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A Study of Credit Risk Associated in Classification of State Bank of India Customers Using Multivariate Analysis Technique

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As India's financial markets become more dynamic and the economy continues to evolve and diversify, investors also need to evolve the way they assess credit risk. Ratings from credit rating organizations are a traditional measure of credit risk and a valuable source of information. Credit risk assessment typically involves looking at the financial ratios of the company as well as consultation with management teams. The ratings process is designed to be a long-term credit view, based on a deliberate consultative approach. This research is based on understanding the Credit Risk Associated in Classification of SBI customers .The objective of this study was to find a process which can increase the speed of the system and accuracy. The study was conducted among 240 SBI customers falling under SEC A1, A2, B1, B2 category households in the region of Pune. The study aids the bankers to take quick decision on classifying the group of customer whether to give credit card or not.
Keywords: *Discriminant Analysis, Credit Risk Analysis, State Bank of India*

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I. Introduction

The financial sector has played an important role in the economic transformation. It has significantly expanded its products, services and operations since 1991, and in this period the proportion of the banked population almost tripled.

The deployment of credit is highly concentrated in the corporate sector, which consumes 50 percent of the credit, followed by 20 percent by the retail sector, 14 percent by MSME, 9 percent by agriculture and 7 percent by financial institutions and others. Keeping in mind the strong and rapid growth pattern, changing regulations, there is a lot of pressure on credit risk departments to take on more responsibility managing their risk exposure.

Credit risk springs from a bank's dealing with an individual, corporate, bank, financial institution or a sovereign.

The decision making process of accepting or rejecting a client's credit by banks is commonly executed through Judgmental Techniques and/or Credit Scoring models. The Judgmental approach used by most banks and financial institution are based on 3c's,4c's or 5C's which are character (reputation), capital (leverage), collateral, capacity (volatility of earnings) and condition. Credit scoring models are very useful for many practical applications especially in banks and financial institution. Credit scoring model is a system creditors used to assign credit applicant to either a good credit one that is likely to repay financial obligations or a bad credit one who has a high probability of defaulting on financial obligation.

Credit Scoring has been used for other purposes such as aiding decision in approving personal applications. Although credit scoring model are widely used for loan applications in financial and banking institutions, it can be used for other type of organizations such as insurance, real estate, telecommunication and recreational clubs for predicting late payments. Credit scoring was first introduced in the 1940s and over the years had evolved and developed significantly. In the 1960s, with the creation of credit cards, banks and other credit card issuers realized the advantages of credit scoring in the credit granting process.

Beaver (1967) and Altman (1968), developed univariate and multivariate models to predict business failures using a set of financial ratios. Beaver(1967) used a dichotomous classification test to determine the error rates a potential creditor would experience if he classified firms on the basis of individual financial ratios as failed or non-failed. He used a matched sample consisting of 158 firms (79 failed and 79 non-failed) and he analyzed 14 financial ratios. Altman (1968) used a multiple discriminant analysis technique (MDA) to solve the inconsistency problem linked to the Beaver's univariate analysis and to assess a more complete financial profile of firms. His analysis drew on a matched sample containing 66 manufacturing firms (33 failed and 33 non-failed) that filed a bankruptcy petition during the period 1946-1965. Altman examined 22 potentially helpful financial ratios and ended up selecting five as providing in combination the best overall prediction of corporate bankruptcy. The variables were classified into five standard ratios categories, including liquidity, profitability, leverage, solvency and activity ratios.

In the 1980s, credit scoring was used for other purposes such as aiding decision in approving personal loan applications. Geske (1977) extends the original single debt maturity assumption to various debt maturities by using compound option modeling. Merton (1974) assumed that the default occurs only at the maturity date, another group of structural models is developed by Black and Cox (1976) and often referred to as –first-passage-time model.

The neural network credit scoring models were tested using 10-fold cross validation with two real world data sets. He results were benchmarked against more traditional methods under consideration for commercial applications including linear discriminant analysis, logistic regression, k nearest neighbor, kernel density estimation, and decision trees. Results demonstrated that the multilayer perceptron may not be the most accurate neural network model, and that both the mixture-of-experts and radial basis function neural network models should be considered for credit scoring applications. Logistic regression was found to be the most accurate of the traditional methods.

In recent years, credit scoring has been used for home loans, small business loans and insurance applications and renewals (Koh, Tan et al., 2004; Thomas, 2000).

Scope of research: This study will aid the banks and other financial companies which deal with credit risk assessment for giving faster and much accurate results. In this competitive world faster operations results in better business .Any company by using the above equation we can predict the future which is categorical in nature it can tell us whether customer is high risk customer or low risk customer and they can decide on this output and decide whether to give credit card or not. Faster process means higher return and if you are able to provide such service will give an edge over your competitor. It can also save time for customer as they don't have to wait for the whole process. Further this study will help banks and NBFC to make their process faster and can take advantage in this competitive world, what are their shortfalls and what their strengths are and how they can work out on various fronts and can gain a significantly strong foothold in the volume and Market.

Objective of research: To Study the Credit Risk Associated in Classification of customers at SBI branch in Pune.

Research Design:. The Research design adopted was descriptive in nature. Secondary source of data was collected from official websites of SBI, CIBIL and RBI banks. Secondary data source helped in understanding the market and gave a direction to work on the objective.
Primary data was collected from a sample frame of SBI customers falling under SEC A1, A2, B1, B2 category households in the region of Pune with a relevant sample size of 240 customers.
Systematic random sampling technique was adopted as a sampling technique for the sample to evenly spread across the population frame.
The data collection method used was Questionnaire, which was pilot tested and produced a significantly high cronbach alpha score of 9.01 in its reliability & validity score.
The questionnaire was structured with maximum questions to be closed ended with fewer open ended questions to get some qualitative insights.

Data Analysis:

The multivariate technique used exclusively for analysis of the data is Discriminative Analysis, in this there is one categorical dependent variable and multiple Independent variable(numerical),it based on equation that is $Y= a + b1X1 + b2X2 +\ldots\ldots bnXn$
Y = dependent categorical variable, X1,X2 =Independent numerical variables, a,b = constants

Output of Discriminative Analysis:

Summary of Canonical Discriminant Functions

Eigen values

Function	Eigenvalue
1	1.142[a]

Table 1

Wilks' Lambda

Test of Function(s)	Wilks' Lambda
1	.524

Table 2

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Age	.311
Income	.798
Years of Marriage	-1.022
Years of working	1.038

Table 3

Structure Matrix

	Function
	1
Income	.781
Age	.842
Years of working	.438
Years of Marriage	.261

Table 4

Canonical Discriminant Function Coefficients

	Function
	1
Age	.028
Income	.050
Years of Marriage	-.421
Years of working	.552
(Constant)	-4.204

Table 5

Functions at Group Centroids

Risk	Function
	1
1.00	1.115
2.00	-1.115

Table 6

Classification Statistics

Classification Processing Summary

Processed		240
Excluded	Missing or out-of- range group codes	0
	At least one missing discriminating variable	0
Used in Output		240

Table 7

Prior Probabilities for Groups

Risk	Prior	Cases Used in Analysis	
		Unweighted	Weighted
1.00	.500	25	25.000
2.00	.500	25	25.000
Total	1.000	50	50.000

Table 8 Classification Results

		Risk	edicted Group Membership		Total
			1.00	2.00	
Original	Count	1.00	20	5	25
		2.00	5	20	25
	%	1.00	80.0	20.0	100.0
		2.00	15.0	75.0	100.0

Table 9

Interpretation of results:

The most important factor in Discriminative analysis before proceeding further is Wilks Lambda – the range is from 0 to 1 ,if the Wilks lambda is closer to 0 the model is more stable and accurate and if the reading is towards 1 its unstable and less accurate.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	**.552**	44.281	4	.000

Table 10

Since the Wiki's Lambda is almost in range and lying in the lower side of the range ,the model is stable .

Functions at Group Centroids

Risk	Function
	1
1.00	1.115
2.00	-1.115

Table 11

Score coming closer to 1.115 are low risk compare to scores close to negative-1.050 which you can see in the table above case wise statistics .

Classification of Results[a]

Risk	Predicted Group Membership 1.00	2.00	Total
1.00	20	5	25
2.00	5	20	25
1.00	80.0	20.0	100.0
2.00	15.0	75.0	100.0

The above test shows 75% of data entered were correctly classified but 15% were classified under wrong group. Since the data given in the input were classified under high and low risk associated with the customer the output shows difference in the result.

II. Conclusion

This research help us to classify the customer. The output from SPSS 23.0 shows that out of 240 samples were classified under wrong group of risk associated with them, data entered in two groups high risk and low risk as per the data and output was generated when given input to the equation given below.

Y= -4.204+.028(Age)+.050(Income)-.421(Years of Marriage)+.552 (Years of working)

It shows the model can generate instant output on giving input of independent variables and can predict the dependent variable output, Banks and other financial firms which provide credit card can use this model for increasing their speed and accuracy for better process.

As the process speed will increase and operational time will reduce it will help banks to reduce overall time taken by bank to certify the risk profile of the customer. Also bank can check and improve their data base by giving the input to the equation by providing all independent variables and can predict the future risk classification of customer.

The model can be implemented on the primary level of operations at the banks, this will help them to provide quick feedback to customer and help them to be competitive with other financial organization as their overall operational time will be reduced.

References

[1]. Ausebel, Lawrence M. “The Failure of Competition in the Credit Card Market.” American Economic Review, 81,1, March 1991.
[2]. Baumol, W.J. “Contestable Markets: An Uprising in the Theory of Industry Structure.” American Economic Review, 72, 1 March 1982.
[3]. Baumol, Panzer and Willig.Contestable Markets and the Theory of Industrial Structure. (CA: Harcourt Brace and Jovanovich, 1982)
[4]. Board of Governors of the Federal Reserve Board.“ Consumer Credit, First Quarter 1998.” June 1999.
Board of Governors of the Federal Reserve. “The Profitability of Credit Card Operations of Depository Institutions Annual Report.” [http://www.ny.frb.org/]. June 1999.
[5]. Calem, Paul and Mester, Loretta. “Consumer Behavior and the Stickiness of Credit – Card Rates.” American Economic Review, Dec. 1985.
[6]. Klemperer, Paul. “The Competitiveness of Markets with Switching Costs.”Rand Journal of Economics, 18,1, spring 1987.
[7]. Shepherd, William G. “ Contestability vs. Competition.” American Economic Review, 74, 4. September 1984.
[8]. Shepherd, William G. The Economics of Industrial Organization. NJ: Prentice Hall, 1990.
[9]. Slocum, John W. Jr. and Matthews Lee H. 1970. Social class and income as indicators of consumer credit behavior. Journal of Marketing, 34(2): 69-74.
[10]. Stavins, Joanna .1996. Can demand elasticities explain sticky credit card rates? Federal Reserve Bank of Boston. New England Economic Review, (July/ August): 43–54.
[11]. Kim, Taehyung; Dunn, Lucia F., and Mumy, Gene E. 2005. Bank competition and consumer search over credit card interest rates. Economic Inquiry, 43(2): 344.
[12]. Whitesell, William C. 1992. Deposit banks and the market for payment media. Journal of Money, Credit and Banking, 24(4): 246-250.
[13]. Worthington, Steve. 2001. Affinity credit cards: a critical review. International Journal of Retail & Distribution Management, 12(2): 484-510.
[14]. Xiao, J. J.; Noring, F. E. & Anderson, J. G. 1995.College students’ attitudes toward credit cards. Journal of Consumer Studies and Home Economics, 19: 155–174.

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