A COLLABORATIVE TRADING MODEL BY SUPPORT VECTOR REGRESSION AND TS FUZZY RULE FOR DAILY STOCK TURNING POINTS DETECTION

JHENG-LONG WU, PEI-CHANN CHANG, KAI-TING CHANG
Department of Information Management,
Yuan Ze University,
Taoyuan, Taiwan
jlwu.yzu@gmail.com
iepchang@saturn.yzu.edu.tw
caty.kaiting@gmail.com

LI ZHANG
Research Center of Machine Learning and Data Analysis, School of Computer Scienceand Technology, Soochow University, Suzhou 215006, Jiangsu, China
zhangliml@suda.edu.cn

ABSTRACT
The daily stock turning point detection problems are investigated in this study. The Support Vector Regression model has been applied in various forecasting applications and proved to be with stable performances. In this research, SVR has been used to predict the trading signal since it could handle overall information effectively even under the complex environment of stock price variations. The trading signals from the historic database is derived from the application of piecewise linear representation of stock price. Therefore, the temporary bottoms and peaks of stock price within the studied period are identified by PLR. TS fuzzy rules were applied to calculate the dynamic threshold which intersects the trading signal and provides the trading points. The fuzzy rules were trained and obtained from the trading signals generated by PLR during the training period. A collaborative trading model of SVR and TS fuzzy rule is used to detect the trading points for various stocks of Taiwanese and America under different trend tendencies. The experimental results show our system is more profitable and can be implemented in real time trading system.

KEY WORDS
Support vector regression, Stock forecasting, turning point detection, TS fuzzy rule.

1. INTRODUCTION

One of the important issues for forecasting market trend is to detect a turning point when the stock prices go through the up/down cycle. The turning point can be applied to make trading decisions in stock investment. In the real world, the turning point detection is very complex since there are lots of factors affecting the movement of the stock price. The stock price variations are even under a high level of noisiness influence. These factors include interest rates, economic environment and so on. Owing to the development in Computational Intelligence tools, a collaborative model can be developed to predict or detect the turning points based on these factors and thus making profitable trading for investors.

In recent years many researches consistently achieve returns since they used forecasting approach in Computational Intelligence tools to reduce investment risk under historic information of stock market [1][2]. In the financial market technical index have been applied to explain the stock price variation and even used to detect turning point for stock trading such as William Index or Relative Strength Index… etc. In traditional forecasting, financial researches usually use mathematic model to predict stock trend or price, but the stock price was quickly changed in a very short time therefore these models cannot immediate adjusts to these dynamic changes. A piecewise Linear Representation too has been applied to decompose a historic stock price data into a series of bottom and peak points. Neural networks are further applied to learn the hidden knowledge among the turning points and the technical indexes. The model has achieved a consistent profit over other traditional approaches as reported in [2].

The collaborative model development in machine learning has provided new approaches for predication such as artificial neural network, fuzzy system, support vector machine and other artificial Intelligence. Among these, support vector machine (SVMs) outperform other approaches in more researches machine has shown better performances than others as in application areas such as [1] [2] [3]. The support vector regression (SVR) is a regression-based model based on support vector machine that SVR model has high toleration error rate and high accuracy in complex problems. The fuzzy system has been considered as an efficient and effective in control uncertainties of systems [4], by using fuzzy rule based system could prove stabile signal for predicting dynamic trading threshold in stock market. The main purposes of this research are:

1*) Develop a Collaborative Trading Model for Daily Stock Turning Points Detection:* Apply machine learning approaches that combine support vector regression and TS fuzzy rule for learning trading signal and dynamic trading threshold, respectively.

2*) Providing investor simple trading derisions:* according to collaborative trading model to generate trading decisions, i.e., buy/sell/hold under daily basis.

2. LITERATURE REVIEW

In past years according to most studies shows that financial time series forecasting usually focus on fundamental or technical analysis. Fundamental analysis could forecast the long term of trade in stock market which may only trade once a year. Therefore, the technical analysis is applied to further improve the long term analysis. Technical indices could provide the trade information in short or medium term. Technical indices of stock are very common applied in financial analysis. An intelligence stock trading system [5] is developed according to these Technical indices and probabilistic reasoning to forecast trading points. The conventional approach to modeling stock market forecasting is using the univariate time series and they include multiple regression, autoregressive (AR), moving average (MA), GARCH and ARIMA [6] models. A strong trading signal detection method must consider not only stock price variations, but also other information that can help investor. As this section describes, these models can help solve the trading signal problem. However, these models require complex mathematical formulas which are not that easy to be understood by the investors. Therefore, it seems there should be another way to solve this problem more efficiently.

A. Computer-Based Approach for Financial Forecasting

The stock market forecasting was very complex that explanation in previous part, recent years the financial time series forecasting appear more new approaches which they are computer-based to learning knowledge in pattern recognition task. The turning point on time series data has more approach to found such as Fourier transforms, Wavelets, and piecewise linear representation (PLR) method on time series database that PLR has been used to support more tasks and it has efficient and effective solutions [7]. The major functions that using some of piecewise to represent various trends. PLR has been applied to stock market for stock price forecasting, the result shows used PLR could improve forecast accuracy [8]. Therefore PLR method used to find turning points that there are promise high profit.

B. Support Vector Regression

Machine learning techniques have been applied for assigning trading signal. Many studies used support vector machine for determining whether a case contain particular class [1] [2] [9] [10]. But the shortcoming is only deal with discrete class labels, whereas trading signal is continuum because a weight of signal can take a buy or sell power. Grounded in Statistical Learning Theory [11], support vector regression is capable to predicting continuous trading signal while still benefiting from the robustness of SVM. SVM have been successfully employed to solve forecasting problems in many fields, such as financial time series forecasting [12], emotion computation [13] and so on. There are still some significant parameters (C,ε,σ) in empirical results and the value is given by experiment in this research. SVM apply in financial time series that it only focused on price or trend to forecasting that cannot direct to transaction in stock market. Therefore, we build a signal for transaction which it call trading signal that the value range from zero to one for decision making.

C. Fuzzy Rule-based System

Fuzzy systems are from fuzzy theory for variables with inference have fuzzy logic and fuzzy set, fuzzy control, fuzzy relation and fuzzy measure [4]. The rule based fuzzy systems are widely application that using fuzzy if-then rule described complex problem. The W-M and TS fuzzy are based on fuzzy if-then rule to propose. W-M has been improved [14] to solve several different problems. The TS fuzzy rule model that uses multiple sub linear system based on fuzzy membership for solved nonlinear problem in control systems [15]. The TS fuzzy system has extends to used simple linear approach of regression for solve complex problem of stock.

3. CTM－A COLLABORATIVE TRADING MODEL BY SUPPORT VECTOR REGRESSION AND TS FUZZY RULE

This paper attempts to build a collaborative trading model to detect daily turning points for stock trading. The system of collaborative trading model developed from SVR and TS-fuzzy rule approach to learning overall trading signal knowledge (all trading signal include buy-sell and holding point) and dynamic trading threshold knowledge (only buy-sell points). CTM goes through five steps, as shown in Fig. 1.

A. Step1: Determining Turning point and Trading Signal

Traditionally, investors have studied the variation in technical indices to make their trading decision. However, it is not easy for every investor to make a good trading decision by studying the variation in technical index.

1) Mining trading point by PLR:

In this paper, we want to use piecewise linear representation method to find turning point with time series data that find the low and high point for next learning model. The steps of PLR are as follows:

First find the points of being (p_1) and end (p_n) on a term of closing prices in ascending order of the dates. Second find a point (p_k) has longest distance with the straight line that between two points of previously found. The k point is a new turning point form two segments of p_1 to p_k and p_k to p_n. Repeated for both segments, recursively when satisfy the distance threshold.

2) Trading signals transformation:

Through PLR segmentation that there have many segments of uptrend and downtrend. A mathematical formula is used to convert these PLR segments of the stock price into trading signal. The point values of trading signal are following as Equation (1) and (2) to conversion.

Up-trend segment:

$$T_i = \begin{cases} 0.5-(i-1)/L & \text{if } i <= L/2 \\ i/L-0.5 & \text{if } i > L/2 \end{cases} \tag{1}$$

Down-trend segment:

$$T_i = \begin{cases} 0.5+(i-1)/L & \text{if } i <= L/2 \\ 1.5-i/L & \text{if } i > L/2 \end{cases} \tag{2}$$

which, L is the length of the uptrend or downtrend series; i is the data point in L; T_i is the trading signal. The range of trading signal is zero to one which if close to turning points intersects at 0.5.

B. Step2: Feature Selection by Stepwise Regression Analysis (SRA)

According to reference shows if select some of important feature could improve effect before learning model [16]. Therefore, we want to use stepwise regression analysis to select features from technical indices that these selected features have high relational feature with trading signal.

C. Step3: Learning Trading Signal Knowledge by Support Vector Regression Model Induction

To learn the function that maps the feature values to the predicted trading signal, we use SVR with ε -insensitive loss function is used where a errors small than a pre-defined parameter ε are considered. We use a nonlinear kernel to learn a nonlinear forecasting model because of the stock complex stock will be better. The input vector from technical indices after feature selection and output vector form trading signal by PLR with transformation.

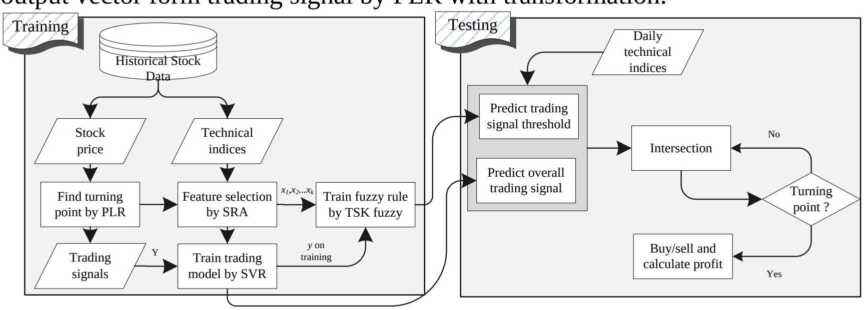

Fig. 1 Framework of collaborative trading model

D. Step4: Learning Trading Signal Threshold by TS Fuzzy Rule

In this section we use TSK fuzzy system to build fuzzy rule for learn trading signal threshold. The input vector form predicting value of SVR on training that due to SVR prediction may has very small moving we hope the trading signal threshold close to trading signal of SVR. The sub rule linear regression that using least squares method to compute regression coefficient as α, β, the if-then rule building as Equation (3).

$$\begin{aligned} &\textit{Rule } i: \textit{ if } x_1(k) \textit{ is } M_1^i \textit{ and ... and } x_n(k) \textit{ is } M_n^i \\ &\qquad \textit{then } y^i = \alpha_0 + \beta_{m1} x_1(k) + ... + \beta_{mn} x_n(k) \\ &\qquad i = 1, 2, ..., N \end{aligned} \tag{3}$$

where, k is discrete time index; x_j is j^{th} feature; M_j^i is a fuzzy term of M_j selected for rule i; β_{mj} is coefficient of selected j^{th} feature for rule i.

E. Step5: Trading Decisions making

In the daily forecasting, if the trading signals of SVR intersect trading signal thresholds. The intersection points are recommending to transaction in stock market which if the trading signal pass through threshold from up to down this means needed to quick to buy stock because very closeness turning point otherwise if the state was bottom to up needed to sell stock.

4. EXPERIMENTAL RESULTS FOR STOCK FORECASTING

We have selected 5 stocks for analysis which collected from American stock market that data period of stock price and technical indices collected were from 1/2/2008 (dd/mm/yy) to 6/30/2009, which uses the period of 1/2/2009 to 6/30/2008 to form the testing data period. There have 2 stocks collected from Taiwan stock market that the dates of training data have from 1/2/2006 to 10/14/2008. The dates of testing data have from 10//15/2008 to 4/9/2009. Due to not have a standard method to calculate the model effect or efficient in stock market when predict the buy-sell signal. In this paper, we calculate the profit how much profit we can capture. The profit is calculated follow as Equation (4).

$$profits = M \prod_{i=1}^{k} \left\{ \frac{(1-a-b) \times C_{S_i} - (1+a) \times C_{B_i}}{(1+a) \times C_{B_i}} \right\} \tag{4}$$

which M is the total amount of the money to be invested at the beginning, a refers to the tax rate of i^{th} transaction, b refers to the handling charge of i^{th} transaction, k is the total number of transaction, C_{S_i} is the selling price of the i^{th} transaction and C_{B_i} is the buying price of the i^{th} transaction.

TABLE I compare to rate of profit between two stock trade models

Stock	PLR-BPN	SVR-TS	Stock	PLR-BPN	SVR-TS
Apple	61.28%	45.16%	XOM	0%	14.78%
CAT	-23.83%	17.01%	2448.TW	44%	35.1%
JNJ	-16.86%	6.31%	2303.TW	74%	38.03%
VZ	15.36%	-1.24%			

According to our system forecasting result show that collaborative trading signal has turning points for acquire stable return. Table I shown as the PLR-BPN model [4] return exist high variation, our model was very small, and the profit standard deviation of PLR-BPN and SVR-TS are 0.38 and 0.17, separately. SVR-TS provided high confidence for investor to investment.

5. CONCLUSION

In this paper proposed trading model of CTM could help investor to capture profit was very stability. Experimental results shown the collaborative trading model by support vector regression and TS fuzzy rule have stabile trading signal and dynamic trading threshold for daily stock turning point detection. However, the primary goal of the investor could be easily achieved by providing him with simple trading decisions.

ACKNOWLEDGEMENT

This work was supported in part by the National Natural Science Foundation of China under Grant Nos. 60970060, and 61033013.

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