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Data mining for assessing the credit risk of local government units in Croatia

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Abstract. Over the past few decades, data mining techniques, especially artificial neural networks, have been used for modelling many real-world problems. This paper aims to test the performance of three methods: (1) an artificial neural network (ANN), (2) a hybrid artificial neural network and genetic algorithm approach (ANN-GA), and (2) the Tobit regression approach in determining the credit risk of local government units in Croatia. The evaluation of credit risk and prediction of debtor bankruptcy have long been regarded as an important topic in accounting and finance literature. In this research, credit risk is modelled under a regression approach unlike typical credit risk analysis, which is generally viewed as a classification problem. Namely, a standard evaluation of credit risk is not possible due to a lack of bankruptcy data. Thus, the credit risk of a local unit is approximated using the ratio of outstanding liabilities maturing in a given year to total expenditure of the local unit in the same period. The results indicate that the ANN-GA hybrid approach performs significantly better than the Tobit model by providing a significantly smaller average mean squared error. This work is beneficial to researchers and the government in evaluating a local government unit's credit score.

Keywords: credit risk assessment, data mining, artificial neural networks, regression approach, Tobit model

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1. Introduction

The evaluation of credit risk and prediction of default probability have long been a research topic in accounting and finance literature. Statistical techniques, opera-

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tional research, artificial intelligence and machine learning techniques have been used substantially to solve these financial decision-making problems [34]. For a detailed elaboration of determinants and methods used for evaluating the credit risk of local government units see [27].

Over the past few decades, especially artificial neural networks (ANNs) have been used for their learning ability to model countless real-world problems. There are many examples of using ANNs for credit risk analysis [[1], [2], [4], [21], [37]] and more specifically, for municipal credit ratings [[5], [6]]. Moreover, there are many examples of combining ANN with genetic algorithm (GA) where GA optimizes the parameters of a ANN, resulting in a hybrid algorithm with improved prediction accuracy [8], [9], [14], [23], [32]. With regard to credit risk, the ANN-GA hybrid system can also be used to classify the credit applicants [26].

This paper aims to test hybrid algorithm capabilities of a ANN and ANN-GA to determine the credit risk of local government units in Croatia. Credit risk is modelled using a regression approach unlike typical credit risk analysis, which is generally viewed as a classification problem. Namely, financial decision making, such as credit scoring and bankruptcy prediction, is usually regarded as the binary classification problem of classifying an observation into one of two pre-defined groups (e.g. bankruptcy or non-bankruptcy). However, the Croatian Bankruptcy Act (OG 44/96, Art. 3, Para. 2) does not allow local units to go into bankruptcy even though their bank accounts are often frozen due to defaulting on their liabilities. Moreover, a system for estimating a local unit's credit risk does not exist in Croatia. Consequently, due to lack of information on credit risk, it is hard to identify the successful local units and present them as good examples [3]. Therefore, a standard evaluation of credit risk using historical data on bankruptcies is not possible, [27] approximated the credit risk of local units in Croatia using the ratio of outstanding liabilities due (arrears) in a given year to total expenditure of local units in the same period. They determined possible indicators that affect a local unit's credit risk in Croatia using a Tobit model. In this paper, the results obtained by an ANN and ANN-GA hybrid using the same dataset as [27] are compared to the results obtained by the Tobit model.

Moreover, the input importance is given by a sensitivity analysis, which measures how the responses are affected when a given input is varied through its domain. To investigate the impact on the credit risk of local units in Croatia, a detailed input influence analysis will be performed using a variable effect characteristic (VEC) curve as proposed by [12]. Despite numerous applications for integrating GA with ANN in various fields of study, to the best of our knowledge, the methodology so far has not been explored for credit risk modelling using the regression approach. The remaining sections of this paper are organized as follows. The second chapter is devoted to data and the methodology. The third chapter deals with the predictive results, i.e., a comparison of methods, with the descriptive results discussed comprehensively in the fourth chapter, followed by the conclusion in the fifth chapter.

2. Data and modelling methodology

The data cover 556 municipalities and cities in Croatia and comprise the values of eleven explanatory variables calculated for the year 2008 in line with the financial reports of the local government units, the Croatian Bureau of Statistics and the State Electoral Commission. The specification of the variables is given in Table 1.

As mentioned before, there is no bankruptcy instrument for local government units in Croatia, hence credit risk is approximated in some other way. Thus, the credit risk of a local unit, i.e., the dependent variable default_proxy is calculated as the ratio of outstanding liabilities due (arrears) of local units to total liabilities due in the observed period, as suggested by [27]. The mean value of the approximated credit risk of local units (default_proxy) is 0.0930, the minimum value is 0, the maximum value is 0.6285 and the standard deviation is 0.1110.

Variable	Description
Status	Binary variable that has the value of 1 if the local government unit is a city, 0 if a municipality
Politika	Binary variable that has the value of 1 if the same political party is in power nationally and in the local government unit, otherwise 0
Izvoz.BDP	Ratio of the value of exports and GDP of a local government unit
lst_nst	Ratio of the population size of a local unit and the total population of Croatia
UNE.LST	Proportion of unemployed in the total population of a local unit
PDOH.TP	Proportion of income tax revenue in operating revenue
NOS.TP	Ratio of net operating balance to operating revenue
GOT.TR	Ratio of cash to operating expenditure
OD.GOT	Ratio of debt servicing to cash
ID.TP	Ratio of direct debt to operating revenue
NFL.TP	Ratio of net financial liabilities to operating revenue

Source: Authors

Table 1: *Specification of explanatory variables.*

In the modelling phase, we adopted three approaches: Tobit regression, ANN and ANN-GA hybrid. All the tests were performed in the R environment [28], an open source, multiple platform and high-level matrix programming language for statistical and data analysis. For these purposes, the data are scaled and centered. For comparing the three different methods, we use the mean squared error (MSE) as a performance measure. Also, a 10-fold cross validation scheme is used. That means that the original sample is randomly partitioned into 10 subsamples of equal size. Of the 10 subsamples, a single subsample is retained as the validation data for testing the model, and the remaining 9 subsamples are used as training data. The process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The subsamples for cross validation are generated randomly with each subsample containing a ceiling of the number of objects in the data set divided by 10. For our data, the subsets contain 56 objects, except for the last four subsamples which contain only 55 objects. This is because the number of objects in our data set is 556 which is not divisible by 10. More on the general k-fold cross validation scheme can be found, for instance, in [16].

2.1. The Tobit regression approach

Analyzing a local unit's credit risk will rely on using a censored regression model, i.e., the Tobit model [36] as suggested in work of [27]. Namely, the dependent variable (local unit bankruptcy) is, for the aforementioned reasons, not observed directly. The value of the latent variable of interest (default_proxy) for a non-negligible part of the sample is equal to zero (18.16%), and at the same time is continuously distributed over the interval [0,1]. The dependent variable in the model is censored to 0, but it is not censored to the upper value of 1 since no values of default_proxy equal to 1 are observed in the sample. For conducting this study, the R package used for implementing the Tobit model was *survival* [33].

2.2. ANN approach

ANN was developed by simulating the working principles of the human brain. It is a flexible non-linear modelling tool, which has the ability to learn from examples. ANN is composed of a number of processing units that are called neurons or nodes, connected through weighted connections [18], [39]. An ANN typically consists of three layers of interconnected neurons: the input layer - corresponding to independent variables in statistics, the hidden layer - where information received from the input layer is processed, and the output layer -

which transmits the information outside of the network and corresponds to a dependent variable in statistics. If the connections between neurons are only in one direction, the ANN is called a *feedforward network*. The network learns by adjusting the connection weights to reduce the error between the output and the true outcome. The training stage is usually done using the backpropagation method, a local search algorithm that employs gradient descent to iteratively update the weights and biases of the neural network in order to minimize the error function.
To implement feed forward ANN with a single hidden layer, R packages *nnet* [38] and *e1071* [24] were used. The training stage of the ANN using the nnet package is done by applying the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm [7][15],[17][31] which is an alternative to the conjugate gradient methods for fast optimization. The BFGS algorithm is the most popular quasi-Newton method for solving unconstrained nonlinear optimization problems. The activation function used in the hidden layer is a sigmoid function.
The ANN models were optimized using an internal 10-fold cross validation (using only training data). Parameter tuning on the number of hidden units was performed by training the nets with the number of hidden units varying from 1 to 5 and choosing the value minimizing the MSE on the validation set. Analogously, the values examined for the decay were 0, 0.0001, 0.001, 0.01 and 0.1. Because of the stochastic nature of the parameter setting routine, the procedure was repeated 5 times, i.e. 5 nets were tuned on each run and the best one was chosen to get the prediction.

2.3. ANN-GA hybrid

GA is an efficient optimization procedure inspired by evolutionary processes, namely, natural selection and genetic variation. GA's search for optimum values does not require a gradient function and it allows simultaneous search for optimal solutions in different directions. Therefore, the chance of getting trapped in a local minimum is diminished and the convergence is fast. The basic principles of GA are well known and extensively documented in literature (see e.g. [25]). The evolution in GA usually starts from a population of randomly generated individuals, whose fitness is evaluated in each generation (iteration). A new population is formed in each generation by stochastically selecting multiple individuals from the current population (based on their fitness), recombining them (by using crossover operator), and possibly performing mutation. Usually, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached.
The optimization of ANN parameters can be improved using GA to achieve better performance. For optimizing the performance of ANN in the present study, ANN is hybridized with GA which in turn is implemented using R packages *nnet* [38]

and *GA* [30]. GA is used for evolving the optimal set of initial weights for the neural network. After that, ANN is trained using these initial set of weights and biases and the algorithm implemented in *nnet*.
Thus, the initial population for the GA comprised of neural network weights. The network architecture - that showed the best performance in testing the ANN approach - was used for GA optimization. Given that the objective is to minimize the MSE,, it was used as a fitness function for the GA (since the fitness in the GA is maximized).
In this study, GA parameters and operators used for optimizing ANN are the default values from the *ga* function in the *GA* package. Therefore, the population size is 50, the crossover probability is 0.8, the mutation probability is 0.1, and the procedure stops after 100 iterations. The initial population is generated randomly by uniformly drawing out real values in the range [-100, 100]. The selection is fitness proportional selection with fitness linear scaling. The function performs local arithmetic crossover and uniform random mutation.

3. Comparison between methods

For testing the significance of differences between multiple means (mean MSE values for the three methods) the most interesting tests are the well-known ANOVA and its non-parametric counterpart, the Friedman test. As suggested by [13], for comparisons of multiple classifiers we use the latter, and its corresponding Nemenyi post-hoc test. Namely, ANOVA is based on assumptions, which are most probably violated when analyzing the performance of machine learning algorithms. The violations of these assumptions have an even greater effect on the post-hoc tests. Thus, as pointed out by [13], ANOVA is not the most suitable test for the typical machine learning studies.
The Friedman test reports a significant difference between the three tested algorithms ($p = 0.02$). The average MSE obtained by TR was 0.998 (st. dev. 0.255) which is not found to be significantly different ($p = 0.973$) than NN which had the average MSE equal to 0.975 (st. dev. 0.304). The average MSE obtained by ANN-GA was 0.902 (st. dev. 0.207) which is significantly different from TR ($p = 0.037$) and for $\alpha = 0.1$ it is also significantly different from NN ($p = 0.065$). It should be noted that the used post-hoc test has lower power than the Friedman test.

4. Descriptive results

The “black box” supervised methods such as NN are capable of accurate predictions, but obtained models are too complex to be easily understood by humans making the results hard to interpret. One of the strategies to increase interpretability from black box data mining models is visualization. Another popular solution is the extraction of rules [35]. However, such extraction is often based on a simplification of the model complexity, hence leading to rules that do not accurately represent the original model. Thus, we chose the visualization approach to open the models for this research. Different visualization techniques can be found in the literature, but most of the recent studies suggest approaches for opening models based on a Sensitivity Analysis (SA) [20], [22]. In this context, SA is a simple method that performs a pure black box use of the fitted models by querying the fitted models with sensitivity samples and recording the obtained responses [29].

In this paper, we use the *rminer* package, which is a coherent SA framework capable of handling any black box supervised model, including ensembles, and applicable to both classification, and regression tasks [10], [11]. In general, the sensitivity methods work by varying an input variable through its range with a certain number of levels, under a regular sequence from the minimum to the maximum value. We use the 1D-SA method which works by considering a given baseline vector [20]. The SA method queries a fitted model in order to obtain a set of sensitivity responses, which can be used to measure input importance. The rationale is that a relevant input should produce substantial output changes when varying its input levels. We use average absolute deviation (AAD) from the median as a sensitivity measure to quantify the input relevance, which is a measure first proposed in [11]. For the baseline vector, we use a vector with the mean values of each attribute from data. The number of sensitivity analysis levels is set at seven (default in the *rminer* function for measuring input importance). To simplify the explanation and analysis, the sensitivity methods and visualization techniques were applied to one model only. In order to do so, the ANN-GA model was retrained using all data. Then, the sensitivity method and visualization techniques were applied to the retrained model. In this way, it was possible to quantify the contribution of a given attribute for the model and to measure how the model was influenced by each of its input attributes as a percentage of the remaining. Figure 1 shows the relative input importance values.

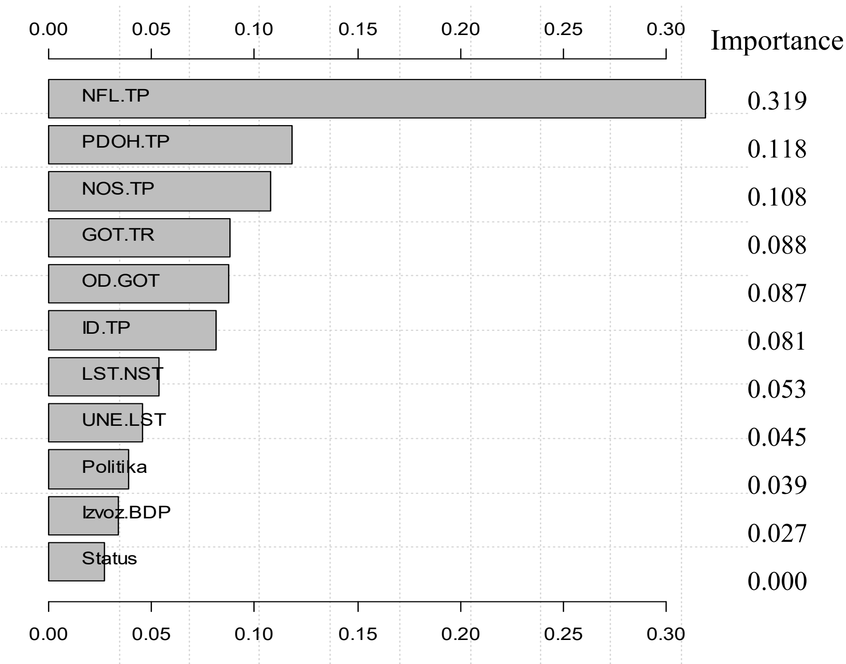
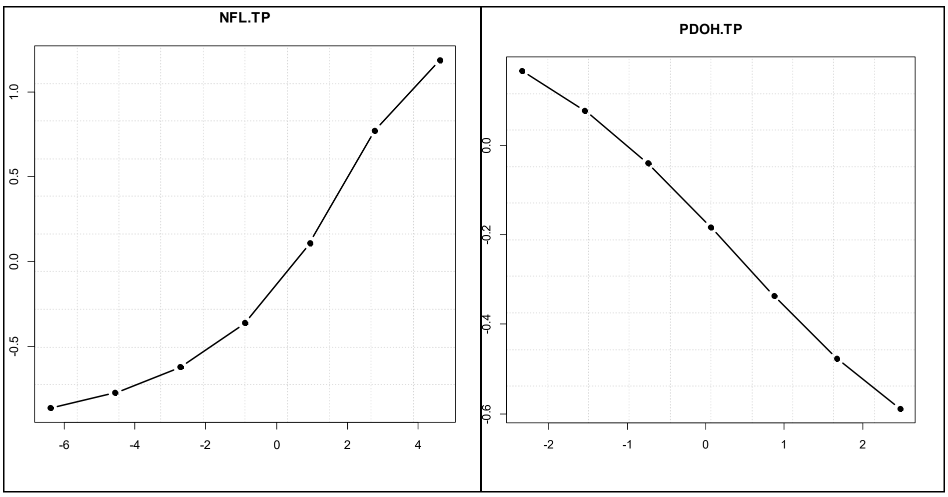


Figure 1: *Relative input importance values*

The most relevant input is the NFL.TP, which on its own explains for almost 32% of the Default_proxy. The individual effect of a given input can be shown using Variable Effect Characteristic (VEC) curves that present the average impact of a given input in the model [12]. To present more influence details, Figures 2 shows the VEC curves for the four most important inputs (input values on x-axis versus the predicted responses on y-axis).



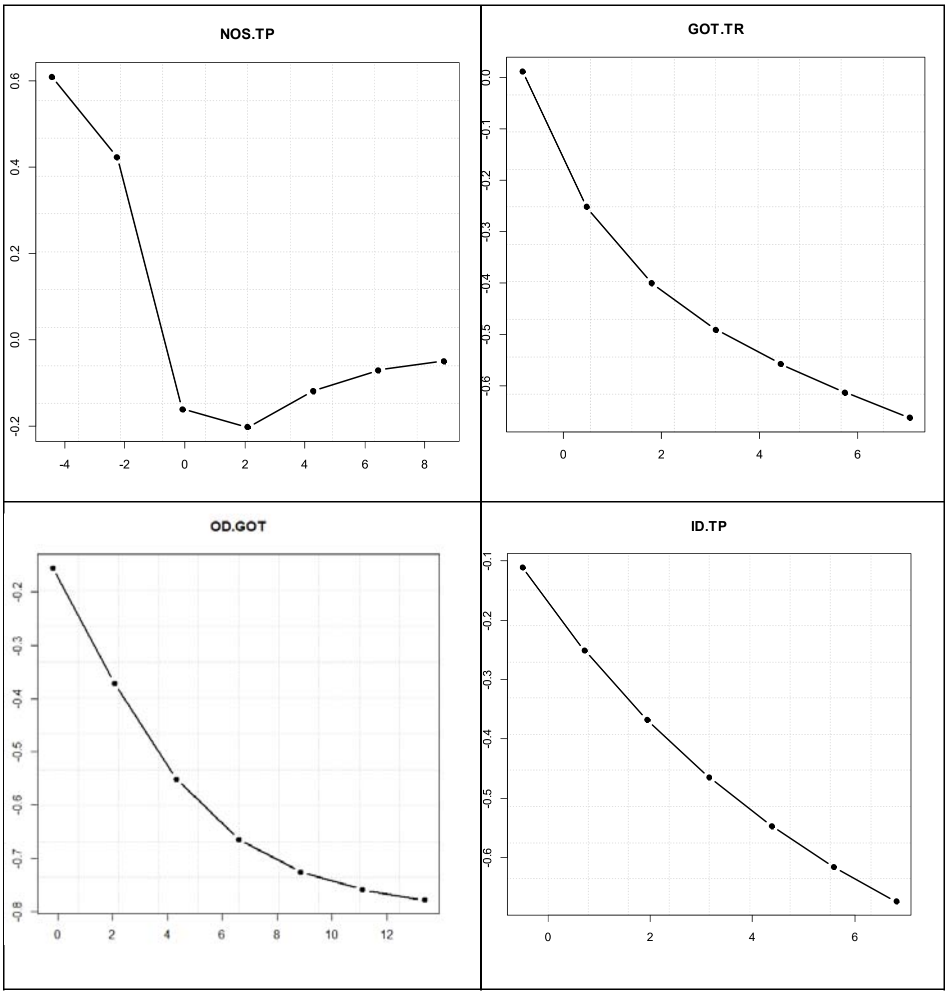


Figure 2: *VEC curves for the four most important inputs*

As seen from Figure 2, NFL.TP seems to have limited impact on Default_proxy for negative values of NFL.TP. This is reasonable since negative values of NFL.TP imply that local government units have financial assets in excess of financial liabilities (they are able to cover the total amount of their financial liabilities with their financial assets) making the fiscal risk from financial liabilities negligible. However, for above zero values of NFL.TP, the values of Default_proxy start to increase rapidly with an increase in NFL.TP. On the other hand, the values of Default_proxy almost linearly decrease with an increase in PDOH.TP. An increase in PDOH.TP reveals improved financial self-sufficiency of local government units because it makes them less dependent on financing from other (uncertain) sources (including that from the central government). It is also worth

noting is that the value of Default_proxy seems to quickly decrease with as NOS.TP increases to zero, which is expected as negative values of NOS.TP are associated with net operating deficit, meaning that the value of a local government unit's expenditure is greater than revenue. A decrease in net operating deficit increases the value of NOS.TP, and consequently has a positive influence on the Default_proxy.
The value of Default_proxy decreases with an increase in GOT.TR. This is in line with the theoretical but also practical view according to which the probability of default largely depends on the amount of cash (as the most liquid asset) a debtor has at his disposal. An increase in the ratio of cash to operating expenditure therefore decreases the Defaut_proxy. Finally, the value of Defa-ult_proxy decreases as OD.GOT and ID.TP increase, which is very unexpe-cted as larger debt in proportion to operating revenue and larger debt servicing in relation to cash should result in greater credit risk.

5. Conclusions

This paper tested the capabilities of the ANN and ANN-GA hybrid algorithms to determine the credit risk of local government units in Croatia. Unlike typical credit risk analysis which is generally viewed as a classification problem, this work modelled credit risk using a regression approach. The results obtained by ANN and ANN-GA hybrid were compared to the results obtained from the Tobit model. According to the obtained average MSE, the tests have shown that ANN does not perform significantly better than the Tobit model in predicting the credit risk of local government units in Croatia based on the research data. However, the ANN-GA hybrid does perform significantly better than the Tobit model and provides a significantly smaller average MSE. Therefore, hybridizing ANN with GA proved to be advantageous. A possible reason is that this strategy decreases the possibility of getting trapped in local minima. Therefore, this is another case that shows how data mining methods known as the "black box" supervised methods can attribute to making better predictions.
The input importance was determined by performing a sensitivity analysis, and measuring how the responses are affected when a given input is varied through its domain. Also, a detailed input influence analysis was performed using the Variable Effect Characteristic (VEC) curve to investigate the impact on the credit risk of local units in Croatia. Therefore, although the "black box" models are often too complex to be easily understood by humans, interpret the results of such models is possible.
There are many other metaheuristic optimization methods that have been shown to perform very well in global optimization problems, hence hybridizing ANN with some other metaheuristic optimization methods may be useful, and is an idea for future research.

The introduction of a transparent and efficient credit risk rating system in Croatia would solve many practical problems posed by local government units taking out loans. Moreover, evaluation of a local government unit's credit risk may assist the Ministry of Finance in allocating guarantees and consents to local government units and their utility companies when taking out loans. Raising awareness of the low-risk profile of local government units – usually viewed as 'corporate' clients – would certainly lead to reduced borrowing costs, whereas publishing their credit risk data may boost competition, and indirectly improve their financial performance.

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