ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the Innovation of Credit Risk Assessment System in Financial Derivatives Market Driven by Digital Financial Technology

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SUMMARY: *Financial derivatives were born for the purpose of reallocating risk resources, often through the purchase of financial derivatives, a certain cost of funds in exchange for the transfer of risk. 3214 enterprises are selected for data preprocessing, 113 indicators of credit risk of financial derivative products are selected for the first time, including profitability, solvency, and macroeconomic environment and other aspects, and principal component analysis is used to determine 8 effective assessment indicators. The XGBoost algorithm is introduced, and the credit risk prediction model of XGBoost-GP is constructed by combining the Bayesian optimization method based on Gaussian process, and by setting up the comparison model, the XGBoost-GP obtains the best prediction accuracy of 84.7% on the dataset, and the XGBoostt-GP model has a fast convergence speed. By combining XGBoost-GP and SHAP method to establish a credit risk assessment model, the model is utilized to evaluate the indicators from the perspective of evaluation indicators, the model can ensure the high accuracy and robustness of the assessment results, profitability plays an important role in the assessment of credit risk of financial derivatives, and the assessment system provides a reference method for the control of risks in the financial derivatives market in the era of digital economy.*

KEYWORDS: *credit risk assessment; principal component analysis; XGBoost algorithm; SHAP; financial derivatives market*

1 Introduction

The global financial derivatives market has become an important part of the international financial market after decades of development. According to the data released by the Bank for International Settlements and the U.S. Office of the Comptroller of the Currency, the notional principal amount of global over-the-counter (OTC) derivatives stood at $714.7 trillion at the end of June 2023, a year-on-year increase of 15.7%. In terms of counterparties, reporting dealers are the most dominant participants, accounting for more than 90% [1]. In terms of geographical distribution, developed economies in Europe and the United States are the center of global financial derivatives trading, but the Asia-Pacific market is growing rapidly and its share is increasing [2, 3].

Throughout the international financial market, the financial derivatives market is developing rapidly. Among them, the trading volume of the financial derivatives market far exceeds the spot market, and about 90% of the global financial derivatives transactions are reached through the over-the-counter (OTC) market, and the OTC financial derivatives market

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https://doi.org/10.65102/is2026705 Published: 30 April, 2026

has been in today's world financial market system has been in a pivotal position [4-6]. In the history of the financial market, from the 1997 Asian financial crisis, the 2008 subprime mortgage crisis, the 2011 European debt crisis, to the 2019 L petrochemical crude oil options trading huge loss event, the 2020 Z bank linked crude oil futures products through the position, the 2021 Wall Street hedge fund Archegos "century of the big burst position In 2021, Wall Street hedge fund Archegos “the big blowout of the century” led to huge losses of investment banks, and all the major risk events and market turbulence are related to the lack of trust risk management and control [7-11]. However, the current financial derivatives market lacks a more objective, scientific and reasonable credit risk assessment system, and the traditional system and assessment methods are difficult to capture the volatility factors in the market [12-14]. Therefore, a good risk assessment of financial derivatives is the key premise and important guarantee for the smooth development of financial derivatives business.

Digital financial technology refers to the technical means of digitalization, automation and informatization of financial services and business through digital and technological means. It deeply integrates the financial business model of big data, cloud computing, artificial intelligence (AI), blockchain and other digital technologies, which involves the fields of digital infrastructure, payment and clearing, financing crowdfunding, investment management and insurance business, and more and more highlights the supportive role in the fields of innovation and entrepreneurship of small and medium-sized enterprises, rural revitalization, green sustainability, and foreign trade, which has become a key proposition for the risk assessment of financial derivatives [15-19].

The widespread application of digital financial technologies in financial markets has disrupted the risk management system in the financial derivatives market. Literature [20] in bibliometric analysis shows that financial derivatives help to promote risk management and financial stability after the financial crisis, and that computational technology plays an important role in derivatives pricing and risk management. Meanwhile, literature [21] mentions AI technology in the field of financial markets, using the advantages of algorithms and predictive models to improve financial derivatives credit risk, reduce financial market risk, and optimize financial derivatives strategies and risk management. Literature [22] integrates spectral clustering and semi-supervised support vector machine models to build a two-stage hybrid system for financial institutions to assess credit risk by mining comprehensive data from financial markets and institutions and users. And literature [23] states that machine learning models can detect transaction frauds in addition to assessing credit risks in financial transactions, thus helping financial institutions or enterprises to make decisions and reduce risks. In addition, literature [24] uses machine learning to reduce model risk in financial derivatives pricing, explores the risky scheme of pricing models based on substitution trees, and emphasizes the need to accurately capture the correspondence between the underlying assets of financial derivatives and their corresponding volatilities. And deep learning models can effectively capture the dynamic time-series relationships between variables. Literature [25] explored the potential of AI technology in financial derivatives market risk and credit risk assessment, in which the deep learning model constructs a risk assessment model by capturing the time-series characteristics of financial data, and the integrated learning algorithm identifies the risk by.

Literature [26] highlights that in the era of digital transformation in Vietnam, the financial derivatives market utilizes IoT technology and digital technology platforms to optimize market transparency and management, and to address investor privacy and security issues, thereby increasing trust in the market. Literature [27] proposes a dynamic system that combines big data analytics with distributed computing to monitor financial derivatives holding dynamic hedging decisions and meeting near-zero latency compliance requirements, thus enabling real-time risk management. Literature [28] proposes a blockchain-based financial ecosystem for a more diversified and resilient financial derivatives market, solving the problems of permission-based derivatives clearing and settlement platforms and distributed ledger technology systems to achieve the "ultimate goal" of systemic risk control. Literature [29] found that blockchain technology is embedded in the management of financial derivatives based on distributed systems to automate consensus clearing and smart contracts to realize the reduction of default risk of financial derivatives transactions. Literature [30] points out that blockchain financial derivatives clusters show significant improvements in the face of information asymmetry and transaction cost optimization, and also have the advantage of changing the form of transactions but retaining financial trust. Literature [31] reveals the details and application methods of smart contract financial derivatives, which combine blockchain technology and financial instruments to build decentralized and automated solutions for their trading sessions. Literature [32] developed a credit risk prediction algorithm for science and technology finance based on cloud computing, in which it also established a credit risk assessment index system based on the correlation between numerous financial indicators, and introduced the principal component analysis method to determine the weights of the indicators. Literature [33] reported that the computational simplicity of cloud computing for higher-order correlations and the multidimensional capabilities of computation, storage, application services, and analytics enable real-time tracking of nonlinear features in financial data over time.

The research centers on the credit risk assessment indexes of financial derivatives market, and 9310 data samples are obtained by selecting 3124 enterprises, initially selecting the indexes of the credit risk status of financial derivatives market, and determining the effective assessment indexes by using the principal component analysis method. Combined with the Bayesian optimization method of Gaussian process (GP), the credit risk prediction model of XGBoost-GP is proposed, and the indicators of accuracy and F1 score are selected to evaluate the model performance. The SHAP interpretation method is utilized in combination with the XGBoost-GP model to elucidate the credit risk assessment results of the financial derivatives market at the macro and micro levels.

2 Selection of Credit Risk Assessment Indicators and Data for Financial Derivatives Markets

2.1 Data sources and pre-processing

2.1.1 Data sets

In this paper, the financial derivatives market is used as a research sample, which is categorized into credit risky firms and non-credit risky firms, and the credit risky sample is scored in T-1 years to ensure its predictability.

From the raw data of more than 40,000 firms, the main liabilities of the firms were screened; these firms were consolidated to obtain 3,124 firms with 10,794 (2012-2022) data. After the exclusion of urban investment companies and T-1 year sample selection, the data obtained totaled 9,310 samples, and the samples were divided into training, validation, and testing groups according to 6:2:2.

2.1.2 Data pre-processing

1. Data pre-processing

1) Normalization of original data. On this basis, the original data of enterprises extracted from the database are normalized to form a normalized data set.

2) Unbalanced sample processing. In this paper, MATLAB programming was used to process the data of unbalanced samples. On this basis, the existing credit risk samples are combined using the SMOTE algorithm, so that the number of financial derivatives market risk samples and financial derivatives market risk samples is 1:1.

2. Sample classification

The sample data are shown in Table 1. According to the data in the table, all the samples N are divided into three groups, which are training group, validation group and test group. Among them, the ratio of training samples, validation samples and test samples is 6:2:2.

Table 1: Sample data

Sample classification	Training sample	Verification sample	Test sample
Number of non-default samples	2755	950	950
Sample of default	2755	950	950
Total sample size	5510	1900	1900

3. Proposed pixelation processing

In this paper, the Python programming language was used to digitally simulate the metrics data and process the images. Sampling digital degradation of data sampling and digital processing of all data in the range of [0-255].

4. Indicator Arrangement Method

Since the database used by this organization has an indicator K=81, a matrix of information expressed as “9*9” was obtained. For the arbitrary configuration method, any configuration A can be obtained by using Python programming to configure a series of indicators according to a 2D rectangle of “9*9”.

Then, a B-type-order arrangement is executed, marking the horizontal and vertical coordinates of $X(i)/Y(i)$ on a 2D positive aspect, and the Euclidean spacing on both positive aspects is obtained by traversing any two indices on the two positive aspects; the secondary Euclidean distance is executed on the indices $R(i), R(j)$ corresponding to the two indices i, j. On the basis of the above criterion of dual Euclidean distance, it is calculated and obtained the value of T in a randomized arrangement, by changing the position of any index, a different value of T can be obtained until the value of T is no longer increasing, at which point the square of the indexes arranged in an orderly arrangement.

2.2 Indicators for assessing credit risk in the financial derivatives market

2.2.1 Selection of indicators

The credit risk problem of the financial derivatives market studied in this paper has a large number of indicators used to measure the credit risk status of the financial derivatives market, which are categorized into six types of indicators: solvency indicators, operating capacity indicators, profit source indicators, growth capacity indicators, profitability indicators, and cash flow indicators. When the initial selection of variables was carried out, a total of 113 indicators were selected in six different evaluation directions on the financial side; on the macro level, a total of two indicators were selected that had a consistent impact on the overall financial derivatives market in all samples, and these two constant variables were not involved in the analysis of the correlation analysis.

2.2.2 Indicator screening methodology

1. Principal component analysis

The principal component analysis method is based on the dimensionality reduction in the field of mathematics, which means that the original number of indicators is transformed into several principal components that can cover more information, which can not only explain the large amount of information contained in the original indicators, but also the correlation between the principal components is relatively weak.

2. Advantages of principal component analysis

The number of variables that can be selected by principal component analysis can be many, as long as it meets the number of sample companies more than the number of indicators, the principal components obtained can retain more than 80% of the information of the original indicators, so the principal component analysis method can be a more comprehensive financial derivatives market as a whole; principal component analysis can be analyzed by downgrading the many financial indicators, and ultimately get a smaller number of comprehensive indicators, as long as the principal components obtained by the analysis can explain more information contained in the original indicators, and the correlation between principal components is weak. Indicators, as long as the analysis of the obtained principal components can be a basic understanding of the financial derivatives market situation, so the principal component analysis method simplifies the process of financial derivatives market evaluation.

3. Steps of Principal Component Analysis

Based on the concept of principal component analysis, the steps of principal component analysis can be summarized as follows:

(1) Construct the original data matrix according to the credit risk evaluation index system of financial derivatives market obtained by index selection.

The matrix X used for evaluating the level of credit risk in the corporate financial derivatives market represents horizontally m financial indicators, respectively $X_2 \cdots X_p (n > p)$, and vertically n sample firms, with the specific matrices:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix} \tag{1}$$

(2) Standardize the data in the original matrix X .

The unit between the financial indicators is not completely consistent, some indicators are in the form of a percentage, and some are in the form of numerical values, so in the principal component analysis, the need to standardize these indicators with different units, to eliminate the impact of different units to the evaluation. The formula for the standardization of the indicators is:

$$x_{ij}{}' = \frac{x_{ij} - \overline{x}_j}{\sqrt{Var\left(x_j\right)}} \tag{2}$$

where $\overline{x}_j$ is the mean of the variable and $\sqrt{Var\left(x_j\right)}$ is the standard deviation of the variable. Where the data analysis software is SPSS 21.0.

(3) Judging whether the original indicators are suitable for principal component analysis

Before carrying out principal component analysis, it is necessary to test the suitability of the original indicators for principal component analysis to determine whether the original indicators can be analyzed by principal component analysis. The judgment is based on the KMO value, Bartlett's spherical test to reach the required value, that is, the KMO value should be more than 0.7 in order to indicate that the original indicators are suitable for principal component analysis.

(4) Extraction of principal components

When judging the number of principal components, the contribution rate of the j eigenvalue and the contribution rate of the previous m eigenvalues should be taken into account, e_j is the contribution rate of a certain eigenvalue, and E_m is the contribution rate of the previous m eigenvalues, and the observation of the number of principal components is to find out the number of eigenvalues with eigenvalue greater than 1 and the sum of the contribution rate greater than 80%:

$$e_j = \frac{\lambda_j}{\sum_{i=1}^{p} \lambda_j} \tag{3}$$

$$E_m = \sum_{j=1}^{m} e_j \tag{4}$$

In determining the number of principal components, you can also take the help of the gravel plot and observe from where the slope of the gravel plot starts to flatten, then the number of indicators before the gravel plot flattens is the number of principal components to be obtained. Observing the gravel plot is also a re-verification of the extraction results.

(5) Economic interpretation of principal components

After extracting the principal components, the principal component loadings should be analyzed, which is aimed at economic interpretation of the principal components, and the formula for the principal component loadings is:

$$I_{ij} = \sqrt{\lambda} u_{ij} (i = 1, 2, \cdots m; j = 1, 2, \cdots, p) \tag{5}$$

Each principal component consists of original indicators, but the loadings between the principal component and each original indicator are different, and the larger the absolute value of the loadings, the closer the relationship between the principal component and the indicator before. According to this rule, you can name the principal components, observe the composition of the indicators with the largest load value of the principal components, and determine the name of the principal components according to the composition of the indicators.SPSS21.0 software will get the component matrix table, the numbers in the table indicate the load factor between each principal component and the indicators, the closer the absolute value of the load factor of the indicators is to 1, the more the principal components can be interpreted.

(6) Determine the formula for each principal component

According to the above steps, each principal component is named, then determine the linear formula for each principal component, the formula is determined with reference to the component matrix table, the value of each column in the matrix table is the coefficient of each financial indicator, where each column represents a principal component. The formulas are expressed as follows:

$$F_j = b_{j1} X_1 + b_{j2} X_2 + \cdots + b_{jp} X_p, j = 1, 2, \cdots m \tag{6}$$

where F_j denotes the j th principal component, there are a total of m principal components; X_i denotes the i th financial indicator, there are a total of p financial indicators, because this paper focuses on the research of the composition of each principal component of the important indexes, so each principal component consists of the most influential indicators of the factors, so that each principal component contains the most important indicators. indicator factors are different.

2.3 Determination of credit risk assessment indicators in the financial derivatives market

2.3.1 Initial screening of indicators

In looking at the Q-Q plot for each indicator, it was observed that the distribution of the samples in the normal plot for each indicator is more in line with the normal distribution, and the distribution results are shown in Figure 1. When conducting the Levine test of equivalence of variances, when the significance has not yet reached 0.05, which we call the hypothetical equal variance, then the sample is consistent with the two-tailed significance level under the hypothetical equal variance in the average and t-test. If the significance is below 0.05, then the sample mean is more significantly different, and there are 39 such indicators; When conducting the Levine's test of variance equivalence, if the significance exceeds 0.05, which is called not assuming equal variance, then the samples' two-tailed significance levels in the t-test of mean equivalence without assuming equal variance are consistent, and if the significance is less than 0.05, then the sample means are more significantly differentiated, and there are a total of nine such indicators. The final total number of indicators screened for more significant differences was 48.

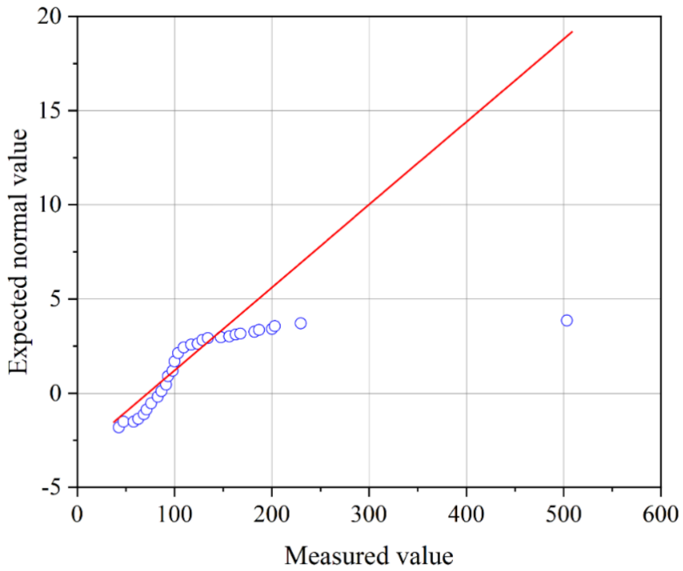


Figure 1: Normal Q-Q plot

2.3.2 Principal component analysis for dimensionality reduction using SPSS

With the help of the Analyze-Downcast-Factor Analysis function in SPSS, the principal components of the data can be better analyzed. In the first principal component analysis of the sample data of the previous indicators, it was found that there are seven characteristic factors will make the correlation matrix appear non-positive definite state, the principal component analysis can not be expanded, and they can only be raised, the principal component analysis can be continued.

Before dimensionality reduction, we should use “KMO and Bartlett's test” to check whether the selected sample consisting of 41 features is suitable for dimensionality reduction by principal component analysis only. The results are shown in Table 2. From the table, we can see that the KMO sampling test tangibility number is higher than 0.8, and the significance is under 0.001, which means that there is no problem to analyze the 41 samples selected for principal component analysis in this paper.

Table 2: KMO and Bartlett's test

KMO sampling adequacy measure		0.851
Bartlett sphericity test	Approximate chi-square	75274.13
	Free degree	825
	Conspicuousness	0.001

In this paper, 8 principal components were extracted and the principal component analysis will show the results in Table 3. The total variance explained in shows that the 41 indicators summarized into 8 principal components have an explanatory degree of more than 82%.

Table 3: total variance explanation

Ingredient	Initial eigenvalue			Extract load square sum			Sum of the squares of rotating load		
	Amount to	Variance percentage	Accumulate %	Amount to	Variance percentage	Accumulate %	Amount to	Variance percentage	Accumulate %
1	17.472	42.615	42.615	17.472	42.615	42.615	8.001	19.515	19.515
2	4.528	11.044	53.659	4.528	11.044	53.659	7.932	19.346	38.861
3	3.395	8.28	61.939	3.395	8.28	61.939	4.873	11.885	50.746
4	2.884	7.034	68.973	2.884	7.034	68.973	4.017	9.798	60.544
5	1.872	4.566	73.539	1.872	4.566	73.539	3.328	8.117	68.661
6	1.317	3.212	76.751	1.317	3.212	76.751	2.401	5.856	74.517
7	1.287	3.139	79.89	1.287	3.139	79.89	1.968	4.8	79.317
8	1.118	2.727	82.617	1.118	2.727	82.617	1.353	3.3	82.617

Based on the results of factor analysis of Table 3 with the rotated component matrix, it is summarized as follows:

The first principal component contains the following eight indicators including ROIC as the return on invested capital, ROA as the net rate of return on total assets, ROA as the return on total assets, ROE (weighted) as the return on net assets, ROE (average) as the return on net assets, cost and expense margins, ROE (diluted) as the return on net assets, and ROE (deducted/average) as the return on net assets, which all can reflect the profitability of the firm. This component provides 42.62% of the explanatory power to define the first principal component as profitability (f1).

The second principal component contains six main negative contribution rate indicators including cost ratio during sales (TTM), administrative expenses/total operating income, administrative expenses/total operating income (TTM), total operating costs/total operating income, cost ratio during sales, and financial expenses/total operating income, which can be used to measure the profitability of the cost-to-output ratio, as well as four positive contribution rate indicators including: net profit/ gross operating income, net sales margin, operating profit/gross operating income, and EBITDA/gross operating income. This component provides 11.04% of the explanatory power and the authors define the second principal component as operating capacity (f2).

The third principal component contains five main positive contribution margin indicators to measure the return on investment, including total net asset margin-excluding minority gains and losses (TTM), return on total assets (TTM), return on invested capital ROIC (TTM), return on invested capital (TTM), and return on human input (ROP). This component provides 8.28% explanatory power, which is defined as earnings cost coverage ((f3).

The fourth principal component consists of the positive contribution of five main indicators that reflect operational capacity, including total asset turnover, total asset turnover (TTM), non-current asset turnover, current asset turnover, and accounts payable turnover. This component provides 7.03% of the explanatory power, referring to it as operational capacity (f4).

The fifth principal component generally includes three positive contribution ratio indicators that reflect short-term solvency, including quick ratio, current ratio, and conservative quick ratio. This component has an explanatory power of 4.57% and is defined as short-term solvency (f5).

The sixth principal component includes the positive contribution of inventory turnover days and business cycle agents, and inventory turnover provides the contribution of payments, which are indicators of long-term solvency. This component provides an explanatory power of 3.21%, defined as inventory management capacity (f6).

In the seventh principal component, which includes a distinction between negative and positive contribution margins, the net debt ratio belongs to the former and the return on equity ROE (net of/diluted) to the latter. This component has an explanatory power of 3.14% and can be categorized as long-term solvency (f7).

The eighth principal component includes two positive contribution margin indicators, such as accounts receivable turnover and operating profit/total profit. This component has an explanatory power of 2.73% and can be categorized as liquidity capacity (f8).

3 Credit Risk Assessment in Financial Derivatives Market Based on XGBoost

3.1 Modeling

3.1.1 Construction principle based on XGBoost algorithm

XGBoost algorithm is an extension of Gradient Boosting Machine (GBM) algorithm, which is an optimization model with the characteristics of both linear model and tree model, and is able to complete regression and classification tasks at the same time.XGBoost algorithm consists of multiple decision trees (CARTs), and achieves machine learning through decision tree integration, and the predicted value of all the decision trees is cumulated to be the model prediction, and is trained by Gradient Boosting Decision Tree (GBDT) algorithm for model training.

In constructing the financial derivatives market prediction model, the XGBoost algorithm approximates the measured deformation values by continuously adding new functions about each factor in the deformation prediction function, i.e:

$$\hat{y}_K = \sum_{i=1}^{K} F_i\left(x_i\right) = F_{K-1}\left(x_i\right) + f\left(x_i\right) \tag{7}$$

where: K is the number of prediction rounds; $\hat{y}_K$ is the value of the deformation prediction function for the Kth round; $f_K\left(x_i\right)$ is the decision tree function on the hydraulic pressure factor, the temperature factor, and the timing factor.

The objective function of XGBoost algorithm is defined as follows:

$$F_0 = \sum_{i=1}^{K} L\left(y_i, \hat{y}_i\right) + \sum_{i=1}^{K} \Omega\left(f_K\right) \tag{8}$$

where: L is the loss function, used to evaluate the loss between the deformed predicted value and the true value; $\Omega\left(f_K\right)$ is the regularization function, used to control the complexity of the control model to avoid overfitting. The regularization function is defined as follows:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \left\|\omega\right\|^2 \tag{9}$$

where: γ, λ is the regular term penalty coefficient; ω is the weight corresponding to the leaf node; and T is the temperature. Rewrite equation (7) and perform a second-order Taylor expansion:

$$F_{OK} = \sum_{i=1}^{n}\left(L\left(y_i, \hat{y}_{i,K-1} + f_K\left(x_i\right)\right) + \Omega\left(f_K\right)\right) \tag{10}$$

$$f(x+\Delta x) \cong f(x) + f'(x)\Delta x + \frac{1}{2} f''(x)\Delta x^2 \tag{11}$$

A further simplification of Eq. (10) can be obtained:

$$F_{OK} = \sum_{i=1}^{n}\left[g_i f_K\left(x_i\right) + \frac{1}{2} h_i f_K^2\left(x_i\right)\right] + \Omega\left(f_K\right) \tag{12}$$

where: g_i is the first order gradient statistics of the loss function; h_i is the second order gradient statistics of the loss function. Finding $f(x)$ to minimize the objective function through iteration is the completion of model training.

3.1.2 Principles of model parameter optimization based on Gaussian process (GP)

Bayesian optimization algorithm is an efficient optimization tool, which can be classified into three categories based on different agent models: Tree Evaluator TPE, Random Forest Regression AMAC, and Gaussian Process GP. With the huge data set of financial derivatives market observation, Gaussian Process with faster iteration speed and higher quality is chosen as the kernel of optimization model.

When performing optimization tasks with a Gaussian process as the kernel, a prior distribution model that satisfies the Gaussian process is often assumed for the objective function $f(x)$, i.e., any finite dimensional combination of the model parameters still satisfies the Gaussian distribution:

$$f(x) \sim GP\left(E(f(x)), C_{OV}\left(x, x'\right)\right) \tag{13}$$

where: E is the mathematical expectation of $f(x)$; $C_{\mathrm{OV}}\left(x, x'\right)$ is the covariance of x.

Each parameter combination $\{x_1, x_2, \cdots, x_i\}$ belongs to a Gaussian distribution and satisfies the following equation:

$$\begin{bmatrix} f(x_1) \\ \vdots \\ f(x_i) \end{bmatrix} \sim N\left(0, \begin{bmatrix} C_{ov}(x_1, x_1) & \cdots & C_{ov}(x_1, x_i) \\ \vdots & & \vdots \\ C_{ov}(x_i, x_1) & \cdots & C_{ov}(x_i, x_i) \end{bmatrix}\right) \tag{14}$$

After the prior distribution function is determined, sampling corrects the model. The more samples, the more accurate the model. To improve the sampling speed, the optimization algorithm determines the next sampling point by defining an acquisition function. The collection function will weigh the optimization direction of the model as exploration or exploitation, where exploration will sample a new region to avoid local optima, and exploitation will carry out further searches around existing local optima in an attempt to find the global optimum. The optimization objective is then to find the set of X in the full set A that maximizes or minimizes the value of $f(x)$ as shown in equation (15):

$$x^* = \arg\max_{x \in A} f(x) \tag{15}$$

3.1.3 Modeling steps

The modeling process is shown in Figure 2 with the following steps.

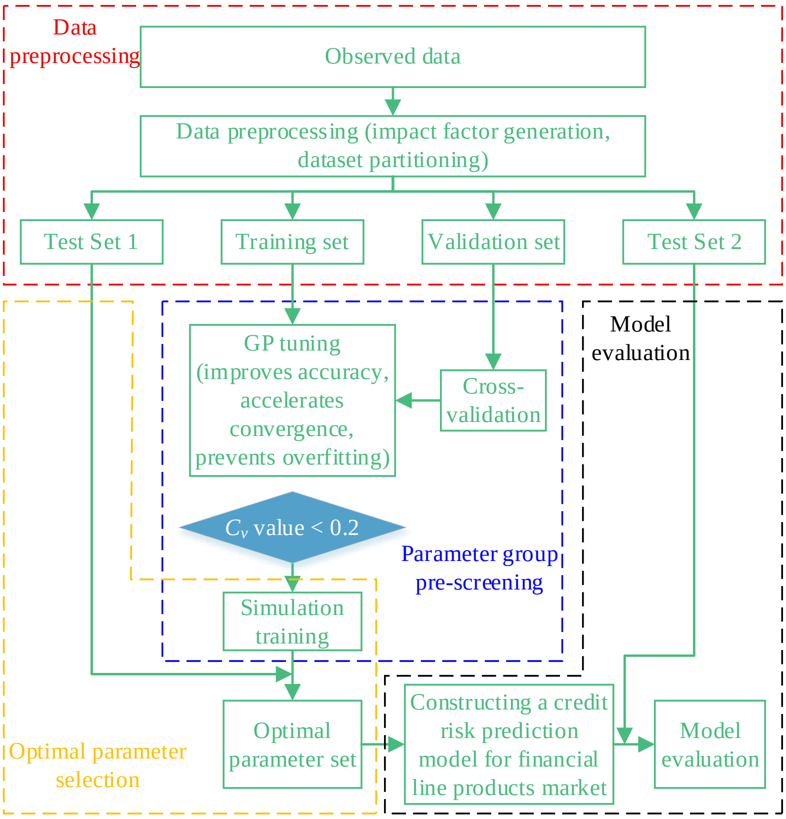


Figure 2: Modeling Process Based on XGBoost-GP Method

Step 1 The delineated training set and validation set are cross-validated to generate the evaluation index C_v, determine the optimization range of each parameter, and bring them into the Bayesian optimization algorithm to carry out optimization iterations. Since the validation set is taken from the training set, in order to avoid local optimization and mutation of predicted values, the parameter group with C_v value less than 10% of the maximum C_v value (0.2 in this case) is selected to construct a prediction model, and the prediction is carried out on the training set 1. If the selected parameter groups have local optimization or mutation of predicted values, then the prediction model will be appropriately relaxed. If the selected parameter groups are locally optimal or the prediction value is mutated, then it is appropriate to relax the C_v threshold, and select the optimal parameter group comprehensively. Comprehensively evaluate the training speed and prediction accuracy of each parameter group, and select the optimal parameter group to construct the credit risk prediction model based on XGBoost-GP for financial derivatives market.

Step 2 Bring the data in test set 2 into the model constructed in step 1 for model evaluation, and make an evaluation of the GP-XGBoost model by comparing it with the model constructed based on the XGBoost algorithm with default parameters, linear regression method, and BP neural network.

3.2 Experimental setup

3.2.1 Contrasting models

In order to verify the effectiveness of XGBoost-GP model in credit risk assessment, nine models that are widely used and effective in the assessment field are used to compare with XGBoost model. These include single learner models (LR, DT, BP-MPL, SVM) and integrated learning models (Bagging-DT, RF, AdaBoost-DT, GBDT).

3.2.2 Evaluation indicators

Prediction accuracy, Type-Ierror, Type-IIerror, precision rate, recall rate, and F1 score were used as evaluation metrics.

Accuracy (ACC), the proportion of correctly predicted samples to the overall samples:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{16}$$

Type-I error, the percentage of all default samples that are misclassified as not defaulting:

$$Type-I\ error = \frac{FP}{TN + FP} \tag{17}$$

Type-II error: the proportion of all non-defaulting samples that are misclassified as defaulting:

$$Type-II\ error = \frac{FN}{TP + FN} \tag{18}$$

Because the financial risk caused by defaulting samples is greater if they are predicted as not defaulting, a problem to be avoided in credit assessment, the model focuses on reducing the value of the Type-I error indicator.

Precision rate, the ratio of the number of samples accurately predicted as defaulted to the number of all samples predicted as defaulted:

$$Precision = \frac{TN}{TN + FN} \tag{19}$$

Recall, accurately predicted as the number of defaulted samples as a proportion of the number of all defaulted samples:

$$Recall = \frac{TN}{TN + FP} \tag{20}$$

The F1 score, which combines the balance of precision and recall. It is the reconciled average of the precision and recall rates, with a maximum of 1 and a minimum of 0:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{21}$$

3.3 Experimental Results of Credit Risk Assessment in Financial Derivatives Markets

3.3.1 Model evaluation results

ACC is one of the most mainstream and intuitive evaluation indicators, representing the overall level of model accuracy. However, in the field of credit risk evaluation, the accuracy of the prediction of default behavior directly affects the operation risk and income of the financial derivatives market, and Type-Ierror reflects the error rate of the prediction of default behavior, so a lower Type-Ierror is an important measure of a good model.F1-score combines the precision rate of the prediction of default behavior and the recall rate of the two indicators, so the F1-score is used as an important measure of the model. So the F1-score is an important measure of a good model.The performance of XGBoost and comparison models on the German dataset is shown in Table 4.

XGBoost-GP obtains the best prediction accuracies of 84.7% and 0.7128. Its ACC is 3.5 percentage points higher compared to the best-performing single classifier, BP-MPL, and 3.9 percentage points higher than the best-performing integrated classifier, RF. The ACC and Type-Ierror of the three XGBoost models are the best performers among all the models, indicating that the XGBoost models have good prediction accuracies for the overall samples and for the minority samples (in this case, the defaulted samples), and that they have an advantage in dealing with the unbalanced data, and their prediction ability for the minority samples in the unbalanced data is very strong. This improved prediction ability for minority samples is attributed to the balancing ability of scale_pos_weight in the XGBoost hyperparameters for sample weights.

Table 4: Result of performances on German dataset on performance measures

Model	ACC/%	Type-Ierror/%	Type-IIerror/%	F1-score/%
LR	73.2	34.64	30.83	0.6321
SVM	77.2	52.7	14.42	0.5933
BP-MPL	81.2	41.41	16.47	0.6466
DT	75.26	62.07	16.33	0.5842
Bagging-DT	80.5	54.76	10.89	0.5852
RF	80.8	55.39	10.17	0.5857
Adaboost-DT	80.4	49.94	13.46	0.6082
GBDT	79.4	53.51	13.13	0.5794
XGBoost-GS	81.2	29.2	21.96	0.6924
XGBoost-RS	83.2	32.38	17.41	0.7056
XGBoost-GP	84.7	33.35	15.02	0.7128

3.3.2 Comparative analysis of models based on statistical methods

In order to verify whether there is a statistically significant difference between the different algorithms, this paper uses the Firedman test and a follow-up test, the Nemenyi test, of nonparametric tests.The Friedman test is used to analyze whether there is a significant difference in the performance of multiple algorithms on multiple datasets. If there is a statistically significant difference between the algorithms, the Nemenyi test can be used to further differentiate between the individual algorithms.

The Nemenyi test was used for further analysis. When the number of datasets is 3, the number of models is 11, and a is equal to 0.1, 0.05, respectively, the values of q_a are 2.897, 3.206, respectively.The calculated CD values are 8.079, 8.724, respectively.

The bars in Figures 3 and 4 represent the average ACC and F1-score rankings of the 11 models on the dataset, sorted in order of ranking, with the two horizontal lines indicating the CD values at significance levels of 0.05 and 0.1, respectively. Models above the horizontal line are significantly worse than the optimal model. As shown in Figures 3 and 4, the XGBoost-based models ranked in the top 4, with XGBoost-GP and XGBoost-RS ranked the highest, followed by XGBoost-GS. Among the comparison models, BP-MPL performs the best. The integrated model outperforms the single classifier models LR, SVM and DT.

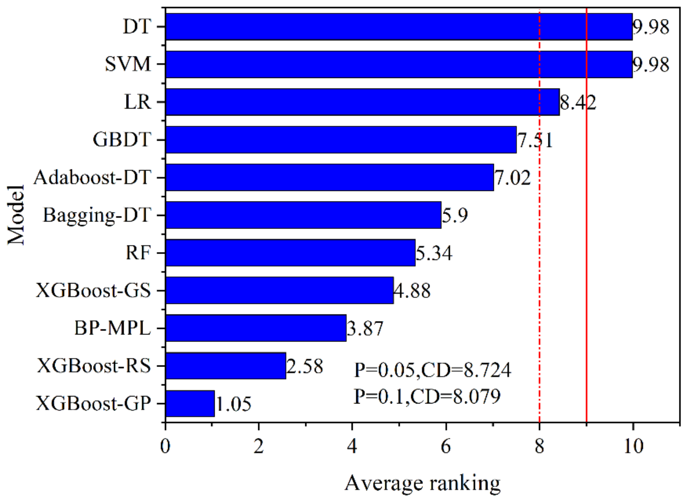


Figure 3: Average rank for ACC of models and threshold of Nemenyi test

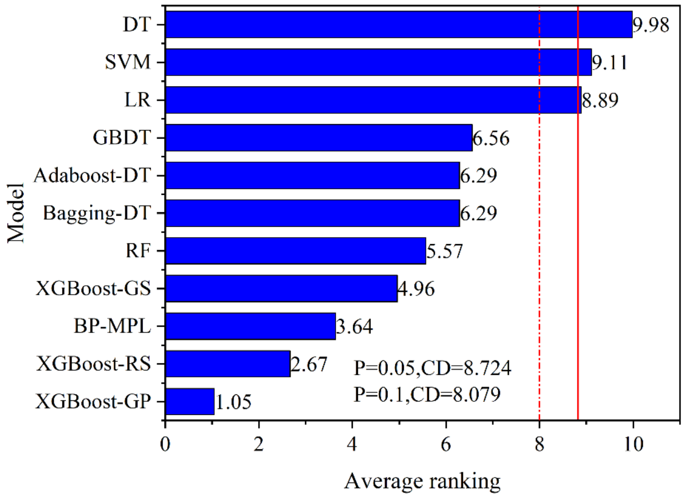


Figure 4: Average rank for ACC of models and threshold of Nemenyi test

3.3.3 Comparison of Hyperparametric Optimization Models

Evaluating the merits of a hyperparameter optimization algorithm needs to be judged from two perspectives: time complexity and optimization effectiveness. The evaluation of hyperparameters is costly because it requires training the model again using the hyperparameters to be evaluated. The time complexity of the hyperparameter optimization algorithm can be determined by the number of times the model is trained with the hyperparameters to be evaluated.The search space of XGBoost hyperparameter optimization is shown in Table 5.In order to prevent the dimension explosion caused by too many search parameters of GS, the Learning rate and Number of boost are set to fixed values, then the number of times GS trains the model with the parameters to be evaluated is 16000. The number of times is 16000 times.

Table 5: XGBoost hyperparameter optimization search space

XGBoost hyperparameter	RS	GS	GP
Learning rate	(0.1,0.3)	0.1	(0.1,0.3)
Number of boost	(10,200)	60	(10,200)
Maximum tree depth	(2,10)	(2,10)	(2,10)
Minimum child weight	(0,5)	0,1,2,3,4	(0,5)
Column subsample ratio	(0.8,1.0)	0.8,0.9	(0.8,1)
Subsample ratio	(0.8,1.0)	0.8,0.9	(0.8,1)
Gamma	(0,0.01)	0,0.1	(0,0.01)
Scale_pos_weigh	(1.0,2.0)	1.2,1.5,2.0	(1.0,2.0)

RS and GP train the model 2400 and 550 times with all hyperparameters involved in the search, 500 iterations, and 5-fold cross-validation, respectively. Figure 5 shows the box line plot of model accuracy for different optimization algorithms for hyperparameter search on the dataset, which shows that GP searches a small range of hyperparameters, but the results are generally better than GS and RS.

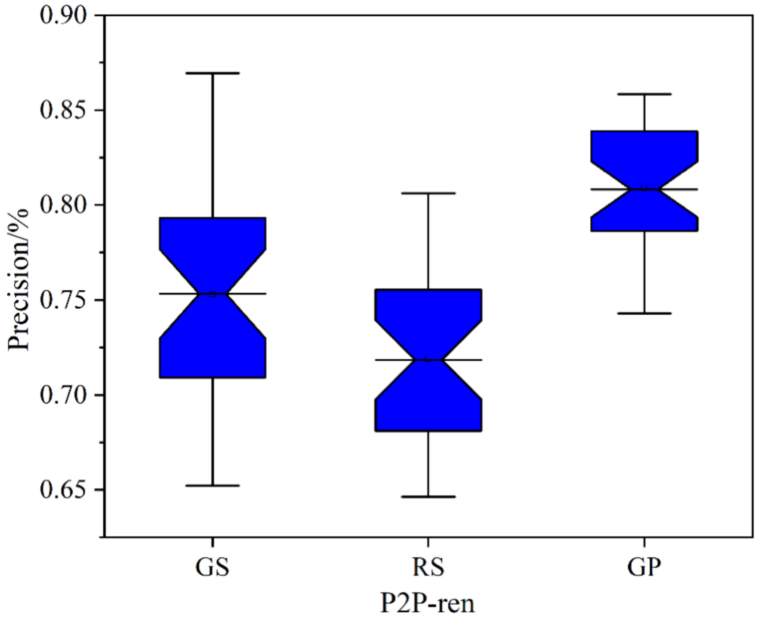


Figure 5: Box plot of the accuracy rate of the hyperparameter algorithm

4 Interpretability of Credit Risk Assessment Models for Financial Derivatives Markets

4.1 SHAP interpretive approach for machine learning models

The idea of SHAP originates from the measurement of the contribution of different players in cooperative games. The basic idea is to treat each sample in the training set of a machine learning model as a game, and treat each factor as a participant in the game, and compute the SHAP value of each factor in each sample, i.e., the contribution of the factor to the predicted value under the sample. SHAP is an ex-post model interpretation method, which calculates the marginal contribution of features to the model output, and then interprets the "black-box model" both globally and locally.SHAP constructs an additive explanatory model, where all features are considered as "contributors".

Considering that the SHAP method can be applied to any machine learning model, it is widely applicable. Therefore, this study uses the SHAP explanatory method to explain each trained machine learning model ex post to investigate the contribution of each influential factor to the credit spreads in the financial derivatives market.

To determine the factor contribution value, denote x_{ij} as the j th factor of the i th sample on the machine learning model $CS(x)$, the set M as the full set of all features, and $|M|$ as the number of elements in the feature set M. The predicted value $CS(x)$ of the machine learning model $CS(x_i)$ on a particular sample point x_i can be expressed as:

$$CS(x_i) = \phi_0 + \sum_{j=1}^{M} \phi_{ij} \tag{22}$$

In Eq. (22), ϕ_0 is the mean value of the dataset $E(CS(x))$, which serves as the baseline value for the model prediction. ϕ_{ij} is the contribution value of the j th influencing factor in the sample x_i, which represents the contribution of the influencing factor j to the predicted value on the sample x_i, when $\phi_{ij} > 0$, it means that the influencing factor j has a positive influence of x_i on this sample, i.e., when there is an influencing factor j will push the credit spread of the sample x_i above the mean value $E(\mathrm{CS}(x))$. When $\phi_{ij} < 0$, it means that the factor has a negative impact on this sample, i.e., when there is an impact factor j it will push the credit spread of the sample x_i below the mean value $E(\mathrm{CS}(x))$. The formula for ϕ_{ij} is as follows:

$$\phi_{ij} = \sum_{S \subseteq M/\{j\}} \frac{|S|!(M-|S|-1)!}{M!}\left[CS_i(S \cup \{j\}) - CS_i(S)\right] \tag{23}$$

In Eq. (23), S denotes the subset of the set M that does not contain the influencing factor j, $CS_i(S)$ denotes the predicted value under the set of features S when the sample is x_i, and $\left[CS_i(S \cup \{j\}) - CS_i(S)\right]$ denotes the change in the predicted value of credit spreads in the financial derivatives market caused by the addition of the influencing factor j to the set of influencing factors S, representing the marginal contribution of the feature j to the set of features S. $\frac{|S|!(M-|S|-1)!}{M!}$ term represents the weight of the feature set S.

Remember that the contribution of the influence factor j is $SHAP_j$, and if there are N samples in the training set, then $SHAP_j$ is inscribed by the mean of the absolute value of the contribution of all samples in the training set on the feature ϕ_{ij}, which is computed by the following formula:

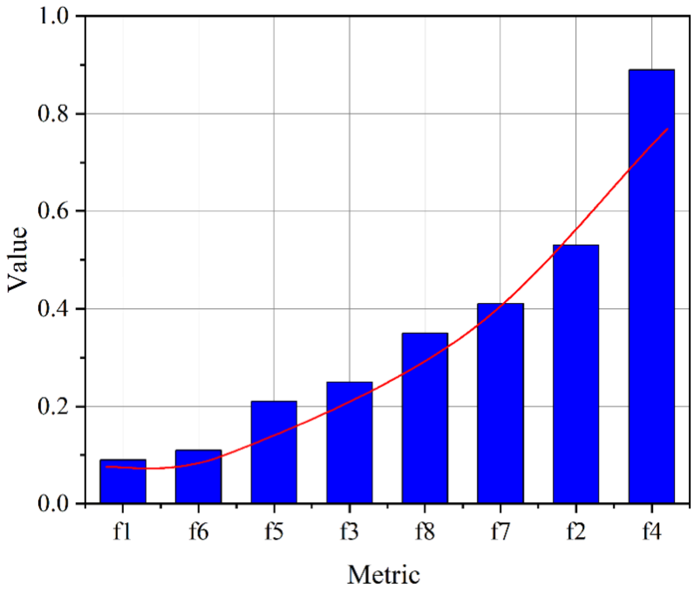
$$SHAP_j = \frac{1}{N}\sum_{i=1}^{N}\left|\phi_{ij}\right| \tag{24}$$

The larger the contribution value $SHAP_j$ of the influencing factor j, the larger the influence of the influencing factor j on the credit spreads in the financial derivatives market, i.e., the higher the degree of importance.

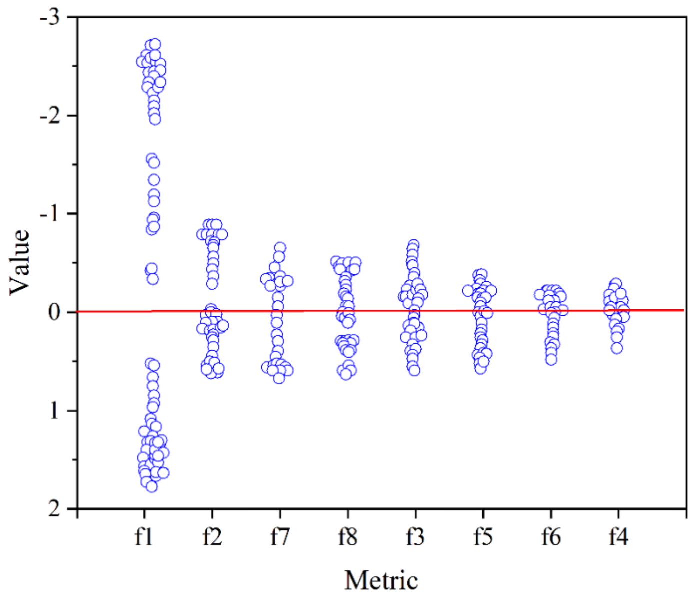
4.2 Interpretation of the results of the risk credit assessment based on the SHAP methodology

4.2.1 Interpretation of macro-level assessment results

After ensuring that the XGBoost integrated learning assessment has high accuracy and robustness, the SHAP method is introduced to interpret it, and then by marking the high and low values of the indicators, and visualizing the output in the form of bar and scatter plots with a consistent ranking of the importance of the indicators and the results of their impact on credit assessment, as shown in Figure 6. When the value of SHAP-value is less than zero, it indicates a negative impact on the probability of non-default, and when the value of SHAP-value is greater than zero, it indicates a positive impact on the probability of non-default, and the greater the absolute value of the value of SHAP-value, the greater the impact. The three indicators of operating capacity, business capacity and long-term solvency have relatively strong influence on the credit risk assessment results of the financial derivatives market.



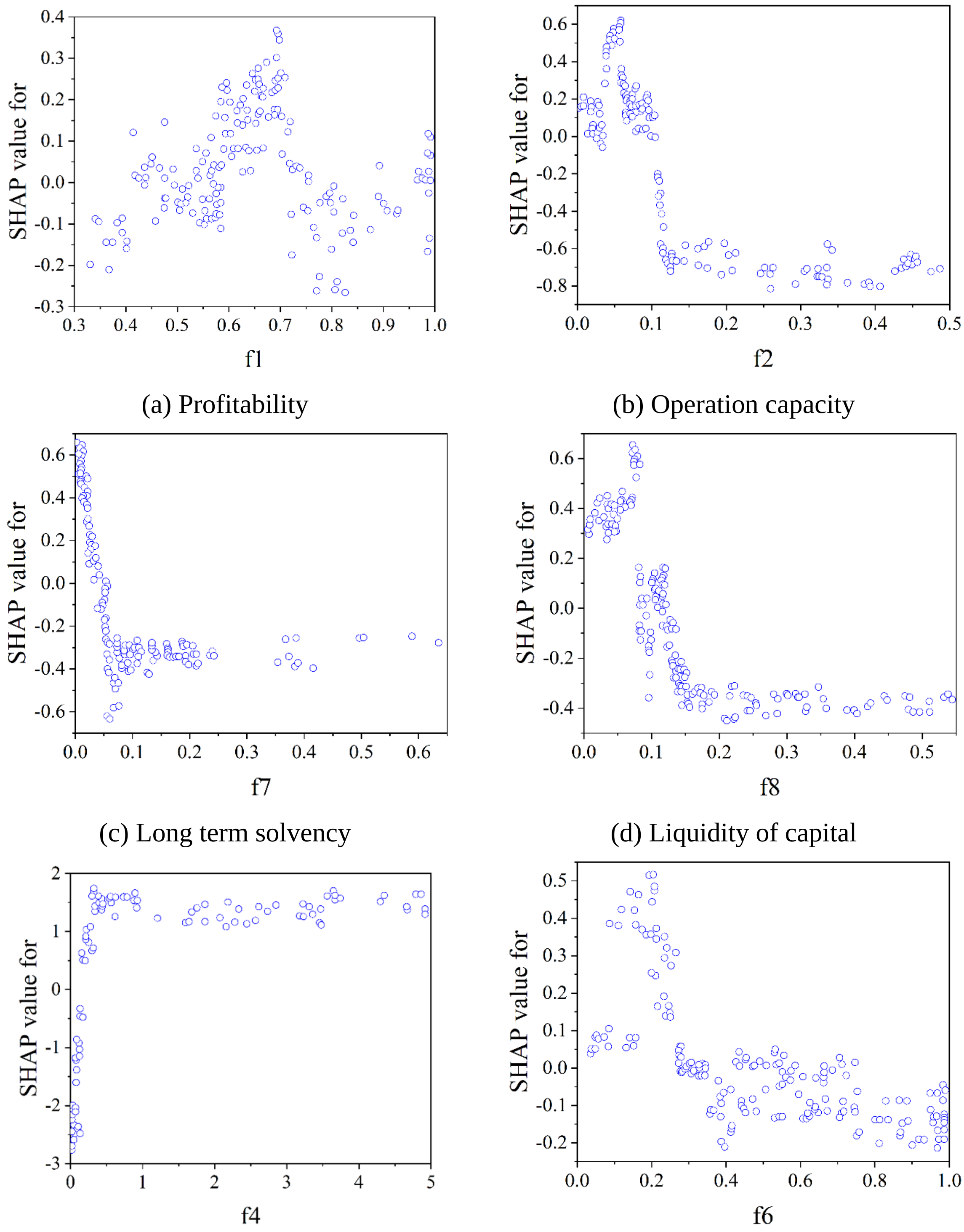
(a)mean(|SHAP value|) (average impact on model output magnitude)



(b) SHAP value impact on model output

Figure 6: Importance Ranking and Its Specific Influence on Default Tendency

By exploring the influence mechanism of individual indicators, we can further deepen the understanding and management of the whole enterprise financial derivatives market. Due to space limitations, several representative indicators are selected for analysis. The impact of profitability, operating ability, long-term solvency, liquidity, operating ability, and inventory management ability on the probability of no default of the enterprise is shown in Figure 7. Figure 7(e) with the increase in the amount of operating capacity, the SHAP-value value increases rapidly above zero and maintains a high positive impact, which contributes to the enterprise's credit risk assessment results tend to be non-default; Figure 7(f) with the increase in the inventory management capacity, the SHAP-value value as a whole shows a first increase, followed by a rapid decline below zero, and then maintains a relatively stable fluctuation, and after more than 0.7 can be seen clearly again after the overall decline in the trend, which can be seen for the inventory management capacity indicators, its credit risk assessment results of enterprises is not a simple one-way influence.



(a) Profitability (b) Operation capacity

(c) Long term solvency (d) Liquidity of capital

(e) Operation capacity (f) Inventory management capability

Figure 7: The Influence of Indicators on the Probability of Default of Enterprises

From a macro point of view: based on this credit risk assessment model, the importance of credit risk assessment indicators in the whole financial derivatives market can be ranked and the interactions between them can be explored, so that the mechanism of the influence of each indicator on credit defaults can be grasped from a global point of view, which will be conducive to the strengthening of the management of the credit environment in the financial derivatives market.

4.2.2 Interpretation of micro-level assessment results

By using Python it is possible to visualize the interpretation of the assessment results of each enterprise, respectively, from the default and non-default samples each randomly selected a sample, to obtain the results as shown in Fig. 8 and Fig. 9, from which it is possible to quantitatively analyze the reasons why each enterprise is assessed as a default or non-default, and when the probability of non-default is greater than 0.5, it is judged as a non-default enterprise, and conversely it is judged to be in default, and at 0.5 Random assignment.

For the first firm, its assessed probability of non-default is 0.95. The population base value is 0.5105, with variables in the red region representing an increase in its probability of non-default and variables in the blue region representing a decrease in its probability of non-default. For the second firm, its predicted probability of non-default is 0.05. Figure 8 shows that firms have low profitability cost coverage and high short-term solvency, with profitability ranging from 0.4 to 0.6; Figure 9 shows that firms have relatively low short-term solvency and high indicators such as operating capacity, although the relatively low profitability cost coverage is a major factor in driving the results of the firms' financial derivatives market credit risk assessment tend not to default, but to a limited extent, so the enterprise finally its assessed as default.

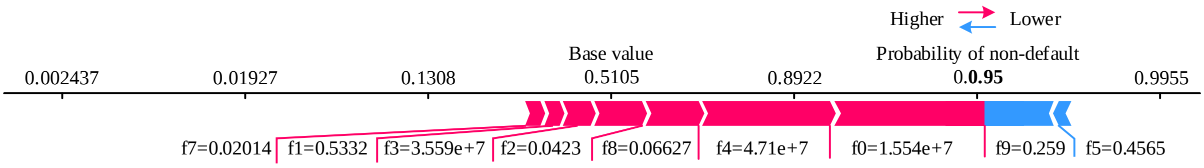


Figure 8: Interpretation of Credit Risk Assessment Results of Non-defaulting Enterprises

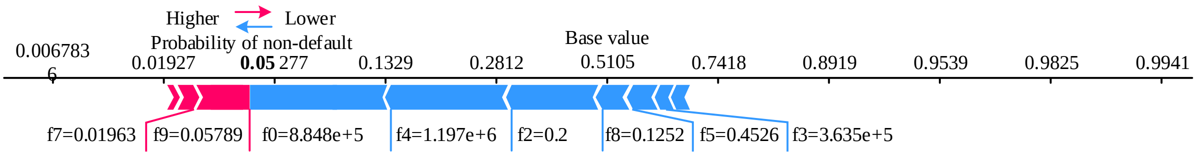


Figure 9: Interpretation of Credit Risk Assessment Results of Defaulting Enterprises

4.3 Fitting the Credit Score Distribution

By bringing the corporate financial derivatives market into the trained XGBoost integrated learning model for assessment and prediction, a credit score for the corporate financial derivatives market is obtained by applying a simple percentage to the resulting non-default probability, which is then fitted to a distribution using kernel density estimation as shown in Figure 10. On the whole most of the firms will be assessed as non-defaulting. For enterprises, when the interpretation of the assessment results can be released to the public, each enterprise can adjust its financial derivatives market management strategy based on the distribution and the interpretation of its own assessment results to improve its credit status and obtain credit financing.

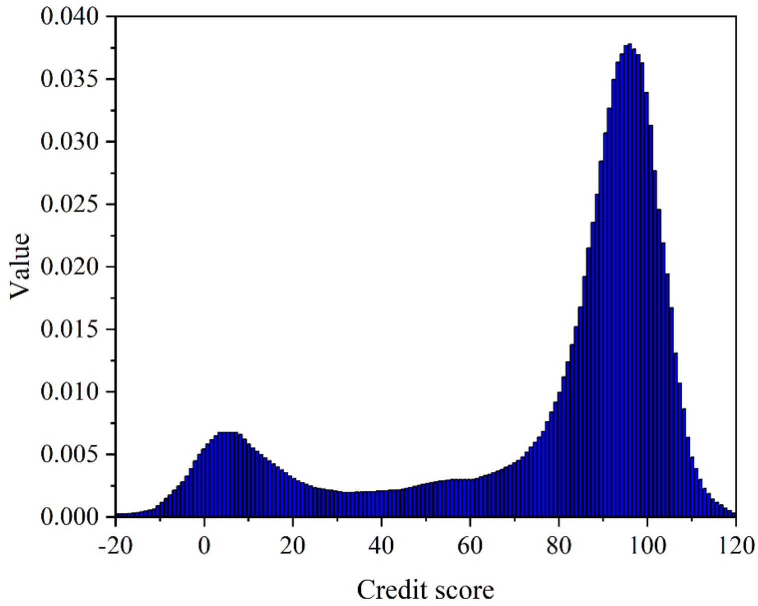


Figure 10: Distribution of Credit Scores for Enterprise Forecasting

5 Conclusion

This paper takes the enterprise financial derivatives market as a research sample, and combines the principal component analysis method to determine eight representative and valid assessment indicators, which lays a data foundation for the risk assessment of the financial derivatives market. Using the Bayesian optimization Gaussian method to optimize the XGBoost for tuning parameters to improve the accuracy and stability of the model, the XGBoost-GP risk assessment model is proposed. By comparing with LR, SVM, BP- MPL, DT, Bagging-DT, AdaBoost-DT, and GBDT methods, XGBoost-GP has excellent performance in all aspects, and it is most outstanding in the recall rate of default samples, which is the most important aspect of risk assessment. Combining XGBoost-GP with the interpretability of the assessment results of SHAP method solves the problem that the accurate stability and interpretability of the credit risk assessment model in the financial derivatives market can't be taken into account, and the profitability has an important significance and role in the assessment of credit risk in the financial derivatives market of enterprises.

About the Author

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