Do Trading Volume and MACD Indicator Contains Information Content of Stock Price? Evidence from China 2014-2015

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***Abstract*—This study investigates the stock price response to some important indicators including Volume, MACD, DIF and DEA. This paper intends to verify the problem that whether trading volume and MACD indicator contains information content of stock price. Our findings indicate that volume, MACD, DIF and DEA have comprehensive effects on the stock price, and the fluctuation of the stock price has internal closely relationship with comprehensive changes of the above four indicators. Since the four indicators mentioned in this paper can be used to predict the stock price, it has significant meaning for the stock investors in making their decision.**

***Index Terms*—Information Content, Stock Price, Volume, MACD**

I. INTRODUCTION

The old problem that concerns investors most is whether their investment in the stock market can create additional profit. Therefore, investors are very sensitive to price change; the price change determines the opportunity of buying and selling. So what factors fundamentally determine the price, or, we can say, what information is contained inside price? This issue has been frequently discussed in academic research. There is no doubt that the price is always linked with the transaction volume, so it can be said that the volume and price is a joint product in the stock market. Stock market prices and trading volume have been discussed for several decades, and the relationship between them is used as the foundation of securities market analysis [1]. Karpoff [2] pointed out the importance of understanding the relationship between price and trading volume. Firstly, as for investors, the understanding of the relationship between price and trading volume helps to understand the stock market structure. When we use various models in predicting the price-volume relationship, actually we are deepening our understanding of information on the basis of the price-volume relationship, for example, we are gaining information about the speed and channels of information dissemination, market size and existence of restrictions on the short selling mechanism and so on. The understanding of the price-volume relationship is understanding the stock market as a whole in essence. Secondly, the price-volume relationship plays a very important role in the event study method. For example, Richardson, Sefcik and Thompson studied the implication of clientele theories [3] in 1986. They found that trading volume shows a marked increase when the shareholder clientele changes. They believe that the main reason for the increase in trading volume is that investors feel confident about the future profit included in the dividend. Thirdly, when it comes to the discussion over the empirical distribution of speculative prices, the price-volume relation makes sense. If we take daily data as a sample, compared to normal distribution, its distribution of return rate shows a kurtosis. Both stable Paretian hypothesis and mixture of distribution hypothesis give their explanations. According to the mixture of distribution hypothesis, the price-volume relation has a link with the phenomenon as just discussed; it means that trading volume is an important thermometer that can be used to measure fluctuations in prices. Fourthly, the research on the price-volume relationship has a far-reaching significance for the study of the futures market. Some scholars believe that the price change is the factor that affects the volume of transactions on the contract's expiry date. Other scholars believe that the time to delivery of a futures contract has an effect on trading volume and price. In conclusion, study of price-volume relationship is very worthwhile and it has a very significant meaning for the equity market.

Fama put forward the efficient market hypothesis and deepened it in 1970. He put forward the hypothesis that under the weak form of efficient condition, market price has fully reflected all the past history of the stock price information; under the semi-strong form of efficient condition, prices have fully reflected all information of business prospects already published; under the strong form of efficient condition, prices have fully reflected all the information about the operations of the company including published or unpublished information, the price of an asset has already reflected all the information about the intrinsic value of the asset, and there is no point in using technical analysis to forecast the stock price. This paper holds the view that the prices can reasonably be predicted and also puts forward thinking that is slightly different from Fama's view. This paper mainly focuses on the information content of price. Fama believes that no relevancy is left for trading volume and price already reflects the information, so price is unpredictable. On this point, many scholars researched this topic and put forward their own point of view. Bajo studied the information content of abnormal trading volume in 2001. He believes that abnormal trading volume reflects relevant information, which is a signal for outside investors to make decisions [4]. Similarly, Antweiler and Frank researched the topic about information content and came to such a conclusion: the stock market news contributes to the accuracy of trading volume forecasting, but it cannot be used in predicting the price [5]. Taiwan scholars Hsieh and He studied the predictive ability of index option. They conclude that foreign institutional investors obtain higher profit leverage through the use of relevant information [6].

II. DATA SAMPLE

This paper selects the closing price, trading volume, MACD, DIF, DEA historical transaction data from Shanghai and Shenzhen 300 index (CSI 300 index) within the period from January 2, 2014 to October 30, 2015 (a total of 445 trading days).

According to the timeliness principle of data selection, this paper selects the latest data of transaction day to best reflect the impact of the closing price on the trading volume in the recent period. Also China's stock market experienced both bull market and bear market within the period from 2014 to 2015. It fluctuated more in comparison to the other years and caused great social repercussions. Therefore the data within this period is better for us to observe the impact of trading volume, MACD, DIF and DEA index change on the impact of price in short term [7].

The description of relevant statistics and correlation coefficient is shown in Table 1 and Table 2:

Table 1.
DESCRIPTION OF STATISTICS

	CSI 300	Volume	MACD	DEA	DIF
Mean	3090.88	207.65	1.014	17.83	16.71
Median	2819.81	156.08	4.55	12.63	12.91
Maximum	5353.75	686.44	109.62	220.76	234.69
Minimum	2086.97	11.944	-244.32	-230.56	-296.25
Std. Dev.	923.75	154.38	54.26	98.32	103.50
Skewness	0.66	0.80	-1.82	-0.22	-0.33
Kurtosis	2.28	2.64	8.54	3.06	3.44
Jarque-Bera	41.90	50.41	814.47	3.71	11.53
Probability	0	0	0	0.16	0.00
Observations	445	445	445	445	445

Table 2.
CORRELATION COEFFICIENT BETWEEN INDICES

Correlation	CSI 300	Volume	MACD	DEA	DIF
CSI 300	1				
JYL	0.852401	1			
MACD	-0.06413	-0.09938	1		
DEA	0.321169	0.359626	0.047874	1	
DIF	0.275687	0.315715	0.287787	0.941438	1

Tables 1 and 2 show the correlation coefficient and statistics data of CSI 300 index's closing price and trading volume, MACD and other indices respectively. We can observe the correlation relationship among these indices from this table.

III. EXPERIMENT AND RESULTS

A. The Experimental Application of SVM model

Support vector machine has similar roots to artificial neural networks, and it demonstrates the well-known ability of being universal approximates of any multivariable function to any desired degree of accuracy. The foundations of support vector machine were developed by Vapnik and co-workers in the 1990s. In recent years, support vector machine has become a very popular method to deal with classification, prediction, and regression problems. SVM model is a computational technique that allows computers to learn automatically based on training data and then classify new data later. SVM is widely used in respect of bioinformatics, data mining, image recognition, text categorization and hand-written digit recognition [8].

The basic idea of SVM is to find a hyper plane, which makes it possible to separate the two kinds of data points correctly. The main goal of SVM model is to learn a function from the training data using a learning mechanism and then infer some general results based on the antecedent knowledge.

Suppose $(x_1, y_1),\ldots, (x_n,y_n), x\in R_n, y\in\{-1,1\}$ is a set of binary variable value to be classified. Yn can be determined by a hyper plane which can be demonstrated as$(w \cdot x) + b =$. Besides, there are another two equations: $(w \cdot x) + b = -1.$ $(w \cdot x) + b = 1.$ It is demonstrated in Figure 5 that the boundary is 2/w. The boundary must be maximal to obtain a classifier with good generalization characteristics. In other words: min $\phi(w)=\frac{1}{2}w^2$.

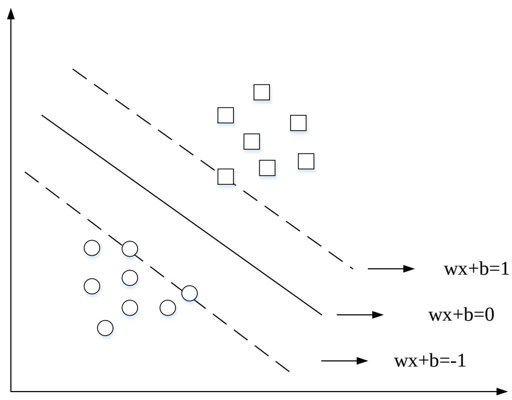


Figure 5: An overfitting classifier and a better classifier

With the introduction of the Lagrange function and $\alpha \in R$, lagrange multiplier, and the considering of the nonlinear space, the decision function becomes:

$$y=\mathrm{sgn}\left(\sum_{i=1}^{k} \alpha_i^* y_i K(x \cdot x_i) + b^*\right) \quad (1)$$

Popular kernel functions in support vector machine learning theories are as follows

Gaussian kernel: $k(x_i,x_j)=\exp\left[-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right]$ (2)

Polynomial kernel: $k(x_i,x_j)=(1+x_i\cdot x_j)^2$ (3)

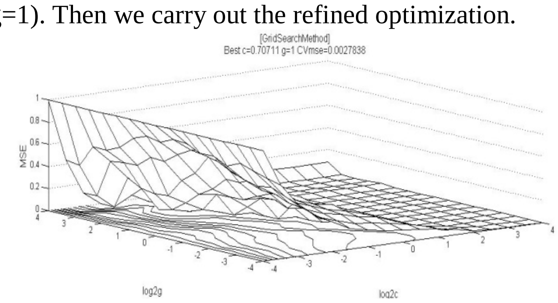
Linear kernel: $k(x_i,x_j)=x_i^T x_j$ (4)

Multilayer perceptron: $k(x_i,x_j)=\tanh[x^T x_i+b]$ (5)

where σ^2 denotes the variance of the Gaussian kernel. A certain value of b is used only in the multilayer perceptron. The Gaussian kernel function is employed as the kernel function in this paper. Among several available kernel functions, the Gaussian kernel function is in general a reasonably good choice since it can handle the non-linear relationship data, has few hyper-parameters, and has less numerical difficulties. This kernel non-linearly maps vectors into higher dimensional space; it can handle the case when the label or attributes is not linear. There are two parameters while using Gaussian kernel function, namely cost and gamma. To have better training performance, the two parameters are chosen by applying rough parameter test and fine parameter test.

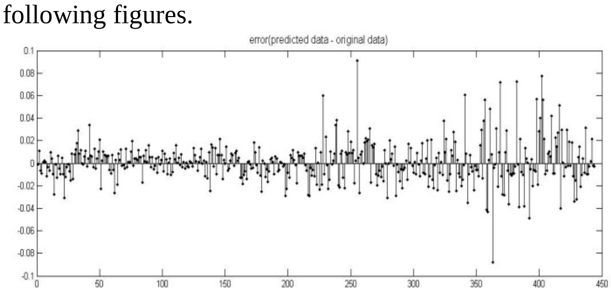
This paper uses support vector machine (SVM) model based on MATLAB software, then divides the set of data into the training group and the forecasting group. Independent variables and dependent variables in the training group formed a set of algorithms and we can use this algorithm to predict dependent variables in the forecasting group.

Firstly, we use parameter optimization algorithm in rough searching of the parameters G and C, the process as shown in Figure 7 to Figure 8. After the rough optimization, we got the optimal c (c=1) and optimal g (g=1). Then we carry out the refined optimization.

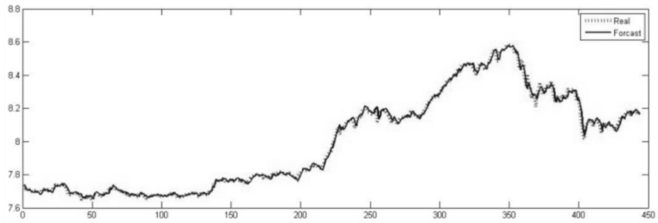


Cubic diagram of refined optimization of parameters

Through parameter optimization, we find the optimal c(c=0.70711) and g (g=1), according to the optimal parameters we establish the model and carry out the forecast process. The difference between the real value and the predicted value we got can be shown in the following figures.



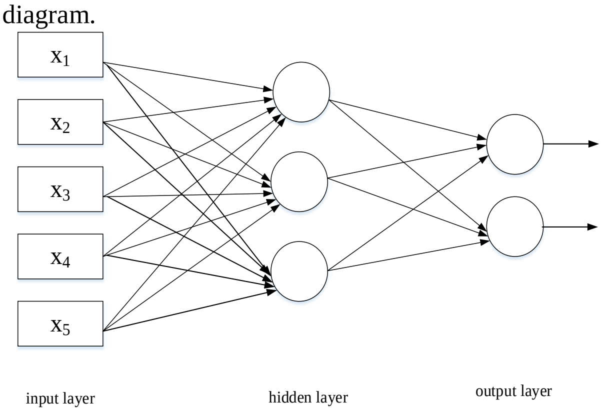
The error of real value and the predicted value



The simulation of real value and the predicted value

B. *The experimental application of ANN model*

Artificial neural network attempts to give computer programs human-like intelligence. Neural networks are usually designed to recognize patterns in data. In recent years, research on artificial neural networks has made great progress. It has successfully solved many problems in the field of pattern recognition, intelligent robots, automatic control, prediction, biology, medicine, economics and so on. The neural network is a computational model composed of a large number of neurons. Each input into the artificial neuron has a weight associated with it and it is these weights that determine the overall activity of the neural network. As the inputs enter the neuron, they are multiplied by their respective weights. The neurons sum all the incoming signals from the input layers, and if the total signal exceeds a threshold value, the neuron fires. The output of the network depends on the network connection mode, the weight value and the incentive function being different. The network itself is usually a kind of nature; it may be a logical strategy of expression. A three-layer neural network is used in this paper, as shown in the following diagram.



A three layer neutral network

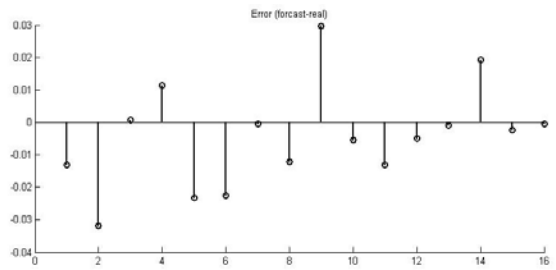
ANN is a good model to deal with a broad range of nonlinear problems, which can approximate some complex nonlinear functions with a high degree of accuracy. No prior assumption of the relationship model form is required in the forecasting; in contrast, ANN is largely determined by the characteristics of the input training data. Single hidden ANN model is characterized by a network of three layers of simple processing units connected by acyclic links (Zhang, 2001). Referring to the research literature of Zhang, the relationship between the output and the inputs has the following mathematical representation:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{oj} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t \quad (6)$$

where α_j(j=0, 1, 2…, q) and β_{ij}(i=0, 1, 2…, p; j=0, 1, 2…, q) are the model parameters called the connection weights; p is the number of input nodes and q is the number of hidden nodes. The logistic function is often used as the hidden layer transfer function, that is,

$$g(x) = \frac{1}{1+\exp(-x)} \quad (7)$$

This paper uses BP model of ANN （artificial neural network） that based on MATLAB software in analysis and prediction. Through the training to samples, the neural network reduced the error to 10-4 level. After 2038 steps of training, the best mean squared error is 0.00099628, which means the error dropped to 10-4 level. We use circular to represent scattered point data and straight line to represent the degree of fitting. So it can be said that the prediction model we made has quite a high degree of fitting. Figure 11 indicates the difference between the predicted and real values under the ANN model.



Error forecast real

C. *Analysis of experiment result*

After the prediction of the closing price of CSI 300 for the fifteen trading days from October 12, 2015 (15 trading days in total) through the support vector machines, neural networks, ARIMA and VAR four models, we get the result as shown in the table below.

TABLE 3.
EXPERIMENT RESULT

Real	SVM	ANN
8.15	8.11	8.11
8.14	8.15	8.15
8.13	8.15	8.14
8.16	8.14	8.13
8.17	8.16	8.17
8.17	8.17	8.17
8.18	8.17	8.17
8.15	8.18	8.18
8.17	8.16	8.16
8.18	8.17	8.17
8.19	8.18	8.18
8.19	8.19	8.19
8.17	8.19	8.19
8.17	8.17	8.17
8.17	8.17	8.17

In addition to the results, we also make a summary of the predict ability and accuracy of the four models, which is shown in the table below.

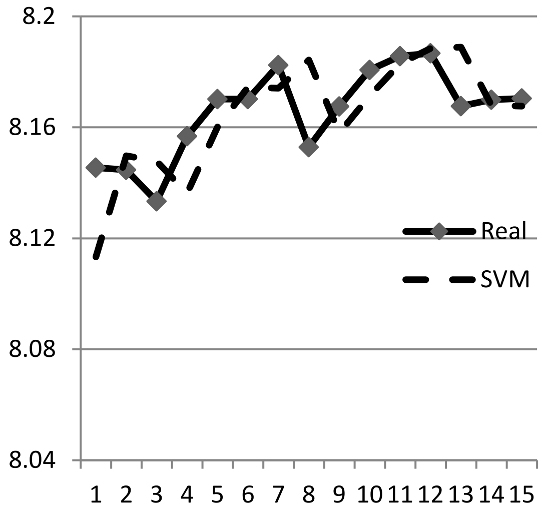
TABLE 4.
COMPARISON OF INDEX OF PREDICTION ACCURACY

	R-square	MSE	MAE
SVM	99.61%	0.0004	0.0117
ANN	100%	0.0010	0.0156
	MAPE	Theil Inequality Coefficient	
SVM	0.1435	0.0002	
ANN	0.1294	0.0002	

From the table we can observe the results of prediction accuracy of four time series models. From the point of view of the case in this paper, the first conclusion we can make easily is: prediction accuracy of Ann and SVM is significantly greater than that of ARIMA and VAR. However, the second problem seems to be troublesome because from the prediction accuracy index comparison table we cannot make judgment on the question that support vector machine and neural network which one is better. Therefore we believe that in this case, both the support vector machine and neural network have their unique advantage and both of them have practical meaning.

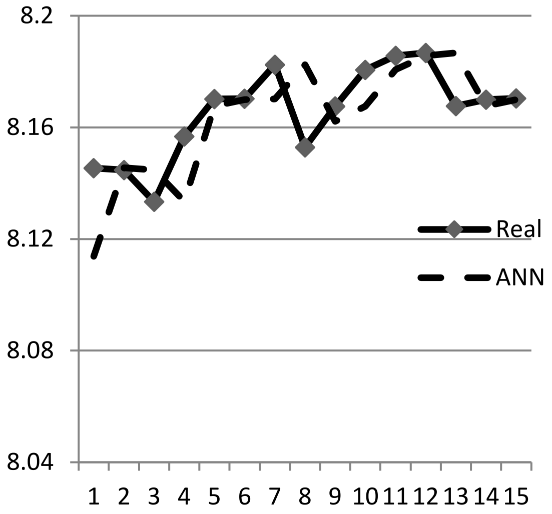
IV. SUMMARY AND CONCLUSION

As we study before, through the experiment on predicting the closing price of the fifteen days since October 12, 2015, we got the predicted closing price. We can look at the price predicted from using these four kinds of time series forecasting model:



Prediction of SVM model

Figure 6 reflects the correlation and difference between the predictive value and the true value of the support vector machine. We can see from the table that the predicted value is fluctuating homogeneously around the true value.



Prediction of ANN model

Figure 7 shows the comparison between the predicted closing price and the real closing price predicted by the neural network model. The predicted value is fluctuating homogeneously around the true value, which is the same as the result of support vector machine model. Are the time series prediction data all the same? The next model will give the answer to this question.

From the above, we can know the prediction effect of the four kinds of model, so what is the condition that investors concerned most about the future? Which prediction result of model used in the case is most close to the real value? The table 4 will give us the answer.

TABLE 4.
PREDICTION ON THE CLOSING PRICE OF THE FIFTEENTH DAY

	Real	SVM	ANN
data	3534.79	3534.05	3533.34
error	0	0.74	1.45

It is obvious that after a whole day of bull-bear war, the closing price of CSI 300 index is 3434.79 yuan. In our experiment, we can see that prediction accuracy of Ann and SVM is significantly greater than that of ARIMA and VAR. More importantly, the support vector machine model is the best model with highest prediction accuracy in the case of this paper. In conclusion, there are many information bytes have information content to stock price. Through the experimental study we found that the price changes are related to the information byte. Information byte can be expressed as a variety of information elements that affect the price of the stock. Trading volume and the MACD index are just two representative examples in numerous kinds of information bytes. In addition to the trading volume and the MACD index, there seems to be more information elements are worthy to explore in the future study. These include financial statement information, RSI index information, etc. These information bytes also have a certain predictive ability for the price. However, what specific information bytes have higher information content or what factors can explain the price changes better still waiting to be answered.

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