Consumer Loan Credit Scoring Model for Pakistani Commercial Banks:

An Application of Discriminant Analysis

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Abstract

During last few years, banks in Pakistan have suffered huge losses due to high defunct rate in portfolio of consumer loans. The main reason for defaults was inadequate mechanism and procedures for sanctioning new loans. In view of increasing infected portfolio of banks in Pakistan, have realized the importance of ascertaining creditworthiness of new consumer loans. In order to decrease the infected portfolio, a credit scoring model has been developed in this study. Discriminant Statistical Technique has been used for developing this credit scoring model. Type 1 and Type 2 error have been worked out to improve the model predicting capabilities.

Keywords: Consumer Loans, Credit Worthiness, Delinquency, Discriminant Statistical Technique.

1. Introduction

In early 2008, Pakistani economy was facing challenges due to rising commodity prices, low foreign direct investment, weak exports, and flight of capital. Some of the reasons for deteriorating economy were political turmoil in the country coupled with sub prime mortgage crisis in the United States and recession in world economies. Consequently these factors adversely affected Pakistani Rupee that fueled inflation in the country. Due to weak economic conditions and higher inflation, consumer started defaulting on their loans. As a result, banks in Pakistan booked huge losses due to increase in non-performing loans. Besides weak economic conditions, main reason for higher consumer defaults was poor examination of customers' balance sheets. Besides inadequates sanctioning procedures had also contributed towards the in-

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crease in infected portfolios.

With a surge in bad loan portfolio, banks in Pakistan changed their lending policies and made stringent regulations especially for consumer loans'. Consequently the quantum of consumer loans decreased significantly including mark up income. In order to expand consumer loan portfolio, banks were in a dire need to develop a good credit scoring tool.

To forecast and reduce the financial risk, this study has developed a consumer credit model using historical credit card consumer loan dataset of Pakistani financial institutions. This model will help in classifying prospective customers into 3 categories (1) 'Good' (2) 'Non-default' and (3) 'Bad' and (4) 'Default' risk based upon demographics, financial situation and loan repayment history. This model will help the bankers to judiciously make loan decisions.

The salient features of this credit scoring model are:

a) Generation of credit scores for new loan applicants
b) Categorization of loan into Cut-off score ranges for 'Good' or 'Non-Default' and 'Bad' or 'Default' risk categories

2. Literature Review

Financial risk forecasting has been playing a vibrant role in the field of finance for the last forty years. Financial Risk Management (FRM) has gained more attention after oil crisis in 1973, which was due to Arab Oil Embargo against the U.S., Western Europe and Japan. The increasing oil prices fueled the inflation and set world economies on a path of recession. The situation created pressure on interest rates which continued to rise till early eighties. Due to this fluctuation, businesses and corporations around the world realized the importance of risk management. Various effective tools like portfolio management, derivative products and other complex contemporary financial instruments were developed from time to time to mitigate the financial risk.

Another type of tool that is used for forecasting financial risk in consumer lending is credit scoring. Credit scoring is an effective tool to help an organization in making decisions on whether to grant a loan to a loan applicant or not. After sub-prime crisis in mid-2007, credit scoring once again came into the limelight of financial institutions around the world as these institutions sustained huge losses in higher consumer loan defaults. At the time of the decision to disburse loans, improper assessment of credit worthiness and ability to repay an applicant were the main reasons behind higher customer defaults. After this crisis, banks and financial institutions around the world adopted stringent regulations before extending consumer loans to costumers in order to avoid financial losses.

According to Bolton, (2009), before the advent of formal credit scoring methods/ models, decisions for granting loan to new applicant were made purely on a judgmental basis. With this method, the credit worthiness of an individual was assessed on the basis of personal characteristics. The method has many shortcomings including unreliability and the limited number applicants it processes. Moreover, the method is subject to personal prejudice, is not reproducible, and it is difficult to teach this method to others.

First scoring model for credit cards was developed in USA in 1941 Anderson, (2007). In his paper Thomas, (2000) explained the brief history of adopting credit scoring on a commercial basis. According to his study, first consultancy firm was formed by Bill Fair and Earl Isaac in San Francisco in early 1950 to serve the finance houses, retailers and mail order firms. The consumer loan boom started with the arrival of credit cards in U.S market in late 1960s Thomas, (2000); and with the launch of Barclay card in 1966 in U.K, Bolton, (2009). Thomas, (2000) states that with the evolution of newly developed credit card consumer loan segment, financial institutions and credit card issuers of that time realized the efficacy of credit scoring, as it became impossible to handle bulk credit card applications without automating the lending decision process.

According to Thomas, (2000) credit scoring based upon statistical techniques is very popular nowadays. The statistical methods being used include Discriminant Analysis (an extension of linear regression), logistic regression and classification trees (also known as recursive partitioning algorithms). The study suggests that scorecard builders can solely use any of the abovementioned techniques or can use in conjunction with other mentioned techniques. In addition to aforementioned techniques, recently developed sophisticated techniques includes neural networks, expert systems, genetic algorithms and nearest neighbor methods. According to Bolton, (2009) most popular statistical techniques for building scorecards are logistic regression and discriminant analysis. Both these techniques are popular as they are being simple to use and implement; and their availability in almost every commercial statistical software tool.

Past research Desai et al., 1996; Blöchlinger & Leippold, (2006); Hoffmann et al., (2007), has made a comparison between the available statistical techniques. The comparison yields two types of results; first result found that advanced statistical techniques are better predictors; while, latter suggests that no obvious differences were found between traditional and advanced techniques in terms of the “percentage of average correct classification or hit rate”. Baesens et al (2003) suggests that simple statistical techniques such as logistic regression and linear discriminant analysis also have a very good performance in credit scoring as cited in (Abdou, El-Masry, & Pointon, 2007).

There is no best technique/method available for building credit scoring model. In order to get correct and desired results, careful consideration is required in selecting correct variables (variables that must cover all possible characteristics of an applicant includes demographics, financial and re-payment history), correct design of categories/ranges for each variable, correct sample size, correct classification of “good” and “bad” accounts based on proper arrear history (Hand & Henley, 1997); (Bolton, 2009).

The most important variable/predicator in credit scoring is "good" and "bad" flag that is used to predict the "default" and "non-default" of the prospective customers. According to Siddiqi, (2005), in order to predict the default probability one must understand the "default" term. He defined the default as "current bad" or "ever bad", he further explains that Basel 2 accord considers those customers bad who are 90 days defaulters or in other words have missed three consecutive months of payments.

Once appropriate variables are selected, the factors that may bias the analysis should be managed carefully in the design. Constangioara, (2006) highlights several issues that may bias the analysis in credit scoring. It is important that constant monitoring of arrears (the period in which delinquency of accounts are observed) is done. The shorter monitoring periods may underestimate the bad rate as accounts does not have time to "go bad". Siddiqi, (2005) stresses that time period should rely on twenty four months observation period. Monitoring period more than twenty four months will result in population drift as population characteristics constantly changes over time and will not be in-line with the sample spared initially for credit scoring analysis Thomas, (2000). Another important issue that may affect analysis is selection bias which arises due to inappropriate selection of accounts in sample. Siddiqi, (2005)recommends sample must randomly include equal number of "defaults", "non-defaults" and "rejected" cases.

Thomas, (2000) in his paper discussed the general working of credit scoring model. He explained that previous applicant details provided in the loan request application form is divided into two subsets. One set should include accounts that turned out "good" and another set include accounts that turned out "bad"; based upon the history of arrears. The new loan applicant will be approved if provided information in loan application form falls in the set of "to be good", and would be rejected if falls in the set of "to be bad".

Samreen & Zaidi, (2012) have developed the Credit Scoring Model for Individuals (CSMI); the only available research model that explores the prospect of credit scoring for consumer loans in Pakistani financial sector. In CSMI, each independent variable is divided into different groups and each group has been assigned some predefined value. The credit score is generated by adding values of all variables and final score is compared with the risk classes for predicting the risk of prospect customer. Risk classes and scores of independent variable are generated on judgmental basis. The study lacks to explain the detailed concept and also is unable to demonstrate practical application of statistical technique for building consumer score cards. This study has been done to build consumer score card model for Pakistani banking sector using Discriminant Analysis.

3. Research Methodology

3.1. Statistical Technique

The main theme of credit scoring is to drive a model by linear combination of independent variables (customer demographics and financial) that discriminates best between the two priori defined groups i.e. 'BAD/DEFAULT' and 'GOOD/NON-DEFAULT' customer groups.

Discriminant Analysis (DA) is a type of multivariate statistical technique; in which group of independent variables predicts the categories of dependent variable. In this technique,a discriminant function is formed, which is used for predicting categories of dependent variable. When values of independent variables are passed to the function, discriminant function score is generated used to predict to which category a combination of independent variables belongs.

Following is the discriminant prediction equation with K independent variables:

$D=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i$

where,

D = Discriminant Function Score

β_0 = Constant

β_i = The Discriminant Coefficient or weight for the ith variable

X_i = Respondents' score for the ith independent variable

u_1= Error term

3.2. Data Collection

Credit card consumer loan dataset of a Pakistani bank has been used in the research. Due to confidentiality of data, 250 "Good" and 250 "Bad" accounts are used in the analysis in order to derive the sample window, which in turn will make the total sample size of 500 accounts.

3.3. Variables Used

3.3.1. Dependent Variable

GBF= Good Bad Flag used to identify the Default/Bad and Non-Default/Good customers. Categories are built on 24-months observation period from the Date of Application (DOA).

GBF = 0: Default/Bad

GBF = 1: Non-Default/Good

3.3.2. Independent Variables

Table 1

Name	Description
CURRENT STATUS	Current delinquency bucket of customer, the range is in between 0 and 12
DC SCORE	DatacheckTM (Credit Bureau) Score at the time of application
REGION	Region of customer where he was living at the time of application
EXISTING	Flag to determine whether applicant is maintaining any other loan or deposit accounts with the bank at the time of application
TIME CUST	If an applicant is customer of the bank at the time of application, then what is the duration of relationship in months
DEPACNTS	Sum of all Deposit/Saving accounts balances (in case if applicant is maintaining deposit/saving accounts with the bank at the time of application)
ASSET BAL	Sum of all loan accounts balances(in case if applicant has borrowed any loan

Table 1 (Continued)

Name	Description
	from the bank at the time of application)
AGE	Age of an applicant in months at the time of application
GENDER	Gender of an applicant
MARITAL	Marital status of an applicant at the time of application, it may include “Married”, “Single”, and “Widowed” status
CURR STATUS	Residential status of an applicant at the time of application. It may include “Company”, “Owner Occupier”, “Parental”, “Rented” and “Spouse”
CURR ADD TIME	Time at current residence in months at the time of application
DEPENDANT	No of dependents of an applicant at the time of application
OCCUPATION	Occupation of an applicant at the time of application
EMP TIME	Employment time in months at the time of application
INCOME	Income of an applicant at the time of application

4. Data Analysis

Following are the results of different statistical tests performed during the working of Discriminant analysis in SPSS. By default chosen significance level is .05 or 5%.

4.1. Wilks’ Lambda Test

Was used to check whether any significant difference exists or not between “GOOD” and “BAD” customer groups based on individual independent variables.

Table 2: Wilks’ Lambda Test

Test of Function(s)	Wilks’ Lambda	Chi-square	df	Sig.
1	.555	288.599	15	.000

In the analysis, significance value is p= .000 and P < .05, suggesting model is good fit for data. This transpires that null hypothesis (no difference exist between groups) can be rejected and there is significant difference exist between “GOOD” and “BAD” customer categories. In this way, Discriminant Analysis will yield the correct results based upon provided sample data.

4.2. Standardized canonical Discriminant Function coefficients Table

The coefficients indicate the relative importance of independent variables in predicting the dependent variable. Variables having large absolute coefficient values correspond to greater discriminating ability in predicting the categories of dependent variable.

Table 3: Standardized Canonical Discriminant Function Coefficients

	Function 1
CURR STATUS	-.487
CURR ARREARS	.146
DC SCORE	.682
EXISTING N	.012
REGION N	.043
TIME CUST	.091
DEP ACNTS	-.051
ASSET BAL	.009
AGE	-.139
GENDER N	-.188
MARITAL N	-.111
CURR ADD TIME	.038
EMP TIME	.024
INCOME	.034
DEPENDANTS	.085

From the table above, DC SCORE and Current Status variables have the highest discriminating power followed by moderate discriminating power variables Gender, Current Arrears, Age and Marital Status.

4.3. Structure Matrix Table

It is another method for determining the relative importance of independent variables in predicting the dependent variable. Matrix table list the variables in the order of relative importance.

Table 4: Structure Matrix

	Function 1
DC SCORE	.809
CURR STATUS	-.698
CURR ARREARS	.465
GENDER N	-.126
AGE	-.084
INCOME	-.068
EXISTING N	-.058
MARITAL N	-.047
TIME CUST	.045
REGION N	.029
DEP ACNTS	.026
CURR ADD TIME	-.010
ASSET BAL	-.009
DEPENDANTS	.001
EMP TIME	.001

The table states that DC Score, Current Status and Current Arrears are variables with strongest discriminating power followed by Gender and Age.

4.4. Canonical Discriminant Function

The canonical Discriminant coefficients are used to form the actual prediction equation which can be used to classify new cases.

Table 5: Canonical Discriminant Function Coefficients

	Function 1
CURR STATUS	-.195
CURR ARREARS	.000
DC SCORE	.004
EXISTING N	.025
REGION N	.018
TIME CUST	.002
DEP ACNTS	.000
ASSET BAL	.000
AGE	-.001
GENDER N	-.809
MARITAL N	-.267
CURR ADD TIME	.000
EMP TIME	.000
INCOME	.000
DEPENDANTS	.046
(Constant)	-.060

From the table above following Discriminant prediction equation is formed for generating discriminating scores.

Discriminant Function or Score (DS)=-0.60-0.195(CURRSTATUS)+0(CURRARREARS)+0.04(DCSCORE)+0.025(EXISTINGN)+0.018(REGIONN)+0.002(TIMECUST)+0(DEPACNTS)+0(ASSETBAL)-0.001(AGE)-0.809(GENDERN)-0.267(MARTIALN)+0(CURRADDTIME)+0(EMPTIME)+0(INCOME)+0.046(DEPENDANTS)+u_i

The equation shows that variables Current Status, DC Score, Existing Customer, Region, Time Customer, Age, Gender, Marital Status and Dependents have impact on score calculations. However variables Current Arrears, Deposit Account Balance, Asset Account Balance, Current Address Time, Employment Time and Income do not have any impact on calculations and these variables can be removed from the equation.

4.5. Functions at Group Centroids

This table is used to establish the cutting point for classifying cases. If the two groups are of equal size, the best cutting point is half way between the values of the functions at group centroids (that is, the average). If the groups are unequal, the optimal cutting point is the weighted average of the two values.

Table 6: Functions at Group Centroids

Function GBFN	1
0	-.896
1	.893

$$\text{CUT SCORE} = \frac{(-0.896+0.893)}{2} = -0.0015 = 0 \text{ (approximately)}$$

If DS≥0,BAD CUSTOMER GROUP
ELSE (DS<0),GOOD CUSTOMER GROUP

4.6. Classification Statistics

In order to check the validity of the DS equation, discriminant analysis performs the Classification Results check which is used to check the Type1 and Type 2 errors.

Table 7: Classification Results

		Predicted Group Membership		
	GBFN	0	1	Total
Original Count	0	186	63	249
	1	52	198	250
%	0	74.7	25.3	100.0
	1	20.8	79.2	100.0

77.0% of original grouped cases correctly classified.

Type 1 error occurs when Bad category is classified as Good category. Type 2 error occurs when Good category is classified as Bad category. The analysis shows that there is 25 % Type 1 error and 21% Type 2 Error, and on overall basis 77% of the cases are correctly classified. It means that model provides 77% of accuracy.

5. Conclusion and Scope for Further Research

The main objective of the research was to develop credit scoring model for Pakistani commercial banks. To achieve this, a multivariate discriminant analysis technique is used with sample credit card consumer loan data of Pakistani commercial bank. Positive outcome of different statistical tests performed in the study suggests that model is applicable for Pakistani commercial bank. Study yields that there is 25 % Type 1 and 21% Type 2 Error, which suggests that model can predict new loan cases with 77% accuracy. The model serves as an automatic tool for making new consumer loan disbursement decisions. This will help financial institutions to make better credit disbursement decisions which in turn help to reduce collection, recovery and litigation charges. In addition, it will also help financial institutions to build better consumer loan portfolio by reducing Non Performing Loans which in turn will increase the profitability of financial institutions.

Currently research is done with small sample size i.e. with 500 accounts. The research will yield better results if entire consumer loans portfolio is used in future research. In addition, current research is done using Discriminant Analysis technique; however other statistical techniques like Logistic Regression, Tree Analysis, and Genetic Algorithm can be used in future for building credit scoring model. In this way more options will be available to financial institutions to select statistical technique(s) having highest accuracy, or in other words technique(s)with lowest Type 1 and Type 2 errors.

Finally, future researcher can further extend the research by monitoring the decision of credit scoring model after implementation. This can be done by reviewing the behavior of accounts for the period of one year based on the output of credit scoring system. In this way decision of credit scoring model can be cross-validated with the actual performance of loan borrowers that will further endorse the validity of the system and will boost the confidence of Financial Institutions in adopting model for future decision making.

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