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Credit Scoring of Personal Loans based on Adaptive Neuro-Fuzzy Inference System and Artificial Neural Networks

Oussama Margheni, Mohamed Benrejeb
LARA Automatique
Ecole Nationale d'Ingénieurs de Tunis
Tunis, Tunisie
oussama.margheni@gmail.com

***Abstract*— The credit risk assessment is a challenge for all financial institutions to minimize losses caused by the default of a borrower, especially for a particular costumer that usually keeps the data collected during the opening of the bank account and, in the best case, when filling the demand for credit. The "credit scoring ", or the credit rating, is one of the methods used to measure the risk of default of the borrower. Several methods are used for credit scoring, including statistical methods and artificial intelligence. This paper presents a neuro-fuzzy approach for credit scoring of personal loans in a private Tunisian bank, combining the use of an Adaptive Neuro-Fuzzy Inference System and an Artificial Neural Network.**

Keywords—Credit risk; default probability; credit scoring; artificial neural networks; neuro-fuzzy; ANFIS

I. INTRODUCTION

Credit is the main product that banks offer to their customers which generates most of gains, but in the same time, causes the most losses in cases of default. Credit risk or counterparty risk is the risk of losses due to the default of a borrower. The simple increase of the likelihood of the risk can negatively affect the value of a portfolio. That's why the decision to grant or reject a credit is a key decision for the bank.

Credit risk poses difficult measurement problems. The simple knowledge of outstanding credit is not sufficient to assess its risk. Possible losses depend on a consideration of commitments as well as the probability of default of counterparties, a probability that is not easily quantifiable. Losses in case of default also depend on guarantees and possible recovery after failures.

In 2005, the Basel Committee on Banking Supervision [1] has published the revised capital adequacy framework "International Convergence of Capital Measurement and Capital Standards" [2] also known as the "Basel II accord"; it is a set of measures and guidelines to limit bank risks, including credit risk.

In 2006, on its circular 2006-19 [3], the Central Bank of Tunisia requires credit institutions and non-resident banks to use a selection process of credits and to dispose of a system to measure these risks.

Credit scoring is to predict the behavior of a borrower from the history of other borrowers of the bank. Customers are classified in different classes according to their behavior during the credit payment. The new credit applicant is associated to one of these classes according to its characteristics. First, customers are classified in two classes. The default class contains borrowers who made a default in payment of their credits. Is considered as a default, according to the Basel committee, a delay of payment of 90 days, or a total abandonment of the debt [2]; The class of not default contains borrowers with regular payment without incidents. Then the classification is detailed into other subclasses that represent the score of the customer. So we can say that credit scoring models are classification problems [4] [5] [6].

Credit score models interest many researchers and professionals, some of them use statistical techniques like Logistic Regression Analysis (LRA), Linear Discriminant Analysis (LDA) [7], Operational Research [8], Artificial Intelligence technologies like Artificial Neural Networks (ANN), Support Vector Machines and Genetic Algorithms [9] and others are hybrid models use combinations of these diverses technics [10].

Since the middle of the 90's, ANN becomes an important alternative in financial prediction. Many researchers were and stay interested with its high prediction accuracy. In research about credit scoring, ANN performs better than both LDA and LRA [11].

Fuzzy Logic [12] also interested researchers in credit scoring [13]; but in the majority of cases it is combined to other technics and especially neural networks approaches.

Neuro-Fuzzy (NF) systems are relatively a new hybrid artificial intelligence technology that combines ANN and Fuzzy Logic (FL). There is little research in applying them to credit scoring modeling [11]. Our study looks to use neuro-

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fuzzy to create a score model that gives a good classification rate.

The paper is structured in five sections. After the introduction, the second section exposes related works. In the third section, the data set used in this study and its pretreatment are described. Section four presents the proposed approach in two parts, the Adaptive Neuro-Fuzzy Inference System (ANFIS) conception: definition of membership functions, inference rules, etc. and the research of the ANN best performance's architecture. The last section exposes the results of the presented approach and compares it with others.

II. Related Works

ANN has been used as a credit scoring models since the 1990's, Desai, Crook and Overstreet [14] developed credit scoring models with ANN using a set of 1962 credit consumers. ANN has the best performance comparing to LDA and LRA models. West [15] compared the performance of five ANN models of credit scoring with LDA, LRA, k nearest neighbors, Kernel Destiny Estimation and Classification And Regression Trees (CART). Malhotra and Malhotra [16] got similar results by using a set of 1078 data. Margheni and Benrejb [17] used ANN in a set of 998 borrowers from a Tunisian bank, and compared results to the scorecard used by the bank that combines a nonlinear regression model to an expert system. ANN performs better than nonlinear regression model, expert system and the combination of the two models.

ANN combined to LDA was also used as hybrid models, Lee, Chiu, Lu and Chen [18] found that their proposed hybrid model has been more successful than that of LDA, LRA, or ANN separately. In a study using Egypt's personal loan data Abdou, Pointon and El-Masri [19] found that ANN is more successful than Probit Analysis, LRA and LDA. Bahrammirzaee, Ghatari, Ahmadi and Madani [20] used a set of 50 customers from an Iranian bank to compare the performance of expert systems, ANN and hybrid model using ANN and expert system and found the better performance by using the hybrid model. Lee and Chen [21] used LRA, LDA, Multivariate Adaptive Regression Splines (MARS), ANN and the combination MARS-ANN models on a data set from a Taiwan bank. ANN witch used variables selected by MARS was the most efficient.

Neuro-fuzzy systems [22] [23] was used too in solving credit scoring problems. Piramuthul [24] studied the performance of neural networks as well as neurofuzzy systems using a data set of 690 examples. They conclude that "*neural networks are probably better for credit-risk evaluation decisions only if we are not interested in knowing how a particular conclusion was made*". Adaptive Neuro Fuzzy Inference System (ANFIS) was used in credit scoring. Odeh, Featherstone and Das [25] built LRA, ANN and ANFIS credit scoring models on data from US bank loans and stated that benchmarking banks internal rating system may be necessary. Akkoç [11] proposes a three stage hybrid ANFIS credit scoring model, based on statistical techniques and NF. He used the credit card data of an international bank operating in Turkey. He compared the performance of the three stage hybrid ANFIS model with LDA, LRA and ANN and found that the proposed ANFIS model has the best credit scoring capability in terms of both the classification accuracy rate and accuracy ratio and estimated misclassification cost.

III. Data

This section contains a description of the used data sets and exposes data pretreatment.

A. *Description of the data fields*

The used data set is issued from a Tunisian bank. From existing personal credit information in the database of the bank, 33 fields are collected. The fields are divided in two types: personal data, listed in table I, and banking data, listed in table II. The collected data set contains 998 customers.

B. *Data pretreatment*

To normalize data and have more significant information, some fields are substituted by calculated fields, for example the age in place of birth date, the ratio (Repayment amount / Repayment capacity) in the place of the repayment amount and account seniority in place of the date of account creation.

When fields with low variation and apparent correlation and fields with lot of blanks are eliminated, the following 15 fields are kept:

1. Gender
2. Age
3. School level
4. Profession
5. Salaried or not
6. Market
7. Work status
8. Job seniority
9. Repayment capacity
10. Housing situation
11. Seniority at current house
12. Account seniority
13. Geographic area
14. Repayment amount/repayment capacity
15. Domiciliation

The correlation matrix between data of these fields is calculated and those with strong correlation are eliminated so 10 following fields are kept:

1. Gender
2. Age
3. School level
4. Job status
5. Job seniority
6. Repayment capacity
7. Housing situation
8. Seniority at current house
9. Account seniority
10. Geographical area

TABLE I. PERSONNAL DATA FIELDS

Fields	Descriptions
Customer's identifier	Digital identifier assigned by the bank to the customer
Birth date	In format dd-abbreviation of the month-yy
Gender	M for male and F for female
Market	PAR for particular and PRF for professional
Profession	Artisans, Lawyers and similar, traders, business leaders private sector employees, Students / Pensioners / Other, Doctors and similar, Liberal profession, Retirees, Private sector employees, Public sector employees, Other liberal professions
Seniority in present habitation	Number of years in current habitation
Housing situation	Owner: P, tenant: L, other: A
Multi-bank customer	Yes: O or No: N
School level	Unschooled: N, primary : P, secondary : S, university : U
Salaried	Yes: O or No: N
Job situation	Contract : C, trainee : S or established : T
Job seniority	Number of years in actual job
Net monthly income	In Tunisian Dinars (TND)
Other monthly incomes	In Tunisian Dinars (TND)

TABLE II. BANKING DATA FIELDS

Fields	Description
Repayment capacity	Customer repayment capacity : fixed by the Central Bank of Tunisia at 40% of the net monthly income
Total repayment	Monthly amount paid by the customer off the credit under study
Declared income	In TND
Account creation date	In format dd-abbreviation of the month-yy
Value of the property	Value of the property purchased with the credit in case of auto loan
Monthly payment	Monthly amount paid by the customer including credit under study
Payment schedule	Monthly: M, quarterly: T or biannual : S
Grace	Number of months before starting credit payment
Vehicle age	Age, in months, of the purchased car (reserved to auto loans)
Life insurance	Yes : O or no : N
Domiciliation	D : domiciled, N : not domiciled, P : retirement benefit, S : salaried
Default	0 : not default, 1 : default, after one year from starting payment

TABLE III. DESCRIPTION OF THE FIELD "DEFAULT"

Default of repayment	Numbers	Percentages
Default	291	29,4%
Not default	698	70,6%
Total	989	100%

Default is the output of the model; the field is taken in its original form shown in the table III.

IV. PROPOSED SCORING NEURO-FUZZY STRUCTURE

For designed data set containing ten fields, with at least three membership functions in each field, the number of rules can reach 310 rules. To minimize the cost of rules elaboration, a combined approach based on ANFIS and ANN techniques is proposed. Then two subsets of data are considered. The first contains continuous variables such as age, seniority at current house, job seniority, account seniority and repayment capacity which constitute the ANFIS inputs. The second subset contains discrete variables such as gender, school level, housing situation, job status and geographical area, combined with the output the ANFIS constitute the inputs of the ANN, the figure 2 show the architecture of the scoring model.

A. Conception of the artificial neuro-fuzzy inference system

1) Definition of linguistic variables and membership functions

For the definition of membership functions for different values of the variables, continuous data are divided in classes. Tables IV to IX and figure 2 describe the membership functions for each considered variable.

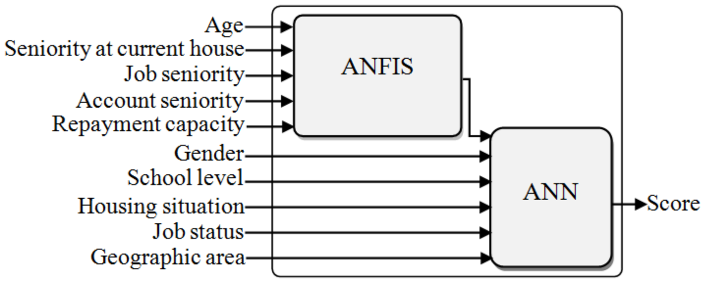

FIG. 1. ARCHITECTURE OF THE PROPOSED CREDIT SCORING MODEL.

TABLE IV. DESCRIPTION OF THE VARIABLE "AGE"

Age	Numbers	Percentages
<30 years	154	15,6%
30 years<= and <60 years	805	81,3%
>=60 years	30	3,0%
Total	989	100%

TABLE V. DESCRIPTION OF THE VARIABLE "SENIORITY AT CURRENT HOUSE"

Seniority at current house	Numbers	Percentages
<1 years	7	0,7%
1 years<= and <5 years	256	25,9%
>=5 years	726	73,4%
Total	989	100%

TABLE VI. DESCRIPTION OF THE VARIABLE "JOB SENIORITY"

Job seniority	Numbers	Percentages
Job seniority	Numbers	Percentages
<2years	57	5,76%
2years<= and <10years	444	44,9%
>=10years	444	44,9%
Blank fields	44	4,4%
Total	989	100%

TABLE VII. DESCRIPTION OF THE VARIABLE "ACCOUNT SENIORITY"

Account seniority	Numbers	Percentages
Less than 3 months	98	9,9%
3months=< and <1year	91	9,2%
>=1year	782	79%
Blank fields	18	1,8%
Total	989	100%

TABLE VIII. DESCRIPTION OF THE VARIABLE "REPAYMENT CAPACITY"

Repayment capacity	Numbers	Percentages
<200 TND	67	6,8%
200<= et <400 TND	447	45,2%
>=400TND	475	48%
Total	989	100%

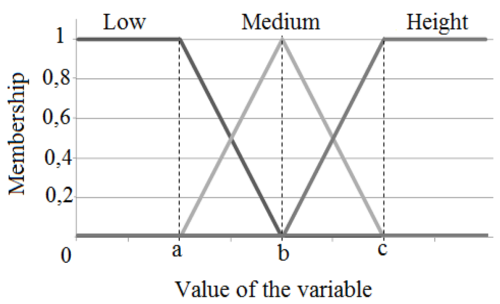

FIG. 2. MEMBERSHIP FUNCTIONS

TABLE IX. VALUES OF USED VARIABLES IN MEMBERSHIP FUNCTIONS GRAPH (FIG. 2.)

	a	b	c
Age	30	45	60
Seniority at current house	1	2,5	5
Job seniority	2	6	10
Account seniority	3	7,5	12
Repayment capacity	200	300	400

2) *On fuzzy inference rules*

Fuzzy system has five input variables. Each variable has three membership functions. Possible combinations memberships are then reaching 35 i.e. 253 possible combinations. When running learning process, the ANFIS calculates automatically these combinations in order to deduce the fuzzy inference rules.

B. *Artificial Neural Network conception*

The output of the ANFIS system is used like an input to the artificial neural network with the five fields:

1. Gender
2. School level
3. Housing situation
4. Work status
5. Geographic area

TABLE X. DESCRIPTION OF THE FIELD "GENDER"

Gender	Numbers	Percentages
Female	228	23,1%
Male	508	51,4%
Blank fields	253	25,6%
Total	989	100%

TABLE XI. DESCRIPTION OF THE FIELD "GENDER"

Gender	Numbers	Percentages
Female	228	23,1%
Male	508	51,4%
Blank fields	253	25,6%
Total	989	100%

TABLE XII. DESCRIPTION OF THE FIELD "SCHOOL LEVEL"

School level	Numbers	Percentages
Unschooled	3	0,3%
Primary	22	2,2%
Secondary	276	27,9%
University	688	69,6%
Total	989	100%

TABLE XIII. DESCRIPTION OF THE FIELD "HOUSING SITUATION"

Housing situation	Numbers	Percentages
Other	98	9,9%
Owner	184	18,6%
Tenant	707	71,5%
Total	989	100%

TABLE XIV. DESCRIPTION OF THE FIELD "WORK STATUS"

Work status	Numbers	Percentages
Established	731	73,9%
Contract	46	4,7%
Trainee	7	0,7%
Blank fields	205	20,7%
Total	989	100%

TABLE XV. DESCRIPTION OF THE FIELD "GEOGRAPHIC AREA"

Geographic area	Numbers	Percentages
Central Tunis	159	16,1%
Northern Tunis	156	15,8%
Southern Tunis	55	5,6%
Cape bon	48	4,9%
North	121	12,2%
Center and Sahel	110	11,1%
Sousse	116	11,7%
Sfax	175	17,7%
South	49	5,0%
Total	989	100%

Data set is divided into three groups, the first contains 60% of data (593 customers), used for training the ANN, the second 20% (198 customers), used for the model validation and the third, 20%, for the test.

To find the optimal ANN architecture which gives the best good classification rate, we begin by a simple neural network without hidden layer and increase the number of hidden layers and its numbers of neurons. Table XVII summarizes some architectures wich lead to the best results. Then confusion matrix and good classification rate are used to measure the performance of the obtained models.

TABLE XVI. CONFUSION MATRIX

Default classed as default	Default classed as not default
Not default classed as default	Not default classed as not default

TABLE XVII. ANN ARCHITECTURES AND RESULTS

ANN	Activation functions	Learning method	Confusion matrix		Good classification rate
Res_0 [6 2]	radbas	traingdm	17	44	30.80%
			27	110	
	radbas	trainlm	7	54	69.69%
			6	131	
	logsig	traingdm	60	1	30.80%
			136	1	
	logsig	trainlm	14	47	70.70%
			11	126	
Res_1 [6 3 2]	hardlim purelin	trainlm	0	61	69.19%
			0	137	
	radbas purelin	trainlm	24	37	75.25%
			12	125	
Res_1 [6 6 2]	radbas purelin	trainlm	17	39	72.22%
			16	126	
	radbas purelin	trainbr	17	39	75.25%
			10	132	
	satlin purelin	trainlm	19	37	76.76%
			9	133	
	satlin purelin	trainbr	21	35	75.25%
			14	128	
	satlin purelin	trainc	21	35	76.76%
			11	131	
	tansig	trainc	28	28	77.77%
			16	126	

V. RESULTS AND DISCUSSION

The best performance realized by our proposed model is 77.77% of good classification. This performance still better than the expert system which gives 65.1%, Nonlinear regression which gives 76.8%, and the combination of expert system and nonlinear regression which gives 73.4% of good classification rate. These models are used by a bank, and tested, with success, by using the same data set to compare the performances.

The use of the combination of ANFIS and ANN reduced the number of fuzzy rules that optimized considerably the conception time and the execution time. Also the ANN gains in conception and execution time by reducing the number of inputs because the five ANFIS inputs are substituted by only the output of the ANFIS.

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