Credit scoring models for the microfinance industry using neural networks: Evidence from Peru

Antonio Blanco \(^a\), Rafael Pino-Mejías \(^b\), Juan Lara \(^c\), Salvador Rayo \(^c\)

\(^a\) Department of Financial Economics and Operations Management, Faculty of Economics and Business Studies, University of Seville, Avda. Ramon y Cajal, 1, 41018 Seville, Spain
\(^b\) Department of Statistics and Operational Research, Faculty of Mathematics, University of Seville, Avda. Reina Mercedes, s/n 41012 Seville, Spain
\(^c\) Department of Financial Economics and Accounting, Faculty of Economics and Business Studies, University of Granada, Campus Cartuja, s/n 18071 Granada, Spain

**A R T I C L E  I N F O**

Keywords: Microfinance institutions Classification rules Multilayer perceptron Linear discriminant analysis Quadratic discriminant analysis Logistic regression

**A B S T R A C T**

Credit scoring systems are currently in common use by numerous financial institutions worldwide. However, credit scoring with the microfinance industry is a relatively recent application, and no model which employs a non-parametric statistical technique has yet, to the best of our knowledge, been published. This lack is surprising since the implementation of credit scoring should contribute towards the efficiency of microfinance institutions, thereby improving their competitiveness in an increasingly constrained environment. This paper builds several non-parametric credit scoring models based on the multilayer perceptron approach (MLP) and benchmarks their performance against other models which employ the traditional linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and logistic regression (LR) techniques. Based on a sample of almost 5500 borrowers from a Peruvian microfinance institution, the results reveal that neural network models outperform the other three classic techniques both in terms of area under the receiver-operating characteristic curve (AUC) and as misclassification costs.

© 2012 Elsevier Ltd. All rights reserved.

**1. Introduction**

Over the last decade, the microfinance sector has grown dramatically, and is currently considered as a booming industry. In the period 1998–2008, the number of microfinancial institutions (hereinafter, MFIs) grew by 474%, and the number of customers increased by 1048%. Attracted by this rapid growth, a large number of international commercial banks have started operating in the microfinance sector, viewing it as a potential for profitable investment. This injection of interest has increased the competition between the players in this industry, and has negatively affected the MFIs. The MFIs therefore need to increase their efficiency in all their processes, minimize their costs, and control their credit risk if they want to survive in the long-term. One way for the MFIs to become more efficient in order to compete with the commercial banks is the implementation of automatic credit scoring systems to evaluate their credit applicants since credit scoring reduces the cost of credit analysis, improves cash flow, enables faster credit decisions, reduces the losses, and also results in the closer monitoring of existing accounts and the prioritization of repayment collection. To this end, Rhynne and Christen (1999) suggest that credit scoring is one of the most important uses of technology that may affect microfinance, and Schreiner (2004) affirms that experiments carried out in Bolivia and Colombia show that the implementation of credit scoring improves the judgment of credit risk and thus cuts, by more than $75,000 per year, the costs of MFIs. Nevertheless, and in contrast to the concentration of research on financial institutions, the development of credit scoring models in the microfinance sector has only undergone minor advances. Furthermore, those models in existence are based on traditional parametric statistical techniques, mainly linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and logistic regression (LR), despite the overwhelming evidence found in numerous studies which indicates that the non-parametric methodologies usually outperform these classic statistical models (for example, see Lee & Chen, 2005; West, 2000). That is, to the best of the authors’ knowledge, in the existing literature...
no credit scoring model designed for the microfinance industry ap-
plies a non-parametric methodology, and therefore, the microfi-
nance industry has not yet benefited from the advantages of
non-parametric techniques to improve the performance of credit
scoring models, and hence are failing to compete on equal terms
with their new competitors, the international commercial banks.

Of the few credit scoring models developed for MFIs, all have used
parametric methodologies, particularly LDA and LR (Kleimeier &
Dinh, 2007; Rayo, Lara, & Camino, 2010; Reinke, 1998; Sharma & Zel-
ler, 1997; Viganò, 1993; Vogelgesang, 2003; Zeller, 1998). However,
the strict assumptions (linearity, normality and independence
among predictor variables) of these traditional statistical models, to-
gogether with the pre-existing functional form relating response vari-
ables to predictor variables, limit their application in the real world.

Several authors (for example, Karels & Prakash, 1987; Reichert, Cho,
&Wagner, 1983) point out that two basic assumptions of LDA are
often violated when applied to credit scoring problems: (a) the inde-
pendent variables included in the model are multivariate and nor-
maally distributed, (b) the group dispersion matrices (or variance–
covariance matrices) are equal across the failing and the non-failing
groups (for a detailed analysis of the problems in applying discrim-
inan analysis in credit scoring models, see Eisenbeis, 1978). In the
cases where the covariance matrices of the two populations are
unequal, theoretically, QDA should be adopted, although LDA is
reported to be a more robust and precise technique (Dillon &
Goldstein, 1984). In the same way as LDA, LR is also optimal under
the assumption of multivariate normal distributions with equal
covariance matrices, and LR also remains optimal in a wider variety
of situations. However, logistic regression requires larger data sets to
obtain stable results, interactions between predictor variables must
be formulated, and complex non-linear relations between the
dependent and independent variables could be incorporated through
appropriate but not evident transformations. For these reasons,
in recent years, non-parametric statistical models, such as the k-nearest
neighbor algorithm (Henley & Hand, 1996), support vector ma-
chines (Vapnik, 1998), decision tree models (Davis, Edelman, &
Gammerman, 1992), and neural network models (Patuwo, Michael,
&Ming, 1993), have been successfully applied to credit scoring prob-
lems. Of these, artificial neural networks (ANNs) constitute one of
the most powerful tools for pattern classification due to their non-
linear and non-parametric adaptive-learning properties. Many stud-
ies have been conducted that have compared ANNs with other tradi-
tional classification techniques in the field of credit scoring models,
since the default prediction accuracies of ANNs are better than those
using classic LDA and LR (Armingier, Enache, & Bonne, 1997; Desai,
Conway, Crook, & Overstreet, 1997; Desai, Crook, & Overstreet,
1996; Hand & Henley, 1997; Lee & Chen, 2005; Lee, Chiu, Lu, & Chen,
2002; Malhotra & Malhotra, 2002; Markham & Ragsdale, 1995; Patu-
wo et al., 1993; Piramuthu, 1999; Srinivasan & Ruparel, 1990;
West, 2000). However, despite yielding satisfactory results, ANNs
also feature certain disadvantages, such as its black box nature and
the long training process involved in the design of the optimal net-
work topology (Chung & Gray, 1999).

The main goal of this paper is therefore to develop a credit scor-
ing model specially designed for the microfinance industry by
using multilayer perceptron neural networks (hereinafter, MLP).
Moreover, we also compare the performance of MLP models
against the three parametric techniques most widely used: linear
discriminant analysis (LDA), quadratic discriminant analysis
(QDA), and logistic regression (LR). Based on a large sample which
contains financial and non-financial variables of almost 5500 bor-
rrowers from a Peruvian MFI, seventeen credit scoring models are
created, of which fourteen are MLP-based models.

The remainder of our paper proceeds as follows. In Section 2,
details of our data set are provided, and a detailed examination
of the variables available is undertaken in order to predict the de-
fect. In Section 3, several credit scoring models specifically de-
signed for MFIs are developed. To his end, various methodologies
are employed: Fisher discriminant analysis, logistic regression,
and multilayer perceptron. In Section 4, the results of different
models are shown and their comparison is made. An extensive dis-
cussion on the results is also carried out. Finally, Section 5 provides
the main conclusion of this study and future research lines are
analyzed.

2. Data and variables

2.1. The data set

We use a data set of microcredits from a Peruvian Microfinance
Institution (Edpyme Proempresa). Our dataset contains customer
information during the period 2003–2008 related to: (a) personal
characteristics (marital status, gender, etc.); (b) economic
and financial ratios of their microenterprise; (c) characteristics of
the current financial operation (type interest, amount, etc.); (d) variables
related to the macroeconomic context; and (e) any delays in the
payment of a microcredit fee. After eliminating missing and
abnormal cases, 5451 cases remain. From among these, 2673
(49.03%) are default cases, and 2778 (50.97%) are not. In line with
other studies (for example, Schreiner, 2004), a microcredit present-
ing a delay in repayment of at least fifteen days is defined as de-
fault microcredit. To perform an appropriate comparison of the
classification models, (LDA, QDA, LP, and MLP), our final data set
is randomly split into two disjoint sub-sets; a training set of 75%
and a test set of 25%. The test sample contains a total of 1363 cases
(51.80% failed and 48.20% non-failed). The configuration of params-
ters of each model is selected through a 10-fold cross-validation
procedure, as described in Sections 3.1–3.3. One advantage of cross-validation is that the credit scoring model is developed with
a large proportion of the available data (75% in this case).

2.2. Description of input variables

Table 1 shows the input variables used in this study.3 They pro-
vide the various characteristics of borrowers, lenders, and loans.
Numerous qualitative variables are considered in our study, since:
(a) Schreiner (2004) suggests that the input variables of the credit
scoring forces the microfinance sector to be more qualitative and
informal than those considered by traditional banks; and (b) recent
literature concludes that the inclusion of qualitative variables im-
proves the prediction power of models. Moreover, since the default
of borrowers has a close relationship with the general economic sit-
uation, variables linked to the macroeconomic context are also con-
sidered as input variables. With respect to the dependent variable,
default of the microcredit, this takes a value of 1 if the microcredit
fails, and 0 otherwise.

The first ratio indicates the number of times the income exceeds
total assets. Therefore, we estimate that the ratio (R1) is inversely
related with respect to the probability of default. The ratio R2 mea-
sures the relationship between the gross and operating costs of the
microenterprise. As with the previous ratio, we expect that the sign
of its coefficient is negative since the higher the value of this ratio,
the more solvent the income/loss of the firm, and the lower the
financial difficulties. The third financial ratio (R3) measures the
liquidity of the microenterprise. Due to the design of this ratio,
the higher its value, the lower the probability of default. Therefore,
the sign of the estimator is expected to be negative. The fourth

3 This table also shows the expected sign of the relationship between each input
variable and the probability of default. The statistical descriptions of all the input
variables are shown in Table 1 and Table 2 of Appendix 1. These statistics are
presented for each group (failed and non-failed).
دریافت فوری متن کامل مقاله

امکان دانلود نسخه تمام متن مقالات انگلیسی
امکان دانلود نسخه ترجمه شده مقالات
پذیرش سفارش ترجمه تخصصی
امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
امکان دانلود رایگان ۲ صفحه اول هر مقاله
امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
دانلود فوری مقاله پس از پرداخت آنلاین
پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات