Expert Systems with Applications 40 (2013) 7285–7293

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Bankruptcy prediction for Russian companies: Application of combined classifiers

Elena Fedorova [a], Evgenii Gilenko [b,*], Sergey Dovzhenko [b]

[a] The Department of Financial and Investment Management of the Financial University under the Government of Russian Federation, 49 Leningradskiy Av., Moscow 125993, Russia
[b] The Faculty of Economics of the St. Petersburg State University, 62 Tchaikovskogo St., St. Petersburg 198123, Russia

ARTICLE INFO

Keywords:
Bankruptcy prediction
Logit-regression
Artificial neural networks
Classification and regression trees
AdaBoost

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.

* Corresponding author. Tel.: +7 (911) 935 83 41; fax: +7 (812) 273 40 50.
E-mail addresses: ecolena@mail.ru (E. Fedorova), e.gilenko@econ.pu.ru (E. Gilenko), serg.dovzhenko@gmail.com (S. Dovzhenko).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.07.032

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.