The ratio of those averages is the relative strength:

$$RS = \frac{EMA[N]\_of\_U}{EMA[N]\_of\_D}.$$