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THE CONSUMER LOAN'S PAYMENT DEFAULT PREDICTIVE MODEL: AN APPLICATION IN A TUNISIAN COMMERCIAL BANK

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ABSTRACT

For the alarming growth in consumer credit in recent years, consumer credit scoring is the term used to describe methods of classifying credits' applicants as `good' and `bad' risk classes.. In the current paper, we use the logistic regression as well as the discriminant analysis in order to develop predictive models allowing to distinguish between "good" and "bad" borrowers. The data have been collected from a commercial Tunisian bank over a 3-year period, from 2010 to 2012. These data consist of four selected and ordered variables. By comparing the respective performances of the Logistic Regression (LR) and the Discriminant Analysis (DA), we notice that the LR model yields a 89% good classification rate in predicting customer types and then, a significantly low error rate (11%), as compared with the DA approach (where the good classification rate is only equal to 68.49%, leading to a significantly high error rate, i.e. 31.51%).

Keywords: Consumer credit, Credit risk, Logistic regression, Discriminant analysis, Tunisian commercial bank, credit scoring.

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Contribution/ Originality

This study tries to compare the performance of the scoring techniques. This study is most probably the first one to provide such an analysis of the consumer behavior in terms of loan's payment default in Tunisian.

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1. INTRODUCTION

Credit scoring methods are part and parcel of companies' risk management. Research in this field assumed that these methods serve the decrease of default payments through identifying, analyzing, and monitoring customer credit risk (Brigham (1992) and Johnson and Kallberg (1986)).

Since customers are often subject to certain risk classes due to their individual propensities to payment default, it is worth measuring the default risk involved by sales on credit. The default probability can be obtained either externally or based on an internal scoring model. The main internal information source on creditworthiness is the Tunisian Central Bank (TCB), being the main provider of data dealing with customers' previous payment behavior and their individual characteristics such as age, loan amount, outstanding credit and socio-professional category.

These features, known as knock-out criteria, normally provide the outright facts on a specific consumer's propensity to payment default.

Therefore, such data are used in order to establish a credit scoring model allowing to predict the probability of new credits' payment default. Researchers, such as Thomas *et al.* (2002) and Crook *et al.* (2007) assume that the applied standard approach allowing the estimation of these probabilities is the Logistic Regression (LR) model. However, this method has remained subject to several strict assumptions (see Malley *et al.* (2012)). For instance, when the most important variables and anticipated interactions are not inserted correctly in the model, then problems of model misspecification can appear. Similarly, these researchers have assumed that the standard regression model cannot deal with multicollinearity, i.e., high correlation between independent variables.

Credit scoring is defined as the set of decision models that include some underlying techniques helping lenders in the decision of granting consumer credits. In other words, these techniques are implemented in order to assess the extent to which a borrower deserves to be granted a loan, the amount of money he/she should be allocated, and the nature of the operational strategies enhancing the profitability of the borrowers to the lenders (see (Long, 1973; Thomas *et al.*, 2002)).

For some researchers (Hand and Henley, 1997; Caouette *et al.*, 1998; Sarlija *et al.*, 2004) the new banking environment requires the investigation of some of the conventional techniques such as the discriminant analysis, the probit analysis and the logistic regression.

It is worth mentioning that the discriminant analysis and the logistic regression are still adopted in implementing and developing credit scoring models.

Knowing that there exists neither an ideal nor a unique technique for all types of data sets, the main challenge of the current paper is to explore the credit scoring models in an attempt to evaluate credit risks in the Tunisian banking sector. This attempt is conducted through a case study and the results are obtained by using parametric methods such as the discriminant analysis and the logistic regression.

In this context, our study is based on an empirical comparison between the performances of multiple scoring techniques so as to identify the consumers' payment defaults. To reach this end, the sample upon which our study is conducted is made up of 633 borrowers who are customers in one of the Tunisian commercial banks. The frequent use of these techniques in developed countries was carried out along with the academic literature focusing on the benefits and the methodological issues dealing with the different models. However, in developing countries, the evidence concerning the credit scoring achievements is rather limited (see, for example, Altman *et al.* (1979) for Brazil; Bhatia (1988) for India; Pascale (1988) for Uruguay; Viganò (1993) for Burkina Faso; Schreiner (2004) for Bolivia, and finally Dinh and Kleimeier (2007) for Vietnam).

To our knowledge, and in this context, our study is most probably the first one to provide such an extensive analysis of the consumer behaviour in terms of loan's payment default.

Hence, our objective is to identify the most performing internal credit scoring model for Tunisian banks, aiming to improve their current predictive power factors. In particular, we first select the indicators which should be collected by a bank. Moreover, we show how to combine these indicators in a credit scoring model. On the basis of the analyzed data, the results reveal that the logistic regression model, having an overall accuracy of 89%, outperforms the other scoring techniques, and the discriminant analysis indicates an overall classification consistency equal to 68.49%.

It is worth noting that the selection of similar qualitative and quantitative indicators, the analysis yielded three prominent statistically relevant variables are predictors of loans' default payment within the chosen Tunisian bank. They are as follows: the amount of loan, the outstanding loan, and the socio-professional category of the borrowers.

Our paper is designed as follows: Section 2 displays the credit scoring models. Section 3 deals with the data base and the adopted research methodology. Section 4 displays the analysis of the obtained results and Section 5 is devoted to the conclusion and some recommendations for further research.

2. CREDIT SCORING

According to Thomas *et al.* (2002) and Heiat (2012) credit scoring is described as a set of decision models having specific underlying techniques that are advocated to give support to lenders when providing credits to customers. Credit scoring is also defined as a decision support system assisting managers in the financial decision-making process. In the same way, the rapid development in credit industry has made credit scoring models of prominent usefulness as they are highly related to decisions on credit admission evaluation (see Chen and Huang (2003)). Therefore, these models were implemented in order to classify credit applications as being "accepted" or else "rejected" with respect to customers' characteristics such as age, income, and marital status. Besides, the lenders' decision on accepting or rejecting customers' applications for credits is based on the extent to which applicants are able to repay their financial obligations. In this sense, these models are adopted in order to incite creditors to construct classification rules by using the previous accepted and rejected applications so that borrowers' credit risk can be anticipated (see (Thomas, 2000; Yap *et al.*, 2011)).

On this basis, the credit scoring model is implemented to determine the credit applicant's capacity to repay his financial obligations by evaluating the credit risk of the loan application (see (Lee *et al.*, 2002; Emel *et al.*, 2003)). Hence, researchers, such as West (2000); Lee *et al.* (2002); Gao *et al.* (2006); Lahsasna *et al.* (2010); Akkoc (2012) admit that credit scoring is a system that classifies credit applicants into two categories: those having a high probability of fulfilling their financial obligations are labeled "good" and those who have a low probability of fulfilling these obligations are labeled "bad".

Moreover, and according to Khashman (2010) application scoring constitutes one of the two scoring tasks which use financial as well as demographic information related to the credit applicant. This information allows the lender to classify the loan applications into "good" or "bad"risk groups.

However, due to the variety of cases and decisions related to consumer lending mechanisms, Khandani *et al.* (2010) admitted that it is vital to adopt models and algorithms rather than human judgment. That is, a credit scoring model is constructed on the basis of statistical techniques such as discriminant analysis (DA) and logistic regression (LR).

According to West *et al.* (2005) these techniques require the adoption of an accurate decision support model for credit admission evaluation and also for monitoring the real health of credit customers. Therefore, a concrete improvement in the accuracy of the credit decision is expected to reduce credit risk and should lead to important future savings (Hand and Henley, 1997; West, 2000; Chen and Huang, 2003; West *et al.*, 2005; Tsai and Wu, 2008; Lahsasna *et al.*, 2010). According to Tsai and Wu (2008) what is worth mentioning is that credit scoring has been widely used in accounting and finance literature, since it influences the lending decisions as well as the profitability of the financial institutions. Usually, a credit scoring model is implemented by using statistical techniques such as discriminant analysis (DA) and logistic regression (LR).

3. METHODS

3.1. The Data

The database of this study is constructed on the basis of information taken from a Tunisian bank and included a sample of 633 consumer loans granted to its customers over the period 2010 - 2012. The database included information that concerns only the allocated loans. This has made researchers believe that credit scoring models are very often biased since they are based only on data of accepted customers (see (Caouette et al., 1998; Thomas, 1998)).Hence, the information about the rejected applications allow to reduce the bias. In this study, we didn't encounter such a problem, since the rejected customers consisted only of those loan applicants that did not fulfill the following simple legal criterion: a loan cannot be granted to the client if the total monthly loan payments are in excess of 40% of his monthly salary.

The credit behavior of the client, to whom the loan was granted, was defined by a binary variable with a value 1, if all liabilities from the loan were not paid in time ("non-performing loans") and with a value 0, if this was not the case ("performing loans"). In the provided sample, only 267 applications (representing 42.18%) were credit worthy, whereas 366 applications (60.69%) were not.

This obviously shows that granting consumer loans is not very encouraging for this commercial bank.

The data collection was based on 4 variables which are shown in Table 1.

Table-1. Proposed variables for building the credit scoring model.

Variables	Type	Variable definition
Age, X_1	Scale/ Numeric	Applicant's age
Loan amount, X_2	Scale	Loan amount
Outstanding credit, X_3	Scale	Outstanding credit
Occupational category, X_4	Scale	Occupational category
Default event, Y	Binary	1 (if there is a payment default) 0 (otherwise)

The dependent variable Y_i is the default event, having the value 1 if a customer i shows a default on payment, and 0, otherwise. The tendency to work with only two values "default event" or "no default event" has been used by several studies (Hand and Henley, 1997; Lee *et al.*, 2002; Thomas *et al.*, 2002; Bensic *et al.*, 2005; West *et al.*, 2005; Huang *et al.*, 2006; Abdou *et al.*, 2007; Tsai and Wu, 2008; Khashman, 2010; Yap *et al.*, 2011; Akkoc, 2012; Blanco *et al.*, 2013). Categorical variables were converted into numerical values (worker, middle executive and senior executive, retired and liberal function). Table 2 presents the descriptive statistical analysis, including borrower's age, loan amount, outstanding credit and socio-professional category.

Table 2 displays descriptive statistics dealing with our data.

Table-2. Descriptive statistics

Variable	Mean	Standard-deviation (std.)	Coefficient of Variation (cv)	Minimum (Min)	Maximum (Max)
Age (in years)	40.9968	8.5831	0.20936	24.0000	68
Loan amount /(10^3) MDT	37.4772	79.2734	2.1153	0.0200	1327
Outstanding credit / (10^3) MDT	31.5277	77.6765	2.468	0.0100	1371
Socio-professional category	51.0084	698.3533	13.690	0	9919

3.2. Research Methodology

3.2.1. Logistic Regression (LR) model

Literature on Thomas (2000) logistic regression (LR) asserts that LR, as a predictive model, is widely used in classification and forecast phenomena. Thus, it is a linear regression where the target variable is a non-linear function of the probability of being good (Thomas, 2000). Moreover, according to him, the classification results of the LR model are sensitive to correlations between the independent variables. Hence, the inserted variables in developing the model should not be strongly correlated. The non-linearity of the credit data is assumed to decrease the LR accuracy (see Lahsasna *et al.* (2008)). On this basis, the main objective of the LR credit scoring model is to identify the conditional probability of each application belonging to one specific class (Yap *et al.*, 2011). In other words, "good" or "bad" customers are evaluated with reliance on the values of the explanatory variables of the credit applicant. It is worth mentioning that researchers, such as Lee and Chen (2005) and Akkoc (2012) are in favor of Yap *et al.* (2011) as they maintained that each application will be assigned only to one class of the dependent variable. However, the logistic regression model limits the generation of the predicted values of the dependent (response) variable to lie in the interval between zero and one. Logistic regression is a common modeling technique which classifies the applicants into two groups, by using a set of predictive variables (Akkoc, 2012). The LR model is represented as in Eq. (1):

$$\ln\left(\frac{p_i}{1-p_i}\right)=\beta_o+\beta_1X_1+\beta_2\,X_2+\beta_3\,X_3+\beta_4\,X_4+\varepsilon_i\ , \quad (1)$$

Where p_i represents the probability of being "good" for a particular customer *i* which is also a function of the predictive variables X_i (X_1 : age, X_2: loan amount, X_3 : outstanding loan, and X_4 : socio-professional category) that represent the applicant's characteristics. β_0 is the intercept, $\beta_j = (1, \ldots, 4)$ represent the coefficients associated with the corresponding predictor X_i ($i = 1, \ldots,$ 4); (ln ($pi/1 - pi$)) represents the default event (Y_i), and ε_i is the errors' term. The multicollinearity is an unfavorable feature of the logistic regression. Nevertheless, it is not a critical issue because the credit scoring model is developed only for prediction.

3.2.2. Discriminant Analysis (DA)

The aim of the discriminant analysis is to find the discriminant function and to classify items into one of two or more groups having certain features describing those items. The main purpose of the discriminant analysis is to maximize the difference between two groups, whereas the differences among particular members of the same group are minimized. In the sphere of credit risk models, one group consists of good borrowers (non-defaulted – group A), while the other includes the bad ones (already defaulted – group B). The differences are measured by means of the discriminant variable – score Z. For a given borrower i, we calculate the score as follows:

$$Z_i = \sum_{j=1}^{n} \gamma_j x_{j,i} \ , \qquad (2)$$

Where x denotes a given characteristic, γ is its coefficient within the estimated model and n represents a number of indicators.

The DA seeks to obtain a linear combination of the independent variables. The aim is to classify the observations into mutually exclusive groups as accurately as possible, by maximizing the variance of the ratio of among-groups to within-groups. The discriminant function has the following form:

$$Z = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + ... + b_m X_m \quad ,(3)$$

Where X_j is the jth independent variable, b_0 is the coefficient for the *j*th independent variable, and Z is the discriminant score that maximizes the distinction between the two groups.

Four variables which are considered as the discriminant variables were used in this study. They were applied in the chosen sample in order to find out the fitted discriminant score which will represent the discriminant criterion allowing to distinguish between the default and the non-default borrowers.

4. RESULTS' ANALYSIS

4.1. Logistic Regression (LR) Analysis of Credit Scoring

4.1.1. Significance of the Model and Interpretation of the Coefficients

Since the logistic regression is applied only for large sized-samples, it is necessary to check the absence of multi-collinearity among items/variables. However, because the number of explanatory variables is reduced to 4 in our study, this problem is not raised. Before turning to the interpretation of the estimated coefficients, we may ask ourselves about the quality or the overall significance of the model by adopting the R-square of Cox and Snell, which is calculated by using the following formula:

$$R^2 = \frac{Var(\hat{y})}{Var(y)} = 1 - \left(\frac{L_o}{L_N} \right)^{2/N} \qquad (4)$$

The R-square represents the explained variance of the model. We notice that the R-square of Cox and Snell is equal to 0.9592, implying a properly fitted model.

The following table presents the model summary.

Table-3. Model summary

Criteria of comparison	Values
Deviance (dev)	44.49
Degree of freedom (df)	599
Chi-square test	661.236
Dispersion	0.39

In light of this table, we can conclude that the total deviance (dev) is much lower than the value of the Chi-square. This finding shows that our model is globally significant.

4.1.2. Predictive Power of the Model and Analysis of Sensitivity

The tested model reveals a sensitivity of 99.41% and a specificity of 1.526%. Then, 0.586% represents the rate of misclassification of default payment in the "non-default" category. This means that our model successfully predicts the quality of borrowers. The results show that the model correctly classifies 89% of the observations of our sample. These results could be stronger in terms of predictive capacity, but we should also consider the experimental nature of this model.

The following table presents the model prediction power as well as the sensitivity analysis.

Table-4. Model prediction power and sensitivity analysis of the LR model

Number of the observed borrowers			Total
	Default Prob. > 0.5 (y=1)	**non-default Prob. < 0.5 (y=0)**	
Default	364	4	368
	default Prob. < 0.5 (y=1)	non-default Prob. > 0.5 (y=0)	
Non default	2	263	265
Total	366	267	633

4.2. Credit Scoring Analysis by Using the DA Model

The model has a fairly weak predictive power because it correctly predicts only 68.49% of cases (as compared with the LR model which is able to predict correctly 89% of the applicants). It has a sensitivity of 75.36% and a specificity of 59.54% implying that the percentage of misclassification of a default in the « non-default » category is 31.51% (100-68.49%). Hence, the results show that the model has correctly classified only 68.49% of the applicants.

The results of DA are shown in Table 5.

Table-5. Predictive power and sensitivity analysis of the DA model

	Default Score > 0 (y = 1)	Default Score >0 (y = 0)	Total
Default	277	107	384
	Default Prob. < 0 (y=1)	Default Prob. < 0 (y=0)	
Non-default	89	160	249
Total	366	267	603

4.3. Comparison between the Logistic Regression (LR) and the Discriminant Analysis (DA) Models

4.3.1. Comparison between the Two Models in Terms of Their Performances

Overall, we have chosen the Logistic Regression model and the Discriminant analysis. According to Table 6, it is possible to identify some elements that help in choosing the best forecasting model.

As demonstrated by the majority of the previous studies (Worth and Cronin, 2003) and other more contemporary research in this field, we can show that the predictive power is weak for models that use less recent information, or for models aiming to provide the payment defaults over a long period.

The results presented in Table 6 show a superiority of the logistic regression model as compared to the discriminant analysis in terms of forecasting payment defaults. The finding of the superiority of the logistic regression (LR) as compared to the discriminant analysis is confirmed by some comparable empirical work (see (Lennox, 1999; Yang *et al.*, 1999). Hence, in terms of performance, it's much better to use the logistic regression (LR) model.

Table-6. Comparison of the predictive power between the logistic regression (LR) and the discriminant analysis models

	Logistic Regression(LR)	Discriminant Analysis(DA)
Sensitivity	99.41%	75.36%
Specificity	98.47%	59.54%
Good classification rate	89%	68.49%
Bad classification rate	11%	31.51%

4.3.2. Comparison between LR and DA by Using the Normality Test

When the normality condition is violated, i.e., under non-normality of the explanatory variables, discriminant function estimation can give misleading results concerning the significance of the logistic regression coefficients. Hence, a slope coefficient which is really zero will tend to be estimated as zero by the logistic regression in large samples. However, this zero estimation will not be necessarily ensured by the discriminant analysis. Therefore, when underlying normality is violated, meaningless variables will tend to be erroneously included in the logistic regressions estimated by discriminant functions.

Consequently, the choice between these two methods is based on the acceptance or rejection of the normality assumption of the distribution of $\underline{X}$ given Y. Four classical tests have been used in the past, namely Shapiro-Wilks, Kolmogorov-Smirnov, the Skewness and Kurtosis tests.

In this paper, we have used a Kolmogorov-Smirnov test, aiming to compare the distributions of the values in the data vectors x_1 and x_2. The null hypothesis stipulales that both x_1 and x_2 belong to the same continuous distribution, whereas the alternative hypothesis assumes that they belong to different continuous distributions. The result h is equal to 1 if the test rejects the null hypothesis at the 5% significance level and equal to 0 otherwise.

Table 7 displays the results of the explanatory variables' normality. It is necessary to note that we have not tested the normality of the variable "socio-professional category" since it is a discrete variable.

Table-7. Normality test of all the explanatory variables

	Y= 1		Y= 0	
	T-statistic	**P-Value**	**T-statistic**	**P-Value**
Age	0.0852	0.1617	0.0753	0.3442
Loan amount	0.3079	9.5969 e^{-15}	0.3316	3.0025 e^{-15}
Outstanding Loan	0.3139	2.7006 e^{-15}	0.1914	2.3097 $e^{-0.5}$

According to the above results, we can conclude that most of the variables are not normal. As an illustration, we take the normal probability plot of the amplitude of the variables used in the model in lead endogenous variable (y) with left ventricular hypertrophy.

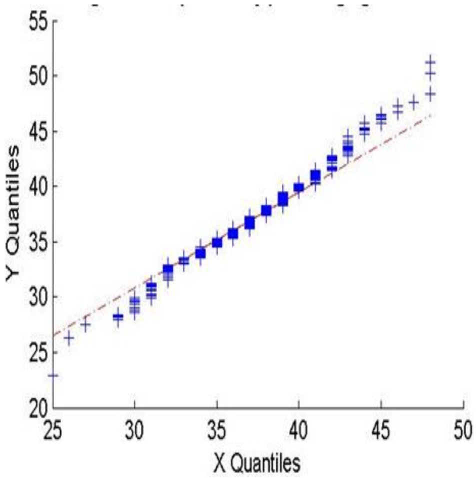

Fig-1. Normal probability plot of Age given Y=0

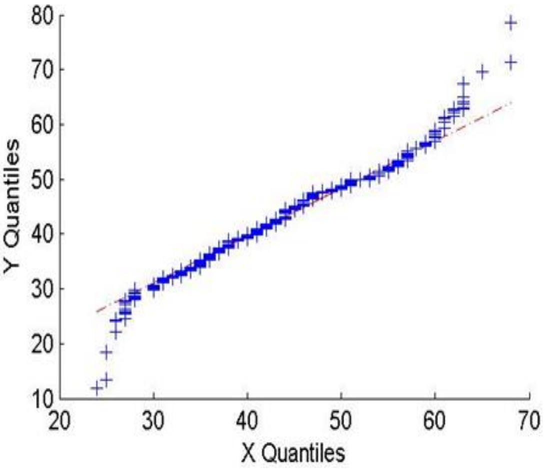

Fig-1'. Normal probability plot of Age given Y=1

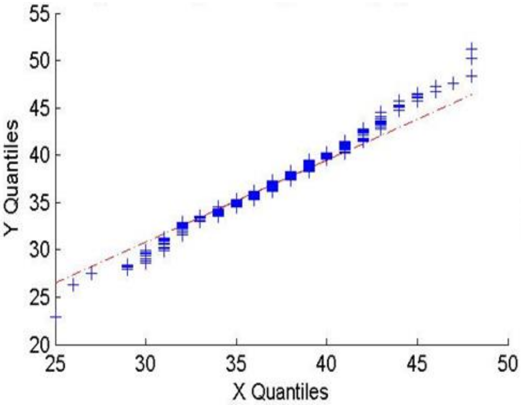

Fig-2. Normal probability plot of Loan Amount given Y=0

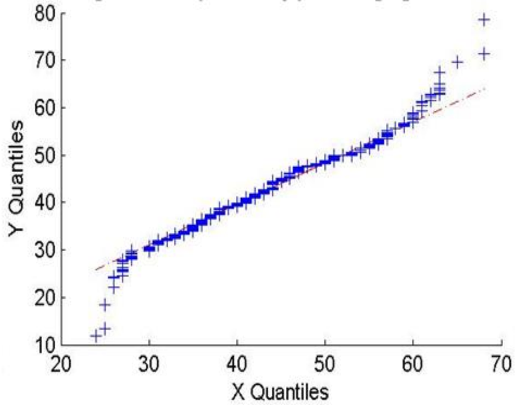

Fig-2'. Normal probability plot of Loan Amount given Y=1

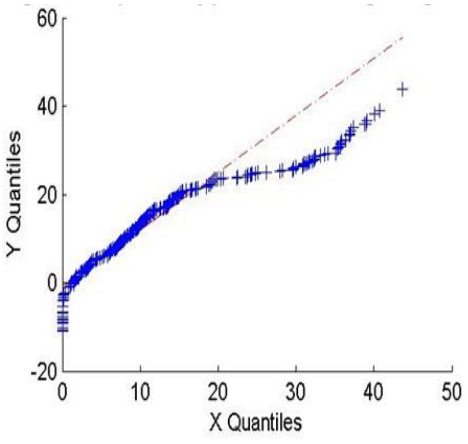

Fig-3. Normal probability plot of Outstanding of Loan given Y=0

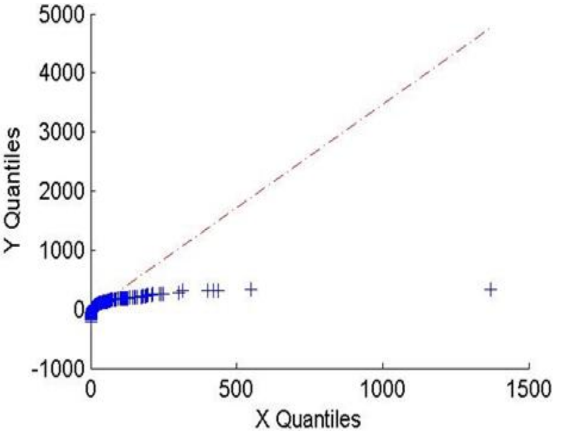

Fig-3'. Normal probability plot of Outstanding of Loan given Y=1

In Fig.1 and Fig.1' (independently of the payment default), the normally distributed "AGE" is presented. This variable has Kolmogorov 0.1616 if Y=1 and 0.3440 if Y=0.

In Fig. 2 as well as Fig.2' (independently of the payment default), the normal probability plot of the variable "loan amount" is given. We notice a vey obvious deviation from the straight line, showing the presence of a severe non-normality (or the almost complete absence of normality). This variable has Kolmogorov 9.5969 e^{-15} if Y=1 and 3.0025 e^{-15} if Y=0.

In Fig.3 and Fig.3' (regardless of the payment default, i.e., when Y=0 and Y=1), the normal probability plot of the variable "Outstanding Loan" is given. Here again, the non-normality of the variable is clearly shown.

4.3.3. Interpretation of Results

The following table presents the results of the LR model.

Table-8. Results of the logistic regression (LR) model

Variable	Parameters (β)	Std. Error	P-Value	T-statistic
β_0	-6,6537213	2,02462516	1,01E-03	-3,29E+00
Age	-0,02661418	0,04579628	0,56114427	-0,58114272
Loan amount	-0,17251174	0,06239788	5,70E-03	-2,76E+00
Outstanding loan	0,25106908	0,07117514	4,20E-04	3,53E+00
Occupational Category	4,72547243	0,76849278	7,80E-10	6,15E+00

Table 8 allows us to observe the variables that were included in the equation and also to investigate their significance. As Table 8 indicates, the variable age is not statistically significant.

According to Table 8, we conclude that only the variable "age" is not statistically significant. This result can be interpreted as follows: the age of the borrower doesn't have any effect on the probability of payment default. Hence, no significant difference was found between "good" and "bad" borrowers in terms of age.

Loan size is the amount of credit the applicant is granted. The customer may have applied for a larger amount but has been denied the loan. He is still able to apply for a lower amount, for a maximum of three times. Several studies have used “loan size” as a predictor variable but the overall results are ambiguous and thus no clear expectations can be deduced. Jacobson and Kasper (2003) show that “loan size” has no significant influence on the default risk. In the study of Kocenda and Vojtek (2009) small loans appear to be riskier if the variable ‘own resources’ is included. However, if this information is not used, the regression identifies that larger loans as riskier than small loans.

However, in our study, we found that the coefficient on the variable credit amount is negative and has a significant sign .This is expected, because a high amount of credit decreases the probability for the creditor to honor its commitment, all other things being equal. “Outstanding loan” also appears to be associated with payment default rather than with proper repayment behavior. It has a positive impact on the likelihood of default of the individual because the greater the amount of outstanding loans, the higher the customer has had opportunities to get into default.

Moreover, it would be more difficult for a customer to avoid default when the amount of outstanding credit is high, which would leave less flexibility to the borrower.

Occupation (Profession) was also an essential factor in determining the creditworthiness of individuals. Hence, we may conclude that employees with a fixed salary have less credit risk and more creditworthiness as compared to businessmen and students. All the unemployed applicants are not considered to be creditworthy as they are not financially strong, having no source of income to repay the loan. The most important factor that must be considered is the credit history of the applicants. We can see from our results and from past literature, that those borrowers who have defaulted previously can be predicted to default in the future.

5. CONCLUSION AND PERSPECTIVES

The prominence of credit scoring systems lies in the fact that they are effective in alleviating bad debt losses. Customers’ individual propensities to make default payments are generally estimated on the ground of information regarding both their previous payment behavior and their own characteristics. In this study, we have used Logistic Regression (RL) and Discriminant Analysis (DA) models in order to assess the required default probability. The present study was based on a sample of 633 individual borrowers who have been granted personal loans from the commercial bank of Tunisia. Among this sample, 366 customers had a default up to 90 days, whereas 267 applicants had a clear history without any default.

The logistic regression model served the reclassification of individual borrowers in their original group with a correct classification rate of 89%. When applying the discriminant analysis model, this rate was reduced to only 68.49%. Hence, we can easily deduce that the credit scoring model that has the lowest classification error rate is the logistic regression model (11%) while the same rate has reached 31.51% when using the discriminant analysis (DA) model. When testing data on default credits, and under non-normality conditions, the results have shown that the logistic regression model has a better performance as compared with the discriminant analysis.

The results of the logistic regression have shown that three factors were proved to be relevant in the formation of the probability of borrowers' default of payment: the "loan amount" has a negative impact on default cases, while both "outstanding loan" and the borrowers' "socio-professional category" have a more positive effect on the probality of non-payment. In fact, there exist other models which were proven to be efficient in assessing the probability estimation problem. Among these, we can mention the neural networks, the special versions of support vector machines, the learning machines, and the penalized least squares (see (Wu and Liu, 2007; Liu *et al.*, 2011; Malley *et al.*, 2012)). These models have provided a different view on the credit scoring problem. Therefore, they are evidenced as effective alternatives to the standard statistical approaches. In sum, the aim of this study was to make an assessment of customers' creditworthiness and an evaluation to those who had already been granted personal loans. This, in turn, is meant to improve the credit approval process and, hence, decrease the non-performing loans in Tunisian commercial banks.

6. RECOMMENDATIONS

The underlying objective the current study is to enhance the use of the proposed "credit scoring model" as it serves commercial banks in making evaluation to customers asking for credits. In this sense, the adoption of this model helps commercial banks reduce the rate of non-performing loans.

Similarly, as far as research in this area is concerned, future studies should use the advanced credit scoring techniques, such as genetic algorithms, fuzzy discriminant analysis, and neural networks.

As for the generalization and accuracy of the results which are generated by the credit scoring models, we recommend the use of larger data of individual borrowers which should yield more significant results. In this sense, the insertion of additional variables can also illuminate researchers as well as bankers of what serves the prediction of the probability of default of individuals and corporations.

Though our study has yielded significant results, it remains subject to certain limitations, notably the use of only the accepted applicants as a sample. So, to obtain more concrete and convincing results we may broaden our data through addressing the rejected applicants.

7. PERSPECTIVES

This paper can be extended so that other eminent variables can be detected, which can help exploring the prerequisites of credit allocation. Then, the expansion of this study may also serve the provision of concrete explanation for the rejection of particular credit requests. In this sense, descriptive statistics on all the variables used in our study are needed in order to identify the most discriminating and relevant ones.

The simulation of other processes of refusal serves a realistic testing of models' robustness and stability already established in this article.

In future research, it will be worth considering the development of other semi-supervised methods and their adaptation to the problem of reintegrating refused cases. In addition, apart from the methods of Boosting, new trends, such as those of Bagging, have emerged for the sake of a better classification of default borrowers.

The interest has become in responding to the question "when" the failure will occur, but not simply in determining whether a default will occur or not. Indeed, the discrimination between the “good” and “bad” borrowers is not the only goal for the banks, mainly for long-term loans. Banks are also interested in determining when clients will not pay back loans. To reach this end, it might be of paramount importance for banks to implement follow-up systems for censored data. This, in turn, can help banker detect and solve the issue of incomplete data (Saporta, 2006).

In short, a follow-up analysis can enable us to consider customers' default payment as the target event and the rejected credit requests as censored data.

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