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 an unstable 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.
In this research, we consider bankrupt companies as the positive
and non-bankrupt companies as the negative class (N).

Several comments are worth making on the results showed in

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

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 classi-
tical textbook models have been proposed. For an excellent over-
view 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 effi-
ciency of classical Russian models for bankruptcy prediction, spe-
cifically, 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 results¹ (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 Ful-
mer’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 cor-
rect 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

¹ To measure the effectiveness of classification, in this paper we use the following
classification performance metrics (see also Chen, 2011): 1. Overall accuracy:
Here TP means true positive, TN – true negative, FP – false positive, FN – false negative.
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