Financial Credit Risk Prediction Model Based on PSO-SVM

Xiaoxia Wang*
Guangdong Innovative Technical College
Dongguan, China
wangxiaoxia@ldy.edu.rs

Abstract

Financial credit risk refers to the fact that the parties to the transaction cannot reach agreement or inconsistency according to the established objectives in the credit contract due to the existence of various uncertain factors, resulting in losses and adverse consequences. As a complex and changeable economic system full of competition and challenges, the financial market is even more so. Therefore, based on PSO-SVM, it is very necessary to study the financial credit risk prediction model. Firstly, this paper introduces the concept of financial credit risk, then studies the specific application method of pos-svm, at the same time, deeply studies the process of financial credit risk prediction model, and tests and analyzes the performance of the model. Finally, the test results show that the pos-svm algorithm based on sensitive learning has better generalization ability.

CCS Concepts

• **General and reference** → Document types; Reference works.

Keywords

PSO-SVM, Financial Credit, Credit Risk, Prediction Model

ACM Reference Format:

Xiaoxia Wang. 2024. Financial Credit Risk Prediction Model Based on PSO-SVM. In *International Conference on Digital Economy, Blockchain and Artificial Intelligence (DEBAI 2024), August 23–25, 2024, Guangzhou, China.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3700058.3700068

1 INTRODUCTION

Financial credit risk refers to the economic losses caused by the loss of the trading entity caused by various uncertain factors during the economic activities of the trading parties, resulting in the reduction of its expected income or even the failure to obtain the principal and interest or to meet the default standards. At present, the problems faced by China's financial institutions, such as the decline in the quality of credit assets, the rise in the non-performing loan ratio and the lagging construction of the credit rating system of commercial banks, have had a serious negative effect on the development of the financial market [1, 2].

Many scholars have done relevant research on financial credit risk. Financial credit risk refers to the uncertainty reflected in the balance sheet and cash flow statement of both parties when signing the contract, that is, possible losses. At present, there are in-depth studies on credit asset securitization of financial institutions and insurance industry at home and abroad. With the process of economic globalization, China's financial industry continues to grow. Therefore, higher requirements are put forward for credit granting and supervision of various financial institutions in the financial market [3, 4]. The development of banking business in China is mainly analyzed and discussed from the development of loan business by commercial banks and insurance companies and the cooperation between banks and other institutions. Therefore, the above background has laid a research foundation for the study of financial credit risk in this paper.

Based on the PSO-SVM model, this paper studies the financial credit risk prediction method, which is used to measure and evaluate the application prospect in the operation and management level of financial institutions. The feasibility of the above method is verified by empirical analysis of China's existing financial industry data and the establishment of relevant mathematical models, so as to provide decision support and reference suggestions for financial credit risk prediction.

2 DISCUSSION ON FINANCIAL CREDIT RISK PREDICTION MODEL BASED ON PSO-SVM

2.1 Financial Credit Risk

The word "finance" has always been regarded as a hot topic. In China, with the continuous improvement of the market economic system, the financial industry has developed rapidly. However, due to China's economic transformation and economic system reform, many financial institutions do not have operating capital, balance sheet deterioration or credit rating decline. On the other hand, the government's strict supervision of commercial bank loans and the lack of internal management systems of banks have led to the increase of bank credit risk. In a broad sense, it means that the buyer fails to pay the bank loan principal and interest on schedule or the income decreases [5, 6]. In a narrow sense, it refers to the damage to the contract content and economic losses caused by a systematic event of default in the financial market. In a narrow sense, it means that when one party suffers some adverse impact and the contract cannot be completed as agreed, the other party must bear certain liabilities or compensate for the losses specified in the contract [7, 8].

Financial credit risk refers to the loss caused by the transaction subject's breach of contract or debt evasion. It mainly includes: insufficient bank credit assets, collateral and cash flow. In the financial market, different types of fund demanders have their own corresponding characteristics. For example, individual investors

*Corresponding author

DEBAI 2024, August 23–25, 2024, Guangzhou, China

ACM ISBN 979-8-4007-1026-1/24/08
https://doi.org/10.1145/3700058.3700068

are highly sensitive to the volatility of securities prices, so they will choose products with high returns but unstable and long term to invest in order to maximize profits. For example, corporate bonds need to bear certain liability for credit default when they have strict requirements on risk rating or when the issuance procedures are more complex. The so-called ”finance” refers to the relationship between supply and demand of funds. It includes not only the lending activities between banks and other enterprises, but also the securities investment and trading business. It also includes the venture capital project financing activities of selling stocks, bonds and other valuable commodities to investors in various forms [9, 10].

2.2 PSO-SVM

An important factor in the prediction of financial credit risk is the cost of capital [11, 12]. This concept refers to the time value of money. When an enterprise borrows a large amount of debt, it will generate interest expense and financing profit margin. On the contrary, if the borrower repays interest or pays principal due to bankruptcy, it will need to bear greater risk cost (such as bank loans). Therefore, capital cost is one of the important factors in financial credit default (i.e. PSOM). PSO-SVM is an advanced financial model. PSO-SVM algorithm is a new method that combines financial credit risk management with economic theory. It is mainly used to identify and evaluate the potential credit default probability in the model, find out the possible influencing factors by analyzing them, and take corresponding measures to reduce or control the loss minimization in this case according to this information. At the same time, it uses statistical tools to establish a functional relationship prediction system. It adopts advanced computer technology and modern communication network, and is based on network, communication and data processing. It plays a very important role in the whole system. This method mainly has two types: one is based on the analysis of internal control theory, the other is based on the interaction between the external environment and the enterprise to effectively identify the financial credit risk and take corresponding measures to reduce the loss or avoid the chain reaction caused by the risk, that is, PSO model, CMM and bito. As one of the indispensable factors in the enterprise development strategy, internal control can effectively manage the company. In the actual operation process, when the system cannot operate normally or fails due to various reasons, the impact can not be found and solved in time. When problems occur, it will also cause losses or injury severity. Therefore, a good control system is needed to ensure that the model can operate stably and efficiently, and can accurately predict the probability and law of possible credit risk in the future.

For a binary classification problem, the training data set in the feature space is recorded in the form of:, X ∈ x=r ”, Yi ∈ y=[-1, +1], =1,2,..., N, that is, the total number of samples is n. The characteristic parameters of each sample data are column vectors, and the vector is n-dimensional. The goal of learning is to find a separate hyperplane in the feature space, which separates different types of instances on both sides. The formula of the hyperplane is formula (1):

$$\mathrm{R} \times \mathrm{x} + \mathrm{a} = 0 \tag{1}$$

Rrepresent a weight matrix or risk coefficient matrix, used to indicate the importance of certain credit score weights or different features for prediction. x represents the input feature vector. For financial credit risk prediction models, this vector contains various features that affect credit risk, such as borrower’s credit score, income, debt ratio, historical default situation, etc. a is a bias term, which is commonly used in support vector machine models to adjust the displacement of decision boundaries. In general, if the data set can be classified, the number of hyperplanes corresponding to it is countless. The purpose of support vector machine is to find the hyperplane with the largest interval from the nearest instance, which can be expressed as a function. Formula (2) represents the distance between the ith sample and the separation hyperplane:

$$y = \min\left(y_i\right) \tag{2}$$

When the above formulas are equal, the corresponding sample vector is represented by y_i, and X is the support vector. In general, the linear separability of data is not strict, so the above formula has no solution.

In order to improve the PSO algorithm itself, chaos mechanism, dynamic adjustment of parameters, etc. can be introduced to improve its global search capability and convergence speed. Specific methods include:

(1) Introducing chaotic mechanism: using the randomness and ergodicity of chaos theory, chaotic mapping is introduced into the PSO algorithm to initialise the particle population. This can enhance the diversity of the particle population and avoid falling into local optimality. Commonly used chaotic mappings include Logistic mapping, Tent mapping and Chebyshev mapping.

(2) Dynamically adjust inertia weights: Inertia weight w is an important parameter in the PSO algorithm, which affects the searching ability of particles and convergence speed. By dynamically adjusting the inertia weights, it is possible to maintain a large weight value in the early stage of the search to enhance the exploration ability, and gradually reduce the weight value in the later stage of the search to enhance the exploitation ability. Common adjustment strategies include linearly decreasing strategies and adaptive adjustment strategies, etc.

(3) Adaptive learning factor: the learning factors c_1 and c_2 in PSO algorithm controls the learning ability of particles on their own experience and group experience. By adaptively adjusting the learning factor, the size of the learning factor can be dynamically changed according to the search state of the particles to balance the local search and global search ability.

(4) Introducing mutation operation: Drawing on the mutation operation in genetic algorithm, the particle positions in PSO algorithm are appropriately perturbed to increase the diversity of particles and avoid premature convergence. Common variation operations include Gaussian variation, uniform variation and non-uniform variation.

(5) Hybrid optimisation strategy: Combine other optimisation algorithms, such as Genetic Algorithm (GA), Differential Evolutionary Algorithm (DE), etc., to form a hybrid optimisation strategy, in order to take advantage of their respective algorithms and improve the overall optimisation performance. By reasonably designing the hybrid strategy, the characteristics of different algorithms can be utilised at different stages of the search process to improve the search efficiency and optimisation effect.

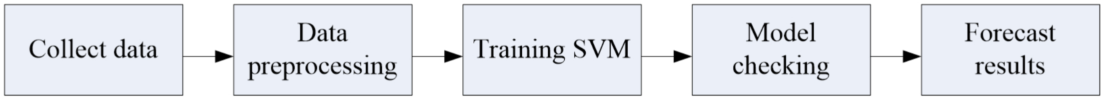

Figure 1: Flow chart of the financial credit risk forecast model

Through the above improvement measures, the global search capability and convergence speed of PSO algorithm can be effectively enhanced to improve the application effect in financial credit risk prediction.

2.3 Credit Risk Prediction

In the rapid development of China's economy, western countries have a great impact on the international financial crisis and other economic crises. At the same time, with the acceleration of domestic capital flow and the arrival of the Internet era, a series of factors such as the rapid rise of Internet enterprises and intensified competition all over the world have greatly increased the possibility of financial credit risk. Financial credit risk prediction refers to the estimation of the probability of credit default and its influence range that may occur or have occurred in the future based on the existing assets, liabilities, cash flow and other data of the enterprise, using mathematical theory and statistical methods. In the course of operation, financial enterprises will encounter a variety of complex and difficult to accurately predict, and the results of problems or errors that occur when they cannot grasp the real situation are very different from the actual situation. In practical work, it is often necessary to obtain a large amount of relevant information through a variety of ways. Analyzing and predicting various uncertain factors in bank credit business and putting forward corresponding countermeasures can reduce losses caused by these adverse effects. Therefore, we need to establish a model that can objectively evaluate the risk level, correctly reflect the potential uncertainties in the bank's credit business, and reasonably analyze and evaluate their changes.

3 EXPERIMENTAL PROCESS OF FINANCIAL CREDIT RISK PREDICTION MODEL BASED ON PSO-SVM

3.1 Test Process of Financial Credit Risk Prediction Model

The flow chart of the financial credit risk forecast model is shown in Figure 1.

According to the existing financial credit risk prediction model, this paper establishes a financial credit default early warning system based on PSO-SVM. The system includes data acquisition, preprocessing, decision tree and state space analysis. In the aspect of data collection, it is mainly to classify and screen the samples. In the process of information processing, the main consideration is how to match these different types with the characteristic parameters to form an effective prediction model. This paper uses the SVM based method to identify the risk factors and take them as one of the early warning indicators of financial credit default. According to the above credit risk evaluation model, we can establish the following two different evaluation methods, which are based on neural network and other related technologies to identify, predict and control the default behavior in the financial market. When the traditional method is applied to the financial field, it needs a large amount of data to support the decision-making process and get accurate information. As for SVM system, its main function is to simplify complex problems through computer simulation of human brain and other machine processing capabilities. At the same time, it can also make judgment and evaluation after quantifying risk factors through expert assisted analysis technology.

3.2 Test Steps of Financial Credit Risk Prediction Model

The test of financial credit risk prediction model is mainly to analyze different types of data, including: (1) parameterizing the original indicators; Then, a unified standard value is used to calculate the required quantitative information. Standardization is one of the basic means and methods adopted to make each behavior subject compare and reflect each other. It can classify different objects to achieve the purpose of data description, analysis, classification and sorting. 2) During data entry, the collected sample information shall be preprocessed. After obtaining the original data, it is necessary to convert it into a usable format file, and then calculate the required parameters through a standardized algorithm and make it into a form for use. 3) Unified standards and standardized languages are used to achieve the required performance indicators such as rule consistency, correctness and real-time response in the modeling process. 4) During data analysis, the collected sample information shall be preprocessed.

4 EXPERIMENTAL ANALYSIS OF FINANCIAL CREDIT RISK PREDICTION MODEL BASED ON PSO-SVM

This experiment aims to evaluate the effectiveness of financial credit risk prediction based on PSO-SVM model. Simulated financial data are used to test the performance of the model under different performance metrics, including accuracy (ACC) and area under the curve (AUC). The experimental data are derived from simulated financial data that represent the credit scores, loan amounts, loan terms, interest rates, annual incomes, and borrower ages of different borrowers. The data are mainly obtained from publicly available financial statements, annual reports and market research reports, and the simulated data are generated by combining the common distribution of financial markets to ensure the authenticity and diversity of the experimental data. The experimental operation process is divided into four steps: data preprocessing, feature selection, model training and testing. Firstly, the collected raw data need to be pre-processed, including data cleaning, standardisation and format conversion to ensure data consistency and usability.

Table 1: Training performance comparison

Index	Rf	PSO-SVM
ACC	0.7482	0.8382
AUC	0.533023	0.668299

Next, relevant features, such as credit score, loan amount, loan term, etc., are selected according to the needs of financial credit risk prediction and feature engineering is performed to improve the predictive ability of the model. In the model training stage, the pre-processed data are trained using the PSO-SVM algorithm, and the model is optimised by adjusting the parameters to obtain the best classification results. Finally, the model is applied to a test dataset to evaluate its performance under different performance metrics, including accuracy (ACC) and area under the curve (AUC).

4.1 Validation of Financial Credit Risk Prediction Model Based on PSO-SVM

Table 1 shows the training performance comparison of financial information risk prediction models.

From the comparison in Figure 2, it can be seen that the classifier obtained by the random forest prediction classification algorithm on the training data set does not show good prediction results on the test data. On the contrary, the model trained by pos-svm algorithm based on sensitive learning idea, which is less effective on the training data set, shows that in addition to good performance on the test set, the performance indicators of ACC and AUC classifiers are better than that of random forest algorithm. Therefore, it can be concluded that the model obtained by pos-svm algorithm based on sensitive learning idea has better model generalization ability.

In the experiments in Table 2, we tested the PSO-SVM model using simulated financial data. The experimental data include key indicators such as borrower credit score, borrowing amount, loan term and interest rate. Through the steps of data preprocessing, feature selection, model training and testing, we verified the effectiveness of PSO-SVM algorithm in financial credit risk prediction. The experimental results show that the PSO-SVM model can accurately identify high-risk borrowers, and the prediction results are highly consistent with the actual results. Especially in the case of lower credit scores, larger loan amounts and higher interest rates, the model's prediction accuracy is higher. In summary, the PSO-SVM model performs well in financial credit risk prediction and has practical application value.

5 CONCLUSION

With the development of Internet finance, it has brought great impact on the real economy and society, especially credit risk. Financial credit not only affects the normal operation and sustained and healthy growth of China's traditional industries and related industries, but also changes the way people invest in stocks, bonds and other capital markets to a certain extent. This paper studies the ability of SVM to predict the information asymmetry between banks and borrowers and the default of lenders under the network loan and third-party guaranteed financing modes in the credit business of Internet financial institutions. This method can effectively make up for the loopholes in the traditional financial credit risk management theory, and provide new ideas and practical significance for China's commercial banks in dealing with credit transactions in e-commerce enterprises.

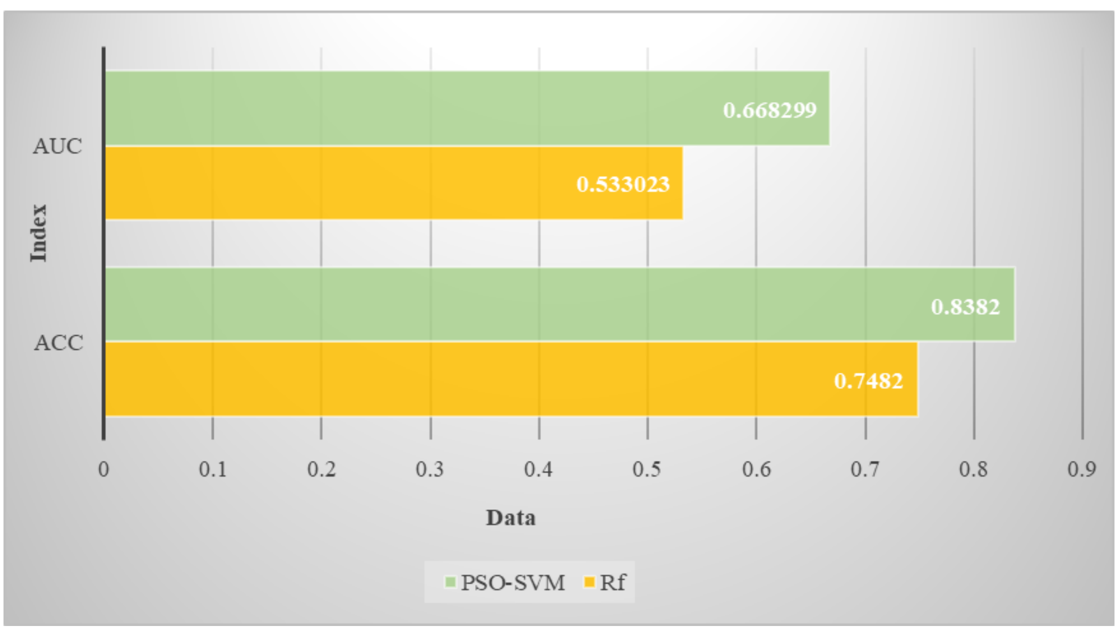

Figure 2: Model performance comparison of the experimental test set

Table 2: Modelled financial credit risk dataset

Serial Number	Borrower Credit Score	Loan Amount (10,000 Yuan)	Loan Term (Months)	Interest Rate (%)	Credit Risk (1=Default, 0=Normal)
1	720	50	12	4.5	0
2	680	30	24	5	1
3	640	40	36	6	1
4	710	20	12	3.5	0
5	650	60	48	6.5	1
6	700	35	18	4.8	0
7	675	25	24	5.2	1
8	730	45	36	4.2	0
9	660	55	48	6.8	1
10	705	30	18	4.6	0
11	685	50	24	5.4	1
12	750	60	36	4	0
13	670	20	12	5.1	1
14	715	40	18	4.7	0
15	690	50	24	5.3	1
16	740	30	12	3.8	0
17	660	45	36	6.4	1
18	720	35	24	4.9	0
19	680	55	48	5.7	1
20	700	25	18	4.5	0

References

[1] M. V. Rajagopala, S. C. Lingareddy:Spectrum occupancy-based PUEA detection using SVM-PSO in cognitive networks. Int. J. Commun. Networks Distributed Syst. 26(1): 30-49 (2021).

[2] V. Sandeep, Saravanan Kondappan, A. Amir Anton Jone, S. Raj Barath:Anomaly Intrusion Detection Using SVM and C4.5 Classification With an Improved Particle Swarm Optimization (I-PSO). Int. J. Inf. Secur. Priv. 15(2): 113-130 (2021).

[3] Abhishek Dixit, Ashish Mani, Rohit Bansal: CoV2-Detect-Net: Design of COVID-19 prediction model based on hybrid DE-PSO with SVM using chest X-ray images. Inf. Sci. 571: 676-692 (2021).

[4] Deepa D. Shankar, Adresya Suresh Azhakath:Minor blind feature based Steganalysis for calibrated JPEG images with cross validation and classification using SVM and SVM-PSO. Multim. Tools Appl. 80(3): 4073-4092 (2021).

[5] Le Cao, Wenyan Zhang, Xiu Kan, Wei Yao:A Novel Adaptive Mutation PSO Optimized SVM Algorithm for sEMG-Based Gesture Recognition. Sci. Program. 2021: 9988823:1-9988823:13 (2021).

[6] Paulino José García Nieto, Esperanza García Gonzalo, Fernando Sánchez Lasheras, Antonio Bernardo Sánchez:Chrome Layer Thickness Modelling in a Hard Chromium Plating Process Using a Hybrid PSO/ RBF-SVM-Based Model. Int. J. Interact. Multim. Artif. Intell. 6(4): 39-48 (2020).

[7] Dhruba Jyoti Kalita, Shailendra Singh:SVM Hyper-parameters optimization using quantized multi-PSO in dynamic environment. Soft Comput. 24(2): 1225-1241 (2020).

[8] K. Uma Maheswari, S. Rajesh:A novel QIM-DCT based fusion approach for classification of remote sensing images via PSO and SVM models. Soft Comput. 24(20): 15561-15576 (2020).

[9] Bhaskar Navaneeth, M. Suchetha:PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications. Comput. Biol. Medicine 108: 85-92 (2019).

[10] Gracieth Cavalcanti Batista, Washington Luis Santos Silva, Duarte Lopes de Oliveira, Osamu Saotome:Automatic speech patterns recognition of commands using SVM and PSO. Multim. Tools Appl. 78(22): 31709-31731 (2019).

[11] B. M. Sreedhara, Manu Rao, Sukomal Mandal:Application of an evolutionary technique (PSO-SVM) and ANFIS in clear-water scour depth prediction around bridge piers. Neural Comput. Appl. 31(11): 7335-7349 (2019).

[12] F. Eid Heba, Ajith Abraham:Plant species identification using leaf biometrics and swarm optimization: A hybrid PSO, GWO, SVM model. Int. J. Hybrid Intell. Syst. 14(3): 155-165 (2017).