MASR - 2010

EVALUATION OF BANKRUPTCY RISKS' ANALYSIS POSSIBILITIES

ОЦЕНКА ВОЗМОЖНОСТЕЙ АНАЛИЗА РИСКА БАНКРОТСТВ

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Outline

- **Overview of bankruptcy financial ratios**
- **Bankruptcy prediction methods**
  - **Multivariate discriminant analysis**
  - **Potential function method**
  - **Neural network approaches**
- **Experiment**

Introduction

- **Bankruptcy prediction has been an important decision-making process for financial analysts**
- **Many techniques have been proposed for helping financial analysts in this process**
- **The status of a firm analyzed is modeled by its financial ratios**

Two basic approaches to bankruptcy prediction

- First approach is based on financial data and comprises working with different ratios
- The second approach uses the data on bankrupt companies that were then compared to the data of the company under consideration

First approach

First approach is considered to be very effective but:

- companies that have financial problems normally publish their financial reports with a delay, hence, specific data might turn to be unavailable years
- even if the data are published, they might be "embellished" artificially, which also does not ensure objective information
- certain indicators of financial activity may give evidence for coming bankruptcy, whereas the others may serve as a reason for considering the company financially stable

Second approach

- The second approach is based on the comparision of financial ratios of yet bankrupt companies with those of "doubtful" ones
- The indicators of bankrupt companies' activity by years are also of great significance

Bankruptcy financial ratios

- In the analysis of the general financial situation of the company a separate group of financial ratios is made, using which it is possible to reason about the threat of bankruptcy

- In general case there is no theoretical background as to which financial ratios might be used in different bankruptcy studying models

- A lot of researchers performing an analysis of the bankrupt enterprise proceed in this way: they calculate several ratios and then select potentially most significant of them

Example: Altman's Z-score

- In Altman's model Z-score operates with five financial ratios
- Altman (1968) supposes that these are the ratios that have the largest prediction possibility:

Altman's Z-score

1. X1= Working capital/total assets (WC/TA)
2. X2= Retained earnings / total assets (RE/TA)
3. X3= Earnings before interest and taxes / total assets (EBIT/TA)
4. X4= Market value equity / book value of total liabilities (MVE/TL)
5. X5= Sales / total assets (S/TA)

Altman's Z-score (cont.)

All the ratios(X1, X2, X3, X4 and X5) are consolidated in Z-number, after they have been multiplied by certain correlation coefficient whose value can give evidence for the importance of the specific ratio.

Z – number is expressed by formula:

$$Z = 1{,}2 * X1 + 1{,}4 * X2 + 3{,}3 * X3 + 0{,}6 * X4 + X5$$

The calculation of the above ratios enables firm's executives to estimate their activities and financial ratios, and to respond to the problems appeared in proper time.

Altman's Z-score (cont.)

- If $Z>3$, the possibility of bankruptcy is low and it is not necessary to perform further analysis of the financial situation
- If $2.7 < Z \leq 3$, bankruptcy may occur. The firm has faced certain problems concerning paying capacity that cannot be diminished
- If $1.8 < Z \leq 2.7$, the possibility of bankruptcy is high. The firm has serious financial problems. A thorough analysis of the financial situation is necessary
- If $0 < Z \leq 1.8$, the possibility of bankruptcy is very high. The firm's financial situation can only be improved by radical changes in the area of finance and investments

Financial ratios in previous bankruptcy prediction studies [2]

Ratios	Study		Ratios	Study
R1 Cash/Current Liabilities	E, D		**R17** Net Income/Total Assets	B, D
R2 Cash Flow/Current Liabilities	E		**R18** Net Quick Assets/Inventory	Bl
R3 Cash Flow/Total Assets	E-M		**R19** Net Sales/Total Assets	R-F, A
R4 Cash Flow/Total Debt	Bl, B, D		**R20** Operating Income/Total Assets	A, T, A-H-N
R5 Cash/Net Sales	D		**R21** EBIT/Total Interest Payments	A-H-N
R6 Cash/Total Assets	D		**R22** Quick Assets/Current Liabilities	D, E-M
R7 Current Assets/Current Liabilities	M, B, D, A-H-N		**R23** Quick Assets/Net sales	D
R8 Current Assets/Net Sales	D		**R24** Quick Assets/Total Assets	D, T, E-M
R9 Current Assets/Total Assets	D,E-M		**R25** Rate of Return to Common Stock	Bl
R10 Current Liabilities/Equity	E		**R26** Retained Earnings/Total Assets	A, A-H-N
R11 Equity/Fixed Assets	F		**R27** Return on Stock	F, T
R12 Equity/Net Sales	R-F, E		**R28** Total Debt/Total Assets	B, D
R13 Inventory/Net sales	E		**R29** Working Capital/Net sales	E, D
R14 Long Term Debt/Equity	E-M		**R30** Working Capital/Equity	T
R15 MV of Equity/Book Value of Debt	A, A-H-N		**R31** Working Capital/Total Assets	W-S,M,B,A,D
R16 Total Debt/Equity	M			

Note: R2, R3, R7, R9, R31 was used in experimental part !

Bancruptcy prediction methods

- Early empirical approaches
  - Multivariate discriminant analysis (MDA)
  - Logistic regression analysis (LA)
- Neural Network approaches
- Other approaches
  - Genetic algorithms (GA)
  - Rule-based learning
  - ID3
  - Pattern recognition methods

I Empirical approaches

Beaver was one of the first who has applied balance sheet data in bankruptcy research. His analysis was comparatively simple and was based on studying one financial ratio and comparing it with other ratios. He has concluded that ratio R4: Cash flow / Total debt is a very essential indicator which has to be accounted in bankruptcy analysis. Beaver's works became a beginning of multicriteria analysis application, which was later developed by Altman et al.

I Empirical approaches (cont.)

- Altman employed classical multivariate discriminant analysis (MDA) in his research. Altman's Z-scores are widely used as input data in neural network algorithms
- Ohlson uses regression approach analysis. It's a linear model with a sigmoid function

$$f(x) = \frac{1}{1+e^{-x}}$$

- In literature, numerous other researchers are also mentioned who work on the basis of MDA: Lev(1974), Deakin(1972), Taffler(1982), Platt and Platt(1980), Gilbert, Menon and Schwartz(1990), Koh and Killough(1990) et al.

II Neural Network approaches

- Odom and Sharda were one of those who first employed NN techniques in bankruptcy analysis. In the input of the network, Altman's Z-scores about 128 companies were used. It was shown that neural network approach yields better results than MDA
- Tam and Kiang have compared different techniques applied in bankruptcy diagnostics (MDA, LA, ID3, single layer network and multilayer network) and have shown that in the „one-year-ahead" data the multilayer network was most effective whereas in the "two-year-ahead" data the LA method turned to be most effective

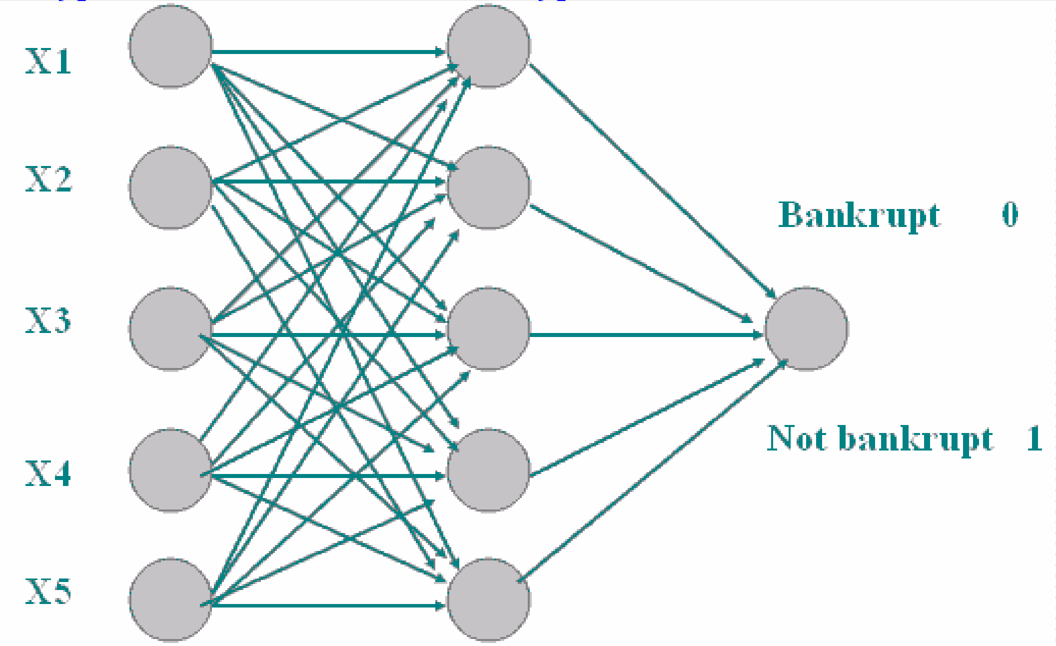
II Neural Network approaches(cont.)

Analysing the NN network application in bankruptcy analysis, these conclusions were made:

- NN ensure approximately 90% accuracy compared to the 80-85% accuracy of other methods (MDA, LA, and ID3)
- Bankruptcy can be predicted several years before it happens, the accuracy of prediction being practically the same for the “one-year-ahead” data and for the “two-year-ahead”

II Architecture of the Bankruptcy Prediction Neural Network

- Multilayer network MLP with error back propagation learning



- Kohonen map

III Other approaches

- Genetic algorithms (GA)
- Rule-based learning
- ID3
- Pattern recognition methods
  - Potential function method

Experimental part

- Main motivation – compare ability of methods
- Dataset
- Environment – SPSS (for MDA) and Matlab

Data

Balance sheet data of 63 companies were used (46 - bankruptcy and 17 - not bankruptcy).
It was decided to calculate the following financial ratios on the basis of the data available and further use them in all the experiments:

- R2: Cash Flow / Current Liabilities;
- R3: Cash Flow / Total Assets;
- R7: Current Assets / Current Liabilities;
- R9: Current Assets / Total Assets;
- R31: Working capital / Total assets.

Experiment I - MDA

To accomplish the MDA, the SPSS statistical package was used. Discriminant analysis classification results:

			Predicted Group Membership		Total
		Bankrupt	0	1	
Original	Count	0	39	7	46
		1	4	13	17
	%	0	84.8	15.2	100.0
		1	23.5	76.5	100.0

- **82.5 % of original grouped cases correctly classified**
- **Misclassified cases are: 14, 26, 28, 35, 36, 37, 41, 58, 59, 60, 62.**

Experiment II – potential functions

As a potential function was used:

$$\varphi(R) = \frac{\lambda}{1 + \alpha R^2}$$

- α - learning parameter
- R – the distance between the point where the potential is calculated and the point of learning set
- λ - the value of potential that is assigned to the point in the process of learning (weight)

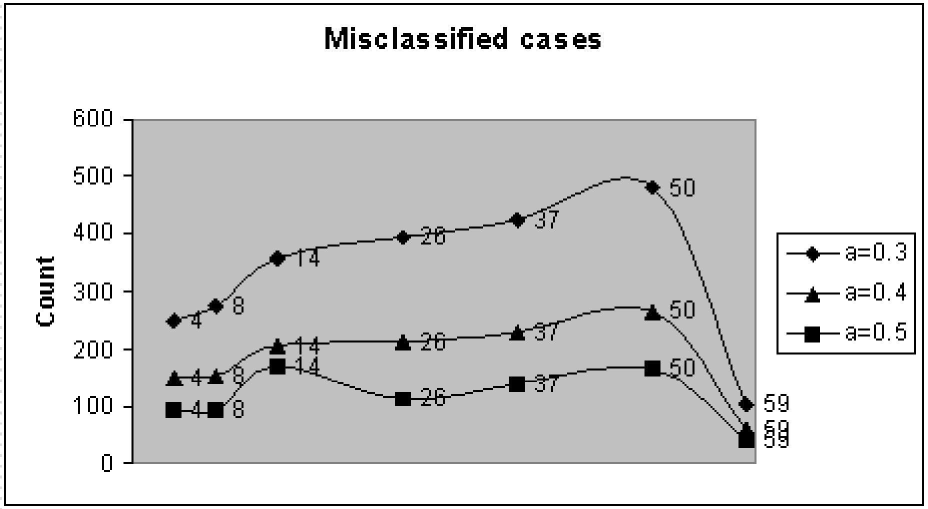
Experiment II – results

Experimental results (misclassified cases and its λ parameter):

α=0.3	Cases	λ
	4	249
	8	274
	14	357
	26	393
	37	424
	50	482
	59	104

α=0.4	Cases	λ
	4	148
	8	153
	14	206
	26	212
	37	228
	50	265
	59	60

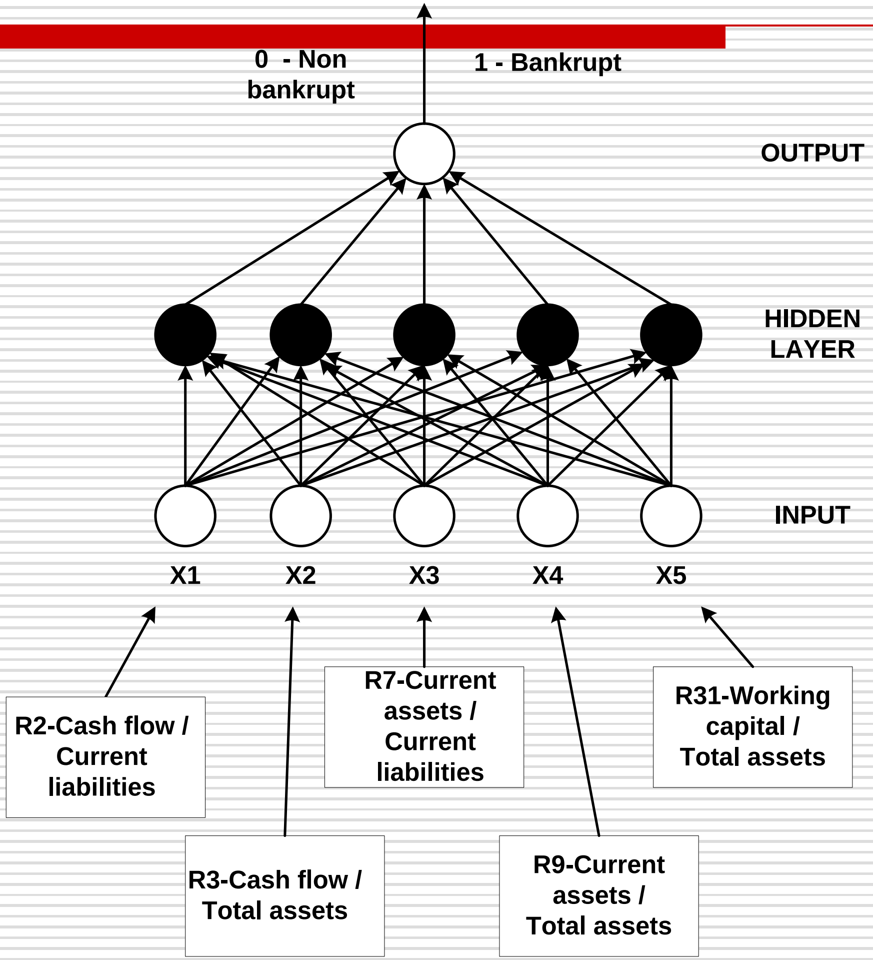
α=0.5	Cases	λ
	4	92
	8	94
	14	168
	26	112
	37	140
	50	165
	59	39



Experiment III –Multilayer feedforward NN

- Input nodes - 5 neurons
- Hidden layer - 5 neurons
- Output nodes - 1 neuron (1- bankrupt, 0 - not bankrupt)
- Learning rate - 0.25
- Stopping condition - the training is stopped if MSE=0.5
- Momentum rate - α
- Slope of the tanh activation function - β

Experiment III – Architecture

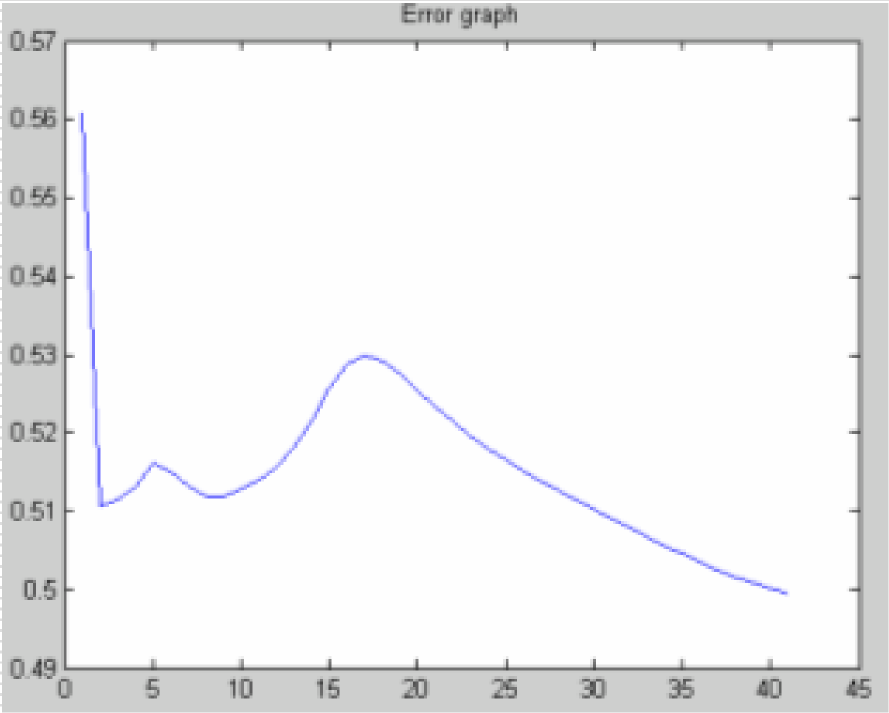


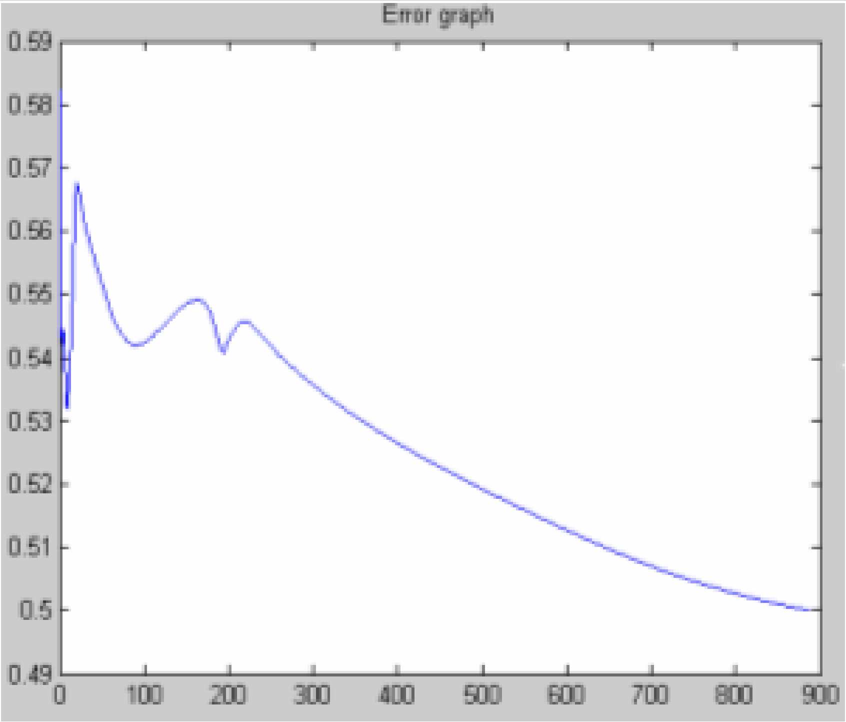
Experiment III – Results

Experimental results (parameters α, β and its misclassified cases)

Parameter α	Parameter β	Epochs	No. of misclassified cases	Cases
$\alpha = 0.8$	$\beta = 0.8$	41	9	14,26,36,37,41,58,59,60,62
	$\beta = 0.9$	889	6	37,50,58,59,60,62
$\alpha = 0.9$	$\beta = 0.8$	46	9	14,26,35,36,37,41,58,59,62
	$\beta = 0.9$	1489	7	37,50,58,59,60,62,63

Experiment III – Error graphs





Error graph (left: $\beta = 0.8$ and right: $\beta = 0.9$)

Summary table about used methods and misclassified cases

Method		Misclassified cases														
MDA				14	26	28	35	36	37	41		58	59	60	62	
Potential		4	8	14	26				37		50		59			
NN-1	$\alpha = 0.8, \beta = 0.8$			14	26			36	37	41		58	59	60	62	
NN-2	$\alpha = 0.8, \beta = 0.9$								37		50	58	59	60	62	
NN-3	$\alpha = 0.9, \beta = 0.8$			14	26		35	36	37	41		58	59		62	
NN-4	$\alpha = 0.9, \beta = 0.9$								37		50	58	59	60	62	63

- For the specific bankruptcy data sample, all the methods are unable to classify data vectors 37 and 59.
- Calculating in absolute numbers, we obtain that NN-2 correctly classified 90.5% cases
- The potential function method and NN-4 - 89% cases
- NN-1 and NN-3 - 85.7%
- MDA - 82.5%.

It can be concluded that for the given data sample the NN method performs bankruptcy data classification more effectively, which actually corresponds to the conclusions about the results achieved by Tam and Kiang.

IV Alternative methods of bankruptcy risks analysis

- Time series analysis

A time series is a sequence of real data, representing the measurements of a real variable at time intervals.

Time series analysis is a sufficiently well-known task, however, recently research activities are being carried out with the purpose to try to use clustering for the intentions of time series analysis. The main motivation for representing a time series in cluster form is to better represent the main characteristics of the data.

IV Alternative methods of bankruptcy risks analysis

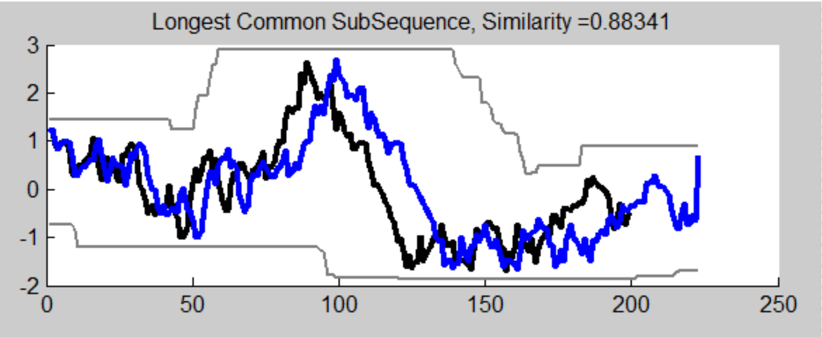
Similarity

- Euclidean distance

$$D(Q,S) = \sqrt{\sum_{i=1}^{n} (q_i - s_i)^2}$$

- LCSS (Longest Common SubSequence)

$$LCSS[i,j] = \begin{cases} 0 & if\ i = 0\ or\ j = 0 \\ 1 + LCSS[i-1, j-1] & if\ a_i = b_i \\ \max(LCSS[i-1, j], LCSS[i, j-1]) & otherwise \end{cases}$$



IV Alternative methods of bankruptcy risks analysis

The aim of the experiment was to verify hypothesis on the suitability of LCSS method in assessing bankruptcy data in the form of time series similarity. The data of three already bankruptcy and three non-bankruptcy firms have been taken.

	Financial ratio					
Firms	R2	R3	R7	R9	R31	Situation
Firm1(B)	0	0	175	67	29	Bankruptcy
Firm2(B)	13	8	175	65	28	Bankruptcy
Firm3(B)	14	8	277	58	37	Bankruptcy
Firm47(N)	4	4	101	93	1	Non-bankruptcy
Firm48(N)	5	5	104	97	4	Non-bankruptcy
Firm49(N)	4	4	105	95	5	Non-bankruptcy

IV Alternative methods of bankruptcy risks analysis

Table displays the results of the application of the LCSS method – bankruptcy data time series have been compared in pairs as a result of which similarity values have been obtained

	Firm1 (B)	Firm2 (B)	Firm3(B)	Firm47(N)	Firm48(N)	Firm49(N)
Firm1 (B)	1	0,4	0,4			
Firm2 (B)	0,4	1	0,4			
Firm3 (B)	0,4	0,4	1			
Firm47 (N)				1	0,5	0,4
Firm48 (N)				0,5	1	0,8
Firm49 (N)				0,4	0,8	1

IV Alternative methods of bankruptcy risks analysis

- It can be concluded that in this case time series Firm1 ir slightly similar to Firm2 (0,4) and Firm3 (0,4). Time series Firm47 is slightly similar Firm48 (0,5) and Firm49 (0,4). Time series Firm48 is similar to Firm49 (0,8). It can be seen that none of the bankruptcy companies' time series have similarities with non-bankruptcy companies' time series.
- Analysing data from Table , it could be assumed that time series Firm 1, Firm2 and Firm3 are located in one cluster, but time series Firm47, Firm48 and Firm49 in another cluster.

IV Alternative methods of bankruptcy risks analysis

- In the next set of experiments in the analysis of time series, the k-means clustering algorithm for two clusters (bankruptcy or non-bankruptcy) has been applied. As a result of the algorithm's activity one cluster has been attributed time series Firm1, Firm2 and Firm3 data, but the second cluster – Firm47, Firm48 and Firm49 data. Cluster centres obtained are as follows: [9; 5; 209; 63; 31] and [4; 4; 103; 95; 3].
- Thus, it can be reasoned that in this example the results of the time series clustering with the help of the k-means algorithm correspond to the results obtained by using the LCSS method. It gives assurance that the results of time series clustering are adequate.

Conclusions - 1

- We have presented potential functions and neural network implementation possibility in bankruptcy prediction. The experiments have shown that these methods can be viewed as alternatives to traditional bankruptcy risk prediction methods. Popular neural network models need significant parameter debugging resources to achieve valid results, whose correctness could be checked with traditional methods. It can be concluded that different methods yield different results and they have to be analysed carefully.

Conclusions - 2

- Time series clustering approach has become popular and its feasibility for bankruptcy data analysis is being investigated. Experiments are performed that validate the use of such methods in the given class of tasks. As a result of the experiment a conclusion has been drawn that the results of time series clustering using k-means algorithm correspond to the results obtained with LCSS method, thus the clustering results of the specific bankruptcy data time series are adequate.

Thanks !