Towards a Comprehensible and Accurate Credit Management Model: Application of Four Computational Intelligence Methodologies

A. Tsakonas, N. Ampazis, G. Dounias, *Member, IEEE*

Abstract—**The study presents methods for classification of applicants into different categories of credit risk using four different computational intelligence techniques. The selected methodologies involved in the rule-based categorization task are (1) feedforward neural networks trained with second order methods (2) inductive machine learning, (3) hierarchical decision trees produced by grammar-guided genetic programming and (4) fuzzy rule based systems produced by grammar-guided genetic programming. The data used are both numerical and linguistic in nature and they represent a real-world problem, that of deciding whether a loan should be granted or not, in respect to financial details of customers applying for that loan, to a specific private EU bank. We examine the proposed classification models with a sample of enterprises that applied for a loan, each of which is described by financial decision variables (ratios), and classified to one of the four predetermined classes. Attention is given to the comprehensibility and the ease of use for the acquired decision models. Results show that the application of the proposed methods can make the classification task easier and –in some cases- may minimize significantly the amount of required credit data. We consider that these methodologies may also give the chance for the extraction of a comprehensible credit management model or even the incorporation of a related decision support system in banking.**

I. Introduction

Recently, there is an increase in the use of different kinds of financial transactions, either in the banking, or in the private business sector, a fact that makes the automation of decision-making processes imperative. However, this automation has to keep the error rates at a low level during the data processing phase, while it should also be as less time consuming as possible. Furthermore, the decisions taken with the use of an automated process should approximate if possible, the corresponding decision of an expert for the same problem. This is the reason why methods that imitate human thought and model human expertise and abilities, have become popular in the last two decades.

The paper deals with the financial application domain of loans, which, is one of the most commonly used financial transactions in banking organizations. A number of intelligent methodologies has appeared during the last years focusing on credit scoring, such as neural networks [1], genetic algorithms [1], machine learning [2], as well as data mining and Bayesian networks, see also [3]. An automated system for monthly credit standing analysis, combining statistics and machine learning, is presented in [4]. Genetic algorithms are also applied in credit problems by Walker *et al.* [5]. The paper of [6] combines optimization algorithms, and uses scoring/rating models in a credit environment of a large European bank. In [7], probabilistic decision rule techniques have been applied, in other words a data mining approach, to support classification of credits into either a good or, a bad class.

In another work [8] genetic algorithms and neural networks are combined in a way that the genetic process designs and fine tunes the neural network model which is used for credit classification. A similar but more recent approach by [9] combines genetic algorithms and neural networks for binary credit classification, trying also to analyze the reasons for rejection of applicants. Neural networks and support vector machines are combined by Huang et al., [10], achieving accuracy of approximately 80% for USA and Taiwan markets. An interesting variation of the credit problem is presented in [4]. The authors attempt to build a model for supervision of debtors with the aid of various standard or intelligent approaches, such as linear discriminant analysis, pattern recognition, genetic algorithms, neural networks and decision trees. In the last couple of years more complicated intelligent approaches have started appearing in literature. The work by [11] proposes a promising combination of self organizing maps and neural networks. Then, the work in [12] attempts another hybrid intelligence approach similar to the previous one, but involving also a k-means clustering approach as an intermediate step. Finally, Ong et al in [13] use standard genetic programming for credit classification which performs well, while they also suggest innovative ways to measure the success of different credit classification methodologies.

Four specific intelligent techniques are examined in this paper. The first one uses the classification ability of the produced inductive decision tree itself *(ML),* built during the phase of feature selection. The second model uses the Optimized Levenberg Marquardt with Adaptive Momentum (OLMAM) algorithm, a very efficient second-order algorithm for training feedforward neural networks, which in some cases it has been shown to achieve the best training results on standard benchmark datasets ever reported in the neural networks literature [14], [15], [16]. The third model uses a hierarchical classification tree *(GP-HCT),* built by genetic programming [17]. The fourth model uses a fuzzy rule-based systems *(GP-FRBS-n),* built also by genetic programming [18]. The paper is organized as follows: A brief reference to the computational intelligent approaches is given in Section II. In Section III we present the acquired results. Finally, in Section IV we draw concluding remarks out of the presented

The authors are with the Departmentt of Financial & Management Engineering, Business School, University of the Aegean, 31 Fostini Street, 82 100 Chios, Greece
phone: +30-22710-35483 / 35454; fax: +30-22710-35499
e-mail: tsakonas@stt.aegean.gr; {n.ampazis,dounias}@fme.aegean.gr

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models.

II. Computational Intelligence Models

This section presents the computational intelligence based components involved in our approaches and discusses the proposed architectures. Several different configurations are examined:

- *Inductive Decision Trees*. The present work deals with Quinlan's approach [19], the most widely used in machine learning for its comprehensibility and simplicity in data processing. The methodology is based on the iterative application of entropy information measurement criteria on a set of training data, for producing meaningful IF/THEN rules able to be represented also in the form of a decision tree. Those decision variables appearing at a higher position in the decision tree are considered more critical for making correct decisions. Those rules that cover a large number of cases belonging to a specific class or category are considered more important for the classification task.
- *OLMAM*. Application of second order neural networks in the entire credit data set, for the production of highly accurate classification mechanisms. The main idea in the formulation of the algorithm is that a one-dimensional minimization in the direction of the previous weight update followed by a second minimization in the current weight update direction does not guarantee that the neural network's cost function has been minimized on the subspace spanned by both of these directions. A solution to the problem of simultaneous subspace minimization is to choose minimization directions, which are non-interfering and linearly independent. This can be achieved by the selection of conjugate directions, which form the basis of the Conjugate Gradient (CG) method [20]. Further details on the OLMAM algorithm can be found in [15].
- *GP-HCT*. Application of Inductive Decision Trees in the data set for feature extraction and GP-generated Hierarchical Classification Trees for decision-making (*GP-HCT*), [21], [22]. This methodology is in fact a hybrid intelligent technique, which produces hierarchical classification trees using genetic programming [17]. The number of decision attributes is primarily reduced to those considered more important, using inductive decision trees. In other words, we reduce the number of attributes by selecting those which appear at high positions in the decision tree and classificate correctly a considerable number of training cases. Then, the remaining attributes are used for building a genetic programming-based hierarchical classification mechanism which can also be presented in the form of related decision (IF/THEN) rules.
- *GP-FRBS*. The fourth methodology examined in this work, it is also considered a hybrid intelligent scheme. The method uses fuzzy rule-based systems produced by genetic programming [18] by applying syntax constraints [21], [22]. There are four alternative genetic programming based fuzzy rule based models, constructed in the paper. In the first three GP-FRBS models presented, the implementation uses *Gaussian* membership functions. In the GP-FRBS-4 model of this paper, the implementation uses *Triangular* membership functions. The output can also be presented in the form of (fuzzy) decision rules, an outcome of rather limited comprehensibility though, due to the "fuzzy" nature of the whole modeling.

III. Results

As stated in the previous paragraphs, the four proposed intelligent methodologies were applied to a specific data set, supplied from a regional European private bank. The data set corresponds to a real credit management problem that the above bank faces during the last years. The bank would like (a) to obtain an objective computer assisted methodology for deciding on loans granting, and (b) to explore knowledge and possible interrelations hidden inside the past data that the bank has stored in its files through the years. The sample consists of 124 firms (cases) applying for a loan, which contains a total number of 76 requested financial attributes for each of the applicants, both of numerical and linguistic nature. The application of the inductive learning methodology reduced the number of important parameters from 76 to 16. This reduced set was tested in the *GP-HCT* and the *GP-FRBS-1* models briefly described methodologically in Section II.

The outcome of the application of inductive machine learning (the well-known algorithm C4.5 invented and implemented by J. R. Quinlan) was a decision tree with a size of 19 branches, which corresponds to a set of handy IF/THEN rules. In these 19 branches only 16 out of the whole 76 attributes can be found. The depth of the produced decision tree varies from 2 to 10 levels. This means that for a certain case to be classified only 2 to 10 attributes are used, which corresponds to a rather low complexity solution for the decision maker. The error rate of classification on the train set was 6,2%, i.e. classification accuracy on training data exceeds 93%. Out of the 124 cases only 8 were misclassified in total and those 8 cases were given a class one level higher or lower. The most important rule extracted from this approach covering more than 30% of the training cases, was the following:

If debt / equity a year ago > -1.948718 and products - services (quality) in [good-exceptional] and net profit margin a year ago > 0.04 and geographical coverage in {local, certain areas} then → average risk

The rule correlates the quality of products and services of a company, its geographical coverage and specific financial ratios performance, for judging their application for loan as average risk decision for credit management staff. The reader may refer to [23], [24], for a more detailed discussion regarding the machine learning approach applied to the specific data set.

Several classification experiments took place with the OLMAM methodology, trying to obtain the best possible network topology. The highest overall classification accuracy with the OLMAM (94.16%) was obtained with a neural network with 9 hidden nodes trained with OLMAM on the standard 76 features of the dataset. OLMAM performs as black-box methodology, so its comprehensibility is rated as low for the expert staff, but its classification performance, especially in 2-4 class problems is outstanding compared to any other intelligent or conventional technique appeared in literature. Thus, the method could be used as an automated second-opinion tool for the credit management staff of financial organisations.

The performance of genetic optimization approaches is generally lower in terms of accuracy, but its comprehensibility is rated as very good. The best genetic programming solution for the hierarchical classification trees using genetic programming (GP-HCT) had an accuracy of 59.7% in the test set (37 / 62 cases). This performance is rather low compared to the rest of our methodologies.

The model *GP-FRBS-1 – (5 classes – 9 Gaussian MFs – membership functions)* uses the reduced data set (16 variables arising from the application of inductive machine learning methodology). The classification accuracy of the extracted solution in the test set is 59.52% (50/84). Yet, the rules produced seem interesting to the credit experts, for example:

If accounts receivable a year ago is below average and sector's accounts receivable is average and accounts receivable a year ago is extremely low then high risk

The model *GP-FRBS-2 – (3 classes – 9 Gaussian MF)* uses the full data set (76 features). Classes [*In_Weak*, *High_Risk*] were combined in this model into a [*Rejected*] class and classes [*Average_Risk*, *Accepted_Risk*] were combined into a [*Accepted*] class. The classification accuracy of the extracted solution in the test set is 69.7% (23/33). The resulted rule base (6 simple rules) can be considered very comprehensible and the rules clearly make sense for the experts. Such a characteristic rule can be considered the following:

If net_savings_minus_deficit_2_years_ago is extremely_high then accepted

The model *GP-FRBS-3 – (3 classes – 3 Gaussian MF)* uses the same setup as the *GP-FRBS-2* one but with the application of only 3 Gaussian membership functions corresponding to the values of *Very Low*, *Average* and *Very High*. The classification accuracy of the extracted solution in the test set is 72.7% (24/33). The extracted solution above is remarkably small (4 rules) 5. Only 4 out of 76 available features are present. This is a very simple yet effective result, which also makes sense for the experts. Two of the produced decision rules were the following:

If earnings_margin_before_depreciation 1_yr_ago is very high then accepted

If buildings suitability and adequacy is very low then rejected

The model *GP-FRBS-4 – (3 classes – 3 Triangular MF)* uses the same settings with *GP-FRBS-2* and *GP-FRBS-3*, except for the shape of the membership functions (triangular membership functions were used here). The derived classification score in the test set is 66.7% (22/33). The extracted solution used only 6 features (out of 76 available ones) and 6 rules. Some indicative decision rules derived from this model are given below:

If total potential runs are low then accepted
If planning/mis is high then accepted

Generally, the four compared intelligent methodologies produce interesting results ranging from performing in a very comprehensible way to achieving very high classification accuracy. All related results are summarized in *Table I.*

IV. Concluding Remarks and Discussion

The paper presented four different computational intelligence-based approaches, for managing the problem of credit risk. The first model (ML) consists of an inductive machine learning methodology applied to a data sample described by 76 decision parameters for 132 cases receiving credit or not, from a regional European banking organization. The comprehensibility issue of the presented method is clear, in comparison to most of the competitive classification methods. Inductive decision trees could be a good alternative when used as feature selection methodology in order to reduce complexity of the training data set. The second model based on feedforward neural-networks trained with second order methods outperformed all others as classification mechanism reaching a very high accuracy score, in classifying correctly credit applicants, a result that appears very attractive and promising for the bank credit expert staff. The rest of the proposed models use genetic programming for the generation of either classification trees (GP-HCT) or fuzzy rule-based systems (GP-FRBS-*n*). Various configurations were tested, each one dealing with a different setup by means of dataset used, variables selected or system tuning parameters.

TABLE I
RESULTS SUMMARY

	ML	NN-OLMAM	GP-HCT	GP-FRBS-1	GP-FRBS-2	GP-FRBS-3	GP-FRBS-4
Data Set (Features and records)	76 124	76 132	16 124	16 124	76 132	76 132	76 132
Accuracy in (unknown) test set	93.8%	94.6%	59.7%	59.5%	69.7%	72.7%	66.7%
Percentage records used for training	99% (10-fold cross-valid.)	90% (10-fold cross– val.)	50%	33.3%	66.6%	66.6%	66.6%
Solution comprehensibility	Very Good	Low	Low	Moderate	Very Good	Very Good	Very Good
Number of classes to classify	5	4	5	5	3	3	3
Number of membership functions	N/A	N/A	N/A	9	9	3	3
Shape of membership functions	N/A	N/A	N/A	Gaussian	Gaussian	Gaussian	Triangular

Accuracy obtained through genetic programming based approaches is rather low (marginally acceptable in most cases), but comprehensibility, generalization ability and knowledge discovery / extraction power seems to be an interesting feature.

One of the advantages of the presented intelligent architectures, as compared to the typical statistical models for credit management (which are currently used by most banks), is that there is no need for a huge amount of cases for the extraction of the classifiers. In all the cases, the acquired rule sets can also very easily be encoded to simple computer programs and used immediately as a decision assistant for risk problems. Note also, that the accuracy obtained within this paper through neural networks (OLMAM) approach (94.6%), stands as one of the highest performances ever observed in related literature, concerning real world credit data sets. Our current research is directed in two ways:

(1) Towards the construction of alternative hybrid computational intelligence methodologies for credit management, based on fuzzy or neuro-fuzzy rule-based systems with the involvement of a data preprocessing phase using different feature selection techniques.

(2) Towards a number of modern nature-inspired intelligent methodologies candidate to be tested on the application domain, such as particle swarm optimization, artificial immune systems, ant colony optimization, etc.

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