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CREDIT SCORING

A MANAGEMENT METHODOLOGY FOR THE PREVENTION AND REDUCTION OF BAD CREDIT

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ABSTRACT

The growth in bad debts has forced financial institutions to pay constant attention to improving credit risk control.

This control aims to regulate lending according to practices that minimize probability of default. When credit risk management adopts more liberal credit policies, the likelihood of doubtful loans increases. A portion of bad credit becomes uncollectible, causing large losses.

The realization of this problem has long been recognized and established by the Basel II Agreement which among several recommendations has suggested to the Banks stricter credit risk controls.

According to the European Payment Index the risk of non-payment in Europe shows in 2008 an increase in default of 2% of total credit granted. According to this study, “Portugal, Greece and Cyprus are the countries where it takes longer to repay a debt”.

To mitigate this problem several practices have been proposed, including the default probability translated as a risk score whose identification in the financial discourse is called *scoring* or *credit scoring*.

In this context, the objective of this study is to identify explanatory factors capable of predict the likelihood that a debtor will be a Good or Bad Payer in the future and assess the predictive robustness of the model used for this purpose.

The research project focused on consumer credit and identified by these explanatory factors was carried out through a database of 4,000 credit card users whose payment habits are known *a priori*.

The empirical research methodology followed in this project consisted of the application of the binary logistic regression model to the data under analysis especially suited to the study in question and because of its simplicity. The identification of most relevant explanatory factors (attributes) were performed using the iterative method forward stepwise (Likelihood Ratio) and which consists of selecting among the independent variables those whose predictive ability of the behavior of Good or Bad Payer is statistically significant.

This thesis is structured in five chapters: Chapter 1 introduces the investigation; Chapter 2 deals with Literature Review; Chapter 3 describes the referential methodological used; Chapter 4 presents the results of the applied methodology; and Chapter 5 closes the study with conclusions, expected contributions and suggestions.

Keywords: Credit scoring, bad credit, logit, revolving credit.

JEL Classification Codes: G17, G21, G32 and C13.

INDEX

CHAPTER 1 - INTRODUCTION

The present research presents as central problem the credit growth bad debt or bad debt credit, in the last five years, in Portugal.

Bad credit means a loan that has not been solved by the debtor in due date and whose receipt is doubtful. This problem results from several causes, one of which is the poor credit risk assessment.

To mitigate this problem, Credit Scoring is proposed. This methodology consists of assess a person's creditworthiness using statistical methods.

Based on the identified problem and the proposed mitigation method, it constitutes the objective of this study is to identify factors that characterize a Good and a Bad payer, applying that methodology to a given database, and to evaluate, through the results obtained, the predictive robustness of the model used.

1.1 Thesis Structure

This thesis is structured in five chapters. The chapters are divided into sections and sections in subsections.

Chapter 1 - Introduction

Section 1 presents the structure of the content.

Section 2 addresses the problem of bad credit growth, with reference to the Basel II Agreement and the European Payment Index 2008 as analytical tools that corroborate the problem under study; some of the origins of the growth of the bad credit in Portugal, in relation to the private segment; and the way that roposes to mitigate the problem.

Section 3 sets out the purpose of the study, based on problem identification and in the methodology that mitigates it.

Section 4 deals with the research methodology, showing in subsection 1 the model statistic used.

Section 5 refers to the empirical framework, focusing on statistical tests performed.

Section 6 reports the limitations present in the elaboration of the empirical study, pointing confidentiality reasons inherent in the financial institution that provided the data and in the estrictions on the “decoding” of the computer tools used by it.

Section 7 endorses for the 2nd Chapter the report of other studies related to credit scoring that used different methods and presented in the Review of the Literature.

Chapter 2 - Theoretical Framework: Literature Review

The second chapter reviews the Literature, briefly presenting some other methods most commonly used in credit scoring.

Chapter 3 - Methodological Framework: Credit Scoring

Section 1 gives a description of how it has come to assess the ability to people's credit by probabilistic methods, using scoring systems that can discriminate between good and bad payers; explains the meaning of scoring of attribution and behavioral scoring.

Section 2 provides a historical review of credit scoring, reporting developments over the past 40 years, and subsection 1 describes the history of credit cards in Portugal, through a brief summary.

Section 3 explains the stages of building a scoring table, giving examples attribution scoring, ie the methods used to credit people who request it for the first time.

Section 4 sets out the techniques used to assess the behavior of debtors payment and the methods used to collect these credits: techniques called behavioral scoring.

Section 5 provides some comments and reasons that explain the difficulties of implementation of this methodology in small and medium enterprises in Portugal.

Chapter 4 - Results

Section 1 deals with the collection, analysis and transformation of sample data, reporting on were analyzed and transformed so that they could be incorporated into the statistical model.

Section 2 describes in subsection 1 the application of the logistic regression model to 3200 credit card users, known as *in-sample data*, results presented by the hit rates, in the classification of good and bad payers; and on

Subsection 2 validates the model using a *hold-out sample* for 800 credit card users. The obtained results confirm the robustness predictive in rating a good and bad payer.

Chapter 5 - Conclusions, Expected Contributions, and Suggestions

Section 1 presents the conclusions of the study, given the results obtained.

Section 2 lists the expected contributions of the study to Theory, Management and for Public Policy.

Section 3 offers some suggestions for future research.

1.2 Problem of Study

According to Popper (1994), “The natural sciences as well as the social sciences begin always because of problems, because something causes us astonishment, like the Greek philosophers they used to say”.

According to the same philosopher, to solve these problems, “the sciences use fundamentally the same method that common sense employs, the method of trying and error. To be more precise, it is the method of experimenting with solutions for the our problem and then dismiss the false ones as wrong. This method presupposes that we work with a large number of experimental solutions. It is tested and one solution after another ”.

Popper (op.cit., P.17) further considers that “at bottom, this procedure seems to be the that is logical ”, presenting a trial and error learning model, It consists of three phases: 1) the problem, 2) the attempts at solution; 3) the elimination.

Although Popper does not consider himself to be a believer in the philosophical current of the positivist, but rather a supporter of metaphysical realism (op.cit., p.43), the philosopher and social anthropologist.

Ernest Gellner (1959) argues that Popper is clearly closer to the positivism than the metaphysical or deductive tradition.

From a scientific perspective, positivist philosophy summed up the idea of “seeing to predict ”and“ predict to control ”, which in a way corresponds to the process behavioral scoring (3.4) that analyzes the behavior of non-compliant for this empirical finding to predict future default based on attitudes similar behavior of other debtors, thereby controlling bad credit.

It can be seen from the previous analogy that Popper “what he had established for the natural sciences in his book The Logic of Scientific Research also had to be valid approach to the social sciences ”(see Great Thinkers Collection, Karl Popper, (Life, Thought and Work, p.48).

The problem identified by empirical finding reveals that bad credit in Portugal it has grown in the last five years. This continuous growth imposes measures of management that mitigate the problem. Among these measures are statistical methods used in credit risk assessment. This assessment will be the better the higher the predictive capacity of the model used.

The predictive robustness of different models used in credit risk assessment has been the focus of many investigations, notably the works of Altman (1968), Martin (1977), Press and Wilson (1978), Srinivisan (1987b), Boyle (1992), Crook et al. (1992), Henley (1995), Hand et al (1996), Desai (1997), Yobas (2000), among others.

In these researches different algorithms were used, namely Z-score function proposed by Altman in 1966, Zeta® function proposed by Altman, Haldeman and Narayanan in 1977, among other discriminating methods and whose results have shown that some have greater predictive power than others when applied in different situations and contexts. Information technologies (IT), in turn, have made a huge contribution to the development and diversity of credit decision support systems.

Not withstanding these valuable aids for credit risk assessment and support for decision on lending, the level of non-performing loans continues to increase, many sometimes the result of structural phenomena that inhibit the technical potentiality of these efforts.

The entities that hold bad debts are: the State, the institutions companies, and individuals.

a) The credit that the State holds over its debtors is basically from taxes not received from households, businesses and financial institutions. The bad credit from the State is mainly from insolvent debtors whose law suits have not yet become final.

It is considered for legal purposes that a debtor is insolvent when it is unable to meet its overdue obligations.

b) Credit held by the Bank originates mostly from loans granted usinesses, individuals, other banks and the State. Business in difficulty recognize that access to bank credit is crucial to their survival, avoiding default with this lender. Banking bad credit may have different treatment, from debt renegotiation with its clients, to claims by judicial means, or by foreclosure.

c) The credit held by the Companies originates mainly from the supplies to credit to your customers. In case of default on the payment dates the credit may, eventually be suspended by the lending company. When this happens, as a general rule, debtors do not pay their past due debts, which in most cases companies continue to deliver on credit in anticipation of older credit recovery.

d) Among individuals there is a diversity of unsolvable loans, many of which are of them settled in court. The recognition of bad credit growth relative to Banking is in line with the empirically evidenced by international recommendations, in particular by the Basel II (Annex 1), and by international indices such as for example the European Payment Index 2008 (Attached 3).

One of the conclusions of the Basel Committee on Banking Supervision (Basel) in June 2004 was that banks had to control risk more evidence of better risk mitigation techniques, using *behavioral scoring* in customer evaluation and better managing their customer base of data (Pillar 1).

It also refers to the Agreement (Pillar 3), which banks will have to disclose more information the formulas they use for credit risk management, as well as implementing a market discipline aimed at achieving healthier and safer banking practices.

From the outset, it is clear that preventing and reducing bad debts is one of the Basel II concerns by recognizing that banks have not controlled the risk of granting credit as effectively as desirable, with this recommendation being based on unsafe banking practices.

1.2.1 - Some reflections of the problem in Portugal: average deadlines receipt

Bad credit is the designation given by non-financial institutions governmental debts to the debts of customers / users / taxpayers whose recovery is doubtful whether or not these debts are in dispute.

The moment from which a credit assumes that designation corresponds to the when accounting records are made, debiting doubtful collection. ”When these credits are considered uncollectible and in the event of not provisioned, will then be considered as costs and losses accounted for by the corresponding income statement (POC).Feb.2009).

Doubtful receivables are based on the existence of payment that generally exceeded their due dates long ago, leading to the designation of “wrongdoer” and the implementation of the above accounting criteria and procedures referred to.

In this regard and according to the European Payment Index 2008 reports, Portugal, in 2008, together with Greece and Cyprus were the countries where more time to pay.

Late payments in Portugal negatively influence the image compared to other countries that show better performances.

This late payment behavior creates difficulties in confidence building.

1.2.2 - Some origins of the problem among “individuals”

Among the structural phenomena mentioned above are some of the reasons substantiating the origin of non-performing loans in Portugal, namely socio-economic context.The social phenomenon strongly associated with bad debts, among the individuals is the so-called misfortune UID (Unemployment, Illness and Divorce).

a) Unemployment is strongly associated with economic cycles and has been a major largest scourge in the world and is expected to reach 210 million people in the 57 million in OECD countries in 2010, according to the International Organization for Labor (IOL). Portugal, unfortunately, is no exception.

The present situation (2009) of unemployed people in Portugal already exceeds half a million people. The official unemployment figures of the National Institute of Statistics (INE) (4th Quarter 2008) non-unemployed, unemployed should be added by INE, known as available inactive, ie unemployed but wanting to work and the sub-employees who are in practice people unemployed, who work less than 15 hours per week. Keeping this low in the economical cycle there will necessarily be an increase in bad credit rates and greater retraction of banks in home and consumer lending.

b) The disease has been, along with unemployment, another reason that motivates the default and the definitive default on the payment of debts. The disease inhibits partial or totally the ability to work, preventing sufficient remuneration, able to guarantee the payment of commitments.

c) Divorce is another cause, usually cited by financial institutions and DECO (Portuguese Association for Consumer Protection), to rates on bad credit. Divorce, as a disruptive element of families, generally creates greater financial difficulties to each of the former spouses, either because of the need to settle common commitments and the need to borrow again.

Doubtful loans in the private segment include loans from greater weight: mortgage and consumer credit.

LOANS OF OTHER MONETARY FINANCIAL INSTITUTIONS TO PRIVATE INDIVIDUALS
By purpose and maturity:

HOUSING (10^6 Euros)

	Up to 1 year	From 1 to 5 years	> 5 years	Loan	Bad loan	%
2004 Dec	214	692	69 928	70 835	1 072	1,51%
2005 Dec	241	759	78 237	79 237	1 177	1,49%
2006 Dec	232	871	90 488	91 591	1 139	1,24%
2007 Dez	235	1 179	99 171	100 585	1 264	1,26%
2008 Dec	99	540	103 827	104 465	1 570	1,50%

CONSUMPTION (10^6 Euros)

	Up to 1 year	From 1 to 5 years	> 5 years	Loan	Bad loan	%
2004 Dec	1 908	3 079	4 072	9 059	454	5,01%
2005 Dec	2 024	2 993	4 390	9 406	292	3,10%
2006 Dec	2 575	3 356	5 448	11 379	369	3,24%
2007 Dec	3 251	3 794	6 746	13 790	505	3,66%

2008 Dec	3 665	4 072	7 715	15 452	759	4,91%

OTHER PURPOSES (10^6 Euros)						
	Up to 1 year	From 1 to 5 years	> 5 years	Loan	Bad loan	%
2004 Dec	4129	2803	3585	10 518	456	4,34%
2005 Dec	4304	2493	4359	11 157	517	4,63%
2006 Dec	4412	2890	4705	12 007	490	4,08%
2007 Dec	4650	2784	5469	12 902	438	3,39%
2008 Dec	4759	2666	5232	12 656	548	4,33%

TOTAL (10^6 Euros)						
	Up to 1 year	From 1 to 5 years	> 5 years	Loan	Bad loan	%
2004 Dec	6252	6574	77585	90 411	1 982	2,19%
2005 Dec	6569	6245	86986	99 801	1 986	1,99%
2006 Dec	7219	7117	100640	114 977	1 998	1,74%
2007 Dec	8136	7756	111386	127 278	2 207	1,73%
2008 Dec	8523	7277	116774	132 574	2 877	2,17%

Source: Banco de Portugal

1.2.3 - Problem mitigation

Mitigating the problem of bad credit growth can draw on several "therapies". In this study, we opted for a methodology capable of early detection of potential defaults on future payments through can identify factors that explain and predict such behaviors.

Those processes, such as preventive methods capable of reducing and preventing non-compliance are not sufficiently publicized and widespread in the business fabric domestic and foreign small and medium enterprises.

This has a particular impact on the quality of credit risk management, leading to financial and non-financial institutions to react to the default of their debtors at a time when the odds of receipt are already very low or even null.

In this sense, whether in the granting of mortgage loans, consumer credit, bank credit to companies, and also among companies, the problem is strictly the same, that is, there is a need to identify in advance situations of potential non-compliance are required.

1.3 Objectives of the study

With bad credit growth being the identified problem and the methodology Credit Scoring your mitigative, is intended with the present thesis:

- identify explanatory factors capable of predicting the likelihood that a debtor will bin the future a good or bad payer;

- evaluate the predictive robustness of the statistical model applied in concession situations revolving credit.

In this sense, it is our purpose:

1- Make known the methodology capable of mitigating the problem:

a) referencing through the Literature Review (Chapter 2) the main credit scoring studies;
b) contributing to the understanding and application of that methodology in companies that intend to implement it (Chapter 3).

2- Experimentally analyze the predictive capacity of the statistical model through the instrumental use of a credit card user database.

(Chapter 4 - Results).

1.4 Research methodology

According to Madeira (2009), the methodology “is a normative discipline whose the systematic and logical study of the principles governing any scientific research, from basic assumptions to research techniques ”.

The same researcher considers that “the methodology, more than a description of techniques and methods to be used in scientific research indicates the option that the researcher did to solve certain situation, or problem (which may be theoretical) or practical (s) related to your research object which must be, necessarily developed within a scientific framework, frame / framed current paradigm (s) or theory (s) ”.

The following research methodology describes different methods that have been used in credit scoring, understanding the same researcher that “The method (methodos) is a reflexively ordered scientific procedure consisting of basic instruments, to which reflection / conjecture and experimentation apply appropriately”.

The aim of the method is to guide the entire research path in order to achieve the objectives pre-established in the research project ”.

From the literature review (Chapter 2) we highlight the mathematical models that represent an econometric conceptualization applied to the empirical data collected by investigators in their credit scoring investigations.

Also according to Madeira (work cit.), “Model is a conceptual or physical representation, a process or a system or a phenomenon or an object ”.

After configuring the meaning of the language used, the following paragraph describes the Logistic regression model.

1.4.1 Logistic Regression

Through literature review, we found that many researchers have studied the theme of credit scoring according to different methods over the last few years.

From the revised literature we selected the logistic regression model because it is especially adaptable to cases where there is a binary dependent variable or dichotomous.

The first study was performed by Ohlson (1980). Wiginton (1980) was one of the first researchers to publish results on credit scoring using this technique.

Logistic regression was also applied by Zavgren and Friedman (1988), Aziz and Lawnson (1989), Persons (1999), Wilson, Summers and Hope (2000), Eklund, Larsen and Bernhardsen (2001), Westgaard and Wijst (2001), Hayden (2002), Platt and Platt (2002), Dong (2007), Mavri et al. (2008).

Although there are other alternative models, namely the analysis of discriminant, linear regression, classification trees, artificial neural networks, genetic algorithms, linear programming, among others, we will apply logistic regression mainly due to its simplicity and adaptability to the present study.

Logistic regression compared to discriminant analysis has the advantage that not having to meet the rigid assumptions of the latter (see Kaltofen, Möllenbeck and Stein (2004), Ewert and Szczesny (2002), Jagtiani et al. (2000), Maddala (1983), Ohlson (1980), Press and Wilson (1978), Martin (1977).

Linear regression is sometimes used to estimate scoring models, although logistic regression is generally preferred because it is especially adaptable to that there is a binary dependent variable.

One of the problems with using linear regression is that it can produce values estimated for probability greater than one and less than zero, which is statistically incorrect.

The logit model avoids such a situation because it is based on the logistic distribution function ensuring that the estimated values necessarily remain within zero and one..

The application of the logistic regression model to the present study is shown particularly appropriate, since the dependent variable assumes the values 0 and 1, whose meaning is commonly referred to as Poor and Good account performance, respectively.

In this sense, it was considered a binary dependent variable that assumes the value 1 when the customer is a good payer and 0 when not. The probability of being good payer will be estimated from the logit model:

$$p(Y_i = 1) = \frac{1}{1+e^{-Z_i}} + \varepsilon_i \tag{1.1}$$

on what:

$$Z_i = \beta_0 + \beta_1 x_{1_j} + \cdots + \beta_k x_{k_j} \tag{1.2}$$

Being:

β_k the parameters of the model;

x_{k_j} the variables representing the explanatory factors of the probability of each user be good payer.

ε_i the error.

The model parameters were estimated by the maximum likelihood method and the estimated equation allows us to relate the probability of a customer being a good payer to the relevant attributes considered.

To select from the 21 original explanatory variables (number of variables identified in the database provided by the financial institution and which supported the empirical study), those which are most relevant for estimating the a credit card's user probability be a good payer, we use the *forward stepwise* method.

This method is based on the incremental explanatory power that each of the variables explanations to be introduced in the model has on the dependent variable, reflected in the increment of the likelihood function.

The method is to start the regression model without including any of the explanatory variables, introducing at each iteration the most important variables and excluding least important until the selection process is completed.

1.5 Empirical Framework

The study has as empirical framework a series of statistical tests that, according to with the database used, aim to identify, within the sample used, the variables most determining factors in rating a credit card user being a Good or Bad payer.

The instrumental part of this investigation was made through the application of the logistic regression to the data of 4,000 credit card payment is known *a priori*.

Knowing the payment behavior of those users will allow classify future users who reveal behavioral similarity.

The collected data were analyzed, identifying 21 factors that characterize those credit card users. These factors were grouped into 3 types (qualitative, quantitative and dates).

Once the data has been analyzed and considered in the model the qualitative variables were transformed into numerical variables (dummy variables) following the classification criterion proposed by Anderson (2007, p.359).

Then, the logistic regression model was applied to the selected data.

1.6 Limitations of the study

Contact with financial institutions capable of providing elements that would allow applying the recommended methodology to real data was very difficult and in most cases all impossible.

The need to obtain data processed according to criteria defined by the author was one of the main reasons given for the failure of this goal.

The mere observation of the growth of bad credit in Portugal, in the last five years, it is easily observable, either from INE (Instituto Nacional de Estatística) data or BdP (Banco de Portugal) reports.

However, the aim of the present study is to identify behavioral factors and able to predict the likelihood of compliance and / or non-compliance with debtors to their creditors and to assess, by means of a Good and Bad Payers, the predictive robustness of the statistical model applied to revolving credit situations.

Notwithstanding the difficulties encountered by various financial entities, obtain from a prestigious credit card issuer after a material that made the empirical part of this draft investigation.

The quantitative analysis of the present study was conditioned to the database obtained from that financial entity. Certainly there would be other elements that would like to include in this study, namely the analysis of the original documents of the credit reporting agencies, credit reporting agencies, Bank of Portugal data and the entire history of the 4 000 credit card users, but we understand that the financial institutions are governed by confidentiality policies and restrictions imposed by for those policies that prevent them from being so available for disclosing this data, the size of this ambitious research.

On the other hand, the credit scoring methodology underlying the valuation processes credit risk, which underpins the functionality of such software, is a intellectual property rights resulting from the know-how of the manufacturers of those systems scoring, protected by trademarks protected by law, and whose contents are not accessible, constituting real black boxes difficult to penetrate and interpret, even for financial institutions using those systems.

Constituting the above limitations a restriction to the present investigation is also a opportunity for future research to be able to develop national and international projects, for the construction of new credit scoring systems.

The benefit of its use in small and medium-sized companies would contribute to significantly, for the prevention and reduction of non-performing loans.

Notwithstanding this limitation, the study is carried out through a process that can be replicated against other databases of other financial and / or non-financial institutions.

CHAPTER 2 - THEORETICAL FRAMEWORK: REVIEW LITERATURE

The need to estimate the likelihood of default on the payment of a debt led credit scoring experts to refine statistical techniques able to discriminate between good and bad payers.

The same need has been found in being able to predict the continuity of companies in the market, separating the Good Companies from the Bad Companies, by identifying certain characteristics to predict the likelihood of their being others fail.

The literature on these matters is no longer recent, more than forty years apart study by Beaver (1966), which has been considered as the pioneering research in the development of this kind of forecasting.

There are currently a number of research papers dealing with this namely Jones (1987), Dimitras, Zanakis and Zopounidis (1996), Altman and Saunders (1998), Balcaen and Ooghe (2004) and Altman and Hotchkiss (2006), Dong (2007), Mavri *et al*. (2008).

Some of the parametric credit scoring studies often cited in the literature Beaver (1966), Altman (1968), Ohlson (1980) and Shumway (2001).

Beaver (1966) used univariate discriminant analysis, demonstrating that the financial ratios can be used to predict corporate insolvency. From here, the insolvency studies were successively improved and refined.

Altman (1968) introduced multivariate discriminant analysis, a model that was known as the Z-score, allowing it to identify in a group of 66 companies those which showed a strong tendency towards insolvency.

Later on Altman, Haldeman and Narayanan (1977) developed a new model which they called Zeta®. The Z-score and Zeta® models were also referenced in more recent investigations, namely by Holmen (1988), Shumway (2001), Ooghe and Balcaen (2002), Chava and Jarrow (2004).

At the end of the 1970s, the models supported by the analysis discriminating multivariate.

However, some problems were identified in this statistical technique which assumed the presumption of a multivariate normal distribution of the considered variables.

Eisenbeis (1978) pointed out some problems in the use of discriminant analysis multivariate, namely the distribution of variables; equality versus inequality group dispersions; the role of the weight of individual variables; problems arising from reduction in the number of variables; problems in the definition of groups (the discriminant analysis assumed that the target groups of investigation were discrete and identifiable); inappropriate use of *ex ante* probabilities in group classification; classification problems in estimation error rates, in accessing model performance.

From the literature review (Fair & Isaac, 2006) it is emphasized that the objective in discriminant generally has two options: - Segment or separate individuals into two or more previously defined groups; and classify a new individual into one of these groups.

In the 1940s and 1950s several researchers stood out for their pioneering contributions, namely, McCulloch and Pitts (1943) who introduced the idea of artificial neural networks as computational machines; Hebb (1949) postulated the first self-organized learning rule; and Rosenblatt (1958) proposed the perceptron as the first model for supervised learning. Just a few years later Makowski (1985) and Coffman (1986) applied it to credit scoring inspired by the works conducted on artificial intelligence.

Another statistic used to classify and discriminate groups completely different from those mentioned so far is referred to as decision trees, also called recursive partitioning algorithms (RPA).

The decision tree literature offers a wide choice of these algorithms, which differ in terms of performance, conditions and fields of application (Hadidi, 2003; Loh and Shih, 1997; Quinlan, 1993 and 1986; Biggs, de Ville and Suen, 1991; Breiman et al., 1984; Kass,1980).

Safavian and Landgrebe (1991) used the same statistics for classification of albeit with different names (CHAID4 and C5), although their methods were identical.

Among other methods used in credit scoring, the genetic algorithm is a procedure to systematically search within a population for potential for solving a problem.

Notwithstanding the proficiency of statistical models developed over the last forty years, other (non-statistical) methods have followed a similar path.

Until 1980 the only known works were based on statistical analysis, but Freed and Glover 1981a), 1981b) recognized in linear programming a more efficient in discriminating two groups when they are not linearly separable using to this end, objectives that would minimize both the sum of the absolute errors and the maximum error.

An advantage of linear programming over statistical methods, in credit scoring, it is the ease of including bias in the development of a scoring table.

Among the specialized literature we came across some researchers who argue that traditional techniques rank credit applicants more correct than evolutionary techniques. Other researchers, however, defend the contrary.

For example, Desai et al. (1996) when they used data from three associations of found that when rating loans accepted on Good and Bad neuronal classifications correctly classified a large percentage of both in all samples.

But when generic models were introduced in the comparative study, the neuronal networks were superior only in the prediction of Bads.

King et al. (1994) compared a large number of algorithms including analysis linear discriminant, neural networks and decision trees (but not genetic algorithms) and found that linear discriminant analysis predicts worse than various types of decision, but better than the neural networks.

On the other hand, Desai et al. (1997) applied the same database as in 1996 for a classification of 3 groups (Good, Weak and Bad) and included the algorithms Chi-squared Automatic Interaction Detector comparative study, and found that logistic regression was superior to other methods except for the classification of the weak where the neural networks showed higher predictive capacity.

By classifying the total sample, they revealed that the performance of the analysis linear discriminant was almost identical to neuronal networks and slightly better than genetic algorithms.

The above methods, briefly described for tool development applicable to credit scoring, have been the subject of comparative studies carried out namely by Srinivasan (1987b), Boyle (1992), Henley (1995), Yobas (1997) and Desai (1997).

Thomas et al. (2002, p.86) and Anderson (2007 p.185) transcribe the same compilation comparative analysis of the classification accuracy studies carried out for the different methods:

Investigator	Linear Regression	Logistic Regression	Classification Trees	Linear Programming	Neuronal Networks	Genetic Algorithms
Srinivasan (1987b)	87.5	89.3	93.2	86.1	-	-
Boyle (1992)	77.5	-	75.0	74.7	-	-
Henley (1995)	43.4	43.3	43.8	-	-	-
Yobas (1997)	68.4	-	62.3	-	62.0	64.5
Desai (1997)	66.5	67.3	-	-	66.4	-

Table nº2.1 Classification accuracy of various studies - Comparison between various methods

From table 2.1 we can see that the tests performed by Srinivasan (1987b), the logistic regression model presented the second best result in the right or wrong rating accuracy rate while Henley's (1995) logistic regression tests showed results identical to the linear regression methods and the classification trees, that were applied to the same database.

The comparative study by Desai (1997) shows that logistic regression presented the best results compared to the linear regression and the neuronal networks.

Credit scoring beyond logistic regression welcomes in its models of classification and pattern recognition, parametric and non-parametric methods whose results do not allow us to conclude that there is an optimal model, as each study differs in terms of structure, availability and quality of the data obtained.

The effort made by researchers to find out which technique produces better results, not yet definitive.

However, the credit scoring methodology cannot be reduced to using a determined statistical method.

The methodology encompasses the entire state of the art that enshrines the development of high technical concepts used in evaluating people applying for credit application scoring), as well as in the evaluation of credit card and behavioral scoring Adaptive Control System that provides the tools you need to deal with the complexity and behavior change.

In Chapter 3 some aspects of this methodology are developed.

CHAPTER 3 - METHODOLOGICAL REFERENCE: CREDIT SCORING

3.1 Introduction

Lending money is one of the oldest practices in the world. Who lends money believes in the person to whom it has lent and hopes that one good will be returned to you at a later date.

This sense of hope is based on a (high) probability of the money borrowed plus getting an additional benefit (interest), notdiscarding, however, the hypothesis of a (small) probability that money will not be recovered.

This possibility of default is the risk (credit risk) that may be incurred when a monetary consideration is to be obtained.

This consideration (interest) will be higher or lower depending on the higher or lower

probability of default (price of credit risk).

One of the instruments that has become predominantly used throughout the century, to assess the creditworthiness of credit if in probabilistic quantification translated by a punctuation.

Quoting (Lewis, 1992, p.1):

«… *Applying scoring to credit risk assessment translates into a process whereby the information obtained about a credit applicant or a client is converted into numbers, which when combined with each other (normally added),produce a score* ».

The result of this score can help, simplify, the decision of the credit analyst whether or not to grant the requested credit, and to monitor compliance with the payments of credits granted in an efficient, consistent and controlled manner.

The information the applicant makes available when completing an application credit account opening, or a proposed broadly similar, both in financial and non-financial institutions.

Also according to Lewis (1992), besides his personal identification, the information, with the most relevant points are: monthly income, number of years in the current employment, age, marital status, monthly responsibilities, number of children, type of housing (own or rented), education, number of years at current address, among others.

Through this process each credit applicant is given a score according to scoring tables (scoring tables or scorecards).The score achieved by a credit applicant is then compared with a referred to as the “cutoff score”. If this score is close to the cutoff, ie within a certain range in the vicinity of the cutoff, becomes necessary to intervention of the credit analyst and, after such analysis, granted or refused credit.

According to Anderson (2007, p.460) this process is called referrals and the analyst or not follow the indication given by the scoring system.

The number of individuals who apply daily for credit from institutions required information analysis and decision-making to in a short time.

This limitation led to the progressive replacement of the personal evaluation and judgment of the credit analyst for computational resources. These means, commonly referred to as information management systems, host in their architectures the processes of analysis, credit decision and monitoring.

According to Cortes (2005, p.4), information management is powered by databases, stored according to certain criteria such as standardization rules, indexes, hits and other criteria that make the use of databases more appropriate and user-friendly.

Generically referred to as computer programs, or computer solutions for decision support, these systems are equipped with data processing modules and are available on the market under registered trademarks.

Upon admission of a credit applicant by the process described above, the same be monitored through historical records of its behavior, or on the basis of other criteria, such as timeliness of payments on due dates, or compliance with the credit limits assigned to it.

The score of this system may be altered either by reducing or increasing the credit limits in force, depending on the respective conduct or behavior of each individual. This behavior also allows you to determine which collecting strategy is most appropriate to the profile of each customer concerned.

It is called attribution scoring or application scoring to the process of first granting credit to a candidate, and by behavioral scoring to the monitoring, surveillance and decision in the second case.

Knowing that experience gained from customer behavior in the past not be much different from their behavior in the near future, the method for assessing the risk of new credit applicants, based on customer experience, whose characteristics show identical attributes.

3.2 Credit scoring historical review

The 1930s and 1940s are those in which the statistical literature consecrates, as seminal scoring works, by the discrimination between groups of individuals or data.

Among the most cited works as pioneers of linear discriminant analysis is the Fisher's experiment (1936), which carried out on a set of 150 samples of the iris flower (setosa, versicolor and virginica), 50 observations of each of the cited species. These observations consisted of recording the length and width of the sepals and each of the three species.

This data set allowed Fisher to develop a new taxonomy technique, based on the discriminant linear function.

With this discovery, Fisher was able to predict which species would belong to a particular species by its characteristics. In this experiment, the function discriminant translated the linear combination of variables to which it was associated certain weight.

The prediction of the group to which a species would belong would result from maximizing quotient between the dispersion observed in flowers of the same species and the dispersion between flowers of the three species. The higher that quotient, the greater the discrimination or separation among groups.

From this moment on other studies followed, as Johnson (2002) reports that states that the beginning of the concept of credit scoring is attributed to Durand (1941) who would have statistical methods, namely the Chi-square test, identifying variables that could satisfactorily distinguish between good and bad loans.

In this study, Durand examined about 7,200 reports on Good and Bad installment loans granted by 37 companies and developed an "technique", showing how one variable was able to differentiate Good from Bad risks. Then he used a discriminating function to develop credit scoring models, whose these uses were not intended for the assessment of customers of financial institutions, but for retail customers.

At this time was the height of World War II whose imperatives dictated due to the difficulties arising from military recruitment, led an executive from Spiegel Inc.

Henry Wells to build a credit scoring system that was used during the period in the military service of their credit analysts took place.

This system aimed to facilitate the tasks that were now performed by personnel withless experience. This work, substantiated by sound statistical techniques, constituted the exception to the fruitless effort so far.

During the 1950s several scoring methodologies were developed, but was with William R. Fair and Earl J. Isaac in 1956 when they founded Fair, Isaac and Company that actually began the implementation of this methodology, driving significantly the credit industry.

The tracks were on which new developments would go, reaching a phase of rapid expansion from 1970, both in the United States of America and in Europe.

At this time it was found that in many institutions consumer credit modality of revolving credit limited by a certain amount (credit limit) and granted for an indefinite period, thus replacing the traditional forms of installment loans.

A new loan model called revolving credit was designed applied by banking and other financial institutions, in most cases materialized through a credit card that would be used as a means of payment.

The credit granted was monthly amortized, giving rise to the possibility of new debts, during the month, up to the established credit limit, without need to submit new information and personal data.

The credit limit could be modified according to its behavior regarding the compliance with due dates and other information produced by scoring.

With this change in the methodology adopted by credit institutions, the current credit cards, namely Carte Blanche®, Master Charge® (later the Master Card®) and BankAmericard® (later Visa®).

The rapid vulgarization and spread of credit cards has replaced the forms of traditional methods of credit analysis by statistical analysis methods, among other methods analytical data that became available through the rapid development that occurred in computational mechanisms. These resources made it possible to monitor and control of credit for industrial robotization processes.

3.2.1 Historical review of credit cards in Portugal

Portugal was no exception to the changes taking place in the United States of America and rest of Europe. The first statute of the legislative body related to the activity of the payment cards date of December 16, 1970, published the Ordinance No. 644/70 which would regulate the business of credit institutions wishing to issue credit cards.

However, only three years later a new Ordinance defined more accurately and regulation of credit card issuing activity. It's the ordinance 360/73 of 23 May repealing the previous legislative act. An order from the Secretary State Treasury of 27 February 1974 authorized the constitution of Unicre - International Credit Card, S.A.R.L. having as shareholders Totta & Açores Banks, Borges and Irmão, Espírito Santo & Lisbon Commercial, Fonsecas and Burnay, National Overseas and Portuguese Atlantic and whose charter of constitution is made one week before the historical date that signals a new milestone in the history of Portugal.

Unicre's corporate purpose was: the granting of credit through the issuance of individual identification cards as well as the conclusion of all contracts and necessary services and the conclusion of exchange agreements with foreign and national counterparts.

Unicre thus became the first Portuguese interbank credit cards having access to a merchant network that was now accepting the card Unibanco, as a means of payment. From March 1975 onwards, the nationalization of banks, major industries and the media.

At this time, the use of the Master Charge® credit card was prohibited in Ministerial Order, with the argument of exchange restrictions and replaced the its graphics based on national colors.

Later, following the study by an initiative working group continued use of the Sottomayor card, VISA® and Unicre image in connection with MasterCard®.

Only in 1982 for companies, with Normative Order 77/82 and in 1986 for the possibility for the Portuguese to use their credit cards abroad.

3.3.1 Consumer credit in Portugal: legislative initiatives

In Portugal, the first legislative initiative on the creation of Financial Companies Credit Acquisition Agreement (SFAC) dates from 1989 with the publication of Decree-Law no. 49/89 of February 22nd.

This diploma described in its preamble the need to stimulate consumption as a increase domestic demand by promoting credit through those societies.

Thus, in the Portuguese financial space, legally constituted entities that finance the acquisition on credit of goods and services by extensive areas, enhancing their usefulness in economic and social terms.

Decree-Law No. 298/92 of December 31 has profoundly reshaped the system Portuguese financial institution which defines the General Scheme of Credit and Financial corporations.

This law regulated the regime of its constitution, the rules on its administration and supervision, as well as the supervision to which they were subject by Banco of Portugal.

Later, Decree-Law No. 206/95 of 14 August repealed Decree-Law No.49/89 of 22 February stipulating in its Article 2 al. (a) that SFACs may finance the purchase or supply of specified goods or services by direct credit to the respective purchaser or supplier or through the provision of guarantees.

Thus, every legislative effort to adapt a new economy current practices in more developed countries with different purposes and objectives, in particular the risk arising from the granting of credit.

3.3.2 Attribution scoring and the need to quantify the risk

The granting of credit is implicitly and inherently associated with the idea of risk, since it assumes its receipt at a future date. The assessment of the probability of default on payment will quantify the risk assumed.

Risk quantification is the core of the development of credit scoring techniques.

In terms of the probability of default in the granting of credit, the fundamental assumption is that the near future is similar to the recent past.

Whether risk assessment by traditional human judgment processes or based on scoring, future predictions are based on past knowledge. Both the methods compare today's credit seekers with the experience gained from previous candidates.

In the personal assessment method, the credit analyst weighs the applicant based on your previous experience. If the application seems similar to one that has obtained a favorable opinion in the past, then consider the new application according to the same criteria.

The same principle is adopted by scoring. Each of the new applications is compared to the information available on previous applications, translated into a scoring table (scoring table).

3.3.3 Correct population selection

For a scoring system to be able to insert each customer into its integration group it is necessary to select the correct population, that is, the one that will contain all the information required for the development of scoring tables.

The construction of a statistically valid scoring table depends on the frequency of occurrences of a lot of data about Good and Bad accounts.

The size of the sample varies according to the type of credit granted (credit to the consumer credit, home loans, car loans, etc.). The number of customers that make up each wallet can range from a few thousand accounts to a few million, so it is necessary to use different sample sizes according to each portfolio credit type.

.According to Lewis (1992, p.31) there is no magic number to quantify the “best” size of a consumer credit sample and experience has shown that anyone can achieve a robust and effective result through a sample of 1500 Good and 1500 Bad accounts.

From this assumption, and according to the same author, that the near future will be somewhat similar to a recent past, collecting a sample of 1500 Good accounts and 1500 Bad accounts over the past 12 to 24 months may give you a more robust and effective table scoring, than another whose time horizon was from an earlier period of 3, 4 or more years.

Financial institutions from which samples are obtained must be stable, ie have remained and operated in the same type of credit activity during the period of time under review.

Only then will the collected samples be stable and homogeneous. If, on the contrary, during the last year, these institutions have changed their strategy in the market where by adopting new expansionary policies or by extending their intervention to other market segments not previously served, it can be expected that the nature of Good and Bad accounts will have a larger set of attributes than those that would obtain if the population served had not been changed.

The homogeneity of the sample is also very important for the quality level, end of scoring table. This homogeneity refers to the type of product offered and clients during the time period under study.

A sample taken from a population using a mix of credit products is less satisfactory as a basis for developing a scoring table than a sample taken from a population using only one credit product.

A stable and homogeneous population, although very attractive from a statistical point of view, for the purpose we want, it is not always possible to obtain it in practice.

If a population has been very volatile or if there has been a lack of due to the variety of credit products offered, due consideration should be given to attention to the selection of only one product in order to limit the study population.

Thus, the more stable and homogeneous the population is, the better system will be.
from the resulting scoring.

Through historical information will be classified the Good and Bad customers according to behavior-based criteria over time.

With those criteria properly parameterized, it becomes possible to develop a computer program that selects clients according to the defined criteria, by searching the customer ledger account.

In general, any customer computer record can provide the historical information needed, over two and three years old.

The correct selection of the population inevitably requires a definition of the criteria which characterize a good and a bad customer. In theory, a good customer is one that a company or institution likes to have and a Bad customer will be one you don't want to have.

These definitions, while true, need to be concise enough to the conclusions drawn there from do not give rise to any doubt as to who analyze. An obvious condition for the development of a scoring system is that the information should be available.

A potential user of a scoring system should be able to identify a1500 Good accounts and 1500 Bad accounts, and should also be able to locate and collect the original applications for those 3000 accounts together with the credit reporting agencies and, if appropriate, consultation with the credit data from Banco of Portugal's Credit Responsibility Center.

Any company that grants credit and is considering developing a credit scoring system should keep all application so that when it comes time to proceed with a credit data is available.

3.3.4 Definition of good and bad accounts

Good and Bad accounts should be defined by criteria that are sufficiently all observers come to the same conclusions about each account. This principle points out that accounts should be defined in terms of how they are of performance.

According to actual data obtained from a confidential source, a classified account Good in a revolving credit operation is that of a customer whose records show that:

At least 1 active account in the last 10 months;

At most 1 delay in the last 12 months;

Maximum of 1 return in the last 12 months;

Profitability and revolving rfm (recency, frequency, monetary) classes 4 and 5;

An average balance of accounts over the last 3 months > = 1,200 €;

Accounts under review without default > = 60 days in the last 24 months;

Billing > = 500 € in the last 3 months.

The condition of having at least one active account in the last ten months and the condition of having an average balance over the last three months of € 1,200 or more still restricts admissible candidates to this category, also removing those whose activity is too low to be meaningful or whose financial involvement is minimal, not meeting the criterion of good account.

According to the same source, a Bad account is a little harder to circumscribe, although the following settings are appropriate:

Accounts that have been in default for more than 4 months, or

Default three times for 60 days in the last 12 months;

Insolvency verified while account is open.

With such criteria it is possible to design a computer program capable of scrutinize an accounting file and identify all other customers who qualify in each of the categories.

3.3.5 Acceptance Rate

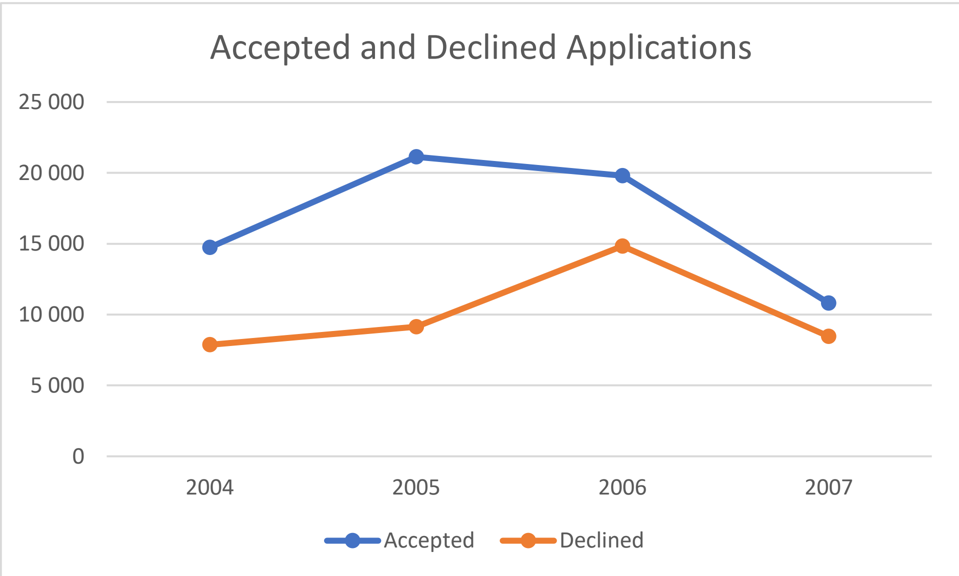
One of the indicators of particular importance for the development of a scoring system is the acceptance rate. This indicator is constructed on the basis of the annual percentage of applications accepted from total proposals received, as illustrated by the actual confidential source data displayed in the Table 3.1. The acceptance fee is not always immediately available and may need to be some prospecting in the database to find it.

Many companies record the acceptance rate by keeping current records of number of accounts accepted and declined.

Actual data from confidential source:

Year	Accepted	Declined	Total of proposals	Acceptance Rate
2004	14 745	7 872	22 617	65.2%
2005	21 131	9 136	30 267	69.8%
2006	19 805	14 835	34 640	57.2%
2007	10 817	8 458	19 275	56.1%

Table 3.1 Number of applications and acceptance rate



Graph 3.1: Evolution of accepted and rejected applications from 2004 to 2007

3.3.6 Calculation of the punctuation in a scoring table

After identifying the characteristics and their attributes and these eventually grouped into classes, we proceed to the next phase. The new step is to prepare a point table called a scoring or scorecard.

Hypothetical example:

Personal characteristics	Attributes	Points
Age	18-23	60
Age	24-25	75
Age	26-28	80
Age	29-34	85
Age	35-46	95
Age	47-51	100
Age	+51	60
Salary income	Up to 500 €	70
Salary income	From 501 to 1500 €	75
Salary income	From 1501 to 2500 €	80
Salary income	+2500 €	90

Table 3.2 Scoring table (partial). Adaptation of Naeem Siddiqi (2006, p.6)

This table shows the number of points that were assigned to each attribute. Second this criterion, all credit applicants with that attribute will, of course, have the same number of points. The sum of the points of all attributes will translate the final score, called a credit score or simply a score.

The identification of the most relevant attributes and their scores will depend on the experience gained and iterative statistical methods leading to the highest score appropriate to each case.

Credit risk rated by a score, as in other predictive models, is method for assessing the level of risk when comparing applicants for credit with existing customers.

However, the scoring system does not identify Good and Bad candidates on a individual assessment but provides the probability of a candidate with a particular score to be Good or Bad.

These probabilities together with other considerations concerning the such as approval rates, profit, recovery effort and losses are then used as references for decision making.

In its simplest form a scoring table consists of a group of statistically determined characteristics which provide for the separation of good accounts from bad. The characteristics of a scoring table can be selected from any data source available at the time of applying for credit.

Examples of sources of such characteristics are: demographic data (age, gender, household family, income, occupation, educational background, nationality, etc.); relationships with third parties (how long have you had a bank account, number of banking products holds in particular: - credit cards, debit cards, home loans, credit leasing, home, car and health insurance, time deposits, savings accounts, retirement savings plan); Bank of Portugal information; agency reports business information; public records; and other information that may be made available for that purpose.

Each attribute is assigned a number of points based on statistical analysis, taking into account various factors such as predictive robustness of characteristics and correlation between characteristics.

The candidate's total score is the sum of the scores of each attribute present in the scoring table. This is the most visible part of a scoring system, however there is a set of reports (3.3.7) which will elucidate in more detail how the scoring system should be.

3.3.7 Reports

According to Lewis (1992, p.104) “the good functioning of a scoring system comes from knowledge about their ability to discriminate between the Good and the Bad credit applications. ”

Knowing that the type of populations changes over time, it is necessary to evaluate the scoring system's reliability to update it with new trends manifested by the permanent evolution / involution of the populations. These updates are based on reports, among which the most common they are:

3.3.7.1 Monitoring

These reports are intended to assure the credit analyst that the score and data entered are correct.

According to the same author's report, at the time of data entry many mistakes have been made and these anomalies should be detected as soon as possible.

This check is called scoring system monitoring and consists of reintroduce the data into the system and compare it with the original results.

There are cases where more than 50% of applications were scored incorrectly after a new scoring system went into operation.

If monitoring is done on a regular and continuous basis, declines can be expected fast and significant errors in the error rate.

One of the most common mistakes made by scoreboard builders with little practice is to ignore or pay little attention to the attributes of the “Position or function that it performs”.

Scores given to the positions or functions that a candidate performs tend to nature to be incomplete given its diversity and meaning of certain functions. Ever an application with a designation of a position or function not known by invariably “sent” to “Other Positions” or “Other Functions”.

When this happens it is necessary to count the number of “other positions and other functions ” compared to the number observed in the original statistics and conclude if it is necessary to consider as a new post certain occupations not considered in the previous system construction.

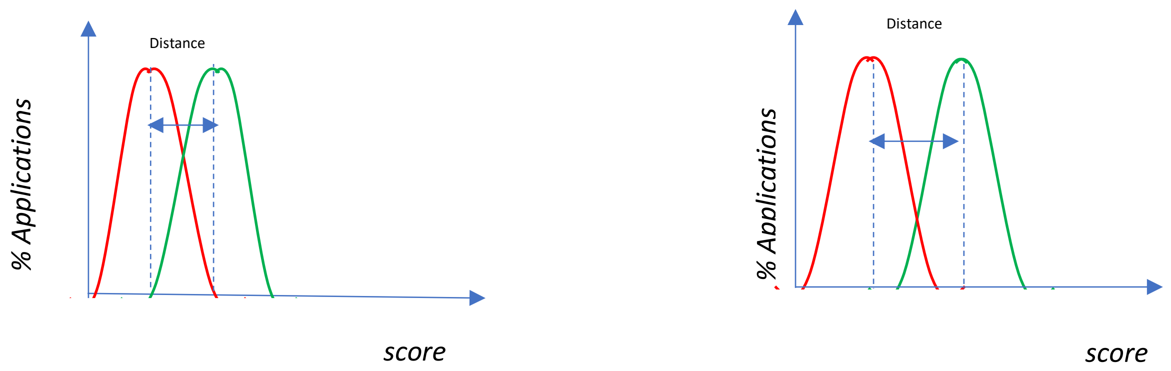
3.3.7.2 Population stability

One question that should always be open when constructing scoring tables is whether the population of recent applications is very different from the original population, ie of the population that served as the basis for the construction of the scoring table in use. If the current population of applications is very different from the original population, the system of scoring becomes less efficient. For this inefficiency many factors contribute to explain the changes in the new admission population. Some of these factors are related to strategies for new customers, particularly in new geographical areas or in sub-areas.

hitherto unknown populations, such as professional associations or Student Associations of certain educational establishments. These differences are all the more pronounced the longer the loan portfolio customers and maintaining the *status quo* that characterizes it. Another source of variation in population are the changes in the economy in general.

If the economy suffers from recession or expansion processes, the number of individuals looking for credit changes both ways. Population Stability Report compares the scores found in the current population with those of the population for which built the scoring system.

The closer these two sets of scores are, the closer you will be to new population of the original.



Graph.n.3.2: Comparison of discriminant power between two scoring systems

When the scoring system is being developed it is intended that the average distribution of the Good accounts is as far as possible from the average distribution of Bad accounts.The robustness measure of the scoring system is given by the distance between the respective distributions.This affection is also referred to in the statistical literature as *Divergence*.

In the case where it is intended to test the proximity of the current population to the original population seeks the opposite, that is, that both distributions are as close together as possible. In this case, the closer the two are greater curves will be the degree of confidence that can be expected from the system.

- Some conclusions on population stability

From the above, it appears that it is necessary to examine the performance of scoring just to be aware of the accounts that have been in the portfolio long enough to show the performance of Good and Bad.

It was also stressed the importance of ensuring that the population of today's candidates should be similar to the population over which the scoring system was since it is necessary to maintain similarity between populations so that the system works satisfactorily.

If in the development of the system there had been differences between the populations not expected, such a situation would alert the credit analyst in due time to possible future problems.

An efficient assessment of the current population versus population over which the system scoring was constructed, it can be done by comparing the distribution of the candidate scores with those that were considered in statistical development.

According to Lewis (1992, p.146), Siddiqi (2006, p.137) and Anderson (2007, p.194) the degree of similarity between the two distributions can be determined by calculating the *Population Stability Index* according to the following formula:

$$Population\ Stability\ Index = \sum_{j=1}^{n}\left\{\left(\frac{c_j}{C}-\frac{d_j}{D}\right)\times\left[ln\left(\frac{c_j}{C}\div\frac{d_j}{D}\right)\right]\right\} \tag{3.1}$$

Where:

c_j is the number of current candidates in the *nth* of a total of n intervals;

C is the total of current candidates;

d_j is the number of members in the development sample in the jth interval;

D is the total number of the development sample.

Table 3.3 illustrates an example of the calculation of the Stability Index of Population:

Score Ranges	Development		Current		A		B	AxB
	Nr Applicants dj	$\frac{d_j}{D}$	Nr Applicants cj	$\frac{c_j}{C}$	$\left\lvert \frac{c_j}{C}-\frac{d_j}{D} \right\rvert$	$\frac{c_j}{C}\div\frac{d_j}{D}$	ln $\left(\frac{c_j}{C}\div\frac{d_j}{D}\right)$	
<160	1 100	0,11	587	0,09	-0,02	0,818	-0,201	0,004
160-179	1 200	0,12	653	0,1	-0,02	0,834	-0,182	0,004
180-189	700	0,07	424	0,065	-0,005	0,928	-0,075	0
190-199	800	0,08	542	0,083	0,003	1,038	0,037	0
200-209	900	0,09	613	0,094	0,004	1,044	0,043	0
210-219	950	0,1	587	0,09	-0,005	0,947	-0,055	0
220-229	1 000	0,1	979	0,15	0,05	1,5	0,405	0,02
230-249	1 500	0,15	1 241	0,19	0,04	1,268	0,237	0,01
>=250	1 850	0,19	901	0,138	-0,047	0,746	-0,293	0,014
Total	D=10 000		C=6 527				Stability Index	0,052

Table No. 3.3: Population Stability Index (Adapted from Edward M. Lewis- An Introduction to Credit Scoring (1992), p.147).

This index measures the separation of two score distributions. Distributions to the represent the Good and Bad accounts show that it is desirable to obtain a high rate of (in the case of divergence) that reflects a strong capacity to differentiate between the two groups of accounts.

In measuring the stability of two populations (that of the candidates and that of the lowest possible index will indicate that the incoming population is stable and that verifies a behavioral similarity in the flow of candidates.

3.3.7.3 Validation

As time goes on, the scoring system must be validated. The procedure that was used at the time of its development may no longer be in use and may have been replaced by new procedures. When this happens the references of the applications that have been rejected, however, accepted applications can be sorted by score. If this sort shows that the higher the score, the higher the values will be.

From the odds it is reasonable to conclude that the system remains effective.

3.3.7.4 Characteristic Analysis

This report compares for each characteristic the percentages of current applicants with the percentages of the candidates at the time the scorecard was built.

An example of a report that can be produced is illustrated, showing that there have been changes in populations.

Illustrative example:

Professional Occupation	% Original Population (1)	% Current Population (2)	Diference (3=2-1)
Retired	10	20	10
Comercial	20	30	10
Technician	35	10	-25
Services	15	20	5
Financial	10	10	0
Others	5	5	0
In blank	5	5	0

Table nº3.4 - Characteristic analysis report. Lewis adaptation (1992, p.148)

For the reasons given above, it is necessary from time to time to compare the flow characteristics of current candidates with those of the original population.

Professional Occupation	% Original Population (1)	% Current Population (2)	Diference $(3 = 2 - 1)$	Points (4)	Difference x Points $(5 = 3x4)$
Retired	10	20	10	40	400
Comercial	20	30	10	35	350
Technician	35	10	-25	30	-750
Services	15	20	5	25	125
Financial	10	10	0	25	0
Others	5	5	0	30	0
In blank	5	5	0	25	0
				Total	125

Table 3.5 - Comparison between the characteristics of current candidates and those of the original population. Lewis adaptation (1992, p.148)

From Table 3.5 the final value of 125 means that an average score of current population is 1.25 points above the average of the original population score.

The characteristic analysis report has value in itself, but it still becomes most useful whenever population stability shows that the current population is significantly different from the original and whenever the credit analyst wishes to know where the differences between populations reside.

3.3.7.5 Failure by score and exposure

The basic proposition made by a credit scoring system is to establish that scores high odds are associated with high odds, while low scores are associated with low. The scoring system is formally valid if it can be shown through a Table 3.9, which shows that the default rate decreases as the score increases, it is possible to distinguish, to some extent, between Good and Bad.

However, it is also important to know how the discriminatory capacity by the current scoring table compares with the discriminating capacity of the scoring at the time the scoring system was built. This comparison can be made through two tables. The first is the table that shows the number of Good and Bad, from the development sample, in each group of score ranges, sorted by growing fear.

Table 3.6 shows, by hypothetical example, a possible distribution of Good and Bad customers at the time the scoring table was developed.

Score	Good	Bad	% Bad
Under 170	138	28	16,9%
170-179	76	7	8,4%
180-189	85	6	6,6%
190-199	94	5	5,1%
200-209	90	4	4,3%
210-219	92	3	3,2%
220-229	93	3	3,1%
230-239	89	2	2,2%
240-249	88	1	1,1%
250-259	90	1	1,1%
260-289	95	1	1,0%
+289	110	1	0,9%

Table nº 3.6- Count in the development sample, by score

Table 3.7 is similar to Table 3.6, but shows the current number of Good and Bad marks in the client portfolio with 12 months old. The easiest way to get this table is to design a computer program that uses as input the file billing master.

Score	Nr.Good	Nr. Bad	% Current Bad	% Bad Develop.
Below 200	106	12	10.2%	
200-209	2690	120	4.3%	10.5%
210-219	2787	92	3.2%	4.3%
220-229	2714	88	3.1%	3.2%
230-239	2571	58	2.2%	3.1%
240-249	2295	25	1.1%	2.2%
250-259	1768	20	1.1%	1.1%
260-289	1291	13	1.0%	1.1%
+289	320	3	0,9 %	1.0%

Table nº 3.7- Number of applications accepted with 12 months old

Note that in Table 3.7, all counts below 200 points are grouped,as these are basically derogations.

The same Table No. 3.7 includes, in the right-hand column, the percentage of Bad from Table 3.6 for comparison. In this case, the two groups of percentage numbers evidence is almost coincident, demonstrating the continued effectiveness of the scoring system.

A more informative table can be obtained by displaying not only the Bad accounts (from according to the definition of Bad used in the development of the scoring system) but also showing accounts with a lower degree of default. In a revolving credit portfolio like a standard credit card, it is also useful to show the number of accounts that have been accepted and the number of keep active. This type of table (hypothetical example, Table 3.8) gives us a more understandable picture of the state of the customer portfolio than the tables referring only the bad accounts.

		Not active accounts	Active accounts Good	Overdue active accounts	Overdue active accounts + 30 days		Overdue active accounts + 60 days		Current Bads		Development Bad Accounts %
Score	Accepted				Qt	%	Qt	%	Qt	%	
<200	2 250	755	1 340	155	84	54.2%	55	35.5%	16	10.3%	10.5%
200-209	82 650	27 561	52 745	2 344	1 627	69.4%	617	26.3%	100	4.3%	4.3%
210-219	105 820	35 276	68 321	2 223	1 606	72.2%	545	24.5%	72	3.2%	3.2%
220-229	90 800	30 270	58 710	1 820	1 378	75.7%	386	21.2%	56	3.1%	3.1%
230-239	107 870	35 959	70 363	1 548	1 251	80.8%	261	16.9%	36	2.3%	2.2%
240-249	155 500	51 827	102 545	1 128	928	82.3%	186	16.5%	14	1.2%	1.1%
250-259	104 360	34 785	68 818	757	660	87.2%	89	11.8%	8	1.1%	1.1%
260-279	71 350	23 781	47 098	471	414	87.9%	52	11.0%	5	1.1%	1.0%
+ 279	17 999	6 003	11 889	107	93	86.9%	13	12.1%	1	0.9%	0.9%

Table No. 3.8- Number of accounts accepted and number of remaining active comparing accounts more current with the Bad accounts at the time of scoring system creation.

If candidate and client populations are reasonably stable, a scoring system can be evaluated through a report showing the default on a customer base by score.

In the simplest form, this report consists of a table showing the rate of non-compliance for each score range from smallest to largest, as illustrated in Table 3.9:

Hypothetical example:

Score Ranges	Default Rate
Below 170	36.5
170-179	16.2
180-189	16.0
190-199	10.4
200-204	9.0
205-209	8.5
210-214	6.7
215-219	6.6
220-224	6.5
225-229	6.4
230-239	3.5
240 and higher	2,1

Table 3.9- Default Rate for each score interval. Default rate decreases as score increases

For this report to be useful, account should be taken only of the accounts they have the same seniority and therefore all of them have had the same exposure to possibility of becoming doubtful.

3.3.7.6 Dynamic Default Report

An important report that can be produced to follow the trail of accounts that presenting similar problems is the Dynamic Default Report. This report shows the default status of account groups that have been charged fo equal periods of time.

This allows management to compare accounts that have been in charge during a period of time, say six months, or any other period wish to select.

The period an account is in charge is called *exposure time*, a since it is the time when the account is exposed to the possibility of becoming a credit of doubtful collection.

3.3.8 Scoring table preparation

The analysis of the initial characteristics that showed greater predictive robustness should be considered for the construction of the final model. At a preliminary stage of the table of scoring various predictive modeling techniques can be used to select that feature set. Some of the statistical techniques most commonly used by credit card issuers credit, are logistic regression, decision trees and neural networks.

In general, the final scoring table produced at this stage should contain between 8 and 15 characteristics, (Siddiqi, 2006, p.88). This is done to ensure the stability of the scoring table should the profile of one or two characteristics have to be changed.

Scorecards with poor characteristics often reveal great weakness of the time factor because they are likely to lose their ability to discriminate because of minor variations in the profile of existing candidates and clients. Regardless of the modeling technique used, this process should produce scoring table consistent with the best combinations found among the taking into account some special situations, such as: correlation between characteristics; final predictive robustness of scoring table; interpretation characteristics by the staff of the adjudication department; ease of implementation; and transparency of the methodology to legal requirements.

3.3.8.1 Risk profile

According to Siddiqi (2006, p.88) scoring tables can be designed according to the its later application. In terms of their functionality scoring tables should be designed to replicate a credit analyst's decision criteria. An experienced professional will never observe just four or five characteristics of accession proposal or will focus on only a few of the historical records from a client to make a decision. You will most likely observe a set of key information to identify a risk profile. Therefore, you will be asked why the scoring tables only include four or five characteristics? The answer seems obvious: - The purpose of the process of the development of a scoring table is the construction of a risk profile that is understandable, about a particular customer and, at the same time, efficient.

This basic understanding not only contributes to the making of scoring tables with predictive ability but will also make them more stable and less vulnerable to any changes that may occur in a specific area.

A risk profile should include characteristics that represent so many typologies of different data as possible. For example, considering a scoring table in credit card activity should include demographic data such as age, type residence, area or region where you live, time in your current job, some information about other sources that identify its heritage, namely through the Land Registry, Automobile Registration or any other property it holds; behavior in the attendance of payments; any public records; financial standing and other information which, in the circumstances, are included in its register.

The concept of risk profile will also assist in subsequent monitoring of the risk table scoring and make it more relevant and valuable. According to confidential information, most analysts would like to obtain monthly reports on “system stability” or “population stability” for confirm the validity of the scoring table in use in both membership applications and existing accounts.

What these reports actually produce is only the changes population, as defined by the scoring table characteristics. A scoring table broadly based on the risk profile would be more realistic by constantly capturing changes in the population than those indicating artificially the change or stability of their populations.

Building a scoring table based on the risk profile is, in theory, no different from any other predictive model, with only the difference in the method of selection of the set of final variables.

3.3.8.2 Scoring table design

The construction of a scoring table that considers the regression model all characteristics may produce results that are not optimal in terms of operative. Although any scoring table builder has confidence in developed model, in view of the statistical tools used, there are however some business objectives that also need to be considered when scoring table development.

The first objective is to choose the best feature set and build the profile more in line with the institution's policies. Ideally, the risk profile should be be constructed using as much independent data as possible, such as demographics, financials, business and banking information, behavioral trends of payments, etc.

The development process should include statistical rules such as correlation and collinearity and other factors that negatively affect the reliability of the own model.

The developed scoring table should be consistent with the decision support structure of the organization. If the model is the sole criterion of agency, it becomes even more concerned with the need to create a risk profile consistent with current credit policies.

If the credit institution is using a computer system to support the decision, then the characteristics to include in the scoring table should be in line with other policies and rules in force.

The scoring table builder has several methods by which it can influence the final scorecard performance. Those methods consist of overvaluing some manipulating regression to maximize the probability of some of them may fit into the final model.

Regression uses various combinations of characteristics at different stages and with significance levels, thus obtaining even greater predictive robustness. These scoring tables are subsequently evaluated by the business's own criteria and by the combination of characteristics and statistical measures used in the reliability of the model.

3.3.8.3 Calculation of scale graduation

The logistic regression model allows a score to be obtained by quantifying the values of the explanatory variables X_i by multiplying by a numerical coefficient β using the equation:

$$logit\ (p_i) = Score = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (3.2)$$

This score is graded on a neperian-based logarithmic scale that is not easy interpretation. To overcome this difficulty, the score becomes a linear scale. To obtain this scale multiply the score by a factor equal to the number of points to be attributed to the scale graduation divided by ln (2) .

Let's take as an example that we want to scale the scale so that from 20 by 20 points the odds double. In this case, we would have to do the following calculation:

$$\underbrace{(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}_{\text{score}} \times \left(\frac{20}{\ln(2)}\right) \qquad (3.3)$$

However and in the present context we intend to relate Odds and Scores, so that Odds are doubled every 20 points leading to the following linear transformation:

$$Score \ = \ "Offset" \ + \ Factor \ \times \ln(odds) \tag{3.4}$$

When the scoring table is being developed using specific odds in a particular score and "*points to double specific odds*" (pdo), *factor* and *"offset"* can be easily calculated using the following system of equations:

$$\begin{cases} Score \ = \ Offset \ + \ Factor \ \times \ln \ (odds) \\ Score + pdo = Offset + Factor \times \ln(2 \times odds) \end{cases} \tag{3.5}$$

Solving the system of equations above to determine the *pdo*, we get::

$$Score \ = \ Offset + \ Factor \ \times \ln \ (odds)$$

$$Score = Offset + Factor \times \ln(2 \times odds) - pdo \tag{3.6}$$

That is:

$$Offset" + \ Factor \ \times \ln \ (odds) = Offset + Factor \times \ln(2 \times odds) - pdo$$

$$Factor \ \times \ln \ (odds) = Factor \times \ln(2 \times odds) - pdo$$

$$pdo = Factor \times \ln(2 \times odds) - Factor \ \times \ln \ (odds)$$

$$pdo = Factor \times [\ln \ (\ 2 \times (odds) - \ln \ (odds)]$$

$$pdo = Factor \times \big((ln2) + \ln(odds) - \ln(0dds)\big)$$

$$pdo = Factor \times \ln(2)$$

$$Factor = \frac{pdo}{\ln(2)} \tag{3.7}$$

$$Offset = Score - \ [Factor \ \times \ln \ (odds)] \tag{3.8}$$

For example, if the scale of a scoring table were to be graded, where the user wanted 50: 1 odds at 600 score points and wanted the odds doubled every 20 points (i.e. pdo = 20), the Factor and Offset would be:

$$Factor = \frac{pdo}{\ln(2)} = \frac{20}{\ln(2)} = \frac{20}{0{,}69315} = 28{,}8539$$

$$Offset = 600 - [28{,}8539 \times \ln(50)]$$

$$= 600 - (28{,}8539 \times 3{,}91202)$$
$$= 600 - 112{,}87712$$
$$= 487{,}12288$$

$$Score \; = \; Offset + \; Factor \; \times \ln \; (odds) \tag{3.9}$$

$$Score \; = 487{,}12288 + 28{,}8539 \times \ln(odds)$$

As expected the score obtained for the imposed conditions would be:

$$Score \; = 487{,}12288 + 28{,}8539 \times \ln(50)$$
$$Score \; = 487{,}12288 + 28{,}8539 \times 3{,}91202$$

$$Score \; = 487{,}12288 + 112{,}87712$$
$$= 600 \, points$$

The same formula can be used for undergraduate scoring tables that triple or quadruple odds. However, "points for doubling odds" (pdo) is the rating commonly used in the area of credit risk assessment.

3.3.8.4 Choice of scoring table

Most scoring table builders produce for a given customer two or three different models in order to choose the one with the best quality. This quality is not always consensual, requiring statistical tests to ensure the best possible effectiveness against the intended objectives.

The question for a builder is whether the application of the scoring tables is scoring well, that is, properly classifying credit applicants as Good or as Bad.

Those scorecards being constructed to predict the probability of a case being Good or Bad are no more than predictive tools used to differentiate (or discriminate) between Good and Bad cases.

For this purpose specific statistics are used to test that discriminating capacity. However, such discrimination in credit risk analysis is not 100% effective because there is always the possibility that a Good candidate will be classified as Bad and vice versa.

Credit analysts are the ones that best confirm this reality, adding a minimum level of acceptance rate of Bads (based on a score) based on the cutoff that serves as the boundary between good and bad (cutoff).

Applicants who for negative information, non-compliance or those who provided false information about your application score below the cutoff and therefore they are refused.

The final scoring table will be the one that offers the best indications about the minimize rating level minimization. To compare the quality of different tables there are several scoring measures used to measure the Bad rankings level.

These measures compare the number of true Good and Bad (ie the current classification of each client) with the number of Good and Bad predicted by the classification of the scoring table for a given cutoff.

That is, there will be a number of really Good cases that would have been probably classified by the scoring table as Bads and vice versa. Here, Good and Bad refer to cases above and below the cutoff in reference.

It is agreed that the classifications provided by the table cutoff criterion of points would be designated by ***g*** for the Good and ***b*** for the Bad.

Similarly, the capital letter G for Good and the letter B for the Bad which corresponds to the *current* classifications or the observed classifications for each client. Once the meanings of each letter are agreed upon, the measures of classification, based on a confusion matrix, as follows:

		Rating Preview (scorecard)	
		good	bad
Current Rating customers	Good	Gg	Gb
	Bad	Bg	Bb

Table No. 3.10 - Confusion Matrix 1

The matrix elements are made up of the combination of a 2 X 2 table.

It remains for us to interpret the meaning of each of them:

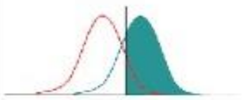
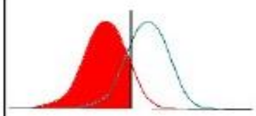
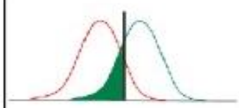
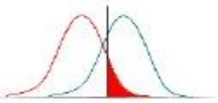
Gg	It means the scoring table predicted to be a good account and observed to be a good account. We will designate this case as ***True Positive***	
Bb	It means that the scoring table predicted to be a bad account and observed to be a bad account. We will designate this case as ***True Negative***.	
Gb	It means that the scoring table predicted to be a bad account and It turned out to be a good account. We will designate this case as ***False Negative*** .	
Bg	It means the scoring table predicted to be a good account and It turned out to be a bad account. We will designate this case as ***False Positive***.	

Table Nr 3.11 - Meaning of Confusion Matrix Classifications

Summarizing in the following Confusion Matrix:Table 3.12

		Rating Preview (scorecard)	
		good	bad
Current Rating customers	Good	***True Positive***	***False Negative***
	Bad	***False Positive***	***True Negative***

This matrix allows in a very simple way to evaluate the predictive capacity of a scoring table calculating the percentage of accounts that were correctly classified. The correctly ranked percentage is calculated from this matrix to:

1) Choose a particular cutoff score;

2) Mark all accounts below the cutoff as probabilistically Bad, and those above the cutoff as being probabilistically Good;

3) Cross tabulate the good (g) and bad (b) accounts provided by the scorecard and Good (G) and Bad (B) accounts classified by observation;

4) Determine the percentage of beads within each cell;

5) Calculate the various ratios that may result from the model.

Correctly classified cases are True Positive and True Negative. Cases that have not been correctly classified will be referred to as False Negatives (Type I Error) and False Positives (Type II Error). From the empirical study presented in Chapter 4 we took the data below (Table 3.13) as an illustrative example:

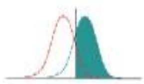
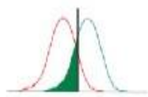
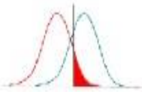
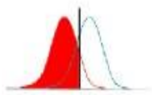
		Predicted Scorecard Rating	
Current Classification	Good	True Positive 1474 	False Negative 167 
	Bad	FalsePositive 126 	TrueNegative 1433 

Table 3.13 Expected versus Current Rating

A high quality scoring table would be one that maximizes "True" cases and minimize "False" cases. For this purpose four measures were used to determine the bad rating: Hit Rate, Error Rate, Sensitivity and Specificity of the scoring table.

Hit rate	$\frac{True\ Positive\ and\ Negative}{Total\ cases}$	$= \frac{1474 + 1433}{1433 + 126 + 1474 + 167} = \frac{2907}{3200} = 90{,}84\%$
Error rate	$\frac{False\ Positive\ and\ Negative}{Total\ cases}$	$= \frac{167 + 126}{1433 + 126 + 1474 + 167} = \frac{293}{3200} = 9{,}16\%$
Sensitivity	$\frac{True\ Positive}{Total\ Positive\ (TP + FP)}$	$= \frac{1474}{1474 + 126} = \frac{1474}{1600} = 92{,}13\%$
Specificity	$\frac{True\ Negative}{Total\ Negative\ (TN + FN)}$	$= \frac{1433}{1433 + 167} = \frac{1433}{1600} = 89{,}56\%$

Table No. 3.14- Four measures to determine poor rating: Hit Rate, Error Rate, Sensitivity, and Specificity.

True Positive (True Good)	→	Acceptance of Good
False Positive (False Good)	→	Acceptance of Bad
True Negative (True Bad)	→	Rejection of Bad
False Negative (False Bad)	→	Rejection of Good

Table 3.15- True positives, False positives, True negatives and False negatives

On the basis of the above four measures a financial institution may decide, for example, to maximize the refusal of bads. In these cases where scoring tables are built to reduce losses caused by poor ratings, the company would choose to scoring table that maximizes *specificity*.

In the event that the company intends to increase its market share and admits approve some Bads, you can minimize Goods refusal by choosing the scoring table that maximizes sensitivity. Here statistics are used in the context of the objectives with which the scoring table will have to be in agreement. This measurement of management tools to business policies is in itself a major objective for the development of organizations.

3.3.9 Predictive Capacity of a Scoring Table

The vast majority of statistical results obtained from databases in the area of credit risk is used for comparative purposes and to minimize problems bad account rating. The predictive robustness of scoring tables is the result of applying these statistics responsible for the performance capacity achieved. In some cases scoring tables used in the past or those in use are compared with other newer build tables. Variations are never so abrupt as to determine the total uselessness of a day-to-day scoring system.

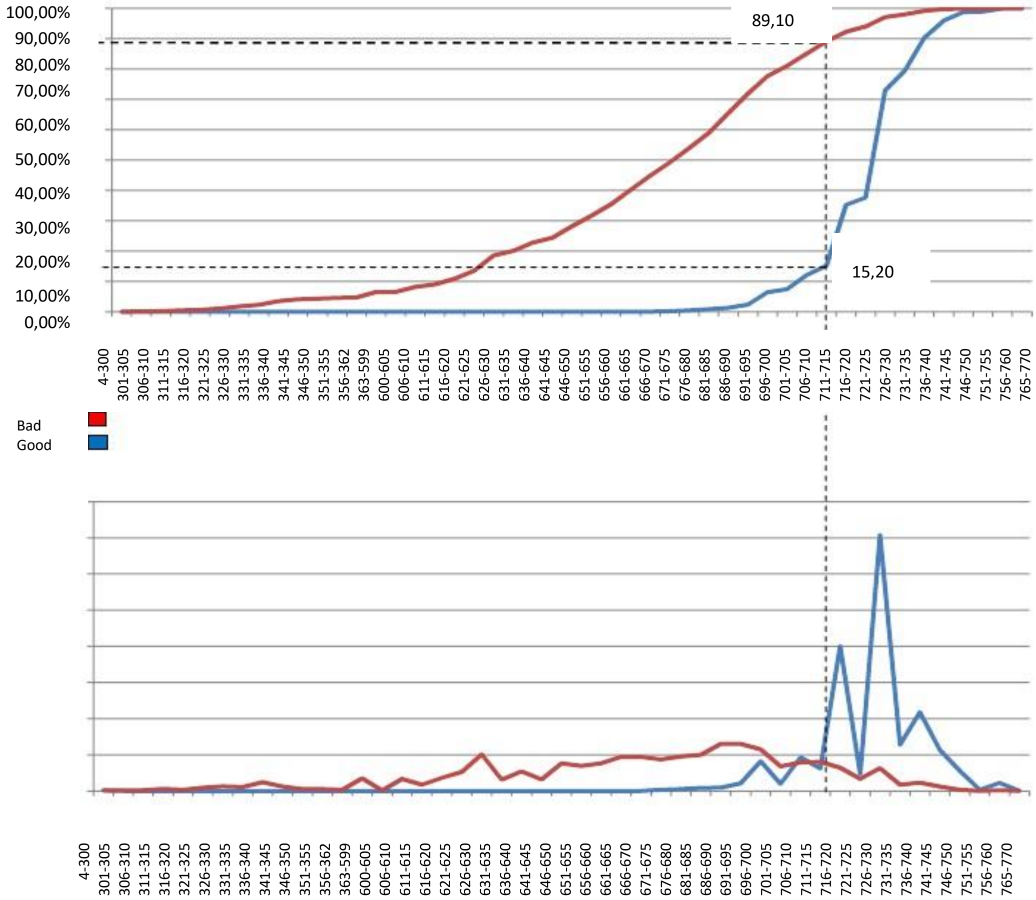
On the other hand, several changes are not recommended at the same time without confirm in advance the system-wide effect of each of these changes in marketing strategies, customer profiles, and other data will make pointless to compare scoring tables produced under these conditions with any other still in force.

Scoring tables should be developed on the assumption of concentrating the better indicators regarding the present data. Some companies use both the new scoring table as the existing scoring table to score an account group until you check which one is the best. If the current scoring table is not stable this exercise is completely irrelevant, because the instability of one of them may in certain cases coincide with the score of the other, as totally diverge.

If a scoring table is so unstable that no comparison is possible could mean that it probably never would have been before and its weaknesses only if checked much later.

3.3.9.1 Statistics Kolmogorov-Smirnov (KS)

This statistical method measures the maximum vertical distance between the distributions of the accumulated frequencies of good and bad. The weakness of this method is that the separation between the two distributions be made at the point of greatest distance from your curves, which may not coincide with the recommended cutoff. If the desired scoring table cutoff is placed to the right or further to the left, this method may not guarantee a good indication of comparison. In these cases it may be preferable to compare the distance at the desired cutoff as it is at this point where maximum separation is required.



Graph was obtained according to the sample data that served as the basis for present investigation, which are transcribed in Table nº3.17

The maximum vertical distance observed was 73.9% of distance between the curves of cumulative distribution of bad and good and which corresponds to the difference between the percentages 89.1% and 15.2% respectively.

If it were assumed that this would be the point where the cutoff would be positioned, ie midpoint of the range of scores 711-715 would sacrifice 15.2% of Good customers to reject 89.1% of the Bad.

	Cutoff	
	Rejected	Accepted
Bad	89,1 %	10,9 %
Good	15,2 %	84,8%

Table No. 3.18- Cutoff Matrix

Table nº3.17

Score	Good	Bad	%Good in T.Good	%Bad in T. Bad		%Accunul.Good	%Accunul.Bad	%Distance.B-G
4-300	1	1	0,05%	0,05%		0,05%	0,05%	0,00%
301-305	0	1	0,00%	0,05%		0,05%	0,10%	0,05%
306-310	0	2	0,00%	0,10%		0,05%	0,20%	0,15%
311-315	0	6	0,00%	0,30%		0,05%	0,50%	0,45%
316-320	0	3	0,00%	0,15%		0,05%	0,65%	0,60%
321-325	0	9	0,00%	0,45%		0,05%	1,10%	1,05%
326-330	0	13	0,00%	0,65%		0,05%	1,75%	1,70%
331-335	0	11	0,00%	0,55%		0,05%	2,30%	2,25%
336-340	0	24	0,00%	1,20%		0,05%	3,50%	3,45%
341-345	0	12	0,00%	0,60%		0,05%	4,10%	4,05%
346-350	0	5	0,00%	0,25%		0,05%	4,35%	4,30%
351-355	0	5	0,00%	0,25%		0,05%	4,60%	4,55%
356-362	0	3	0,00%	0,15%		0,05%	4,75%	4,70%
363-599	0	35	0,00%	1,75%		0,05%	6,50%	6,45%
600-605	0	1	0,00%	0,05%		0,05%	6,55%	6,50%
606-610	0	33	0,00%	1,65%		0,05%	8,20%	8,15%
611-615	0	17	0,00%	0,85%		0,05%	9,05%	9,00%
616-620	0	36	0,00%	1,80%		0,05%	10,85%	10,80%
621-625	0	53	0,00%	2,65%		0,05%	13,50%	13,45%
626-630	0	101	0,00%	5,05%		0,05%	18,55%	18,50%
631-635	0	31	0,00%	1,55%		0,05%	20,10%	20,05%
636-640	0	54	0,00%	2,70%		0,05%	22,80%	22,75%
641-645	0	32	0,00%	1,60%		0,05%	24,40%	24,35%
646-650	0	76	0,00%	3,80%		0,05%	28,20%	28,15%
651-655	0	69	0,00%	3,45%		0,05%	31,65%	31,60%
656-660	0	76	0,00%	3,80%		0,05%	35,45%	35,40%
661-665	0	94	0,00%	4,70%		0,05%	40,15%	40,10%
666-670	0	94	0,00%	4,70%		0,05%	44,85%	44,80%
671-675	3	87	0,15%	4,35%		0,20%	49,20%	49,00%
676-680	5	95	0,25%	4,75%		0,45%	53,95%	53,50%
681-685	8	100	0,40%	5,00%		0,85%	58,95%	58,10%
686-690	9	130	0,45%	6,50%		1,30%	65,45%	64,15%
691-695	21	130	1,05%	6,50%		2,35%	71,95%	69,60%
696-700	82	115	4,10%	5,75%		6,45%	77,70%	71,25%
701-705	20	68	1,00%	3,40%		7,45%	81,10%	73,65%
706-710	93	79	4,65%	3,95%		12,10%	85,05%	72,95%
711-715	62	81	3,10%	4,05%		15,20%	89,10%	73,90%
716-720	401	64	20,05%	3,20%		35,25%	92,30%	57,05%
721-725	47	34	2,35%	1,70%		37,60%	94,00%	56,40%
726-730	708	63	35,40%	3,15%		73,00%	97,15%	24,15%
731-735	128	17	6,40%	0,85%		79,40%	98,00%	18,60%
736-740	218	23	10,90%	1,15%		90,30%	99,15%	8,85%
741-745	113	12	5,65%	0,60%		95,95%	99,75%	3,80%
746-750	56	3	2,80%	0,15%		98,75%	99,90%	1,15%
751-755	3	0	0,15%	0,00%		98,90%	99,90%	1,00%
756-760	22	2	1,10%	0,10%		100,00%	100,00%	0,00%
	2000	2000	100,00%	100,00%				

However, these rules do not obey exclusively a statistical logic, but also to business strategies defined in the respective internal policies. Although in the example shown the cutoff could be placed on scores In this case, the scoring table should be compared with inquiring into company policies the reasons that led her to abdicate 15.2% of Good customers as a safeguard against 89.1% non-acceptance (refusal) of Bads.

In theory, positioning this boundary may seem simple. If profit is damage from Good and Bad accounts are known then it is simple to calculate the profit for the percentage of Good accounts that is required to cover the costs caused by the bad accounts.

In this perspective, the ratio between the percentage of Good accounts and the percentage Bad Accounts defines the odds at which the incremental gain equals the loss incremental and the score associated with that odds will be the recommended cutoff.

However, in practice it is not that simple because the true profit of a Good account and the real damage of a bad account are very difficult to determine. One of the reasons for this difficulty are the trade policy adopted, the market competition, changes in internal credit policies,existing ultimately. This forces slight cutoff shifts, either left or right, in function of all the conditions mentioned. This does not mean, however, that sudden changes sometimes without the necessary common sense, prudence and balance that critical point requires. Experience advises that the initial cutoff of a scoring system be close to or same as before, ie close to the acceptance rate in the last two to three years.

3.3.10 OVERRIDES - PREVALING DECISIONS

Several authors have mentioned in their works the importance of decisions made by analysts which contradict the guidance given by the scoring system (Lewis, (1992, p. 89);

Mays, (2001, p.293); Thomas, (2002, p.144); Siddiqi, (2006, p.158); Anderson, (2007, p.82). Among the testimonies of those researchers are practices and understandings about the decisions that prevail over the scoring system guidelines and which highlight some of this evidence and understanding. The cutoff score establishes the rule in which the punctuated accounts on your right are accepted and the your left are refused. Any decisions taken in the granting of credit other than follow the criteria defined by that boundary are called overrides.

Override thus translates into decision making that is contrary to the recommendations of the scoring system. That is, no loan is granted to a customer, although the score is above the cutoff point or loans are granted to those whose score is below the cutoff. These situations may occur because the financial institution has more information than the one in the scoring table or because company policy so determines, or because they were due to a subjective assessment of the credit analyst.

Thus, there are three types of overrides: 1) Based on information; 2) Based on the credit institution policies; and 3) Based on the credit analyst's intuition.

3.3.10.1 Information-Based Overrides

A credit analyst who is in possession of occasional or other information that is notconsidered in the evaluation process, your decision on the recommendation dictated by the scoring system. Information-based overrides that contradict the scoring system criteria they are rare. It is uncommon for a credit analyst to recognize the identity of the person whose application has under consideration and also have specific information about that applicant.

Although very rare, these situations may occur. In this sense, the credit department should be alert to take account such eventualities. In any of the situations, and according to the authors mentioned in 3.3.10, the credit analyst should always make a written record of the facts that justified the decision made. In cases where applications with cutoff scores are accepted, can be analyzed later and see if the decision made by the credit analyst was right.

3.3.10.2 Overrides based on institution policies

Such decisions occur when management establishes special rules for certain applications. Overall, institutional policy-based overrides act applications that were rejected when they were only support the information given by the score.

If a company decides to stimulate a particular target group of potential customers, can grant that specific group, for example 10 additional points, during a certain promotional period. For example, if the Administration admits that students from a university may bring, in the near future, good results for the will accept those students, even if at that time their score does not allow it.

It is a strategy of customer loyalty whose peculiar future status is that of interest of the credit institution. Overrides based on institutional policies are frequent when granted credit to applicants who do not reach the sufficient score. However, they may be good customers in other financial institutions.

This is the most common case in national banks with the attribution of credit cards to customers who already have a current account or other interest to the banking institution.

However, decision prevalences should not be automatic but should be framed written policies, duly explicit, and not in an appeal that can be applied subjectively by any credit analyst. People's relationships with their banks must be carefully special an individual may have a personal account with a small balance and be the manager or manager of a company that owns an account with that bank moving amounts very high.

It is not wise to consider refusing a personal credit card to an individual, in this situation, although your balance is very small and you do not have any other products. Common sense dictates in these cases to grant you a credit card even if the your score is below the cutoff. Other examples may be given about policy-based overrides. institutional It is the case that the credit institution's management decides to grant credit cards to all managers of a particular company who request it, even if not all managers are elected to obtain it.

There are multiple strategies that anticipate decision making contrary to the scoring system recommendations. The important thing to keep in mind is to avoid that these decisions are subjective and taken without the necessary foundation.

3.3.10.3 Overrides based on credit analyst intuition

Such decisions are the most common and least justified. It occurs when a credit analyst reverses the decision recommended by the score for reasons other than based on institutional policies or loose information. This inversion is usually made to decline a credit request.

For reasons that the analyst himself sometimes cannot explain, he considers that the application is “weak”, telling him that it will be unwise to grant credit to that candidate.

Otherwise it is also possible considering a “strong” candidacy despite translate a score below the cutoff. In either case the analyst almost always cannot explain his decision unless be invoking your conviction, supported by your experience. In fact, the analyst says that his experience applied to that particular case resulted in a more accurate decision than the recommendation of the scoring system implemented in the organization.

Also for reasons they can't explain, most credit managers allow their analysts very liberally to make decisions contrary to the scoring system recommendations, based on your intuitions and beliefs. Some credit managers give their analysts freedom and authority to exceed standard limits within certain scoring ranges, ie give you the freedom to increase or decrease the cutoff value by 5 to 10 points.

It is in the vicinity of the cutoff that the scoring system is most critical and valuable. The difficulty of the decision will not be certain to grant credit to those who are 100 pointsabove or refuse credit to anyone who is 100 points below the cutoff. It is in the vicinity of this point is that the scoring system demonstrates its effectiveness.

Permission to make decisions contrary to those established is sometimes justified by the analysts themselves who complain that their professional experience would be worth nothing if his personal contribution to risk reduction could not be manifested. These analysts want to be seen as useful and thus protect their that is, the fact that they have to accept all the recommendations of an automatic system scoring could possibly question the need for its existence. In many cases, the prevalence of intuition decision is allowed, more so to maintain morale of those people, than to bring better consistency to the scoring system. The way around this delicate situation is to redefine the role of the analyst, assigning you the task of verifying and validating your own decisions.

3.3.11 CUTOFF SCORE CHANGES

According to Lewis (1992, p.113), after the installation of the system any credit analyst or user of the scoring system should be prepared to adjust the cutoff when checking that the refusal rate is very different from the initial predictions. Also according to the report of that author (ibidem), during the development of the system data may reveal that a cutoff score at 200 points results in 40% refusals, this number can be chosen as the initial cutoff. After one month, or after a significant number of applications have entered,

For example, the refusal rate is only 35% or increased to 45%. If the distribution of scores is identical to the original sample, the refusal rate is reached. through a slight change in the cutoff.

Still according to Lewis (ibid) it is not necessary to make many adjustments to the score of the cutoff to get the desired result. In these circumstances it is necessary to examine the cutoff after the scoring system had been in operation for a few months and there had been sufficient time for changes in social conditions and direct or indirect influence on the operation of the credit institution.

A credit manager wishing to reduce the risk should in this case increase the cutoff by amount of points that the statistic suggests. Alternatively, another credit manager want to accept a higher risk you must, of course, accept a cutoff reduction.

From time to time, a credit manager modifies the cutoff score to achieve a specific purpose. For example, you may decide to attract a particular future target group clients such as university students or reach specific groups of individuals who have not yet expressed a particular interest in the credit institution's offers. In such cases, the credit manager may choose a different cutoff from that established for attract customers in a specific market, while recognizing that there is always a cost when adopting these strategies.

Creditors should not change their cutoff score as a reaction to the change external conditions without careful analysis. Credit institutions are not unheard of consider changing their cutoff scores when the economy turns around unexpected. In these cases, the credit bureau would have considered that it should “fasten its seat belt” by the cutoff, thus avoiding some damage. In this attitude there are two errors:

- The first mistake is a cutoff change that however drastic it may be will affect new applicants, doing nothing to improve the quality of current accounts. Any change in the cutoff will not be reflected in the quality of the global population of customers until the open accounts under the new cutoff model significant percentage of the entire population, which can take a long time to happen.

- The second error manifests itself by altering (especially in raising) the cutoff before the evidence of an economic crisis, which is not necessarily true that this has any effect on the customer population.

The push to raise the cutoff is based on the idea that the risk measured by the system scoring advises so, due to the change in the economy. This idea is not seems right because when an economic crisis happens people don't open credit accounts suddenly on the assumption that they cannot pay them off.

The economy shows that when a crisis arises, the volume of applications drops, because people take more precautions in the face of uncertainty.

The cutoff score should never be changed on the assumption of dressing for a supposed malfunction of the scoring system. No cutoff changes will improve a “poorly designed” scoring system; what needs to be done in such a case is to develop a completely new scoring system.

3.4 BEHAVIORAL SCORING

According to information of a confidential nature obtained and from practices of FICO (Fair & Isaac, Co), individuals accepted by financial users as credit card users thereafter become analyzed and monitored for their behavior.

An individual's behavior is defined in terms of volume of purchase and punctuality From related payments, passing to be designated by Behavioral Scoring scores given to those characteristics. This methodology was first implemented by Fair, Isaac and Company in the late 1960s. The methodology applied to the development of a behavioral scoring system is almost the same as that used in producing an attribution scoring system, but the way data are prepared for use is quite different. The difference lies that the accounts to be used for behavioral scoring are, obviously among those who already have a track record, while accounts accepted in the scoring of assignment have no previous records. As in the case of an attribution scoring table it is necessary to obtain a Good and Bad set. In this case, the accounts to be used are, obviously among those who already have a track record. By carrying out an analysis of the current master file of the financial institution, identify a set of accounts that meets the definition of Bad and another that satisfies the Good definition. As in the case of attribution scoring the Good and Bad definitions must be objective, so that a computer program able to identify them.

The objective is to determine from known data over a certain period of time, what is the risk of an individual defaulting at a later time. Unlike an assignment scoring system, the scoring table can be applied monthly, as part of the billing during which each account is examined, making it possible to detect any changes in the risk position. The described procedure allows to develop a behavioral scoring system provided that the information contained in the invoicing system master file is sufficient, the that does not always happen, making it impossible to follow that procedure. A more common practice is to start by planning a master file format that contain the kind of information that is required to make such a system.

In many cases, a financial institution knowing that it will adopt sooner or later behavioral scoring starts by getting the right files with great advance, making scoring table construction much faster than it would have beenif you have to wait for the sample to be created. Once a master file is planned and installed data begins to accumulate. When sufficient data are available (usually collected over a period of ranging from 6 to 24 months), the “moment zero” is declared and time starts counting from of this moment. About six months later (observation period) it is possible to identify some accounts as good and some as bad. If there are enough accounts each, the system the scoring data can be constructed based on the master file data.

According to Allen Jost (1998) when building a scoring model an analyst uses historical data for each individual in the development sample. In the simplest case, a point in time or “observation point” is selected after 6 months to 2 years. The known information about the individual at this point is used to predict the future performance. Because the vantage point is in the past, “future” performance.The so-called “exit period” is used to evaluate the effectiveness of the scoring model. The historical construction period is used to develop the forecast variables in the score model. Once a credit model is built the accounts are scored “Today”, that is, on the date the credit was requested. In the areas of revolving credit, scores constructed to evaluate new accounts are called whether application or attribution scores and those constructed to predict the type of future performance of existing accounts are referred to as behavioral scores (behavior scoring), as already mentioned above.

Several approaches are used in the construction of the sample on which to base the scoring system. One is to use the entire account portfolio and build the system about accounts that turned out to be good at “moment zero” but were split between Good and Bad in the “observation period”.

Another approach is to use only the subset of the old accounts which, at zero ”, have reached the first level of default. In some cases, that level may be five days late, another thirty days or more. Although the behavioral scoring system is constructed in this way, the result final is a scorecard that can be deployed in the billing system that will calculate the risk of it becoming a Bad account in the near future.

3.4.1 GOOD AND BAD ACCOUNTS IN REVOLVING CREDIT

According to a confidential financial institution report, a Good Account in revolving credit can be characterized through billing records and other files of the company in which there are some elements to classify it as such. As a hypothetical example: - the account has been open for over 18 months; have had 6 months of activity in the last 10 months; have made movements of at least 100 € in at least 3 months in the last 18 months; no 30-day late payment records past 18 months, among other conditions that had been established for the definition of of a good account.

A bad account is more difficult to describe because even though the delay is not in payment these bills are the most taxed in interest, by default, and therefore most profitable on the one hand, but at greater risk on the other.

According to Siddiqi (2006, p.38) the definition of a bad account is based on several considerations such as:

a) The definition must be in accordance with the objectives of the organization and the purpose for which the scorecard was built, ie based on quantitative variables, namely those defining the amounts of the debt; the number of days late; The time after which a debt must be written off.

b) The definition must be easily interpretable and explicit by parameters such as “whenever debt is 90 days past due”, “whenever 30 days late three times in a year ”;

According to the same author, companies can classify an account as Bad with accounting criteria or in accordance with the credit policies adopted.

An account rated Bad may be profitable for the financial institution if offer little risk. This is the case of customers who always pay with considerable delays, due to negligence or forgetfulness of the due dates of the obligations. With the above criteria and definitions it is possible to develop software to scan the invoice file and identify all accounts integrate into each of the groups.

However, it should be noted that these definitions should be consistent with the organizational objectives of the company ie credit policies should be established according to the company's objectives by defining the rules ... which guarantee the pursuit of those goals (Batista, 2004, p.67).

In some cases it is convenient to have coherent definitions between the various tables of scoring used in the company. This precept enables more uniform, coherent and especially in companies with different strategic business units in which different scoring tables are used.

Associated with Bad Account definitions must be graded scales with reducing training and programming costs in redesigning scoring.

The Basel II Accord is a good example of these “bad” assumptions considering all bank accounts with delays exceeding 90 days, taking a pragmatic position defining the different segments of economic activity as “risk pools” homogeneous".

This segmentation can be performed by statistical grouping techniques (clustering) that identify groups that are similar to each other. In most Portuguese companies the definitions Bad / Good accounts are not written in the credit policies, when they exist, classifying as Bad Account, only information provided by the ancient map of balances, whose reporting time horizon rarely exceeds 6 months.

3.4.2 BEHAVIORAL SCORING IN PRACTICE: ADAPTABLE CONTROL SYSTEM

Behavioral scoring is useful in many decision areas related to a credit operation and may be used in conjunction with a more complex structure Adaptable Control System.

This structure (ACS) has given a new impetus and precision to Behavioral Scoring by rapid adaptation of the customer profile to billing strategies, the definition of credit card suspension, among other strategies that experience has established.

The Adaptive Control System thus became able to differentiate between among the various accounts, those that allow Credit Management to apply the their strategies according to the different risk groups with great precision.

3.4.3 ADAPTABLE CONTROL

Behavioral scoring itself is a powerful tool and it becomes even more powerful when integrated into a system that can examine strategies credit control alternatives, namely collections strategies, which can be adapted to various situations. Such a system continuously seeks the best set of lending and recovery strategies.

Credit scoring for both application scoring and assessment of payment behavior of existing customers (behavioral scoring) may be a key component in determining the credit policy. Once the objective credit policy is established, a computer program capable of implementing all policy components that do not require human intervention. Once a strategy has been adopted it is pertinent to question whether will be the best to achieve a certain goal.

Without the existence of a system that allows the application of various strategies, in day-to-day lending operations, it becomes extremely difficult to apply two competing strategies to find out which one is the best.

Adaptive Control System makes it possible to evaluate alternative strategies allowing two (or more) credit strategies to work simultaneously any credit decision area. ACS also enables the performance of each strategy are quantified, allowing them to be compared.

The computer program designed for this purpose should be programmed to deploy new strategies and remove or modify the old ones without the need for intervention by company data processing services.

The Collecting Manager will convert performance objectives to a strategy that relate the conditions of the defaulting accounts (the current degree of default, the outstanding balances, previously observed default, and other known facts) with several actions that the billing department can undertake.

Possible actions include (in addition to doing nothing) sending copies of extracts bills, recovery letters, phone calls, visits, litigation, debt cancellation / reduction and selling the account to a billing firm.

The flow of events begins with the behavior of the clients themselves. The customer base data information is received in the form of purchase orders, payments and non-monetary transactions, such as address changes, limit change requests, answers to phone calls, etc.

The database provides the information needed to prepare customer invoices as well as the data from which the reports are prepared. Generally speaking, there are two categories of reports: financial and operational.

Financial reports on charges show different amounts overdue over time intervals and the amounts charged. These reports should be sent to other company departments including the Billing Manager himself.

Operational reports report on the various actions carried out in different groups of bills. The database is the source of information for the billing department regarding concerns overdue accounts, since it is in the find the oldest and most grouped accounts on the ageing of the trade receivables.

The recovery strategy will be applied to each of the non-performing accounts and is appropriate action is specified for each of them.

From here the specified action is taken either automatically (if the action required is to send a copy of the statement or a letter of recovery) personally, through instructions passed to a collection team member. The information resulting from these actions will be added to the customer database, giving rise to reporting.

3.4.4 Circumstantial factors in the revaluation of credit cards

The revalidation of credit cards involves the analysis of circumstantial factors that determine a new issue. Cards are generally valid for a certain period of time, usually a year, but are often valid for two or three years. According to information from a confidential source, some of the circumstantial factors key factors for re-issuing a credit card are: account activity; its antiquity; the type of balances the account has been presenting; and the history of default, if any. Behavioral score, when available, becomes an additional factor for reach the decision to reissue.

Table 3.19 shows a relatively simple type of revalidation strategy for a credit card which can be used when you have a behavioral scoring system.

Level of non-compliance	Account Activity			
Cycles of Default current	Months since last activity	Max No. of cycles in non-compliance	**Score Behavioral**	**Revalidation credit card months**
0	0-12	0-1	Below 320	18
			321-399	24
			400 or more	36
		2 or more	Low 320	12
			321 or more	18
1	13 or older	n.a	n.a	0
	0-12	0-1	Lower 320	12
			321 or more	18
			Low 320	0
			321 or more	12
2	13 or older	n.a.	n.a.	0
	n.a.	n.a.	n.a.	0

Table 3.19- Credit Card Revalidation Strategy. Lewis Adaptation (1992) "A Introduction to credit scoring (p. 125)

The strategy presented combines the level of default with account activity, highest level of past non-compliance and behavioral score. Yet since these strategies are automated in the computer program the time of processing does not suffer any appreciable load. The system examines all accounts in each billing cycle and all factors in presence, greatly improving the overall performance of the customer base.

3.4.5 MODIFICATION OF CREDIT LIMITS

According to Lewis (1992, p. 126) changing the credit limit may have an effect surprising in the overall performance of a credit operation. The higher credit limits, without increasing the risk, the greater the likelihood of the transaction being profitable. On this assumption, the institution shall provide each client, through its own credit department, a limit that encourages you to use credit and at the same time keep you as a low-default customer. When a new account is accepted a certain limit of credit the initial limit may cover one of the following situations: granting the same amount of credit to all accepted accounts; or set a different limit for the different candidate groups. These criteria vary between lending institutions. Credit policy may consider several factors such as; the applicant's heritage; their responsibilities; the type of job; and any other items that they think are important. Starting in the first few months of an account's life, and facing her/his behavior, the credit manager may recommend changing the credit limit.

The credit bureau can build a strategy table of the type illustrated (partially) in Table 3.20. The complete strategy would include the full range of other factors that characterize that specific account. The strategy advocated in the same Table # 3.20 can be made simpler. or more complex depending on the objectives of the credit management. You should start with a relatively simple strategy by measuring your results and then verify that the changes improve overall performance. In the last column of Table 3.20 an action code was entered instead of describe its action, as it may be factors. Example:

Cycles of Delinquency current	No. Max cycles that has been delinquent	Months since the last activity	Months waitting for payment	Score behavioral	Action Code
0	0	0-5	1-12	<128	0
				128-200	1
				201+	2
			13 or more	<128	0
				128+	2
		6 or more	n.a.	n.a.	0
	1-2	0-5	n.a.	<200	0
					1
		6 or more	n.a.	n.a.	0
	3+	n.a.	n.a	n.a	0
1	0	0-5	1-12	<128	0
				128+	1
			13+	<128	0
				+128	1

Table nº 3.20 - Strategy Table (partial). Adapted from Lewis, An Introduction to Credit Scoring (p.127)

Different changes to the credit limit may be made depending on: current account the percentage used against the current limit; of the highest percentage the limit that has always been used; and the time since the last change.

As with the card revalidation strategy, this strategy can be very starting with a relatively simple strategy until interpret well how to deal with other strategies. Accounts for credit limit increases should be evaluated on a periodic basis, quarterly or semi-annually. The credit limit may also be increased to customer request. The credit management must carefully reflect on the objective it intends to achieve and should build a table that best serves that purpose.

3.4.6 COLLECTIONS

The first area of interest for any credit bureau is the efficiency obtained in the billing process. In this area, the credit management may determine which action recovery to be undertaken at various risk levels and at various levels of default. Table 3.21 is an illustrative example of what a billing strategy looks like, addressed to accounts with 30 days of default. All kinds of alternatives are possible and each credit operation will have as many special conditions as they wish to include.

Illustrative example:

Score	Default on debt intervals			
	<100 €	$ 100 - $ 300	301 € - 500 €	Above 500 €
Below 200	Letter # 1	Phone call	Phone call	Letter from lawyer
201-210	Letter # 2	Letter # 2	Phone call	Phone call
211-240	Resubmission of extract	Letter # 2	Letter # 3	Phone call
Above 240	Resubmission of extract	Resubmission of extract	Letter # 2	Letter # 3

Table 3.21- Collection Strategy. Adapted from “An Introduction to Credit Scoring” p.128

The letters will have different content according to the gravity of the situation. For the others levels of default will require similar strategy tables which should take into account all factors deemed appropriate by the credit management to include in the decision process. Whenever a new strategy is followed, space should be provided in the master file to record any action that should take place so that it can be analyzed, thereafter the effectiveness of each action.

The question that arises for each strategy is to know the results they produce. In this sense, one might ask: “In which percentage of the cases did resending bank statements result in receipts? ”,“ Were the various letters effective? ”,“ Did the phone calls produced results? ”.

The answers to these questions may lead to partial changes in the policy of the parts of this policy which have proved to be appropriate should be retained.

3.4.6.1 Accounts Exceeding Credit Limit

Despite setting credit limits some accounts exceed this limit. This may occur as a result of a purchase authorization or alow value purchases, each within the automatically authorized amount, but which when accumulated exceeds the authorized credit limit. In both cases, the creditor institution shall provide a strategy for each case. in particular.

Since the behavioral score quantifies a risk measure presented by the account, the credit management may establish a risk-oriented strategy, determining the action to be taken. As with collections, financial institutions may want to use a behavioral score and the amount owed, plus the credit limit, to determine the strategy to follow, but in other institutions they may have other criteria for evaluation.

3.4.6.2 Credit Card Payment Authorizations

Credit card authorizations are closely linked to communications. In the past not too distant, communication was still present at a point of sale to obtain a payment authorization.

Today, satellite communications and the continuing development in technologies that support this route of communication have increased the quality in the speed of credit card payments. This quality improvement can be seen in the possibility of establishing the long distance communication between the cardholder and the issuing institution. In the recent past it was very difficult to control permits, especially for distant distances and to zones with very different time zones. It's still hard today for a national citizen, traveling in certain countries of the African continent to obtain a quick authorization for any credit card payment. Although communications are easier and cheaper today, the volume of requests for authorization is increasing. The speed of response is very important for both the consumer who does not like to wait, as for the seller who does not want to lose the sale caused by the buyer's withdrawal from his impatience.

Successive advances in communications technologies are a big help improving payment commitments. Currently, each point of sale is linked directly to the central billing system and it is possible to call the authorizations whenever there is a “sign” of sale. Thus, the purchase authorizationsThey have become relatively easy and lead times are usually short. In these cases, may take place many permits automatically second criteria incorporated into the company's computer system. Delays only occur when the program decides that human intervention is needed. Purchase authorizations where the card is not associated with any chain store-specific, are considerably more difficult. The customer may be in a local and financial entity over a long distance. In these cases the communication has to be established at some point that can make the decision.

Technological advances are constantly facilitating this process by allowing the card incorporates encoded information into the magnetic stripe which may be made available and modified by the point of sale machine.

If the card shows that there is plenty of room for the credit limit to purchase, the financial institution may establish a strategy in which it is not necessary no phone calls and the purchase can be approved automatically. If the purchase is much higher than the amount set by the credit institution then you will to make a call to somewhere in between where you can calculate the score and apply the appropriate strategy. Today it is possible to send copies of complete master files to decision points allowing almost all decisions to be taken, locally or at such points without having to resort to the central file.

3.4.6.3 “Champion” versus “Challenging” Strategy

One of the questions for any credit manager is whether recommended are acceptable for different levels of default. Or for others words, if there will be a different strategy that produces better results than that is being used. The answer to this question can only be given by trying another strategy and compare the results.

A collection strategy that is in use is one that in principle produces best results using traditional “Champion” strategy designations and their “Challenging” strategy (see Philip Kotler, 1991, p.373), (Anderson, 2007, p.575), (Lewis, 1992, p.134), (Siddiqi, p.143).

To know which of the two strategies produce better results in the processes of collection allows both to be tested and reveal through their financial reports, the results that each one obtained. If it turns out after a while of testing that the “Champion” strategy is the one that continues to show better results than the Challenging strategy, so the latter is discarded and replaced by a new “Challenging” strategy that will measure “strengths” with current strategy. The process develops by systematic comparison between the two strategies, until “Challenging” strategy emerges that produces better results than the “Champion” strategy, taking its place, that is, becoming the new “Champion” strategy and so successively. The simultaneous operation of the two competing strategies cannot be applied to all the bills at once. The reasons for this limitation relate to the accuracy of the forecast of the “Challenging” strategy.

The Adaptive Control System has two features that allow the manager to test the “Challenging” strategy safely and with minimal risk:

- The first of these characteristics is to allow the credit manager to indicate the percentage of accounts you want to submit to the Challenging strategy. If this strategy does not differ greatly from the “Champion” strategy, the credit could send 25-50% of accounts to the “Challenging” strategy. If instead the “Challenging” strategy is very different from the “Champion” strategy that manager may prefer to send only 4 to 5% of accounts, in the sense of the competing strategy.

The Adaptive Control System also allows you to change the percentage of account handled the various strategies at any time as confidence in Alternative strategy increases.

-The second feature addresses the issue of ensuring that account percentages submitted for each of the competing strategies are statistically equivalent. For the performance of the two strategies to be accurately compared, they must be the sets of accounts dealt with by their strategies have a similar composition. Competition between the “Champion” vs. “Challenging” strategies is not just about have a “Challenging” strategy but several at the same time. This procedure produces faster results as there is no need to wait for the end of the experiment one strategy to start the next.

The strategies used for billing non-compliant accounts, billing that have exceeded the credit limit, credit limit changes, authorizations, and reissue allow credit managers to conduct their operations SCA. This system recognizes that the world we live is in constantly changing and that solutions to yesterday's problems may not be appropriate to today's problems that we are facing, neither those who will emerge in the future.

The Adaptive Control System provides the tools you need to deal with the complexity and the change. Through continuous testing applied by the strategies in presence, it is detected that the current strategy (“Champion”) may no longer produce the best results in light of changes in the customer universe and the economic environment which frames the current moment. In these situations, the credit manager may adapt the system to the new economic and social and realities conditions.

3.4.6.4 Final Comments on Behavioral Scoring

Behavioral scoring concerns the behavior of individuals and this is shaped by change. In this sense, it is not necessary to know if it is the universe of customers that changed or were the changes in the surrounding responsible for change.

What is important is to detect change and the necessary adaptation of its implications new economic, social, technological and environmental realities. Once change and human complexity cohabit the same space, an ACS is a continuous process and not a mere expedient or a temporary appeal. Under these assumptions, the biggest challenge will lie in inventing new strategies that are able to distinguish the different particularities displayed between the defaulting accounts.

3.5 SOME COMMENTS

The state of the art of credit scoring does not end with development here summarized, but reveals the potential for applying this methodology.

Attribution scoring and behavioral scoring methodologies were explained by concurrent processes and techniques. This methodology can be replicated for any lending activity, whether a financial institution or not financial.

The empirical finding leads us to accept that most Portuguese SME (Small And Meddium Enterprises) do not use this tool for the following reasons:

1) It is unknown to most SMEs;

2) Not all companies that know this tool have databases properly organized and prepared to accommodate the implementation of these techniques;

3) Specialized personnel in this area are scarce;

4) Making a scoring system built for a particular company is very costly;

5) Most business associations do not yet have databases handled which they represent and do not always receive from appropriate statistical information, partly due to reluctance to disclose sometimes due to a manifest lack of confidence in the very entity that represents;

6) The scarcity of scoring system manufacturers;

7) The business community is not sufficiently aware of the benefits of this methodology, generically called credit scoring.

CHAPTER 4 - RESULTS

4.1 DATA COLLECTION, ANALYSIS AND TRANSFORMATION

4.1.1 DATA COLLECTION

Data collection was carried out at a credit card issuing financial institution. The data collected refer to clients of this institution whose classification of Good or Bad customer knows himself *a priori*.

The criterion adopted in data collection followed the method proposed by several authors, notably Lewis, (1992, p.31), Mays, (2001, p.41), Siddiqi, (2006, p.70), Anderson, (2007, p. 260) and already explained in 3.3.3 and 3.4. This method consists of recording the payment behavior of debtors for a period ranging from six to twenty-four months, at the end of which agreed to designate for moment zero.

During this period all the information the account was providing was recorded without however, if they draw any conclusions. From moment zero a new period of another six months begins. This period is intended to observe and compare payment behavior with the previous period, referred to as the observation period. After this observation and comparison, and according to the criteria defined by the credit, Good accounts and Bad accounts were identified.

Observations recorded during the observation period include, stand out among others, late payment days, average account balance, maximum and minimum balance, amount and total number of transactions, the number of times the credit limit has been exceeded, the number of letters sent reminding the payment. From the database of this financial institution the sample used here was taken, containing data already processed by the methods described in 3.3.3 and 3.4 for 2,000 accounts Good and 2,000 Bad accounts, as of June 30, 2007.

The financial institution criterion used in the classification of Good and Bad customers was the next:

Good customer

With at least one active account in the last 10 months (2006-09 the

2007-06)

Maximum a delay in the last 12 months

Maximum of one return in the last 12 months

Profitability and revolving rfm classes 4 and 5

Average account balance over last 3 months> = 1,200 €

Non-performing accounts under review> = 60 days in last 24 months

Billing> = 500 € over the last 3 months (2007-04 to 2007-06)

Bad customer

Accounts at least once in default> = 90 days in past

24 months with current balance> = 500 €

Accounts three or more times past due> = 60 days in last 12

months with current balance> = 500 €

Accounts that in 2007-06 are in portfolio.

The criterion adopted for the selection of 4,000 accounts (2,000 Good accounts and 2,000 Bad accounts) was as follows:

1- The selection of our sample was followed by the experience reported by Lewis (1992),

(see 3.3.3). The sample has approximately the same size and specificity as the Lewis's report (ibid.).

2- The sample was divided into two:

a) One called *in-sample* containing 80% of the Good and Bad at the same rate (1600 Good and 1600 Bad) that were used to estimate the parameters of the model;

b) and another sample called *out-of-sample* or *holdout sample* containing the remaining 20% of the data (400 Good accounts and 400 Bad accounts) that were used to validate the estimated model outside the sample previously.

Taking into account the above criteria, the following methodology was defined:

1- Created the COD variable that assumes the value 1 when it is a Good account and the value 0 when it is a Bad account.

2- Then proceeded to the characterization of the *in-sample* data. For this we resorted to the descriptive statistics measures and the logistic regression model was estimated, using the Statistical Package for the Social Sciences (SPSS®) programs (version 16) and EVIEWS® (version 6.0).

3- After statistically validation the model proceeded to the classification of *holdout sample* customers who confirmed the model's predictive capability previously estimated. Thus we found a model that allows us to relate the probability of a customer is a good payer with his or her personal characteristics including respective account.

4.1.2 DATA ANALYSIS

When analyzing the characteristics of the 4,000 credit card users, 21 were identified, which should constitute (totally or partially) the explanatory variables in the logistic regression model, as shown in Table 4.1:

1 *v_co_scoring* - behavioral scoring value for current customer account

2 *v_co_limite_credit* - credit limit (maximum amount the customer can spend on uses with their card)

3 *v_co_saldo_actual* - present value of debt

4 state_ci_identify - identifies the state code the account is in

5 *ci_co_class* - identifies the account classification code (ci_co_state is a combination of multiple account classifications)

6 *v_co_revolving* - amount in revolving ie amount left unpaid in previous statement

7 *m_renderability* - monthly return value account

8 *c_tp_mes* - identifies the month to which the data refers (format = yyyymm)

9 *d_co_class* - classification code description

10 *d_co_state* - description of state code

11 *delinq_60 days* - Delinquent account for more than 60 days

12 *delinq_90days* - Delinquent account for more than 90 days

13 *gender- (M / F)*

14 *cod_post- postcode*

15 *date_nasc - date of birth*

16 *civil_state - marital status*

17 *habilit*-educational qualifications

18 *region*- geographic region

19 *profession*

20 *years old*

21 *income*

Table nº 4.1- List of characteristics of credit card users regarding the sample used in the study.

These 21 characteristics were grouped into three categories (Qualitative, Quantitative and Dates) and summarized in Table # 4.2:

Qualitative Variables	Quantitative Variables	Date Variables
state_ci - identifies the state code in which the account is	v_co_scoring - value of behavioral scoring for current customer account	date_nasc - date of birth
d_co_state - description of state code	v_co_limite_credit - credit limit (amount maximum that the customer can spend on uses with his card)	c_tp_mes - identifies the month to which respect the data (format =(YYYYMM)
d_co_class - classification code description	v_co_saldo_actual - present value of debt	
ci_co_class - identifies theclassification code of the account (state_ci_co is a combination of several account ratings)	v_co_revolving - amount in revolving ie unpaid amount in the previous statement	
delinq_60 days - Delinquent account for more than 60 days	m_renderability - monthly return value account	
delinq_90days - delinquent account for more than 90 days	age	
gender- (M / F)	income - net monthly remuneration	
cod_post- postcode		
estado_civil - marital status		
habilit- literacy		
region- geographic region		
profession		

Table 4.2- Types of explanatory variables

Since the meaning of the variables may not be clear due to the abbreviations and simplifications, it was decided to describe them in more detail as follows:

a) Status of account “d_co_estado” and “ci_co_estado”

The account status description (d_co_state) and its identification code (ci_co_estado) are shown in table 4.3:

ci_co_state * d_co_state Crosstabulation

		d_co_stado			
		Active Accounts	No Active Accounts	No Accounts Usable	Total
ci_co_state	1	2602	0	0	2602
	2	0	281	0	281
	3	0	0	317	317
Total		2602	281	317	3200

Table nº 4.3- ci_co_estado cross table (account stay identification code) and d_co_state (account state description).

From the crossing of these variables we found that the account description has three different states: Active Accounts, Non-Active Accounts and Unusable Accounts. Each of these accounts has a unique account identification code that stands for:

Description (d_co_state)	Identification code (ci_co_state)	Total
Active Accounts	1	2602
Non-Active Accounts	2	281
Unusable Accounts	3	317
Total		3200

Table # 4.4- Description of Accounts by Identification Codes

b) Account class "d_co_class" and "ci_co_class"

The account class description (d_co_class) and its identification code (ci_co_class) are shown in table 4.5:

ci_co_class * d_co_class Crosstabulation												
	d_co_class											
ci_co_class												Total
	0	0	0	0	0	0	0	0	0	0	0	34
	1	114	0	0	0	0	0	0	0	0	0	114
	2	0	55	0	0	0	0	0	0	0	0	55
	3	0	0	22	0	0	0	0	0	0	0	22
	6	0	0	0	16	0	0	0	0	0	0	16
	7	0	0	0	0	30	0	0	0	0	0	30
	8	0	0	0	0	0	0	27	0	0	0	27
	9	0	0	0	0	0	0	0	30	0	0	30
	13	0	0	0	0	0	0	0	0	256	0	256
	19	0	0	0	0	0	0	0	0	0	2577	2577
	20	0	0	0	0	0	39	0	0	0	0	39
Total	34	114	55	22	16	30	39	27	30	256	2577	3200

Table # 4.5- Cross Table d_co_class and ci_co_class

Similarly, it has been found that the account class description (d_co_class) is also classified by a numeric code (ci_co_class).

c) Accounts overdue for more than 60 days and 90 days "delinq_60 days" and "delinq_90 days"

Count		60 days delinquence		
		0	1	Total
90 days delinquence	0	2913	153	3066
	1	0	134	134
	Total	2913	287	3200

Table # 4.6- Cross Table delinq_60 days and delinq_90 days

From the previous table it was found that 2913 accounts are considered non-defaulting and of the total of 3200 accounts, only 153 reached 60 days of default and 134 had reached 90 days of default.

Overdue (defaulting) accounts are classified by 1 and unpaid accounts by 0

d) Gender

		Frequency	Percent	Valid percent	Cumulative percent
Valid	F	951	29,70%	29,70%	29,70%
	M	2249	70,30%	70,30%	70,30%
	Total	3200	100%	100%	100%

Table nº 4.7- Frequency table by Gender

Table 4.7 shows the large difference between the number of users of the gender male (70.3%) and female (29.7%). Asked the financial institution about the reasons for this difference, we know that this is a “pseudo-anomaly”, because the all married male users are automatically issued an another card for the wife, although both cards are given the same identification as account.

In table 4.8, and as already mentioned, the code 0 (COD = 0) represents Bad Payer and the Code 1 (COD = 1) represents Good Payer.

Genre * COD Crosstabulation

Count		COD		
		0	1	Total
Genre	F	553	398	951
	M	1047	1202	2249
Total		1600	1600	3200

Table 4.8 Quantity of Good and Bad Payers by Gender

From Table 4.8 it can be extracted that from 951 women, 58% are classified as Bad accounts, while this percentage is 47% in 2249 men.

e) Marital status (estado_civil)

Table 4.9 shows the attributes of marital status and the classification of Good and Bad payer by gender.

Gender			Widower By code		Married By code		Divorced By code		Separate By code		Single By code		No reply By code		Total By code	
		0	23	4,20%	208	37,60%	66	11,90%	3	0,50%	87	15,70%	166	30,00%	553	100,00%
F	COD	1	25	6,30%	219	55,00%	68	17,10%	2	0,50%	52	13,10%	32	8,00%	398	100,00%
		Total	48	5,00%	427	44,90%	134	14,10%	5	0,50%	139	14,60%	198	20,80%	951	100,00%
		0	7	0,70%	514	49,10%	61	5,80%	5	0,50%	108	10,30%	352	33,60%	1047	100,00%
M	COD	1	20	1,70%	918	76,40%	93	7,70%	6	0,50%	59	4,90%	106	8,80%	1202	100,00%
		Total	27	1,20%	1432	63,70%	154	6,80%	11	0,50%	167	7,40%	458	20,40%	2249	100,00%
			75	2,34%	1859	58,10%	288	9,00%	16	0,50%	306	9,60%	656	20,50%	3200	100,00%

Table nº 4.9- Marital Status by Frequency and Gender by Code

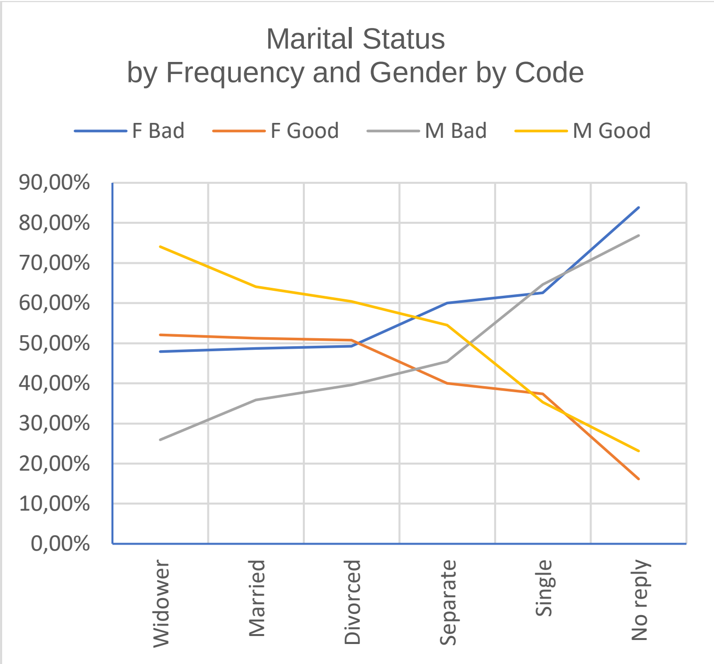
When the previous paragraph analyzed the “Gender” according to the classification Good and Bad all accounts, 58% of women were found to be Bad payers versus 47% of men. However, Table 4.9 shows a reversal of this trend in married women which is 37.6% of Bad accounts versus 49.1% of married men. In all other marital states women have a higher percentage of poor payers than men with the exception of “No Answer”. Divorced women and single women have a higher percentage of bad accounts than men (11.9% and 15.7% against 5.8% and 10.3% respectively). Women who did not respond had 30% of Bad Accounts versus 33.6% of Men Among widowers women also have a higher percentage of accounts for men. As we look further into these results to understand what the phenomenon is associated with the married woman who makes her better off than the married man.

We have empirically verified a possible reason for this reversal. When opening account of a married man, the financial institution issues another card with the same account number for wife. When she uses the card and does not meet the payments on due dates, the default is recorded in the husband's account. So married men, even if not use credit card, aggravate statistically their “credibility” .

Gender			Widower Within widower		Married Within married		Divorced Within divorced		Separate Within separate		Single Within single		No reply Within “No reply”		Total	
		0	23	47,92%	208	48,71%	66	49,25%	3	60,00%	87	62,59%	166	83,84%	553	58,15%
F	COD	1	25	52,08%	219	51,29%	68	50,75%	2	40,00%	52	37,41%	32	16,16%	398	41,85%
		Total	48	100,00%	427	100,00%	134	100,00%	5	100,00%	139	100,00%	198	100,00%	951	100,00%
		0	7	25,93%	514	35,89%	61	39,61%	5	45,45%	108	64,67%	352	76,86%	1047	46,55%
M	COD	1	20	74,07%	918	64,11%	93	60,39%	6	54,55%	59	35,33%	106	23,14%	1202	53,45%
		Total	27	100,00%	1432	100,00%	154	100,00%	11	100,00%	167	100,00%	458	100,00%	2249	100,00%

Table No. 4.10- Marital Status by Frequency and Gender by Code

	Widower	Married	Divorced	Separate	Single	No reply
F Bad	47,92%	48,71%	49,25%	60,00%	62,59%	83,84%
F Good	52,08%	51,29%	50,75%	40,00%	37,41%	16,16%
M Bad	25,93%	35,89%	39,61%	45,45%	64,67%	76,86%
M Good	74,07%	64,11%	60,39%	54,55%	35,33%	23,14%

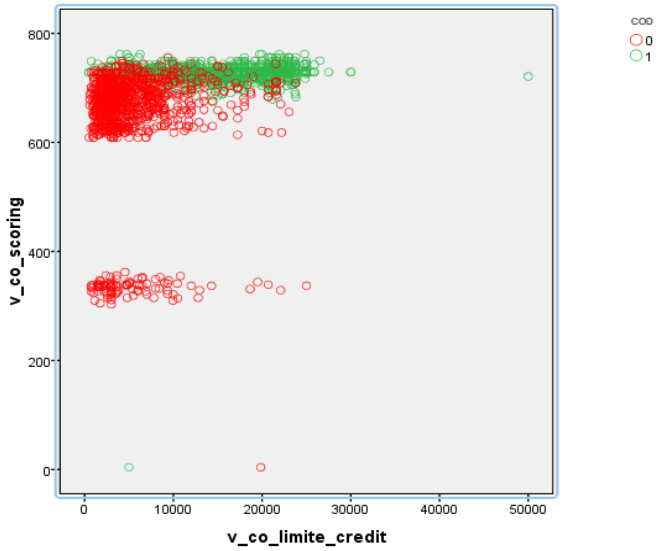


f) Behavioral scoring value for the customer's current account (v_co_scoring) Table 4.11 groups the number of accounts by Good and Bad payers by intervals score:

Score	Bad	Good	Score	Bad	Good
4-300	1	1	651-655	0	69
301-305	0	1	656-660	0	76
306-310	0	2	661-665	0	94
311-315	0	6	666-670	0	94
316-320	0	3	671-675	3	87
321-325	0	9	676-680	5	95
326-330	0	13	681-685	8	100
331-335	0	11	686-690	9	130
336-340	0	24	691-695	21	130
341-345	0	12	696-700	82	115
346-350	0	5	701-705	20	68
351-355	0	5	706-710	93	79
356-362	0	3	711-715	62	81
363-599	0	35	716-720	401	64
600-605	0	1	721-725	47	34
606-610	0	33	726-730	708	63
611-615	0	17	731-735	128	17
616-620	0	36	736-740	218	23
621-625	0	53	741-745	113	12
626-630	0	101	746-750	56	3
631-635	0	31	751-755	3	0
636-640	0	54	756-760	22	2
641-645	0	32	765-770	0	0
646-650	0	76		2000	2000

Table 4.11- Good and Bad Frequencies by Score Intervals

g) Credit limit is the maximum amount the customer can use with their credit card. (v_co_limite_credit). To analyze the relationship between the scoring variable and the credit limit variable the following dispersion diagram was constructed:



Graph nº 4.2- Distribution of Good and Bad Accounts by Credit Limit and Scoring

Graph 4.2 gives us the following explanations and comments:

g1) The dispersion of good and bad customers occurs at credit limit levels ranging from 0 euros to 50 000 euros.

g2) The scoring interval between the highest echelons (700 to 770 points) records good and bad customers, which is as shown in table 4.11 above.

g3) In the range between 200 and 400 of the ordinate v_co_scoring one Bad payers set. According to information from the financial institution, this set of accounts concerns pre-litigation, litigation or other situations special situations.

h) Current account balance (v_co_saldo_current) is the amount due at the observation date

i) Amount of unpaid account in previous statement (v_co_revolving)

j) Amount of profitability of the account (m_renderability)

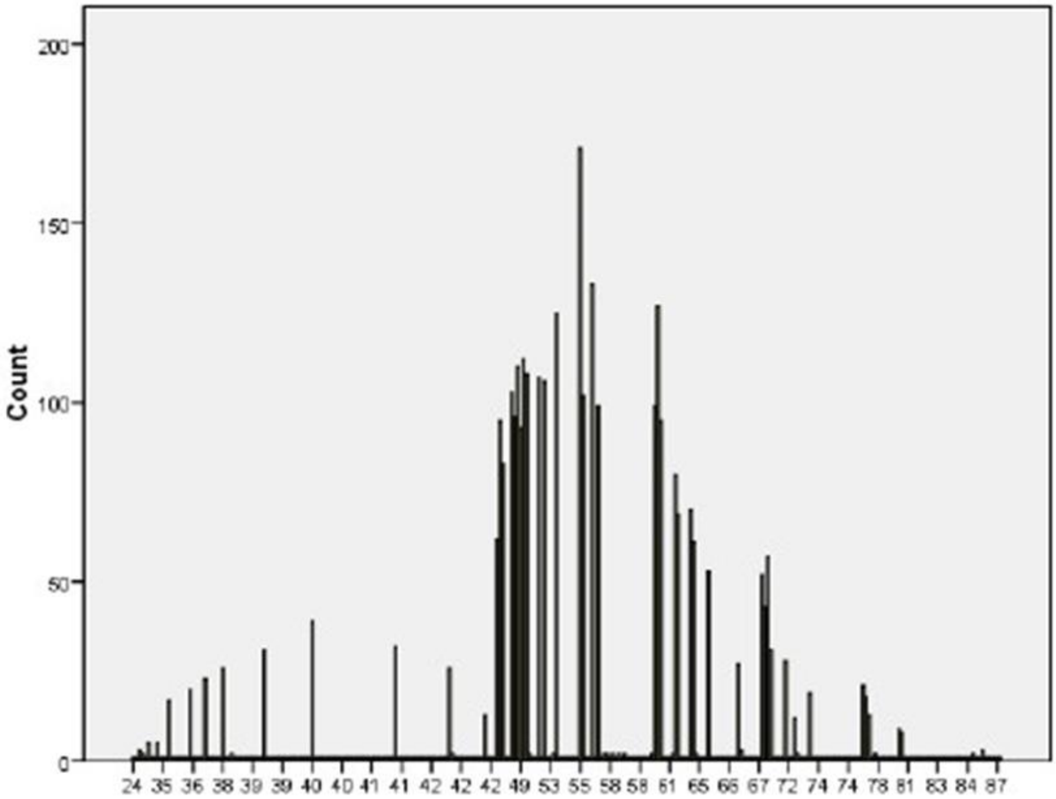
k) Age

Sample customers have an average age of 55 years old:

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	3200	24	93	54.64	10,066
Valid N (listwise)	3200				

Table nº 4.12- Descriptive statistics of the characteristic “age”



Graph nº 4.3- Frequencies of sample users' ages

l) Literary qualifications (habilit_d)

		Frequency	Percent	Valid percent	Cumulative percent
Valid	12th grade	21	0.7	0.7	0.7
	High School	9	0.3	0.3	0.3
	Superior / Degree / Master	329	10.3	10.3	11.2
	Compulsory education	12	0.4	0.4	11.6
	Less than schooling	4	0.1	0.1	11.7
	Others	1727	54.0	54.0	65.7
	No reply	1098	34.3	34.3	100.0
	Total	3200	100.0	100.0	

Table 4.13- Frequencies of the different typologies of educational qualifications

m) Income - net monthly remuneration (income)

This feature was not considered in the model because it presents the value of the yield, in the vast majority of cases equal to zero.

Other variables such as zip code, geographical region, occupation, date of birth and date of the month to which the data relate, did not merit further explanationbecause they are obvious.

The following procedure consisted of transforming some of the qualitative variables in dummies having chosen to do this transformation manually rather than the identify as categorical variables and thus allow the statistical program SPSS® made choices that might contradict the common sense imposed by reality. This one subject will be developed in 4.1.3 Data Transformation.

4.1.3 DATA TRANSFORMATION

To make it easier to interpret the estimates for the coefficients of some of the qualitative variables, they were transformed into fictitious numerical variables (dummy variables). The transformation of the variables is done according to a dichotomization of the attributes according to Table 4.14:

Categorical Variables Codings

		Frequency	Parameter Coding	
Habilit Dummy	0	2825	0	
	1	375		1
ci_co_class (Dummy)	0	2577	0	
	1	623		1
d_co_class (Dummy)	0	3058	0	
	1	142		1
d_co_estado (Dummy)	0	2602	0	
	1	598		1
Género (Dummy)	0	2249	0	
	1	951		1
Região (Dummy)	0	2310	0	
	1	890		1
Estado Civil (Dummy)	0	1859	0	
	1	1341		1
ci_co_estado (Dummy	0	2602	0	
	1	598		1

Table 4.14- Frequencies of categorical variables by codes

The criterion followed for the assignment of codes 0 and 1 was to consider as zero the attributes that contained the largest number of observations (Anderson, 2007, p.359), as shown in Table 4.15:

Characteristic	Attributes	Frequency	Reference Category Control Group	Category Answer Treatment Group
			0	1
Region	Alentejo	135		1
	Algarve	158		1
	Beira Interior	30		1
	Centro	168		1
	Ilhas	136		1
	Lisboa	1063	0	
	Lisboa Cidade	749	0	
	Litoral	211		1
	Norte	52		1
	Porto	342	0	
	Porto Cidade	156	0	
ci_co_class	0	34		1
	1	114		1
	2	55		1
	3	22		1
	6	16		1
	7	30		1
	8	27		1
	9	30		1
	13	256		1
	19	2577	0	
	20	39		1
d_co_class	A-Nao cumpriu	34		1
	C-2 Mese	114		1
	D-3 Mese	55		1
	E->=4 Me	22		1
	H-Saldo>	16		1
	I-1 Mes-	30		1
	J-2 Mese	39		1
	K-3 Mese	27		1
	L->=4 Me	30		1
	P-1 Mes-	256		1
	Sem Clas	2577	0	
Habilit	12º Ano	21		1
	Curso Mé	9		1
	Curso Su	329		1
	Escolari	12		1
	Menos qu	4		1
	Outros	1727	0	
	Sem Resp	1098	0	
Estado Civil	Casado	1859	0	
	Divorcia	288		1
	Sem Resp	656		1
	Separado	16		1
	Solteiro	306		1
	Viúvo	75		1
ci_co_estado	1	2602	0	
	2	281		1
	3	317		1
Género	F	951		1
	M	2249	0	
d_co_estado	Contas A	2602	0	
	Contas N	598		1

Table 4.15- Frequency of attributes by Reference and Response Categories

How categories are coded will determine the meaning of the odds ratios as well as the sign of the coefficient estimates (Tabachnick, B. G., and Fidell, L. S. (2007, p.464). SPSS® and EVIEWS® programs give the estimated equation for probability dependent variable is equal to "1", while the SAS® program solves the equation for the category coded by "0". In other words, an odds ratio of 4 on SPSS® represents, for example, a ratio of 80% Good Payers and 20% Bad Payers); but if the program used is SAS® (SA Institute Inc) the odds ratio will be 0.25 between 20% Bad Payers and 80% Good Payers).

For a better interpretation, the “disease” dichotomy is often used as the response category coded by “1” and “health” as coded reference category by "0". In the previous table we give the example of the variable “d_co_estado” whose attributes are “Active Accounts” (healthy) coded as reference category (0) and “Non Accounts” Active ”and“ Unused Accounts ”(patients) coded as a response category (1)

4.1.4 CHARACTERIZATION OF VARIABLES BY STATISTICAL MEASURES DESCRIPTIVE

For a better characterization of the variables, in terms of descriptive statistics, Tables Nos. 4.16 and 4.17 are presented:

Univariate Statistics

				Missing		No. of Extremes[a]	
	N	Mean	Std. Deviation	Count	Percent	Low	High
v_co_scoring	3200	686,33	82,832	0	0	137	0
v_co_limite_credit	3200	8678,06	6957,993	0	0	0	110
v_co_saldo_actual	3200	4283,3460	4303,24032	0	0	0	186
v_co_revolving	3200	3618,3288	3809,90513	0	0	0	176
m_rendibilidade	3200	66,4332	77,21507	0	0	0	156
ci_co_estadoDummy	3200	,19	,390	0	0	0	598
ci_co_classDummy	3200	,19	,396	0	0	0	623
d_co_classDummy	3200	,19	,396	0	0	0	623
d_co_estadoDummy	3200	,19	,390	0	0	0	598
delinq_60dias	3200	,09	,286	0	0	0	287
delinq_90dias	3200	,04	,200	0	0	0	134
GéneroDummy	3200	,30	,457	0	0	0	0
EstadoCivilDummy	3200	,42	,493	0	0	0	0
RegiãoDummy	3200	,28	,448	0	0	0	0
Rendimento	3200	185,90	925,187	0	0	0	103
Habilit.Dummy	3200	,46	,499	0	0	0	0
Idade	3200	54,98	10,173	0	0	22	97
ci_co_estado	3200	1,29	,634	0	0	0	317
ci_co_class	3200	16,92	4,984	0	0	241	0
c_tp_mes	3200	200706,00	,000	0	0	.	.

a. Number of cases outside the range (Mean - 2*SD, Mean + 2*SD).

Tabela nº 4.16- Medidas de estatística univariada

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
v_co_scoring	0	1600	643,17	107,297	2,682	637,91	648,43	4	756
	1	1600	725,23	22,656	,566	724,12	726,34	4	762
	Total	3200	684,20	87,722	1,551	681,16	687,24	4	762
v_co_limite_credit	0	1600	4779,66	3906,821	97,671	4588,09	4971,24	500	25000
	1	1600	14549,75	6241,813	156,045	14243,67	14855,82	452	50000
	Total	3200	9664,71	7139,633	126,212	9417,24	9912,17	452	50000
v_co_saldo_actual	0	1600	2909,563125	3,2349773E3	80,8744331	2750,932075	3068,194175	-292,0000	27742,0000
	1	1600	6475,208125	5,0623481E3	126,5587015	6226,969726	6723,446524	-2815,0000	30464,0000
	Total	3200	4692,385625	4,6065205E3	81,4325478	4532,720354	4852,050896	-2815,0000	30464,0000
v_co_revolving	0	1600	2597,038125	2,9586205E3	73,9655136	2451,958566	2742,117684	,0000	25926,0000
	1	1600	5350,391875	4,5895978E3	114,7399456	5125,335360	5575,448390	,0000	27796,0000
	Total	3200	3973,715000	4,0987917E3	72,4570843	3831,647973	4115,782027	,0000	27796,0000
m_rendibilidade	0	1600	48,3644	65,14222	1,62856	45,1700	51,5587	-14,00	1585,00
	1	1600	96,7456	86,68579	2,16714	92,4949	100,9964	-67,00	497,00
	Total	3200	72,5550	80,38967	1,42110	69,7686	75,3414	-67,00	1585,00
Idade	0	1600	51,666875	9,2238320	,2305958	51,214573	52,119177	30,0000	87,0000
	1	1600	58,963750	9,1679451	,2291986	58,514189	59,413311	35,0000	89,0000
	Total	3200	55,315312	9,8921166	,1748696	54,972445	55,658180	30,0000	89,0000
GéneroDummy	0	1600	,30	,460	,012	,28	,33	0	1
	1	1600	,21	,407	,010	,19	,23	0	1
	Total	3200	,26	,437	,008	,24	,27	0	1
EstadoCivilDummy	0	1600	,48	,500	,012	,46	,51	0	1
	1	1600	,26	,437	,011	,24	,28	0	1
	Total	3200	,37	,483	,009	,35	,39	0	1
HabilitDummy	0	1600	,12	,326	,008	,10	,14	0	1
	1	1600	,15	,353	,009	,13	,16	0	1
	Total	3200	,13	,340	,006	,12	,14	0	1
ci_co_classDummy	0	1600	,42	,493	,012	,39	,44	0	1
	1	1600	,01	,111	,003	,01	,02	0	1
	Total	3200	,21	,411	,007	,20	,23	0	1

Tabela nº 4.17- Medidas de estatística descritiva das variáveis independentes

Table 4.16 shows that the logistic model will not be negatively affected missings and Table 4.17 an observation of the minimum and maximum values allows ensure that the logistics model will not be negatively affected by outliers either.

4.2 – APPLICATION OF THE LOGIT MODEL TO SAMPLE DATA

To analyze the relationship between a customer's likelihood of being a Good Payer and their personal characteristics, including account data, we use the logit model, whose parameters were estimated from EVIEWS®.

As dependent variable, we considered the COD variable that assumes the values 0 and1, for bad and good paying customers, respectively.

As independent variables were initially considered, fourteen variablesas shown in Table 4.18:

v_co_scoring

v_co_limite_credit

v_co_current balance

v_co_revolving

delinq_60 days

delinq_90 days

m_renderability

age

state_ci (dummy)

ci_co_class (Dummy)

genre (Dummy)

privileg_state (Dummy)

region (Dummy)

enabled (Dummy)

Table 4.18- Fourteen independent variables initially considered in the model

Results obtained directly from EVIEWS® are shown in the tables below of the following subsection.

4.2.1 APPLICATION OF THE MODEL TO IN-SAMPLE DATA

As a starting point all explanatory variables were included in the model initially considered. In a second step, and following the principle of parsimony, variables whose estimated coefficients were not statistically significant at a significance level of 10%. The excluded variables were:

state_ci (dummy)

delinq_60 days

delinq_90 days

region (Dummy)

Table 4.19 presents the estimation results.

Dependent Variable: COD
Method: ML - Binary Logit (Quadratic hill climbing)
Sample: 1 3200
Included observations: 3200
Convergence achieved after 23 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
V_CO_SCORING	0.066500	0.003795	17.52427	0.0000
V_CO_LIMITE_CREDIT	0.000261	2.05E-05	12.74539	0.0000
V_CO_SALDO_ACTUAL	0.000499	0.000110	4.526730	0.0000
M_RENDIBILIDADE	-0.008396	0.002934	-2.861424	0.0042
IDADE	0.018678	0.007091	2.634029	0.0084
HABILIT__D	-0.602927	0.132102	-4.564096	0.0000
CI_CO_CLASS_D	-1.434070	0.349123	-4.107634	0.0000
V_CO_REVOLVING	-0.000384	0.000120	-3.201036	0.0014
ESTADO_CIVIL_D	-0.578892	0.134513	-4.303619	0.0000
GENERO_D	0.808648	0.144411	5.599634	0.0000
C	-49.89290	2.752544	-18.12610	0.0000

McFadden R-squared	0.653876	Mean dependent var	0.500000
S.D. dependent var	0.500078	S.E. of regression	0.260019
Akaike info criterion	0.486704	Sum squared resid	215.6077
Schwarz criterion	0.507573	Log likelihood	-767.7269
Hannan-Quinn criter.	0.494186	Restr. log likelihood	-2218.071
LR statistic	2900.688	Avg. log likelihood	-0.239915
Prob(LR statistic)	0.000000		

Obs with Dep=0	1600	Total obs	3200
Obs with Dep=1	1600		

Table 4.19- Explanatory variables that remained in the model, after excluding the variables whose estimated coefficients were not statistically significant.

4.2.2 ASSESSMENT QUALITY ASSESSMENT

To conclude about the goodness of adjustment in the in-sample data we started by analyze some of the previous results.

The model is globally valid because the null hypothesis in the ratio test is rejected (LR statistics) comparing the maximum logarithm value of the likelihood of two models, with and without the explanatory variables: Log likelihood and Restr. Log likelihood, respectively.

Since the probability associated with the LR test (0.0000) is clearly lower than the significance levels conventionally used, there is at least one coefficient estimated to be statistically significant; the same is to say that there is at least one explanatory variable whose variation is statistically related to the probability of a customer is a good payer.

Therefore, the model with all explanatory variables shows better predictions of the than those resulting from the model with only the constant. The estimated coefficients are all statistically significant, given the value and the probability associated with the Z tests. This means that all explanatory variables are statistically relevant to describe the probability of the COD variable being equal to 1 (the good paying customer).

Table 4.19 also gives us information on the contribution or importance of each one of the explanatory variables.

Estimates for the coefficients β (2nd column) are the values that were used in the logistics distribution function to estimate the probability of a customer being a good payer.

There are also positive and negative estimates that indicate the direction of the relationship between the explanatory variables and the dependent variable, that is, how the variation in one of the explanatory variables is reflected, on average, in the probability of customer be a good payer.

Thus, negative values indicate that, on average, an increase of one unit in the explanatory variable will result in a decrease in the probability of being a Good Payer.This explanation will result in a decreased likelihood of being a Good Payer. These are the cases of variables: m_renderability, habilit_dummy, ci_co_class_dummy, v_co_revolving and civil_dummy_state.

Positive values indicate that on average an increase of one unit in the explanatory variable will increase the likelihood that the customer will be a good payer. In this case the variables, v_co_scoring, v_co_limit_credit, v_co_scale_date, age, and gender_dummy.

When referring to the impact of explanatory variables on the probability of the variable equal to 1, the exponential of the estimate is usually calculated for each of the coefficients. The resulting values are estimates of odds ratios for each of the independent variables. The odd ratios represent the variation expected (increase or decrease if the ratio is less than 1) in the dependent variable when the value of the independent variable varies by one unit.

McFadden's Pseudo-R^2 value is 0.65, which means there is an increment maximum value of the likelihood logarithm when all explanatory variables are considered in relation to the model that includes only the constant.

In addition to the logit model, probit and gompit models (based on standard normal distributions and type I end point distributions, respectively). For conclude which model is the most appropriate to describe the data generating process, Vuong's test (1989) was used because it allows to compare nonnested models in the form functional as are the logit, probit and gompit models.

Three tests were performed considering under null hypothesis each of the models logit, probit and gompit) and alternatively each of the other two models. Like this:

Test 1:H_0: Logit model,H_1: Probit model;

Test 2: H_0:: Logit model, H_1: Gompit model;

Test 3: H_0:: Probit model, H_1: Gompit model.

The results obtained were as follows:

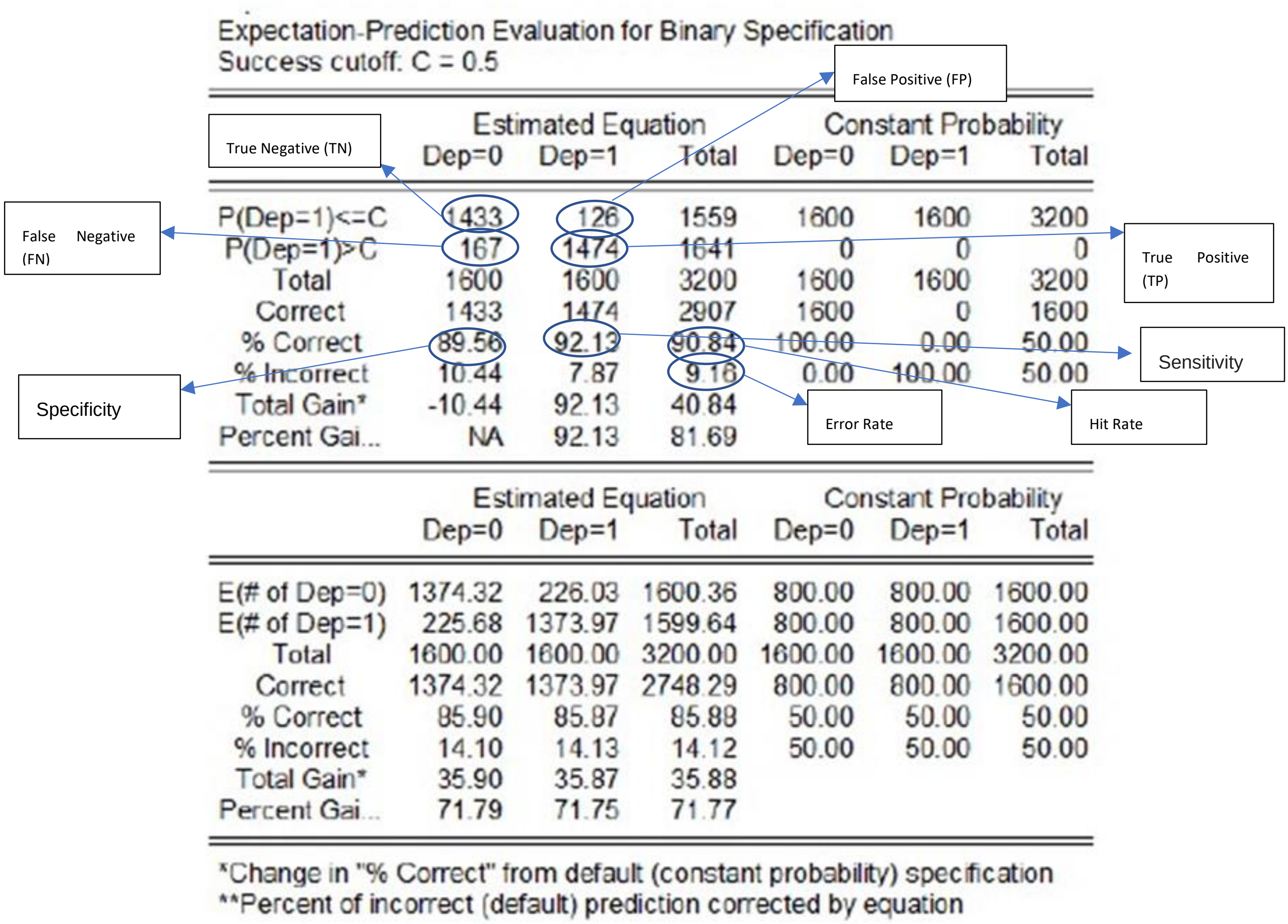
	Test 1	Test 2	Test 3
Vuong	2,73	-0,72	-1,76

Table 4.20- Vuong Test Results

Since the value of test 1 falls in the positive part of the critical region (to a level of significance level of 0.05 the critical value of standardized normal in a bilateral test is approximately 2, it is concluded that the logit model is more appropriate than the probit model to describe the generating process of the data that make up our sample. By the result tests 2 and 3, and since the null hypothesis is not rejected, the differences in the maximum value logarithm of likelihood function are not statistically significant logit and gompit models, on the one hand, and between probit and gompit models, on the other.

Therefore, given the results of the Vuong test, and taking into account the superiority of the logit model on the probit model, it was decided to proceed with the analysis of the results of logistic regression. To conclude on the goodness of adjustment one can also build a summary table where customers are classified.

If the estimated probability resulting from the model is less than 0.5 (value considered by default) the customer is rated as Bad Payer. Otherwise, it is considered that Y = 1, that is, the customer is a good payer. The results obtained are presented in Table 4.21:



Expectation-Prediction Evaluation for Binary Specification
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	1433	126	1559	1600	1600	3200
P(Dep=1)>C	167	1474	1641	0	0	0
Total	1600	1600	3200	1600	1600	3200
Correct	1433	1474	2907	1600	0	1600
% Correct	89.56	92.13	90.84	100.00	0.00	50.00
% Incorrect	10.44	7.87	9.16	0.00	100.00	50.00
Total Gain*	-10.44	92.13	40.84			
Percent Gai...	NA	92.13	81.69			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	1374.32	226.03	1600.36	800.00	800.00	1600.00
E(# of Dep=1)	225.68	1373.97	1599.64	800.00	800.00	1600.00
Total	1600.00	1600.00	3200.00	1600.00	1600.00	3200.00
Correct	1374.32	1373.97	2748.29	800.00	800.00	1600.00
% Correct	85.90	85.87	85.88	50.00	50.00	50.00
% Incorrect	14.10	14.13	14.12	50.00	50.00	50.00
Total Gain*	35.90	35.87	35.88			
Percent Gai...	71.79	71.75	71.77			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Table 4.21- E-Views results of the logistic regression model, showing the overall hit rate of 90.84%

The information given in Table 4.21 can be summarized in tables 4.22 and 4.23.

Classification Table[a]

			Predicted		
			COD		
			0	1	Percentage Correct
Observed	COD	0	1433	126	89,56
		1	167	1474	92,13
		Overall Percentage			90,84

a. The cut value is ,500

Table 4.22 Final classification

Hit rate	$\frac{TRUE\ Positive\ and\ Negative}{Total\ cases}$	$\frac{1474+1433}{1474+126+1433+167}=\frac{2907}{3200}=90{,}84\ \%$
Error Rate	$\frac{FALSE\ Positive\ and\ Negative}{Total\ cases}$	$\frac{126+167}{1474+126+1433+167}=\frac{293}{3200}=9{,}16\ \%$
Sensitivity	$\frac{TRUE\ Positive}{Total\ positive\ (TP+FP)}$	$\frac{1474}{1474+126}=\frac{1474}{1600}=92{,}13\%$
Specificity	$\frac{TRUE\ \ Negative}{Total\ negative\ (NT+NF)}$	$\frac{1433}{1433+167}=\frac{1433}{1600}=89{,}56\%$

Table 4.23- Classification Measures: Hit Rate; Error Rate; Sensitivity; Specificity. Calculations

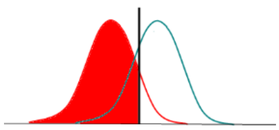
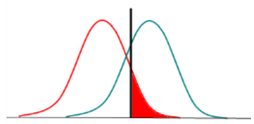
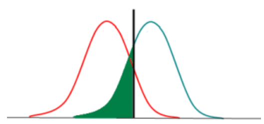
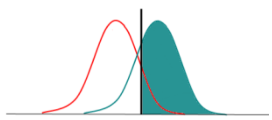
	Expected scorecard rating		
		Bad Payer (0)	Good Payer (1)
Current rating	Bad Payer (0)	$TRUE\ \ Negative\ (1433)$  It means that the scoring table predicted to be a Bad Account and in practice noted to be a Bad Account. We will designate this case as True Negative.	$FALSE\ Positive\ (Type\ I\ \mathrm{Error})(126)$  It means that the scoring table predicted to be a good account and in fact turned out to be a bad account. We will designate this case as False Positive.
	Good Payer (1)	$FALSE\ Negative\ (Type\ II\ Error)(167)$  It means that the scoring table predicted to be a Bad Account and in fact turned out to be a Good Account. We will designate this case as False Negative.	$TRUE\ Positive\ (1474)$  It means that the scoring table predicted to be a good account and in practice noted to be a good account. We will designate this case as True Positive.

Table nº 4.24- Classification Matrix and respective graphs

The values in the Classification Table (Table 4.22) gave the indication of how the model is able to predict the correct category (Good / Bad) for each case. One can still to note the forecast improvement when the explanatory variables are introduced in the model.

The model correctly classified 90.84% of all cases, whereas in the model only with the constant the hit rate was only 50%.

The results presented in this table can also be used to calculate the sensitivity of the model which is the percentage of good customers who have been identified by the model (the true positives), ie 92.13%.

The specificity of the model, ie the percentage of bad customers correctly rated (true negatives) was 89.56%.

4.2.3 MARGINAL EFFECTS OF EXPLANATORY VARIABLES ON CUSTOMER PROBABILITY TO BE GOOD PAYER

Direct interpretation of the coefficients is sometimes complicated since in a model with binary dependent variable the estimates for the coefficients cannot be directly interpreted as the marginal effect of each of the explanatory variables over the dependent variable (exception for the Linear Probabilistic Model).

The marginal effect of the explanatory variable Xj with respect to the probability of Y = 1 is the logistic probability density function by estimating the coefficient it is associated. A procedure suggested by several authors, Greene (2002) for example, and as far as possible consists in assessing the marginal effect for each observation and considering the average of the individual marginal effects.

When it is a dummy variable, and since it is not a continuous variable, the previous procedure is not the most appropriate for calculating the respective marginal effect. In this case it is customary to calculate the difference in the estimated probabilities resulting from Dummy = 1 and Dummy = 0 at the midpoint of the remaining explanatory variables.

It is these two procedures that underlie the results presented in the Table 4.25:

V_CO_SCORING	0.004906
V_CO_LIMITE_CREDIT	0.000019
V_CO_SALDO_ACTUAL	0.000037
M_RENDIBILIDADE	-0.000619
IDADE	0.001378
HABILIT__D	-0.114342
CI_CO_CLASS_D	-0.217117
V_CO_REVOLVING	-0.000028
ESTADO_CIVIL_D	-0.110437
GENERO_D	0.193188

Table of Marginal Effects

4.2.2 INTERPRETATION OF THE COEFFICIENT SIGN OF EXPLANATORY VARIABLES

4.2.2.1 Dummy Variables

- ci_co_stado

The odds ratios correspond to the increase (or decrease, if the ratio is less than 1) observed in the dependent variable, when the value of the independent variable increases by one unit. The independent variable ci_co_state has been transformed into a dummy variable whose EXP (B) <1, ie has a value B <0.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
ci_co_estadoDummy	-18,833	1115,594	,000	1	,987	,000	,000	.

The reference category (0) was assigned to attribute 1 (Active Accounts) and attributes 2 (Non-Active Accounts) and 3 (Unusable Accounts) were included in the response category or treatment group (1). The more Non-Active Accounts (2) and Unusable Accounts (3) there are, the less likely the response is to be a Good Customer, that is, for each additional unit in Attributes (2) and (3) the odds of rating Good decrease. by a factor equal to EXP (B), ceteris paribus.

		d_co_estado			
		Active accounts	Non active accounts	Unusable accounts	Total
ci_co_estado	1	2602	0	0	2602
	2	0	281	0	281
	3	0	0	317	317
	Total	2602	281	317	3200

Table nº34- ci_co_stado and d_co_estado cross table

Characteristics	Attributes	Frequency	Reference Category Control Group	Responce Category Treatment Group
			0	1
ci_co_estado	1	2602	0	
	2	281		1
	3	317		1

Table # 35- Frequency of Reference and Response Attributes (ci_co_state)

- Marital status

The independent variable Marital Status was transformed into a dummy variable (Marital Status (Dummy). This variable has a negative coefficient (B) (-455) and the exponential of (B) equal to 0.635.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
EstadoCivilDummy	-,455	,139	10,685	1	,001	,635	,483	,834

The reference attribute “Married” was constituted as reference category or control group (0). All other attributes (divorced, unanswered, separated, single and widowed) fall into the response category or treatment group (1). The greater the number of divorced, unresponsive, separated, single and widowed, the greater the likelihood of not being Good, that is, the odds of classifying as Good decrease by a factor equal to EXP (B) = 0.635 per unit of good. increase in the attributes of the independent variable, ceteris paribus.

Characteristics	Attributes	Frequency	Reference Category Control Group	Responce Category Treatment Group
			0	1
Marital status	Married	1859	0	
	Divorce	288		1
	No Resp	656		1
	Separate	16		1
	Not married	306		1
	Widower	75		1

Table 36 Attribute frequency by Reference and Response categories (Marital Status)

Estado Civil(Dummy) * Marital Status Crosstabulation

		Marital Status						
		Married	Divorce	No Resp	Separate	Not married	Widower	Total
Marital Status (Dummy)	0	1859	0	0	0	0	0	1859
	1	0	288	656	16	306	75	1341
	Total	1859	288	656	16	306	75	3200

Table nº 37- Cross table Marital Status (Dummy) and Marital Status (Attributes)

	0 (Bad)		1 (Good)	
	# Cases	%	# Cases	%
Married	722	22,56%	1137	35,53%
Divorce	127	3,97%	161	5,03%
N/Resp	518	16,19%	138	4,31%
Separate	8	0,25%	8	0,25%
Single (Not Married)	195	6,09%	111	3,47%
Widower	30	0,94%	45	1,41%
Total	1600	50,00%	1600	50,00%

Table No. 38- Number of Good and Bad Cases by Attributes of Marital Status

The independent variable ci_co_class has been transformed into a dummy variable (ci_co_class Dummy). This variable has a negative coefficient (B) (-1,106) and the exponential of (B) equal to 0,331.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
ci_co_classDummy	-1,106	,358	9,549	1	,002	,331	,164	,667

Reference attribute “19” has been set up as reference category or control group (0). All other attributes (0, 1, 2, 3, 6, 7, 8, 9, 13, and 20) fall under the response category or treatment group (1).

When you increase a unit to any of the attributes in category (1), the odds of classifying Good decrease by a factor.

Characteristics	Attributes	Frequency	Control Group Reference Category	Treatment Group Answer Category
			0	1
ci_co_class	0	34		1
	1	114		1
	2	55		1
	3	22		1
	6	16		1
	7	30		1
	8	27		1
	9	30		1
	13	256		1
	19	2577	0	
	20	39		1

Table # 39- Frequency of Attributes by Reference and Response Category (ci_co_class)

Characteristics	Attributes	Frequency	Control Group Reference Category	Treatment Group Answer Category
			0	1
Género	F	951		1
	M	2249	0	

Table 40- Frequency of attributes by Reference and Response Category (Gender)

4.2.2.2 Categorical Variables

- genre

The gender independent variable entered the model as the categorical variable. The reference attribute “Male” was constituted as a reference category or control group (0) and entered the model first (first in SPSS®). The other attribute (1) Female is in the response category or treatment group (1).

This variable has a negative coefficient (B) (-0.810) and the exponential of (B) equal to 0.445.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
Genre(1)	-,810	,149	29,489	1	,000	,445	,332	,596

When one unit is increased to the attribute-independent variable (1), that is, whenever the universe of women grows, the probability of the account being classified as Good is lower, since the percentage of Bad (58.14%) is greater than Good (41.86%). Increasing one unit in the independent variable decreases the probability of being Good, so the odds of classifying Good decrease by a factor equal to EXP (B) = 0.445 *ceteris paribus*.

Characteristics	Attributes	Frequency	Control Group Reference Category	Treatment Group Answer Category
			0	1
Género	F	951		1
	M	2249	0	

Table 40- Frequency of attributes by Reference and Response Category (Gender)

COD * Gender (Dummy) Crosstabulation

		Gender				
		M	F	Total		
COD	0	1047	46,55 %	553	58,14 %	1600
	1	1202	53,45 %	398	41,86 %	1600
	Total	2249	100,00 %	951	100,00 %	3200

This negative direct relationship with the graph produced by the CHAID tool is confirmed.

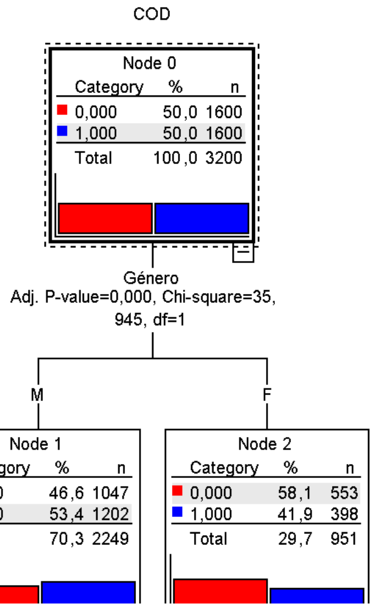


Chart # 7- Sorting tree (CHAID) by Genre

4.2.2.3 Quantitative Variables

- v_co_scoring

This variable has a direct positive relationship with the dependent variable (B = 0.067). In other words, the higher the scoring value, the greater the likelihood of being rated Good.

In other words, whenever the independent variable increases by one unit, the probability of classifying as Good (odds) increases by a factor equal to EXP (B) = 1,069 *ceteris paribus*.

Variable		B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
								Lower	Upper
Step 10[j]	v_co_scoring	,067	,004	288,873	1	,000	1,069	1,061	1,077

This direct relationship is confirmed by the CHAID tool, whose decision tree is as follows:

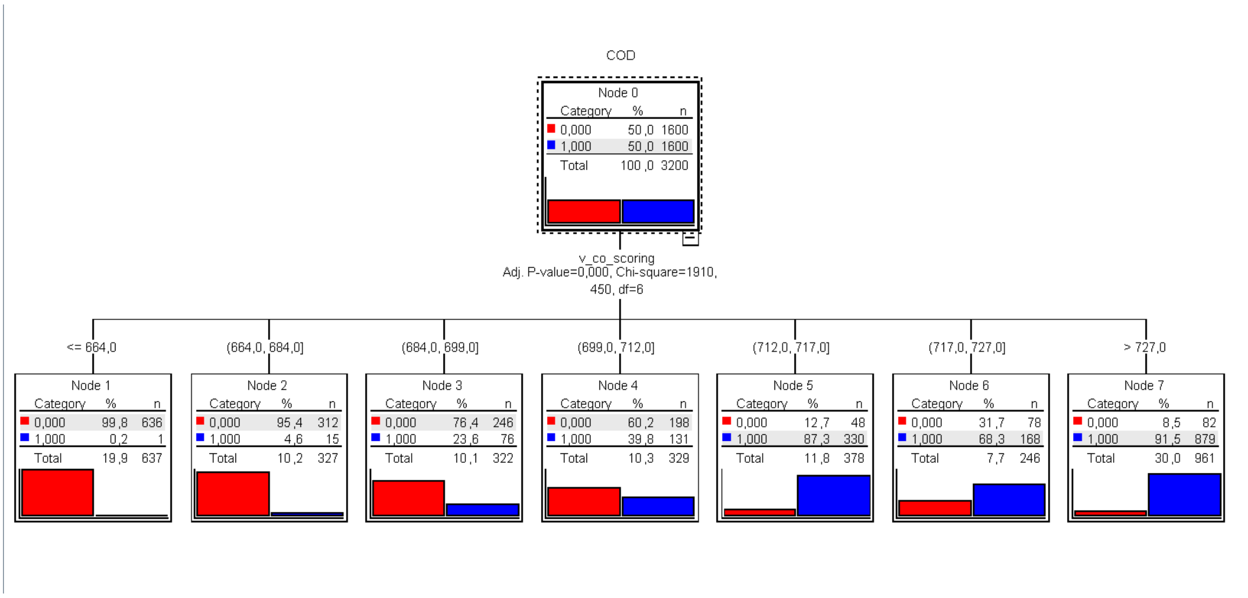


Chart # 8- Classification tree (CHAID) by v_co_scoring

- *v_co_limite_credit*

The independent variable v_co_limite_credit has a direct positive relationship with the dependent variable. This means that higher credit limits will be more likely to belong to a Good account. To illustrate this assumption, the following cross-table shows the average value of accounts classified as Bad (0) and Good (1) where their average is much higher.

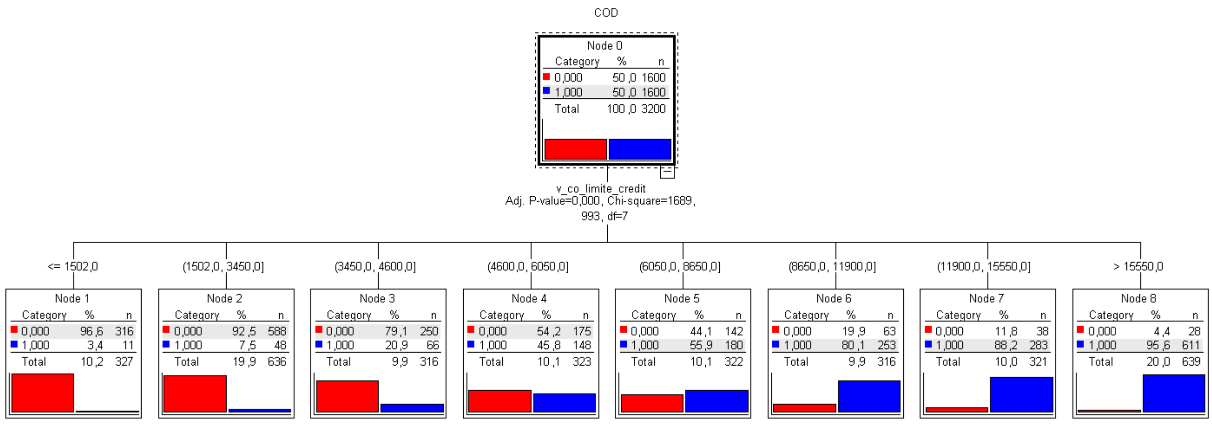
Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
v_co_limite_credit	,000271	,000	160,413	1	,000	1,000271	1,000	1,000

Therefore, whenever the credit limit increases by one currency, Good's odds increase by a factor of 1,000271, *ceteris paribus*.

Case Summaries		
v_co_limite_credit		
COD	N	Mean
0	1600	3997,47
1	1600	13358,64
Total	3200	8678,06

To confirm this relationship we used the following CHAID program:

Gráfico nº 9- Árvore de classificação (CHAID) por *v_co_limit_credit*



- *v_co_saldo_actual*

The v_co_saldo_current variable has a direct positive relationship with the dependent variable. This means that higher balances are more likely to belong to Good accounts.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
v_co_saldo_actual	,000131	,000	9,638	1	,002	1,000131	1,000	1,001

To illustrate this assumption, we use a crosstab that confirms that Good accounts have a higher average value than Bad accounts. Therefore, whenever the average balance increases by one currency, the odds of classifying Good increase by a factor of 1,000371, *ceteris paribus*.

Case Summaries		
v_co_saldo_actual		
COD	N	Mean
0	1600	2488,0865
1	1600	6078,6055
Total	3200	4283,3460

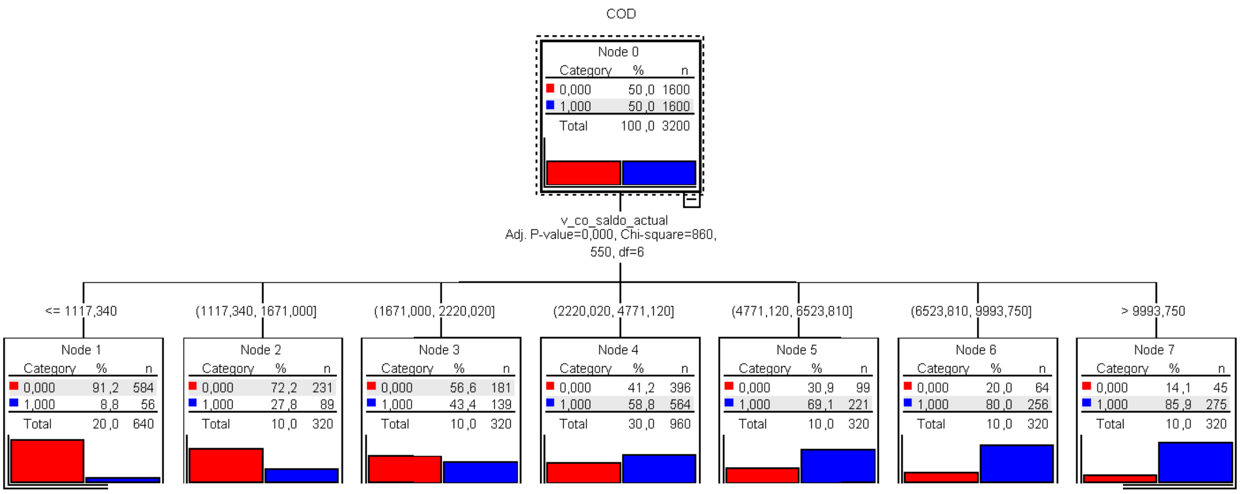


Chart # 10- Classification Tree (CHAID) by v_co_saldo_actual

- *v_co_revolving*

Revolving (credit) means the amount left unpaid on the previous month's statement. A direct negative relationship (B = -0,000255) with the dependent variable is not explainable by the average values observed in the Good and Bad accounts. If this were so, a positive direct relationship would be observed, which is not the case.

Although it is a very weak relationship, that is (B≅0) the relationship with the dependent variable is that the odds of being Good decrease that probability by a factor of 0.999945 (≅1).

The validity of the coefficient sign could be questioned, since it is the accounts in which the unpaid debts at the end of each month are those which are the most profitable, since interest on the outstanding balance is due and therefore would increase. the likelihood of being a good account.

On the other hand, the outstanding balance is associated with a risk (credit risk), and in this perspective the higher the risk the greater the likelihood of becoming a bad account.

An economic interpretation based on these two arguments may not be entirely enlightening.

The reasons that may possibly better support the explanation of the negative relationship between the revolving variables and v.d. are the data from Banco de Portugal, which recorded an increase in bad loans to individuals for three consecutive years. In this sense, an increase in bad credit may mean that the outstanding balances in recent years have contributed to the negative ratio of the revolving variable. Thus for each currency unit of unpaid credit (remaining outstanding balance) at the end of each month, the odds of classifying as Good decrease that probability.

Variable							95,0% C.I.for EXP(B)	
	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
v_co_revolving	-,000255	,000	4,606	1	,032	0,999745	1,000	1,000

Case Summaries

v_co_revolving

COD	N	Mean
0	1600	2198,9510
1	1600	5037,7067
Total	3200	3618,3288

- *m_rendibilidade*

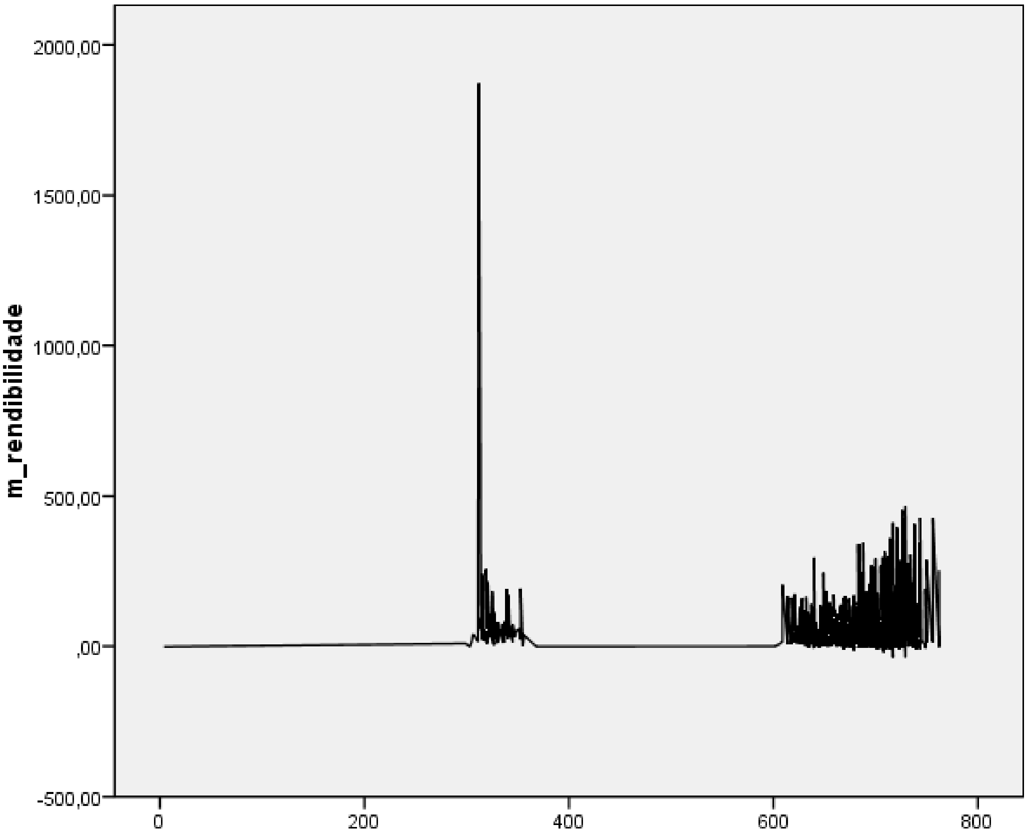
The monthly profitability of the account has a negative relationship (B = -0.009) with the dependent variable. That is, the accounts with the highest return will be those whose probability of being Good is lower.

In other words, for each currency unit most recorded in the monthly balance, the assigned credit limit will be reduced by the same amount. In an extreme situation the outstanding balance would be equal to the credit limit granted.

From this point on, no use of the card can be made if the user does not make any amortization of the outstanding capital in order to recover the activity of his account. From that moment on its scoring is reduced (positioned on a scale between 300 and 400 points), starting to pay monthly interest on the capital value.

Graph 10 shows this negative relationship with the dependent variable and has the reasons as described above.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
m_rendibilidade	-,009	,003	9,765	1	,002	,991	,985	,997



Graph # 11- Higher profitability at lower score levels (inverse relationship)

In the abscissa are represented the scoring values, where it is verified that the highest profitability values are in lower scoring positions.

- age

The age variable has a direct positive relationship (B = 0.019) with the dependent variable. This means that higher age levels are more likely to belong to Good accounts. This tells us that for each year of age the probability of being a good account grows by a factor of 1.019, *ceteris paribus*.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
Age	,019	,007	6,871	1	,009	1,019	1,005	1,034

To confirm this relationship, we resorted to the CHAID (Chi-Squared Interaction Detection) program. This feature allowed subdividing the age variable into groups that have a direct relationship with the dependent variable.

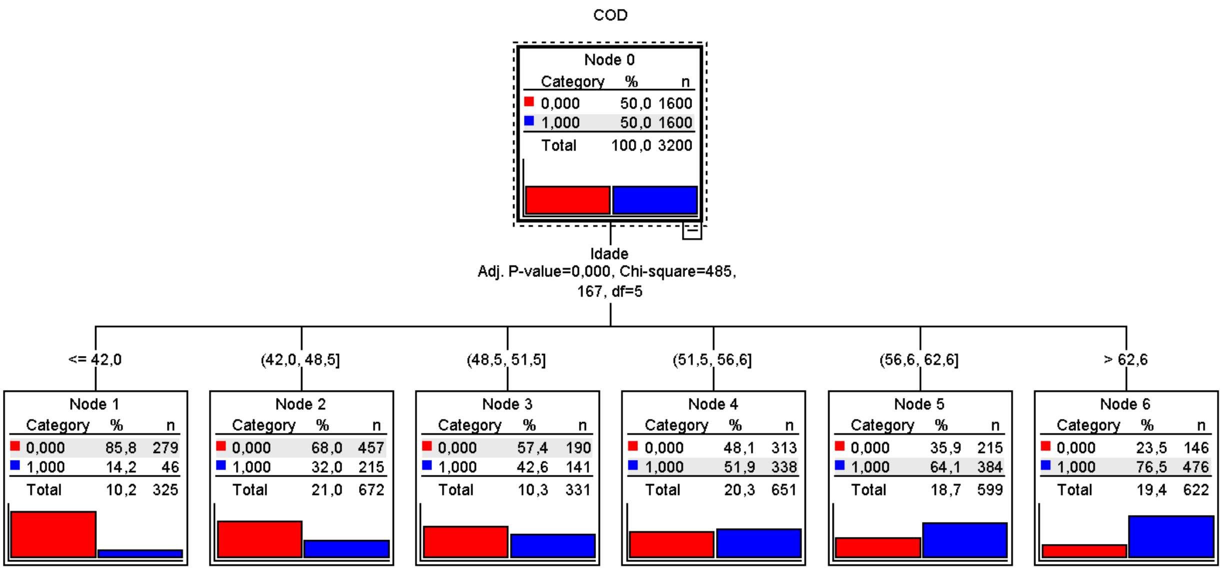


Chart # 12- Age rating tree (CHAID)

The age grouping was done by criteria of CHAID itself that considered the following decision tree:
1) in node1 included individuals up to 42 years of age, having found 325 of which only 14.2% are Good (46). This age group represents 10.2% of the total of 3,200 individuals in the sample;
2) in node 2 included individuals between 42 and 48 and a half years, having found 672 people in this age group, of which 215 are Good (32.0%). This group represents 21.0% of the sample;
3) in node 3 included individuals between 48 and a half to 51 and a half, having found 331 clients of which 141 are Good (42.6%). This group represents 10.3% of the sample.
4) in node 4 included individuals between 51.5 years and 56.6 years, having found 651 clients of which 338 (51.9%) are Good. This group represents 20.3% of the total sample;
5) in node 5 included individuals between 56.6 years and 62.6 years, having found 599 clients of which 384 (64.1%) are Good. This group represents 18.7% of the sample;
6) in node 6 included individuals older than 62.6 years, having found 622 clients of which 476 (76.5%) are Good. This group represents 19.4% of the sample.

We also verified the direct positive relationship of the age variable with the dependent variable.

HABILIT__D

-0.114342

On average the probability that a customer belongs to the “Answer” Category is Good payer is 0.114342 less likely as customers to be in Category
"Reference", assuming everything else constant.

4.2.4 TEST TO ERROR HETEROCEDASTICITY

Heteroscedasticity is considered a serious problem in models with variable binary dependent because if the error variance is not constant the estimators for the coefficients are no longer the most efficient. To conclude about the homoscedasticity of the errors we will calculate the value of the LM test proposed by Davidson and MacKinnon (1993) assuming that v_co_limit_credit10 is the variable responsible for heteroscedasticity.

The LM test statistic is the explained squared sum (ESS) of the auxiliary regression. whose dependent variable is the standardized logistic regression residues and has a Chi-square distribution with q degrees of freedom, where q is the number of variables considered to explain heteroscedasticity. In this case q = 1 corresponds to a value critical of 3.84.

To calculate the test value we follow Davidson and MacKinnon methodology (1993) and resorted directly to EVIEWS®, giving the value of ESS = 37.82.

As this value is higher than the critical value, the null hypothesis is rejected and it is concluded that the errors are heteroscedastic.

As a consequence, the estimators for the logistic regression coefficients leave to be the most efficient. To obtain consistent estimators for the variance of the estimators we use the Huber-White procedure that is available through EVIEWS®. The results obtained are presented in table 4.33:

The Huber-White procedure corrects only the variance of the estimators, not modifying the estimates for the coefficients previously presented.

Despite the variance correction, the estimates for the coefficients continue to be significant differences confirming the statistical relevance of the explanatory variables considered.

Dependent Variable: COD
Method: ML - Binary Logit (Quadratic hill climbing)
Sample: 1 3200
Included observations: 3200
Convergence achieved after 23 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
V_CO_SCORING	0.066500	0.003411	19.49323	0.0000
V_CO_LIMITE_CREDIT	0.000261	2.21E-05	11.80743	0.0000
V_CO_SALDO_ACTUAL	0.000499	0.000132	3.788578	0.0002
M_RENDIBILIDADE	-0.008396	0.002957	-2.839041	0.0045
IDADE	0.018678	0.006731	2.774966	0.0055
HABILIT__D	-0.602927	0.128098	-4.706776	0.0000
CI_CO_CLASS_D	-1.434070	0.385528	-3.719759	0.0002
V_CO_REVOLVING	-0.000384	0.000130	-2.953830	0.0031
ESTADO_CIVIL_D	-0.578892	0.128583	-4.502090	0.0000
GENERO_D	0.808648	0.130033	6.218793	0.0000
C	-49.89290	2.462915	-20.25766	0.0000

McFadden R-squared	0.653876	Mean dependent var	0.500000
S.D. dependent var	0.500078	S.E. of regression	0.260019
Akaike info criterion	0.486704	Sum squared resid	215.6077
Schwarz criterion	0.507573	Log likelihood	-767.7269
Hannan-Quinn criter.	0.494186	Restr. log likelihood	-2218.071
LR statistic	2900.688	Avg. log likelihood	-0.239915
Prob(LR statistic)	0.000000		

Obs with Dep=0	1600	Total obs	3200
Obs with Dep=1	1600		

v_co_scoring	0,066500
v_co_limite_credit	0,000261
v_co_saldo_actual	0,000499
m_rendibilidade	-0,008396
idade	0,018678
habilit_d	-0,602927
ci_co_class_d	-1,434070
v_co_revolving	-0,000384
estado_civil_d	-0,578892
genero_d	0,808648
constante	-49,892900

4.3 VALIDATION OF THE MODEL THROUGH OUT-OF-SAMPLE

The values obtained for the independent variables that entered the model are as follows:

Variables in the equation	Code	β
v_co_scoring	A	0,066500
v_co_limite_credit	B	0,000261
v_co_saldo_actual	C	0,000499
m_renderability	D	-0,008396

Age	E	0,018678
Habilit (D)	F	-0,602927
ci_co_class (D)	G	-1,434070
v_co_revolving	H	-0,000384
Marital Status (D)	I	-0,578892
Genre (D)	J	0,808648
Constant		-49,89290

Table 4.34- Values of coefficients B of the variables present in the logistic regression equation

Model validation was performed through an out-of-sample containing 800 clients (400 Good and 400 Bad) (See Annex 4), and applied to the logistic regression model according to the following equation:

$$p(Y_i = 1) = \frac{1}{1 + e^{-Z_i}} + \varepsilon_i$$

On that $Z_i = \beta_0 + \beta_1 x_{1_i} + \cdots + \beta_k x_{k_i}$

Where:

β_k represents the model parameters

x_{k_i} the variables that represent the factors explaining the probability of each user being a good payer;

ε_i *error*

$$Z_i = -49{,}89290 + 0{,}066500 \times A + 0{,}000261 \times B + 0{,}000499 \times C - 0{,}008396 \times D + 0{,}0186 \times E - 0{,}602927 \times F - 1{,}434070 \times G - 0{,}000384 \times H - 0{,}578892 \times I - 0{,}808648 \times J$$

$$p(Y_i = 1) = \frac{1}{1 + e^{-(-49{,}89290 + 0{,}066500\times A + 0{,}000261\times B + 0{,}000499\times C - 0{,}008396\times D + 0{,}0186\times E - 0{,}602927\times F - 1{,}434070\times G - 0{,}000384\times H - 0{,}578892\times I - 0{,}808648\times J)}} + \varepsilon_i$$

The values obtained are summarized in the following table, which proves the predictive robustness of the model.

IN SAMPLE

Observed		Predicted COD 0	Predicted COD 1	Percentage Correct
COD	0	1433	126	**89,56%**
	1	167	1474	**92,13%**
	Overall Perc			**90,84%**

HOLDOUT SAMPLE

Observed		Predicted COD 0	Predicted COD 1	Percentage Correct
COD	0	356	43	**89,00%**
	1	27	374	**93,50%**
	Overall Perc			**91,25%**

CHAPTER 5th

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CONCLUSIONS, CONTRIBUTIONS EXPECTED AND SUGGESTIONS

5.1 Conclusions of the Empirical Study

From the present empirical study the following conclusions are highlighted:

1-The main explanatory factors identified by the logistic model (variables identified with the highest predictive force) were: v_co_scoring, v_co_limite credit,v_co_saldo_current, m_renderability, age, habilit_d, ci_co_class_d, v_co_revolving, privileg_d state and gen_d.

2- The methodology presented in this study showed that binary logistic regression is able to correctly classify 90.84% of individuals (1474 FP + 1433 TN = 2907; 3200);

3–The model ranked the Best Payers better (92.13%; FP = 1474; 1600) than the Bad payers (89.56%; TN = 1433; 1600);

4–The predicted Good Payer rating for 126 individuals turned out to be observed to be Bad Payers (FP; Error Type II) and the Bad Payer rating predicted for 167 individuals turned out to be good payers (FN; Error Type I).

5- Of the 21 original independent variables only 10 (6 quantitative and 4 dummies) were used in the forecasting model.

6- The validation of the model through an out-of-sample database proved to be capable of correctly classify 91.25% of subjects (374 TP + 356 TN = 730; 800). It was demonstrated that the methodology used identified ten main factors Good and Bad Payers, confirming the predictive model.

5.2 CONCLUSIONS ON METHODOLOGY

5.2.1 INTRODUCTION

The methodology used in this study is the result of the choice made among other sets of methods and techniques that can mitigate the problem of bad credit growth. Credit scoring compiles a set of methods that have been refined, improved and refined, over the last four decades, with the contribution of many academics (See Chap.2), managers, credit analysts and financial institutions.

The gathering of all that knowledge has in fact only become useful to the when it was possible to offer all the know-how through a management tool that could be used as a tool for repairing problems resulting from the granting credit.

This tool has gained notoriety among the business community through William R. Fair and Earl J. Isaac (1956) in designing, according to standardized forms of analysis, the steps that should be taken in support of the decision to grant credit through the use of statistical methods.

The protection of the “secret” of all acquired knowledge has given way to black boxes, making it difficult for other scoring manufacturers to replicate that tool. FICO (Fair Isaac Company) became a pioneer in creating that tool and yet today ensures the leadership in the development of scoring systems with application to other areas.

Direct Marketing, commonly referred to as “Mail Sales”, was one of those areas benefiting from the application of the binary logistic regression model in sending letters to potential consumers, with the strong support for the decision to 'send letter' or 'do not send according to the previous knowledge of characteristics that identify the profile of consumer.

The classification of customer types and the proper management of databases helped identify potential consumers for certain products, namely through cross-selling techniques in which the identification of someone who had consumed a particular product, would be a potential consumer of a new product that would fit your behavioral profile (behavioral scoring).

The development of computational resources gave new impetus to scoring due to the speed of processes, the accuracy of its results and the extraordinary volume of information prospected by Data Mining The offer to consumers of revolving credit by institutions financial and non-financial, the credit card materialized as a means of payment. All The credit card structure of a credit card is credit scoring methodology.

Credit card users throughout the world have benefited from technological revolutions of the satellite media, allowing authorizations for long-distance payment from the credit source.

5.2.2 Main conclusions

1-The credit scoring methodology constitutes one of the main tools for the credit risk mitigation. By mitigating the problem, bad credit is reduced and this reduction is achieved at the expense of early detection of potential non-compliant. From the finding of the results offered by the study, we conclude that credit scoring is a methodology capable of predicting and reducing doubtful accounts.

2-The credit scoring methodology distinguishes the methods applied to applicants for (application scoring) of those who have already benefited from the concession and whose payment behavior allows indications of future behavior scoring.

Finding results among 4,000 credit card users (behavioral scoring), we conclude that behavioral scoring allows us to predict the probability of default through the prior construction (definition) of the profile of Good and Bad payer.

3-The widespread use of credit cards is largely due to the fact that development of this methodology associated with new communication technologies in real time, enhancing and generalizing this means of payment.

4-Databases, properly treated, constitute one of the basic premises for the success of this methodology.

5-The cost associated with processing databases is very high, not only for the time spent on data compilation, such as the cost of building scoring.

6-The high costs inherent in the development and implementation of this methodology, restrict the universe of application, leaving most SMEs out of reach.

7-The absence of a "statistical culture" in most companies and unfamiliarity of the benefits resulting from scoring result in a lack of attention methodology and the shortage of specialized staff in this area.

8-The scoring methodology has application in other areas than credit, insurance, business intelligence agencies, marketing, in production management, in human resources.

5.3 EXPECTED CONTRIBUTIONS

5.3.1 FOR THEORY

Since the beginning of scientific thinking, the understanding of nature has been for the simplicity of scientific propositions. Human nature and the complex component associated with it, should obey this same principle as the most powerful method for your understanding.

The reduction in the risk of lending in decision making by the methodology presented assumes moderation and simplicity in the evaluation methods. This dissertation accepted the principle of parsimony and the adequacy of forecasting when modeling the logit function with only ten variables from an initial set of twenty-one features.

In a broader perspective on Credit Risk Management Theory, we believe that it will be enriched if the credit scoring methodology has a most prominent presence. This enrichment will allow a better understanding of the theories that explain the processes that describe grant decision aid of credit risk.

The realization of the usefulness of this contribution to theory will only be better when financial and non-financial institutions recognize their merits when applying them to credit risk management processes.

5.3.2 FOR MANAGEMENT

The logistic regression model, despite its popularity with the community far from being a commonly used tool in many economic activities.

Given the low use of statistical methods in credit management, it is recommended that that the processing of business data is one of Management's priorities. The processing of such data may be carried out by research centers which make available to the various economic activities the main factors characterizing the risk profile of your clientele. Deeper knowledge of the behavior of risk groups would reduce uncertainty and would better explain the consequences of unsafe decision-making properly considered.

5.3.3 FOR PUBLIC POLICIES

Data processing has allowed institutions in particular, and the Portuguese State in general, a better efficiency in its management processes. Without that treatment and relationship of this information the management processes would be longer and less effective. In this way the interrelativity of the management systems with a direct influence on professional behavior and conduct and Social Failure to invest in data mining, data cleaning and processing delays the knowledge and in the absence of this the chances of making good decisions are smaller. Banco of Portugal, INE, Public Institutes among other bodies should conciliate specific information in various areas of economic interest, making available to society a public asset (knowledge) building up to now unexplored development models.

The discovery of knowledge through governmental databases, identification of development patterns should be one of the concerns reduce waste, increase productivity and replicate of success applied in other contexts. The promotion of a “statistical culture” within organizations based on the knowledge derived from data mining will result in decision with lower risk, greater consistency and greater temporal sustainability. In this perspective, new job opportunities would open for young people specialized in these matters. The inevitable improvement in risk assessment processes increase the knowledge of organizations, making them more effective and better protected from threat of non-payment.

5.4 SUGGESTIONS FOR FUTURE INVESTIGATIONS

The methodology presented in this study may constitute a starting point for other studies that aim to investigate issues related to credit risk, investment risk, insolvency risk, among many others. Increasing public investment has been one of the economic policies mitigate economic crises, although their application to the economy can be with high degrees of risk.

Public investment has been one of the areas of political decision making that has revealed a high degree of risk, not only for the amounts involved but also for the uncertainty of their success.

Between the decision to carry out a project or not to carry it out there should be a set of variables already identified by previous projects that assessed the likelihood of success of these investments.

The need for these studies becomes even greater when in times of great economic and social turmoil wrong decisions take too much effort from the public purse.

This social sacrifice cannot be exhausted by decision errors, often based on political subjectivities or studies of dubious credibility, some of them tailored to the results to be evidenced.

The execution of public works of great investment, without knowledge of the risk associated, has produced frequent financial overruns and in some cases these works they are very debatable public utility, given the demonstrated cost-benefit ratio. The logit model is an important statistical tool in this type of study. Yet the effectiveness of its usefulness is strongly questioned whether variables with higher predictive capacity are ignored, unknown or bad interpreted.

The question seems pertinent to us when we question the reasons why they are repeated today the same mistakes that have been made in the past. Why are the explanatory factors of these errors not known to statistically model new projects?

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