

Customer Credit Risk Rating Reduction and Scientific Financial Planning

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Abstract: In this paper, we first analyze the customer's capital status based on the Bank flow data, establish a standard to classify the credit risk, and screen out the customers with high possibility of money laundering risk. Then, combined with the annual interest rate of four products of loan, deposit, installment and financial management, we provide reasonable choice suggestions for high-quality customers, and predict the change trend of the four products in the next three years. Finally, the sensitivity and stability of the model are tested. Aiming at the problem of customer credit risk classification, we use risk gradient reduction model for qualitative analysis. Firstly, two concepts of default principal and default probability are defined, in which default principal represents customer value to a certain extent. TOPSIS Model Based on entropy weight method is used to calculate the scores of various users. In view of the problem of product portfolio recommendation, starting from the net transaction volume n between customers and banks in 2018 and considering the capital status of customers, in order to make the proposal more tendentious, we propose a propensity utility function, which divides the portfolio into two types: inward investment and outward credit, and then combines the two indicators of transaction frequency and relative conversion rate, as well as the four products of loan, deposit, installment and financial management. The interest rate situation provides targeted portfolio suggestions for customers respectively.

1. Introduction

The list of transactions between bank customers and the bank in a period of time is called bank flow. By analyzing the personal bank flow, we can not only judge the income, capital flow, private lending, but also judge whether the customer has the tendency of money laundering.

As a kind of financial criminal activities, many commercial banks have suffered huge losses and greatly disturbed the national economic order. The fifth recommendation of "40 + 9 recommendations" states that financial institutions should adopt the customer identity due diligence measures listed in the recommendations, and determine the scope of application of these measures on the basis of risk sensitivity based on customers, business relationships or transaction types. In addition, certain products or services provided by banks may cause higher risk of money laundering or terrorist financing. Therefore, it is very important to establish effective customer credit risk standards in order to intelligently master the capital status of users and facilitate the development of bank credit and personal business.^[1]

2. Gradient reduction model of credit risk

Because the standard RFM model is divided into eight different categories in the three-dimensional space composed of R, F and m, combined with the topic analysis, we only need two indicators, through the number and amount of transactions between customers and banks, supplemented by cluster analysis, we can understand the customer value of customers, namely default principal, and preliminarily qualitatively analyze the credit risk level of customers.

For high-end customers, we directly identify them as users with high credit risk. For ordinary users, we use the utility maximization model to judge.

In order to facilitate classification and statistics, we divide each index into three categories. The specific classification basis is shown in Table 1 (based on the survey data of existing research papers on individual customer value of commercial banks)

Table 1 customer value standard division

category index	1	2	3
Frequency of transactions (F / time)	<2	2~6	>6
Maximum trading volume (M / 10000 yuan)	<20	20~50	>50

The interval divided by the above two indicators can clearly reflect the customer value. We think that the larger the customer value is, the higher the credit risk is. As a high-risk credit customer with money laundering motivation, it is worth exploring how to take a relatively safe way of money laundering in front of the protection measures of banks.

1) Possibility division of potential money laundering motive -- utility maximization model;

In order to discuss the choice of money laundering channels for money laundering customers, we draw the two-dimensional coordinates P_1, P_2 . The isoline of money laundering, as shown in the figure, is the equivalent line -- the indifference curve in microeconomics. The utility is the satisfaction of money laundering customers to the risk of money laundering. According to the properties of the indifference curve, we can know that $U(P_1, P_2) = C$. It is a set of monotonically decreasing, convex and disjoint curves. along with C . The specific form of the curve is determined by the vigilance of money laundering customers to transaction frequency and maximum transaction volume, as well as the target utility to be achieved.

Suppose that the weights of the vigilance values of the suspected money laundering customers for the transaction frequency and the maximum transaction volume are a and B respectively. (among them $a + b = 1$) The maximum acceptable vigilance value of suspected money laundering customers is p, then there is

$$a * P_1 + b * P_2 \leq P \quad (1)$$

The so-called utility maximization is to determine the choice of transaction frequency and single maximum transaction volume of suspected money laundering customers according to formula (1), so as to make the utility function $U(P_1, P_2)$ To the maximum.

The feasible area is the lower left part of the line, which is the yellow area. In this case, the point m where the utility function reaches the maximum must be unique and utility function $U(P_1, P_2)$ The tangent point of the straight line shown.

2) The results of the model are summarized as follows:

In the two-dimensional standard division, each index is divided into three types, so there are nine customer types **RFMF**

The initial definition of the two indicators, one of which is high customer credit risk level is high, the other is medium. If one of the two indicators is low, the customer credit risk can be reduced by one level;

3. Customer judgment of money laundering risk

1) Customer safety score calculation:

First of all, we use the gradient reduction model to preliminarily determine the customer groups with money laundering risk, which are five customer groups with extremely high risk level and high risk level respectively. According to the three indicators of transaction frequency, maximum transaction amount and relative conversion rate, all kinds of user groups are screened out.

2) Calculation of index weight by entropy weight method:

First of all, the three indicators are forward processed, and then the X matrix obtained by the positive transformation is standardized. It is necessary to judge whether there is a negative number in

the Z matrix. If there is a negative number in the Z matrix, another method is selected to standardize the X matrix, that is

$$\tilde{z}_{ij} = \frac{x_{ij} - \min \{x_{1j}, x_{2j}, \dots, x_{nj}\}}{\max \{x_{1j}, x_{2j}, \dots, x_{nj}\} - \min \{x_{1j}, x_{2j}, \dots, x_{nj}\}} \quad (2)$$

4. Suggestions on optimal product mix

1) High quality customer selection:

Based on the credit risk gradient model established in (1), in order to balance customer value and credit risk, we select low and medium risk customers as high-quality customers, and subdivide customers. At the same time, combined with two indicators of transaction frequency series and relative conversion rate, as well as the interest rate of loan, deposit, installment and financial management products, it provides specific portfolio suggestions for customers.

2) Suggestion tendency:

According to 5.2, we know that the credit risk level is the result of classification according to customer value and corrected by relative conversion rate. In order to reflect the tendency of the proposal, we will clarify the direction of the proposed correction through the relative conversion rate again, and divide the portfolio into two types, namely, transfer in investment and transfer out loan, and give suggestions respectively.

4.1 Sug utility function based on RCR

Suppose the total amount of initial deposit is 1 and the transfer in investment coefficient is 1^α The transfer out credit coefficient is β In which $(\alpha, \beta > 0)$ Then there are:

$$SUG = \alpha * \max \{RCR, 0\} - \beta * \max \{-RCR, 0\} \quad (3)$$

As for suggestion tendency, we can assign the actual standard according to the actual situation. Here we select the standard as 0, then there are:

$SUG > 0$ We give priority to recommending customers to invest;

$SUG \leq 0$, We give priority to recommending customers to transfer out credit;

4.2 Four product portfolio weights based on transaction frequency

According to the attributes of the four products relative to customers, there are:

$$\begin{aligned} PD &= CK + LC \\ ND &= f(DK, FQ) \end{aligned} \quad (4)$$

Among them, the CK stay PD The proportion is S_1 , then LC The proportion is $1 - S_1$;

1) Initial weight criteria

According to the statistical data released by the Bank of China from 2010 to 2018, the data of the four products involved in the household part of the financial account are analyzed. The results are shown in Appendix 1. It is found that it is reasonable and feasible to give weight to deposit and financial products according to the proportion of annual interest rate, and it is regarded as the initial weight standard.

Similarly, we give specific weights to the internal types of deposits and financial management

Table 2 Initial weighting criteria

product type		Proportion	weight
Deposit (CK)	Current deposit	0.125	3.25%
	Time deposit	0.875	22.75%
Financial management (LC)	Current financing	0.41	30.34%
	Regular financial management	0.59	43.66%

2) Weight correction

After the transaction frequency is changed, the weight of time deposit is $r_1, 1 - r_1$ The weight of current financing and regular financing is $r_2, 1 - r_2$ Then there are

Table 3 Weight correction table

product type		Proportion	weight
Deposit (CK)	Current deposit	r_1	$0.26 * r_1 * 100\%$
	Time deposit	$1 - r_1$	$0.26 * (1 - r_1) * 100\%$
Financial management (LC)	Current financing	r_2	$0.74 * r_2 * 100\%$
	Regular financial management	$1 - r_2$	$0.74 * (1 - r_2) * 100\%$

5. Future trend forecast of products

1) Test of quasi exponential law

According to the data collected in Appendix 1, the quasi exponential law was tested and analyzed in MATLAB

The data of demand deposit, time deposit and medium and long-term loans all pass the test of quasi index law, while the smooth ratio of index 2 of short-term loan is less than 0.5, and the data accounts for nearly 90%, which can also be considered to pass the test of quasi index law. In the past three years, we use the grey model to forecast the trend of the total amount of deposits in the country.

The data of financial products fail to pass the quasi exponential law test. We choose time series model to fit and forecast the financial data. According to the operation results of expert modeler in SPSS, we get Brown model as the optimal model for fitting and forecasting data.

We can see from the ACF and PACF graphs of residuals that the autocorrelation coefficient and partial autocorrelation coefficient of all lag orders are not significantly different from 0. In the model fitting degree and model statistics, our stationary R-square is approximately 0 and R-square is 0.919, which indicates that our fitting effect is better, and the Q-test statistic is not shown (which may be caused by our special model).

Table 4

Q-test statistics				
Model fitting statistics	Young books Q (18)			Number of outliers
	Statistics	DF	Significance	
Stationary R-square				
-.001	.	0	.	0

So we think that the residual is white noise sequence, and brown model can better identify the data of financial products.

2) Product forecast results:

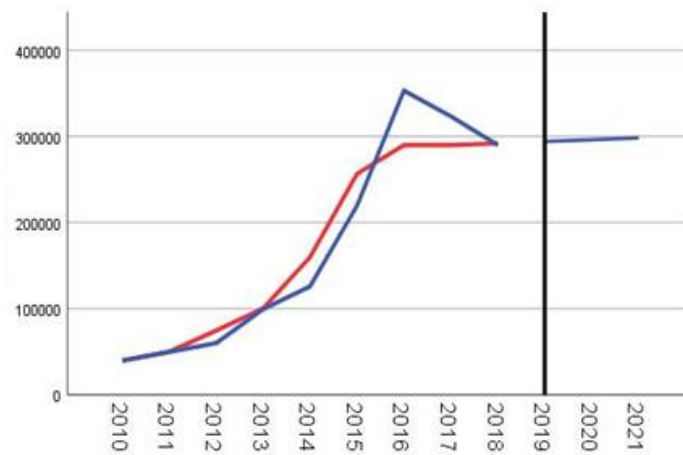


Figure 1 prediction results of brown model

According to the forecast data in the next three years, it can be concluded that the total amount of deposits and loans (we consider credit card installment as a kind of short-term loans) shows an upward trend, while the total amount of financial management shows a downward trend. We recommend that customers reduce the purchase of financial products year by year and pay more attention to deposit.

6. Evaluation and promotion

Gradient reduction model has good universality and can be applied to most fields. In addition, gradient reduction model is a qualitative analysis of a large number of data, which can well explain the existence of some potential phenomena, and has the ability to predict the evolution of future phenomena. Moreover, the model can be improved by extrapolation.

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