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Partnership credit scoring classification Probem: A neural network approach

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Abstract: The credit scoring has long been an important and widely studied topic in banking. For lots of commercial banks, it remains the most important and difficult risk to manage and evaluate. Credit scoring methods became standard tool of banks and other financial institutions to estimate whether an applicant for credit/goods will pay back his liabilities. Microfinance institutions play a very important role in reducing poverty in developing countries. The risk of default in microfinance, due to asymmetric information between the micro-entrepreneur and the Microfinance Institutions, remains a major challenge that threatens the sustainability of Microfinance Institutions (MFI's). In this work we represent a new way to develop credit scoring model which take into account multi-criteria of partnership contract using multilayer perceptron neural networks in Moroccan microfinance institution. This research represents the first application of credit scoring in Partnership microfinance. To present the results developed with our credit scoring model we used different performance criteria such the Mean square error, the regression rate, the classification rate and the misclassification rate. These results were compared with the other statistical credit scoring techniques known as linear regression and discriminant analysis.

AMS subject classification:
Keywords: credit scoring, microfinance, partnership contract, neural networks.

1. Introduction

Microfinance institutions aim to grant small sums of money to small traders who have a high growth potential but which are deprived of access to the traditional banking system. Engaging poor people through business partnerships is an innovative approach being advocated these days in the form of social entrepreneurship and inclusive business models. This approach is particularly helpful as poverty alleviation strategy and aims at Small and Micro-enterprise development. However before engaging in a partnership project, microfinance institutions face difficulties in assessing the riskiness of the applicants. The risk of default in microfinance, due to asymmetric information between the micro-entrepreneur and the Microfinance Institutions, remains a major challenge that threatens the sustainability of Microfinance Institutions (MFIs). One way to control the negative effects of asymmetric information and transaction costs is the use of credit scoring. Credit scoring consists in predicting the behavior of applicants from the history of other bank's applicants. This is in fact classify the various bank customers into different classes according to their behavior during the repayment, then associate the new applicant to one of these classes with the supplied data. Although the definitions attributed to credit scoring differ from one author to another, it is generally accepted that credit scoring is a risk management tool that aims to predict the probability of default of a new loan using previous loans. Thus, according to Thomas and al. [38] credit scoring is âŁža set of decision models and their underlying techniques that aid credit lenders in the granting of creditâŁž. Furthermore Hand and Jacka [22] define the credit scoring as a model of assessing the creditworthiness of an applicant, implying that a customer is expected to pay on time, whereas a customer is expected to fail to pay on time. Although the application of credit scoring is old and dates back more than sixty years, it is relatively new to microfinance particularly in developing countries [34]. To our knowledge, there is few studies dedicated to scoring in the microfinance field.

In this paper we propose to study the credit scoring in Moroccan microfinance institution. Moreover the microfinance sector in Morocco was launched around twenty years ago and is dominated by conventional banks that use interest rates, which often means that many Moroccan do not have an alternative way to obtain capital.

The main aim of this paper is to present a new model of credit scoring which takes into account multi-criteria of partnership contract using neural network in Moroccan microfinance institution. These partnership contracts are built on sharing profit and loss where there are buyers and sellers on different projects and not borrowers and lenders. Here it is only the profit sharing ratio, not the rate of return itself that is predetermined. Then the applicant can enter into partnerships business projects with the MFI's offering these type of products.

To analyze the topic, this case is structured as follows: section 2 presents a review of literature on credit scoring l and specially in credit scoring in microfinance, section 3 outlines our Modeling Approach and define multi-criteria of credit scoring for entering into a partnership, section 4 present the results obtained with neural network and a comparison with linear regression and discriminant analysis and finally section 5 concludes the research findings and suggests areas for future research.

2. Credit scoring classification problem

2.1. Credit scoring

The concepts and ideas of credit scoring emerged about 75 years ago with Durand [18]. Since then credit scoring has been successfully applied in multiple domains such as marketing [15,25,37], accounting, finance in fields of bankruptcy prediction [26,39,42], in classification problems [12,**?**] and in scoring applications [23,34,43]. The credit scoring is a binary classifications that classify credit customers into predefined "good" and "bad" applicants. Hence according to Feldman [19] credit scoring process is the assignment of a rating to a borrower to estimate the future performance of its loan. This process uses quantitative measures of performance and characteristics of past loans to predict the performance of future loans with similar characteristics. Furthermore there are several techniques for credit scoring, the most popular one are traditional models based on statistical analysis such as regression analysis, discriminant analysis, logistic regression and decision tree and also advanced techniques such as neural networks, genetic programming, Fuzzy logic, support vector machine, Bayesian networks. In this context many authors compare different classifications techniques for credit scoring data [11], [43] and also propose a hybrid methods to improve the performance [6,**?**,**?**]. In addition each author choose his criteria to evaluate the performance of credit scoring, such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) the confusion matrix or the estimated misclassification cost, the Average Correct Classification (ACC) rate, the receiver operating characteristics (ROC) curve, GINI coefficient.

2.2. Credit scoring in microfinance

Many theorist indeed taking innovative steps in the form of Microfinance and social entrepreneurships and to combact poverty. Credit scoring in microfinance has actually emerged with Mark Schreiner works [32], [33], [34]. He argues that the scoring system seek to determine the links between repayment rates and a number of the key features. The study of Vigano [40] was the first one dedicated to the development of a credit scoring model in the context of microfinance, she does not give an exact definition of her models but considers them as a means helping analysts to obtain a complete picture of the borrower particular features. It is, in this case, a complex process that involves a careful analysis of information about borrowers to estimate the probability that the requested loan is regularly repaid. In literature the model of Vigano [40] is the best credit scoring one for microfinance. It links the default with 53 characteristics in a rural developbank in Burkina Faso. Furthermore Schreiner suggests that scoring for microfinance can indeed improve the judgment of risk and thus cut costs. He affirmed that credit scoring can play an important role in microfinance yet it is less powerful in poor countries than in rich countries. He also insisted that scoring is a supplement and can't replace the current microfinance technologies [32]. In another work [33], Schreiner, considered the credit scoring as the new revolution in microcredit. The requirements to the credit scoring application for a microfinance institution are also advanced. Schreiner [34] initiated a pilot work in microfinance in developing a model of credit scoring for a Bolivian microfinance. Furthermore many authors highlight in recent years the importance of credit scoring in Microfinance [9], [10]. In Moroccan case Aboulaich and al. [5] used a fuzzy model for credit scoring in order to help the MFI's to take the right decisions. Their data major findings are carefully selected and supported by the ARDI Moroccan foundation of Microcredits.

2.3. Partnership Credit scoring

Partnership is an inter-firm relationship which is characterized by asset, information and risks/rewards sharing, and joint decision-making. Partnership contract or profit and loss sharing contract is relationship between two or more persons to engage a business venture through a mutual contract and distribute the profits or losses of the business. The profit will be shared based on pre-agreed ratio, and the if there is loss, it will then be shared in proportion to each partnerâŁ™s share of capital. Traditional microfinance proposed to the poor people very high interest rate some up to 30%, the application of the partnership contract help the poor applicants to avoid this high interest rate and only shared a pre-agreed ratio. We present in this paper a partnership between MFI's and applicants who want to start a new project.

To understand the problem we may consider the financing needs of an applicant who want to start a new project, he learns about a Partnership microfinance program and decides to approach it with his financing request. Hence he think that he will benefits in partnership with Microfinance program since the contract is clear, prices are known, profits can be calculated and at the end of partnership borrower or partner will purchase the share capital of the Microfinance program on its face value. But the concept of partnership or profit and loss sharing contracts includes the moral hazard and asymmetric information between the financier and the entrepreneur. According to Al-Suwailem [7], the asymmetric information regarding the realized output of the entrepreneur's project is revealed by the financier through a random auditing strategy. Credit scoring can be a good alternative to reduce the issue of asymmetric information which can lead to adverse selection and moral hazard. The performance of a partnership has been investigated using both theoretical approaches and mathematical models. Using credit scoring in partnership contract can help the financier to know the behavior of the entrepreneur in the project. The applications of credit scoring has been devollopped in conventional banks and other financial institutions, the first application of credit scoring modeling technique without taking into account interest rates was by Abdou and et al. [4]. They build a scoring model for Islamic financial house in UK. They found that the scoring models can be of great benefit to Islamic finance houses in regards to their decision making process of accepting and rejecting new credit applications and thus improve their efficiency and effectiveness. In this paper we propose an alternative of traditional credit scoring which is partnership credit scoring. The purpose of our model is to add specifics criteria of partnership to traditional criteria of credit scoring and to choose the appropriate modeling technique to build the proposed model.

3. Modelling approch

The data used in this paper consists of accepted and rejected applicants in morrocan microfinance insitution which used partnerships contracts. We analyze the ability of the artificial neural network model to forecast the credit scoring this microfinance institution. The modeling approch proposed in this study consists of steps

1. Define the criteria of partnership credit scoring.
2. Define the classical criteria of credit scoring.
3. Use the multilayer perceptron neural network in partnership credit scoring.
4. Compare the results with other forcasting methods.

3.1. Criteria of partnership credit scoring

There are different criteria for partnership contract, the most common are, customer service [8], [35], [36], financial factors [28], marketing advantage [8], [24], [35], product development [24], [35], product diversification [8], [24], [35] and joint investment [8], [35]. For a successful partnership, each partner should define his criteria individually. The current literature indicates that clear criteria and consistency in measuring performance are the key to successful partnership [20]. In our case the partnership is between the microfinance institution and the applicant, and we are interested to develop credit scoring that could help MFI to accept or to reject the project proposed by the applicant. So our aim is to define only the criteria of the applicant. In this study we choose some of the partnership criteria that we consider important for a successful partnership project, and these criteria are: development of the project, marketing, cost optimization, seniority in the project, competence, diversification and evaluation of the tender charge.

Moreover for the dependent variable in credit scoring, authors often need to create their own variables when the required data is not directly available or when the purposes of the rating model require a specific variable [21]. Then for the criteria of classical credit scoring, values from corresponding data sheets were used, while for the partnership criteria the MFI doesn't dispose the data related on these criteria. Then each financier estimate these criteria based on the questions he will ask to the applicant. For example, for the characteristic of seniority in the project the financier can ask the applicant if he is very old, old or new in his domain and for development characteristic he can ask him if the project can be developed or not in the future.

The dataset contains customer information related to:

– Personal characteristics (marital status, Age, etc.)
– Characteristics of the partnership project between microfinance institution and the micro-entrepreneur.

The data set is a real one used by Aboulaich and et al. [5] who collected data which is selected and supported by the ARDI Moroccan foundation of Micro credits. It comprises 620 cases, of which 432 are accepted applicants and 188 are rejected applicants. This data set is linked to 16 independent predictor variables, in addition to the dependent binary variables, which are explained by two values, 1 for accepted applicants and 0 for rejected applicants. The data set is divided into two subsets. The training subset which is used in building the proposed scoring models consists of 434 cases (representing 70 per cent of the overall data set), and the testing subset which is used to test the predictive capabilities of the fitted models consists of 186 cases (representing 30 per cent of the overall data set).

3.2. Multilayer perceptron neural network for partnership credit scoring

Generally two essential linear statistical tools, discriminant analysis and logistic regression, were most commonly applied to develop credit scoring models. The important question here is to explain the choice of neural network. The utilization of linear discriminant analysis and logistic regression has often been criticized by many authors because they are linear methods that don't take into account situations where the dependent and independent variables exhibit complex nonlinear relationships. Many various types off neural network have been specified in the literature but the multilayer perceptron is especially suitable for classification and is widely used in practice. According to Riplay [?] the neural network is a system based on input variables, also known as explanatory variables, combined by linear and non-linear interactions through one or more hidden layers, resulting in the output variables, also called response variables .The perceptron was created in 1958 by Frank Rosenblatt [31]. Perceptron is a simplified, artificial neuron, that takes in a vector of n inputs, which are being multiplied by their associated weights $\sum_{i=0}^{n} x_i w_i$ and gets the output y by feeding it to the activation function σ. This can also represented as a dot product of two vectors.

$$y = \sigma\left(\sum_{i=0}^{n} x_i w_i\right) = \sigma(\mathbf{w}^T\mathbf{x})$$

.

Graphically it can be represented as shown in Figure 1.

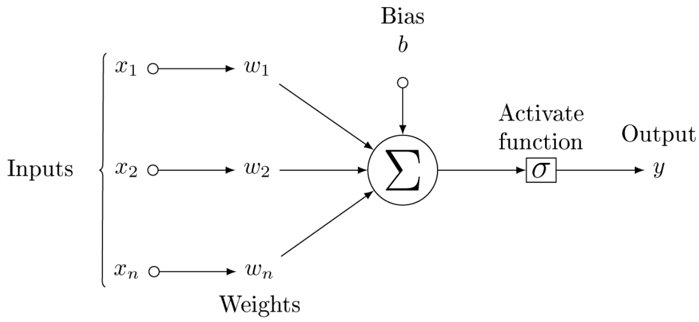

FIG. 1. Building blocks of an artificial Neural Network

The bias is an "offset" added to each unit in a neural network layer that's independent of the input to the layer. Bias b has the effect of applying a transformation to the weighted sum:

$$y = \sigma(\mathbf{w}^T\mathbf{x} + b)$$

.

Whether the weighted sum of neuron's inputs trigger the output is decided by activation function. Classically there are three types of activation functions: linear, threshold (step) and sigmoid (soft-step). Sigmoid function is a special case of logistic function that is characterized by its S-shaped curve. It is often used as it introduces non-linearity to the network and is easily derivable for weight learning. Based on the output range sigmoid functions is divided into: logarithmic sigmoid, which is range from [0, 1] and a scaled version of it, hyperbolic tangent sigmoid, that is in the range of [−1, 1].

- Identity (Linear)

$$\sigma(x) = x$$

- Binary step

$$\sigma(x) = \begin{cases} 0 \text{ for } x < 0 \\ 1 \text{ for } x \geq 0 \end{cases}$$

- Logarithmic sigmoid (Soft step)

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Table 1. Credit scoring criteria.

Variable	Description	Quantification method
Personal characteristics		
Gender	Male=0 or female=1	Data
Family situation	Single=0, Married=1 divorced=3 unknown=4	Data
Age	Between[20-65]	Data
Occupation	1=commercial, 2=artisant, 3=agricalture, 4=student	Data
Present employment since	1=unemployed, 2=$\leq 1year$, 3=[1-7]years, 4=$\geq 7years$	Data
Housing	1=rent, 2=own, 3=for free	Data
Status of existing checking account	1=0 Dhs, 2=[0-2000]Dhs, 3=$\geq$ 2000 dhs	Data
Credit history	Actual credit history	Data
Other debtors or guarantors	1=none, 2=co-applicant, 3=guarantor	Data
Partnership caracteristics		
Competence	1=exellent, 2=very good, 3=good, 4=pretty good, 5=lazy	estimated
Seniority	1=very old, 2= old, 3=new	estimated
Cost optimization	1=transportation, 2=stock out, 3= no cost optimization	estimated
Developpement	1=can be developed, 2=can't be developed	estimated
Marketing	1=reputation, 2=perceived value of a product	estimated
Diversification	1=product variety, 2=service variety, 3= product flexibility	estimated
Developement of tender charge	1= own a tender Charge, doesn't have a tender Charge	estimated

- Hyperbolic tangent sigmoid (TanH, Tansig)

$$\sigma(x) = \frac{2}{1 + e^{-2x}} - 1$$

- Softmax

$$\sigma(x) = \frac{e^x}{\sum e^x}$$

Perceptron itself can only do linear classification, which at the time of its invention was the main criticism over it. For example, it can successfully learn logical 'AND' and 'OR', yet classifying 'XOR' is impossible, as the classes of it are not linearly separable. However, if perceptrons are connected together into multiple layers, they can be far more powerful. Multilayer Perceptron is a directed network of artificial neurons organized in layers and where information travels in one direction, from the input layer to the output layer. MLP is typically composed of an input layer, one or more hidden layers and an output layer, each consisting of several neurons. Neurons are connected together by weighted connections. It is the weight of these connections that govern the operation of the network and "programmed" an application of the input space to the space of the outputs with help of a nonlinear transformation. The multi layer perceptron architecture is shown in Fig. 2.

The input layer of the MLP model has a vector of predictor variables such as $(x_1 \ldots x_n)$. The input layer distributes each of these values of the neuron to the hidden layer where they are multiplied by a weight $(w_1 \ldots w_n)$. This values is fed into a transfer function (σ), which outputs a value $(h_0^{(1)} \ldots h_{m^{(1)}}^{(1)})$. The output of this hidden layer is then disseminated to the output layer. Each neuron is then multiplied by weight $(w_{i1} \ldots w_{in})$, and the resulting values are added together creating a combined value $(h_0^{(L)} \ldots h_{m^{(L)}}^{(L)})$ and is again fed into a transfer function (σ) that produces a value $(y_1^{(L+1)} \ldots y_C^{(L+1)})$, which is the output of this model. In credit scoring different authors give a comparison between the methods. Desay and et al. [17] investigate a multilayer perceptron neural network, a mixture of an expert's neural network, linear discriminant analysis, and logistic regression for scoring credit applicants in the credit union industry. Their results indicate that customized neural networks offer a very promising avenue if the measure of performance is the percentage of bad loans correctly classified. According to Abdou and et al. [2], the neural networks have the highest average correct classification rate when compared with other traditional techniques, such as discriminant analysis and logistic regression, taking into account the fact that results were very close.

4. Results

The multilayer perceptron neural network structure is applied for partnership credit scoring using the 16 predictor variable. As mentioned above for the designing of our model, the 434 data sets are used for training and the next 186 data sets are used for diagnostic testing. The dependant variable in the model is categorical variable whereby 1= accepted and 0=

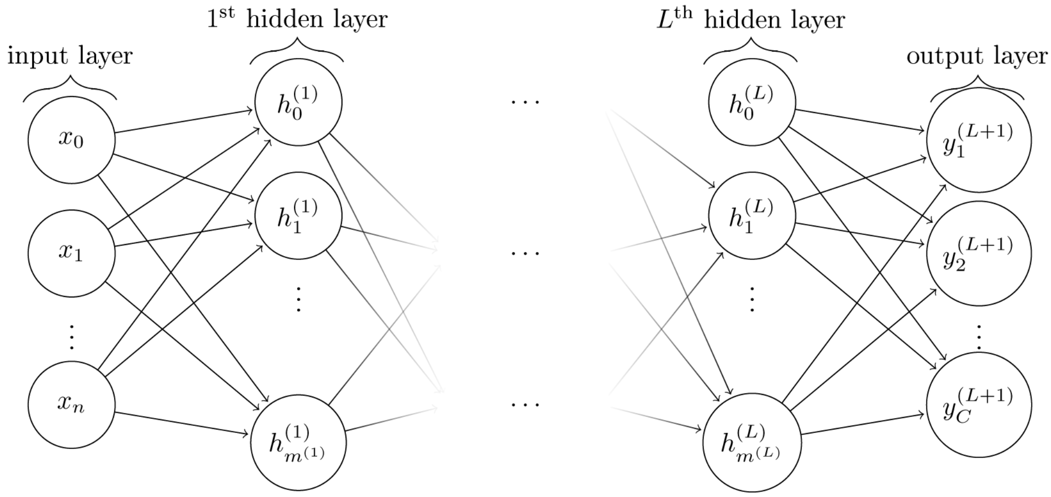

FIG. 2. Network graph of a $(L + 1)$-layer perceptron with D input units and C output units. The l^{th} hidden layer contains $m^{(l)}$ hidden units.

rejected. For comparative analysis, the simulations results of MP neural network are compared with simulations results of the partnership credit scoring based on linear regression and discriminant analysis.

In building the proposed scoring model with MP neural network we used Mathlab Software and for comparison with linear regression and discriminant analysis we used SPSS 20.

To evaluate the performance of a scoring model different performance evaluation criteria are used, such as the confusion matrix or the Correct Classification rate (CCR), mean square error (MSE) and the estimated misclassification cost To present the results of our partnership credit scoring model and evaluate his performance we used two methods, the regression and the classification.

For the regression we used:

- the Mean Squared Error is the average of carees the difference between the outputs and targets. The error function can evaluate the performance of a neural network during learning. It indicates how network predictions are close to the target values t_i and, therefore, what adjustment should be made to the weight by the learning algorithm at each iteration. The error function represents the eyes and ears of the learning algorithm to determine if the network is efficient or not, given the current state of learning (and therefore, what adjustment must be given to values of its weight). Zero means no mistake, most of 0.6667 signifies an elevated error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - t_i)^2 \tag{4.1}$$

  n represents the number of learning observations, y_i is the forecast (network output) and t_i is the target value for the ith observation.
- The linear regression between the network outputs. Regression R values measure the correlations between outputs and targets. An R-value of 1 means a perfect relationship, 0 a random relationship.

For the classification we used the Confusion Matrix or the Correct Classification Rate and the misclassification cost.

A confusion matrix [29] contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The confusion matrix also known as classification matrix shows the number of cases that were correctly classified (on the diagonal of the matrix) and those that were misclassified as the other category.

$$ConfusionMatrix = \begin{Bmatrix} TruePositive(TP) & FalsePositive(FP) \\ FalseNegative(FN) & TrueNegative(TN) \end{Bmatrix} \tag{4.2}$$

with the following notations

- True Positive(TP): Good applicants classified as good
- False Positive(FP): Bad applicants classified as good
- False Negative(FN): Good applicants classified as bad
- True Negative(TN): Bad applicants classified as Bad

Classification is the accuracy of that model as the number of correct predictions from all predictions made. we used in classification:

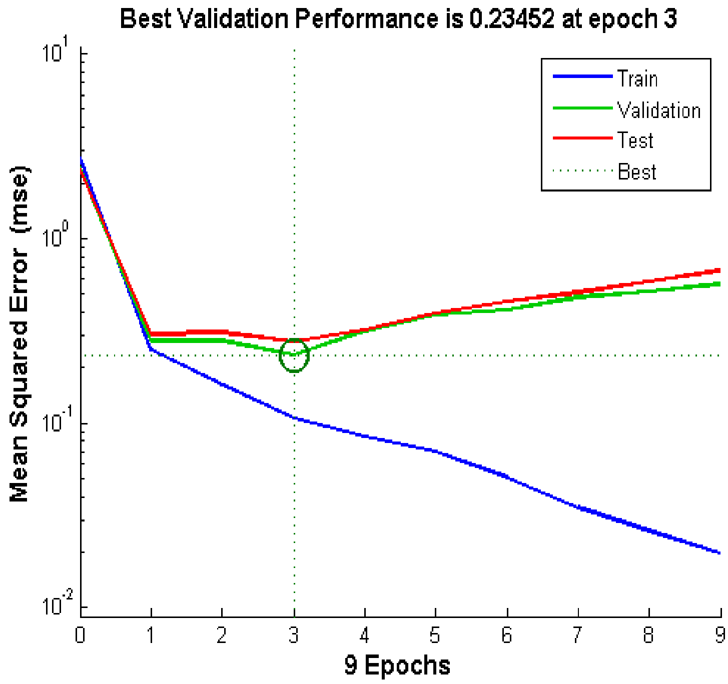

FIG. 3. MSE obtained during simulation with thirty hidden neurons

- The correct classification rate(CCR) is the ratio of correct predictions of a model, when classifying cases into class 1 or 0. ACC is defined as

$$CCR = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + FalseNegative + TrueNegative} \quad (4.3)$$

- Sensitivity (SEN): also known as Recall or True Positive Rate is the fraction of the cases that the technique correctly classified to the class 1 among all cases belonging to the class 1. SEN is defined as

$$SEN = \frac{TP}{TP + FN} \quad (4.4)$$

- Specificity (SPE): also known as True Negative Rate is the ratio of observations correctly classified by the model into the class 0 among all cases belonging to the class 0. SPE is defined as

$$SPE = \frac{TN}{TN + FP} \quad (4.5)$$

- Precision (PRE): is the fraction obtained as the number of true positives divided by the total number of instances labeled as positive. It is measured as

$$PRE = \frac{TN}{TN + FP} \quad (4.6)$$

- False Negative Rate also known as Type I Error is the fraction of 0 cases misclassified as belonging to the 1 class. It is measured as

$$ErrorTypeI = \frac{FN}{TP + FN} \quad (4.7)$$

- False Positive Rate also known as Type II Error is the fraction of 1 cases misclassified as belonging to the 0 class. It is measured as

$$ErrorTypeII = \frac{FP}{TN + FP}. \quad (4.8)$$

For the multilayer perceptron neural network model results based on 16 predictor variables the training is carried out for 9 epochs. The simulations were performed using twenty, thirty and sixty hidden neurons.

The MSE values using thirty hidden neurons were plotted as follow:

In the figure 1 a plot of the training errors, validation errors, and test errors appears. According to this figure the learning is stopped at iteration 9 because the performance validation begins to rise from this iteration. During learning the Best value of MSE was 0.23452. The result is reasonable because the final mean-square error is small and the test set error and the validation set error has similar characteristics.

Moreover regression plots display the network outputs with respect to targets for training, validation, and test sets.

For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. The following figure shows the results

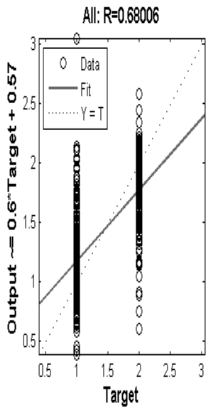

FIG. 4. Regression for all data sets

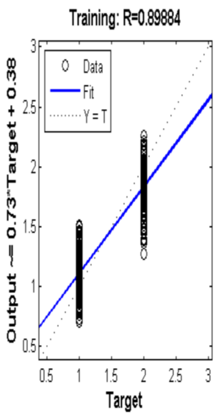

FIG. 5. Regression for training

In figure 4, the fit is reasonably good for all data sets(training, validation and testing sets), with R value of $\simeq$ 0.7. In figure 5, the fit is also good for the training set which represent 70% of overall data sets, with R value of $\simeq$ 0.9.

The following table 2 demonstrates simulations OF MSE results using different number of hidden neurons: 20, 30, 60.

As shown in Table 1, the increase of the number of the hidden neurons increases training and testing accuracy. The use OF MP neural network for learning allows obtaining low MSE value and allows improving the performance of the model.

The following Table 3 compares the performance of classical credit scoring and partnership credit scoring:

As shown in table 3 the classification of Partnership credit scoring has been performed. The MSE of classical credit scoring for the training subset is 0.1223 and for testing subset is 0.0326 while the MSE of partnership credit scoring for training subset is 0.1640 and for testing subset is 0.05552. That's mean that the addition of the partnership criteria is crucial in term of prediction.

The result of the simulation of MP neural network is also compared with results of simulation of the linear regression and Discriminant analysis. Table 4 summarizes the training and testing results of the CC rates for conventional techniques, namely, Discriminant analysis and Linear Regression, and for the advanced technique, namely, Multilayer Perceptron neural network. The CCR is crucial in determining the classification efficiency of the partnership scoring models

The MP neural network model classification results are better than the other two models, namely, DA and LR, in terms of testing the prediction capabilities, i.e. 83.24 per cent for MP neural networks compared with 66.64 and 75.4 per cent for LR and DA, respectively. However, we obtained the same results when considering the training subset, i.e. 79.95 per cent for MP neural networks compared with 74.65 and 73.04 per cent for LR and DA, respectively. These results show the robustness of MP neural networks in credit scoring. These results obtained in our partnership credit scoring is very similar with the literature which use the conventional credit scoring.

In addition we used the misclassifying cost rate (MCR) in order to evaluate the overall credit scoring capability and effectiveness and to compare different scoring models results. MCR is important in terms of estimating the costs of misclassifying a client as being rejected (good credit misclassified as bad credit: Type I error formula 7) or as being accepted (bad credit misclassified as good credit: Type II error formula 8). It is based on the confusion matrix. The following equation is used in computing the MCR:

$$MC = C(R/A)P(R/A)\pi_2 + C(A/R)P(A/R)\pi_2 \quad (4.9)$$

where C (predicted rejected/actually accepted) and C (predicted accepted/actually rejected) are both corresponding MC of both Type I and Type II errors. P (predicted rejected/actually accepted) and P (predicted accepted/actually rejected) measure the Probabilities of Type I and Type II errors. π_2 and π_1 are the prior probabilities of rejected and accepted [43].

It is complicated task to estimate the misclassification costs, as valid prediction might not be available [14]. Moreover the costs associated with Type I error and Type II error are different and the misclassification costs associated with Type II errors are much higher than the misclassification cost associated with Type I errors [14]. So it is a challenging task to have actual MCs specific to Morocco. Consequently, the ratio of MCs associated with Type II and Type I errors used in this paper is 5:1, as noted by Hofmann, who used German

Table 2. Simulation results for MP neural network using different number of hidden neurons.

Number of hidden neurons	Epochs	Performance	MSE for training	MSE for testing
20	7	0.1668	0.1448	0.2159
30	9	0.1975	0.1885	0.2232
60	8	0.2344	0.1956	0.3397

Table 3. MSE for classical credit scoring and partnership credit scoring.

	performance	MSE for training	MSE for Testing
Classical credit Scoring	0.1430	0.1223	0.0326
Partnership credit scoring	0.23452	0.1640	0.0552

Table 4. Simulation results for MP neural network.

Scoring model	Training sub set				Testing sub set			
	Accepted	*Rejected*	Total	%	*Accepted*	*Rejected*	Total	%
MP neural network								
Accepted	123	47	170	72.3	20	31	51	53.56
Rejected	40	224	264	84.85	32	103	135	76.2
Total			434	79.95			186	89.24
Linear regression								
Accepted	115	55	170	67.64	18	33	51	64.70
Rejected	60	204	264	77.27	40	95	135	70.3
Total			434	74.65			186	64.64
Discriminant analysis								
Accepted	118	47	170	69.41	17	34	51	66.66
Rejected	65	199	264	75.37	28	107	135	79.25
Total			434	73.04			186	75.4

credit data set in his research (West, 2000) [43]. This relative cost ratio has been used in different researches in credit scoring [43], [14], [1], [3], [4]. So P (predicted rejected/actually accepted) =1, and P(predicted accepted/actually rejected)=5.

The prior probabilities of accepted and rejected credit are set as 69.67% of all accepted loans, i.e. 432/620, and 30.32% of all rejected loans, i.e. 188/620. So $\pi_2 = 69.67\%$ and $\pi_1 = 30.32\%$. The following table concludes the type I, type II errors and the estimated misclassification costs for MP model, LR and DA.

Table 5 shows the training and testing results of the CCR, errors and the MCR for advanced technique MP neural network and for linear regression and discriminant analysis. We can remark that MP neural network has the lowest Type I error of 0.1152 and the lowest Type II error of 0.2370 under the training subset. This is supported by the fact that the MP model has the lowest MCR of 0.3431 under the training subset. Furthermore under the testing sub set the MP model has also the lowest Type I of 0.2370 and the lowest Type II error of 0.2313. This is also supported by the fact that the MP neural network model has the lowest MCR of 0.5157 and has the highest CCR of 79.95% under the training subset and the highest CCR of 89.24% under the testing subset. This shows that advanced technique MP neural network in our case are better than linear regression and discriminant analysis in building the partnership scoring model. Moreover the addition of partnership criteria to criteria of conventional credit scoring gives similar results i.e. advanced techniques such as MP are better than conventional techniques such as LR and DA in predicting new client's behavior.

5. Conclusion

The credit scoring is one of the important applications of data mining and classification problems that have attracted more attention during the past decades. The proposed approach using artificial neural networks for partnership credit scoring gives good classification of applicants. This research

Table 5. Credit scoring model error function

Scoring model	CCR rates				Errors				Misclassification costs	
	Training sub-set		Testing sub-set		Training sub-set		Testing sub-set		Training sub-set	Testing sub-set
	A	R	A	R	Error I	Error II	Error I	Error II	MC	MC
MP neural network	72.3	84.85	53.56	76.2	0.11522	0.1734	0.2370	0.2313	0.3431	0.5157
Linear regression	67.64	77.27	64.7	70.3	0.3428	0.2123	0.6896	0.2578	0.5606	0.8693
Discriminant analysis	69.41	75.37	66.66	79.25	0.3551	0.191	0.62	0.2411	0.5369	0.7974

presents a credit scoring modeling in assessing credit applications for partnership contracts. The neural network approach in Partnership credit scoring can help MFIs to reduce their losses. Our investigation shows that the addition of partnership criteria using MP neural network in credit scoring gives better results than conventional credit scoring in term of performance. Moreover the using of MP neural network helps to have a good mean square error and good regression. In addition, the MP neural network model is compared with conventional techniques such as linear regression and discriminant analysis. The results shows that the Multilayer perceptron models have the highest CCR in the testing and the training subset compared to other modeling techniques and they also have the lowest MC in the training and testing subset.

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