Support Vector Machines을 이용한 공급사슬관리의 지속적 협업 수준에 대한 의사결정모델

임세헌*

성공적인 공급사슬관리에 있어 성과에 따른 지속적 협업 통제는 매우 중요하다. 본 연구에서는 기계학습 알고리즘인 SVM(Support Vector Machines)을 이용해 균형성과표에 기반한 공급사슬관리 성과에 따른 지속적 협업 통제 모델을 개발하였다. 우리는 지속적 협업 통제모델 개발에 있어 108명의 전문가를 상대로 실증조사를 수행하였다. 본 연구 수행에 있어 4가지 형태의 SVM 커늘 (1) linear, (2) polynomial, (3) Radial Basis Function(RBF), (4) sigmoid kernel을 이용해 공급사슬관리 지속적 협업 예측 정확도를 비교하였다. SVM 커늘 4가지 중 linear kernel의 예측성과가 가장 좋았다. 그리고 본 연구에서는 SVM linear kernel의 예측성과를 ANN(Artificial Neural Network)의 예측성과와 비교하였다. 분석결과 SVM linear kernel이 공급사슬관리에 있어 지속적 협업 예측에 우수한 예측성과를 보여주는 것을 발견하였다. 이러한 결과는 SVM linear kernel이 공급사슬관리의 지속적 협업 예측 통제에 있어 우수한 대안을 제공해 줄 것이다. 그러므로 공급사슬관리를 추구하는 기업들은 본 모델을 통해 지속적 협업 통제에 유용한 정보를 얻을 수 있을 것이다.

Keywords: SVM(Support Vector Machines), SCM(Supply Chain Management), ANN(Artificial Neural Networks), SC(Sustainable Collaboration)

Ⅰ. Introduction

Support Vector Machine(SVM), based on Statistical Learning Theory(SLT), is outstanding machine learning algorithms. SVM is based on structure risk minimization principle whereas the traditional Artificial Neural Network(ANN) algorithm is based on empirical risk minimization principle(Vapnik 1995, 1998). That is, SVM is characterized to minimize the

* 중앙대학교 정보시스템학과 겸임교수

upper bound of a generalization error whereas the ANN model focuses to minimize false classification error. SVM, a novel Neural Network model, can fix an overfitting problem inherent in the ANN model by overcoming a limitation of the local optimum. Using obvious theory, it also eases the interpretation of the results and provides faster classification learning with a smaller sample of data.

Several studies using SVM have been done in the major area of business management such as in stock market index forecasting(Kim 2003), bankrupt prediction(Park, Kim and Han 2004), evaluation of bond(Shin and Kim 2005; Huang et al. 2004), pattern recognition (Osuna et al 1997), Personalized Marketing(Kwok-Wai et al. 2003), and so forth.

In this research, SVM is applied to solve problems in forecasting a Supply Chain Management(SCM) Sustainable Collaboration(SC). An SCMSC is achieved until a successful SCM result is shown in the current cooperation or a substantial result has been achieved(Stuart and McChucheon 2000; Kumar and Dissel 1996). Therefore, the SC of an SCM implies its success.

However, there are no guidelines to determine the need for an SCMSC, nor are there any models for forecasting an SCM. Therefore, this research has developed a model for forecasting an SCMSC by adjusting the measurements index in the framework which was formed by Brewer and Speh(2000), based on the Balanced Scorecard(BSC) presented by Kaplan and Norton(1992; also see Maisel 1992). In developing the most accurate forecasting model for an SCMSC, four types of SVM models (linear, polynomial, Radial Basis Function(RBF), sigmoid kernel) of forecasting performances were compared. Then this study compares SVM prediction performance with ANN prediction performance

This study is structured as follows: Section Ⅱ introduces basic concepts of SVM and previous research applications in business management. In section Ⅲ, this article selects prediction variables to SC in an SCM. Then explanations on the research and experiment structure are followed. Section Ⅳ analyzes the empirical results. Finally, this article concludes and mentions limitations of the study.

Ⅱ. Research Background

As a theoretical background, this section introduces the basic concept of SVM, its practical application to business management, ANN and BSC as a performance measurement tool.

1. The concept of SVM

SVM is a statistical learning theory based on the ANN model[1]. SVM enables mathematical classification of data by matching nonlinear problems in an input space to linear problems in a high-dimensional feature space(Hearst, Dumaus, Osman, Platt, and Scholkopf 1998).

SVM was a very popular method in computer science area in its early stage. For example, recently SVM is frequently employed for the purpose of classification and prediction in business management arena(i.e. stock index prediction(Kim 2003) bankruptcy prediction(Shin 2004), and bond rating(Huang et al. 2004; Shin and Kim 2005) that deal with time series data). This study applies SVM to predict SCMSC in Korea. Some exceptional features of SVM are as follows:

First, SVM is easily able to define the factors that affect learning because the analysis using SVM requires smaller number of parameters to be controlled than other methods. Also, SVM allows to minimize the structural risk so that we can avoid lower performance or under-fitting and overfitting problems resulted from using too many data.

Second, SVM utilizes the learning algorithm in search of a hyperplane or a categorization criterion, when it classifies a training data set into two different classes. The PCA(Principal Component Analysis), SOM(Self Organized Map), VQ(Vector Qualtizer) are the few examples of the learning algorithms. SVM can lose, however, valuable information if it is mapping the input data X in a low-dimension feature space. Therefore, mapping the input data X in a high-dimension feature space allows SVM to find a separable hyperplane that maximizes the margin(equivalently, maximum margin hyperplane) between the two different classes. Training data set that is closest to the maximum margin hyperplane is called Support Vector (hereafter SV)[2] (Vapnik 1998; Park et al. 2004).

Third, SVM performs global optimization via selection of the best SV. It is very difficult to adjust SV in an empirical estimation as well as in an application of classification task.

Therefore, practicing the structure risk minimization(SRM) is very difficult. Most

1) SVM was developed by Vapnik (1998), a Professor of London university, Britain.

2) Vapnik suggests the Structure Risk Minimization(SRM) technique to find optimum support vector. Classification error can be classified into the true error and the empirical error. The value of true error is decreasing until it reaches to a specific SV resulting the underfitting problem. On the other hand, when it passes the specific SV, it shows the overfitting problem. The value of the empirical error, however, continuously decreases by the decrease of the value of the true error.

of the prior studies using SVM minimize the estimation error and enhance the prediction ratio by adjustment of C value and δ^2(Vapnik 1995; Tay and Cao 2001; Kim 2003).

We can break SVM down into two cases: the linearly separable case and the non linearly separable case. The linearly separable case denotes that a hyperplane classifying learning data set into two categories exists if the outcomes of the learning data in SVM have values in binary figure such as {-1, +1}.

The nonlinear separable case represents that we cannot have any hyperplane that makes the learning error zero. The linearly separable case can be expressed using the following two equations (1) and (2). The maximum margin hyperplane in linearly separable case can be defined using SV as in the equation (2). Figuring the linearly separable case would be the same as solving a linearly constrained quadratic programing[3] that defines the SV and the parameters b and a.

In the equation (1), y, x, and i represent outcomes training weights, and value number respectively. In the equation (2), y_i denotes class value of the training data $x(i)$, the dot (·) refers dot product, x represents SV, and finally b and a represent parameters. Also w_i is parameter.

$$y = w_i + w_{i+1}x_{i+1} + w_{i+2}x_{i+1} + w_{i+2}x_{i+2} + w_{i+3}x_{i+3} + w_{i+4}x_{i+4} \quad \cdots\cdots (1)$$

$$y = b + \sum \alpha_i y_i x(i) \cdot x \quad \cdots\cdots (2)$$

The nonlinear separable case represented in equation (3) denotes nonlinear separable case of input data. To solve this problem, SVM maps input data space in a higher dimension feature

3) Nash and Sofe(1997), Here, Quadratic Programming means Convex Programing. Convex Programing solve to use Lagrangian Duality. In this problem, restrict condition is Convex Function, target function is CP. For example, optimal hyperplane is $f(x) = w^t + b$, this problem is following Convex Programing problem

$$Min \ \frac{1}{2} w^t w$$
$$s.t. \ \ d_i(w^t x_i + b) \geq 1 \quad \text{for } i = 1, 2, \ldots\ldots, N$$

This problem is changed to duality problem

$$Q(\alpha) = \sum_{i=0}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j x_i^t x_j$$
$$s.t \sum_{i=1}^{N} \alpha_i d_i = 0, \alpha_i \geq 0$$

space. Through this process we can approximate the nonlinear function to a linear function and find the maximum margin hyperplane in a feature space.

$$y = b + \sum \alpha_i y_i K(x(i), x) \quad \cdots\cdots\cdots\cdots (3)$$

The function of the nonlinear separable case, $K(x(i), x)$ is referred as a kernel function. In practice, we have various types of kernel function such as polynomial kernel function, Gaussian RBF(radial basis function), perceptron function in SVM.

· P is the degree of the polynomial kernel function : $(1 + x^y)^p$

· δ^2 is bandwidth Gaussian RBF : $\exp[-\frac{1}{2}\delta^2 \| x - x_i \|^2]$

· 2 layer perceptron function(β is the parameter) : $\tanh(\beta_o x^T x_i + \beta_1)$

We can generalize the results of SVM if we add 0 to the lower bound of the parameter a_i of the kernel function in case of a separable case, and if we add C to the upper bound of the parameter a_i of the kernel function in case of a non-separable case(Kim 2003).

2. Support Vector Machines and their Application in Business

SVM is a Statistical Learning Theory (SLT) based on the ANN(Artificial Neural Network) model. SVM enables mathematical classification of data by matching nonlinear problems in an input space to linear problems in a high-dimensional feature space(Vapnik 1998).

As mentioned, SVM can overcome the inherent problems of ANN technique. SVM was used in the area of pattern recognition and classification problem in its early stage. For example, Joachimes (1998) proves that SVM outperforms various mechanical learning models in the document classification process. Osuna et al.(1997) also proves that SVM shows an excellent image and character recognition ratio in the area of image science. In a medical research. The medical research, Guyon et al.(2002) shows that SVM generates the best result out of various machine-learning algorithms in cancer cells classification test.

Recently SVM is frequently employed for the purpose of classification and prediction in business management arena too(i.e. stock index prediction, and bond rating that deals with time series data). Kim(2003) proves that SVM is a promising method for the prediction of financial time series in korea stock market. Also Tay and Cao(2001) examined financial forecasting with SVM. They proves that SVM outperformed the Back Propagation Neural Network(BPNN) on normalized mean square error, mean absolute error, directional symmetry and weighted directional symmetry using SVM theory in regression approximation. Recently, Hur and Lim(2005) applied the SVM in the prediction of customer churning in case of on-line auto insurance. Also this study compares the results of SVM analysis with those of the ANN model and the logit model. Our results can provide auto insurance firms practical connotation. Shin and Kim(2005) show that SVM examined predictability of SVM to bond rating forecasting. This study applies SVM to predict the probability of SCMSC.

3. ANN

ANN is powerful tool for business forecasting. ANN suggests the superior performances over logit analysis or discriminant analysis. Therefore, ANN is used in following fields of study: forecasting of stock price, bankruptcy, and customers churning.

ANN is a theory of mechanical drills imitating human brain activity based on their experiences and knowledges. In 1943, McCulloch and Pitts made a model of neuron for the first time. In 1949, a Canadian psychologist Hebb suggested the systematic rules in controling of linkage intensity. Then ANN has been applied in diverse fields after Rosenblatt showed ANN algorithm.

ANN is consists of input layer, hidden layer, and output layer. It has the processing elements which is modeled from neuron as a basis. Linkage weighting between the processing elements can be calculated through circulation of Input layer, hidden layer, and output layer. The most used activation function is the sigmoid function in ANN.

4. Balanced Scorecard

The BSC is excellent performance measurement tool(Kaplan and Norton 1992). The BSC measurement modules are composed of customer performance, process performance, financial performance, learning performance. The BSC measurement tool is used in ERP(Enterprise Resource Planning), CRM (Customer Relationship Management), and e-Business performance measurement. Recently, the BSC measurement tool is used in SCM.

A study of SCM performance measurement using BSC is Brewer and Speh(2000) that suggests BSC-based SCM performance measure framework. But they do not empirical test SCM framework. Their SCM framework has following limitations: Firstly, the relation among the SCM measurement factors and SC is not described. Secondly, the SCM framework don't suggest decision making point of SCM sustainable collaborative.

Nevertheless, Brewer and Speh(2000) framework offers powerful benefits. Firstly, it emphasizes the inter-functional and inter-company nature of supply chains and recognizes the need to ascertain the extent to which firms effectively work together and the extent to which functions are coordinated and integrated. Secondly, it will increase the chance that a "balanced" management approach in indeed practiced within firms and among the supply channel enterprises. Thirdly, it is suggested stimulate management to create other measures appropriate to their specific environment. Fourth, it is a novel approach. It help SCM managers focus on achieving goals that are beyond the typical measures of performance used within firms(Brewer and Sheh 2002).

Therefore, it is used in various SCM study and also provided research background. For example, Suh and Kwon (2001) suggested SCM framework of supply relationship quality using SCM framework of Brewer and Speh(2000).

Ⅲ. Methodology

1. Research Variable

In this research, the independent variables were established as learning perspective, internal process perspective, customer perspective, and financial perspective based on an BSC framework which was formed by Brewer and Speh(2000). Survey questionnaires to measure the independent variable were modified appropriately to fit in distributing and manufacturing companies. Each question was given values over a 7-point Likert scale. For developing decision support model in an SCMSC purposes, the dependent variable, that is, sustainable collaboration, was measured with a 7-point Likert scale, such as, '1' in very weakly an SCMSC and '7' in very strongly an SCMSC.

This survey was administered from June through September, 2003, to an SCM specialists of distributing and manufacturing companies that are carrying out an SCM. Out of 300 questionnairs distributed, 120 were collected and 108 were used in the analysis after discarding questionnairs with incomplete answers. The statistical values of the variables are shown in <Table 1>.

<Table 1> BSC Description Statistics

Feature Name		Mean	SD
Learning Perspective	Product and process innovation	4.361111	1.179722
	Partnership management	4.333333	1.059007
	Information flows	4.231481	1.115787
	Threats and substitutes	4.425926	1.161724
Internal Process Perspective	Waste reduction	4.277778	1.092312
	Time compression	4.314815	1.116136
	Flexible response	4.305556	1.147597
	Unit cost reduction	4.342593	1.153313
Customer Perspective	View of product/service	4.314815	1.132759
	View of timeliness	4.259259	1.113808
	View of flexibility	4.351852	1.087867
	View of customer value	4.166667	1.045685
Financial Perspective	Profit margins	4.416667	1.086235
	Cash flow	4.268519	1.046637
	Revenue growth	4.240741	1.012726
	Return on assets	4.203704	1.039044

2. Research Method

This article compares the forecasting performance of an SCMSC using four types SVM model as mentioned earlier. And the SCM kernel of best performance is compared with ANN prediction performance. The SVM data ratio of the training data, test data and holdout data set is 60:20:20 for the test. The holdout data is used to test the result with the rest of the data which was not utilized to develop the model. And this research uses SVM^{dark} software to perform experiments. The ANN data sets are composed of training data set and holdout data set. About 20% of the data is used for hold out and 80% for training. The software for empirical test uses SPSS Clementine 8.1

Ⅳ. Experimental Design and Results

1. Experimental Design

In this study, SVM is employed for an SCMSC forecasting. First, we analyze (1) linear, (2) polynomial, (3) RBF (Radial Basis Function), (4) sigmoid kernel for fining best SVM kernel. The SVM kernel conditions are as the followings: (1) SVM linear kernel don't control any condition (2) SVM polynomial kernel is d [0,5], s [0,5], c[0,5], (3) SVM RBF is gamma [-5,5], (4) SVM sigmoid kernel is s [5,-5], c [-5,5], C value = form 0 to 1000, epsilon value = form 0 to 1, 10 runs for test data.

As summarized in <Table 2>, SVM linear kernel reveals outstanding results, over the other kernels: polynomial, RBF, sigmoid kernel(linear > polynomial > sigmoid > RBF). Thus, this study focus SVM linear kernel. This study analyzes the optimal values for the best prediction performance supported by SVM[dark] software: c [0,1], epsilon [0,0.0001].

This study compares the performance of SVM with that of ANN method which uses various components such as input layer, hidden layer, and output layer. Since the design of ANN is rather close to an art, its performance is dependent on the levels of hidden layer number, hidden nod number, learning rate, and momentum. Due to small empirical data set, this study control hidden layer number as 2. In addition, we use the basic options of SPSS Clementine 8.1: quick algorithm, Alpha 0.9, Initial Eta 0.3, Eta decay 30, High Eta 0.1, Low Eta 0.01, to assign the value of the learning rate.

2. Empirical Result and Business Application

This paper employs SVM linear kernel and ANN method to explain SCMSC control model. First, we select the cases

〈Table 2〉 Average prediction accuracy of an SVM

Kernel	Time	Optimal C	MSE (Mean Squared Error)
Polynomial	0.03	432.173	2.294
Sigmoid	0.03	399.273	3.389
RBF	0.10	651.906	2.839
Linear	0.02	702.444	0.000~1

〈Table 3〉 An Average Prediction Performance of Holdout Data Set

Data Set	SVM	ANN
Holdout Data Set	85.80%	82.88%

which generate the average prediction performance with our holdout data. The results as in the <Table 3> show 85.80% of SVM accuracy in the holdout data in our test. Second, as explained, this study controls hidden layer numbers as 2 and uses basic options provided in SPSS Clementine 8.1 program for other conditions. When the number of hidden layer is 2, we have 82.88% of ANN accuracy with the holdout data.

In Table 4, we analyses the predictive ability of SVM model for the control model of an SCMSC. Table 4 shows the forecasting control level of an SCMSC. The SVM model shows forecasting performance 85.80% for holdout data. The results indicate the feasibility of SVM forecasting in an SCMSC.

〈Table 4〉 Average prediction control level of an SCMSC

Firm No	Holdout data	SVM forecast value	Prediction Accuracy
1	3.000	5.145	0.694
2	4.000	5.469	0.790
3	4.000	4.196	0.972
4	4.000	4.583	0.917
5	5.000	5.050	0.993
6	5.000	4.012	0.859
7	5.000	4.760	0.966
8	5.000	3.744	0.821
9	5.000	4.318	0.903
10	7.000	5.490	0.784
11	6.000	5.532	0.933
12	5.000	3.868	0.838
13	5.000	4.441	0.920
14	5.000	4.824	0.975
15	6.000	4.382	0.769
16	6.000	4.820	0.831
17	6.000	4.189	0.741
18	6.000	4.886	0.841
19	6.000	4.165	0.738
20	6.000	5.870	0.981
21	6.000	5.646	0.949
22	7.000	4.655	0.665

Using the 16 variables shown in <Table 1>, we can control the SC for an SCM of the coming year or the next business level. In the <Table 4>, prediction accuracy tells that firm n [n = from 1 to 22] will be control an SCMSC level. Likewise, SVM linear model can provide more accurate prediction on the SCMSC model than any other model using an BSC data set. This result may be very useful in corporate decision making especially for pursuing SCMSC.

The management implications are followings. First, the SCMSC control model is useful for sustainable collaboration processing and making decision. Second, the SCMSC control model reduced the cognitive burden of SCM managers in various cases to determine which controls fit for a company's specific organization environment. Thus SCMSC model overcomes SCM managers' cognitive limitations and biases on the complexity of decision making situations. Third, the SCMSC model suggested effective information of controls for each firm's specific organizational environment.

V. Conclusions

This paper tests the performance of SVM and ANN in the control model of an SCMSC. The research findings show that using SVM linear kernel to forecast an SCMSC is the most outstanding. The results tell that SVM linear kernel is an excellent alternative to the other methods in the prediction of an SCMSC. This result is very significant in confirming a more accurate SCMSC control model. SCM managers can determine which control fits for various organization context best.

However, this research has some limitations.

First, the evolution of an SCM is in the early stage in the Korean business market. Due to an insufficient number of samples, SVM tests were not diverse enough. Therefore, for future research it is necessary to collect more samples of corporations using an SCM to increase the diversity of feature weighting and feature selection in the comparison of actual analysis.

Second, the variables for measuring an SCM performance were used with the partially altered variables supplied by Brewer and Speh(2000). The feature of each field of corporation where an SCM is used should be reflected in future research. SVM analysis should be more elaborate and quantitative analysis and should be used in measuring the index of an SCM performance.

논문접수일 : 2005. 03. 20
논문게재일 : 2005. 06. 27

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A Decision Support Model for Sustainable Collaboration Level on Supply Chain Management using Support Vector Machines

Sehun Lim*

Abstract

It is important to control performance and a Sustainable Collaboration (SC) for the successful Supply Chain Management (SCM). This research developed a control model which analyzed SCM performances based on a Balanced Scorecard (BSC) and an SC using Support Vector Machine (SVM). 108 specialists of an SCM completed the questionnaires. We analyzed experimental data set using SVM^{dark}. This research compared the forecasting accuracy of an SCMSC through four types of SVM kernels: (1) linear, (2) polynomial, (3) Radial Basis Function (RBF), and (4) sigmoid kernel (linear > RBF > Sigmoid > Polynomial). Then, this study compares the prediction performance of SVM linear kernel with Artificial Neural Network (ANN). The research findings show that using SVM linear kernel to forecast an SCMSC is the most outstanding. Thus SVM linear kernel provides a promising alternative to an SC control level. A company which pursues an SCM can use the information of an SC in the SVM model.

Keywords: SVM(Support Vector Machines), SCM(Supply Chain Management), SC(Sustainable Collaboration)

* Adjunct Professor, Department of Information System, Chung-Ang University.