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Two-step classification method based on genetic algorithm for bankruptcy forecasting

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ABSTRACT

By present, many models of bankruptcy forecasting have been developed, but this area remains a field of research activity; little is known about the practical application of existing models. In our opinion, this is because the use of existing models is limited by the conditions in which they are developed. Another question concerns the factors that can be significant for forecasting. Many authors suggest that indicators of the external environment, corporate governance as well as firm size contain important information; on the other hand, the large number of factors does not necessary increase predictive ability of a model. In this paper, we suggest the genetic algorithm based two-step classification method (TSCM) that allows both selecting the relevant factors and adapting the model itself to application. Classifiers of various models are trained at the first step and combined into the voting ensemble at the second step. The combination of random sampling and feature selection techniques were used to ensure the necessary diversity level of classifiers at the first step. The genetic algorithms are applied at the step of features selection and then at the step of weights determination in ensemble. The characteristics of the proposed method have been tested on the balanced set of data. It included 912 observations of Russian companies (456 bankrupts and 456 successful) and 55 features (financial ratios and macro/micro business environment factors). The proposed method has shown the best accuracy (0.934) value among tested models. It has also shown the most balanced precision-recall ratio. It found bankrupts (recall = 0.953) and not bankrupts (precision = 0.910) rather accurately than other tested models. The ability of method to select the task-relevant features has been also tested. Excluding the features that are significant for less than 50% of the classifiers in the ensemble improved the all performance metrics (accuracy = 0.951, precision = 0.932, recall = 0.965). So, the proposed method allows to improve the advantages and alleviate the weaknesses inherent in ordinary classifiers, enabling the business decisions support with a higher reliability.

1. Introduction

The problem of bankruptcy forecasting is one of the most actively studied nowadays among practical and theoretical issues of company management. Assessment of the current financial status and determination of bankruptcy probability are of interest to shareholders, suppliers, creditors and others aiming is to deal with perspective and reliable business partners.

Although more than 150 bankruptcy models employing above 750 different factors have been proposed, these models are rarely used in practice (Bellovary, Giacomino, & Akers, 2007). In our opinion, this is since different economic environments have various properties that do not allow reusing models and related sets of factors in other conditions. This fact has been confirmed by comparative studies of models for different countries (Liang, Tsai, & Wu, 2015; Peng, Wang, Kou, & Shi, 2011). For developing countries, with the economic structure significantly different from the developed countries this fact is particularly significant (Fedorova, Gilenko, & Dovzhenko, 2013). In addition to the financial ratios, new factors may be required for forecasting in such conditions (Liang, Lu, Tsai, & Shih, 2016; Tinoco & Wilson, 2013). However, it is not possible to predict in advance which indicators will affect the predictive ability, so the features selection is necessary.

In this paper, we design a predictive model that can be easily adapted to any new situation, both in terms of model architecture and the features used. We combine the following techniques: at the first stage, we select the significant features for ordinary classifiers, which are combined into a voting ensemble in the second stage. For both stages (features selection and determination of the weights of the ensemble) a genetic algorithm is used.

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The proposed method has been tested on the balanced set of data that consists of 912 observations of Russian companies (456 bankrupts and 456 successful companies) and 55 features (financial ratios, macro and micro business environment factors). The research data set was divided into a training set and a test set in a proportion 80/20. The proposed method has shown the best accuracy (0934) among tested models on the test set. It has also shown the most balanced precision-recall ratio. It determined bankrupts (recall = 0.953) and not bankrupts (precision = 0.910) with a higher accuracy compared to the other tested models.

An another advantage of the proposed method is the ability to select the conditions-depended features. Elimination of features significant for less than 50% of classifiers in the ensemble increases all the performance metrics (accuracy = 0.951, precision = 0.932 and recall = 0.965).

2. Related works

Nowadays a number of studies are devoted to the problem of bankruptcy probability assessment. All researches of this subject can be conditionally divided into two groups. The first one consists of the researches concerning the choice of measurable characteristics (features) set providing a high precision forecasting (Kumar & Ravi, 2007). The most extensive of these studies concerns the indicators of financial condition (du Jardin, 2016; Fedorova et al., 2013; Lee & Yeh, 2004; Zięba, Tomczak, & Tomczak, 2016). There are works which are focused on corporate management factors (Bredart, 2014; Chan, Chou, Lin, & Liu, 2016; Lee & Yeh, 2004; Liang et al., 2016; Salloum & Azoury, 2012), environmental factors (Alifiah, 2014; Bruneau, de Bandt, & El Amri, 2012; Delas, Nosova, & Yafinovych, 2015; Duffie, Saita, & Wang, 2007; Karas & Režňáková, 2014; Tinoco & Wilson, 2013; Vlamis, 2007), level of legislation development (Rowoldt & Starke, 2016), etc. In most cases, the forecasting model of bankruptcy includes characteristics from all of these factors sets (Chan, et al., 2016; Liang et al., 2016; Tinoco & Wilson, 2013). According to Bellovary et al. (2007), who reviewed bankruptcy prediction studies from 1930 to mid-2000s, a total of 752 different factors are used in researches, yet 674 of the factors are utilized in only one or two studies. The number of factors considered in one study ranges from 1 to 57 and the average number of factors is 10.

The second group of studies focuses on forecasting methodology. The bankruptcies prediction is commonly considered as a two-class classification problem: there is a set of same type objects (in our case – firms) which belong to known classes (in our case – bankrupts and non-bankrupts); the goal is to design an algorithm capable of classifying analogical objects of unknown class.

Aziz and Dar (2006) stated that bankruptcy prediction models can be divided into three main categories: statistical models, artificial intelligence expert models and theoretical models. According to Bellovary et al. (2007), prior to the 1990s, the basic prediction methodologies were based on statistical methods including logit and probit models, and the most common was discriminant analysis (DA), first applied in the seminal work of Altman (1968). DA attempts to derive a linear combination of features, which best 'discriminate' between the classes. Altman (1968) determined 5 financial ratios, which linear combination helps to calculate a discriminant score for the US manufacturing firms; this model is well-known as Z-score.

After the 1990s, artificial intelligence expert systems including machine-learning techniques became the primary method for bankruptcy prediction. Most often artificial neural networks (ANN) were used (Bellovary et al., 2007), especially the multilayer perceptron (MLP). It should be noted, however, that many researchers stated that ANNs have some shortcomings (Dos Gordini, 2014; Santos, E.M., & Maupin, 2009): (1) a researcher should have great experience in order to select the control parametres properly, (2) it is difficult to generalize the results due to overfitting, and (3) ANNs have lack of explanatory power, so it is difficult to explain the prediction results.

In addition, some authors have investigated the applicability of other artificial intelligence methods to bankruptcy prediction, for example, the case-based reasoning (Ahn & Kim, 2009; Sartori, Mazzucchelli, & Di Gregorio, 2016).

Bellovary et al. (2007) come up with the following conclusions in their review: (1) there are over 150 models available, many of which have shown high predictive ability, so the focus of future research should be on using the existing models as opposed to the development of new ones; (2) a large number of factors does not necessary increase model's predictive ability; (3) existing models are poorly used in practice, so researchers should attempt to establish stronger connection with practice.

We disagree with the first limitation. First, the existing gap with practice, noted by Bellovary et al. (2007), is the consequence of the bounded applicability of available models. Many studies show that it is impossible to use models prepared for a specific industry, market or country in other conditions. Liang et al. (2015) examined data of four different countries (Germany, Australia, Taiwan, and China). Their results indicate that there is no single best combination of feature selection method and the classification technique over the four data sets. Similar results were obtained by Peng et al. (2011), who analyzed bankruptcies in Japan and Korea. Fedorova et al. (2013) showed that the Altman Z-score, based on the five financial ratios identified by Altman (1968), does not yield acceptable results for Russian companies. Moreover, an attempt to build a new DA model that separates Russian bankrupts and successful firms also does not provide significant results (the confirmation of this statement is presented below in a section describing research results). In addition, the size of the firms studied significantly affects the model. Gordini (2014) showed that the models for small and medium-sized enterprises differ from those for large enterprises. Therefore, the development of new models (or, to be precise, the adaptation and combination of known techniques) and use of new factors are required for each specific case.

At the same time, we believe there is no need in limiting ourselves to using models proposed 20 years ago and earlier. Many new machine learning techniques are known today, which can also be successfully applied to the problem of bankruptcy prediction that is confirmed by flow of scientific publications. Both ordinary methods of classification (logistic regression (LR), k nearest neighbors (kNN), support vector machine (SVM), naive bayes (NB), decision trees (DT)) and methods based on classifiers ensembles are used to solve this problem. Numerous works have been devoted to comparative efficiency analysis of various classification techniques applied to bankruptcy forecasting in differnet countries (Chang & Yeh, 2012; Fedorova et al., 2013; Heo & Yang, 2014; Liang et al., 2016; Peng et al., 2011; Tsai, Hsu, & Yen, 2014; Zhou, Lai, & Yen, 2014).

Secondly, the use of new factors in addition to financial ratios can provide new useful information. We agree that the large number of factors in general does not increase the accuracy of the model, and it is not possible in advance to predict which of them will be informative. Therefore, it is advisable to combine an increase in the number of factors with methods of features selection (Liang et al., 2016).

Thus, the goal of our work can be formulated as following: to develop a more or less universal method that allows to build an effective classifier, which can adapt to different conditions. The proposed method should (1) select significant features and (2) determine the architecture of the classifier. To achieve this goal, we propose using evolutionary techniques, namely genetic algorithm (GA). Such approach should ensure high applicability in practice.