Journal of Applied Sciences

ISSN 1812-5654

ANSInet
an open access publisher
http://ansinet.com

Journal of Applied Sciences 13 (19): 4082-4086, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.4082.4086

By Using Normal Least Squares Support Vector Regression Model to Carry out Market Forecasting

Liu Hongxia
Faculty of Finance and Economics, Kaifeng University, 475002, Kaifeng, Henan, China

Abstract: Forecasting of the market sale is an important part of supply chain management.It is well known that traditional forecasting method for market sale is based on the market demand evaluation of the different departments. In order to derive a more robust least squares support vector regression model, a novel normal least squares support vector regression model is proposed in this study. Compared with least squares support vector regression model, normal least squares support vector regression model incorporates the data information in a global way. It is indicated that the forecasting ability for sales volume of normal least squares support vector regression model is more excellent than those of least squares support vector regression model and traditional support vector regression model.

Key words: Normal direction, regression method, market forecasting

INTRODUCTION

Forecasting of the market sale is an important part of supply chain management (Qu *et al*., 2012; McCarthy Byrne *et al*., 2011; Wong and Guo, 2010; Taylor, 2007). Traditional forecasting method for market sale bases on the market demand evaluation of the different departments (Yu *et al*., 2011; Chang and Wang, 2006).

Support vector regression method is powerful for the regression problems characterized by small samples, nonlinearity and high dimension. Currently, Support vector regression method is an active field in artificial intelligent technology. Artificial neural networks use the empirical risk minimization principle, which is generally employed in the classical methods. Support vector regression method based on the SRM principle (Xie, 2012; Huang, 2012; Kazem *et al*., 2010; Cho *et al*., 2009), which seeks to minimize an upper bound of the generalization error.Least squares support vector regression method alters inequality constraints into equal conditions and employs a squared loss function, which can make least squares support vector regression method achieve higher calculation speed and efficiency (Esteki *et al*., 2010; Patil *et al*., 2005).

In order to derive a more robust least squares support vector regression model, a novel normal least squares support vector regression model is proposed in this study. Compared with least squares support vector regression model, normal least squares support vector regression model incorporates the data information in a global way. In the experiments,sales volume of Guangbai Tianhe store from 2004.1 to 2007.6 are used to study the sale forecasting performance of normal least squares support vector regression model compared with other prediction techniques. It is indicated that the forecasting ability for sales volume of normal least squares support vector regression model is more excellent than those of least squares support vector regression model and traditional support vector regression model.

NORMAL LEAST SQUARES SUPPORT VECTOR REGRESSION METHOD

Considering a set of dataset with the input vector and the corresponding output, the form of least squares support vector regression model can be given by:

$$f(x) = w.\varphi(x)+b \qquad (1)$$

where, is the weight vector and is the bias term.

Least squares support vector regression model can be obtained by formulating the regression problem:

$$J_1(w,b,e) = \frac{1}{2}\|w\|^2 + \frac{1}{2}C\sum_{i=1}^{n} e_i^2 \qquad (2)$$

Subject to:

$$y_i = [w' \cdot \varphi(x)] + b + e_i$$

where, e_i is the error.

Introduce the Lagrangian as:

$$T_1(w,b,e_i,\alpha_i)=\frac{1}{2}\|w\|^2+\frac{1}{2}C\sum_{i=1}^{n}e_i^2-\sum_{i=1}^{n}\alpha_i(w'\varphi(x_i)+b_i-y_i+e_i) \quad (3)$$

where, $\alpha = [\alpha 1, \alpha 2...,\alpha n]$ refers to the Lagrange multiplier vector.

The conditions for optimality are:

$$\frac{\partial T_1}{\partial w}=0\rightarrow w=\sum_{i=1}^{n}\alpha_i\varphi(x_i) \quad (4)$$

$$\frac{\partial T_1}{\partial b}=0\rightarrow \sum_{i=1}^{n}\alpha_i=0 \quad (5)$$

$$\frac{\partial T_1}{\partial e_i}=0\rightarrow \alpha_i=Ce_i \quad (6)$$

$$\frac{\partial T_1}{\partial \alpha_i}=0\rightarrow w'\varphi(x_i)+b+e_i=y_i \quad (7)$$

Then, the optimal solution will be calculated according to the linear equation:

$$\begin{bmatrix}0 & I' \\ I & P\end{bmatrix}\begin{bmatrix}b \\ a\end{bmatrix}=\begin{bmatrix}0 \\ y\end{bmatrix} \quad (8)$$

where, y = [y1,...,yn], I = [1,1,...1] and P = K+V:

$$K=\left(k\left(x_i,x_j\right)\right)_{n\times n} \quad (9)$$

$$V=\text{diag}\left\{\frac{1}{C},\frac{1}{C},\cdots,\frac{1}{C}\right\} \quad (10)$$

Hence, the regression function of least squares support vector regression model becomes:

$$f(x)=\sum_{i=1}^{n}\alpha_i k(x,x_i)+b \quad (11)$$

In order to derive a more robust least squares support vector regression model, a novel normal least squares support vector regression model is proposed in this study. Then, we modify the constraints in traditional least squares support vector regression model as follows:

$$\frac{y_i-\left(w'\varphi\left(x_i\right)+b\right)}{\sqrt{1+\|w\|^2}}=e_i \quad (12)$$

Combining with the same objective function, we derive the following least squares support vector regression model:

$$J_2(w,b,e)=\frac{1}{2}\|w\|^2+\frac{1}{2}C\sum_{i=1}^{n}e_i^2 \quad (13)$$

Subject to:

$$\frac{y_i-\left(w'\varphi\left(x_i\right)+b\right)}{\sqrt{1+\|w\|^2}}=e_i$$

Compared with least squares support vector regression model, normal least squares support vector regression model incorporates the data information in a global way.

Then, we have the following Lagrangian:

$$T_2(w,b,e_i,\alpha_i)=\frac{1}{2}\|w\|^2+\frac{1}{2}C\sum_{i=1}^{n}e_i^2-\sum_{i=1}^{n}\alpha_i\left(\frac{y_i-\left(w'\varphi\left(x_i\right)+b\right)}{\sqrt{1+\|w\|^2}}-e_i\right) \quad (14)$$

Finally, we can obtain the solution of Eq. 14 using the same method as least squares support vector regression model.

EXPERIMENTAL RESULTS

As shown in Fig. 1, sales volume of Guangbai Tianhe store from 2004.1 to 2007.6 are used to study the sale forecasting performance of normal least squares support vector regression model compared with other prediction techniques. The sales volume of Guangbai Tianhe store from 2006.11 to 2007.6 are used to test the sale forecasting performance of normal least squares support vector regression model.

The experimental data must be normalized to improve the smoothness of the prediction techniques:

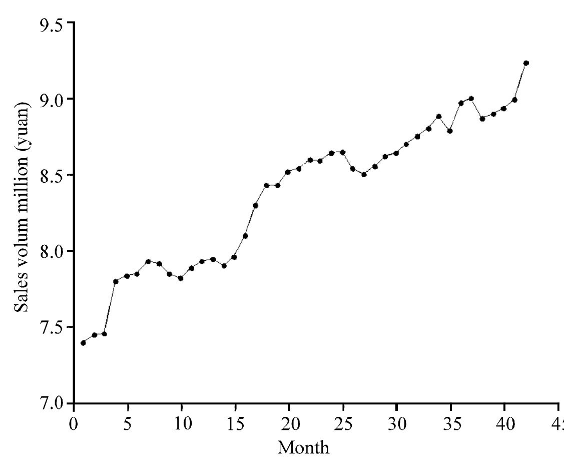

Fig. 1: Sales volume of Guangbai Tianhe store from 2004.1 to 2007.6

$$d'_i = \frac{d_i - d_{min}}{d_{max} - d_{min}} \quad (15)$$

where, d_{min}, d_{max} are the minimum and maximum value, respectively.

Figure 2 gives the comparison between actual curve and sale forecasting curve of normal least squares support vector regression model and the sale forecasting error of normal least squares support vector regression model is given in Fig. 3. As shown in Fig. 2 and 3, the maximum sale forecasting error of normal least squares support vector regression model is less than 1.4%. Then, Fig. 4 gives the comparison between actual curve and sale forecasting curve of least squares support vector regression model and the sale forecasting error of least squares support vector r egression model is given in Fig. 5. As shown in Fig. 4 and 5, the maximum sale forecasting error of least squares support vector regression model is less than 4%.

Finally, Fig. 6 gives the comparison between actual curve and sale forecasting curve of support vector regression model,and the sale forecasting error of support vector regression model is given in Fig.7. As shown in Fig. 6 and 7, the maximum sale forecasting error of support vector regression model is less than 9%.

The testing results show that the forecasting error for sales volume of normal least squares support vector regression model is smaller than that of least squares support vector regression model and the forecasting error for sales volume of least squares support vector

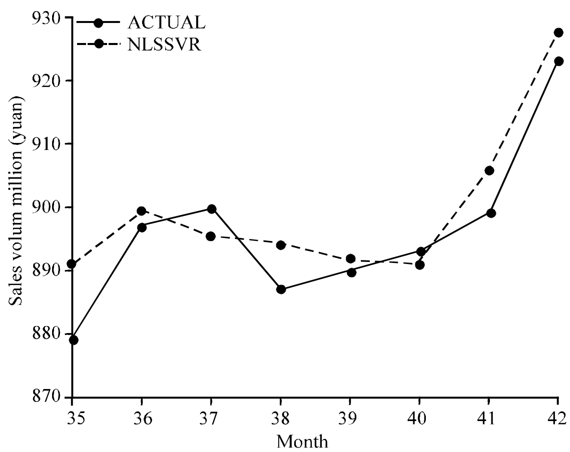

Fig. 2: Comparison between actual curve and sale forecasting curve of normal least squares support vector regression model

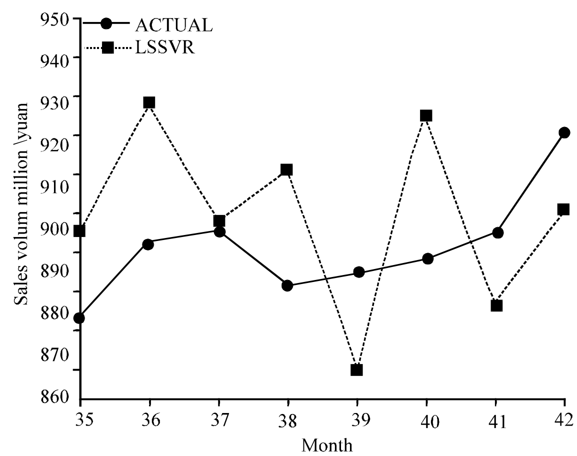

Fig. 4: Comparison between actual curve and sale forecasting curve of least squares support vector regression model

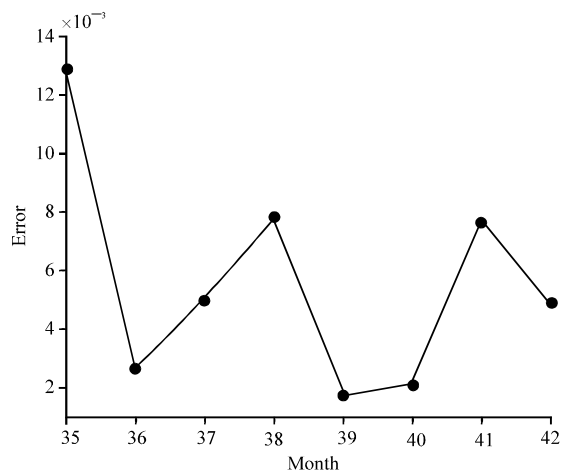

Fig 3: Sale forecasting error of normal least squares support vector regression model

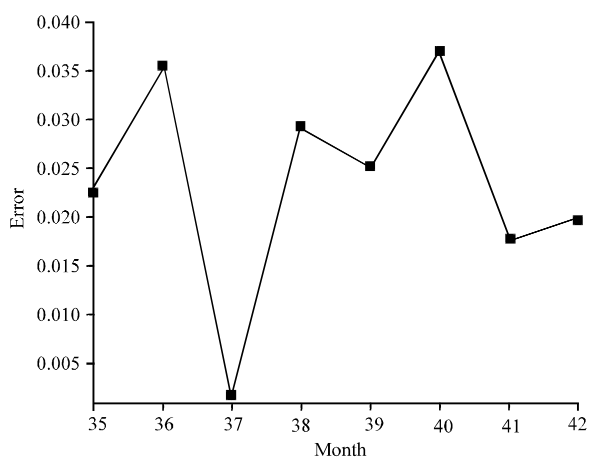

Fig. 5: Sale forecasting error of least squares support vector regression model

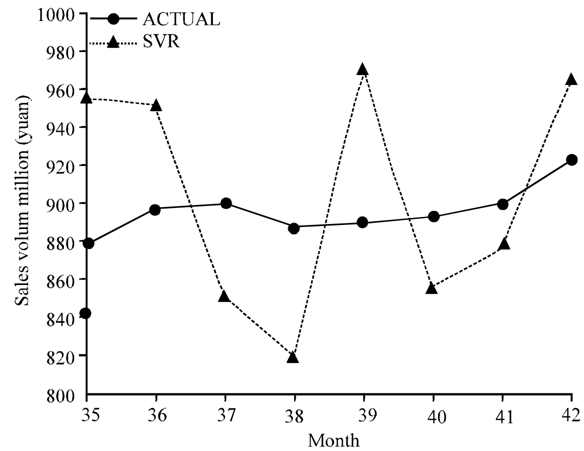

Fig. 6: Comparison between actual curve and sale forecasting curve of support vector regression model

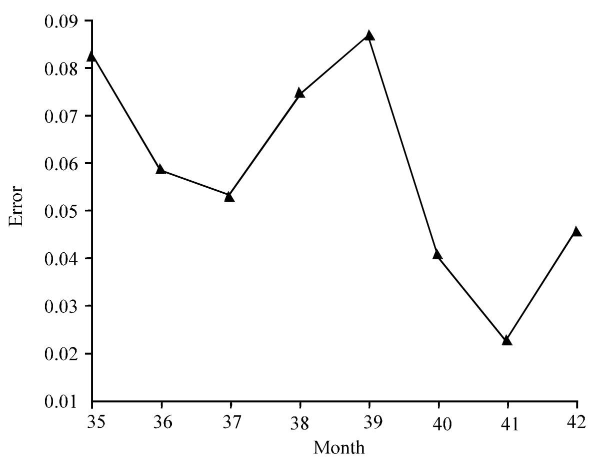

Fig. 7: Sale forecasting error of support vector regression model

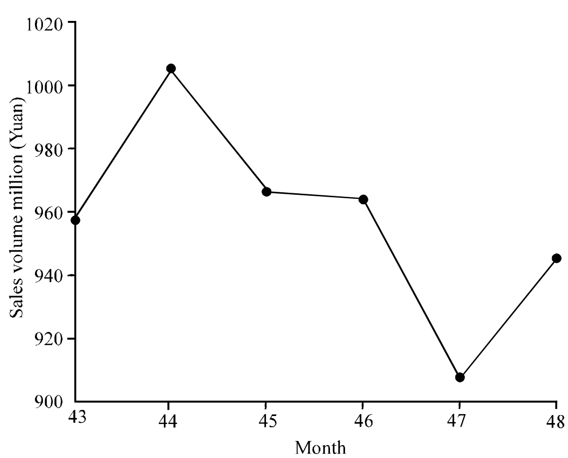

Fig. 8: Sales volume prediction results of normal least squares support vector regression model

regression model is smaller than that of traditional support vector regression model. Therefore, we can conclude that the forecasting ability for sales volume of normal least squares support vector regression model is more excellent than those of least squares support vector regression model and traditional support vector regression model.

Then, we employ normal least squares support vector regression model to predict sales volume of Guangbai Tianhe store from 2007.7 to 2007.12 and 2007.7~2007.12 are denoted as 43~48. The sales volume prediction results of normal least squares support vector regression model are given in Fig. 8.

CONCLUSION

A novel normal least squares support vector regression model is proposed in this study. Compared with least squares support vector regression model, normal least squares support vector regression model incorporates the data information in a global way. It can be seen that the forecasting ability for sales volume of normal least squares support vector regression model is more excellent than those of least squares support vector regression model and traditional support vector regression model.

REFERENCES

Chang, P.C. and Y.W. Wang, 2006. Fuzzy Delphi and back-propagation model for sales forecasting in PCB industry. Expert Syst. Appl., 30: 715-726.

Cho, Y.J., H. Kim and H.B. Oh, 2009. Generating rules for predicting MHC class I binding peptide using ANN and knowledge-based GA. JDCTA, 3: 111-119.

Esteki, M., M. Rezayat, H.S. Ghaziaskar and T. Khayamian, 2010. Application of QSPR for prediction of percent conversion of esterification reactions in supercritical carbon dioxide using least squares support vector regression. J. Supercrit. Fluids, 54: 222-230.

Huang, Y.L., 2012. Intelligent technique for robot path planning using artificial neural network and adaptive ant colony optimization. JCIT, 7: 246-252.

Kazem, B.I., A.H. Hamad and M.M. Mozael, 2010. Modified vector field histogram with a neural network learning model for mobile robot path planning and obstacle avoidance. Int. J. Adv. Comput. Technol., 2: 166-173.

McCarthy Byrne, T.M., M.A. Moon and J.T. Mentzer, 2011. Motivating the industrial sales force in the sales forecasting process. Ind. Marketing Manage., 40: 128-138.

Patil, N.S., P.S. Shelokar, V.K. Jayaraman and B.D. Kulkarni, 2005. Regression models using pattern search assisted least square support vector machines. Chem. Eng. Res. Des., 83: 1030-1037.

Qu, Y., F. Wang, F. Liu and Z.Y. Liu, 2012. Wholesale price contract and revenue sharing contract in retailer-leading supply chain. AISS, 4: 89-95.

Taylor, J.W., 2007. Forecasting daily supermarket sales using exponentially weighted quantile regression. Eur. J. Oper. Res., 178: 154-167.

Wong, W.K. and Z.X. Guo, 2010. A hybrid intelligent model for medium-term sales forecasting in fashion retail supply chains using extreme learning machine and harmony search algorithm. Int. J. Prod. Econ., 128: 614-624.

Xie, J., 2012. Study on vehicle scheduling algorithms for logistics operations based on cloud computing and neural network. AISS, 4: 190-196.

Yu, Y., T.M. Choi and C.L. Hui, 2011. An intelligent fast sales forecasting model for fashion products. Expert Syst. Appl., 38: 7373-7379.