Credit Decisions of Small, Medium and Micro Enterprises Based on Topsis Model

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Abstract: Small, medium and micro enterprises play an important role in supporting the national economy, but they have few credit records and poor guarantee capabilities. Therefore, commercial banks for small and medium enterprises must do adequate pre-lending management. This article separately analyzes the financial indicators of companies with credit records and those without credit records, establishes an accurate, appropriate, and systematic risk assessment model, and gives credit strategies for these companies based on the results of quantitative evaluation. We also optimize the Topsis model based on the entropy weight method. As a non-subjective method of assigning weight to the evaluation index, starting from data analysis alone, the weight of the evaluation index can be calculated without any subjective method.

1. Problem background

Small, medium and micro enterprises are an important part of the real economy, the "main force" for absorbing employment, and an important support and source of vitality for national economic growth. [1] In practice, due to the relatively small scale of small, medium and micro enterprises and lack of collateral assets, banks usually rely on the credit policy at the time, information on transactions between enterprises and the influence of upstream and downstream enterprises to stabilize supply and demand. Provide loans to companies with good financial status and strong strength, and give preferential interest rates to companies with high credit ratings and low credit risks.

Since the beginning of this year, under the impact of the epidemic, small and micro enterprises have ushered in the capital chain test and urgently need to expand financing channels. In order to further strengthen the precise drip irrigation of the real economy, the banking industry should focus on the development of small, medium and micro enterprises, continuously improve the credit access mechanism, promote the application of digital transformation, and increase incentives and guidance. [2] At present, most of the small, medium and micro enterprises have been established for a short period of time, and in production and operation, no matter the management mode, organizational structure, governance mechanism, property rights system, and financial system are perfect. At the same time, due to the small scale of these enterprises, lack of credit records, and insufficient guarantee capabilities, small, medium and micro enterprises face difficulties in financing and poor financing capabilities in the course of their operations. In the transaction process of small, medium and micro enterprises, due to the frequent use of credit contracts, authorizations, agreements and even promises and other credit methods for commodity transactions, this has also increased the risk of default risks in the process of corporate transactions. The lack of corporate credit risk further increases the risk of loan default.

Therefore, commercial banks must do adequate pre-lending management for the credit management of SMEs. Banks will first evaluate the credit risk of small, medium and micro enterprises based on their strength and reputation, and then determine whether to lend and credit strategies such as loan quotas, interest rates and maturities based on factors such as credit risk ratings.

2. Problem analysis

The main goal of the bank is to maximize benefits, so we use revenue expectations to express it. The income expectation of the bank is related to the loan amount and interest rate of each enterprise. But high interest rates represent an increase in customer churn rate, so revenue expectations are also related to customer churn rate. In addition, each company's loan repayment ability and reputation are different, which will also affect the recovery of funds. So we use the maximization of income expectation as the objective function to establish a nonlinear programming model.

The most important factor in the non-linear programming model is the credit risk of each company. We must first quantitatively analyze the credit risk of each company, and then put it into the non-linear programming model to obtain the final optimal loan interest rate and loan amount . If an emergency occurs, we can quantify the impact factor based on the impact of the emergency on the operating effects of different industries and different companies, and then integrate it into the nonlinear model.

We use the data in the attachments to establish indicators, and then use the Topsis model to establish an evaluation system, so that the credit risk of each enterprise can be quantified.

The indicators we consider can include the credit rating of each company, whether the company has a record of default, the input tax and output tax information of each company, the amount of input bills and the amount of output bills of each company, and the sales parties and sales of each company over a period of time. The stability of the purchaser unit judges whether the supply and demand relationship of the enterprise is stable.

For 123 companies with credit records, we directly use the corporate reputation rating data in Annex 1, and for 302 companies without credit records, we build Fisher and neural network models to predict the credit ratings of these companies.

3. Model establishment and solution

3.1 Establish a nonlinear programming model

If the objective function or constraint condition contains a nonlinear function, this kind of programming problem is called a nonlinear programming problem. Generally speaking, solving nonlinear programming is much more difficult than solving linear programming problems. Moreover, unlike linear programming, the simplex method is a general method. Non-linear programming currently has no general algorithm suitable for various problems, and each method has its own specific scope of application. This article first establishes a nonlinear programming model, and then solves it according to the problem.

The goal of the bank is to maximize revenue, but due to the risk that funds will not be recovered, we have transformed the goal of the bank into maximum expected revenue. Regarding the first and second questions, the expected income of banks is affected by the company's ability to repay loans, loan lines, interest rates, and customer churn rates. These influencing factors are interrelated and have limited scope. Therefore, we build the following nonlinear model:

$$max\, r = \sum_{i=1}^{n} o_i * p_i * a_i * (1 - u_i)$$

$$\begin{cases} 100000 \le p_i \le 1000000 \\ 0.04 \le a_i \le 0.15 \\ \sum_{i=1}^{n} p_i = still\ number \\ o \in [0,1] \\ i、a_i \to u_i \\ a_i \propto -o_i \end{cases}$$

The o value is positively correlated with the company's ability to repay loans. The larger the value of o, the stronger the company's ability to repay loans. According to the relationship between the company’s credit rating and the customer churn rate given in Annex III, when the values of a_i and i are determined, that is, the company is determined, and then the company’s credit rating and loan interest rate are determined. The customer churn rate of the enterprise is determined. Because banks will give preferential interest rates to companies with high credit ratings and low loan risks, a_i should be negatively correlated with the value of o.

Regarding the third question, the bank’s expectations are not only affected by the company’s ability to repay loans, loan quotas, interest rates, and customer churn rates, but also by the risks of emergencies.

$$\max \mathrm{r} *= \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{f}_i * o_i * p_i * \mathrm{a}_i * (1 - \mathrm{u}_i)$$

The f-value represents the percentage of the emergency that is expected to reduce the company's ability to repay loans to the original repayment ability.

3.2 Modeling for predicting the level of companies with no loan records

Linear Discriminant Analysis (LDA) is a multivariate statistical method aimed at finding the linear projection of high-dimensional observations to low-dimensional space. When the preconditions are met, LDA allows to define the optimal linear decision boundary in the result space.

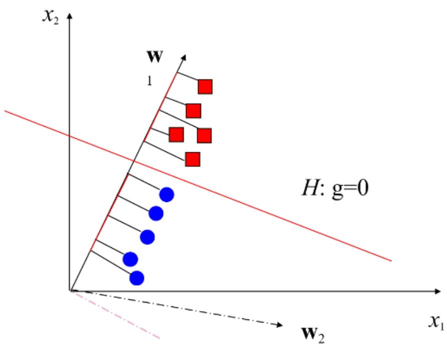

Figure 1 Schematic diagram of Fisher linear classification concept

The core idea of Fisher linear classification is to divide all points on both sides of the hyperplane W^TX=0, and then it can be concluded that each point can be projected onto the normal vector of W, so that the distance between classes can be large. The inner distance is small.

$$X = (x_1, x_2, \cdots, x_n)^T = \begin{pmatrix} x_1^T \\ x_2^T \\ x_3^T \\ \vdots \\ x_n^T \end{pmatrix}_{N \times P}, Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}_{n \times 1}$$

First calculate the projection dimension Z of each point X on the normal vector, take |w|=1, then$z_i = |x_i|cos\theta$, and

$$\begin{cases} z_i = w^T x \\ \bar{z} = \frac{1}{N}\sum_{i=1}^{N} w^T x \\ S_z = \frac{1}{N}(z_i - \bar{z})(z_i - \bar{z})^T \end{cases}$$

Let us denote the between-group variance as S_b, and the within-group variance as S_w:

$$\begin{cases} S_b = (\overline{x_1} - \overline{x_2})(\overline{x_1} - \overline{x_2})^T \\ S_w = \frac{1}{N_1}\sum_{i=1}^{N_1}(\overline{x_i} - \overline{x_1})(\overline{x_i} - \overline{x_1})^T + \frac{1}{N_2}\sum_{i=1}^{N_2}(\overline{x_i} - \overline{x_2})(\overline{x_i} - \overline{x_2})^T \end{cases}$$

$$\hat{w} = argmaxJ(w) = argmax\frac{W^T S_b W}{W^T S_w W} = argmaxW^T S_b W(W^T S_b W)^{-1}$$

A large number of processing units are interlaced and connected in a large area to produce a complex network system. This network system is a neural network. There are many similarities between the structure of the neural network and the human brain. The strong self-learning ability is the neural network algorithm. One of the important features.

3.3 Enterprise Risk Evaluation Model Based on Topsis Method

The Topsis method is an evaluation method that evaluates the pros and cons of multiple samples based on different indicators. The core of the method is to determine the best sample value and the worst sample value in the evaluation object, and then find the distance between each evaluation object and the best sample value and the worst sample value, so as to determine each evaluation object and the best sample value. The similarity between sample values is the standard for evaluating sample values.

Topsis method is a method to determine the optimal strategy for a limited program and multiple goals in a comprehensive evaluation method. In order to reduce the impact of dimensional differences on different evaluation indicators, this method will forward and standardize the data matrix. And it can truly reflect the differences of different evaluation objects.

Compared with the evaluation model based on the analytic hierarchy process, the establishment of an evaluation model using the Topsis method can greatly reduce the irrationality caused by the subjective factors of the evaluator.

(1) Generate the original data matrix: assuming we have n evaluation objects and m evaluation indicators, we can generate an n×m original data matrix A:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix}$$

(2) Forward processing: Filter out the low-quality indicators in the original data matrix. Because in the Topsis evaluation system, different indicators should have the same trend, so we need to forward the filtered inverse indicators to get Matrix B:

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nm} \end{bmatrix}$$

(3) Standardize and calculate the score: the matrix after normalization of B is marked as C, then each element in C

$$c_{ij} = \frac{b_{ij}}{\sqrt{\sum_{i=1}^{n} b_{ij}^2}}$$

Among them, the standardized matrix is:

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix}$$

Among them, after standardization, we can calculate the score of the i-th (i=1,2,...,n) evaluation object without normalization processing: the processed matrix is:

$$G_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

(4) Normalization processing: record the normalized score as G_i'', then:

$$G_i' = \frac{G_i}{\sum_{i=1}^{n} G_i}$$

3.4 Problem solving and result analysis

From the above indicators, it is obvious that each indicator is treated as a benefit indicator, so there is no need for normalization. These indicators form a decision matrix:

$$A = \left(a_{ij}\right)_{123\times6}$$

$$C = \left(c_{ij}\right)_{123\times6}$$

We calculate the value of o for each company. We assign different credit ratings A, B, C, and D to the company to generate dummy variables as 4, 3, 2, 1 respectively. Since companies with a reputation rating of D do not lend in principle, First, predict whether the company's rating is D. Since the reputation of the dependent variable is a categorical variable, we can use logistic regression to process the dependent variable. If the rating is D, it is recorded as 1, and if the rating is not D, it is recorded as 0. Therefore, we estimate the probability of whether the reputation rating of the assessed company is D. When the probability P≥0.5, it means that the event occurs, and when P<0.5 it means that the event does not happen.

We input each evaluation index parameter of the evaluation object into two Bayesian discriminant functions, calculate the function value of the two Bayesian discriminant functions, and classify the evaluation index into calculation The one with the highest value.

According to the classification ,the discriminant function of whether the rating is the logical value of D is:

$$L_0 = -0.519 \times PR - 0.014 \times SR + 0.015 \times LR + 3.849 \times J - 2.12 \times C$$

$$L_1 = -0.32 \times PR - 0.003 \times SR + 0.003 \times LR + 4.138 \times J - 2.315 \times C$$

The above classification function can predict whether the credit rating of a company with no credit record is D. The prediction accuracy rate for the prediction group member information of 0 is 76.8%, and the prediction accuracy rate for the prediction group member information of 1 is 23.2%. The prediction accuracy rate is 67.5%, and the Fisher linear discriminant analysis prediction value of 302 credit ratings of D is shown in Supporting Material-Attachment g: Attachment 2 Enterprise Credit Rating Prediction Results.xlsx.

Integrating the goodness of fit R with the minimum mean square error and the number of iterations, we selected the training results of the quantitative conjugate gradient method to obtain effective parameters. For 302 companies with no credit records (the previous article has been eliminated based on Fisher linear discriminant analysis to predict reputation A company with a grade of D) will make a prediction on its reputation level.

Delete the company whose reputation rating is predicted to be D, because in principle such companies will not grant loans, and then solve the reputation ratings of other companies.

We use the data of 123 companies with credit records as the overall data sample, and select 70% of them as the training set of data samples used for model fitting, and 15% for the validation set separately set aside in model training. The validation set can be Reasonable optimization of model hyperparameters, while the verification set can also verify the model's evaluation ability. The remaining 15% of the data is used as a sample for evaluating the final generalization ability of the model.

First, we choose the gradient descent method to solve the model. The mathematical formula of the gradient descent algorithm is as follows

$$\theta^1 = \theta^0 - \alpha \nabla J(\theta) \ evaluated \ at \ \theta$$

The parameter α in the formula is the learning rate of the neural network, that is, the step size. Too high a step size will cause the model to miss the minimum value, and a too low step size value will cause the model to run at a too low speed, and it is impossible to find the lowest point concisely and efficiently. , The minimum point of the function can be found after multiple iterations from the above formula:

We first use the Levenberg-Marquardt algorithm, with the number of hidden layers set to 10. The advantage of this method is that it can calculate the numerical solution of the nonlinear local minimization, and it can improve the Gaussian -Newton’s algorithm and the unreasonable part of the gradient descent method.

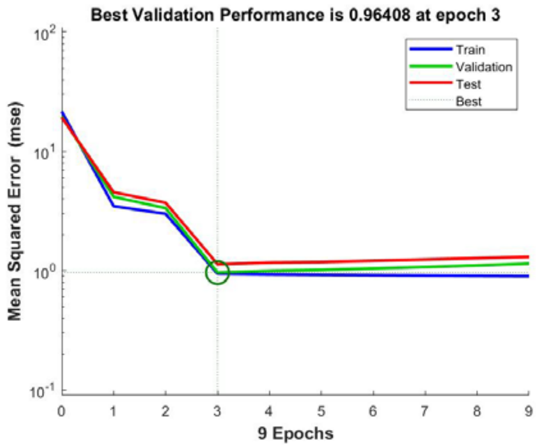

Figure 2 Levinberg-Marquardt method neural network training performance

It can be seen from the above figure that the training process converges after 3 iterations, and the mean square error MSE of the optimal verification set reaches the minimum value of 0.96408 at the third iteration. Regress the fitted value with the true value, where R represents the goodness of fit. From the figure above, it can be seen that most of the data points are concentrated in the vicinity of the prediction curve.

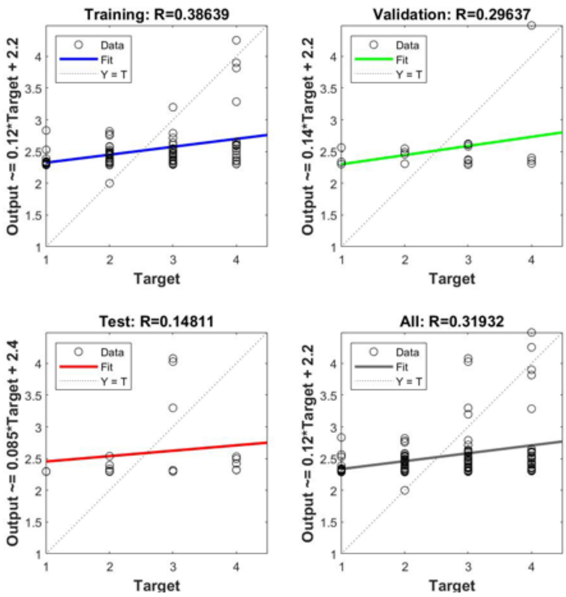

Figure 3 Regression results of neural network training

4. Model testing and sensitivity analysis

We changed the quantitative standard of corporate reputation rating as a basis for checking whether the model is correct, and changed the quantitative standard of reputation rating to: A-90, B-80, C-70, D-60, as the test data, and Other quantifications are not changed, and then the Topsis model is used to score the companies in Annex 1 again, and finally the scores of the test data obtained are compared with the original scores. Figure 13 shows the scores of the companies obtained from the test data (the ordinate is Score, the abscissa is enterprise):

For the model we built, the most important thing is the quantification of corporate credit risk, and the o-value (scored by the Topsis model) is the embodiment of the quantitative result of corporate credit risk, so we conducted a sensitivity analysis on the o-value. Through comparison, it can be found that the score obtained by changing the quantitative standard of reputation rating is very small, that is, the difference in o value is very small. Therefore, we believe that within a certain error tolerance range, the model we build has a strong The reliability.

5. Evaluation and improvement of the model

We did not consider the factors of the stability of the company's supply and demand relationship. If we analyze the company's transaction bill traders, count the number of the same traders, and obtain the variance, we can analyze whether the distribution of the company's supply and demand objects is stable, and then determine the company's supply and demand relationship. Happening.

As a non-subjective method of assigning weights to evaluation indicators, the core idea of the entropy method is that the greater the difference between the indicators, the greater the amount of information contained in the indicator, and the higher the weight it is assigned. In other words, starting from data analysis alone, the weight of evaluation indicators can be calculated without any subjective methods (such as expert evaluation). Note that in the training performance results of the quantified conjugate gradient method neural network, the mean square error MSE has a tendency to decrease to the lowest value and then rise, which indicates that the model has overfitting. The main method to solve the over-fitting phenomenon in the neural network model is the weight decay method, that is, select a small factor to reduce the weight in the iterative process.

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