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Research on Credit Risk Quantitative Model of Internet Consumer Finance Based on LightGBM Algorithm

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Keywords: Internet consumer finance; Credit risk; LightGBM algorithm; Heckman two-step method; Risk control model

Abstract: Internet consumer finance has developed rapidly since 2013 by providing small loans to meet users' credit needs. However, due to the imperfect credit reporting system, it is difficult for the platform to capture customer information, which makes it difficult to identify and quantify credit risks. In 2022, the industry's average non-performing loan ratio reached 3%, and risk control is particularly important. Traditional logistic regression algorithms exhibit issues of low running speed and decreased predictive ability when processing high-dimensional data. This paper applies causal inference theory to screen variables, selects LightGBM algorithm, and improves Heckman two-step method to build a risk control prediction model of Internet consumer finance based on Heckman two-step method with sample selection bias correction, and selects KS and AUC indicators to evaluate the model effect. Based on the customer credit data of a consumer finance company, this paper analyzes the characteristics and credit risks of Internet consumer finance, and builds a whole process big data risk control model. Research has shown that risk control models constructed using Heckman two-step method and LightGBM algorithm have improved KS and AUC indicators, effectively quantifying borrower credit risk, predicting and controlling default probability, and thereby reducing credit risk. The research results provide new ideas and references for the credit risk control of Internet consumer finance.

1. Introduction

With the rapid development of Internet consumer finance in China, the market scale is expanding rapidly. Although the market growth will slow due to the COVID-19 in 2020, the market continues to grow rapidly in the post-epidemic era. It is expected that by 2023, the market size is expected to reach 10 trillion yuan, and the user scale will reach hundreds of millions of people. Although the prospect is broad, but the development is still not perfect, especially the credit investigation system. Faced with millions of low-income users applying for loans, the platform is difficult to capture customer information, leading to difficulties in identifying and fying credit risks. The non-performing loan ratio has increased year by year to 2.8% by 2021. How to effectively identify

and control the credit risk of Internet consumer finance has become particularly important. At present, the risk control system usually combines rules and risk control models. Traditional risk control models are mostly based on logistic regression algorithms, such as scoring card model, which are widely used in the banking system and credit institutions. However, in the face of high dimension and complex data generated by the Internet, the logical regression algorithm is limited and cannot effectively quantify the credit risk of customers. In recent years, scholars have tried to improve the performance of risk control model by optimizing algorithms, such as neural network algorithm and support vector machine, but most of these methods are single algorithm models, which fail to solve the problem of sample selection bias. In this paper, we improve the two-step Heckman method and combine it with LightGBM to establish a more accurate credit risk assessment model. Based on the theory of causal inference, we reduce the dimension of high-dimensional data, screen out the variables that really affect credit risk, and improve the effect of the model. This paper provides new ideas and methods for the establishment of credit risk assessment model, and puts forward corresponding strategic suggestions to help the industry better manage credit risk.

2.related research

2.1. Logistic regression model

It is a statistical learning method used to handle classification problems, particularly suitable for binary classification problems, where the target variable has only two values. Its basic idea is to convert the output of linear regression into an estimate of class probability through a linear regression model and a transformation called a logistic function, in order to make classification predictions. R Qin designed support vector machines and logistic regression models in his article for detecting accounting fraud. Enhance the learning and generalization ability of unknown situations using support vector machines. The experimental results of RM Kumar and his team members in the article indicate that the multi-layer perceptron neural network (MLPNN), which has been standardized and rescaled by covariates, performs slightly better in prediction than the logistic regression (LR) model. In the testing and validation stage of sample cases, its correct classification rate reached 82.8%.In the article, O Takawira et al. focused on using logistic regression (LR) to model sovereign credit rating (SCR), aiming to identify its determining factors and predict future rating changes. L Xiaojie et al. used three data mining algorithms, including support vector machine, decision tree, and logistic regression, to build a stock classification prediction model in the article.

2.2. LightGBM algorithm

It is a machine learning algorithm based on gradient boosting framework, developed by Microsoft, aimed at solving machine learning and data mining problems on large-scale datasets. Y Meng et al. proposed an arc fault detection algorithm based on a fully trained LightGBM model in the article,which can efficiently and accurately detect multiple arc faults. In their article, Lin et al. optimized the parameters of the LightGBM algorithm using genetic algorithm, and LightGBM based on GA optimization achieved significant performance improvement. The optimized model has improved average accuracy and average running time by 0.5% and 72.12%, respectively.

2.3. Data Warehousing and Data Mining

AH Carlson The regression model was using the two-step consistency estimator of Heckman. It is similar to a two-step consistent Heckman estimator but allows heteroscedasticity in the first step

and a more general control function specification. AC Jaures In their study,used the travel cost method, descriptive statistics, and two-step Hekenman method to analyze the use and economic value of indigenous seasonal climate forecast (ISCF) in Benin. A Krishnan et al. used the Heckman two-step program (1979), and the results show that the ECB has a positive impact on the OFDI of enterprises. The results show that companies using more leverage and ECB are those with higher OFDI intensity. MAJi-Liang et al. estimated the determinants of family behavior in commercial legume planting through the Heckman two-step model, and used the endogenous treatment regression (ETR) method to examine the impact of commercial legume planting on family economic welfare.

3. Method

3.1. Data collection and organization

Data preparation is the first step in model construction, and data processing is a key step in ensuring data quality.

(1) Conduct exploratory data analysis (EDA), analyze data through statistical methods, and discover patterns and trends behind the data. This step helps to understand the characteristics of the data, identify potential issues, and provide a basis for subsequent data processing and modeling.

(2) Clean the data to remove duplicate data, outliers, and missing values, ensuring the accuracy and completeness of the data. For example, for missing values, one can choose to delete severely missing records or use appropriate methods to fill them in.

(3) Convert non numerical data to numerical data, such as converting categorical variables to numerical variables (such as unique hot coding), to adapt the data to the requirements of machine learning algorithms.

(4) Delete variables that are unrelated or do not contain valid information to the target variable, in order to improve the operational efficiency and prediction accuracy of the model.

(5) Standardizing variables of different dimensions, such as converting them to normal distribution data with a mean of 0 and a variance of 1, can help eliminate dimensional differences between variables and avoid certain variables having a significant impact on the model.

3.2. feature selection

Due to the high dimension of Internet consumption finance data, variables need to be screened before modeling. This study used two methods, IV (Information Value) and causal inference, to screen variables. The IV value is used to measure the predictive ability of a variable towards the target variable. The larger the IV value, the stronger the predictive ability of the variable. The specific calculation formula is:

$$IV = \sum \left(\frac{g_i}{G} - \frac{b_i}{B} \right) \bullet \ln \left(\frac{g_i / G}{b_i / B} \right) \quad \text{(Formula 1)}$$

Among them, g_i and b_i represent the number of good and bad samples for each value point, G and B represent the total number of good and bad samples, respectively. Divide variables into five levels based on their IV values, and select variables with higher IV values as input features for the model. Causal inference uses a causal relationship diagram to describe the causal relationships between variables and screen out variables that truly have causal relationships.

3.3. model building

The dataset covers a total of 230 independent variables, including personal basic information, occupational information, credit data, behavioral data, device information, geographic location information, and loan application status. The data processing stage includes single value processing, missing value processing, and text processing. In single value processing, 16 invalid data variables were removed; In the missing value processing, 20 variables with a missing rate exceeding 80% were removed, and for variables with lower missing rates, median or mode was used to replace the missing value; In the text processing stage, feature extraction and categorical data encoding are performed on textual variables. Before constructing the risk control model, randomly divide the samples into a training set (70%) and a testing set (30%) to evaluate the model's generalization ability.

3.4. Model evaluation

Model evaluation is an important step in measuring model performance. This study used two indicators, KS and AUC, to evaluate the predictive ability of the model. The KS (Kolmogorov Smirnov) value is used to measure the ranking ability of the model, and the higher the KS value, the stronger the model's discriminative ability. The KS value is between 0 and 1. It is generally believed that a KS value less than 0.2 indicates weak discriminative ability of the model, a value between 0.2 and 0.4 indicates good discriminative ability, a value between 0.4 and 0.75 indicates strong discriminative ability, and a value greater than 0.75 indicates strong discriminative ability. The AUC (Area Under the Curve) value indicates the effectiveness of the model's prediction. The AUC value is between 0.5 and 1, the larger the value, the better. Generally speaking, 0.5 to 0.7 indicates low prediction performance, 0.7 to 0.9 indicates average prediction performance, and 0.9 to 1 indicates good prediction performance.

4. Results and discussion

4.1. Descriptive statistics

The distribution of loan application situations in the sample and the overdue situation of each loan application situation are shown in Figure 1:

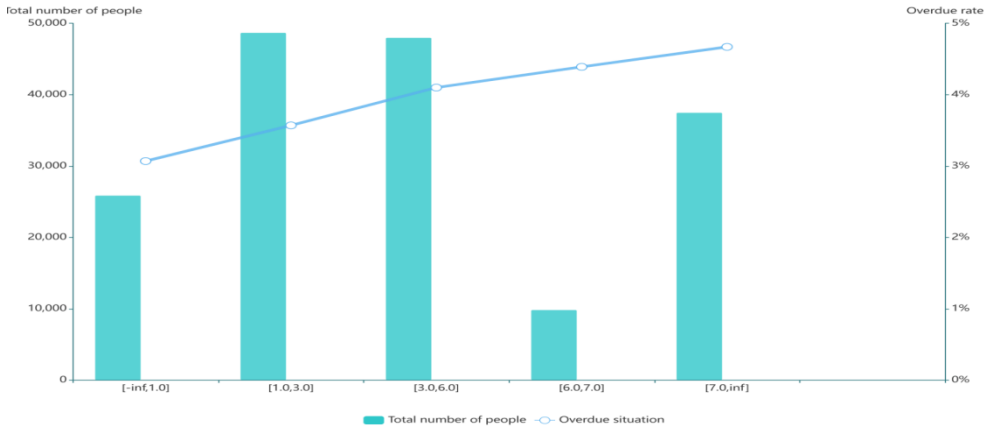

Figure 1 Loan application status distribution and overdue status

According to the chart, the majority of loan applicants have concentrated their multi head queries below 6 times in the past three months, accounting for approximately 73% of the total, indicating that the majority of people have a relatively small loan demand. However, with the increase of multiple queries in the past three months, the overdue rate has also shown an upward trend,

especially when the number of queries reaches 7 or more, the overdue rate is about 4.67%. Therefore, Internet consumer finance companies should pay more attention to customer groups who have repeatedly inquired about loan information recently, especially when applying for loans, they should focus on assessing their credit risk to ensure that the risk is controllable.

The distribution of credit situation in the sample and the overdue situation of each credit situation are shown in Figure 2:

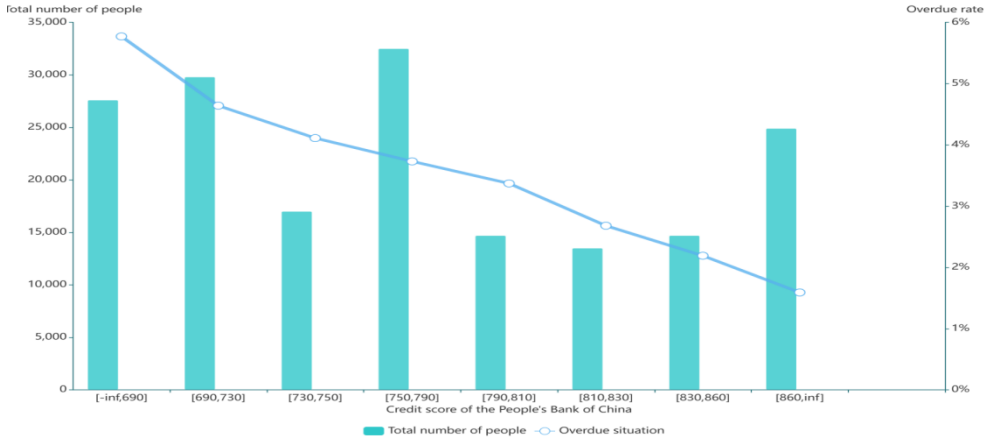

Figure 2 Credit score distribution and overdue situation of the People's Bank of China

The data shows that as the customer's credit score of the People's Bank of China increases, their overdue rate shows a downward trend. This indicates a significant negative correlation between the customer's credit status and overdue risk.

4.2. An Empirical Study of LightGBM Model

The LightGBM algorithm was used to obtain the importance ranking of each feature, and the results showed that the People's Bank of China credit score ranked first in the importance ranking, while age was relatively high. In terms of model parameter settings, by setting different parameters, the generalization ability and accuracy of the model can be improved. During the parameter tuning process, such as selecting the learning rate, the optimal value of 0.1 was obtained by traversing the learning rate list. Similarly, other parameters also underwent a similar optimization process, ultimately obtaining the optimal parameter combination. Under optimal parameters, after model training, the KS of the test set was 0.304 and AUC was 0.71, demonstrating good performance. The performance of the final model was demonstrated through the ROC curve, with an AUC value of 0.71, further validating the effectiveness of the established LightGBM model in quantifying credit risk.

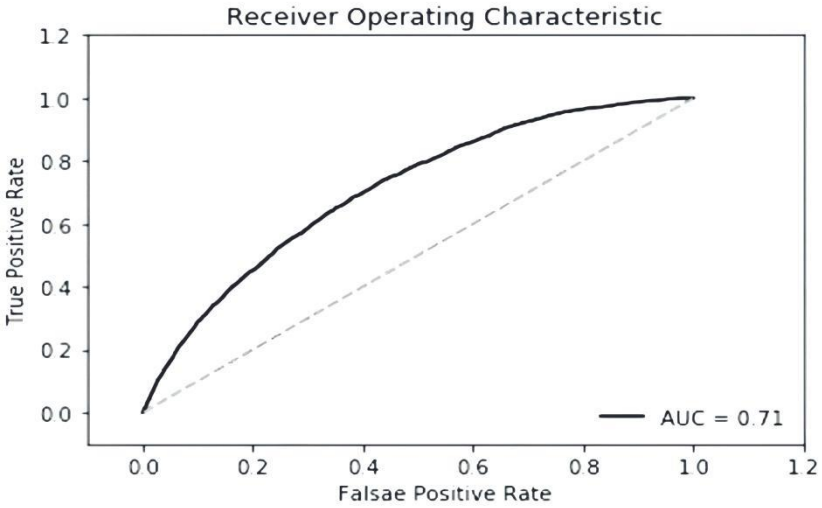

Figure3 ROC curve

The ROC curve is a curve drawn based on the false positive rate and true rate under different thresholds, while the AUC value represents the area size under the ROC curve, reflecting the model's ability to distinguish between positive and negative samples. In this model, the AUC value is 0.71, indicating that the model has a certain discriminative ability, that is, it can distinguish positive and negative samples well under different thresholds.

The final KS curve is shown in Figure 4, with a KS value of 0.304. The KS index measures the model's discriminative ability by comparing the cumulative distribution function (CDF) of the probability values of positive and negative samples predicted by the model. In short, the calculation method of KS value is to find the maximum difference in the proportion of true positive and negative samples after sorting the sample scores. Therefore, the higher the KS value, the stronger the model's ability to distinguish between positive and negative samples. In this model, the KS value reaches 0.304, which means that the model has a certain discriminative ability, that is, it can effectively distinguish positive and negative samples.

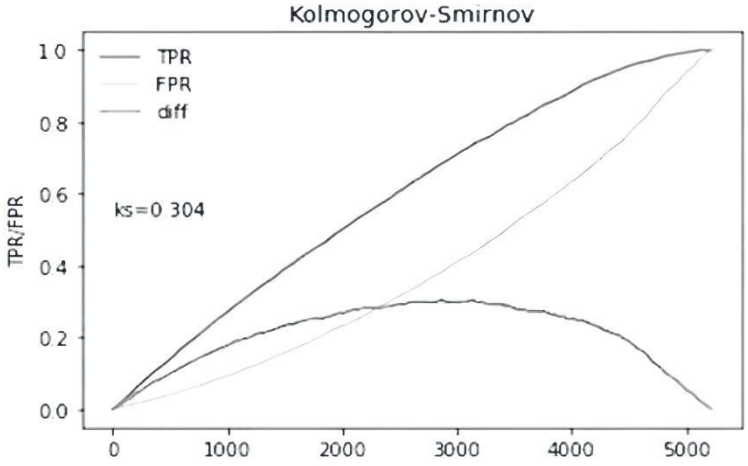

Figure4 KS curve

4.3. LightGBM model with sample selection bias correction

Due to sample selection bias in the original model, the Heckman two-step method was used for correction. Firstly, based on the original model, the IMR calculated in the first step of the Heckman

two-step method was introduced as a new variable, while maintaining the same parameter settings for model training. In the revised model, the KS value of the test set was increased to 0.312 and the AUC value was increased to 0.72. The revised model's ROC curve shows a higher AUC value of 0.72. Compared with the model without sample selection bias correction, the modified model has an improved AUC value, indicating that the model with sample selection bias correction has stronger predictive ability.As shown in Figure 5.

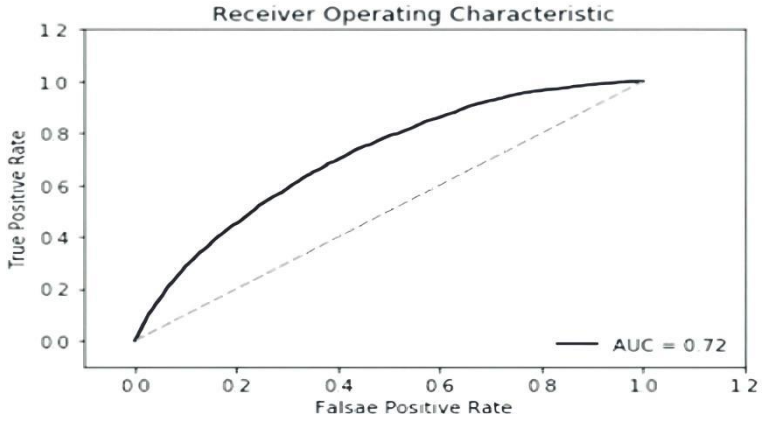

Figure5 ROC curve

Figure 6 shows the KS curve of the model with sample selection bias correction, corresponding to a KS value of 0.312. Comparing the models before and after sample selection bias correction, it was found that the KS value of the corrected model was slightly higher than that of the uncorrected model, with values of 0.312 and 0.304, respectively. This means that the model corrected for sample selection bias performs better in prediction.

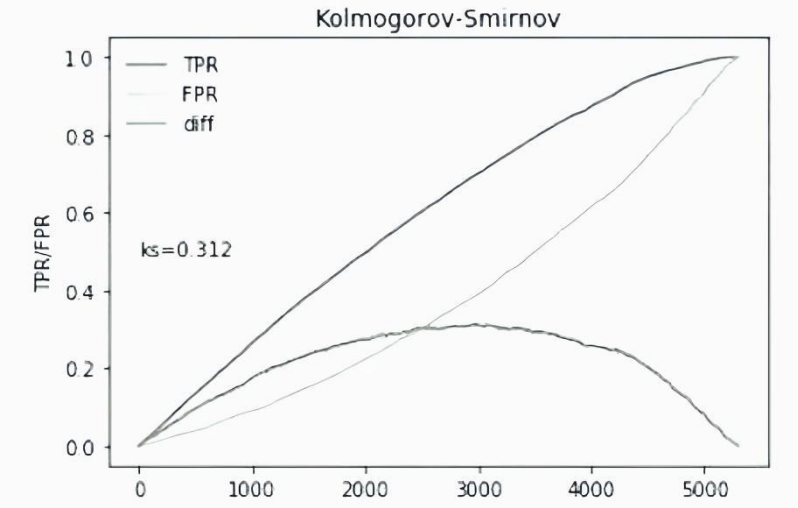

Figure6 KS curve

5. Conclusion

In this paper, IV information value and causal inference were used for variable screening, IV information value selected variables with strong predictive ability, and causal inference selected causal variables, which significantly improved the predictive performance of the model. In the process of model development, the LightGBM algorithm demonstrates its advantages in processing large-scale data and high-dimensional features, and builds strong learners, which greatly improves the prediction performance of the model. The experimental results show that the model performs

well in evaluating customer credit rating and default risk, and can effectively help financial institutions to control risks and improve efficiency. KS and AUC indicators were used in the model evaluation, and the results showed that the model performed well in both discriminatory ability and prediction effect, which verified the applicability and superiority of LightGBM in the credit risk quantification model. Through the continuous monitoring of the model, it ensures its stability and efficiency in practical application, finds and corrects the abnormalities in time, and ensures the continuous efficiency and accurate prediction performance in the constantly changing data environment.

The credit risk quantitative model of Internet consumer finance based on LightGBM algorithm significantly improves the efficiency and accuracy of credit risk management through the systematic modeling process and scientific evaluation method, and provides an efficient and accurate risk management tool for financial institutions. Future studies can further optimize the model performance and explore more advanced feature engineering and algorithms to further improve the credit risk management capability.

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