CUSTOMER SATISFACTION DEGREE EVALUATION MODEL IN LOGISTICS USING SVM

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Abstract: Customer satisfaction is important for the development of advanced logistical distribution. The paper presents a novel evaluation model of customer satisfaction degree (CSD) based on support vector machine(SVM). The relations of the suppliers and customers are analyzed, then the evaluation index system and fuzzy quantitative methods are provided firstly. The CSD evaluation system including nine indices and three ranks based on one-against-one mode of SVM is built. Last the simulation experiment is given to support the theoretical result.

Keywords: Support vector machine, Logistics distribution, Customer satisfaction degree, Evaluating index , Model.

1. INTRODUCTION

One of the main challenges of today's manufacturing is to be both efficiency and contributing to high effectiveness, i.e. customer satisfaction. Customer service is a main stage in logistics and supply chain. The degree of customer service is the key factor to satisfy the customers and attract the customer successors. Going too far in customization would ruin efficiency. On the other hand, too rigid an approach to supply chain management (SCM) would risk customer satisfaction. In recent years, many sellers have placed increased emphasis on satisfying their customers in order to tailor their product and service offerings to the customers' needs. The evaluation of the customer satisfaction is an important means to see the service quality and improve the efficient for companies. Mihelis and Grigoroudis, *et al.* (2001) show some research on customer satisfaction in bank sector. However, there are few practical evaluation method and system studies on customer satisfaction in logistics.

SVM is a machine learning algorithm and it is a recent development of statistical learning theory (Vapnik, 1995). SVM obtains an optimum network structure based on the principle of structural risk minimization (SRM) and overcomes the drawback of local minimum and empirical risk minimization of artificial neural network(ANN). It was not until the early 1990s that the techniques used for SVM began to emerge and become practical, with the increased computing power available. SVM has been applied in the machine learning, computer vision and pattern recognition communities for high accuracy and good generalization (Chappelle and Vapnik, 2000; Burges, 1998). Sun, *et al*. (2004) introduced a SVM approach coupled with one-against-one method to classify mechanical drive types. Heisele, *et al.* (2003) built a hierarchy of SVM classifiers for object detection systems in computer vision. Brown, *et al.* (1999) used SVM for optimal classification of mixture and verified SVM algorithms were better than other methods used before.

In this paper the evaluation of customer satisfaction degree in logistics is discussed and the correlative evaluation variables are given. The fuzzy membership functions are used to fuzzify the variables, firstly. Then an evaluation model is built using "one-against-one" method of the SVM and the simulations are finished. The results show that the model of customer satisfaction evaluation based on SVM can be used in real logistics, which will help suppliers enhance their management and improve the efficient.

The remainder of this paper is organized as follows. Section 2 presents evaluation indices and quantitative methods. The customer satisfaction evaluation model is built up in section 3. Then the simulation results are provided in section 4. Finally, summary and conclusion are presented in last section.

2. EVALUATION INDICES AND QUANTITATIVE METHOD

Customer satisfaction involves keeping customers happy both in day-to-day interactions and from a more global, long-term perspective (Hunt, 1977; Johnson and Fornell, 1991). Competitive pressures mandate that firms identify customer requirements and develop strategies that allow them to meet or beat the service levels provided by other vendors (Verwijmeren, *et al.*, 1996).

2.1 Fuzzy Numbers

In our problem we will need a special type of fuzzy numbers, which is relatively easy to handle and still suffices for most practical applications.

The linear membership function is written as:

Definition 1: Set A in a base set X can be described by a membership function $\mu_A : X \to \{0,1\}$ with $\mu_A(x)=1$ if $x \in A$ and $\mu_A(x)=0$ if $x \notin A$. If it is uncertain, whether or not element x belongs to set A , the above model can be extended such that the membership function maps into interval $[0,1]$. A high value of this membership function implies high possibility, while a low value poor possibility. This leads to the following definition of a fuzzy set:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\} \tag{1}$$

where $\mu_{\tilde{A}}$ is called the membership function of $\tilde{A}$.

2.2 Determination of evaluation indices

Specification of evaluation indices used to explore the degree of customer satisfaction in distribution service is the first step in developing the proposed methodology. For specifying the decision variables of customer satisfaction. For the analysis of customer satisfaction grade, we first investigated the relations between customer service on the supply side and customer satisfaction on the demand side. From a supplier point of view, there seems to be a consensus that five major measures of effectiveness (ME) can be used to examine, directly and indirectly, the capability of logistical distribution service: (1) safety, (2) transit time, (3) transportation cost, (4) accessibility, and (5) service quality. The implications of these supply indices associated with the customer satisfaction in the demand domain include primarily: (1) security, (2) reliability, (3) economic concern, (4) convenience, and (5) satisfaction in servers quality; and these are herein taken to be the major customer concerns. However, in real-world operations, the aforementioned customer concerns may not be perfectly consistent with the supply-driven ME indices, and to a certain extent, they may conflict, internally and externally, with each other. For instance, to provide a customer with high accessibility, the logistical supplier may need to invest heavily in restructuring distribution networks, and as a consequence, logistical costs including transportation cost must increase. Nevertheless, such conflicts are allowed in demand oriented logistical control and management strategies because the benefits gained from the increased amount of new customers derived from the strategy of high convenience service may pay off the increased cost.

With the aforementioned postulations to determine the decision variables, two procedures were executed, including specification of variable candidates and a questionnaire survey. In the first stage, we tentatively proposed 12 candidates of decision variables derived from the aforementioned five major concerns of customers in a logistical distribution service. The candidates for these decision variables were presumed as the factors in segmenting customers for the proposed demand-responsive logistical distribution algorithm. A civil questionnaire mail survey of the logistics-related community was then conducted in the second stage. Considering the comprehensiveness of the samples to be surveyed, we included customers in this fields and freight transportation/logistics business operators. In this survey, the total sample size was 160, collected randomly from the above target groups. Among the 160 samples, 85 samples were valid, meaning that their mail responses were received and assessable. Each survey respondent was asked to rate the 12 candidates of decision variables with a positive integer bounded by 1 and 10, corresponding to “not significant”, “significant” and “most significant”, respectively. By factor analyses, we obtained a total of 9 variable candidates for the decision variables, with the generalization that they were classified into the group of significant factors. The denotations as well as explications of these finalized decision variables are summarized as follows.

X_1^i represents out of stock rate when customer i ordering. X_1^i is usually given by:

$$X_1^i = \frac{n_{OS}}{n_{OP}} \tag{2}$$

where n_{OS} and n_{OP} correspond to the out of stock quantity and the total quantity ordered by customer i .

X_2^i represents the time lag between the deadline to customer i and the distribution time k , In real-world operations, it is permissible to deliver products to those customers associated with the time windows $[ET_i, LT_i]$, where ET_i and LT_i are the earliest and latest time to start to service customer i . The usual way to model an imprecise servicing time using fuzzy logic is to define it by a triangle membership function (Kerr and Walker, 1989), which defines the possibility distribution of the considered servicing time (See Fig.1).

The triangle membership function in Fig. 1 can be written as:

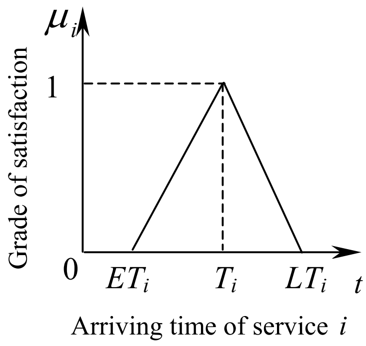


Fig.2 Definition of an imprecise serving time

$$\mu_i = \begin{cases} 0 & \text{if} \quad x_i \le ET_i \\ \dfrac{x_i - ET_i}{T_i - ET_i} & \text{if} \quad ET_i < x_i < T_i \\ 1 & \text{if} \quad x_i = T_i \\ 1 - \dfrac{x_i - T_i}{LT_i - T_i} & \text{if} \quad T_i < x_i < LT_i \\ 0 & \text{if} \quad x_i \ge LT_i \end{cases} \tag{3}$$

X_3^i represents out of stock rate when customer i are served. X_3^i is given by:

$$X_3^i = \frac{n_{DS}}{n_{DP}} \tag{4}$$

where n_{DS} and n_{DP} correspond to the values of the out of stock quantity and the total quantity when customer i is served .

X_4^i represents the service's quality to customer i . It is commonly agreed that the server's personal quality, including the time spent in responding to customers' demands, the server's personal attitude and the server's confidence, determines the customer's satisfaction with the logistical distribution system. Herein, this variable serves to qualitatively indicate the customer's personal demand for the server's quality.

X_5^i represents the time lag between the deadline to customer i and the distribution time k at exchanging product, the definition is similar to X_2^i .

X_6^i represents the substitute probability of product. X_6^i is given by

$$X_6^i = \frac{n_{SP}}{n_{OP}} \tag{5}$$

where n_{SP} and n_{OP} correspond to the substitute quantity and the total ordering quantity.

X_7^i corresponds to the value of the product distributed to customer i , and to a certain extent it may depend on the market price of the product. X_7^i is given by:

$$X_7^i = p_A - p_F \tag{6}$$

where p_A and p_F correspond to the value anticipated by a customer i and the actual value.

X_8^i is defined as the satisfaction of customer i with respect to the security of the distributed product. This variable implies, to a great extent, a customer's personal demands in terms of condition of the product. In effect, this variable will be affected by the product performance.

X_9^i represents the life cycle of the product distributed to customer i . This reflects the fact that most customers are concerned with either the expiration dates or the product values during their market lives. X_9^i is given by

$$X_9^i = lc_A - lc_F \tag{7}$$

where lc_A and lc_F correspond to the life cycle anticipated by a customer i and the factual life cycle, respectively.

Aforementioned decision variables X_1^i , X_2^i , X_3^i , X_5^i , X_6^i , X_7^i , X_9^i are measured with corresponding equations. X_4^i and X_8^i are given a positive number bounded by 0 and 1. All the variables are converted finally into numbers between 0 and 1.

2.3 Ranks of customer satisfaction evaluation

All the determination variables above are used as the inputs of SVM. The customer satisfaction degrees are evaluated with three ranks, i.e., satisfaction (S), neutrality (N) and dissatisfaction (Ds). So the customer satisfaction degrees are described by:

$$R = \{ y | y \in \{S, N, Ds\} \} \tag{8}$$

3. CUSTOMER SATISFACTION EVALUATION MODEL BASED ON SVM

The customer satisfaction evaluation has nine indices $X = \{X_1^i, X_2^i, \cdots, X_9^i\}, i = 1, \cdots n$. n is the number of samples. The problem is classifying the customer satisfaction into three ranks $R = \{ y | y \in \{S, N, Ds\} \}$ according to nine indices, which is a multi-class problem.

Currently there are many types of approaches for multi-class SVM such as one-against-all, one-against-one (Platt et al, 2000). Both methods can be adapted to different problems. In this paper, the classification number is small and the high classification accuracy is demanded. Therefore, one-against-one method is adopted to model the customer satisfaction degree.

The customer satisfaction degree evaluation problem is described as classifying n customer satisfaction degree training examples including nine characters $X=\left\{X_1^i, X_2^i, \cdots, X_9^i\right\}, i=1,\cdots n$ into k ranks. Here $k=3$, i.e., $R=\left\{y \middle| y\in\{S,N,Ds\}\right\}$.

1-*v*-1 method of SVM build a classifier model $f(x)$ according to the samples. It constructs $k(k-1)/2$ classifiers, where k is the number of the classes, each classifier is trained on data from two classes. The i th SVM is trained with all of the examples in the i th class with positive labels, and all other examples with negative labels. Thus give m training data $(X^1, y_1), \cdots, (X^i, y_m)$, where $X^i \in X, i=1,\cdots,m$ and $y_m \in \{1,\cdots,k\}$ is the class of X^i, the i th SVM solves the following problem:

$$
\begin{aligned}
&\min_{\omega^{ij}, b^{ij}, \xi^{ij}} \quad \frac{1}{2}\left(\omega^{ij}\right)^T \omega^{ij} + C\sum_t \xi_t^{ij}\left(\omega^{ij}\right)^T \\
&s.t. \quad \left(\omega^{ij}\right)^T \Phi\left(x_t\right) + b^{ij} \geq 1-\xi_t^{ij} \quad if \quad y_t = i \\
&\qquad \left(\omega^{ij}\right)^T \Phi\left(x_t\right) + b^{ij} \leq -1+\xi_t^{ij} \quad if \quad y_t = j \\
&\qquad \xi_t^{ij} \geq 0 \qquad j=1,\cdots m
\end{aligned}
\tag{9}
$$

There are different methods for doing the future testing after all classifiers are constructed, here we decide to use the following voting strategy: if sign $\left(\left(w^{ij}\right)^T \Phi\left(x\right) + b^{ij}\right)$ says x is in the i th class, then the vote for the i th class is added by one. Otherwise, the j th is increased by one. Then we predict X^i is in the class with the largest vote.

By solving the Wolf dual of (9), the quadratic protruding programming can be obtained:

$$
\begin{aligned}
&\max \quad W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\
&\text{s.t.} \quad \sum_{i=1}^{l} \alpha_i y_i = 0,\ 0 \leq \alpha_i \leq C,\ i=1,\ldots,l
\end{aligned}
\tag{10}
$$

where α_i is the Lagrange factor, α_i which is not zero corresponds to support vector (SV).

Practically we solve (10) whose number of variables is the same as the number of data in two classes. Hence if in average each class has l/k data points, we have to solve $k(k-1)/2$ quadratic programming problems where each of them has about $2l/k$ variables. For each quadratic programming problem, the separating hyperplane is given by

$$f(x) = \text{sgn}\left(\sum_{i\in sv} \alpha_i y_i \Phi(x_i)\, \Phi(x) + b\right) \tag{11}$$

where $\Psi\left(x_t, x\right) = \Phi\left(x_t\right) \cdot \Phi\left(x\right)$ is the kernel function defining the inner products of the nonlinearly mapped examples $\Phi\left(x\right)$ in the feature space, b is found by enforcing the empirical risk to be zero. The margin is bound by the set of examples $\left\{x \mid f\left(x\right) = \pm 1\right\}$.

In general, the kernel functions of SVM are respectively nonlinear function, Gauss function, polynomial function and perception function. The four functions are respectively formulated by Formula (12)-(15):

$$K(x_i, x) = x_i \cdot x \tag{12}$$

$$K(x_i, x) = \exp(-\|x - x_i\|^2 / 2\sigma^2) \tag{13}$$

$$K(x_i, x) = (x_i \cdot x + 1)^d \tag{14}$$

$$K(x_i, x) = \tanh(\beta x_i \cdot x + b) \tag{15}$$

While the SVM scheme can take a learning approach to identify different class among the input pattern, once the training finished, the class label for each user can be obtained through the discriminate function of support vector classifier (SVC), and then the class will be finished.

In standard SVM problem, Karush-Kuhn-Tucker (KKT) condition is necessary and sufficient for the optimal solution of a positive definite QP problem (Vapnik, 1998). Applying KKT condition to SVM optimization, we have

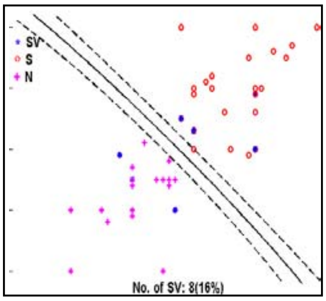
$$
\begin{aligned}
&\alpha_t = 0 \Leftrightarrow y_t f\left(x_t\right) \geq 1 \\
&0 < \alpha_t < C \Rightarrow y_t f\left(x_t\right) = 1 \\
&\alpha_t = C \Rightarrow y_t f\left(x_t\right) \leq 1
\end{aligned}
\tag{16}
$$

In terms of definition of support vectors (SVs), only those that lie inside or on the margin are SVs, which corresponds to nonzero α_t, in many practical applications, only a small percentage of training data are SVs, from (16) we know that only those SVs take effect in deciding which class each training data belongs to, if we remove those training data with a zero α_t, we can still ensure a correct solution to SVC.

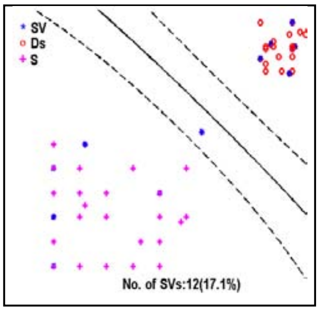
4. SIMULATION AND RESULTS

In this section we simulate the problem described above and present experimental results, the number of training set $N=85$. Three one-against-one mode SVMs in parallel are used to classify three classes.

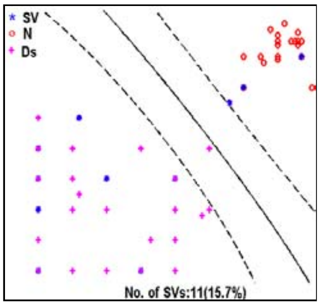
The training results of SVM classifiers are revealed in Fig. 2(a)-(c). The training time of every classifier is less than 0.7s.A series of data points are shown, circles (class A), pluses (class B) and asterisks (SVs). From the figures we can conclude that the previous problem are classifiable.



(a) satisfaction and neutral classifier



(b) dissatisfaction and satisfaction classifier



(c) neutral and dissatisfaction classifier

Fig 2 Training results of classifiers

Table 1 Training parameters of classifiers

Classifier	S & N	S & Ds	N & DS
Kernel function	Quadratic polynomial	Gauss	Gauss
SVM Number	8	12	11
Sample Number	50	70	50
Accuracy	100%	100%	100%

The training example and SV number, Kernel function and the accuracy rate of classifiers are listed in Table 1.

Training examples are tested in every SVM, all the success rates are 100%, which evaluate the performance of each classifier is high. Then we use 110 testing examples to test in parallel-mounting SVMs. The accuracy of the testing is 92.7% and the testing time is about 0.5s. The flowchart of testing process is shown in Fig 3.

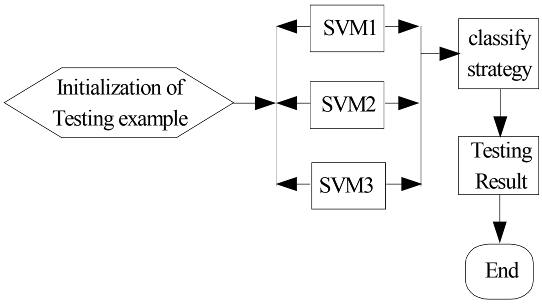


Fig 3 Testing flow chart

5. CONCLUSION

The customer satisfaction evaluation is affected by many factors and the effect is very complex. So it is difficult to construct a model for the problem. In this paper we build an evaluation model using the one-against-one classified algorithm of SVM, which is by transforming evaluation problem to classified problem and build three classifiers. The classifier based on multi-class classification of SVM includes a solution in two aspects, an efficient SVC frame and an effective detection algorithm. The former is constructed through one-against-one mode; standard QP solution is used as the algorithm. The latter part focused mainly on the implementation of the evaluation of customer satisfaction under SVC environment. The validity of such an algorithm is given by the simulation result. It provides a fast and effective method for logistics and avoids some unscientific traditional methods.

The last aspect need to be pointed out is, one-against-one mode is applied to the system, DAGSVM and other improved algorithms applied to the mechanical drive system is worthwhile to be investigated carefully. They are under our consideration in near future.

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