Expert Systems With Applications 55 (2016) 194–211

Contents lists available at ScienceDirect

Expert Systems With Applications

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

Computational Intelligence and Financial Markets: A Survey and Future Directions

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ARTICLE INFO

Keywords:
Financial markets
Computational intelligence
Trading systems
Deep learning
Online learning

ABSTRACT

Financial markets play an important role on the economical and social organization of modern society. In these kinds of markets, information is an invaluable asset. However, with the modernization of the financial transactions and the information systems, the large amount of information available for a trader can make prohibitive the analysis of a financial asset. In the last decades, many researchers have attempted to develop computational intelligent methods and algorithms to support the decision-making in different financial market segments. In the literature, there is a huge number of scientific papers that investigate the use of computational intelligence techniques to solve financial market problems. However, only few studies have focused on review the literature of this topic. Most of the existing review articles have a limited scope, either by focusing on a specific financial market application or by focusing on a family of machine learning algorithms. This paper presents a review of the application of several computational intelligent methods in several financial applications. This paper gives an overview of the most important primary studies published from 2009 to 2015, which cover techniques for preprocessing and clustering of financial data, for forecasting future market movements, for mining financial text information, among others. The main contributions of this paper are: (i) a comprehensive review of the literature of this field, (ii) the definition of a systematic procedure for guiding the task of building an intelligent trading system and (iii) a discussion about the main challenges and open problems in this scientific field.

1. Introduction

Financial markets are very important for the economical and social organization of modern society. Financial activities play an important role in the world economy, since they influence the economic development of several countries worldwide (Lin, Chiu, & Lin, 2012). In these kinds of markets, the success of an investor depends on the quality of the information he uses to support the decision-making, and on how fast he is able to take decisions. Due to its practical importance, the analysis of financial market movements has been widely studied in the fields of finance, engineering and mathematics in the last decades (Yoo, Kim, & Jan, 2005). Recently, some statistical and soft computing mechanisms have been proposed to provide support to the decisions of investors in different financial market segments.

Two approaches commonly used to analyze and predict financial market behaviors are (i) the fundamental analysis and (ii) the technical analysis. The former approach studies the economic factors that may influence market movements, and it is best suited for a longer term prediction spectrum. The technicians, on the other hand, believe that the price already includes all the fundamentals that affect it. In this sense, technicians usually model the historical behavior of a financial asset as a time series, believing that the history tends to repeat itself (Murphy, 1999). This modeling approach avoids the analysis of those subjective economic factors.

Financial time series prediction can be considered one of the main challenges in the time series and machine learning literature (Tay & Cao, 2001). In the last decades, several approaches have been proposed to predict financial time series and to provide decision-making support systems (Teixeira & Oliveira, 2010). Two major classes of work which attempt to forecast financial time series are the statistical models and machine learning approaches (Wang, Wang, Zhang, & Guo, 2011). Traditional statistical methods

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http://dx.doi.org/10.1016/j.eswa.2016.02.006
0957-4174/

generally assume that the time series under study are generated from a linear process (Kumar & Murugan, 2013), and try to model the underlying time series generation process in order to make predictions about the future values of the series. However, financial time series are essentially complex, highly noisy, dynamic, nonlinear, nonparametric, and chaotic in nature (Si & Yin, 2013).

Machine learning techniques have been applied with relative success in modeling and predicting financial time series (Lee, 2009). Many machine learning techniques are able to capture nonlinear relationship between relevant factors with no prior knowledge about the input data (Atsalakis & Valavanis, 2009). Among these techniques, artificial neural networks (ANN) have been widely used in forecasting time series, since they are data-driven, self-adaptive methods able to capture nonlinear behaviors of time series without any statistical assumptions about the data (Lu, Lee, & Chiu, 2009; Tay & Cao, 2001). Due to these advantages, several types of ANNs and hybrid mechanisms have been used in forecasting financial time series (Atsalakis & Valavanis, 2009).

In the last years, some researches, motivated by the fundamental analysis, have investigated how to predict future market movements by mining informations in textual format. In this branch of research, financial news (Groth & Muntermann, 2011; Schumaker, Zhang, Huang, & Chen, 2012), financial reports (Wang, Huang, & Wang, 2012), and even information in micro-blogs (Ruiz, Hristidis, Castillo, Gionis, & Jaimes, 2012) are considered relevant source of informations for predicting future market behavior. These approaches investigated how mining important features on textual data or how to identify author sentiments in the news to improve the forecasting of future financial values.

The main purpose of this article is to review the recent computational intelligence approaches designed to solve financial market problems. Despite the high number of scientific papers which propose intelligent and expert systems, techniques and algorithms applied to financial markets, just a few review articles have been published in relevant journals and conferences in the last years. Most of the existing review articles have focused on a specific financial market application or on a family of machine learning algorithms. In this article, we make a comprehensive survey of machine learning methods applied to the financial context published from 2009 to nowadays. The scope of this review includes articles dealing with preprocessing and clustering of financial data, forecasting of future market movements, mining of financial information, among others. This survey not only summarizes the main primary studies, but also it identifies some challenges of applying machine learning techniques to solve financial problems and discusses some open problems and promising future researches in this field.

The remainder of this paper is organized as follows. Section 2 discusses the research method used in this survey and some other surveys related to this work. Section 3 describes some basic concepts which represent a background for this research. In addition, a methodology for constructing an intelligent trading system is proposed in this section. Section 4 provides a description of the main primary studies selected for be reviewed. These primary studies were grouped according to their main objectives. Section 5 provides a general discussion about these main primary studies. Section 6 provides a discussion about the challenges and open problems of this research area. Section 7 provides the final considerations of this paper.

2. Research methodology and related work

The primary studies discussed in this survey were recovered from Science Direct, Google Scholar and IEEExplore digital libraries for the period from 2009 to 2015. This publication year criterion was adopted because we observe a lack of literature review articles with the same scope as the research presented in this paper. Three main research questions were formulated to guide this research: (i) What kind of financial market problems have been solved by computational intelligence algorithms?; (i) What kind of computational intelligence algorithms have been proposed to solve these financial problems?; (iii) What are the main challenges and research opportunities that remain open in this research field?. In this survey, we have used combinations of the following keywords: “financial markets”, “stock markets”, “portfolio” “financial time series”, “forecasting”, “machine learning”, “computational intelligence”, “neural networks”, “support vector machines”, “extreme learning machines”, “fuzzy systems”, “novelty detection”, “clustering”, “feature selection”, “text mining”, “survey”, “review”, “comparative study”. The criterion to include the primary studies in this survey was that the article should propose the use of any computational intelligence technique to solve a financial problem. Articles that propose an expert system for automatic negotiation had priority of inclusion.

It is important to highlight that the results of this review do not include all applications of computational intelligence methods to financial market problems. Papers not published in reputable journals and conferences or with poor description of the intelligent method used, of the learning algorithm, or with a weak evaluation method were not included in this survey.

Each selected article was organized and discussed according to its primary goal into three main categories and some subcategories:

1. Preprocessing: 1.1 feature selection and extraction; 1.2 denoising and outlier detection; 1.3 time series segmentation; 1.4 clustering.
2. Forecasting: 2.1 artificial neural networks; 2.2 support vector machines; 2.3 hybrid methods; 2.4 optimization methods; 2.5 ensemble methods; 2.6 others approaches.
3. Text mining.

We started the survey by examining review articles that cover applications of computational intelligence methods to financial market problems. In the literature, there are not many review articles that cover this topic. Most of the published surveys found in the literature are specialized in some computational intelligence technique, such as ANNs or genetic algorithms (GA). Vanstone and Finnie (2009) proposed an empirical method for developing automatic trading systems using ANN. In that study, the authors reviewed some work that use fundamental and technical analysis to construct intelligent trading systems. They also described some key steps in using ANN for this purpose, namely the selection of inputs and outputs, the determination of the neural architecture and how to process the output signals produced by an ANN to create rules to enter and exit trades.

Li and Ma (2010) surveyed the application of neural networks in several subareas of financial markets. They enumerated some primary studies that apply ANN to exchange rates forecasting, stock market forecasting, and prediction of banking and financial crisis. In that short paper, no details of which ANN architectures or learning strategies were used in the primary studies surveyed. The work proposed by Roshan, Gopura, and Jayasekara (2011) surveyed the use of ANN in forecasting financial time series. In that paper, the authors surveyed the literature under two perspectives: the preprocessing mechanisms applied to input data and the neural network design used in primary studies. Soni (2011) also surveyed the application of ANNs to stock market prediction. That paper provides a brief history of ANNs and basic concepts of stock market before enumerating some primary studies that use this approach to solve the stock market forecasting problem. Despite the fact that these reviews have an intersection with the period of our research, they have a limited scope, since they focus in just one family of computational intelligence algorithms.

Most of the machine learning approaches proposed in the literature to solve the financial forecasting problem rely on quantitative data arising from technical analysis. But some primary studies have investigated the use of techniques that rely on qualitative data arising from financial news, company financial reports, among others. Nikfarjam, Emadzadeh, and Muthaiyah (2010) surveyed some primary studies which implement text mining techniques to extract qualitative information about companies and use these informations to predict the future behavior of stock prices based on how good or bad are the news about that companies. In that work, authors provide a comparison of the main text mining-based methods proposed in the literature considering some characteristics of the primary studies, namely (i) the feature selection technique, (ii) the feature representation approach, (iii) the news source used, (iv) the classifier applied, (v) the number of categories or goal classes and (vi) the directional accuracy. Our review also covers primary studies which proposed text mining approaches for assisting in financial market analysis, however we provide an updated discussion of this topic in comparison to that review.

An important work related to the present research was proposed by Atsalakis and Valavanis (2009). In that paper, the authors have surveyed over 100 scientific articles that apply soft computing techniques to solve the stock market forecasting problem. The examined primary studies were classified over five different perspectives: (i) the stock market investigated, (ii) the input variables used, (iii) the methods and parameters used to build the predictors, (iv) the benchmarks used in each study, and (v) the performance measures used to evaluate the proposed methods. Despite the valuable contribution of that paper in organizing this literature field, it is concentrated in machine learning methods applied to forecasting. In contrast, our survey presents different perspectives of the literature, since it investigates several areas related to computational intelligence and financial markets, not only forecasting. Besides, the review made by Atsalakis and Valavanis (2009) is relatively old, and several advances were made from 2009 to nowadays.

A very recent survey (Tkáč & Verner, 2016) reviewed primary studies which have used ANNs in business applications, such as auditing and accounting, crediting scoring, financial analysis, inflation, marketing, among others. Our scope is more restricted in terms of the financial applications investigated, since we focus on expert and intelligent systems designed to financial market analysis and prediction. However our scope is wider in terms of the algorithms covered. Aguilar-Rivera, Valenzuela-Rendón, and Rodríguez-Ortiz (2015) review the application of evolutionary computation methods, such as genetic algorithms, genetic programming and evolutionary algorithms, to solve financial problems. This review is also very recent, however it has a more restricted scope, since it discuss just evolutionary-inspired methods. Our review has a broader scope.

3. Basic concepts

In this section, we discuss some key concepts that will provide a foundation for the remainder of the paper.

3.1. Technical and fundamental analysis

Market analysis comprises the study of several market attributes and features that influence on prices of financial assets. The main goal of market analysis is to understand market behaviors in order to help in the decision-making process. Two main widely used approaches for analyzing financial markets are the fundamental and the technical analysis. Both approaches have the primary goal of understanding the price movements and predict their future directions. However, the major difference between these two strategies is related with the nature of market features considered by each approach (Murphy, 1999).

Fundamental analysis started in 1928 with an important investor, Benjamin Graham, which stated that investors need to study some fundamental attributes of a company before investing, such as the size of firm, capitalization and price-earnings ratio (Vanstone & Finnie, 2009), revenue, expenses, assets, liabilities and other financial aspects of a company. Fundamental analysts believe that the stock price of a company is reflected by several political and economical factors which are internal and external to the company. Several quantitative tools and indicators were developed to assist in studying the fundamentals of a company, such as management policy, marketing strategy, product innovation, financial ratios, among others (Lam, 2004). In order to improve the analysis, some other factors such as market trends, legislation, and even financial news, web and social networks have been used to study the fundamentals of a company.

Technical analysis, on the other hand, does not take explicitly into consideration the internal and external characteristics of a company in the study of market price movements. Technicians believe that all the fundamentals that influence the market movements are immediately incorporated in the price (Murphy, 1999). Based on this strategy, technicians abstract the fundamentals of a company, avoiding the analysis of all those subjective economic factors. Basically, technicians try to identify patterns in price, volume, breadth and trading activities, believing that these informations are enough to determine future values. Technical indicators, which are mathematical formulas applied to price or volume data, are built and used in order to model some aspect of stock prices or indices movement (Teixeira & Oliveira, 2010). Technical analysis uses charting, relative strength index, moving averages, on balance volumes, momentum and rate of change, directional movement indicators, among several others as tools for market analysis (Lam, 2004; Tsinaslanidis & Kugiumtzis, 2014).

Based on several technical indicators, technicians organize and analyze historical data of a stock or market index sequentially spread in time in order to predict future values of the financial asset, believing that they tend to repeat itself. However, despite the flexibility in this approach when compared to fundamental analysis, some authors argue that it cannot help investors decision-making. Early in 1964, Godfrey, Granger, and Morgenstern (1964) proposed the hypothesis that stock prices present a random walk behavior, in which successive changes in price behave as independent, identically distributed random variables. That theory implies that price changes have no memory and the past cannot be used to predict future prices effectively. The Efficient Market Hypothesis (Fama, 1965) supports that theory by stating that prices immediately incorporate all available information about an stock, and only new information is able to change price movements. As the arrival of new information is unpredictable, so are the price changes. Since the technical analysis is based on historical data to predict future prices, it could be concluded that this market analysis approach cannot work effectively (Vanstone & Finnie, 2009).

However, regardless of these theories, several investors, financial economists and brokerage firms have used technical analysis in predicting stock market with considerable success (González, García-Crespo, Palacios, Guldrís-Iglesias, & Berbís, 2011). In 1995, Lui and Mole (1998) conducted a questionnaire to survey the use of technical and fundamental analysis by foreign exchange dealers in Hong Kong. The results showed that 85% of the responders rely on both fundamental and technical analysis. Results showed also that technical analysis was more frequently considered in investments at shorter horizons and more useful in forecasting trends and turning points. Several scientific papers in the literature have used technical analysis to solve the stock market prediction

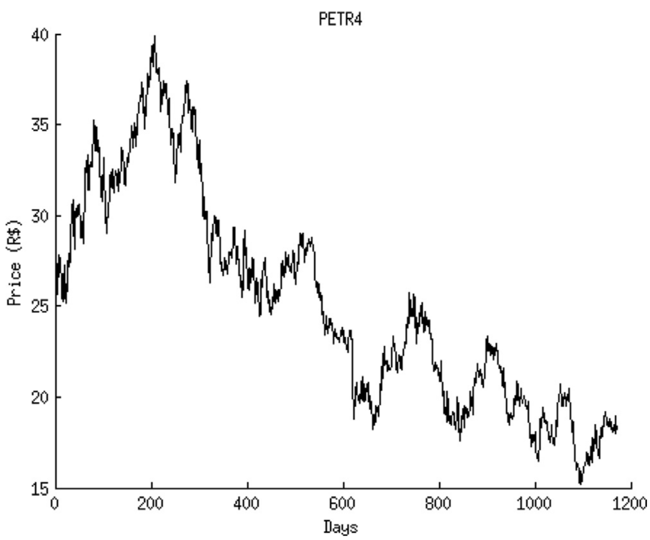

Fig. 1. Brazilian oil company stock price time series.

problem (Aghabozorgi & Teh, 2014; Evans, Pappas, & Xhafa, 2013; González et al., 2011; Li, Deng, & Luo, 2009; Martinez, da Hora, de M Palotti, Meira, & Pappa, 2009).

3.2. Traditional statistical and soft computing mechanisms

An important advantage of using technical analysis is that it simplifies the problem of predicting future market movements to a pattern recognition problem, in which inputs are derived from historical prices and technical indices and outputs can be estimated from these past data (Teixeira & Oliveira, 2010). As a consequence, several alternatives to approach the problem have been proposed, which range from traditional statistical modeling to methods based on computational intelligence algorithms. Both approaches generally model the financial data as a time series. A time series is a sequence of numerical data observations recorded sequentially in time (Brockwell & Davis, 2009; Wang et al., 2012). Several dynamic processes can be characterized as a time series, such as stock prices (Fig. 1), monthly sells of a company, a company payroll, the temperature of a city, electricity consumption, electrocardiogram, among others. Organizing financial data as a time series allows modeling the time series behavior and predicting future behavior of the time series by using several time series tools (Oliveira & Meira, 2006). These tools provide easier ways to perform time series data mining tasks, such as identification of trends, presence of seasonal effects, cycles and outliers (Cryer & Chan, 2008). All these features extracted from financial time series can be used to define buying and selling points, which can be used to maximize investors profits (Murphy, 1999).

The prediction problem for financial time series data consists in learning a model from a given financial time series data set, $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_n, y_n)\}$, where $\mathbf{x}_i \in X$ is a data observation and $y_i \in \mathbb{R}$ is the predicted value. The learned model is used to make accurate predictions of y's for future and unknown values of $\mathbf{x}$'s (Yang, Huang, King, & Lyu, 2009). However, this problem is considered one of the most challenging problems of modern time series forecasting (Wang et al., 2012). In the last decades, several approaches have been proposed in order to predict financial time series and to provide decision-making support systems (Teixeira & Oliveira, 2010). Two major classes of work on forecasting financial time series are the traditional statistical models and the machine learning approaches (Wang et al., 2011).

Traditional statistical models are generally based on the assumption of linearity among normally distributed variables (Wang et al., 2011). These models include time series regression, exponential smoothing, autoregressive integrated moving average (ARIMA) and its variations, generalized autoregressive conditional heteroskedasticity (GARCH), among others (Lin et al., 2012; Wang et al., 2012). These techniques generally assume that the time series under study is generated from a linear process and try to model the underlying process based on this assumption. However, some specific characteristics of financial time series make this kind of data more difficult to predict, when compared with other kinds of time series. These specific characteristics make traditional statistical methods not effectively applied to financial context. Financial time series present an abundance of uncertainty and noise (Vanstone & Finnie, 2009). Furthermore, this kind of data presents a nonlinear behavior and no identical statistical properties may be observed at each point of time. Besides, dynamic changes in the relationship between independent and dependent variables happen frequently in financial time series (Hsu, Hsieh, Chih, & Hsu, 2009). Another aggravating factor that makes prediction of future financial values harder is the high volatility in the time series (Atsalakis & Valavanis, 2009). Volatility in the financial context can be defined as the intensity of the fluctuations in the market pricing of a financial asset and it is intrinsically related to investment risks (Tung & Quek, 2011). This inherent characteristic of financial time series can be explained by the fact that financial prices are influenced by many economic factors, investors psychology and expectations, movement of other stock markets, political events, among others (Kara, Acar Boyacioglu, & Baykan, 2011).

Since financial markets are considered complex, evolutionary, noisy, and nonlinear and non-parametric dynamic system (Huang & Tsai, 2009), more adaptive and flexible mechanisms are required to improve forecasting accuracy. With the recent advances in soft computing techniques, some computational intelligence mechanisms have been used as tools in forecasting financial markets (Lin et al., 2012). Soft computing techniques, such as expert systems, fuzzy systems and artificial neural networks, have been applied with relative success in modeling and predicting financial time series (Lee, 2009). Many of these soft computing techniques are able to capture nonlinear relations among relevant market factors with no prior knowledge or statistical assumptions about the input data (Atsalakis & Valavanis, 2009). Soft computing mechanisms present several advantages when compared with traditional statistical methods. They generally exhibit high tolerance to imprecision and perform well in noisy data environments; they are numeric, data-driven, non-parametric and self-adaptive mechanisms; they require less historical data than traditional statistical models (Cheng & Wei, 2014). According to Liang, Zhang, Xiao, and Chen (2009), it is generally believed that non-parametric methods outperform the parametric methods in predicting future financial market behaviors.

3.3. Intelligent trading methodology

Despite the fact that several researchers have investigated how to use computational intelligent systems to predict financial market movements, there is no well-established and tested methodology which describes how to create an autonomous trading system (Vanstone & Finnie, 2009). According to Vanstone and Finnie (2010), the main reason is that successful autonomous trading methods are not communicated to the scientific community, since investors try to keep their intellectual capital saved. In this section, we attempt to summarize the main components of a forecasting methodology applied to financial markets. This methodology enumerates the main steps for guiding researchers and practitioners in building an intelligent trading system. We, however, are not going into detail of the complete architecture of a trading system. Our

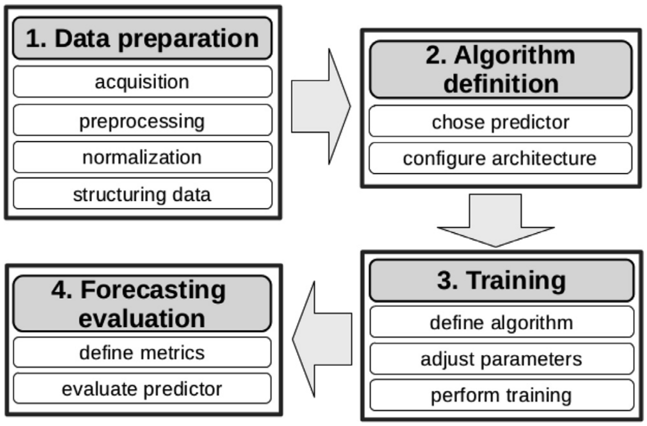

Fig. 2. Conventional forecasting methodology.

purpose is to discuss the main components of an intelligent trading system with the focus on forecasting of financial data.

In the context of general time series prediction using computational intelligence, a common systematic procedure used for forecasting includes the following operational steps (Palit & Popovic, 2006): (i) data preparation, (ii) algorithm definition, (iii) training and (iv) forecasting evaluation. Data preparation, the first step, consists in preparing data for the learning process. The main activities on this step are acquisition, preprocessing, normalization, and structuring data, which means the determination of training and test data sets. The second phase, the algorithm definition, consists in determining the soft computing method to be used for modeling and forecasting the data and the definition of the architecture of the method. The training phase consists in selecting the training algorithm, adjusting training parameters and executing the training procedure in order to create a model of the learned data. The last phase, the evaluation, consists in defining the evaluation metrics and in measuring the accuracy of the results obtained by running the trained method on the test dataset. Fig. 2 summarizes these four steps of the conventional forecasting methodology.

Some primary studies proposed in the literature have used the conventional forecasting methodology to solve financial market problems. However, some specific issues of financial markets need to be addressed in order to build a successful intelligent method. The first main issue of financial markets is the choice of input variables to be modeled by a machine learning method and output signals to be predicted and used in defining the rules to enter and exit the market and by the risk and money management strategies. Other very important issue of financial problems in comparison to other machine learning problems is the evaluation step. Since the main goal of an autonomous trading system is to maximize the profit when a applied to real markets, the evaluation step must have as its objective to measure the ability to make profits in a real or simulated trading environment. These issues need to be addressed, under the penalty of constructing a forecasting method which is not applicable in practice or which can cause severe financial damages to investors. So, in order to build an intelligent trading method, some steps need to be included in this conventional methodology and some existing steps must be adapted.

In the data preparation step, data to be used for analysis and forecasting are collected and prepared to be modeled by a machine learning method. In the context of financial market applications, several technical or fundamental input variables are available and the choice of which variables to use is not a straightforward task. Generally, this choice depends on the investment horizons. Technical variables are indicated in case of short-term trading, such as daily, weekly or monthly (Evans et al., 2013). Fundamental inputs are typically used in the case of long-term trading (Vanstone & Finnie, 2009). Among the technical variables, there are numerous technical artificial indexes that can be used. Atsalakis and Valavanis (2009) summarize several inputs used in more than 100 scientific papers. Several computational intelligence methods can be used to automate this phase. These methods have as main objective the selection or extraction of relevant features from input data in order to improve forecasting of financial signals to be used in trading rules.

Another important sub-phase of data preparation is the selection of output variables to be used. This can be considered a trivial step in other time series prediction applications such as electrocardiogram, electricity consumption, sales of a company, rainfall records, among others. In the context of forecasting financial market movements, there are several signals that can be predicted and used by a trade system to define the enter and exit rules. The most common output signal used in literature is the price for the next day. Other variables used are the price for the next n days, the relative strength indicator (RSI), a sign of the rise of fall in prices, the next turning points, among others.

After defining the input and output variables to be used in forecasting, the data are acquired, preprocessed to eliminate noise and outliers, normalized and structured. These structured data are used by a machine learning method in order to learning the market behaviors. The second, third and fourth phases of the corresponding intelligent trading methodology can be conduced in a similar way to the phases of the conventional forecasting methodology (Fig. 2). In these phases, the forecasting algorithm should be selected and trained for modeling the chosen input data and for forecasting the output signals. The predicted values are used to evaluate the forecasting accuracy of the proposed approach. Forecasting evaluation can be performed by using conventional machine learning accuracy measures, such as mean absolute error, mean absolute percentage error, root mean square error, among others.

In the financial forecasting methodology, two additional phases need to be incorporated to the traditional methodology, namely (i) the trading strategy and (ii) the money evaluation. A trading strategy is fed with the predicted signals and uses these values to negotiate in the real-world market based on those expected future values. According to Chande (1999), a successful trading strategy needs to implement three main features. The first of them consists of a set of rules which specifies when to enter and exit trades. These rules use the predicted output signals to identify the best moment to buy or sell stocks. The main goal of the trading rules is to maximize the financial profits. In practical terms, it uses the predicted output signals to buy assets which are cheap but which tend to appreciate in the future.

The second feature of a successful trading system is a risk control mechanism, which is a set of rules that protect the invested money, such as stop-loss orders for example Teixeira and Oliveira (2010). Risk control strategies should define profit objectives in each trade as well as it should define when leaving a non-profit position which does not behave as predicted. The third feature is the money management mechanism, which manages the position size, i.e., the amount of resources to be used in a trade considering the total capital available and the risk involved in the trade. It is important to highlight that these three strategies of the trading strategy need to take account of real-world constraints, such as the transaction costs, slippage, volume constraints, splits, order routing, among others. Further discussion of trading system architectures can be found in Aldridge (2009) and Durenard (2013).

The last added phase is the money evaluation, which consists in accessing the performance of the trading system in terms of making profits in a real market. This is an important phase, since this evaluation gives guarantees that the proposed expert trading method is able to make profits in the market in an autonomous

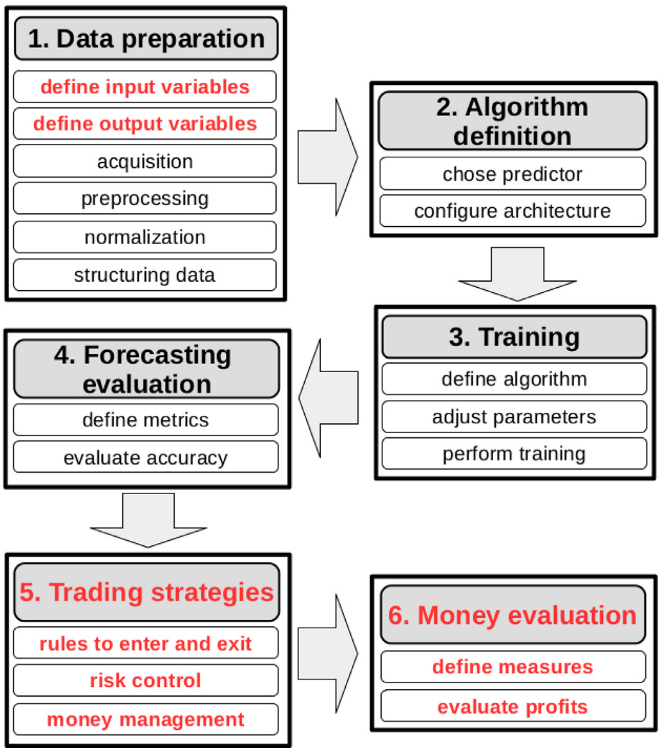

Fig. 3. Financial trading framework with forecasting.

way. There are lots of metrics that can be used to evaluate the profit performance, such as annualized return, drawdown, Sharpe ratio, among others. Vanstone and Finnie (2009) summarize several trading system metrics that can be used for profit evaluation. Fig. 3 illustrates the whole methodology for building an intelligent trading system.

4. Description of primary studies

This section provides a description of each primary study found in the literature. The articles discussed here are organized according to their primary goal or main contribution to computational intelligence applied to financial markets literature.

4.1. Preprocessing mechanisms

Data preparation is the first step of any successful intelligent trading method. After defining the input and output variables to be used for modeling the financial asset and acquiring the input data to be used in training, the application of some preprocessing procedure on these data may be very useful, since they may be used to improve the accuracy of an intelligent predictor in several ways. Feature selection or extraction methods can be applied to a dataset in order to select the best representative features of the input data which reduces the input dimension and consequently minimizes the training time. Preprocessing mechanisms can be used to filter irrelevant features and noise from input data or detect and correct outliers, which may improve the forecasting accuracy. Some preprocessing mechanisms can be used to decompose the input data, in order to divide the modeling problem into smaller subproblems. In this section we discuss some mechanisms proposed in the literature which perform some kind of preprocessing on input data before the training step.

4.1.1. Feature selection and extraction

According to the framework described in Fig. 3, the primary activities on defining a computational method able to forecast financial markets is the definition of inputs and outputs of the forecasting model. Based on that initial definition, a machine learning method is used to model the relation among these inputs and outputs. An incorrect choice of input variables can lead to a model which does not describe the real behavior of the financial market and which can be considered obsolete in forecasting future movements.

In the literature, proposed approaches differ regarding the number and types of variables used in modeling financial behavior. Fundamental analysis provides several macro and microeconomic attributes of an individual company and of the whole market, such as size of firm, capitalization, price-earnings ratio, cash flow, leverage, profitability, among others. Technical analysis, on the other hand, provides a bunch of technical attributes, such as moving averages, volatility, on balance volume, momentum, relative strength index, among several others (Vanstone & Finnie, 2009). However, in the literature, there is no consensus on which input variables are the best to be used.

The selection of which input variables are more representative and useful for effective forecasting is not a straightforward task. Some of these variables can be redundant and/or irrelevant to the modeling task. In order to help in deciding which variable set is better suited to a financial forecasting context, some work have investigated the use of automatic feature selection or extraction mechanisms. The main advantage of feature selection or feature extraction is dimensionality reduction, which consequently reduces the computational efforts of the machine learning method used as well as it reduces the risk of overfitting. The elimination of irrelevant features leads to better prediction performances (Tsai & Hsiao, 2010).

According to Webb (2003), there is an important distinction about feature selection and feature extraction. Feature selection mechanisms, also called feature subset selection, identify those variables that are not relevant for modeling the data to be learned. Feature extraction mechanisms, on the other hand, try to find a transformation from the original feature set to a lower-dimensional feature space. Feature selection and extraction methods can be classified as filters and wrappers, according to the operation of the method. Filter methods perform the selection of important features independent of any machine learning method (Lee, 2009). These methods generally work by direct analysis of the input data, and operate by estimating important features through some statistics over the data. Methods as discriminant analysis, stepwise selection, principal component analysis (PCA) are examples of mechanisms used as filter methods.

Wrapper methods, on the other hand, rely on a machine learning algorithm to select important features. These methods use the classification performance of a given learning algorithm in order to evaluate how good is a subset of features used as input. Such methods work by searching the best subset of input features, trying to optimize the predictor accuracy.

Despite the fact that wrappers perform better, since they work directly with the accuracy measures of a given classifier, they have high computational costs (Lin, Liang, Yeh, & Huang, 2014). As the feature space increases, the search space may become intractable. Filter methods generally lead to a lower accuracy, however they present a higher computational scalability.

Lee (2009) proposed a hybrid feature selection mechanism that takes the advantages of filter and wrapper methods, namely the lower computational costs and better accuracy, respectively. An F-score measure is used as a filter in order to help in deciding the best subsets for a given feature set. Next, a support vector machine (SVM) classifier is used as a wrapper prediction method to refine the initial selection provided by the filter, which produces a reduced set of features. Tsai and Hsiao (2010) used the ensemble technique to build a feature selector, which combines PCA, GA and Classification and Regression Decision Trees. The authors compared the feature selector ensemble using three combination strategies, namely union, intersection and multi-intersection of the features selected by each individual selector.

Lin et al. (2014) combined expert knowledge with a GA-based wrapper to select the best features to financial distress prediction problem. A set of financial features is pre-classified using expert knowledge, and features are grouped into some major categories. The idea behind grouping features is to reduce the search space, by eliminating highly correlated features from the search space. An SVM algorithm is used as the wrapper prediction model.

4.1.2. De-noising and outlier detection

Real-world applications of machine learning typically face the presence of noise and outliers in the input data (Chuang, Su, Jeng, & Hsiao, 2002). Noise and outliers are observations considerably different from the remainder of data. Noise can be caused by several reasons, typically derived from failures in collecting data, due to mechanical faults, human error or instrument error. Outliers can appear on the data due some abnormal situations, such as system behavior, fraudulent behavior or natural deviations in data population. Since these observations are inconsistent with the remainder of data, they may cause several damage in modeling data. In the financial context, the presence of noise and outliers can cause poor data modeling and lead to poor forecasting, consequently (Grané & Veiga, 2010).

In the literature, some authors have investigated how to filter noise from data, detect outliers and correct them as a preprocessing step in the financial context. Some work have used independent component analysis (ICA) to identify independent components of a data set which present normal behavior and filter then from noise (Dai, Wu, & Lu, 2012; Kao, Chiu, Lu, & Yang, 2013; Lu et al., 2009). Lu et al. (2009) proposed the use of nonlinear ICA (NICA) in combination with support vector regression (SVR) to predict stock prices. NICA is a variant of the ICA which assumes that data are a nonlinear combination of latent source signals, which are more suitable to financial data. Independent components that contain less informations about the main features of the original time series are considered noise and filtered from the data. Kao et al. (2013) proposed the use of NICA in combination with an SVR to predict stock prices. NICA is first applied to the data, in order to identify the independent components, and these components feed the SVR in order to predict the future stock prices. Dai et al. (2012) compared the performance of conventional ICA and NICA in combination with a multilayer perceptron (MLP) trained with backpropagation. Results showed that predictions that used NICA as a preprocessing step presented better results.

Wang et al. (2011) investigated how to improve the forecasting accuracy of an MLP by using the wavelet transform (WT) as a preprocessing mechanism. WT is a widely used method in signal analysis and applied to various fields. In that work, WT is used to remove noise from data before the learning process. An index closing price time series is decomposed using low-pass and high-pass filters. Data filtered by the low-pass filter represent the main data of the signal, whereas data filtered by the high-pass filter represent the noise. Then the low frequency data are used to train an MLP using the backpropagation algorithm. Lu (2010) compared the performance of ICA and WT in filtering input data from noise before modeling financial data. The comparison involved the following approaches: (i) ICA in combination with MLP, (ii) WT in combination with MLP, (iii) a single MLP and (iv) the random walk. Results showed a better accuracy of ICA + MLP followed by WT + MLP.

Grané and Veiga (2010) investigated the use of WT as an outlier detection and correction method. The proposed method can be applied to the residuals of different volatility models whose error may follow any known distribution. Authors tested the proposed method in several volatility models, such as GARCH and the autoregressive stochastic volatility model (ARSV), with errors following a Gaussian or a Student's *t* distribution. Grané and Veiga (2014) compared several techniques proposed in literature to minimize the effects of outliers in the context of risk measurement.

Ji-lin, Qin, Sai, and Yu-mei (2009) proposed a nonparametric outlier detection method based on Voronoi diagram. In the proposed approach, a Voronoi diagram is constructed for the dataset. Then, the Voronoi average distance, which measures the average distance for each point to its nearest neighbors in the diagram, is computed. The points with larger Voronoi average distance are considered outliers, since they differ significantly from the other points and can be eliminated from the input dataset.

4.1.3. Time series segmentation

Financial time series data comprise numerous historical data points, which are typically dynamic and nonlinear by nature. This characteristic makes harder the trend analysis task as well as the prediction of future values. A common technique used in the literature as a dimension reduction tool is the segmentation of the time series (Li et al., 2009; Yin, Si, & Gong, 2011). Segmentation is a preprocessing step usually used for representing the time series with less data, which allows the identification of technical patterns easier than by analyzing the whole data (Si & Yin, 2013).

Some common segmentation methods applied to financial time series are perceptually important points (PIP) and turning points (TP) identification. Both methods have been used to identify some significant points of a financial time series and they use these important points to represent the whole series without loss of information. This idea is based on the fact that fluctuations, trends and patterns within a time series are reflected by only a small number of data points, which themselves are able to preserve the overall shape of the time series (Si & Yin, 2013). By using just these important points, an intelligent system can model and predict the time series with less effort and improve accuracy.

In Si and Yin (2013), PIPs are selected from the original time series as follows. The first and last observations are defined as PIPs. The subsequent PIPs are iteratively computed as the point with maximum distance to the previously identified PIPs. Common distance metrics used are the Euclidean distance, perpendicular distance and vertical distance. Tsinaslanidis and Kugiumtzis (2014) proposed a forecasting method based on PIPs and dynamic time warping (DTW). PIPs are used to identify significant data points which are used to segment the series into different subsequences of data. DTW is then used to find similar historical subsequences and make predictions based on the manner that these best matches evolve in the past, believing that similar behaviors would happen in future.

Turning points are basically local minimum and maximum points on a time series, or in practical terms, the peaks and troughs (Li et al., 2009; Si & Yin, 2013). TPs can be considered landmarks in the time series and can be interpreted as events of great importance in the underlying process. TPs indicate the change of the financial time series during a period, which can be used to identify the beginning or end of a transaction period (Yin et al., 2011). Li et al. (2009) used an ensemble of ANNs trained with backpropagation to predict TPs from Dow Jones Industrial Average (DIJA). Croce and Haurin (2009) investigated how to predict TPs in the context of housing market by studying some leading indicators of changes in that market. Yin et al. (2011) used TP segmentation method to decompose financial time series in different levels of granularity. In the experiments, the proposed approach was compared with PIP strategy in terms of curve fitting and preservation of the original time series. Si and Yin (2013) proposed a method for identifying TPs which evaluates the degree of importance of each TP. This measure is computed based on the difference between the original series and the resulting series without a TP. In that primary study, TPs were stored in a binary search tree according to their degree of importance in order to allow the recovery of more important points with low cost.

4.1.4. Clustering

Clustering is an unsupervised learning method which is used in several application domains of pattern recognition and data mining. The aim of clustering techniques is to organize a set of items in groups such that items within a group present high similarity and items in different groups present high dissimilarity (Carvalho, Lechevallier, & De Melo, 2013). In the financial context, one important goal of clustering time series is to identify groups of stocks or exchange markets that exhibit similar behavior (Aghabozorgi & Teh, 2014). Co-movements in stock markets are very common, in which the movement of a stock market or index in a country is affected by the movement of stocks in another country. This can also happens in different but related market sectors. Grouping similar time series is very useful to help in predicting stock prices and make profitable investments.

Aghabozorgi and Teh (2014) proposed a clustering method which is able to identify time series that are similar in shape, even if they are dissimilar in time, i.e., they are co-moving but with some shifts or daily lead–lag relationships. The proposed cluster method operates in three phases. In the first step, time series are preprocessed, transformed in a low dimensional space and then grouped using the k-modes clustering method. In a second phase, the pre-clustered groups are refined in order to improve the initial cluster quality. Prototypes are chosen as best cluster representatives and similar time series are grouped using Euclidean distance based on similarity in time. In the third step, the produced subclusters are merged to construct the ultimate clusters. DTW metric is used to compute groups of time series which are similar in shape.

D'Urso, Cappelli, Di Lallo, and Massari (2013) investigated how to cluster financial time series using a fuzzy approach. Two different distance measures based on GARCH model were proposed in order to take account of non-stationarity, nonlinear relationship between subsequent observations of squared values and local volatility. The first distance measure used in the clustering algorithm is based on the autoregressive representation of the GARCH model. This distance metric computes the dissimilarity between each pair of time series by comparing autoregressive coefficients. The second distance measure proposed is based on a parametric approach that uses the information about the estimated GARCH parameters and their estimated covariances. The methods were applied to group Euro exchange rates against 29 other currencies, and experimental results showed that they were able to identify similar fluctuation in the volatility of daily returns and classify exchange rates according to their stability.

Zhou, Li, and Ma (2009) investigated how to cluster financial multivariate time series data. Financial data are typically represented as a multivariate time series composed by several technical indicators such as high price, low price, opening price, closing price, trade volume, trading amount, among others. In the proposed approach, Local Linear Embedding (LLE), a technique for local dimensionality reduction, was used to preprocessing the multivariate time series data. The k-means clustering algorithm is used to cluster the time series data modified by LLE.

Huang and Tsai (2009) were interested in creating a stock index predictor with high accuracy and low training time. That work combines self-organizing feature map (SOFM) technique with a filter-based feature selection method. In the proposed hybrid method, feature selector filters unimportant features, SOFM clusters the training samples into disjoint clusters, and several individual SVR models are applied to learn and predict each individual cluster.

A similar work was proposed by Hsu et al. (2009). In that work, the authors proposed a two-stage architecture to predict stock index time series composed by a self-organizing map (SOM) and SVR. In the first stage, SOM is used as a division function to decompose the financial heterogeneous data into homogeneous regions with similar statistical distributions, in order to capture nonstationary property of the data. In the second stage, an SVR model is used to learn and forecast data belonging to each homogeneous regions identified by SOM previously.

4.2. Forecasting models

Financial time series forecasting can be considered one of the main challenges of time series and machine learning literature (Tay & Cao, 2001). In the last decades, several approaches have been proposed in order to predict financial markets and to provide decision-making support systems (Teixeira & Oliveira, 2010). Soft computing techniques, such as expert systems, fuzzy systems and ANNs, have been applied with relative success in modeling and predicting financial time series (Lee, 2009). In contrast to traditional statistical forecasting methods, soft computing techniques are able to capture nonlinear relationship among relevant factors with no prior knowledge about the input data distribution (Atsalakis & Valavanis, 2009). In this section, we discuss the more common soft computing techniques applied in forecasting financial time series.

4.2.1. Artificial neural networks

In the last decades, ANNs have become very popular in the context of financial market forecasting. The main reason for the wide use of ANNs in these problems is because these mechanisms are able to handle data characterized by nonlinearities, discontinuities and high-frequency polynomial components (Liu & Wang, 2012). ANNs are data-driven and self-adaptive methods able to capture nonlinear behaviors of time series without any statistical assumptions about the data (Lu et al., 2009). Several kinds of ANNs proposed in literature were designed and applied in financial market forecasting.

According to Martinez et al. (2009), the majority of work which proposed the use of ANNs for solving the financial forecasting problem have used a multi-layer feed-forward neural network (MLP) trained with the backpropagation algorithm with great success. In that work, the authors used an MLP to learn the relationship among some technical indicators and to predict daily maximum and minimum stock prices. The predicted prices are used in a day trading system which negotiates in a real stock market. Dhar, Mukherjee, and Ghoshal (2010) used an MLP to predict one-step ahead closing stock index from Indian Stock Exchange. The MLP used in that work was a classical three-layer network trained with the backpropagation algorithm. The authors investigated several combinations of network parameters, namely the number of input neurons, hidden neurons and learning rate in order to find the best MLP configuration in terms of accuracy. Oliveira, Zarate, de Azevedo Reis, and Nobre (2011) used an MLP with three layers to predict stock prices of a Brazilian Oil Company. A version of the traditional backpropagation learning algorithm called resilient backprogation was used to train the MLP.

Jasemi, Kimiagari, and Memariani (2011) used an MLP to learn hidden patterns in Japanese candlestick charts. The focus was in discovering reversal signals in prices, which are indicated in candlestick analysis by some patterns on charts, such as morning stars, inverted hammer, harami, engulfing, among several others. These reversal signals represent buying or selling points according to candlestick analysis. Kayal (2010) investigated the use of MLP in forecasting the foreign exchange market (FOREX) by using some technical indicators, such as simple and exponential moving averages, RSI and the standard deviation from several different periods. Chen and Du (2009) used MLP to learn some financial ratios and balance sheets of companies in order to classify companies with financial distress. Vanstone, Finnie, and Hahn (2012) used an MLP to create an automatic stock trading system applied in Australian stock market. The MLP implemented used as input four variables arising from fundamental analysis: price earning ratio (PE), book value, return on equity (ROE) and dividend payout ratio. The MLP outputs a strength signal that represents the expect returns of the predicted stock, and it feeds a trading system which decides when to buy or sell the stock.

Despite all the advantages of MLP in forecasting financial time series, this model is high sensitive to several network parameters, such as input and output variables, neural architecture (feedforward or recurrent), number of hidden layers, number of hidden neurons, learning rate, transfer function, training algorithm, among others. To tackle this issue, Lasfer, El-Baz, and Zualkernan (2013) investigated the problem of choosing the best parameters for an MLP used to forecast financial time series. This investigation was done by developing numerous experiments and performing statistical analysis on these experiments. The goal of this analysis was finding which parameters more influence in forecasting accuracy, as well as, discovering the relationship among parameters.

Due to some of these issues, several variations of ANNs have been proposed and used in the financial context. Majhi, Panda, and Sahoo (2009) proposed the use of the functional link artificial neural network (FLANN) and the cascaded functional link artificial neural network (CFLANN) to predict exchange rates. These neural networks are more robust and present lower computational cost when compared with the MLP trained with the backpropagation. Mahdi, Hussain, and Al-Jumeily (2009) compared two variations of MLP, namely the self-organized MLP (SOMLP), which is an adaptive MLP, and FLANN with the conventional MLP. Results showed that highest profits were achieved by using FLANN and SOMLP in FOREX market. Ghazali, Jaafar Hussain, Mohd Nawi, and Mohamad (2009) also investigated the use of neural networks in the context of FOREX. In that work, they proposed a higher order neural network called dynamic ridge polynomial neural network (DRPNN). In a set of experiments, DRPNN showed better performance when compared with ridge polynomial neural network (RPNN) and with pi-sigma neural network (PSNN) for some currency pairs. Shahpazov, Velev, and Doukovska (2013) investigated three neural network models in order to predict some indices from Bulgarian stock market: (i) an MLP trained with backpropagation, (ii) a radial basis function (RBF) neural network with Gaussian radial function and (iii) the general regression neural network (GRNN).

Lu and Wu (2011) proposed the use of cerebellar model articulation controller neural network (CMCNN) scheme, which is a technique typically used in classification tasks. CMCNN is a supervised technique that uses the least mean squares algorithm for training. The authors compared the forecasting performance of CMCNN with SVR and with traditional MLP in forecasting stock indices. Results showed superior performance of CMCNN and shorter training time. González et al. (2011) proposed the use of a generalized feedforward neural network (GFNN) trained with backpropagation to learning the RSI of some stocks listed in the Spanish IBEX 35 stock market. The predicted RSI values are used in a trading system which advises when buy or sell stocks. Liu and Wang (2012) proposed the use of the Legendre neural network to predict stock indices. In that approach, historical data have different impact on predicting new values. A tendency function and a random Brownian volatility function were applied to describe the behavior of the time strength. Experimental results showed that the Legendre network in combination with those functions presented superior accuracy when compared with simple Legendre neural networks.

Ticknor (2013) proposed the use of Bayesian networks to predict stock prices. A Bayesian network is a kind of ANN in which the link weights are considered random variables and they density functions are written according to the Bayes rule. The adjustment of weights during the learning process consists of determining the probability density function for each weight. A three layered feedforward neural network is used in this paper to predict stock price movements. Nine technical indicators are used as input and the predicted next day stock price is the output. Tangent sigmoid function was used as hidden layer transfer function.

In a very recent work (Wang & Wang, 2015), authors proposed the use of stochastic time effective function neural networks (STNN) with PCA to forecast some stock indices, namely: Shanghai Stock Exchange Composite Index (SSE), Hong Kong Hang Seng 300 Index (HS300), Dow Jones Industrial Average Index (DJIA), and Standard & Poor's 500 Index (S&P500). The proposed method uses PCA to extract the principal components (PCs) from the input data. These PCs are used by an integrated model of MLP with backpropagation algorithm and stochastic time strength function to perform the forecasting. The stochastic process is based on a drift function and Brownian motion to compute the degree of impact of each time series, depending on their occurrence in time. The proposed method overperformed traditional MLP, PCA-MLP and single STNN.

4.2.2. Support vector machines

Despite the fact that ANNs have been widely used to forecasting financial time series, these approaches still present some limitations in learning patterns, mainly in the financial context, in which data are highly noise, non-stationary and with high dimensionality (Kara et al., 2011). SVMs are statistical intelligent learning methods that have been widely used as an alternative for ANN in pattern recognition tasks. SVM learning mechanism implements a risk function that considers the empirical error and a regularized term based on the structural risk minimization principle (Chen, 2010). SVM constructs a hyperplane as the decision surface such that the margin of separation between points in different classes is maximized. Decisions are made based on support vectors, which are data points that define the classification boundaries on the training set. In contrast with the empirical risk minimization principle, which tries to minimize the miss-classification error, the structural risk minimization principle implemented by SVM seeks to minimize an upper bound for the generalization error. According to Yuan (2013), the solution of SVM may be global optimum, while conventional ANNs tend to produce just local optimum solution.

Due to its strongly nonlinear approximation ability, SVM have been applied both in classification (SVC) and regression problems (SVR) (Guo-Qiang, 2011). In the financial forecasting field, several work have used SVR to predict stock prices, indices and exchange rates. In Chen (2010), the authors investigated how to predict stock indices by using SVR to learn the relationship among several technical indicators and the index price. The grid search method was used optimize the SVR model parameters. Guo-Qiang (2011) used particle swarm optimization (PSO) to optimize the parameters of the SVR in predicting stock closing prices of the third day ahead. Luo, Wu, and Yan (2010) used SVR in combination with traditional regression models and neural network models to predict stock indexes. Bao, Yang, Xiong, and Zhang (2011) used SVR to make multi-step-ahead forecasting of crude oil prices by using both recursive and direct strategy of multiple-step forecasting. Kara et al. (2011) compared several different MLP architectures with SVR using polynomial and radial basis function in predicting whether stock price index will increase or decrease.

An important issue in applying SVR to financial time series forecasting is that SVR learns data in a global fashion only. Due to this characteristic, SVR creates a fixed margin for all data points. To handle this issue, Yang et al. (2009) proposed an extension of SVR to capture local behaviors, called localized support vector regression (LSVR). LSVR is able to handle the local volatility of the data by adaptively and automatically setting a small margin in low-volatile regions and a large margin in high-volatile regions. The proposed LSVR model tries to learn a linear approximation function by making the function locally as nonvolatile as possible while keeping the error as small as possible.

Chao, Li-li, and Ting-ting (2012) combined wavelet analysis with SVR to forecast financial time series. In contrast to other work that used wavelet in data preprocessing, in this work, the authors used wavelet to build the SVR kernel. Wavelet mechanism performs a multi-resolution analysis of data, and it can easily extract information from this data. Three variations of wavelet were applied to build SVR kernel functions, namely Morlet wavelet, Gaussian wavelet and biorthogonal spline wavelet Bior(4,4). In the experiments, the authors compared the forecasting accuracy of the wavelet kernel SVMs with standard polynomial and Gaussian kernel SVRs. Results showed that the biorthogonal spline wavelet Bior(4,4) kernel SVR presented a better accuracy when compared with standard kernel functions.

In a recent work (Liang, Chen, He, & Chen, 2013), the authors took the Efficient Market Hypothesis (EMH) into consideration to build an intelligent approach to forecast financial markets. Since EMH claims that financial information plays a crucial role in affecting the volatility of the financial market, the authors used SVR to learn the relationship between web information and stock prices volatility. A daily web information time series was built by summing the sentiment values of the words in several published articles about some stock during the day. The SVR was used to build the mapping from web information time series to price values. Experimental results showed that the use of web information was effective in improving forecasting accuracy when compared with single SVR.

4.2.3. Hybrid mechanisms

In this paper, we have discussed several individual machine learning approaches which were employed in financial forecasting tasks which relative success. However, it is important to note that these individual approaches present some drawbacks, such as local optima, overfitting, the difficulty in choosing many parameters, among others, which directly affect forecasting accuracy (Gheyas & Smith, 2011). It is also important to highlight that the forecasting performance of these approaches sometimes vary when applied to time series data with different behaviors. Thus, it is not straightforward to decide which is the best configuration for each case. This definition depends on many factors, such as the nature of data and the adopted methodology (Evans et al., 2013).

In choosing a single intelligent approach to solve a learning problem, other mechanisms or different architectures of the same mechanism are discarded from the solution. To solve this issue, several researchers proposed the use of hybrid mechanisms, which combine individual solutions of different intelligent approaches (Tresp, 2001). The combination of individual approaches may allow the reduction of parameter adjustment uncertainties and stochasticity in training (Kourentzes, Barrow, & Crone, 2014). By facing the problem with dividing and conquer approach, two or more intelligent approaches may contribute with their individual knowledge to improve the forecasting performance of the whole group.

In the financial market forecasting literature, several approaches have implemented this idea of combining individual intelligent algorithms to improve the forecasting accuracy. Liang et al. (2009) proposed an hybrid approach to effectively forecast option prices. The proposed approach is a cascade method composed by a parametric and a nonparametric approaches. The parametric approach is first performed to model the trend of price movements. Next, the nonparametric approach is used to learn the residuals that result from the application of the parametric approach. The parametric methods investigated in that work were the Binomial tree method, the finite difference method and the Monte Carlo method. The nonparametric methods investigated were the linear neural network, MLP and SVR.

A similar work was proposed by Wu and Shahidehpour (2010). In this work, the authors investigated how to forecast a day-ahead electricity prices using a hybrid mechanism composed of three approaches. The first method used is the autoregressive moving average with exogenous variables (ARMAX) model, which is applied in modeling the linear relationship among historical price returns and other explanatory data. Subsequently, the GARCH model is used to identify heteroscedastic characteristics of the residuals from the ARMAX model. Finally, the adaptive wavelet neural network (AWNN) was applied to forecast the residuals from GARCH.

In Zhu and Wei (2013), a hybrid approach is used to forecast carbon prices. In that work, carbon prices are divided into a linear and a nonlinear component, and ARIMA and least squared support vector machine (LSSVM) models are used to learn and forecast these components, respectively. At the end, the forecasting values are integrated to build the overall output of the proposed mechanism. Nayak, Mishra, and Rath (2015) presented a hybrid model integrating SVM with K-nearest neighbor (KNN) approach for stock market indices prediction, focusing not only on predicting the closing price but also the trend, the volatility and the momentum of the stock market. Patel, Shah, Thakkar, and Kotecha (2015) proposed a two stage scheme to predict future values of stock market indices. In the first stage, support vector regression is used to prepare inputs for a prediction model in the second stage. An ANN, random forest and SVR were used in the second stage to predict future stock market values.

4.2.4. Optimization and forecasting

Some work have investigated the use of optimization algorithms in order to improve forecasting accuracy of some intelligent mechanisms. Brasileiro, Souza, Fernandes, and Oliveira (2013) proposed a hybrid method composed by artificial bee colony (ABC) optimization algorithm and the KNN algorithm. In that work, KNN was used to decide the best moment to buy or sell stocks. ABC is used to select the best time lags and to adjust KNN parameters. Hsieh, Hsiao, and Yeh (2012) investigated the use of evolutionary ABC (EABC) in combination with penalty guided support vector machine (PGSVM) to predict financial distress. In this approach, the EABC is used to optimize the parameters of PGSVM. Results showed superior accuracy of EABC-PGSVM when compared with MLP and classic SVM.

In Evans et al. (2013), a GA was used to search the best network topology of an MLP in order to improve the forecasting accuracy. Huang (2012) used GA to optimize the parameters of SVR and to select the inputs to the model. Pulido, Melin, and Castillo (2014) proposed the use of PSO to find the best architecture for an ensemble of MLPs. PSO is used to optimize several parameters of the ensemble, namely the number of individual MLPs which should compose the ensemble, and the parameters of individual MLPs, namely the number of hidden layers and number of neurons per layer. In this work, fuzzy logic was used to combine individual outputs of the individual models which compose the ensemble. Abdual-Salam, Abdul-Kader, and Abdel-Wahed (2010) compared differential evolution algorithm (DE) and PSO in optimizing an MLP architecture to forecast stock prices.

Pinto, Neves, and Horta (2015) proposed a multi-objective evolutionary system, using multi-objective genetic algorithm to optimize a set of trading or investment strategies (TSs), aiming predict the future trends in stock market. Majhi and Anish (2015) proposed two multi-objective Legendre polynomial based adaptive nonlinear (LPBAN) forecasting model with derivative free training scheme and fuzzy decision making rule.

4.2.5. Ensemble methods

In machine learning literature, several researchers have used a combination of individual learning models instead of using a single model. This strategy is called ensemble learning. The use of ensembles allows exploring additional information and the consensus among individuals that compose the ensemble with the goal of improving the generalization performance when compared with an individual learning method. Several ensemble techniques have been applied to solve financial market problems.

Neto, Tavares, Alves, Cavalcanti, and Ren (2010) investigated the usage of ensemble of MLPs and RBF networks. An important contribution of this work is the use of exogenous time series to improve the prediction of a stock time series of interest. The results showed that MLP committees presented better accuracy than RBF committees. Results also showed that the use of exogenous time series improved the accuracy of the used predictors. Cavalcante and Oliveira (2014) compared the use of ELM and OS-ELM ensembles in building an intelligent trading systems to autonomously negotiate in stock markets. Mabu, Obayashi, and Kuremoto (2015) propose the use of an ensemble learning mechanism that combines a rule-based evolutionary algorithm and MLP to make profit decisions in the stock market. In this approach, a genetic network programming creates stock rules and the MLP selects the best rules for operating in the stock market. Ballings, Poel, Hespeels, and Gryp (2015) provide a comparative study on evaluation performance of ensemble methods, namely the random forest, adaboost and kernel factory, against single classifier models, namely ANN, logistic regression, SVM and KNN, in predicting stock price movements. The obtained results showed that the ensemble methods outperform the single classifiers. Random forest provided the best overall performance followed by SVM.

4.2.6. Other forecasting approaches

Hafezi, Shahrabi, and Hadavandi (2015) proposed a multi-agent framework called bat-neural network multi-agent system (BNNMAS) to deal with the distributed nature stock prediction problem, focusing on fundamental and technical analysis to improve the accuracy of long term prediction. Preprocessing functions such as data normalization, time lag selection and feature selection are distributed and executed in parallel by the agents on the system. An ANN trained with the bat algorithm, which is a training heuristic for optimizing the neural network weights, is used as forecasting method. Experiments demonstrated that BNNMAS outperform some models such as genetic algorithm neural network (GANN) and some standard models like GRNN.

Hu, Feng, Zhang, Ngai, and Liu (2015) proposed a hybrid evolutionary method that combines trend following (TF) investment strategies with the eXtended Classifier Systems (XCS) as an evolutionary learning method. This method, called eTrend is able to operate both long-term and short-term investment horizons. The XCS allow the discover of many valuable trading rules at runtime. This online rule discovery makes this approach more robust, since it is able to automatically adapt itself to market directions and uncover reasonable and understandable trading rules, avoiding irrational trading behaviors of common investors. The analysis of the computational experiment results revealed that eTrend outperforms the buy-and-hold strategy, decision tree and ANN forecasting methods.

4.3. Text mining and forecasting mechanisms

As discussed previously, technical analysts approach the financial market by studying several historical technical indices, believing that past market behaviors tend to repeat itself in the future. The majority of computational intelligent mechanisms proposed in the literature have used technical indices in order to learn a model of market behavior and to predict future movements. Schumaker et al. (2012) put forward an important question: “does price history matter?”. Supported by the EMH, which claims that only new information is able to change price movements, some work in the literature investigated the use of qualitative information in modeling financial markets. With this in mind, some researchers have applied text mining mechanisms to analyze and classify financial news according to their content, in order to help in predicting future behavior of a financial asset based on how good or bad is news related to it. Nikfarjam et al. (2010) claim that news are one of the most influential sources that affect financial markets. In that study, the authors surveyed the process of mining financial news.

Wang et al. (2012) proposed the use of sentiment analysis to improve the accuracy of financial time series forecasting. In that work, textual data are represented as feature vectors by using the bag-of-words approach, a widely used text mining technique. The data are organized as a time series and a hybrid model of ARIMA and SVR is used to model and forecast this series. The ARIMA model is used to fit the linear component of the time series and SVR is used to fit the nonlinear component. The authors tested the proposed algorithm in the quarterly ROE time series of six security companies. The results were compared with the use of simple ARIMA and hybrid ARIMA and SVR applied solely to the quantitative data. Results showed that the use of market sentiment improved the forecasting accuracy of the ARIMA and SVR predictor.

Schumaker et al. (2012) claimed that it is a naive strategy executing trades based only on history prices especially after unfavorable news events are published. Differently from other financial sentiment analysis approaches, this work focus on evaluating intricacies of news sentiment, the author tone and on whether subjectivity impact the stock prediction. Authors compared the predictability of the stock market when the input articles are modeled in three different ways: (i) just the proper nouns of the news article and the price of the stock at the time the article was released; (ii) the sentiment classification of the article features as objective, subjective and neutral (tone); and (iii) the subjective classification of the features of the article as positive, negative and neutral (polarity).

Ruiz et al. (2012) investigated the correlation between the activity on Twitter and financial time series, with the goal of verifying if published tweets can influence stock price movements or volume. 150 companies listed in the S&P 500 index were analyzed and tweets related to these companies were filtered in the first half of 2010. Each collection of tweets from a company were represented as a graph containing some features and the relationship among these features. Tweets were timestamped, in order to allow the analysis together with time series data. Some features were extracted from these graphs, such as the number of hashtags, the number of tweets, number of users (activity-based features) and link-structure of the graphs (graph-based features). These features were used to analyze the correlation of the tweets and the time series of a stock in terms of closing prices and trading volume. Cross-correlation coefficient was used to estimate the relation between variables at different time lags. Results showed that the trade volume of a stock was correlated with the number of connected components in the graph of that stock and with the number of tweets in the graph. However, the authors found that the price of a stock are weakly correlated with the analyzed features.

The work developed by Groth and Muntermann (2011) was motivated by the theory which claims that unstructured (textual) data represents a valuable source of information in the context of financial risk management. The authors aimed to find news that are highly associated with intraday market risks. The dataset used in this study was a collection of corporate disclosure news, which were empirically considered related with abnormal price reactions. In that work, the use of a text mining approach was proposed in order to identify published news of corporate disclosures which cause abnormal volatility levels. These abnormal volatility levels represent potential source of market risks. Four classifiers were implemented in that work, namely naive Bayes, KNN, MLP and SVM, in order to classify unseen news as positive or negative corporation disclosures. Experimental results showed that SVM outperformed the other classifiers in terms of accuracy, precision and recall.

Gunduz and Cataltepe (2015) proposed a forecasting method which combines the analysis of news articles and stock prices to predict future market movements. In this approach, text mining techniques specific for Turkish language were used to transform news articles obtained in finance websites into feature vectors. Since these vectors are composed by thousands of features, a feature selection method called balanced mutual information (BMI) was used to identify the more relevant features to determine the market direction. A naive Bayes algorithm is then used to model the feature vectors and stock prices, and to predict the future market movements.

Nassirtoussi, Aghabozorgi, Wah, and Ngo (2015) proposed an approach to predict intraday directional-movements of a currency-pair in the FOREX market based on text mining of financial news-headlines. In this work, authors proposed a three-layered text mining approach that performs (i) semantic analysis of the news terms, (ii) sentiment analysis to identify investors sentiment about the market and (iii) a dimension reduction of the extracted news features. This third layer is designed to deal with a stream of text, and it updates the models with the most recent information available, being robust to concept changes in the market behavior.

5. Discussion

In this work, we surveyed several machine learning methods applied to solve financial market problems. We started the discussion with two main approaches used to analyze financial markets: the fundamental and technical analyzes. Fundamental analysis models the market as a set of quantitative and qualitative variables that describe political and economical factors which are intrinsic to a company, to a market segment or to the whole economy. Fundamentalists believe that stock prices or indices are directly related to the size of a firm, the volume of sales, market strategy, among others. Technicians, on the other hand, believe that just historical prices, volume of transactions and some artificial technical indicators derived from the prices are relevant in forecasting future market behaviors. In the literature, there is no consensus on which of these two analyzes are most prominent. Both have been used to analyze the market with relative success.

The discussion follows with a description of the advantages of using machine learning techniques in mining financial data instead of the traditional statistical approach. The complex, noisy and chaotic nature of financial data require non-parametric methods which are free from statistical assumption about the data. However, despite this main advantage of soft computing mechanisms, the traditional statistical methods were not entirely discarded from the set of effective solutions. Methods such as ARIMA and GARCH have been used in combination with intelligent methods in order to model linear components or residuals of financial time series and to improve the forecasting.

The main goal of the majority of work proposed in literature is forecasting the future behaviors of the market with maximum accuracy possible. These predicted future movements can be used to support decisions on buying or selling financial assets in order to maximize investors profit. However, it is important to note that, to the best of our knowledge, there is no well established methodology to guide the construction of a successful intelligent trading system. Some work propose an intelligent forecasting mechanism but the majority of them provide no rules to negotiate in the market or even to manage investment risks. The profit evaluation of the proposed methods when used in real-world applications are generally neglected. To solve this lack, in this paper we proposed the main steps in building and evaluating an intelligent trading system (see Fig. 3).

In this work, we examined several primary studies which proposed the use of intelligent and expert system applied to the financial context. We classified the selected primary studies according to five important attributes: (i) the main goal of the research; (ii) the financial application investigated; (iii) the input variables used; (iv) the intelligent techniques proposed and (v) whether the work propose some kind of trading system.

Table 1 summarizes the primary studies surveyed. In this table, the reader can observe that the majority of investigated approaches focus on forecasting future behavior of a financial market. However, some work have also focused on segmentation, outlier detection, clustering, among other objectives. Table 1 also shows that the forecasting of stock prices and indices are the most financial applications investigated in literature, but applications such as exchange rates prediction and financial distress prediction have also been investigated. Commodity prices, such as carbon and crude oil, as well as electricity prices have been investigated by a few primary studies.

Table 1 also shows that technical analysis is the most used approach in the study of financial markets in the surveyed papers. This is due to the fact that technical analysis works directly with quantitative, objective attributes of the market, which are in numerical format. This makes easier the modeling of market behaviors with computational intelligence approaches. Fundamentalists have to handle qualitative, subjective data related with macro and microeconomic, which may difficult the modeling of market behavior. However, despite some additional difficulties, some primary studies have investigated the use of web news, tweets, financial reports and other inputs presented in textual format, considering the sentiment of authors as a relevant feature. These researches typically investigate the use of text mining mechanisms to extract useful information from these data. The important features of the texts are generally modeled as a time series and used to train a forecaster method.

The last column of the table reinforces our argument which states the need of the last step of our proposed financial forecasting methodology: the money evaluation. The majority of investigated primary studies provide no profit evaluation in their proposed forecasting approaches. This last step is important in the sense of giving some empirical guarantee that the proposed method can be used in real-world. Without this evaluation step, investors, students and other practitioners cannot completely trust on these proposed mechanisms.

Fig. 4 shows a correlation wheel, a graphical tool which shows the co-occurrence of some concepts in a graphical way. This figure shows the correlations of the main concepts present in Table 1, which means the co-occurrence of these concepts in the primary studies surveyed. The main goals of the primary studies investigated in this paper are illustrated in violet color. Applications are in red color. Input variables are in green. The intelligent methods are in orange. In this figure, it can be seen that these concepts are highly correlated. It is worth mentioning that "forecasting",

Table 1
Summary of primary studies.

Article	Main goal	Application	Input variables	Techniques	Trading system
Ghazali et al. (2009)	Forecasting	Exchange rates	Technical	DRPNN	No
Hsu et al. (2009)	Forecasting	Stock indices	Technical	SOM and SVR	No
Huang and Tsai (2009)	Feature selection and clustering	Index futures	Technical	SOM and SVR	No
Ji-lin et al. (2009)	Outlier detection	Stock prices	Technical	Voronoi diagram	No
Lee (2009)	Feature selection	Stock index	Technical	F-score, SVM, MLP	No
Li et al. (2009)	Segmentation	Stock prices and indices	Technical	Turning points, MLP ensemble, GA	Yes
Liang et al. (2009)	Forecasting	Option price	Technical	MLP and SVR	No
Lu et al. (2009)	De-noising	Stock indices	Technical	ICA and SVR	No
Mahdi et al. (2009)	Forecasting	Exchange rates	Technical	SOMLP, FLANN and MLP	Yes
Majhi et al. (2009)	Forecasting	Exchange rates	Technical	FLANN and CFLANN	No
Martinez et al. (2009)	Forecasting	Stock prices	Technical	MLP	Yes
Yang et al. (2009)	Forecasting	Stock indices	Technical	LSVR	No
Zhou et al. (2009)	Clustering	Stock prices	Technical	LLE, k-Means	No
Chen (2010)	Forecasting	Stock indices	Technical	SVM	No
Dhar et al. (2010)	Forecasting	Stock indices	Technical	MLP	No
Grané and Veiga (2010)	Outlier detection	Stock indices	Technical	Wavalet, GARCH and ARSV	No
Kayal (2010)	Forecasting	Exchange rates	Technical	MLP	No
Lu (2010)	De-noising	Stock indices	Technical	ICA, WT and MLP	No
Neto et al. (2010)	Forecasting	Stock prices	Technical	MLP, RBF, committees	No
Abdual-Salam et al. (2010)	Forecasting	Stock prices	Technical	DE, PSO and MLP	No
Teixeira and Oliveira (2010)	Forecasting	Stock prices	Technical	kNN	Yes
Tsai and Hsiao (2010)	Feature selection	Stock prices	Fundamental	PCA, GA, MLP Decision trees	No
Vanstone and Finnie (2010)	Forecasting	Stock indices	Technical	MLP	Yes
Wu and Shahidehpour (2010)	Forecasting	Electricity prices	Technical	ARMAX, GARCH, AWNN	No
Bao et al. (2011)	Forecasting	Crude oil prices	Technical	SVR	No
González et al. (2011)	Forecasting	Stock indices	Technical	GFNN	Yes
Groth and Muntermann (2011)	Forecasting	Market risk	Financial news	Naive Bayes, kNN MLP and SVM	No
Jasemi et al. (2011)	Forecasting	Stock prices	Technical (charts)	MLP	No
Kara et al. (2011)	Forecasting	Stock indices	Technical	MLP and SVM	No
Oliveira et al. (2011)	Forecasting	Stock prices	Technical	MLP	No
Wang et al. (2011)	Feature selection	Stock indices	Technical	WT, MLP	No
Yin et al. (2011)	Segmentation	Stock prices	Technical	Turning points	No
Chao et al. (2012)	Forecasting	Stock index	Technical	SVM with wavelet kernel	No
Dai et al. (2012)	De-noising	Stock indices	Technical	LICA, NLICA and MLP	No
Hsieh et al. (2012)	Forecasting	Financial distress	Fundamental	PGSVM and EABC	No
Huang (2012)	Forecasting	Stock prices	Fundamental	GA and SVR	Yes
Liu and Wang (2012)	Forecasting	Stock indices	Technical	Legendre neural network	No
Ruiz et al. (2012)	Forecasting	Stock prices	Tweets and technical	Text mining and auto-regression	Yes
Schumaker et al. (2012)	Forecasting	Stock prices	Financial news	Sentiment analysis and SVR	No
Vanstone et al. (2012)	Forecasting	Stock prices	Fundamental	MLP	Yes
Brasileiro et al. (2013)	Feature selection	Stock prices	Technical	ABC and kNN	Yes
Wang et al. (2012)	Forecasting	Stock prices	Financial reports	ARIMA, SVR and sentiment analysis	No No
Evans et al. (2013)	Forecasting	Exchange rates	Technical	MLP, GA	Yes
Kao et al. (2013)	De-noising	Stock prices and indices	Technical	NICA and SVR	No
Liang et al. (2013)	Forecasting	Stock indices	Web information	Text mining, SVR	No
Lasfer et al. (2013)	Forecasting	Stock indices	Technical	MLP	No
Ticknor (2013)	Forecasting	Stock prices	Technical	Bayesian neural network	No
Shahpazov et al. (2013)	Forecasting	Stock indices	Technical	MLP, RBF, GRNN	No
D'Urso et al. (2013)	Clustering	Exchange rates	Technical	GARCH, fuzzy clustering	No
Si and Yin (2013)	Segmentation	Stock indices	Technical	Turning points	No
Zhu and Wei (2013)	Forecasting	Carbon price	Technical	LSSVM, ARIMA and PSO	No
Lin et al. (2014)	Feature selection	Financial distress	Fundamental	GA, SVM	No
Cheng and Wei (2014)	Forecasting	Stock prices	Technical	EMD and SVR	No
Grané and Veiga (2014)	Outlier detection	Stock indices	Technical	WT, GARCH	No
Tsinaslanidis and Kugiumtzis (2014)	Segmentation	Stock prices and exchange rates	Technical	PIP, DTW	No
Aghabozorgi and Teh (2014)	Clustering	Stock prices	Technical	K-Modes and DTW	No

"technical" and "MLP" concepts co-occur several times in combination with other concepts on primary studies.

6. Challenges and future directions

Over the past decades, there has been a growing interest in designing soft computing mechanisms for the analysis and forecasting of several financial market segments, such as exchange rates, stock prices, commodities prices, financial distress prediction, among others. However, despite the fact that this is not a new research area, several challenges remain as open problems in this literature. In this section we discuss some of these challenges.

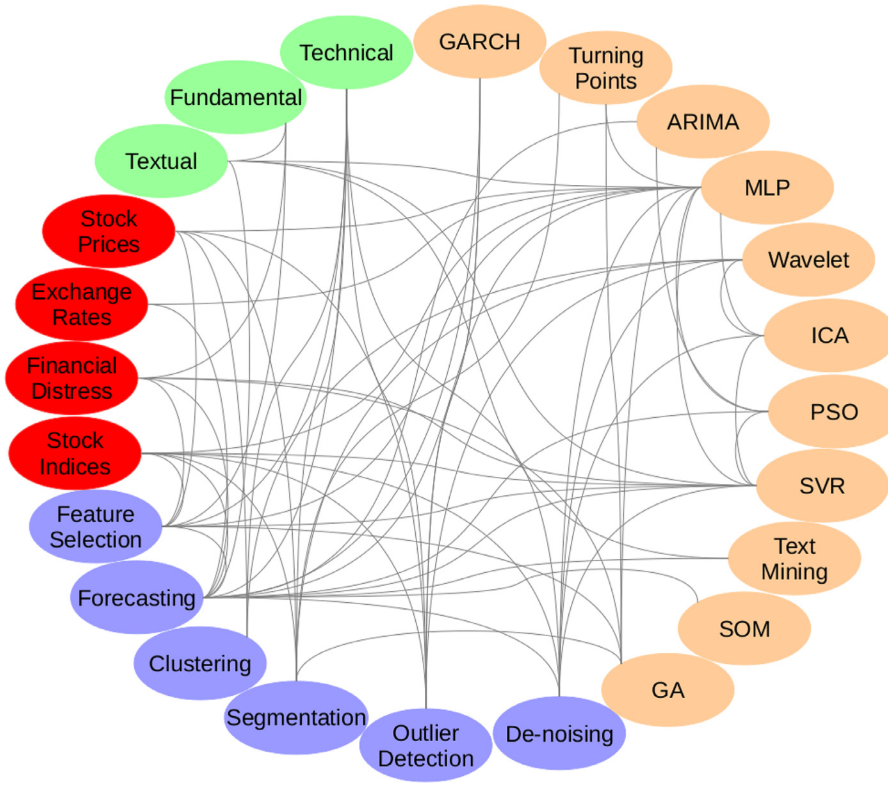

Fig. 4. Correlation wheel for the main concepts in primary studies applied to financial markets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6.1. Deep learning and financial markets

Recently, the attention of the machine learning and pattern recognition communities has been devoted to applying different methods to hierarchically learn useful features from a large amount of data (Bengio, Courville, & Vincent, 2013). The main goal of these approaches is to model complex real-world data by extracting robust features that capture the relevant information (Hinton, Osindero, & Teh, 2006). The extraction and recognition of the patterns occur through a deep nonlinear network topology, in which the layers of feature representations can be stacked to create deep networks capable of modeling complex structures in the data (Le Roux & Bengio, 2008). The deep learning approach has been successfully applied to tasks such as classification (Lee, Grosse, Ranganath, & Ng, 2009), speech recognition (Zhang & Wu, 2013) and dimensionality reduction (Hinton & Salakhutdinov, 2006). The mainstream deep machine learning approaches include convolutional neural networks (Krizhevsky, Sutskever, & Hinton, 2012), deep belief networks (Hinton et al., 2006) and stacked auto-encoders (Vincent, Larochelle, Bengio, & Manzagol, 2008).

However, the application of deep leaning methods to the field of financial forecasting remains a relatively unexplored area. The main challenge here is to investigate if deep architectures can be adapted to enhance trading patterns recognition and decrease the overall risk for trading strategies. A relevant work on deep learning applied to finance was proposed by Yoshihara, Fujikawa, Seki, and Uehara (2014) where the combination of Restricted Boltzmann Machine and deep belief network was applied for dealing with the temporal effects in market data. This work proposed an approach to predict the trend of stock prices from Nikkei Stock Exchange by focusing on news events with long-term effects. The same problem was approached in Ding, Zhang, Liu, and Duan (2015), where a combination of neural tensor network and a deep convolutional neural network was presented to model both short-term and long-term influences of events on stock price movements. Recently, a novel method for forecasting exchange rates was proposed in Shen, Chao, and Zhao (2015) by combining an improved deep belief network and a conjugate gradient method. In that work, a comparison with traditional feedforward neural network was performed and the results showed that the deep learning approach outperforms the traditional methods.

The main challenge to apply deep learning methods for financial forecasting is the modeling of complex, high-dimensional, and noisy real-world time series through a deep representation of the data. Some approaches to deep learning on tasks such as time series modeling are presented in Kuremoto, Kimura, Kobayashi, and Obayashi (2014), where a predictor is constructed by a deep belief network with two Restricted Boltzmann Machines. This approach was evaluated by the modeling of chaotic time series and the prediction results showed that the proposed method provided higher forecasting precision when compared with MLP and ARIMA. In general, an important contribution and future direction for the field of financial time series forecasting is to investigate if stacked structures can be applied to capture trading patterns in raw data.

The problem of deep representations for time series is similar to the unsupervised feature learning for static data. In Längkvist, Karlsson, and Loutfi (2014), some relevant methods for feature learning in deep networks were reviewed and their application for time series domain was investigated. Despite the fact that unsupervised feature learning has been successfully applied in tasks such as computer vision, its application for financial data is not prevalent in the literature. The main challenge here is to apply dimensionality reduction techniques with no losses of valuable information. Thus, the feature learning methods for financial time series have to be adapted in order to adjust the temporal information generated by the financial markets. Since additional information from sources that affect the stock market can be obtained and disposed into hierarchical layers, a future direction for time series prediction is the application of deep learning methods to learn features that related just at some past values of the stock itself. A similar approach is presented in Qiu, Zhang, Ren, Suganthan, and Amaratunga (2015), where an ensemble of deep belief network combined with support vector regression was applied in benchmark datasets for time series forecasting. Since this method has not been applied directly to financial data, a future direction for research is to investigate if the aggregate output of different deep structures, such as deep belief networks or stacked auto-encoders, can be used to improve the forecast precision.

6.2. Portfolio management

The application of machine learning methods for financial market have been closely tied up with the task of predicting values for financial assets. However, the use of these methods for portfolio management has attracted the attention of the machine learning community. Typically, the portfolios are constructed via taking expected stock returns and then applying some optimization process (Irlicht, 2014), such as proposed in the classical work of Markowitz (1952), or by estimating regression coefficients using earnings expectations data, price momentum variables, and reported financial data (Guerard, Markowitz, & Xu, 2015). When considering machine learning for portfolio management, one can refer to the use of association rule mining and fuzzy logic in order to build a list of recommended assets (Paranjape-Voditel & Deshpande, 2013). Furthermore, fuzzy logic can be combined with technical indicators to support portfolio construction decisions (Yunusoglu & Selim, 2013). Despite the use of association and fuzzy rule based models, there are other methods employed in portfolio applications. In Liao and Chou (2013), data mining techniques are combined with association rules and clustering analysis in order to investigate the co-movement of financial markets and the resulting model is used for portfolio recommendation. The work presented in Chourmouziadis and Chatzoglou (2016) highlights an intelligent short term stock trading fuzzy system for portfolio management, in which soft computing techniques are combined with technical indicators for the selection of a set of assets. A challenge and future direction in portfolio management research is to investigate the use of novel machine learning methods for optimal assets selection, including the combination of time series forecasting with sequential learning, as early proposed in Chapados and Bengio (2001).

6.3. Concept drift and financial markets

The majority of the primary studies discussed in this paper which are based on technical analysis typically model the technical indices as a historical time series. By using time series as an abstraction of the complexity of a market, several researches try to build a computational model from the past experience of what has been observed in that market. In practical terms, the goal of these approaches is to learn a regression model from the historic time series data in order to forecast future values.

However, despite the fact that there is a vast literature on time series analysis, the majority of the existing approaches does not take into consideration that a financial time series is a special kind of data stream (Cavalcante & Oliveira, 2015). Most of these researches are based on the assumption that time series concepts are stationary in such a way that the time series observations follow a fixed and immutable probability distribution. This assumption, however, may not hold for several financial time series. For example, the time series of stock prices of a company may change its behavior due to changes in political and economical factors or due to changes in the investors psychology or expectations; the time series of a currency exchange pair may change due to changes in government exchange rates policy.

As a special case of data stream, financial time series frequently have concept drift. Concept drift consists in a change in the relation between input data and the target variable over time (Gama, Žliobaitė, Bifet, Pechenizkiy, & Bouchachia, 2014). This evolution imposes a big challenge to traditional batch learning algorithms, since the model learned from the data can become obsolete. There is a very high risk involved in using an outdated prediction model in financial markets, which can cause financial damage. However, just a few researches have investigated the concept drift problem in financial time series and how to handle it in order to keep the learned model up-to-date and able to make accurate predictions during its operation.

Concept drift has been widely studied in classification problems (Gama, 2012). The methods proposed for handling concept drift can be divided into two main groups: (1) implicit or blinding methods and (2) explicit detection methods. Implicit methods are those that update the decision model in regular intervals, independent of the occurrence of concept drifts. The main issue with these approaches is that they are not transparent to the user, since they work as a black-box. According to Zliobaite et al. (2012), real-world applications require reliable and transparent methods to the user. Informing the user when a concept drift occurs may increase the trust in the prediction process, mainly in financial market applications.

In a very recent work, Cavalcante and Oliveira (2015) investigated the concept drift effects in financial time series prediction. Two explicit drift detection tests originally proposed for classification problems were adapted to handle the financial time series forecasting problem. These tests were combined with a batch learning algorithm to build an adaptive learning system. When the concept drift test detects a concept drift, the batch decision model is retrained with the time series observations which belong to the new concept. The experimental results of that work showed that the proposed adaptive forecasting method which considers concept drift improved the forecasting of financial time series.

An interesting way to go further in this research branch is the investigation of intelligent trading systems that combine explicit drift detection, adaptive learning systems and trading rules for automatic negotiation. These trading rules should take concept drifts into consideration during the real-world negotiation in order to avoid extra risks due to periods of concept changes.

7. Conclusions

This work presented a review of computational intelligence techniques proposed to solve financial market problems. This survey covered primary studies proposed from 2009 to present. Papers dealing with preprocessing and clustering of financial data, forecasting future movements and mining financial information have been investigated and discussed in this work.

The first main contribution of this work is a review of the recent literature of this topic. Despite the fact that other reviews have been published recently, they differ from this work in scope or in the covered primary studies investigated. The results of the discussion provided in this paper were summarized in a table that classifies the main primary studies according to several perspectives, namely: (i) the main goal of the primary study, (ii) the main application of the proposed intelligent, (iii) the input variables analyzed, (iv) the intelligent techniques used to solve the problem and (v) whether the work proposed a trading system. A figure also illustrated the co-occurrence of main topics in the primary studies reviewed.

A second important contribution of this work was a discussion of basic concepts of this topic. An intelligent methodology which summarizes the main steps for building an intelligent trading system was illustrated and discussed. This methodology can be useful to guide students, investors and practitioners in building an inteligent financial forecasting method.

The third main contribution of the present research was the discussion about the main challenges and future directions of this research area. A discussion of open problems and opportunities of the application of computational intelligence to solve financial problems was provided, which may be very useful for the expert systems literature.

Acknowledgments

This work was supported by the National Institute of Science and Technology for Software Engineering (INES[1]), funded by CNPq and FACEPE, grants 573964/2008-4 and APQ-1037-1.03/08, and CNPq (Brazilian Council for Scientific and Technological Development), grant 484164/2013-9.

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