Proceedings of the 7th WSEAS International Conference on Neural Networks, Cavtat, Croatia, June 12-14, 2006 (pp73-78)

Modelling Municipal Rating by Cluster Analysis and Neural Networks

PETR HÁJEK, VLADIMÍR OLEJ
Institute of System Engineering and Informatics
Faculty of Economics and Administration
University of Pardubice
Studentská 84, 532 10 Pardubice
CZECH REPUBLIC

Abstract: - The paper presents the design of the parameters for long-term municipal rating. Modelling of the rating is realized by means of unsupervised methods, because the rating classes are not known a priori. The model design based on statistical methods (neural networks) is represented by cluster analysis (self-organizing feature maps).

Key-Words: - Credit risk, rating, unsupervised learning, cluster analysis, K-means algorithm, neural networks, Kohonen's self-organizing feature maps.

1 Introduction

Statistical methods [1] and neural networks [2,3] are used in technical and in economic fields of practice. The models of technical analysis [4], bankruptcy prediction [5], credit risk [6], etc., are used as examples.

Credit risk is the risk resulting from the probability that the counterparty will default its existing debt. Models of credit risk can be divided into the models based on rating [7], scoring systems [8], Value at Risk [8] and structural models [8]. Rating is the independent evaluation, whose aim is to find out how this object is capable and willing to meet its payable obligations especially based on complex analysis of all known risk factors (parameters) of assessed object [7]. Short-term rating is designed to evaluate the up-to-one-year expiration obligations; long-term rating is designed to evaluate the over-one-year obligations. According to the assessed object there are ratings of the state, company, municipality, financial institution, single bond, etc. The evaluation results in the rating class, which is defined on the rating scale [7]. High rating class (i.e. low credit risk) takes effect in lower interest rates from credits. The rating is the important information about risk for investors, which they undergo by granting the credits. The development of municipal rating informs the citizens about the quality of municipal economy.

This statement demonstrates that modelling rating is a classification problem. Classification can be realized by the supervised methods (if rating classes are known) or unsupervised methods (if the classes are not known). Statistical methods (discriminate analysis [9], logarithmic regression [9]), neural networks [6] and Support Vector Machines [6] were used for the supervised methods. Statistical methods (e.g. multidimensional scaling [10]) were used for unsupervised methods.

Only several municipalities of the Czech Republic have assigned the rating class. Therefore, the article presents a design of long-term rating parameters of Czech municipalities and its modelling by cluster analysis [1,11] and neural networks.

2 Municipal Rating Parameters Design

In [7,12] common categories of parameters are mentioned, namely economic, debt, financial and administrative. The economic, debt and financial parameters are pivotal [7]. The differences in models based on rating are in the used parameters and their weights. Models in [7,12] assume high fiscal autonomy of municipalities. This allows the municipalities to influence their revenues through local taxations and charges for municipal services. On the other hand, the municipalities of Czech Republic have low fiscal autonomy. Therefore, the parameters of rating differ from the models.

2.1 Economic Parameters Design

Economic parameters affect long-term credit risk. The municipalities with more diversified economy and more favourable social and economic conditions are better prepared for the economic recession [12]. The economic growth, however, is able to enlarge public services and thereby to increase the indebtedness. Stable municipal economy can indicate economic stagnation. There is no synthetic parameter that would quantify the level of municipal economies. The economic parameters for credit risk evaluation can be designed as follows:

Parameter $p_1 = PO_r$, (1)

where PO_r is population in the r-th year. Higher value of the parameter p_1 entails especially higher municipal tax revenues. The tax revenues depend on the number of inhabitants and on the coefficient, which indicates the size category of the municipality. Larger municipalities have higher share in tax yield, because the more populated municipalities have higher spending for the infrastructure and other public goods. Higher population is a guarantee of future municipal revenues for the creditors. At the same time it decreases the credit risk [13].

Parameter $p_2 = PO_r / PO_{r-s}$, (2)

where R_{r-s} is population in the year r-s, and s is the selected time period. The change in the number of inhabitants is a good criterion of the economic vitality of a municipality [7]. The economic growth of the municipality leads to the growing number of its inhabitants. Sudden growth of the parameter should be assessed prudently, because the real trend is not needed.

Parameter $p_3 = U$, (3)

where U is the unemployment rate in a municipality. The rate of unemployment evaluates the general economic wealth of the municipality. The economic growth reduces the unemployment in the municipality. Therefore, low rate of unemployment indicates good economic conditions. High unemployment rate entails higher expenses for social services. Jobs deficiency also reduces the price of real estates, which decreases the budget revenues from the real estate tax.

Parameter $p_4 = \sum_{i=1}^{k} (PZO_i/PZ)^2$, (4)

where PZO_i is the employed population of the municipality in the i-th economic sector, i=1,2, … ,k, PZ is the total number of employed inhabitants and k is the number of the economic sector. Parameter p_4 represents the concentration of employment in economic sectors and presents the measure of municipal economic concentration. Low value of parameter p_4 means long - term flexibility of the municipal economy and the protection against bankruptcy of one sector. According to [7] the parameter p_4 is the most considerable factor of municipal rating.

2.2 Debt Parameters Design

Debt parameters include the size and structure of the debt. Ratios are often used to measure both the debt of the municipality and its ability to pay off a debt service. Using the ratios is, however, efficient, only if the parameters for comparable municipalities are available. The comparison with those municipalities informs about the current debt and financial situation of the municipality. On the basis of the mentioned facts, the debt parameters can be designed:

Parameter $p_5 = DS / OP$, (5)

where $p_5 \in <0,1>$, DS is debt service and OP are periodical revenues. It is the crucial debt factor measuring the ability of the municipality to pay off the DS from regular budget revenues [13]. The debt service includes the yearly interest and the annuity payment. Periodical revenues are total revenues minus nonrecurring and capital revenues. The value of the parameter p_5 above 0.15 can be considered a signal of the imminent debt trap.

Parameter $p_6 = CD / PO$, [Czech crowns], (6)

where CD is a total debt. The indicated parameter measures gross measure of indebtedness of the municipality, i.e. how much debt accrues to one inhabitant. Its absolute value is not predicative itself. It is necessary to compare the value with those of other municipalities in the region, or the whole country [7].

Parameter $p_7 = KD / CD$, (7)

where $p_7 \in <0,1>$ and KD is short-term debt. It analyses the structure of a debt. A short-term debt is designed to meet the short-term engagements resulting from the insufficient cash flow. The short-term debt should be paid off during a fiscal year. If the KD is intended to cover a budget deficit or to finance the capital projects, it should be considered a dangerous signal since it negatively influences the credit risk [13]. The interest rates of the KD are usually floating rates. This may cause the inability to pay the debt service.

2.3 Financial Parameters Design

Financial parameters inform about the implementation of budget. Their values are extracted from the budget of the municipality. The financial parameters for credit risk evaluation can be designed this way:

Parameter $p_8 = OP / BV$, (8)

where $p_8 \in R^+$ and BV are current expenditures. The parameter p_8 reports on the quality of the budget implementation. If it is greater than 1 constantly, i.e. current budget is in excess, and at the same time a growing trend is indicated, the financial condition of the municipality is good. Good financial standing enables the municipality to use the common surplus to finance its engagements. On this account, the parameter is regarded as a key factor in [13].

Parameter $p_9 = VP / CP$, (9)

where $p_9 \in <0,1>$, VP are own revenues and CP are total revenues. Higher share of own revenues on total revenues entails a higher fiscal autonomy of the municipality. The higher fiscal autonomy leads to lower indebtedness of the municipality. According to [13], the size of the fiscal autonomy affects the municipality decision making management. The municipal management chooses a combination of the VP and the debt on public goods financing. The higher is the fiscal autonomy of the municipality, the smaller the need for the debt as a financing tool.

Parameter $p_{10} = KV / CV$, (10)

where $p_{10} \in <0,1>$ and KV are capital expenditures, CV are total expenditures. Higher value of the parameter indicates capital activity of the municipality and a good common management enabling its further development [13]. This hypothesis complies with the intergenerational theory of justice where both the contemporary as well as future users of the public goods should take part in capital expenses.

Parameter $p_{11} = IP / CP$, (11)

where $p_{11} \in <0,1>$ and IP are capital revenues. The debt is primarily intended to finance the capital (investment) expenditures (projects). The higher is the parameter p_{11}, the smaller is the need of next indebtedness to finance capital projects.

Parameter $p_{12} = LM / PO$, [Czech crowns], (12)

where LM is the size of the municipal liquid assets. The municipalities manage their own assets. These are often used as bank's credit collateral. The banks grant a credit only on condition, that the collateral assets are liquid enough, i.e. cashable in short time. The liquid assets of the municipality include suitably situated extensive land properties, commercial buildings, agricultural land properties and assets for commercial use being in possession of the municipality.

2.4 Vector of Parameters for Municipal Rating

The parameters p_1 to p_{12} constitute a vector **p** of the parameters for the municipal rating of Czech municipalities. The vector **p** is in this form

$$\mathbf{p} = (p_1, p_2, \ldots, p_{12}). \quad (13)$$

For n municipalities O_n the designed model can be expressed in the form of data matrix

$$\begin{array}{c|ccccc} & p_1 & \cdots & p_j & \cdots & p_m \\ \hline o_1 & x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ o_i & x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ o_n & x_{n,1} & \cdots & x_{n,j} & \cdots & x_{n,m} \end{array},$$

where n is the number of objects (municipalities), m is the number of parameters, x_{ij} is value of the j-th parameter p_j for the i-th municipality O_i, $j \in \{1,2, \ldots ,12\}$.

3 Sample Municipal Rating and its Analysis

Modelling of the rating is a classification problem. It is generally possible to define it this way:

Let $F(\mathbf{x})$ be a function defined on a set A, which assigns picture $\hat{x}$ (the value of the function from a set B) to each element $\mathbf{x} \in$A, $\hat{x} = F(\mathbf{x}) \in$B,

$$F : A \rightarrow B . \quad (14)$$

The problem defined this way it is possible to model by the supervised methods (if rating classes of the objects are known) or by unsupervised methods (if these classes are not known). Several Czech municipalities have assigned the rating class. Therefore it is appropriate to model the municipal rating by e.g. statistical methods (e.g. cluster analysis methods) and neural networks (e.g. self-organizing feature maps). It is possible to create the classes on the basis of the objects' similarity by using these methods.

3.1 Modelling Municipal Rating by Cluster Analysis

The cluster analysis [1,11] belongs to the methods which deal with the search for the similarity among multidimensional data objects and with their classification to classes (clusters). The classes in cluster analysis are not assigned to data objects. The number of classes or clusters is unknown, too. The found clusters represent the data structure only with reference to the selected parameters. This method does not contain a technique capable of distinguishing the significant and insignificant parameters, it only distinguishes the clusters.

The goal of the rating is classification of the objects (municipalities) to the rating classes. In terms of definition of the cluster analysis scope, the data are standardized by normalization of each of the parameters to its Z-score [1]. The standardization facilitates mutual comparison of parameters' values (their average is 0 and the standard deviation is 1). The positive values are then above-average and the negative are below the average. All the parameters are of quantitative type. Therefore the distance measures can be used. Further it is necessary to choose the clustering algorithm and to resolve upon the expected number of the clusters. Both the mentioned decisions have influence on the results interpretation. There are two basic algorithms of clustering, namely hierarchical and partitioning algorithms [11]. The hierarchical algorithms construct a tree structure of the clusters, so-called dendrogram [11]. These algorithms are not suitable for the analysis of extensive samples, the results are affected by outlying objects and the undesirable preceding combinations persist in the analysis. In the partitioning algorithms [11] (K-modes, K-means algorithms etc.) the objects are assigned to the number of clusters given in advance. First step is the setting of initial cluster centres and all the objects situated inside the given distance to a cluster centre are assigned to this cluster. The choice of the initial cluster centres is crucial. The K-means algorithm is used for the analysis of the rating. A disadvantage of this algorithm is the dependence of the clustering results on the initial cluster centres. Therefore the initial cluster centres are set up by the hierarchical algorithm (Ward's method [1]). The results of the cluster analysis are negatively affected by the existence of outlying objects and by multicolinearity of the parameters [1]. The outlying objects are identified by the Mahalanobis distance and removed in consequence. The multicolinearity has not been noticed. The unknown number of clusters is the next problem of the cluster analysis. This number is set by empirical experience and Dunn's index [11].

3.2 Modelling Municipal Rating by Kohonen's Self-organizing Feature Maps

Kohonen's self-organizing feature maps (SOFM) are a neural networks models based on competitive learning strategy [2,3]. Output neurons of the network compete for their activity. The self-organizing feature maps are based on unsupervised learning. The aim of the unsupervised learning is to approximate the probability density p($\mathbf{x}$) of the real input vectors $\mathbf{x}\in R^n$ by the finite number of representatives (codebook vectors) $\mathbf{w}_i\in R^n$, where i=1,2, … ,h [2]. When the codebook vectors are identified, the representative $\mathbf{w}_{i*}$ (winner, the best matching unit, BMU) is assigned to each vector $\mathbf{x}$, for which

$$i^* = \operatorname{argmin} \|\mathbf{x} - \mathbf{w}_i\|, \qquad (15)$$

where i* is the index of the winning neuron. The SOFM is a two-layer neural network with the completely connected units among the layers. The input layer is formed by n neurons, which serves the distribution of the input values $\mathbf{x}$. The units in the output layer serve as the representatives. They are organized into topological structure (most often a two-dimensional grid), which designates the neighbouring network units.

On the learning process it is necessary to define the concept of neighbourhood function, which determines the range of cooperation among the neurons, i.e. how many weight vectors belonging to neurons in the neighbourhood of the BMU will be adapted, and to what degree. Gaussian neighbourhood function is in common use, which is defined this way

$$h(i^*, i) = e^{\left(-\frac{d_E^2(i^*,i)}{\lambda^2(t)}\right)}, \qquad (16)$$

where h(i*,i) is neighbourhood function, $d^2_E(i^*,i)$ is Euclidean distance of neurons i and i* in the grid, $\lambda(t)$ is the size of the neighbourhood in time t. After the BMUs are found the adaptation of weights (learning) follows. The sequential and batch learning algorithm are available. The principle of the learning algorithm is, that the weight vectors of the BMU and its topological neighbours move towards the actual input vector according to the relation

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \alpha(t).h(i^*,i).[\mathbf{x}(t) - \mathbf{w}_i(t)], \qquad (17)$$

where $\alpha(t)\in(0,1)$ is learning rate. The batch learning algorithm of the SOFM is a variant of the sequential algorithm. The difference consists in the fact that the whole training set passes through the network only once and only then the weights are adapted. The adaptation is realized by replacing the weight vector with the weighted average of the input vectors. The weight factors are represented by the values of the neighbourhood function

$$\mathbf{w}_i(t+1) = \frac{\sum_{j=1}^{n} h(i^*,i)(t)x_j}{\sum_{j=1}^{n} h(i^*,i)(t)}, \qquad (18)$$

where j is index of an input value, n is the number of the input values. The learning algorithm proceeds in two phases: rough phase with high values of neighbourhood radius and high value of learning rate and fine tune phase with low values of neighbourhood radius and learning rate.

The created SOFM is clustered by K-means algorithm. The number of clusters is determined by the Davies-Bouldin's index minimisation [11].

4 Analysis of the Results

The K-means algorithm assigns every object to a single cluster. The clusters can be interpreted on the basis of the centroids (i.e. the average points in the multidimensional space defined for each cluster), a group of distant points, decision trees or logical rules [11]. The logical rules are designed in terms of the known classification of the objects to the clusters. For each cluster r, where r∈{1,2, … ,9}, logical rules $V_{r,k}$ were created, where k is the sequence of a rule for the r-th cluster. The algorithm PART (partial decision trees) was used for the rules creation [14]. The algorithm is a combination of a method generating the decision trees and a method based on separate and conquer paradigm. The rules are presented in Table 1.

Table 1 Logical rules

$V_{1,1}$	IF $p_{10} \leq 0.324$ AND $p_7 > 0.861$ AND $p_3 \leq 13.58$ AND $p_5 \leq 0.206$ AND $p_2 > 0.896$	THEN r=1
$V_{1,2}$	IF $p_6 \leq 1021.1$ AND $p_{10} \leq 0.332$ AND $p_7 > 0.25$ AND $p_1 \leq 1513$ AND $p_5 \leq 0.311$ AND $p_3 \leq 18.627$ AND $p_6 > 87.43$	THEN r=1
$V_{1,3}$	IF $p_5 \leq 0.071$ AND $p_3 \leq 9.15$ AND $p_3 \leq 8.387$	THEN r=1
$V_{1,4}$	IF $p_4 \leq 0.249$ AND $p_{10} \leq 0.266$ AND $p_5 \leq 0.006$	THEN r=1
$V_{2,1}$	IF $p_7 \leq 0.438$ AND $p_8 \leq 0.511$ AND $p_2 > 0.917$	THEN r=2
$V_{2,2}$	IF $p_1 > 2570$	THEN r=2
$V_{3,1}$	IF $p_8 > 1.623$ AND $p_9 \leq 0.263$ AND $p_5 \leq 0.224$	THEN r=3
$V_{3,2}$	IF $p_1 \leq 3321$ AND $p_{10} > 0.376$ AND $p_8 \leq 1.573$AND $p_5 \leq 0.008$ AND $p_{11} \leq 0.309$	THEN r=3
$V_{4,1}$	IF $p_7 \leq 0.438$ AND $p_6 \leq 17059.46$ AND $p_9 \leq 0.168$ AND $p_4 \leq 0.266$ AND $p_{10} \leq 0.333$ AND $p_3 \leq 13.761$ AND $p_{11} \leq 0.2$	THEN r=4
$V_{4,2}$	IF $p_1 \leq 3321$ AND $p_7 \leq 0.861$ AND $p_{10} \leq 0.233$ AND $p_3 \leq 18.367$ AND $p_8 > 1.055$	THEN r=4
$V_{4,3}$	IF $p_9 > 0.117$ AND $p_{12} \leq 114975.75$ AND $p_9 \leq 0.273$ AND $p_3 > 13.235$	THEN r=4
$V_{4,4}$	IF $p_1 \leq 2570$ AND $p_5 > 0.04$ AND $p_9 \leq 0.134$ AND $p_1 \leq 698$ AND $p_6 > 2081.73$	THEN r=4
$V_{4,5}$	IF $p_7 \leq 0.714$	THEN r=4
$V_{5,1}$	IF $p_{10} \leq 0.324$ AND $p_9 > 0.263$ AND $p_4 \leq 0.225$	THEN r=5
$V_{5,2}$	IF $p_9 > 0.11$ AND $p_5 \leq 0.236$AND $p_{12} > 108095.75$	THEN r=5
$V_{6,1}$	IF $p_7 \leq 0.438$ AND $p_6 \leq 17059.46$ AND $p_9 \leq 0.168$ AND $p_{11} > 0.24$ AND $p_{11} > 0.26$ AND $p_3 \leq 17.753$	THEN r=6
$V_{6,2}$	IF $p_{10} > 0.376$ AND $p_9 \leq 0.162$ AND $p_8 \leq 1.33$	THEN r=6
$V_{6,3}$	IF $p_1 \leq 3321$ AND $p_{11} > 0.115$ AND $p_4 \leq 0.233$ AND $p_3 \leq 15.686$ AND $p_2 > 0.96$	THEN r=6
$V_{6,4}$	IF $p_6 > 1110.63$	THEN r=6
$V_{7,1}$	IF $p_{10} \leq 0.237$ AND $p_{11} \leq 0.587$ AND $p_6 \leq 1021.1$ AND $p_3 > 10.833$ AND $p_6 > 7.86$ AND $p_4 > 0.214$	THEN r=7
$V_{7,2}$	IF $p_6 \leq 1021.1$ AND $p_{10} \leq 0.332$ AND $p_1 \leq 1513$ AND $p_7 \leq 0.25$ AND $p_2 \leq 0.759$	THEN r=7
$V_{7,3}$	IF $p_1 \leq 3054$ AND $p_5 > 0.04$ AND $p_9 \leq 0.134$ AND $p_3 > 15.513$ AND $p_2 > 0.903$	THEN r=7
$V_{7,4}$	IF $p_5 \leq 0.071$ AND $p_3 > 9.15$ AND $p_6 \leq 5807.03$ AND $p_1 > 110$ AND $p_3 > 12.632$	THEN r=7
$V_{7,5}$	IF $p_4 > 0.234$ AND $p_2 \leq 0.938$	THEN r=7
$V_{8,1}$	IF $p_7 \leq 0.438$ AND $p_5 > 0.255$ AND $p_6 \leq 17059.46$ AND $p_5 > 0.326$	THEN r=8
$V_{9,1}$	IF $p_{10} > 0.376$ AND $p_6 > 12353.67$ AND $p_6 > 17059.46$	THEN r=9

The representatives of the SOFM were clustered by the K-means algorithm (Fig. 1). Classification of the representatives to the clusters is evident in Fig. 1. The clustering is in contradistinction to cluster analysis realized only after SOFM has been made, which keeps the structure of the original data.

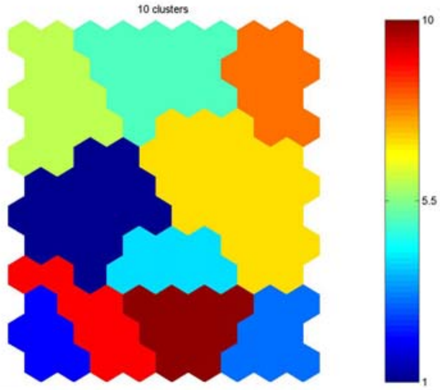

Fig. 1 K-means algorithm in SOFM

The result of the clusters' interpretation is an assignment of clusters to rating classes (RC) (Aa, Aa-, A+, A, A-, Baa+, Baa), Table 2. The RC's labelling consists of the rating agencies' one [12].

The clusters can be interpreted on the basis of values of the parameters for the representatives of the SOFM (Fig. 2). The values of parameters for individual clusters can be derived this way.

Table 2 Rating scale

Legend: RC is rating class, r_{CA} are clusters created by cluster analysis, r_{SOFM} are clusters created by SOFM.

RC	Description of belonging municipalities	r_{CA}	r_{SOFM}
Aa	Booming, good implementation of budget, no problems with indebtedness	3	4
Aa-	Excellent economic environment, no investment development	1,2,4	1,2,6
A+	Average debt, good economic environment, good investment development	6	7,9, 10
A	Bad economic environment, no indebtedness, average implementation of budget	7	5
A-	Big liquid assets, average debt, signals of economic recession	5	8
Baa+	High debts, good investment development	9	3
Baa	High debt service, bad economic environment, good investment development	8	

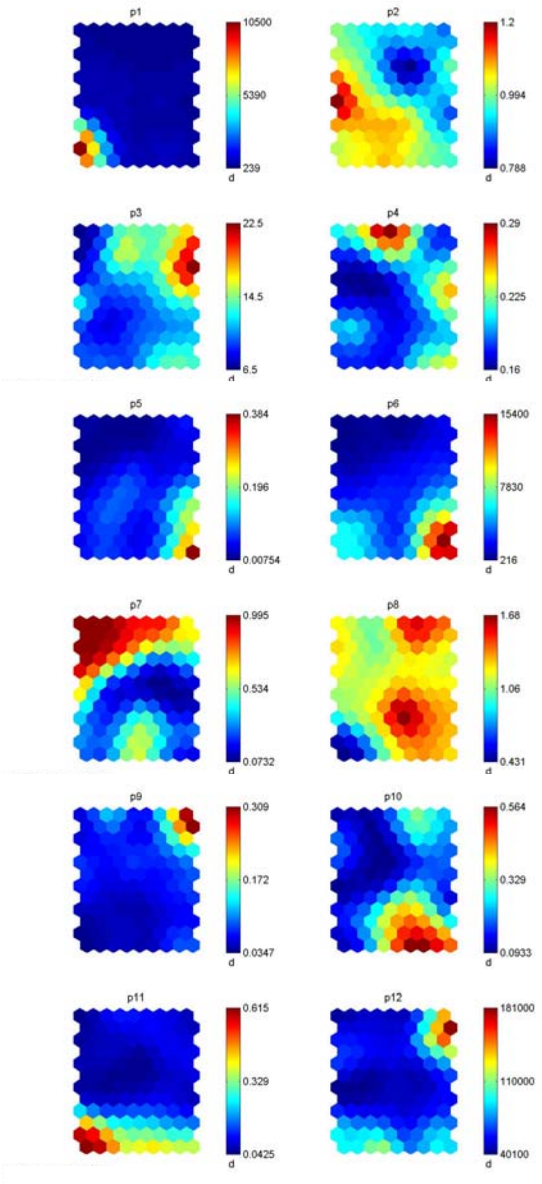

Fig. 2 Values of parameters for SOFM representatives
Legend: p_1,p_2, … ,p_{12} are parameters of rating, d is a scale of parameters' values.

5 Conclusion

The vector of parameters is designed in the article. The parameters influence long-term rating of the Czech municipalities. On the basis of selected parameters similarity, the municipalities are assigned the RC. The municipalities with similar level of credit risk are situated in each RC.

The selection of parameters is crucial in modelling rating. If selected parameters do not influence the credit risk or there are other parameters missing, the results of cluster analysis and SOFM are inaccurate. In further research the models would be suitable, which exactly classify, are able to generalize, can be easily interpreted and, at the same time, they can competently work with the expert's knowledge. The combination of Mamdani fuzzy inference system and feed-forward neural network is feasible.

The designed models were carried out in Statistica 6.0 (cluster analysis) and MATLAB (self-organizing feature maps) in operation system Windows XP.

References:

[1] W. Hardle, L. Simar, *Applied Multivariate Statistical Analysis*, Springer-Verlag, 2003.

[2] S. S. Haykin, *Neural Network: A Comprehensive Foundation*, Upper Saddle River, Prentice-Hall, 1999.

[3] D. J. C. MacKay, *Information Theory, Pattern Recognition and Neural Networks*, Cambridge Press, 2003.

[4] V. Olej, *Modelling of Economics Processes on the Basis Computational Intelligence*, M and V, Hradec Králové, 2003, (in Slovak).

[5] A. F. Atyia, Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results, *IEEE Transactions on Neural Networks*, Vol.12, No.4, 2001, pp.929-935.

[6] Z. Huang, Credit Rating Analysis with Support Vector Machines and Neural Networks: A Market Comparative Study, *Decision Support Systems*, No.37, 2004, pp.543– 558.

[7] G. J. Miller, *Handbook of Debt Management*, Marcel Dekker, New York, 2003.

[8] D. Duffie, K. J. Singleton, *Credit Risk: Pricing, Measurement and Management*, Princeton University Press, 2003.

[9] J. Galindo, P. Tamayo, Credit Risk Assessment using Statistical and Machine Learning: Basic Methodology and Risk Modelling Applications, *Computational Economics*, Vol.15, No.1-2, 2000, pp.107-143.

[10] C. Mar Molinero, P. Apellaniz, C. Serrabo-Cinca, A Multivariate Analysis of Spanish Bond Ratings, *International Journal of Management Science*, Vol.24, No.4, 1996, pp.451-462.

[11] A. K. Jain, M. N. Murty, P. J. Flynn, Data Clustering: A Review, *ACM Computer Surveys*, Vol.31. No.3, 1999, pp.264-323.

[12] L. H. Lipnick, Y. Rattner, L. Ebrahim, The Determinants of Municipal Credit Quality, *Government Finance Review*, No.12, 1999, pp.35-41.

[13] B. Benito, F. Bastida, The Determinants of the Municipal Debt Policy in Spain, *Journal of Public Budgeting, Accounting and Financial Management Boca Raton*, No.4, 2004, pp.492-525.

[14] G. Holmes, M. Halland, E. Frank, Generating Rule Sets from Model Trees, *Proc. of the 12th Australian Joint Conference on Artificial Intelligence*, Sydney, Australia, 1999, pp.1-12.