The Evaluation Model of Construction Industry Financial Risk Based on SVM

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Abstract The model of evaluating profession financial risk can be added with industry characteristic indicator, a general evaluation model is more suitable for a particular industry, and it can improve the accuracy. This paper has chosen 23 financial indexes aims at six respects such as solvency, profitability, cash flow, asset management ability, development ability and capital structure of construction industry, and has built the evaluation index system of building trades. Selected the construction enterprises in the Shanghai and Shenzhen listed as samples, applied cluster analysis on samples to preprocessing, then using the theory of support vector machine, respectively constructed polynomial Gauss radical, Sigmoid three kernel function SVM evaluation model of construction industry financial risk, and has verified them, The results shows that the SVM model that applied in the financial risk evaluation of construction industry has a high accuracy.

Keywords Construction industry · Financial · Cluster analysis · Support vector machine · Kernel function

1 Introduction

In recent years, the research which on enterprise financial risk model mainly concentrated on the general model widely used are statistical model and artificial intelligent model. Statistical model contains Z score model, multivariate discriminate analysis model, Logistic regression model and principal component analysis model. Artificial intelligence model mainly contains fuzzy evaluation model and neural network model [1].

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Management model, organization model, products and risk of construction industry have characteristics different from other industry have characteristics different from other industry. Using a general model to evaluate the financial risk will be biased. Constructing a financial risk evaluation model that specialized for construction industry to monitor and evaluate it's financial situation, it has important significance for guarding against and defusing financial risk of construction enterprises [2]. But the above model in application must depend on a lot of Historical samples, it will affect its accuracy for construction industry which has less data.

This paper aimed at the realistic situation of less samples of construction enterprise, using small sample learning method-support vector machine (SVM-Support Vector Machines), has established the evaluation model of construction industry financial risk based on SVM, in order to improve the accuracy of evaluation.

2 The Selection of Sample and Cluster Analysis

2.1 The Selection of Sample

The study samples are A shares of construction and whose enterprises that listed on the Shanghai and Shenzhen stock exchange. This paper have selected 38 companies that are listed in Shanghai and Shenzhen, whose financial data have announced and whose main businesses are civil, design planning, engineering contracting and real estate development. The datum in samples are directly obtained from the public annual accounting report or obtained by processing.

2.2 Cluster Analysis

2.2.1 The Theory of Cluster Analysis

Cluster is composed data object into different classes, so that the similarity between different types become smaller while similarity between similar object become larger [3]. Cluster analysis is a kind of common statistical analysis method that is studying (sample or index) the classification problems. Clustering is an unsupervised, observed learning process, it not gen people's subjective judgment and based on data, so it is objective and fair, cluster analysis can be separately as a tool to obtain the distribution of data, then through analyze the data, it also can be used as a preprocessing step for other algorithms. In this study, before building evaluation model of construction enterprise financial risk, using cluster analysis to classify the selected 38 construction enterprises without a priori, so that avoid classifying the samples confine within ST and Non ST.

2.2.2 Application of Cluster Analysis

According to the above evaluation index system and sample data, cluster analyzing relevant financial data of construction enterprises by common hierarchical cluster method.

Through the cluster analysis of spss17.0, the risk finance of construction not only covers the construction enterprise that has been defined as ST, such as ST Huitong, but also Not ST construction enterprise, contains: Shenzhen Universe Group Co. Ltd, NORINCO International, Xiamen Academy of Building Research Group Co., Ltd, Shanghai Pudong Road and Bridge Construction Co. Ltd, Longyuan Construction Group Co. Ltd, Tengda Construction Group Co. Ltd, Longjian Road and Bridge Co. Ltd, Keda-Group Company, China Railway Construction Corporation Limited. This reflects that using cluster analysis can eliminate the priori interference. Classifying potential financial crisis enterprises into dominant financial crisis enterprises is more predictable.

Now, we constructing a more accurate financial risk evaluation model by using support vector machine based on cluster analysis.

3 The SVM Model of Financial Risk Evaluation

3.1 Support Vector Machine Theory

SVM is a kind of universal learning machine, it is a statistical learning method that realized by Vapnik based on statistical theory, then formed a small samples learning method that based on statistical theory [4].

SVM has a solid theoretical foundation in Mathematics. It is specifically for the small sample learning problems, the method is based on the VC dimension theory of statistical learning theory and structural risk minimization principle. According to the limited information, finding the best compromise between the model complexity (that is the learning accuracy of specific training samples) and the learning ability (that is the capacity to identify any sample without error), it has a stronger generalization ability [5].

The basic idea of SVM is summed up: changing the input space into a high dimensional space by nonlinearity, solving convex two quadratic programming problems with a constraint in this new space, then can obtain the global unique optimal solution.

SVM has the following characteristics:

Model training needs fewer parameter to indentify, and determining the model parameter is an optimization problem of convex objective function.

SVM is a machine learning method of hard structural risk minimization, it finds the structural risk minimization through the generalization error bound, so it has avoided the defect of empirical risk minimization of the general statistical learning methods.

SVM can transforms linear inseparable vector quantity into linear separable one by using the method of mapping low dimensional output space to high dimensional feature space, then calculating the best graphic classification.

SVM using the kernel function of original space, cleverly replaces the inner product operation in the high dimensional feature space, that is $Q_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j)$, so it can avoid the rapid growing problem in the process of mapping low dimensional output space to high dimensional feature space.

3.2 Establishing SVM Model of Construction Industry Financial Risk Evaluation

For the sample set [6]:

$$(x_1, y_1)\ldots(x_i, y_i)\ldots(x_l, y_l) \in R^N \times R \tag{1}$$

The required function form of fitting:

$$f(x) = W^T \phi(x) + b, \quad W, \phi(x) \in R^N,\ b \in R \tag{2}$$

where, W is parameter column vector, $\phi(\cdot)$ is column vector of a function, it has mapped input sample to feature space from input space.

The obtained fitting function $f(\cdot)$ need to minimize the following performance index. That structural risk:

$$R^{\varepsilon}_{reg} = \frac{1}{2}\|W\|^2 + C \cdot R^{\varepsilon}_{emp} \tag{3}$$

where, constant C is penalty factor, and $C > 0$, that is the punishment degree of the samples of beyond error, it can get a compromise between training error and the model complexity, so that the obtained function $f(x)$ has a better generalization ability.

Empirical risk:

$$R^{\varepsilon}_{emp} = \frac{1}{l}\sum_{i=1}^{l} |y_i - f(x_i)|_{\varepsilon} \tag{4}$$

Defining the insensitive loss function ε:

$$|y - f(x)|_\varepsilon = \begin{cases} 0, & |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon, & |y - f(x)| > \varepsilon \end{cases} \tag{5}$$

Transforming approximation problem of function into the optimization problem as follows:

$$\min\left(\frac{1}{2}W^T W + C\left(v\varepsilon + \frac{1}{l}\sum_{i=1}^{1}\left(\zeta_i + \zeta_i^*\right)\right)\right) \tag{6}$$

$$W^T\phi(x_i) + b - y_i \le \varepsilon + \zeta_i \tag{7}$$

$$y_i - W^T\phi(x_i) - b \le \varepsilon + \zeta_i^* \tag{8}$$

$$\zeta_i, \zeta_i^* \ge 0, \varepsilon \ge 0, \quad i = 1, \ldots, l \tag{9}$$

where, $0 \le v \le 1$, insensitive loss function ε shows that $W^T\phi(x)$ in $y \pm \varepsilon$, and do not account for loss.

The presence of insensitive loss function has increased the model tolerance, compromising maximum of classification interval and minimum of misclassified samples, getting the generalized optimal classification face, obtained the generalized optimal classification face.

Solving the optimization problems, defining Lagrange function:

$$\begin{aligned} L(W, b, \zeta, \zeta^*, \alpha, \alpha^*, \eta, \eta^*) = \frac{1}{2}\|W\|^2 + Cv\varepsilon \\ + \frac{C}{l}\sum_{i=1}^{l}\left(\zeta_i + \zeta_i^*\right) - \sum_{i=1}^{l}\left(\eta_i\zeta_i + \eta_i^*\zeta_i^*\right) \\ - \sum_{i=1}^{l}\alpha_i\left(\varepsilon + \zeta_i + y_i - W^T\phi(x_i) - b\right) \\ - \sum_{i=1}^{l}\alpha_i^*\left(\varepsilon + \zeta_i^* - y_i + W^T\phi(x_i) + b\right) - \beta\varepsilon \end{aligned} \tag{10}$$

Because $\frac{\partial L}{\partial W} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial \varepsilon} = 0, \frac{\partial L}{\partial \zeta_i^*} = 0$, so

$$W = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)\phi(x_i) \tag{11}$$

$$\sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) = 0 \tag{12}$$

$$Cv - \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) - \beta = 0, \tag{13}$$

Introducing a kernel function to find the dot product of the feature space $K(x,y) = \phi(x) \cdot \phi(y)$, so obtaining an optimization problem of quadric form:

$$\min\left(\frac{1}{2}\sum_{i,j=1}^{l}\left(\alpha_i^* - \alpha_i\right)K\left(x_i, x_j\right)\left(\alpha_j^* - \alpha_j\right) - \sum_{i=1}^{l} y_i\left(\alpha_i^* - \alpha_i\right)\right) \tag{14}$$

$$st: \sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right) = 0 \tag{15}$$

$$0 \leq \sum_{i=1}^{l}\left(\alpha_i + \alpha_i^*\right) \leq Cv \tag{16}$$

$$0 \leq \alpha_i, \alpha_i^* \leq C/l, \quad i = 1, \ldots, l \tag{17}$$

We expresses standard quadric form planning type by matrix:

$$\min\left(\frac{1}{2}(\alpha - \alpha^*)^T Q(\alpha - \alpha^*) + y^T(\alpha - \alpha^*)\right) \tag{18}$$

$$st: e^T(\alpha - \alpha^*) = 0, e^T(\alpha + \alpha^*) \leq Cv \tag{19}$$

$$0 \leq \alpha_i, \alpha_i^* \leq C/l, \quad i = 1, \ldots, l \tag{20}$$

where, e is a unit matrix.

Q is a kernel matrix, the elements:

$$Q_{ij} = \phi(x_i)^T \phi\left(x_j\right) = K\left(x_i, x_j\right) \tag{21}$$

The common kernel function contains polynomial kernel function, Gauss radial basis function, the Sigmoid kernel function and custom function [7].

Polynomial kernel function:

$$K(x,y) = ((x \cdot y) + 1)^d, \quad d = 1, \ldots n \tag{22}$$

Gauss radial basis function:

$$K(x,y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \tag{23}$$

where, σ is an undetermined constant.

Sigmoid kernel function:

$$K(x,y) = \tan(\phi(x \cdot y) + \theta) \tag{24}$$

SVM output function:

$$f(x) = \sum_{i=1}^{l} \left(\alpha_i^* - \alpha_i\right) K(x_i, x) + b \tag{25}$$

The author has respectively complied the polynomial kernel function, radial basis function, and Sigmoid kernel function Matlab procedures of SVM model.

Compiling Matlab grogram as follows:

Selecting the before 30 samples of sample set as training sample, the remaining 8 samples for the validation sample.

For output, +1 is the normal financial output, −1 is the financial crisis output.

Model parameters obtained by the methods of cross validation and lattice search.

Training the input model of training sample until obtains the satisfactory accuracy, this optimal classification function is the SVM model of construction industry financial risk.

3.3 Verifying the SVM Model of Construction Industry Financial Risk Evaluation

Respectively inputting training samples into above three kinds of SVM evaluation model of kernel function, testing the evaluation accuracy of training samples, then respectively inputting verification sample into model, it can verify the accuracy of the model for sample prediction, then evaluate the generalization ability of model. Obtaining the comprehensive accuracy of various model by calculating.

Comparing the model test results in Table 1 can be seen, the prediction accuracy of the three kernel model for training samples is the same, comprehensive prediction accuracy is generally high, so it is viable for SVM applying to construction industry financial risk evaluation. The prediction accuracy of radial basis kernel function model is higher than other two ones for testing samples. So Gauss radial basis kernel function model can better evaluate the construction industry financial risk.

Table 1 The model test results in

Samples	Accuracy		
	Sigmoid kernel function (%)	Polynomial kernel function (%)	Radial basis function (%)
Training samples	89.3	89.3	89.3
Verifying samples	80	80	90
Comprehensive	86.8	86.8	89.5

4 Conclusion

1. This paper has preprocessed the sample by cluster analysis and eliminated the inherent limitations of ST classification and Non ST, increased the seldom industry modeling possibilities of enterprises.
2. Trained samples using SVM theory, complied the polynomial kernel function, Sigmoid kernel function, radial basis function is superior to other kernel function ones, can better evaluate construction enterprise financial risk.
3. The choice of model parameters is difficult, such as penalty factor *C*, insensitive loss function ε, kernel parameter and so on. To optimize these parameters is worth further studying.

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