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Credit Risk Classification Using Discriminant Analysis for Punjab National Bank Customers

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Abstract:

The way investors evaluate credit risk must change as India's financial markets grow more dynamic and the country's economy continues to change and diversify. Credit rating agencies' ratings are a reliable source of information and a conventional indicator of credit risk. Assessing credit risk usually entails speaking with management teams and examining the company's financial data. A purposeful consultation approach forms the basis of the ratings process, which is intended to provide a long-term credit assessment. Understanding the Credit Risk Associated with PNB Customer Classification is the foundation of this study. The study was conducted among 354 PNB customers falling under SEC A1 & A2 category households in the region of Thane. The study aids the bank to take an informed decision on classifying the group of customers with regards to their credit risk.

Keywords: *Discriminant Analysis, Credit Risk Analysis, Punjab National Bank*

I. Introduction

Credit risk classification and credit scoring are pivotal components in the financial ecosystem, serving as the backbone for prudent lending practices and risk management in the banking sector. In India, where the financial landscape is characterized by a diverse customer base, rapid economic growth, and evolving regulatory frameworks, the ability to accurately assess and classify credit risk is of paramount importance. Indian banks, both public and private, are increasingly leveraging advanced credit scoring models to enhance decision-making processes, mitigate default risks, and ensure financial stability. These models, which incorporate a blend of traditional financial metrics and innovative data analytics, play a critical role in determining the creditworthiness of individuals and businesses, thereby influencing loan approvals, interest rates, and overall portfolio management.

The Indian banking sector has witnessed significant transformation over the past decade, driven by technological advancements, the proliferation of digital banking, and the introduction of stringent regulatory norms by the Reserve Bank of India (RBI). Despite these advancements, challenges such as non-performing assets (NPAs), economic volatility, and the inclusion of underserved populations in the formal credit system persist. In this context, robust credit risk classification and scoring mechanisms are essential not only for safeguarding the interests of banks but also for fostering financial inclusion and sustainable economic growth.

This research paper delves into the intricacies of credit risk classification and credit scoring practices employed by Indian banks, examining their effectiveness, challenges, and potential for innovation. By analyzing the methodologies, data sources, and regulatory influences shaping these practices, the study aims to provide a comprehensive understanding of how Indian banks navigate the complex terrain of credit risk management. Furthermore, the paper explores the role of emerging technologies such as machine learning, artificial intelligence, and big data analytics in revolutionizing credit scoring, offering insights into their applicability and impact on the Indian banking sector. Through this exploration, the study seeks to contribute to the ongoing discourse on enhancing credit risk assessment frameworks, ultimately supporting the dual objectives of financial stability and inclusive growth in India.

Measuring the risk for credit issuance can be done either solely on the expert judgment (credit analyst) or by implementing a classification criterion based on the current and historical financial strength of the client (Crook, 1996). It gains importance in the risk management system to embody predictive methods to estimate a reliable risk measure. Credit scoring relies on a number of mainstream modeling approaches, among which discriminant analysis and logistic regression are quite popular due to their comprehensibility and practicality on implementation.

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.

In recent years, credit risk assessment performed by combining fuzzy set analysis with ML techniques has been shown to be more effective in improving model performance (Bai et al., 2019). For instance, Malhotra and Malhotra (2002) propose the use of neuro-fuzzy modeling in consumer credit applications and demonstrate the advantages of neuro-fuzzy systems over traditional statistical techniques. Ramkumar (2016) builds a risk assessment model for third-party e-procurement systems by using fuzzy inference system and a modified analytical network process.

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 help banks and other financial institutions that handle credit risk assessment provide more accurate and timely findings. Faster operations are necessary in this competitive environment. With the help of the aforementioned equation, any business may forecast the future in a categorical manner. It can determine if a client is a high-risk or low-risk customer, and based on this information, it can determine whether to grant credit. A quicker procedure yields a larger return, and if you can offer this service, you'll have an advantage over your rival. Because they don't have to wait for the entire procedure, they may also save time. This research will also benefit 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 PNB branch in Thane.

Research Design:

The Research design adopted was descriptive in nature. Secondary source of data was collected from official websites of PNB, 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 PNB customers falling under SEC A1 & A2 category households in the region of Thane with a relevant sample size of 354 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 8.91 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 +……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	1.102[a]

Table 1

Wilks' Lambda

Test of Function(s)	Wilks' Lambda
1	.582

Table 2

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Age	.421
Income	.821
Years of Marriage	-1.342
Years of working	1.391

Table 3

Structure Matrix

	Function
	1
Income	.821
Age	.892
Years of working	.561
Years of Marriage	.368

Table 4

Canonical Discriminant Function Coefficients

	Function
	1
Age	.034
Income	.054
Years of Marriage	-.484
Years of working	.681
(Constant)	-4.84

Table 5

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Functions at Group Centroids

Risk	Function 1
1.00	1.425
2.00	-1.425

Table 6

Classification Statistics

Classification Processing Summary

Processed		354
Excluded	Missing or out-of- range group codes	0
	At least one missing discriminating variable	0
Used in Output		354

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			Dedicted 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	**.582**	48.48	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	1.425
2.00	-1.425

Table 11

Score coming closer to 1.425 are low risk compare to scores close to negative -1.425 which you can see in the table above case wise statistics .

Classification of Results[a]

Risk	Predicted Group Membership		Total
	1.00	2.00	
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.

Conclusion:

This research help us to classify the customer. The output from SPSS 25.0 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= -4.84+.034(Age)+.054(Income)-.484(Years of Marriage)+.681 (Years of working)

It demonstrates that the model can predict the output of the dependent variable and produce immediate results when independent variables are entered. This model may be used by banks and other financial institutions who offer credit cards to improve their speed and accuracy. Banks will be able to cut down on the amount of time they need to certify the customer's risk profile as process speed increases and operational time decreases. Additionally, by supplying all independent factors as input to the equation, the bank may verify and enhance their database and forecast the future risk rating of its customers. The concept may be applied to the banks' core business activities, which will enable them to respond promptly 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]. Hosna, A., Manzura, B., & Juanjuan, S. (2009). Credit risk management and profitability in commercial banks in Sweden. rapport nr.: Master Degree Project 2009: 36.

[7]. Kithinji, A. M. (2010). *Credit Risk Management and profitability of commercial banks in Kenya*. School of Business, University of Nairobi.

[8]. Kolapo, T. F., et al. (2012). Credit risk and commercial banks’ performance in Nigeria: A panel model approach. *Australian Journal of Business and Management Research*, *2*(2), 31–38.

[9]. 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.

[10]. Shepherd, William G. The Economics of Industrial Organization. NJ: Prentice Hall, 1 990.

[11]. 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.

[12]. Stavins, Joanna .1996. Can demand elasticities explain sticky credit card rates? Federal Reserve Bank of Boston. New England Economic Review, (July/ August): 43–54.

[13]. Whitesell, William C. 1992. Deposit banks and the market for payment media. Journal of Money, Credit and Banking, 24(4): 246- 250.

[14]. Worthington, Steve. 2001. Affinity credit cards: a critical review. International Journal of Retail & Distribution Management, 12(2): 484-510.

[15]. 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.