LOGISTIC REGRESSION AND MULTICRITERIA DECISION MAKING IN CREDIT SCORING

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Abstract: The paper aims to develop models for evaluating credit risk of small companies for one Croatian bank using two different methodologies – logistic regression and multicriteria decision making. The first method's result is the probability of default while the second method's result is the classification of the firms regarding predefined criteria for credit scoring. The paper gives the hints how to combine these two methods in order to construct an efficient strategy for achieving high performance.

Keywords: credit scoring, logistic regression, multicriteria decision making

1 INTRODUCTION

In a very aim of the banking business is providing loans to the clients. During this process and in order to make a decision whether to approve or reject a loan the bank is interested in examining a credit worthiness of a client. In the past this decision was made based on the individual judgment of bank's experts who qualitatively graded the risk after examining financial statements of the company, business plan, and interviewing the owner. During the time it has became clear that such a system was not efficient in a more complex environment and growing competition. Therefore, researchers and practitioners have started to develop quantitative models and analytical techniques in credit risk evaluation. These techniques were becoming more and more popular thanks to the information technology development and credit scoring. There are many definitions of it, but we will follow the one stating that credit scoring is the system helping the decision maker such as credit manager to determine whether or not to provide loan to clients, on the basis of a set of predefined criteria.

Credit scoring has been used in retail, corporate and small business lending. Most of the credit scoring systems vary regarding the type and quantity of the data needed for decision making. Personal and business activities have both been found relevant in a small business credit scoring system ([5], [12], [13] and [14]). In evaluating business activities researchers aim to discover financial ratios that are crucial in determining repayment prospects of the company. Most of the corporate credit scoring models use variables or financial criteria that are grouped into five categories – short-term and long-term solvency, utilization, profitability, leverage and performance. One of the first was Altman's z-score ([1]). There are authors who have developed scoring models of the companies representing a specific country. Dvoracek et al. studied bankruptcy forecasting in Czech Republic ([10]. Chancharat et al. ([6]) applied survival analysis in identifying the probability of corporate survival for Australian companies. Ciampi and Gordini ([7]) applied discriminant analysis and logistic regression in developing small enterprise default prediction model for manufacturing firms in Northern and Central Italy. Altman et al. ([2]) developed two failure prediction models for Korean companies, one for non-public entities and the other for public and private companies. Zekić et al. ([26]

created small business credit scoring for Croatian micro companies. It was proved that both personal and business characteristics are relevant in small business credit scoring systems. Among personal characteristic of entrepreneurs, entrepreneur's occupation was found to be the most important one. Among small business characteristics 4 variables were found important: clear vision of the business, the planned value of the reinvested profit, main activity of the small business, and awareness of the competition.

Also there is a group of researchers who compared different methods in developing credit scoring. One of the most frequently used method is logistic regression. Altman et al. ([3]) compared linear discriminant analysis, logistic regression and neural networks in distress classification. Desai et al. ([9]) tested multilayer perception, LDA and LR. Yobas et al. ([24]) compared the predictive performance of LDA, NN, genetic algorithms, and decision trees. Galindo and Tamayo ([15]) made a comparative analysis of CART decision trees, NN, the k-nearest neighbor and probit analysis. West ([22] compared five NN algorithms with five more traditional methods.

The aim is to assess the risk of default associated with a credit product/decision. More recent papers use neural networks, evolutionary computation and genetic algorithms ([18], [20]) and support vector machine ([23]). In the last paper three link analysis algorithms based on the preprocess of support vector machine are proposed. It is shown that the genetic link analysis ranking methods have higher performance in terms of classification accuracy. There are some results in the literature obtained by linear integer programming ([16]).

Also there are some works considering the credit scoring as a multicriteria decision making problem (detailed description of the multicriteria decision making problems can be found in [11]) and applying a group decision making technique ([25]). In this study, a novel intelligent-agent-based fuzzy group decision making model is proposed as an effective multicriteria decision analysis tool for credit risk evaluation. Some artificial intelligence techniques are used to replace human experts. Thus, these artificial intelligence agents can be seen as decision members of the decision group.

In this paper we are giving some hints how to combine logistic regression and multicriteria decision making in order to construct an efficient strategy for achieving high performance. The aim is to describe how each of the method can be used in credit scoring, what kind of results can be produced and what are the assumptions, advantages and disadvantages of the methods. Furthermore, it is discussed what a bank can obtain by using logistic regression and what by using multicriteria decision making. Important characteristics in credit scoring models for small companies in Croatia are also discussed because their specific features influence the criteria choice and some input parameters for the methods used in the paper.

The structure of the paper is as follows. In Section 2 the problem of credit scoring with the data from the Croatian bank is described. Section 3.1 presents logistic regression method used for credit risk evaluation with the data given in Section 2, while Section 3.2 presents multicriteria decision making used for the same purpose. In Section 4 the discussion of the results and some concluding remarks are given. Section 5 presents some hints for future research.

2 PROBLEM DESCRIPTION

The problem of credit scoring considered in this paper is the problem of credit risk evaluation in one Croatian bank. In the present moment it is performed based on the individual judgment of bank's experts. To evaluate the applicant's judgmental credit score, 14 criteria are used and are described as follows: (1) sales; (2) profit margin; (3) total debt ratio; (4) current ratio; (5) inventory turnover; (6) repayment ratio = (EBIT + depreciation)/outstanding debt ; (7) net cash flow; (8) client's credit history; (9) personal character in repayment; (10) business experience in the industry; (11) 1-total debt ratio; (12) average cash on business account; (13) industry risk; (14) business and marketing plan. Also, we were given the data for 60 clients which was a great problem because the procedure of collecting the data is very complicated, not available on-line, the clients have to come personally in the bank and fulfill the documentation. The data are then used in order to create so called credit card of the client. Some data are also given to the bank by Croatian Credit Bureau. The example of one credit card is given bellow:

Table 1: The credit card for Client 1

Client	***1. Sales***	***2. Profit margin***	***3. Total debt ratio***	***4. Current ratio***	***5. Inventory turnover***
Client 1	1.197	0,92%	0,14	5,79	1,62

6. Repayment ratio	***7. Net cash flow***	***8. Client's credit history***	***9. Personal character in repayment***
0,25	-178	1-2 loans	excellent

10. Business experience in the industry	***11. 1-total debt ratio***	***12. Average cash on business account***	***13. Industry risk***	***14. Business and marketing plan***
3+ years	85,66%	10000+	medium	excellent

For every of all 60 clients the same credit card was provided from the Croatian bank and used as the input for both methods used in this paper for credit risk evaluation.

3 METHODOLOGY FORMULATION

To solve the problem of credit risk evaluation presented in Section 2, we use two ways, one is the application of logistic regression methodology and the other is considering the problem as a multicriteria decision making problem. The purpose of using two methodologies is as follows. Namely the result of the first one is the probability of default for a certain client. The result of the second one is a set of groups of clients ranging from the group of best clients to the group of bad clients. In the practice the decision maker is often not so rigid making the decision. Sometimes he/she is not so sure should he/she approve the loan or not. In order to give him/her some additional information and to help him/her to make a decision the combination of different methodologies is welcome. Also, it is interesting to see what are the advantages and disadvantages of using the first or the second methodology.

3.1 Logistic regression

Previous research of methods used in credit scoring has shown that statistical methods such as the logistic regression, the linear regression, the discriminant analysis, and decision trees are mostly used. It has also been shown that the best methodology for credit scoring modeling has not been extracted yet, since it depends on the dataset characteristics. Altman et al. ([3]) showed the best result by using LDA. Desai et al. ([9]) got the best results by multilayer perception. Desai et al. ([8]) showed that LR outperformed NN. Yobas et al. ([24]) produced the best results using NN while Galindo and Tamayo ([15]) using CART decision tree.

Logistic regression modeling is widely used for analyzing multivariate data involving binary responses that we deal with in credit scoring modeling. It provides a powerful technique analogous to multiple regression and ANOVA for continuous responses. Since the likelihood function of mutually independent variables $Y_1,\ldots,Y_n$ with outcomes measured on a binary scale is a member of the exponential family with $\left(\log\left(\frac{\pi_1}{1-\pi_1}\right),\ldots,\log\left(\frac{\pi_n}{1-\pi_n}\right)\right)$ as a canonical parameter (π_j is a probability that Y_j becomes 1), the assumption of the logistic regression model is a linear relationship between a canonical parameter and the vector of explanatory variables $\mathbf{x}_j$ (dummy variables for factor levels and measured values of covariates):

$$\log\left(\frac{\pi_j}{1-\pi_j}\right) = \mathbf{x}_j^\tau \boldsymbol{\beta}$$

This linear relationship between the logarithm of odds and the vector of explanatory variables results in a nonlinear relationship between the probability of Y_j equals 1 and the vector of explanatory variables:

$$\pi_j = \exp(\mathbf{x}_j^\tau \boldsymbol{\beta}) / (1 + \exp(\mathbf{x}_j^\tau \boldsymbol{\beta}))$$

Detailed description of the logistic regression can be found in Harrel [17]. Logistic regression procedure is made using SAS software. Input variables for logistic regression scoring model are given in Section 2 of this paper. Those are 14 business criteria that are the basis for credit risk evaluation. As the output, we use credit scoring in the form of a binary variable with one category representing good applicants and the other one representing bad applicants. An applicant is classified as good if repayment ratio is equal or greater than 1. The data sample organized in such a way consisted of 58,3% bads and 41,7% goods. The good clients are: 2,3,12,15,22,25,26,28,32,37,40-47,49,50,54,56,57,59,60 and the bad clients are: 1,4,5-11,13,14,16,17,18,21,23,24,27,29-31,33,34,35,36,38,39,48,51-53,55,58.

The aim of logistic regression modeling is to estimate credit risk and to extract variables that are found important in credit risk prediction. We used logistic regression procedure available in SAS software, with standard overall fit measures. Variables together with their level of significance are given in Table 2.

Table 2: Variables in logistic regression model with their significance

Variable	***p-value***
net cash flow	0,0001
business experience	0,0001
total debt ratio	0,0919
inventory turnover	0,5512
industry risk	0,7191
profit margin	0,7789
personal character in repayment	0,8156
client's credit history	0,9232
average cash on business account	0,9761
sales	0,9778

In Table 2 it can be seen that the most predictive variables are net cash flow, client's business experience and total debt ratio. Looking at the regression coefficient shows that the odds of the company of being bad are increasing with the increase of total debt ratio. On the contrary, odds of the company of being good increases with the increase of the net cash flow. Concerning the client's business experience, it is shown that odds of being bad of the company with business experience of 1 to 3 years is increased in relation to those companies with more then 3 years experience in the business.

Fitting measures such as Likelihood ratio = 54,558 (p=0,0001), Wald = 8,358 (p=0,0038) and Score = 18,956 (p=0,0001) show that the model fits well. In order to test how well model classifies applicants, hit rates are calculated, good hit rate=96% and bad hit rate= 94,3%. The estimated good clients are: 2,3,5,12,13,15,22,25,26,28,32,37,40-47,50,54,56,57,59,60 and the estimated bad clients are 1,4,6-11,14,16,17-21,23,24,27,29,30,31,33-36,38,39, 48,49,51,52, 53,55,58.

3.2 Multicriteria decision making problem

We have already mentioned that there are some works considering the credit scoring as a multicriteria decision making problem and applying a group decision making technique (Yu, Wang, Lai, 2009). In that study, in order to obtain a group decision the artificial intelligence agents are used to replace human experts. This reminds us on the problem of defining the weights of criteria in mutlicriteria decision making. In the literature there are mathematical models based on multi criteria optimization, data envelopment analysis, analytic hierarchical process (AHP) and other multi-attribute rating techniques, but we do not use these approaches. We think that usually the decision maker wants to participate in the decision process, but he/she does not want to be involved too much. In order to respect this in this work we use the modification of the approach developed in [21] (partly inspired by [4]). Namely, we do not ask the decision maker to assign the weights to the criteria. The only task that he/she has to do is to group the criteria in three groups, very important criteria, less important and the least important criteria. Following this philosophy the Croatian bank which is our decision maker decided to group the criteria as follows. Very important criteria (1) sales; (2) profit margin; (3) total debt ratio; (4) current ratio; (5) inventory turnover; (6) repayment ratio = (EBIT + depreciation)/ outstanding debt ; (7) net cash flow. Less important criteria: (8) client's credit history; (12) average cash on business account; (13) industry risk; (14) business and marketing plan. The least important criteria: (9) personal character in repayment; (10) business experience in the industry.

After grouping the criteria in these three groups by the decision maker, the heuristic developed in [21] assigns the weights to the criteria inside a group based on Monte Carlo simulations.

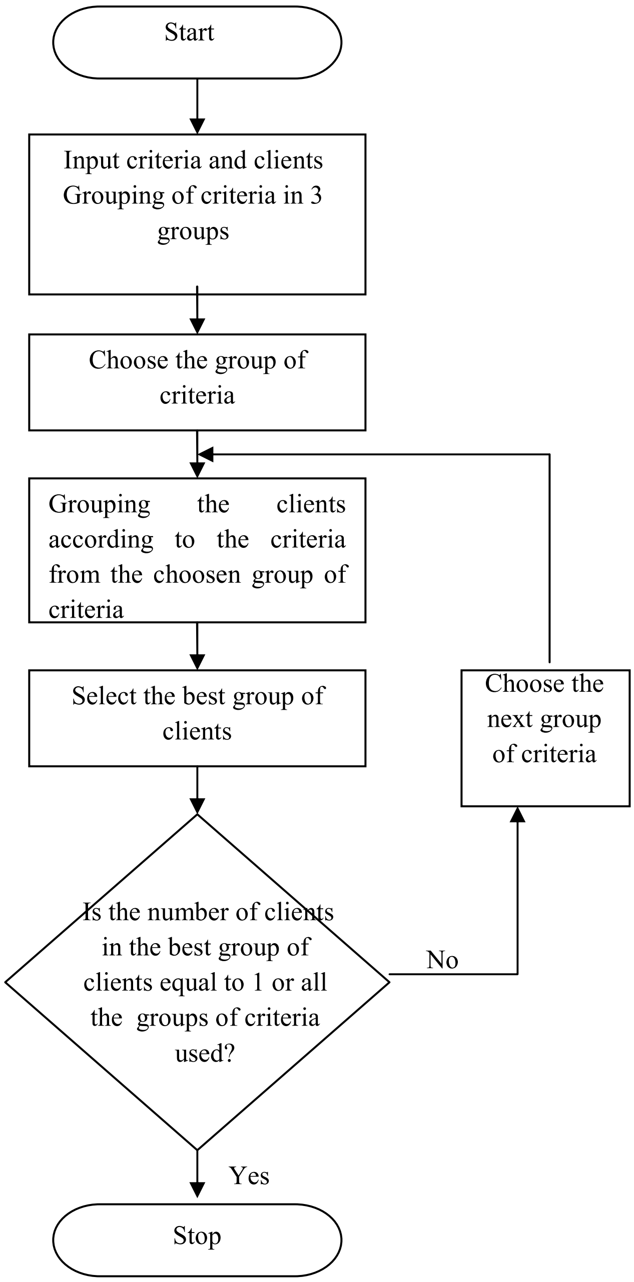

Figure 1: Block diagram of the heuristic used in [21]

Having the weights, in the first iteration the heuristic groups the clients according to their similarities with respect to the most important criteria. In the second iteration the heuristic takes the best group of clients from the first iteration and groups them according to their similarities with respect to less important criteria. Finally in the third iteration the heuristic takes the best group of clients from the second iteration and groups them according to their similarities with respect to the least important criteria. The best group is then taken as the group of clients which can be considered for approving the loan. We can notice that the heuristic from [21] gives us the relative result. Namely the result is the group of clients that is the best group but comparing with the other clients. In order to approve the loan or not the decision maker should be asked. But in order to avoid this last step of involving the decision maker in the decision process we are combining the heuristic from [21] with the method explained in 3.1.

In this work we use the modification of the heuristic developed in [21] in the sense that after obtaining the best group of clients, we eliminate them from the list and apply the whole heuristic again to the remaining clients. The result is again the best group of clients which is now the second best group. In this way in the case of the mentioned Croatian bank seven groups of clients were created starting from the best to the worst one. Also, for every client the heuristic gives the probability of belonging to the certain group which can be good information for the decision maker in the decision process of approving the loan.

The result obtained by the modification of the heuristic used in [21] is the following classification:

Table 3: Clients' classification

Group	***ID Client (probability of belonging to the group)***
1	56(1), 57(0.74), 59(0.66), 2(0.53), 6(0.2), 15(0.13), 21(0.11), 60(0.05), 1(0.03), 13(0.02), 4(0.01), 26(0.01)
2	9(1), 34(0.31), 17(0.29), 29(0.28), 14(0.16), 50(0.15), 10(0.14), 41(0.13), 38(0.09), 16(0.08), 12(0.07), 53(0.07), 52(0.06), 8(0.05), 35(0.05), 51(0.05), 37(0.04), 19(0.02), 23(0.02), 55(0.02), 27(0.01), 31(0.01)
3	36(1), 25(0.66), 45(0.46), 3(0.33), 42(0.23), 43(0.23), 5(0.14), 44(0.13), 32(0.04), 54(0.04)
4	22(1), 46(0.82), 39(0.74), 40(0.5), 48(0.34), 28(0.08)
5	20(1), 58(0.62), 11(0.45), 24(0.44), 30(0.38)
6	7(1), 18(1), 33(1)
7	47(1), 49(1)

4 CONCLUSIONS

As we have already mentioned in Section 3, to solve the problem of credit risk evaluation presented in Section 2, we use two ways, one is the application of logistic regression methodology and the other is considering the problem as a multicriteria decision making problem. The purpose of using two methodologies is as follows. Namely, every methodology has its own result and no methodology gives the optimal result. In the practice sometimes it is very hard for the decision maker to make a decision based on only one methodology because in the practice the decision makers are taking into consideration many qualitative influences. In that situation the decision maker wants to have a "quantitative based argumentation" for making a decision. In order to help him/her we proposed the combination of logistic regression and multicriteria decision making. The reason of choosing these two methods was in the fact the first one as the result gives us the default probability and the second one gives us the classification of the clients. The first one is good if the decision maker wants to be sure that the client will be able to pay a loan, while the second one is good if the decision maker has to approve the loan to some clients applied for it regardless to the default probability.

Also, in developing logistic regression credit scoring a bank has to have a data set consisted of repayment history and companies' financial data. Results of the credit scoring depend on default definition and quality of data set. If there is a small data set, quality of the scoring model could be decreased. The same could happen if there is a data set with a short repayment history. In both cases, it is justify to more rely on multicriteria decision making which as input needs just a set of defined criteria that are well know by the experts in a bank. Or, in both cases the combination of both methods is very welcome.

From the obtained results (good or bad clients in the first method and the classification from the second method) we will say that for the clients 2, 13, 26, 56, 57, 59 and 60 the decision maker can be sure that they are good clients and that they will repay the loan regularly. Since there are many good and bad clients from the first method belonging to the second and the third group from the second methods we can conclude that the problem is in the choice of the important criteria. Namely, from Table 2 it can be seen that the most predictive variables are net cash flow, client's business experience and total debt ratio. From the other side, our decision maker, the Croatian bank defined the following very important criteria: sales, profit margin, total debt ratio, current ratio, inventory turnover, repayment ratio and net cash flow. In this case the next step is to talk to the decision maker and with the information of the most predictive variables ask him/her if he/she is ready to think over his/her definition of very important criteria. In this way the new interactive method could be developed.

5 FUTURE RESEARCH

Both logistic regression and multicriteria decision making have several good reasons to be used in credit scoring modeling, some of which are described in this paper. It is clear that in an environment that is becoming more and more complex, using just judgmental systems for credit risk evaluation is just not enough so practitioners and researchers are constantly in searching for new algorithms. We believe that the further research in combining logistic regression and multicrieteria decision making has several directions.

Probability of default could be one of the criteria in multicriteria decision making. In such a way making decisions concerning credit risk in banks could be improved since other criteria usually not incorporated into the scoring model could be included in model of multicriteria decision making, such as macroeconomics indicators, trends in industry, forecasting about economy etc.

Also, we could think the other way around and result of multicrieteria decision making include as an independent variable in logistic regression. This variable can be the rank of a certain client obtained by the mutlicriteria decision making or the probability of belonging to a certain group. It is to expect that a final scoring model would have higher quality with such a strong predictor.

The third possibility is to use logistic regression result of significant variables selection as the most important and as such include them in the group of the most important criteria. Also, the significance of variables obtained by logistic regression could be used to define the weight of every criteria which is, as we know, a big problem in multicriteria decision making. This way of obtaining the weights in multicriteria decision making could substitute Monte Carlo simulations in the heuristic used in [21].

Further the new heuristic could be created as a combination of logistic regression and the modification of the heuristic used in [21] where the clients with a small probability of belonging to a certain group can be eliminated from this group and added to the list of remaining clients again for the next iteration of ranking. In order to define the lower bound for the probability of belonging to a group the logistic regression result could be used.

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