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Bankruptcy prediction for Russian companies: Application of combined classifiers

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ABSTRACT

The problem of bankruptcy forecasting is one of the most actively studied nowadays, posing the task of building effective classifiers as well as the task of dealing with dataset imbalance. In this paper, we apply different combinations of modern learning algorithms (MDA, LR, CRT, and ANNs) in order to try to identify the most effective approach to bankruptcy prediction for Russian manufacturing companies. Simultaneously, we try to find out whether the financial indicators stipulated by Russian legislation provide an effective set of indicators for bankruptcy prediction.

1. Introduction

The problem of critical situations forecasting and, in particular, bankruptcy of a company, holds a special place among the existing theoretical and practical company management problems. For the developing economy of Russia, just as for any other developing economy, the ability to effectively forecast a company's failure is of crucial importance. In order to ensure that the company is managed effectively in instable market environment, it is necessary to perform financial analysis of the company's reports to identify its status.

There has been a great strand of literature concerning the ways and methods for prediction of a company's failure, starting with the classical models of bankruptcy prediction, based on one specific method of forecasting (see Ghodrati & Moghaddam, 2012 for an extended overview of the classical models), and ending with modern approaches which generally tend to combine the output from different learning algorithms or to integrate several learning methods to develop a hybrid classifier (see, for example, Brezigar-Masten & Masten, 2012; Chen, 2011; Cho, Hong, & Ha, 2010). One of the most well-known algorithms of learning methods combination is a so-called AdaBoost, an ensemble learning algorithm that constructs its base classifiers in sequence using different versions of the training data set (see Freund & Schapire, 1997). For an excellent overview of modern ways to combine machine learning algorithms see, for example, Polikar (2006).

AdaBoost methodology can be applied to artificial neural networks (ANNs) to increase their forecasting power (although ANNs are able to give high overall accuracy of forecasting on their own). Thus, one of the purposes of this study is to apply the algorithm of ANNs to the sample of Russian manufacturing companies, given that while there has been a great strand of literature concerning bankruptcy prediction for Western and Asian economies, little has been done to develop such bankruptcy prediction models for Russian economy.

On the other hand, one of the peculiarities of Russian legislation in the field of bankruptcy is that it clearly stipulates the financial indicators that should be taken into account when deciding whether a company is bankrupt or not (see 118-MinEcon and 367-GovRF, and Table 4 below). Thus, another purpose of this study is to test whether the financial indicators recommended by Russian legislation are indeed efficient in bankruptcy forecasting.

In this research, we apply a combination of different learning algorithms (multivariate discriminant analysis (MDA), logit-regression (LR), classification and regression tree (CRT), artificial neural network (ANN) and AdaBoost methodology) to a sample of Russian manufacturing companies some of which were declared bankrupt during the period of 2007–2011. The application of these learning algorithms allows us achieving 89% of overall accuracy of bankruptcy forecasting, as compared to at most 82% of overall accuracy of forecasting provided by the classical models.

To be more specific, the current study consists of the following steps. Firstly, after obtaining and cleaning the data we check the overall accuracy of the classical Western and Russian models on the obtained sample. Secondly, to select the variables for ANNs from among the initially constructed financial indicators we choose the statistically significant indicators by using different learning algorithms. We also build ANNs using the indicators stipulated by Russian legislation. Thirdly, since in this study we seek to find a way to maximize the overall accuracy of bankruptcy prediction based on a combination of ANNs, we apply AdaBoost methodology to combine the outputs of the initially built ANNs.

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Table 1
The efficiency of bankruptcy prediction of classical Western and Russian models.

Model	Overall accuracy, %	Precision, %	Sensitivity, %	Specificity, %	F-measure, %
Classical Western models					
Altman's model	77.5	71.2	92.3	62.6	80.4
Fulmer's model	**82.0**	**85.0**	**77.7**	**86.3**	**81.2**
Springate's model	77.2	70.7	93.2	61.3	80.4
Taffler's model	73.9	66.7	95.5	52.3	78.5
Zmijewski's model	78.9	72.4	93.7	64.2	81.6
Classical Russian models					
Sayfulin-Kadykov model	70.0	64.9	87.2	52.9	74.4
Davydova-Belikov model	75.7	73.9	79.3	72.1	76.5
Zaytseva's model	58.6	55.5	86.3	30.9	67.5

Source: authors' calculations.

The rest of the paper is organized as follows. Section 2 reviews the literature and describes application of the classical Western and Russian models to our dataset. Section 3 gives the descriptive statistics of the data. Section 4 presents the empirical findings and discussion. Section 5 concludes.

2. Motivation and literature review

As it has already been mentioned, since publishing one of the pioneering papers of Altman (1968) there have been many studies on the bankruptcy prediction problem and a number of now classical textbook models have been proposed. For an excellent overview of the classical studies see Ghodrati and Moghaddam, (2012).

At the first step of this research we estimated the efficiency of bankruptcy prediction of the classical Western models of Altman (1968), Fulmer, Moon, Gavin, and Erwin (1984), Springate (1978), Taffler (1983) and Zmijewski (1984). We also analyzed the efficiency of classical Russian models for bankruptcy prediction, specifically, Sayfulin-Kadykov model (described in Minavev & Panagushin, 1998), Zaytseva's model (see Zaytseva (1998)), and Davydova-Belikov model (see Davydova & Belikov, 1999). For our sample of 888 large and medium-sized Russian manufacturing companies (see the description of the dataset construction below in Section 3.1), we obtained the following results[1] (see Table 1). In this research, we consider bankrupt companies as the positive class (P), and non-bankrupt companies as the negative class (N).

Several comments are worth making on the results showed in Table 1.

In terms of overall accuracy, classical Western models are more effective in forecasting the bankruptcy of companies as compared to classical Russian models. Among the Western models, the Fulmer's model has the highest overall accuracy (82%), although the efficiency of per-group predictions is modest (sensitivity is 77.7% and specificity is 86.3%). On the other hand, the percentage of correct predictions of the models of Altman, Springate, Taffler, and Zmijewski are much more tilted towards bankrupt companies (this may be useful if the only task is bankrupt companies identification). Zmijewski's model has the highest F-measure that combines precision and sensitivity measures and is used to evaluate overall performance for predictions on bankrupt companies. However, the F-measure of Zmijewski's model is just a little bit higher as compared to that of Fulmer's model.

Therefore, the result of the classical Western models application is ambiguous: either there is high overall accuracy of prediction and modest per-group results, or there is high efficiency of bankrupt companies forecasting, but the efficiency of healthy companies forecasting and overall accuracy are comparatively low.

The models proposed by Russian authors demonstrate lower efficiency of forecasting as compared to the Western models. It is also worth noting that Davydova-Belikov model provides the highest overall accuracy (75.7%) as compared to the other Russian models.

Modern approaches to bankruptcy forecasting tend to have more than 90% of overall accuracy, especially when using artificial neural networks (see, for example, Chen (2011); Tseng & Hu, 2010). From this point of view, comparatively low results obtained from the classical Western models can be explained by the fact that these models were built on Western datasets and may not take into account the peculiarities of Russian economic environment. In addition, the number of explanatory variables used in the classical models is limited. On the other hand, speaking about the classical Russian models, most of them contain explanatory variables that were selected only by expertise without applying any fundamental mathematical methods.

It is also worth noting, that a high level of overall accuracy of a classifier is often the result of proper cleaning of the sample. It is a common feature of the classification problems to have imbalanced classes of observations: one class of observations (the minority class or the positive class) may be up to hundreds and even thousands times smaller than the other class of observations (the majority class or the negative class) (see Chawla, Japkowicz, & Kolcz, 2004).

In the presence of imbalance problem, the standard classifiers (LR, CRT, ANN, etc.) were shown in many research papers as heavily biased in terms of recognizing the positive class (see Visa & Ralescu, 2005). The degradation of performance in many standard classifiers is not only due to the imbalance of class distribution, but is also due to class overlapping caused by class imbalance (see Gu, 2007). The solutions of the class-imbalance problem proposed in the literature include many different forms of re-sampling, such as random over-sampling with replacement; random under-sampling; etc. (see Chawla et al., 2004). Both under-sampling and over-sampling have known drawbacks (McCarthy, Zabar, & Weiss, 2005). Recent studies tend to use under-sampling as the way to balance the sample (see Lee, 2006; Min & Jeong, 2009). In this study, we are also using the under-sampling approach to balance the initial sample.

As Kiang (2003) puts it, modern "...studies in comparing the performance of different classifiers classification have shown that no single method is best for all learning tasks". In general, there are two different approaches to utilization of multiple classifiers: the first is to combine outputs from different learning methods, and the other is to integrate several learning algorithms to develop a hybrid classifier. In this study, we use the first approach in two different manners. First, in Section 4.2 we combine the variables selected by different classifiers into different sets of variables and

[1] To measure the effectiveness of classification, in this paper we use the following classification performance metrics (see also Chen, 2011):1. Overall accuracy: (TP + TN)/(TP + TN + FP + FN).2. Precision: TP/(TP + FP).3. Sensitivity: TP/(TP + FN).4. Specificity: TN/(TN + FP).5. F-measure: 2∗Precision∗Sensitivity/(Precision + Sensitivity).Here TP means true positive, TN – true negative, FP – false positive, FN – false negative.

then run artificial neural networks (ANNs) on these sets of variables. In Section 4.3, we use the regression and AdaBoost approaches to combine the outputs of several ANNs.

Thus, it is of practical importance to elaborate the application of different classifiers and their combinations under the problem of bankruptcy forecasting in general and specifically for Russian companies.

This research has the following distinguishing features:

1. We use a wide range of financial indicators including those considered in classical and modern literature and recommended by Russian legislative practice.
2. We employ a combination of different modern techniques to choose the appropriate financial indicators and achieve higher forecasting efficiency.
3. We use a large dataset of Russian manufacturing companies for the period of 2007–2011.

In the following sections we describe the methodology of this research and the results.

3. Data and variables selection

3.1. Sample selection

In Russia, bankruptcy of a company is a complicated process with many stages that in total can last for several years. Thus, in this study we chose the juridical approach to define bankrupt companies. So we call a company bankrupt if according to Russian Federal Law No. 127-FZ (see 127-FZ – Russian Federal Law No. 127-FZ of October 26 (2002)) this company was undergoing bankruptcy proceedings (the final stage of bankruptcy) at the moment of sample collection.

The sample set of the study covers the periods 2007–2011 and contains financial ratios of 3505 (504 bankrupt and 3001 non-bankrupt ones) large and medium sized Russian manufacturing companies (according to Russian legislation, a company is considered to be medium or large-sized if it has at least 100 employees, see 209-FZ). For bankrupt firms, we gathered financial ratios for one year prior to bankruptcy. The data were obtained from Interfax SPARK, a database containing approximately 2.5 million financial statements of Russian companies in different industries of Russian economy (see Interfax SPARK).

As per common approach specified in the literature, removal of outliers and balancing the sample to be undertaken first, and then features to be selected (see, for example, Min & Jeong, 2009). In this paper, we also adopt this approach. Here we specify the steps we took to obtain the final sample (see also Table 2).

1. We obtained all available initial balance sheets of the companies included in the Interfax SPARK database. The initial sample consisted of 3505 companies, 504 out of which were bankrupt.

Table 2
Sample volumes after each step of cleaning-up the dataset.

No.	Step	After the step	
		Total number of companies	Bankrupt companies
1	Initial dataset	3505	504
2	Checking balance-sheet equalities	3173	473
3	Boxplot analysis	3056	444
4	Balancing dataset	888	444
5	Selecting training set (randomly, approx. 90% of the balanced dataset)	790	395

Source: authors' calculations.

Table 3
The values of financial indicators recommended by Russian legislation.

Financial indicator	Interval of recommended values
Current ratio	1–2
Quick ratio	>1
Inventories/current liabilities	0.5–0.7
Total liabilities/equity	<0.7
Working capital/current assets	>0.1
Working capital/equity	0.2–0.5

Source: see 118-MinEcon.

2. For these companies we first checked main balance-sheet equalities:
   (1) Assets = Liabilities and Shareholders' Equity;
   (2) The structure of Assets;
   (3) The structure of Liabilities and Shareholders' Equity.

Totally, only 3173 companies passed this checking, with 473 being bankrupt.

3. Taking into account the literature review, we calculated 104 unique financial indicators. For each of the indicators we constructed boxplots in order to determine and remove possible outliers. After removing outliers, we got 3056 companies left, with 444 of them being bankrupt.
4. In order to balance the sample, we randomly selected 444 healthy companies out of 2612 healthy companies.
5. We also randomly split the full sample into the training set (approx. 90%) and the testing set (approx. 10%). Thus, in the training sample, we have 395 healthy and 395 bankrupt companies, and in the testing sample we have 49 healthy and 49 bankrupt companies.

3.2. Selecting the initial set of features

In order to create the initial set of variables, we started with revision of the previous literature on the subject to investigate a list of explanatory variables, which were to include in our initial set. The complete list of variables is given in Table 4. All the variables are divided into 7 groups, and thus we initially obtained 98 unique financial indicators in total.

Groups 1–5 are based on the previous studies on the subject (see, for example, Cho et al., 2010; Chen, 2011). Group 6 contains all financial variables used in the classical Western and Russian models. Group 7 contains the variables stipulated by Russian legislation.

It also should be noted here, that for some of the indicators Russian legislation specifies intervals of recommended values (see 118-MinEcon). In accordance with Russian legislation, a company has a high probability of bankruptcy and the structure of its balance sheet may be declared unsatisfactory if these indicators of the company are beyond the recommended thresholds (see Table 3).

3.3. Variable selection using selecting procedures

In this study, the process of variable selection consists of two major steps.

First, we applied the univariate ANOVA analysis to the obtained balanced dataset of 888 companies to separate variables, which statistically significantly distinguish healthy and bankrupt companies. Out of the 98 financial indicators, 75 variables were selected based on the ANOVA test. Thus, 23 indicators, two of which are stipulated by Russian legislation (specifically, total liabilities/equi-

Table 4
Groups of financial indicators.

Group no.	Name	Number of indicators	Description of indicators		
Group 1	Cash-flow indicators[a]	9	Cash-flow2/total liabilities	Cash-flow1/equity	Cash-flow2/total sales
			Cash-flow1/total assets	Cash-flow2/equity	Cash-flow1/current liabilities
			Cash-flow2/total assets	Cash-flow1/total sales	Cash-flow2/current liabilities
Group 2	Profitability indicators	19	Gross profit/total sales	Gross profit/total assets	EBT/total liabilities
			Profit on sales/total sales	Profit on sales/total assets	Net income/total liabilities
			EBT/total sales	EBT/total assets	Profit on sales/current liabilities
			Gross profit/cost of goods sold	Profit on sales/equity	Net profit/current liabilities
			Profit on sales/cost of goods sold	Gross profit/total liabilities	Gross profit/current liabilities
					EBT/cost of goods sold
			Gross profit/equity	Profit on sales/total liabilities	Net profit/cost of goods sold
Group 3	Turnover indicators	12	Sales/fixed assets	Sales/equity	(Cost of goods sold – depreciation)/accounts payable
			Sales/current assets	Sales/total liabilities	(Cost of goods sold – depreciation)/inventories
			Sales/(cash + invested funds)	Sales/current liabilities	Sales/(cash + invested funds + accounts receivable)
			Sales/accounts receivable	Sales/working capital	
				Cost of goods sold/finished goods	
Group 4	Liquidity and solvency indicators	5	Cash/current liabilities	Short-term accounts receivable/accounts payable	(Cash + invested funds)/(costs/365)
			(Equity – fixed assets)/current assets	Quick assets/(costs/365)	
Group 5	Balance structure indicators	21	Quick assets/total assets	Long-term liabilities/equity	Cash/total assets
			Quick assets/current assets	Current assets/total liabilities	Cash/current assets
			Short-term liabilities/total liabilities	current assets/total assets	Revenue reserves/equity
			Long-term liabilities/fixed assets	(Cash + invested funds)/total assets	Revenue reserves/total assets
			Long-term liabilities/total liabilities	(Equity + long-term liabilities)/total assets	Revenue reserves/total liabilities
			Current liabilities/total liabilities		Working capital/inventories
			Long-term liabilities/total assets		Accounts payable/total liabilities
			Retained earnings/equity		Fixed assets/total assets
Group 6	Indicators from classical Western and Russian models (see also Table 1)	19	Accounts payable/accounts receivable	Log (tangible total assets)	Debt/total assets
			Profit before tax/current liabilities	Working capital/total debt	Equity/total liabilities
			Working capital/total assets	Log (EBIT)/interest	Net profit/costs
			Retained earnings/total assets	EBT/equity	Current liabilities/(cash + invested funds)
			Sales/total assets	EBIT/total assets	Total assets/sales
			Cash-flow1/total debt	No-credit interval	
			Current liabilities/total assets	Net profit/equity	
Group 7	Indicators stipulated by Russian legislation	13 (unique indicators)	Stipulated by 118-MinEcon:		
			Quick ratio	inventories/current liabilities	total liabilities/equity
			Current ratio	*working capital/current assets*	working capital/equity
			Stipulated by 367-GovRF:		
			Cash ratio	total assets/total liabilities	current liabilities/(sales/12) net profit/sales
			Equity/total assets	accounts receivable/total assets	net profit/total assets
			Current ratio	*working capital/current assets*	
	Total number of unique indicators	**98**			

Source: authors' analysis.
[a] Here cash-flow1 refers to the sum of net profit and amortization. Cash-flow2 is cash-flow1 minus the change of working capital as compared to the previous year.

ty and working capital/equity), were dropped out as a result of ANOVA application.[2]

Second, we applied three most popular classification procedures to the same set of 75 variables: (a) multivariate discriminant analysis (MDA), (b) classification and regression tree (CRT) and (c) logit-regression (LR). We needed all these three

[2] See Appendix A for the details.

Table 5
The results of application of variable selection procedures.

No.	Selection procedure	Number of selected indicators	Description of the selected financial indicators
Complete set of indicators (75 variables)			
1	Multivariate discriminant analysis	13	Accumulated profit/total assets sales/current assets Cash-flow1/total assets cash/current assets Inventories/current liabilities cash/current liabilities Quick assets/costs/365 gross profit/cost of goods sold Log (tangible total assets) current assets/total assets Equity/total liabilities no-credit interval Sales/(cash + invested funds)
2	Classification and regression tree[a]	6	Cash flow/sales sales/current liabilities Cash/current liabilities accumulated profit/total assets Cash /current assets inventories/current liabilities.
3	Logit-regression	8	Cash/current assets net profit/total liabilities Log (tangible total assets) inventories/current liabilities Sales/total liabilities fixed assets/total assets Gross profit/cost of goods sold current assets/total liabilities
Indicators from Russian legislation			
4	Logit-regression based on 118-MinEcon	3	Dummy for inventories/current liabilities Dummy for working capital/equity Dummy for total liabilities/equity
5	Logit-regression based on 367-GovRF	5	Current ratio total assets/total liabilities Current liabilities/(sales/12) working capital/current assets Net profit/total assets

Source: authors' calculations.
[a] See the graph of the CRT in Appendix B.

Table 6
The classification metrics for ANNs application (testing sample).

	Model	Overall accuracy	Precision	Sensitivity	Specificity	F-measure
Multi-layer perceptron						
1	MDA-assisted	74.5	80.0	65.3	83.7	71.9
2	**CRT-assisted**	**86.7**	**86.0**	**87.8**	**85.7**	**86.9**
3	**LR-assisted**	**87.8**	**86.3**	**89.8**	**85.7**	**88.0**
4	118-MinEcon-assisted	70.4	71.7	67.3	73.5	69.5
5	367-GovRF-assisted	84.7	80.4	91.8	77.6	85.7
Radial basis function network						
6	MDA-assisted	70.4	73.8	63.3	77.6	68.1
7	CRT-assisted	78.6	75.0	85.7	71.4	80.0
8	LR-assisted	80.6	82.6	77.6	83.7	80.0
9	118-MinEcon-assisted	70.4	71.7	67.3	73.5	69.5
10	367-GovRF-assisted	78.6	78.0	79.6	77.6	78.8

Source: authors' calculations.

procedures to identify the minimal set of variables that can effectively forecast bankruptcy. These methods are supposed to "assist" with selection of statistically significant variables (factors) which are used later as input variables for neural networks. The results of variable selection using these procedures are given in Table 5 (see Nos. 1–3).

When applying multivariate discriminant analysis (MDA), there are two ways to construct the discriminant function: the direct method and the stepwise method. In this research, we used the stepwise method applying Wilk's Lambda to sequentially select significant variables from the set of 75 variables. When employing stepwise selection method we set an entry value of 0.01 and an excluding value of 0.05 as the levels of significance for the F-statistic. It is worth noting that the set of variables resulting from MDA, among others, includes the *logarithm of tangible total assets* used in Fulmer's model; *no-credit interval* used in Taffler's model; and the reverse of one of the indicators from Russian legislation, namely, *equity/ total liabilities*.

Like the MDA, classification and regression tree (CRT) approach selects important variables that can effectively classify observations. With regard to the results of CRT application to the set of 75 financial indicators, it is worth noting that the variable *inventories/current liabilities* stipulated by Russian law proved to be a significant indicator.

In logit-regression (LR) we also employed stepwise selection method, where we set an entry value of 0.01 and an excluding value of 0.05 as the levels of significance for z-statistic. The variables selected by logit-regression, among others, include the variable from the Fulmer's model (logarithm of tangible total assets) and the variable stipulated by Russian legislation (inventories/current liabilities).

Since we are especially interested in the effectiveness of financial indicators, stipulated by Russian legislation, we also separately estimated two logit-regressions for the two sets of financial indicators, specified in the Order of the Ministry of Economy of Russian Federation No. 118 and the Decision of the Government of Russian Federation No. 367 (see 118-MinEcon and 367-GovRF). Since the Order 118-MinEcon identifies specific recommended intervals for the values of financial indicators (see Table 3), for each financial indicator stipulated by the Order 118-MinEcon, instead of using these indicators, we generated a dummy variable which is equal to 1 if the corresponding indicator for a company lies within the recommended range of values and to 0 otherwise. The results of variables selection by means of logit-regression (at the 5% level of significance) for the two normative acts are given in Table 5 (see Nos. 4–5). It can be seen from the table that only one indicator from Russian legislation (inventories/current liabilities) complies with the results of MDA-, CRT- and LR-selection.

4. Results and discussion

4.1. The neural network approach

The variables, chosen at step 2, were used as input variables to neural network models. Thus, we have considered MDA-assisted, LR-assisted and CRT-assisted neural network models.

One of the purposes of this study is to employ artificial neural networks approach to the problem of bankruptcy prediction. Specifically, in this paper we consider two types of neural networks: back-propagation multi-layer perceptron (MLP) and the radial basis function network (RBFN). The classification metrics of these two types of neural networks applied to the five groups of variables, pre-selected at the previous stage (see Table 5), are given in Table 6. The training sample consisted of 790 companies, and the testing sample comprised 98 companies (see Table 2).

It can be seen that MLP has higher performance for bankruptcy forecasting in each of the five groups of variables than the RBFN. Moreover, the MLPs built with CRT and LR assistance demonstrates the highest results.

It should be noted that our results are in line with previous research in this field. Boyacioglu, Kara, and Baykan (2009) used the data from 1996 to 2003 on 21 bankrupt and 44 healthy Turkish banks applying MLP-neural network, SOMs, MDA and logit-regression to the problem of bankruptcy prediction. The authors used more than 20 financial indicators (most of them are used in CAMELS system). The results proved MLP to be the most effective tool for bankruptcy forecasting: MLP correctly classified 100% of the banks in the training data set, and 95.5% of the banks in the validation set. However, logit-regression showed good efficiency too: it correctly predicted 86.04% of the banks in the training set and 81.81% in the validation set.

4.2. Combining the sets of variables

In order to obtain better results (as compared to the results, given in Table 6), we first formed new sets of variables in the following manner (see also Table 7).

Table 8
The classification metrics for combined results.

No.	Model	Overall accuracy	Precision	Sensitivity	Specificity	F-measure
Multi-layer Perceptron (variable set combination)						
1	Combination on the basis of significance	87.9	91.1	83.7	92.0	87.2
2	**Combination on the basis of intersection**	**88.8**	**88.0**	**89.8**	**87.8**	**88.9**
3	Combination on the basis of CRT and LR	88.8	93.2	83.7	93.9	88.2
Combination of outputs of several ANNs						
4	LR approach	87.8	86.3	89.8	85.7	88.0
5	**AdaBoost approach**	**88.8**	**88.0**	**89.8**	**87.8**	**88.9**

Source: authors' calculations.

1. *Combining sets of variables based on statistical significance.* This set of variables was formed as follows: we used two most significant variables, received from MDA, LR and CRT.
2. *Combining variable sets based on variables intersection.* In this approach, for construction of the dataset we chose a variable if it was significant in at least two out of three methods (MDA, CRT, LR).
3. *Combining sets of variables based on CRT and LR.* Since the ANNs, built on the variables selected by CRT and LR, proved to have the highest accuracy in this study (see Table 6), we combined the variables chosen by these methods. Moreover, we used the branches identified in CRT analysis (see Table 5 and Appendix B) to create additional dummy variables that equal to 1 if values of the variable that defines a branch fall into the region above the threshold, and equal to 0 otherwise. The same approach was used in Brezigar-Masten and Masten (2012).

We used these three groups of variables to build MLP ANNs on them and obtained the following results (see Table 8, Nos. 1–3).

It can be seen that the MLP ANN applied to the variable set built as the intersection of the most statistically significant variables obtained from the three methods (MDA, CRT and LR) provides higher accuracy of forecasting (as compared to the results in Table 6).

Table 7
Combined sets of variables.

Combination method	Number of variables	Variables description
Combining on the basis of significance	6	MDA: no-credit interval sales/(cash + invested funds) CRT: accumulated profit/total assets inventories/current liabilities LR: net profit/total liabilities sales/total liabilities
Combining on the basis of intersection	6	MDA + CRT: accumulated profit/total assets cash/current liabilities MDA + LR: gross profit/cost of goods sold log(tangible total assets) LR + CRT: cash/current assets inventories/current liabilities
Combining on the basis of CRT + LR	14	Cash/current assets net profit/total liabilities Log (tangible total assets) inventories/current liabilities Sales/total liabilities fixed assets/total assets Gross profit/cost of goods sold current assets/total liabilities Dummy (=1 if cash-flow/sales $\leqslant$ -0.01) Dummy (=1 if sales/current liabilities $\leqslant$ 1.31) Dummy (=1 if cash/current liabilities $\leqslant$ 0.01) Dummy (=1 if accumulated profit/total assets $\leqslant$ 0.003) Dummy (=1 if cash/current assets $\leqslant$ 0.002) Dummy (=1 if inventories/current liabilities $\leqslant$ 0.45)

Source: authors' analysis.

4.3. Application of logit-regression and AdaBoost approaches to individual classifiers combination

Another implementation of combining technique is constructing a conjunction of the outputs of learning algorithms. At the last stage of the research using the logit-regression and AdaBoost approaches, we combine the outputs of the ANNs constructed in Section 4.1 in an attempt to build a new classifier and increase the accuracy of forecasting.

As early as in the beginning of the 1990s, it was shown that combinations of the decisions of individual classifiers substantially improve overall accuracy of classification. At the early stages the regression approach (and in particular, logit-regression approach) was used to obtain a combined classifier (see, for example, Ho, Hull, and Srihari (1992)). Since there are only two outcomes of forecasting of the status of each firm (bankrupt or non-bankrupt), in this study we apply logit-regression to combine the results (forecasts) of bankruptcy prediction obtained from the five ANNs (see Section 4.1). The results of application of this approach are given in Table 8, row 4. Unfortunately, these results exactly coincide with the accuracy metrics of the LR-assisted ANN (see Table 6, row 3). Thus, this approach simply attributed the highest weight to the most powerful of the five ANNs, giving much less weight to the others. Therefore, we decided to apply a more adaptive algorithm, specifically, AdaBoost, to override this problem.

AdaBoost, short for Adaptive Boosting, is a machine-learning algorithm proposed by Freund and Schapire (1997). This meta-algorithm is used to improve the performance of other learning algorithms, although it is sensitive to noisy data and outliers (which we got rid of at the step of data cleaning). AdaBoost is adaptive in the sense that subsequent combined classifiers are tweaked in favor of the instances misclassified by previous classifiers. During each iteration the weight of each incorrectly classified example is increased, and the weight of each correctly classified example is decreased, so the new classifier being built focuses on the examples which have so far been incorrectly classified. The results of application of AdaBoost approach to the five ANNs built earlier (see Table 6, rows 1–5) are given in Table 8, row 5.

It can be seen that the application of AdaBoost approach provides better results as compared to the efficiency of LR-based combination, although these results are the same as the accuracy metrics of the ANN built on the intersection of the most significant indicators (see Table 6, row 2).

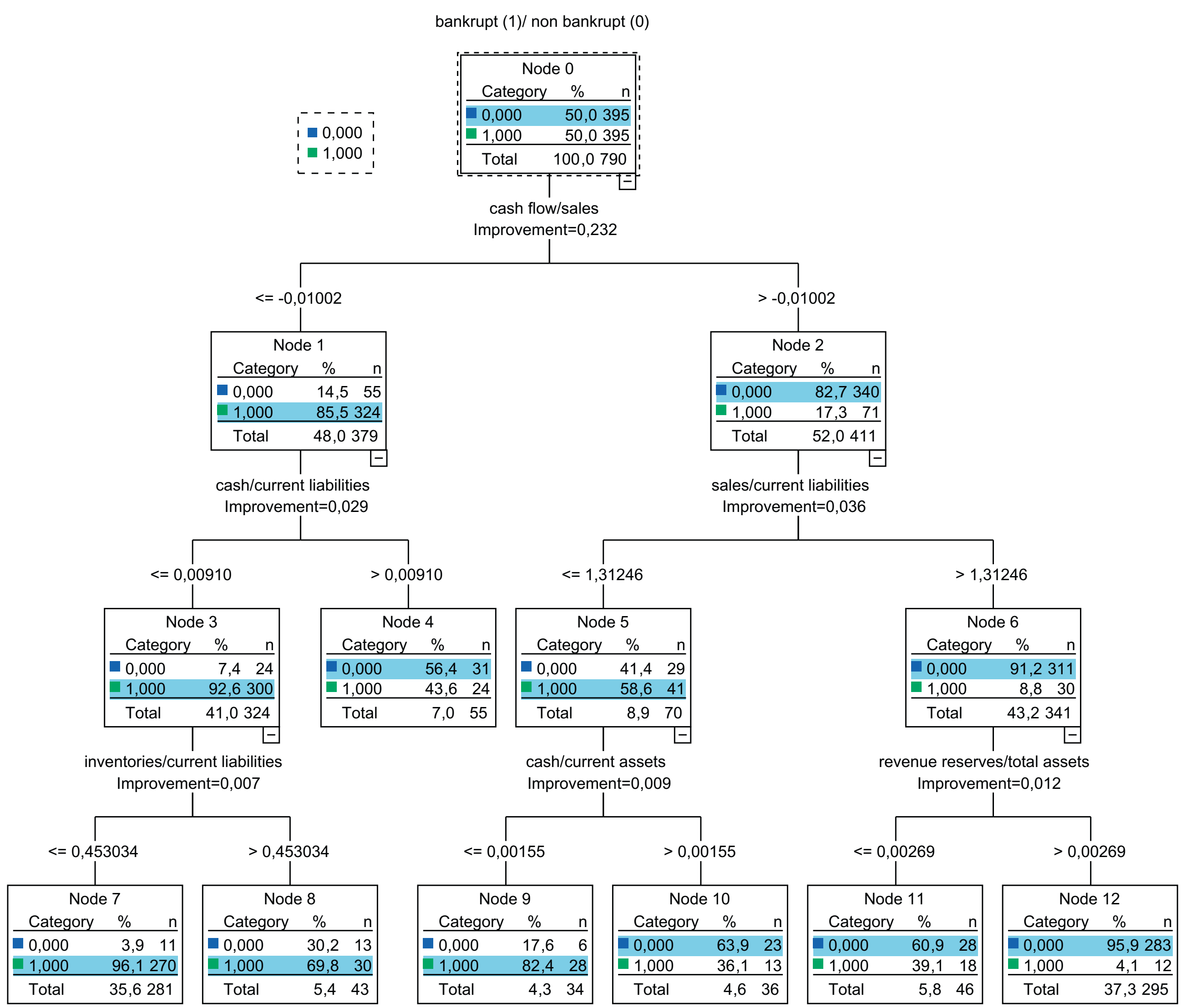

Fig. 1. The Classification and Regression Tree for financial indicators selection.

5. Conclusion

The problem of bankruptcy prediction for Russian manufacturing companies has been studied in this paper.

More than 15 years have passed since the Order of the Ministry of Economy of Russian Federation introduced in 1997 the methodological recommendations concerning a company reformation and financial analysis. In addition, more than 10 years have passed since the introduction of the Decision of the Government of Russian Federation on the guiding lines for bankruptcy analysis of Russian companies. Our analysis has shown that only one out of the thirteen financial indicators recommended by these two Russian legislative acts for bankruptcy analysis proved to be statistically significant in bankruptcy prediction. Thus, there is a strong need to revise the set of financial indicators stipulated by the legislation.

Simultaneously, there is a need to implement modern approaches and techniques in order to develop a more efficient classifier. In the study we applied both ANNs based on combinations of financial indicators chosen by different learning algorithms and combinations of different ANNs outcomes. This allowed us achieving 88.8% of overall accuracy of bankruptcy prediction, which is in line with the results of other modern studies. It is worth noting that our previous attempt to construct an effective classifier on the same dataset using only one learning algorithm provided at most 84.7% of overall accuracy (see Fedorova et al., 2013).

Appendix A. The list of financial indicators, excluded by ANOVA analysis

1. Cash-flow1/Equity.
2. Cash-flow2/Equity.
3. Gross profit/Equity.
4. Profit on sales/Equity.
5. EBT/Equity.
6. Net profit/Equity.
7. Sales/Fixed assets.
8. (Cost of goods sold – Depreciation)/Inventories.
9. Sales/Accounts receivable.
10. Sales/Equity.
11. Sales/(Cash + Invested funds + Accounts receivable).
12. Quick assets/Total assets.
13. Long-term liabilities/Fixed assets.
14. Long-term liabilities/Total liabilities.
15. Current liabilities/Total liabilities.
16. Long-term liabilities/Equity.
17. Retained earnings/Equity.
18. Revenue reserves/Equity.
19. Short-term liabilities/Total liabilities.
20. Accounts payable/Total liabilities.
21. (Cash + Invested funds)/(Costs/365).
22. Total liabilities/Equity.
23. Working capital/Equity.

Appendix B. Appendix B. The graph of classification and regression tree

See Fig. 1.

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Further reading

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