International Journal of Economics and Finance; Vol. 8, No. 9; 2016
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

The Risk Management of Commercial Banks——Credit-Risk Assessment of Enterprises

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Received: June 3, 2016 Accepted: June 21, 2016 Online Published: August 25, 2016

doi:10.5539/ijef.v8n9p69 URL: http://dx.doi.org/10.5539/ijef.v8n9p69

Abstract

With the diversified developments of the financial market, commercial banks are confronted with various risks, among which the credit risk is the core, and thus the assessment of enterprises' credit risks is especially important in the credit process of the commercial banks. Based on the relevant researches about commercial banks' credit risk management, the paper carries out a deep analysis on the factors that may affect the credit risk assessment and then establishes a relatively comprehensive credit risk assessment system. In this paper, we apply our risk assessment model, which is established on the basis of GRNN neural network model, to make an empirical analysis with the selected sample data. And the results suggest that the hit rates of identifying high quality enterprises and low quality enterprises are 92.16 percent and 93.75 percent, respectively, indicating that the model has realized a good prediction.

Keywords: risk management, enterprise credit risk assessment, GRNN neural network, machine learning

1. Introduction

Modern banks are actually intermediary organizations that major in disposing risk, the core competitiveness of whom, doubtlessly, shall be the ability of managing risks. From 1980s, with more and more digging and understanding in risks, commercial banks keep exploiting and enhancing their approaches and skills in risk management. Nowadays, the bad debt ratios of most commercial banks are so high that the assessment of credit risk not only associates with the profitability of commercial banks but also plays a significant role in maintaining the stability of the entire financial system, which could influence the national economy and citizens' life. Therefore, it's quite essential to develop an efficient credit-risk assessment model. However, traditional statistic method is inapplicable to abnormal distributions, and since we could tell from the subprime crisis in USA that the credit-risk assessments used by banks aren't normal distributions. So exploitation for new assessment methods is necessary. Since the 20th centuries, the theory of machine learning is increasingly popular along with the high speed development of computer science, and there are always some scholars trying to establish risk assessment models by utilizing those relevant theories.

1.1 Foreign Literatures

In the foreign credit-risk assessment field, as the excellent papers do, new methods emerge from time to time. Because of the BASEL II and the financial crisis in the USA, banks keep trying to update and improve their credit-risk assessment models, making the bankruptcy prediction a heated topic in the function prediction field.

Perez (2006) summarized 30 papers, in which enterprises were classified through neural network, and discussed their setting of parameters, selections of inputs and outputs and analyses of results. As the first one applying machine learning to enterprise classification, Perez's paper provided new clues and ideas about credit assessments, though the parameters of it were not precisely set. Efstathios Kirkos (2015), in his literature review of papers, all written before 2012, which are major in bankruptcy prediction, compared, analyzed and summarized the algorithm used in recent years. From his review, we could see that the application of neural network is unusually popular, that the new algorithm owns a high status in the bankruptcy prediction field and that all machine learning algorithm are still static indexes. And that's why Milad Malekipirbazari (2015) used random forest algorithm, included in the machine learning, to assess the credit status of borrowers from the internet P2P loans, and carried out a dynamic estimation for the probabilities of repayments.

1.2 Domestic Literatures

On account of the lack of valid data and the gap existing in quantitative finance between foreign countries and China, domestic researches are relatively undeveloped and immature when compared with foreign researches.

On the basis of SVM model, Liu Yuntao, Wu Chong (2005) established an enterprise credit-risk assessment model, whose accuracy of sample test reached to 80 percent, proving that the theory of machine learning is applicable. Cheng Jian, Zhu Xiaoming (2007) came up with a verification model of a enterprise credit-risk assessment model, which includes the AUC value and the proportion of the conditional entropy, and compared it with the linear discriminant model, Logit model, Probit model and neural network model. It turns out that the neural network model has the best testability within samples while it doesn't perform well beyond selected samples, and yet this paper didn't explain the specific settings of the models and their pretreatments of data. Despite the fact that they still didn't provide the hit rate of high quality enterprises and low quality enterprises, Wu Chong and Xia Han (2009) established a credit-risk assessment model on the basis of the 5-level classification, consisting of the vectors level, and the performance of their model is impressive, having a total success rate up to 87 percent.

Later on the probabilistic aspect, after acquiring the original data from a commercial bank, Zhou Lili and Ding Dongyang (2011) calculated all borrowers' probabilities of violating contracts by using the Bayesian hierarchical model and the sampling simulation of MCMC. However, the results of their research are unconvincing because the realistic prediction intervals are quite large.

In the research conducted by Zhao Yijun(2013), the cash flow data of the enterprises were used to establish a credit-risk assessment model. Since the cash flow is the only index used in this model and the hit rate is just slightly higher than 60 percent, the applicability of this model is unguaranteed.

1.3 Literature Review

The achievements of domestic researches and foreign researches share some resemblances. Superficially, the premises, the features of distributions, the forms of functions and the calculation of assembling loss of those models are different. But actually except from selecting different probability distributions, the models, most of which apply value at risk though the degrees of credit loss are calculated by different methods, all have similar basic theoretical structures that are composed of same basic elements.

When comparing the domestic researches with the foreign ones, we notice that the domestic scholars probably have some deviations in understanding the models. While the complexity of the models used in the domestic papers is more than enough, some foundational works mentioned below, on the other hand, are not well accomplished.

While pretreating data is one of the essential steps, which could significantly affect the accuracy of the final results, in the theories of machine learning, the pretreatments of data in some domestic papers are insufficient. Besides, it seems that some domestic scholars, who established models without clearly pointing out the settings of parameters, just muddled through their works, which are thus indemonstrable. Also, the selections of inputs were paid little attention, impairing the effectiveness of the results.

In addition, applications of the neural networks vary from different situations. For example, there are rigid regulations on the amount of nodes in the BP neural network, making it suitable to scholars with much practical experience. Meanwhile, the GRNN neural network is preferred and widely used because of its simple settings and impressive performance in the nonlinear approximation. In this paper, with appropriate pretreatments of data that could promote the accuracy of predictions, we try establishing a risk assessment model, in which the GRNN neural network is applied to assess the credit-risk of enterprises.

2. Establishment of the Indexes

2.1 Selection of the Indexes

Indexes associated with the commercial banks' credit-risk assessments vary across wide ranges and aspects, and papers selecting indexes based on empirical judges are likely to omit some essential indexes or wrongly choose the unimportant ones. As a result, the index system might be subjected to relatively strong correlations, and caused the results of risk assessments might be unreliable, deflecting the credit decisions of banks. Hence, to ensure the rationality and feasibility of the assessment indexes, the establishment of the index system in this paper complies with two steps as below: First, extract the influential factors according to the experts' suggestions. Second, apply statistic methods to the filtration of those extracted indexes, removing the indexes that are helpless to the credit-risk assessment or have strong correlations, and counting in some useful indexes that are omitted.

With these two steps finished, we have a completed index system, based on which the credit-risk assessment index system designed for commercial banks can finally be established.

With a full consideration of various elements, this paper tries not to miss any significant indexes so that the completeness of the index selections and the comprehensiveness of the final assessment are both guaranteed. In order to establish an index system with a hierarchical structure, this paper applies the purpose analysis method to the classification of indexes.

According to the experts' experience and suggestions, factors that influence the indexes of the credit-risk assessment can be classified into five sorts: profitability, development capacity, operating capacity, solvency and enterprise capacity. The results of the classification to these five second-level indexes are showed in the table below.

Table 1. Establishment of the assessment index system

First-level indexes	Second-level indexes	Third-level indexes
The credit-risk assessment system of commercial banks	Profitability	Return on total assets ×1
		Net profit margin on sales ×2
		Profit margin on net assets ×3
	Development capacity	Growth rate of main business income ×4
		Growth rate of total assets ×5
		Growth rate of earnings per share ×6
	Operating capacity	Inventory turnover ratio ×7
		Total assets turnover ratio ×8
	Solvency	Current ratio ×9
		Debt to assets ratio ×10
	Enterprise capacity	Brand dependencies ×11
		Independent coefficient ×12

The index system in this paper is composed of quantitative indexes only, which are both precise and reliable because they can be directly obtained from the financial reports of the listed enterprises. As for some other qualitative indexes such as brand, image and so forth, this paper is not taking them into account since the data of these indexes mostly come from questionnaires and professors' appraisals, in which subjectivity and bias could be inevitable. Thus, the qualitative data are not fit for the application of machine learning.

2.2 Description of the Indexes

2.2.1 Profitability

1) Return on total assets

$$\text{return on total assets} = \frac{\text{earnings before interest and tax}}{\text{average total assets}}$$

This index, representing the amount of benefits that can be achieved when an enterprise makes full use of all its resources, is essential in assessing the operational effectiveness of an enterprise. The higher this ratio is, the more efficient the utilization of assets is. If an enterprise has a growing return on total assets, the profitability and operating capacity of it would be better and better.

2) Net profit margin on sales

$$\text{net profit margin on sales} = \frac{\text{net profits}}{\text{net sales}}$$

This index is an important measurement of an enterprise's operation and management, reflecting the profitability on sales. A higher net profit margin on sales indicates that the enterprise can earn more profits by enlarging its sales scale.

3) Profit margin on net assets

$$\text{profit margin on net assets} = \frac{\text{net profits}}{\text{average net assets}}$$

This ratio, which reflects the overall efficiency of an enterprise, is the most representative index in measuring incomes that can be earned by an enterprise that utilizes all its equity capital and accumulated capital. A higher profit margin on net assets means that the enterprise is operating more smoothly and can make better use of its equity capital, and the creditors' benefit or the investors' benefit is then better guaranteed.

2.2.2 Development Capacity

1) Growth rate of main business income

$$\text{growth rate of main business income} = \frac{\text{main business income this term - main business income last term}}{\text{main business income last term}} \times 100\%$$

This index is fit for measuring the development condition and market share, after which an enterprise's developing trend of its main business can be predicted. If the index of an enterprise is larger than 0, the income of its main business grows. The higher this index is, the better the future of an enterprise will be. In contrast, an enterprise with this index less than 0 is probably suffering from reduction of market share, caused by inappropriate pricing, poor services, inferior products, etc.

2) Growth rate of total assets

$$\text{growth rate of total assets} = \frac{\text{the growth of total assets this year}}{\text{total assets in the begining of this year}} \times 100\%$$

This index is designed to measure the development capacity of an enterprise from its growth of total assets, indicating the influence of the growing scale to the development potential of an enterprise. In a certain period, a higher ratio indicating a higher speed in which the scale of assets is growing.

3) Growth rate of earnings per share

$$\text{growth rate of earnings per share} = \frac{\text{earnings per share this term - earnings per share last term}}{\text{earnings per share last term}} \times 100\%$$

This index represents the growth of profits per share, usually the higher the better. The distinction between this index and earnings per share is that the former focuses on the dynamic development while the latter focuses on the entire operating condition.

2.2.3 Operating Capacity

1) Inventory turnover ratio

$$\text{inventory turnover} = \frac{\text{selling cost}}{\text{average inventory}} \times 100\%$$

This index, which shows how many times the inventory can turnover within a certain period, is not only an important indicator of the liquidity of an enterprise's current assets but also a comprehensive standard that weights the turnover efficiency in different stages of the production chain. On one hand, a higher inventory turnover ratio suggests that the enterprise has a better cashability and less capital being occupied. However, if the ratio is unusually high, the enterprise might have troubles in the inventory managements, including lack of inventory that can easily lead to a stock-out, frequent replenishment and so on. On the other hand, a low inventory turnover ratio is usually resulted from poor sales and inefficient management, indicating that it is better for the enterprise to improve the sales strategies and create more outlets for its over-sufficient inventory. Finally, sometimes a low inventory turnover ratio occurs just because the enterprise changes their operation strategies and requires more inventories.

2) Total assets turnover ratio

$$\text{total assets turnover} = \frac{\text{main business incomes}}{\text{average total assets}} \times 100\%$$

This index, which is also named as the utilization rate of total assets, is a significant indicator of the total assets' operation efficiency, reflecting the turnover rate of the enterprise's total assets during the operation period, started from investing to yielding. Representing the operation efficiency and management quality of the total assets, this index is in positive proportion to the utilization rate of total assets as well as the operation condition of an enterprise. In short, the higher this index is, the better an enterprise's credit status is.

2.2.4 Solvency

1) Current ratio

$$\text{current ratio} = \frac{\text{current assets}}{\text{total assets}} \times 100\%$$

This index indicates an enterprise's capacity of repaying a debt. If the ratio is high, the cost recovery of an enterprise is efficient. In contrast, if this ratio is low, the risk of repaying a debt could be huge since there is a large amount of capitals that are occupied. And the fact that plenty of capitals are occupied will inevitably impair the credit status of an enterprise.

2) Debt to assets ratio

$$\text{debt to assets ratio} = \frac{\text{total debts}}{\text{total assets}} \times 100\%$$

This index reflects the solvency of an enterprise from an overall aspect. It shows the proportion of debt in the total assets, representing the degree in which the enterprise can guarantee the creditors' benefits. The enterprise of which the proportion of debts in total assets is small will have a low debt to assets ratio and, correspondingly, own a stronger solvency. In contrast, an enterprise with a large proportion of debts in total assets might have difficulties in repaying its debts.

2.2.5 Enterprise Capacity

1) Independent coefficient

$$\text{independent coefficient} = \frac{\text{profits of the parent firm}}{\text{total profits}} \times 100\%$$

This index states the contribution of the parent firm to the total profits. The growth of this coefficient indicates that the parent firm is becoming more independent while the branch firms are becoming less independent, and we can tell from the growing coefficient that the enterprise is still in an early developing stage or that the enterprise behaves poorly in expanding its scale. If the independent coefficient is small, the branch firms are independent and can run smoothly in a self-governed way.

2) Brand dependencies

$$\text{brand dependency} = \frac{\text{intangible assets}}{\text{total fixed assets}} \times 100\%$$

This index shows the significance of an enterprise's brand image. The brand image, as a distinct feature or symbol of the products in the society, reflects the quality and essence of an enterprise and also the impressions and recognitions from customers, playing an important role in the developments of enterprises. The bigger this index is, the better the brand image is. Having a good brand image means that the enterprise earns an extensive popularity among customers and is comparatively competitive in the market. As a result, the sources of profits are well guaranteed.

3. Establishment of the Risk Assessment Model

On the basis of the several selected indexes that shall be considered in the credit-risk assessment of enterprises, the credit-risk assessment model is established. The traditional multi-element discrimination theories might have poor performances in analyzing the loans, because the loan of commercial bank itself is a complicated nonlinear system and the common linear theories are not capable of embodying the pattern of the loan system. Thus, the nonlinear modeling method of machine learning is applied to the establishment of the credit-risk assessment model. In addition, when using the BP neural network, the selections of nodes and layers are totally empirical. So this paper decides to use the GRNN neural network, which has a comparatively fixed structure, so as to avoid over-fitting or under-fitting in a certain extent.

3.1 GRRN Neural Network

There is structural similarity between GRNN network and RBF network. The GRNN network is constructed by four layers including the input layer, the pattern layer, the summation layer and the output layer, as shown in the Figure 1 below. The corresponding network input is $X = [x_1, x_2, ..., x_n]^T$, and the corresponding output is $Y = [y_1, y_2, ..., y_k]^T$.

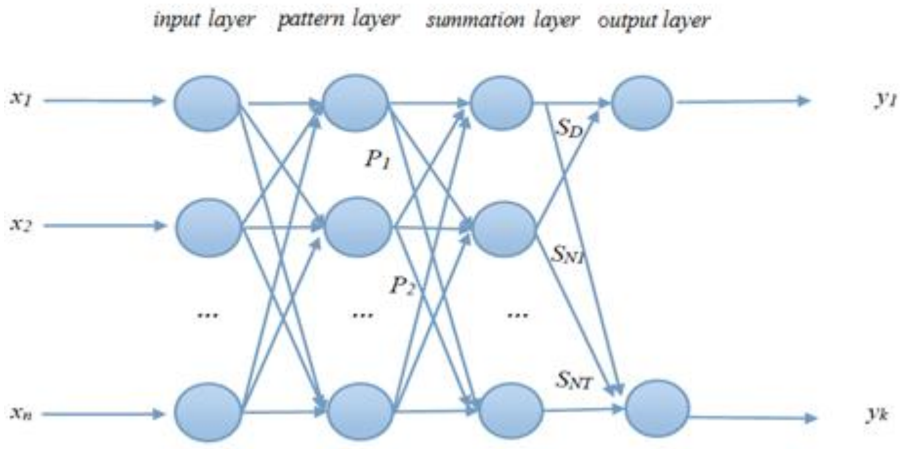

Figure 1. Network structure of the general regression

1) Input layer

The number of neurons in the input layer is equal to the number of input vectors' dimensions in the learning samples, and in the meanwhile, each node is a simple distribution unit that can directly transmit the input variables to the pattern layer.

2) Pattern layer

The number of neurons in the pattern layer is equal to the number of learning samples, *n*. There is a one-to-one correspondence between samples and neurons, and the transmitting function of neurons in the pattern layer is as below.

$$p_i = \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right], i = 1, 2, \ldots n$$

3) Summation layer

There are two types of neurons that are applied to summation layer.

The first formula used is $\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]$, which is used to sum the outputs of all neurons in pattern layer. The weight that connects the pattern layer and the neurons is 1, and the transmitting function is as below.

$$S_D \sum_{i=1}^{n} P_i$$

Another formula is $\sum_{i=1}^{n} Y_i \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]$, which is used to sum the neurons of all pattern layers with weighted coefficients. The weight that connects the *i*th neuron in the pattern layer and the *j*th numerators summed neuron in the summation layer is equal to the *j*th element of the *i*th output sample Y_i. And the transmitting function is as below.

$$S_{Nj} = \sum_{i=1}^{n} y_{ij} P_i, \ j = 1, 2, \ldots k$$

4) Output layer

The number of the neurons in the input layer is the same as the number of the input vectors' dimensions, *k*, in the learning samples. After each neuron divided by the output of the summation layer, we can obtain the output from neuron *j*, which is corresponding to the jth element of the predicted result Y(X). The expression is shown as below.

$$y_j = \frac{S_{Nj}}{S_D}, \; j = 1, 2, \ldots, k$$

The theoretical basis of GRNN is the nonlinear regression analysis. *Y* is a dependent variable while the *x* is an independent variable, and the essence of the regression between *x*, as the regressor, and *Y* is calculating the *y* with the biggest probability. With the value of *x* being X and the Assumption that *f(x, y)* is the joint probability density function of *x* and *y*, which are both random variables, we can have the conditional mean written as below.

$$Y = E\left(y / X\right) = \frac{\int_{-\infty}^{\infty} y f\left(X, y\right) dy}{\int_{-\infty}^{\infty} f\left(X, y\right) dy}$$

$\hat{Y}$ here means the predicted output of Y when the input is X .

Applying the Parzen nonparametric estimation method, we can estimate the density function $\hat{f}(X, y)$ with the sample data set $\{x_i, y_i\}_{i=1}^{n}$.

$$f\left(X, y\right) = \frac{1}{n(2\pi)^{\frac{p+1}{2}} \sigma^{p+1}} \sum_{i=1}^{n} \exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right] \exp\left[-\frac{\left(X - Y_i\right)^2}{2\sigma^2}\right]$$

Where X_i, *Yi* are the sample observed values of the random variables *x* and *y*, respectively; the value of *n* equals the samples size; the value of *p* equals the dimensions of *x*; *σ*, named as the smoothing factor in this paper, is the width coefficient of Gaussian function.

After substituting the function above into $Y = E\left(y / X\right) = \frac{\int_{-\infty}^{\infty} y f\left(X, y\right) dy}{\int_{-\infty}^{\infty} f\left(X, y\right) dy}$, we and swopping the order of the integral and summation can acquire the function below.

$$\hat{Y}\left(X\right) = \frac{\sum_{i=1}^{n} \exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right] \int_{-\infty}^{+\infty} y \exp\left[-\frac{\left(Y - Y_i\right)^2}{2\sigma^2}\right] dy}{\sum_{i=1}^{n} \exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right] \int_{-\infty}^{+\infty} \exp\left[-\frac{\left(Y - Y_i\right)^2}{2\sigma^2}\right] dy}$$

With $\int_{-\infty}^{+\infty} z e^{-z^2} dz = 0$, we can acquire the output $Y(X)$ of the network by calculating the two integrals. $Y(X)$ is as below.

$$\hat{Y}\left(X\right) = \frac{\sum_{i=1}^{n} \exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right]}{\sum_{i=1}^{n} \exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right]}$$

The estimated value $\hat{Y}(X)$ is the weighted average of all sample observed values, and each weight of the observed value *Yi* is equal to the exponent of the Euclid squared distance between the corresponding sample *Xi* and *X*. When the smoothing factor *σ* is extremely large, $\hat{Y}(X)$ is nearly equal to the mean of all sample dependent variables. In contrast, if the *σ* approaches to 0, $\hat{Y}(X)$ approximates the training sample. Considering facts that predicted values of dependent variables are very close to the corresponding dependent variables of the samples if the points needed to be predicted are included in the training samples and that the performances of predictions can be poor if there are points outside the training samples, we can reach a conclusion that the generalization capacity of network is disappointing. With an appropriate *σ* and all dependent variables of training samples counted in, the sample points, which are close to the predicted points, are appended with bigger weights when calculating the predicted value of $\hat{Y}(X)$.

3.2 Modification of the GRNN

Since the learning rate is an undetermined coefficient, the iteration algorithm can be applied to solve the most appropriate learning rate. Aiming at minimize the sum of the squared errors, we try substituting a range of values, from 0.1 to 2, into the learning rate with each step size equal to 0.1. The value that minimizes the objective function is the most appropriate value for the learning rate.

4. Empirical Analysis

4.1 The Selection and Pretreatment of Data

Extracting the data about loans and defaults of the enterprise clients from commercial banks is the primary obstacle in our research, because the data, no matter domestic or oversea, about bad debts and defaults are business secrets that researchers can hardly get access to. Therefore, obtaining the sample data from commercial banks is the first problem that we have to solve out in the research. Considering the limitations on time and resources, we decide to employ the data of listed enterprises as samples of our research, as the domestic researches on credit-risk assessment commonly do.

Hence, 2584 listed enterprises, counted up to year 2014, are selected for analysis in the first place. And after we eliminated the B share enterprises, financial enterprises and those with problematic financial data, the remaining ones are confirmed as primary samples.

Before separating the high quality enterprises and low quality enterprises, we fill the missing values with means of the corresponding industries.

Then looking at the conditions of enterprises in 2014, we find out all ST enterprises, which suffer from deficits continuously. Because these ST enterprises are in financial dilemma, having net assets per share lower than the price of their stocks and great difficulties in repaying debts, we label them poor credit and put them in the default sample group, the members of which all have relatively big probabilities of defaults. Meanwhile, the non-ST enterprises are labeled good credit and put in the normal sample group.

However, it turns out that there are only 43 poor credit enterprises while the amount of the good credit enterprises is about 2000. In the neural network, if the distinction between different types of learning samples is too large, the results may be over-fitting, badly impairing the accuracy of predictions. Thus, we must select representatives in a certain proportion from the listed enterprises. In this paper, with 100 good credit enterprises and 30 poor credit enterprises selected as representatives, 50 percent of them are used for training, and the rest are used for test.

Without grades of the listed enterprises, we employ the earnings per share as the criterion to judge the conditions of enterprises. The EPS (Earnings per share) is a commonly used index that reflects the operation condition, profitability of stocks and the investing risks of an enterprise. Usually, many information users, such as investors, deem the EPS as an indicator of the profitability and development potential of an enterprise and make economic decisions based on the EPS.

Obviously, enterprises with a high EPS can bring comparatively high incomes to the stockholders, and thus it's economically acceptable to employ the EPS as the criterion. Moreover, using the EPS will not cause systematic deviations in the model since the EPS is uncorrelated to other assessment indexes, making the employment of EPS even more reasonable.

4.2 Empirical Results

By applying the risk assessment model established earlier, we put 50 high quality enterprises and 15 low quality enterprises in the sample training, and the other 50 high quality enterprises and 15 low quality enterprises are tested as data beyond samples. Notice that 0.5 is the critical value. Enterprises with outputs greater than 0.5 are of good quality; Enterprises with outputs less than 0.5 are of low quality. The empirical results are shown in the table below.

Table 2. Results of the simulation judgment on test samples (GRNN)

Item	Group	Results of judgment		Total
		High quality	Low quality	
Quantity	High quality	47	4	51
	Low quality	1	15	16
Proportion	High quality	92.16%	7.84%	100%
	Low quality	6.25%	93.75%	100%

We train the data within samples and test the data beyond samples. The final results are as follow: The hit rate of distinguishing high quality enterprises is 92.16 percent; the hit rate of distinguishing low quality enterprises is 93.75 percent; the total hit rate is 92.537 percent, which is quite accurate when compared with the probability of choosing a high quality enterprise from a group of enterprises that are composed of 100 high quality enterprises and 30 low quality ones. In a word, the model in this paper is practically feasible and useful.

5. Conclusions

Based on the relevant researches about commercial banks' credit risk management, the paper carries out a deep analysis on the factors that may affect the credit risk assessment and then establishes a relatively comprehensive credit risk assessment system. Establishing a risk assessment model on the basis of GRNN neural network model, the paper applies the model to empirical analyses with selected samples and obtains comparably accurate results of judgments.

First, appropriate pretreatments of data can improve the hit rate of the model's prediction. As shown in the paper in detail, we pretreat the data and reasonably determine the sample size, finally acquiring a relatively high accuracy of the prediction.

Second, the GRNN neural network works well in the procedures of credit-risk assessment. The fact that the final model, which is based on the GRNN neural network and has accuracy over 90 percent, exceeds many traditional statistic methods such as multi-targets regression indicates that the GRNN neural network is excellent when applied as a modeling method.

Third, a reasonable credit-risk assessment system of commercial banks is significant in assessing the credit-risks of enterprises. Based on some theoretical researches about commercial banks' credit risk management, the paper carries out a deep analysis on the factors that may affect the credit risk assessment and then establishes a relatively comprehensive credit risk assessment system. Besides, selecting 12 quantification indexes from five aspects is an inspiring procedure, which has some reference value, in a certain extent.

The applications of machine learning and some other advanced statistic model in China are still in an early stage, and the domestic scholars shall spend more efforts in digging and studying.

References

Chong, W., & Han, X. (2009). On credit-risk assessment model of commercial banks based on the 5 classifiers SVM. *Prediction, 28*(4), 57-61.

Jian, C., & Xiaoming, Z. (2007). Experimental verification on the prediction capacity of a credit-risk assessment model. *Academic Journal of Shanxi University of Finance And Economics, 29*(2), 86-92.

Kirkos, E. (2015). Assessing methodologies for intelligent bankruptcy prediction. *Artificial Intelligence Review, 43*(1), 83-123. http://dx.doi.org/10.1007/s10462-012-9367-6

Lili, Z., & Dongyang, D. (2012). Bayesian layered credit-risk assessment model based on MCMC simulation. *Statistics and Information Forum, 26*(12), 26-31.

Malekipirbazari, M., & Aksakalli, V. (2015). Risk assessment in social lending via random forests. *Expert Systems with Applications, 42*(10), 4621-4631. http://dx.doi.org/10.1016/j.eswa.2015.02.001

Perez, M. (2006). Artificial neural networks and bankruptcy forecasting: A state of the art. *Neural Computing & Applications, 15*(2), 154-163. http://dx.doi.org/10.1007/s00521-005-0022-x

Yijun, Z., & Chi, X. (2013). Influences of flows on the value of enterprises ---- Based on CFaR model. *Social Science of Hu Nan*, (4), 154-158.

Yuntao, L., Chong, W., & Ming, W. (2005). On credit-risk assessment model of commercial banks based on SVM. *Prediction, 24*(1), 52-55.

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