A New Logistic Management Quality Evaluation Method based on Support Vector Machine

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Abstract. In order to achieve more effective logistics management, make full use of data resources, and build in line with the development of a healthy enterprise logistics management mode. A new analysis model for evaluating the quality level of logistics management based on support vector machine theory is put forward. Through analyzing the influence factors in the logistics business process, the proposed model forecasts management efficiency of logistics operations implementation, and provide theoretical support for logistics management system optimization. Compared with the BP neural network model, the support vector machine has a more accuracy and efficiency, which is feasible for the quality evaluation of logistics management.

Introduction

In the development and construction of logistics information system, the existing logistics system design approach is usually based on work flow mode, which the business process designing is limited to personal management experience, the development cycle is shorter, the impact of the success of logistics and cost savings are not fully considered. These defects result in the original data can not be fully used in evaluation and forecasting of the logistics activities, and the data are wasteful [1,2].

Reverse logistics include the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of origin to the point of consumption for the purpose of conforming to customer requirements. Reverse logistics was attracting more and more attention in recent years. Even many firms were putting up or had put up the system already to manage their reverse logistics. These firms shared the same opinion that the reverse logistics could help them perform better with enhancing the firm’s core competence. According to the literature review, researches had made many contributions in this field. The reverse logistics theory had been fully developed and the framework of the reverse logistics had been built already. The methods and the significance of managing reverse logistics had been investigated by many academicians. Many of them were centering on how to construct the reverse logistics system and operate the system efficiently. The performance evaluation of the RL management system was few discussed in the literatures at hand[3-5].

It is a big problem need to be solved that how to fully inspire the parties involved in the logistics information system, analyze the various risk factors, correctly evaluate the influence of various factors, establish the quality evaluation model of logistics system management and achieve the maximum benefit [6]. Support vector machine (SVM) can get the optimal solution under the existing information in the limited sample space [7]. Through using the appropriate kernel functions and parameters, SVM can replace the inner product algorithm in the high-dimensional feature space, which can avoid the dimensionality curse occurred in the high dimensional space inner product, and can be effectively utilized for multi-dimensional quality evaluation of logistics management [8-10].

Quality evaluation index system of logistics management

In the logistics business implementation process, the main objects involves logistics enterprises and staff in each sectors. Due to the implementation of the logistics business is not done by a single person, but collaboration is done by multiple logistic personnel, so only set a post evaluation when considering the impact of human factors. Therefore, logistics management quality evaluation index system in the designing process contains two major factor: the logistics enterprises evaluation index system and logistics individual evaluation system, which is shown as follows:

(1) Basic information: Storage quality (X1), The number of loading and unloading equipment (X2), Freight vehicle mass (X3), The average age of employees employed (X4), The proportion of college education (X5).

(2) Human factors: The driver working years (X6), The number of traffic violations (X7), Traffic accident rate (X8), The number of road congestion (X9), Service attitude (X10).

(3) Logistics quality: Distribution correct rate (X11), On-time delivery rate (X12), Commodity good rates (X13), Packaging intact rate (X14), Back to a single complete rate (X15).

(4) Service quality: Remind inspection rate (X16), Promise to honor the rate (X17), Customer complaint rate (X18), Credit scores (X19), Service innovation rate (X20).

Support vector machine

SVM is a new learning method based on structural risk minimization principle of the machine, which can make full use of the limited sample learning acquisition decision function with high generalization ability. Considering a two classification models, a training sample is defined as $\{(x_i, y_i)\}$, where x_i represents the input vector and y_i represents the classification sign. The two classes of linear discriminant function of separable cases are as follows:

$$f(x) = w \cdot \varphi(x) + b \tag{1}$$

Where x is the sample vector, w is the weight vector, b represents the classification threshold. This process can be described as Fig 1.

Supposing there is a classification decision plane:

$$f(x) = w \cdot \varphi(x) + b = 0 \tag{2}$$

Which satisfies:

$$f(x) = \begin{cases} w \cdot \varphi(x) + b > 0 & y_i = +1 \\ w \cdot \varphi(x) + b < 0 & y_i = -1 \end{cases} \tag{3}$$

Thus, Eq.(2) is defined as the classification and ultra flat surface of support vector.

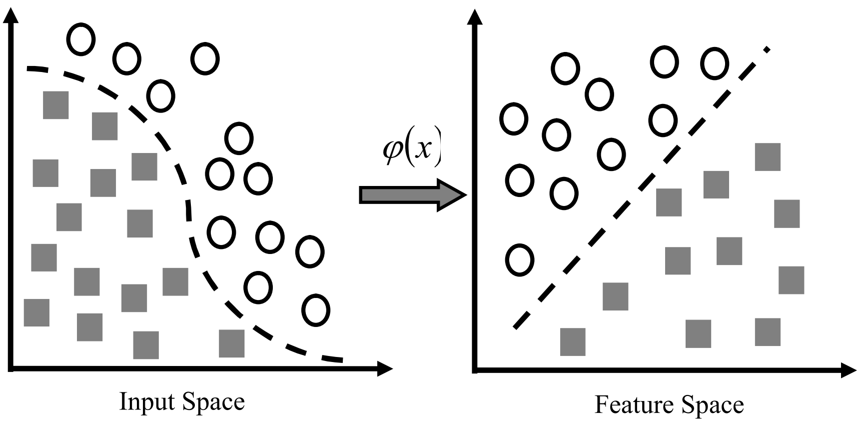

Fig 1: Illustration of the transformation process of SVM model

A two types of linear separable linear sample set $\{(x_i, y_i)\}^N$, $i = 1,2,\cdots,n$ is given. The weight vector w in hyperplane and classification threshold b are both obtained. As to any support vector x_{sv} and its classification label y_{sv}, it satisfies the following condition.

$$f(x_{sv}) = W^T x_{sv} + b = \begin{cases} +1 & y_{sv} = +1 \\ -1 & y_{sv} = -1 \end{cases} \tag{4}$$

The maximum interval of the classification plane can be calculated as $2/\|w\|$, Therefore, the maximum class interval is equivalent to the minimum. If the surplus plane need to classify all samples correctly, it must satisfy:

$$y_i\left(W^T x_i + b\right) - 1 \geq 0 \qquad i = 0,1,2,\cdots,N \tag{5}$$

Thus, the SVM hyperplane by solving the following constrained optimization problem was the solution:

$$\min_w \frac{1}{2} W^T W \tag{6}$$

Which is a A typical quadratic programming problem. The optimal solution is a saddle point of the following Lagrangian:

$$L(w,b,a) = \frac{1}{2}(w,w)^T - \sum_{i=1}^{l} \alpha_i \left[(x_i w - b) - 1 \right] \tag{7}$$

Where a_i is the Lagrange multipliers, The above optimization problem inverts into a dual form to get the solution:

$$\max W(\alpha) = \min\left(-\frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i u_j k(x_i, x_j) \right) \sum_{i=1}^{n} \alpha_i \tag{8}$$

According KKT conditions, those points on the boundary of two types of sample points fall in support vector machine SVM required solution. Classification decision function is obtained as follows:

$$f(x) = sign\left(\sum_{i,j=1}^{n} \alpha_i y_i k(x_i, x_j) + b \right) \tag{9}$$

Where $k(x_i, x_j)$ is the kernel function.

The Gaussian kernel function is selected as the support vector machine kernel function in this paper. The form of Gaussian kernel function is shown as follows:

$$K(x,y) = \exp\left(-\frac{\|x-y\|^2}{\sigma^2} \right) \tag{10}$$

Thus, the optimal separating hyperplane is required:

$$f(x) = sign\left(\sum_{i,j=1}^{n} \alpha_i y_i \exp\left(-\frac{\|x_i - x_j\|^2}{\sigma^2} \right) + b \right) \tag{11}$$

For SVM with Gaussian kernel function, the parameters conclude penalty parameter C and core width σ. The penalty parameter C is made between the structure and the risk of sample error compromise. The value of C is related to the tolerable error. A larger value allows small error and the smaller value allows larger errors. Core width σ is related to the input space of learning sample or the width. If the extent of the input sample is large, the value is large. On the contrary, if the extent of the input sample is small, the value is also small.

Specific exam and results analysis

The logistics management information system data of a certain company is selected as a sample in this paper. There are total 150 samples after sorting. The former 140 samples are regarded as the training samples, the remaining 10 samples are regarded as the testing samples.

(1) The selection of parameters in SVM.

Firstly, keep penalty parameter C as 10, gradually adjust the value of core width σ until the mean square error (MSE) of the overall test is minimum, the optimal core width σ^* is obtained. Then, in the same way, keep σ as σ^*, gradually adjust the value of C until the mean square error (MSE) of the overall test is minimum, the optimal penalty parameter C^* is obtained. The fitness function in the adjustment process and the various steps is selected as MSE. MSE is defined as follows:

$$MSE = \sqrt{\sum_{i=1}^{n} \frac{\left(y^* - y_i\right)^2}{n}} \quad . \tag{12}$$

Where y_i is the actual value and y^* is the forecasting value.

The selection process of parameters is shown in Table 1.

Table 1: Parameters selection of SVM

$C=10$		$\sigma=20$	
σ	MSE	C	MSE
0.1	0.9245	1	1.12487393e-5
0.5	0.8749	30	1.12428236e-5
0.9	0.5612	70	1.12398213e-5
1.0	0.2108	80	1.12398209e-5
8.0	0.0038	82	1.12398162e-5
12.0	1.2175e-4	83	1.12398134e-5
16.0	8.2417e-5	84	1.12398120e-5
20.0	2.1231e-5	89	1.12398136e-5
30.0	4.1290e-5	800	6.17923212e-4
38.0	8.5356e-4	1500	0.00781919
42.0	9.9609e-4	2000	0.00812939
50.0	4.1243e-3	2500	0.01798102

As can be seen from Table 1, when C is kept as 10, σ takes 20, which can make the MSE minimum. When σ is kept as 20, C takes 86, which can make the MSE minimum. Therefore, the optimal penalty parameter C is 86 ,and the optimal core width σ is 20.

(2) Training and testing.

The former140 samples of the total 150 samples are regarded as the training samples. The optimal parameters selected above are put into SVM. Through the training process, the result shows that the number of support vector is 113, the value of b is 0.0002376. Thus, the support vector regression model is shown as follows:

$$f(x) = \sum_{i=1} \left(a_i - a_i^*\right)\left(x \cdot x_i + 1\right) + 0.0002376 \quad . \tag{13}$$

Put the remaining 10 testing sample in the trained SVM, and the test results are shown in Table 2.

Table 2: Test results of SVM

Testing sample	Actual value	Output value of SVM	Relative error [%]
141	0.67	0.671	0.19
142	0.28	0.279	0.50
143	0.47	0.478	0.34
144	0.52	0.511	0.81
145	0.35	0.355	0.91
146	0.29	0.288	0.15

147	0.77	0.777	0.41
148	0.66	0.659	0.16
149	0.54	0.537	0.85
150	0.24	0.245	0.24

As can be seen from Table 2, the largest relative error in testing sample is 0.91%, the lowest relative error in testing sample is 0.16%, and the average relative error is 0.46%. Each testing sample's relative is below 1%, which indicates that the proposed model has a good generalization. Therefore, SVM model can be applied to evaluate the quality of logistics information management system, and provide the decision-making basis for optimization of logistics information management system.

In order to verify the SVM model for evaluating the quality of logistics management, and its superiority in the promotion and training efficiency, the BP neural network model are introduced in this paper to be a comparison. The comparison results are shown in Table 3.

Table 3: The comparison results of SVM and BP neural network

Testing sample	Actual value	Output of SVM		Output of BPNN	
		Evaluation value	Relative error [%]	Evaluation value	Relative error [%]
141	0.67	0.671	0.19	0.715	2.56
142	0.28	0.279	0.50	0.289	2.07
143	0.47	0.478	0.34	0.501	12.11
144	0.52	0.511	0.81	0.576	11.18
145	0.35	0.355	0.91	0.398	0.42
146	0.29	0.288	0.15	0.342	5.26
147	0.77	0.777	0.41	0.851	12.56
148	0.66	0.659	0.16	0.649	10.81
149	0.54	0.537	0.85	0.439	7.71
150	0.24	0.245	0.24	0.342	2.15
MSE		1.12399e-5		0.001512	

As can be seen from Table 3, the evaluation results of SVM model and BP neural network model and are basically the same, but the difference between each test sample error is obvious. Although， the fitting effect for training data of BP neural network has reached a very high accuracy, but the test error is significantly higher than that of support vector machine, which shows that although BP neural network training can achieve high accuracy, but can not ensure good generalization ability, resulting in over-learning phenomenon.

Conclusions

Through processing the data of logistics system, the quality evaluation indexes of logistics management are obtained. According to the training sample set, the quality evaluation of logistics management model based on support vector machine is established. The influence of single effective logistics activities from four sub- index systems including basic situation of the company, human factors, affecting the quality of logistics, and quality of service can be analyzed. The sub-index systems also have their lower index decomposition, which form the twenty secondary indicators as the key research targets. Examine its impact on the company's efficiency and use training sample set and test sample sets for evaluation to verify and compare the test with BP neural network. The test error of SVM is low, and SVM has a high efficiency, which can be applied to practice, evaluate the quality level of logistics management and provide a theoretical basis for decision support development system.

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