Stock Price Reversal Point Prediction Based on ICA and SVM

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ABSTRACT

In the stock market, stock price reversal point prediction plays an important role when investors make Investment decisions. A prediction method of stock price reversal point based on Independent Component Analysis（ICA） and Support Vector Machine（SVM）is presented in this paper. The underlying structure characteristics of stock prices are extracted by ICA. Then reversal points of restructured stock price are calculated. Finally, support vector machine is used for reversal point prediction. The empirical results show that the recall and precision of our method are better than those of SVM algorithms.

CCS Concepts

Computing methodologies→Modeling and simulation→Model development and analysis→Modeling methodologies

Keywords

Stock price reversal point; ICA; SVM; Stock market

1. INTRODUCTION

Morphological analysis [1], trend analysis [2] and technical analysis [3] are commonly methods for inversion point prediction at present. But these methods rely more on investors' subjective judgment and analysis, and do not fully exploit the objective law of stock price changes.

Independent Component Analysis (ICA) is an analysis method based on information theory. The main idea is to make linear projection of observed multivariate time series, which can be transformed into an independent component in statistical sense by maximizing non-Gauss. It can effectively suppress Gauss noise, extract signal features and analyze potential factors of signals. Therefore, ICA can be used to analyze the stock market and extract the characteristics of stock price, which is conducive to fully tapping the objective law of stock price changes. Support Vector Machine (SVM) is a supervised learning model. It has many unique advantages in solving small samples, non-linearity and high-dimensional pattern recognition. It can be used for data analysis, pattern recognition, classification, and regression prediction.

There have been some studies for prediction of stock price reversal points by using SVM and ICA. For example, Huang [4] used SVM to mine the technical index combination of stock price, realized the prediction of stock price reversal point. It overcomes the shortcomings of BP neural network method [5]. Zheng [6] used PLR-WSVM model to classify and predict inversion points. Although the validity of the method is proved, the accuracy is less than 50%. D. Back [7] used ICA to extract large volatility characteristics affecting stock prices at first, then using the extracted features, the stock price is reconstructed and the daily return rate of the stock is studied.

We propose a method for prediction of stock price inversion point which combing ICA with SVM in this paper. This method can overcome some problems such as inaccurate calculation of inversion point, over-fitting and easily falling into local minimum.

2. ICA-SVM ALGORITHM FOR STOCK PRICE REVERSAL POINT PREDICTION

2.1 Feature Extraction and Restruction of Stock Series Using ICA

Given a data set $X=\left(x_{ij}\right)_{m\times n}=\left(\boldsymbol{x}_1,\boldsymbol{x}_2,\cdots\boldsymbol{x}_m\right)^T$

whose m rows are n-dimensional stock time series, each element x_{ij} in the matrix X corresponds to the price at time j for the ith stock time series. We consider that the matrix X is generated by mixing m mutually independent components expressed by

$$X_{m\times n}=A_{m\times m}S_{m\times n} \qquad (1)$$

where $\boldsymbol{A}$ is the matrix of coefficients (a_{ij}) of the linear combination, named mixing matrix, while S is the matrix of independent component $\boldsymbol{s}_j$.

ICA can reveal underlying structures in financial time series [7]. Because only a few ICs contribute to most of the movements in the stock return and large amplitude transients in the dominant ICs contribute to the major level changes, while the non-dominant components do not contribute significantly to level changes, we extract the stock large volatility characteristics and restructure the stock price by size reduction, and a number of $k < m$ of the dominant independent components (ICs) can be selected by a threshold

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$$\delta = \frac{1}{r}\sum_{i=1}^{n}|y_i| \quad (1 \le r \le 9) \qquad (2)$$

so that

$$X_{m\times n} \approx A_{m\times k} S_{k\times n} \qquad (3)$$

each stock series $\boldsymbol{x}_i$ is decomposed into a linear combination of ICs given by

$$\boldsymbol{x}_i = \sum_{j=1}^{k} a_{ij} s_j \qquad (4)$$

for every i =1, 2, … ,m, so that each stock series is restructured by the coefficients of each independent component of the mixture.

2.2 Definition of Reversal Point

2.2.1 Definition of True Reversal Point

Let x_j is the price at time $t_j\,(j=1,2,3)$ for the ith stock time series, take closing price of the ith stock series for example, which have restructured by ICA.

If $(x_{t_1}-x_{t_2})/x_{t_2} > \boldsymbol{r}$ and $(x_{t_3}-x_{t_2})/x_{t_2} > \boldsymbol{r}$ then $\boldsymbol{t}_2$ is the upward reversal point.

If $(x_{t_2}-x_{t_1})/x_{t_2} > \boldsymbol{r}$ and $(x_{t_2}-x_{t_3})/x_{t_2} > \boldsymbol{r}$ then $\boldsymbol{t}_2$ is the downward reversal point.

2.2.2 Definition of Technical Indicators Reversal Point

Three technical indicator reversal points [8] are defined in Table 1.

Table 1. Definition of technical indicator reversal points

Technical index	MACD	CCI	BIAS
Definition of reversal points	When the MACD column stops to hit a new high or a new low, this day is a reversal point.	***Upward reversal poin***t $CCI \in [0,100] \to 100 < CCI$ $CCI < -100 \to CCI \in [-100,0]$ ***Downward Inversion Point*** $+100 < CCI \to CCI \in [0,+100]$ $CCI \in [-100,0] \to CCI < -100$	***Upward reversal poin***t When the positive deviation rate rises to a certain percentage ***Downward Inversion Point*** When the negative deviation rate falls to a certain percentage
Reverse point graphics			

2.3 ICA-SVM Algorithm

Denote the reversal point judgment vector at the jth day as {Rj, Mj, Cj, Bj } j=1,2…n, where Rj (or Mj, Cj, Bj) values one when the jth day is a real (or MACD, CCI, BIAS) reversal point, otherwise, it values zero. Extract the vectors according to $|M_i|+|C_i|+|B_i|>0$ asSVM training and testing set.

Step1 Input m stock price, take the closing pricefor example, $x_i, i=1,2,\cdots m$.

Step2 ICA is applied to x_i so that get independent components $y_i, i=1,2,\cdots,m$.

Step3 Restructure x_i with the ICs y_i whose absolution is greater than the threshold δ.

Step4 Calculate the reversal point judgment vectors $\{R_i, M_i, C_i, B_i\}$.

Step5 The vectors which satisfy the condition $|R_i|+|C_i|+|B_i|>0$ are extracted and are used as SVM data set to predict stock price reversal points. Seventy percent of the data used as the training set and the rest are the test set.

3. EMPIRICAL RESEARCH

3.1 Evaluating Indicators

The evaluating indicators include recall rate, precision rate and F_measure.

$$recall = \frac{n_{RT}}{n_{RT}+n_{R\bar{T}}}, \qquad precision = \frac{n_{RT}}{n_{RT}+n_{\bar{R}T}},$$

$$F\_measure = \frac{2\cdot recall \cdot precision}{recall + precision}$$

where n_{RT} is the number of both real reversal points and technical reversal points. $n_{R\bar{T}}$ is the number of real reversal points but not technical reversal points. $n_{\bar{R}T}$ is the number of technical reversal points but not real reversal points.

3.2 Description of the Data

To investigate the effectiveness of ICA-SVM techniques for stock price prediction, we apply ICA-SVM to data from the

Shanghai Stock Exchange. We use daily closing prices from January 1st, 2010 until March 9th, 2018 of eight large Banks, including Industrial and Commercial Bank of China (ICBC), Pudong Development Bank, China Merchants Bank, Min sheng Bank, Industrial Bank, Bank of China, Agricultural Bank, CITIC Bank. The historical data of 1988 trading days are obtained from the Wind website (http://www.wind.com.cn/). The adjacent data averaging method [9] are applied to process the missing data.

3.3 Results

In this experiment, Select four stocks including Industrial and Commercial Bank, China Merchants Bank, Bank of China, Agricultural Bank for empirical analysis, ICA-SVM, the traditional SVM are applied to the data respectively. The empirical analysis results of four stocks are shown in Table 2.

In order to describe the empirical analysis results of four stocks more vividly and intuitively, a comparison result chart is given. Figure 1 shows the evaluation indicators of ICBC's SVM, and ICA-SVM methods. Figure 2 shows the evaluation indicators of China Merchants Bank's SVM and ICA-SVM methods. Figure 3 shows the evaluation indicators of Bank of China's SVM and ICA-SVM methods. Figure 4 shows the evaluation indicators of the Agricultural Bank's SVM and ICA-SVM methods.

Table 2. Contrast Table of Four Stocks Experiments

Stock type	Model	recall	precision	F-Measure
Industrial and Commercial Bank	SVM	83.33%	71.43%	76.92%
	ICA-SVM	87.5%	95%	91.09%
China Merchants Bank	SVM	73.11%	79.09%	75.98%
	ICA-SVM	93.75%	71.45%	81.08%
Bank of China	SVM	67.54%	80.21%	73.33%
	ICA-SVM	90.38%	77.05%	83.19%
Agricultural Bank	SVM	95.59%	69.15%	80.25%
	ICA-SVM	100%	83.33%	90.91%

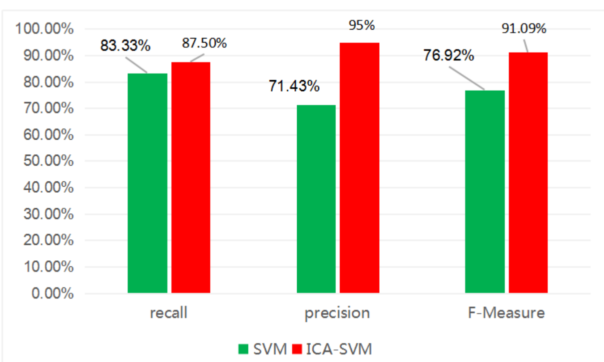

Figure 1. Evaluation indices of SVM and ICA-SVM

It shows that the ICA-SVM is more accurate than the SVM algorithms to predict the inversion point. Compare to SVM and ICA-SVM algorithms, ICA-SVM performs the best. Comparison of SVM algorithm, ICA-SVM improves 4.17% recall rate, 8.26% precision rate, and 5.75% F_measure .

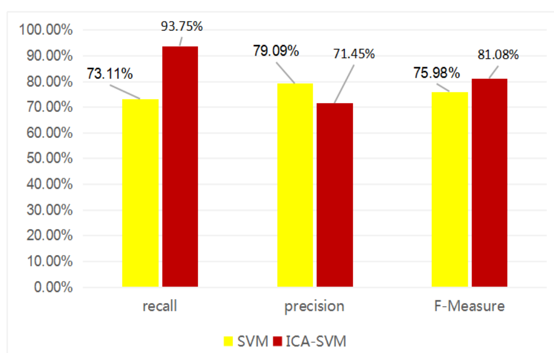

Figure2. Evaluation indices of SVMand ICA-SVM

It shows that the ICA-SVM is more accurate than the SVM algorithms to predict the inversion point. Compare to SVM and ICA-SVM algorithms, ICA-SVM performs the best. Comparison of SVM algorithm, ICA-SVM improves 20.64% recall rate, but reduce5.98%precision rate, and improves 5.1% F_measure .

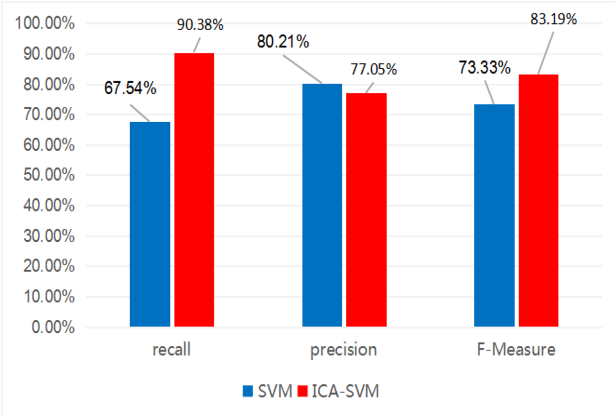

Figure3. Evaluation indices of SVMand ICA-SVM.

It shows that the ICA-SVM is more accurate than the SVM algorithms to predict the inversion point. Compare to SVM and ICA-SVM algorithms, ICA-SVM performs the best Comparison of SVM algorithm, ICA-SVM improves 22.84% recall rate, but reduce3.16%precision rate, and improves 9.86% F_measure.

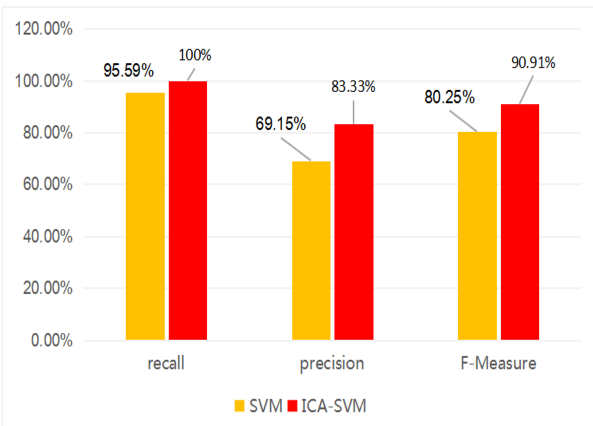

Figure4. Evaluation indices of SVM and ICA-SVM.

It shows that the ICA-SVM is more accurate than the SVM algorithms to predict the inversion point. Compare to SVM and ICA-SVM algorithms, ICA-SVM performs the best. Comparison of SVM algorithm, ICA-SVM improves 4.41% recall rate, 14.18%precision rate, and improves10.66% F_measure.

4. CONCLUSIONS

ICA is applied to decompose eight series of bank stock price in statistically independent components and the mixing matrix coefficients was used for restructuring the stock price in this paper. ICA gives a new perspective to the problem of understanding the mechanisms that influence the trend of the stock price. ICA-SVM is testified a good method to predict stock price reversal points. More ICA-SVM applications in financial tie series will be researched in our following work.

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