

BUSINESS FAILURE PREDICTION USING CART-BASED MODEL: A CASE OF SLOVAK COMPANIES

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Abstract: Over the last decades, many financial distress prediction models have been created all over the world. Usually, these models are not very useful for Slovak companies because of their lower accuracy. The main aim of the paper is to create a business failure prediction model for the companies in Slovakia. To achieve it, we use the financial data of more than 100,000 real companies, covering the year 2016 and 2017, operating in the Slovak national economic conditions. Realizing the CART algorithm, the most significant predictors of the company prosperity are identified and the final model is formed. This model achieves 92% overall classification ability. Obtained results are important for companies themselves, but also for their business partners, to eliminate financial and other corporate risks related to the business failure situation of the companies.

Keywords: business failure prediction, decision tree, CART, prediction ability

JEL Classification: G17, C52, C53

1 Introduction

Business failure prediction has been a very interesting topic over the last decades because of its great importance for companies, interested stakeholders and even for the economy of a country. If this prediction is reliable, managers of companies can initiate remedial measures to avoid business failure situation. Also, investors can make the company profitable and adjust their investment strategies to reduce anticipated losses related to investments. However, the rapid development of the capital market and the globalization has increased the number of companies that over the years suffer from financial distress. (Valaskova et al., 2018)

Every company has an economic and moral responsibility to stockholders to perform well financially. In Slovakia, the number of financial distress companies is probably excessively large with no apparent macroeconomic cause. Therefore, it is possible that managers in Slovakia rarely behave responsibly and definitely do not behave ethically. Incompetent management decisions can produce substantial losses for all stakeholders such as creditors, investors, auditors, financial institutions, stockholders, employees, and customers; this

undoubtedly reflects in the economics of the countries concerned (Koyuncugil and Ozgulbas, 2012).

The originality of the research lies in the using of a large dataset of financial indicators of more than 100,000 Slovak companies. Determination of significant prosperity predictors in Slovak conditions can help form a complex Slovak multi-industry prediction model, which would be beneficial for all market subjects.

The main aim of the paper is to extend the knowledge about the identification of business failure situation of the company, which is done by the creation of the prediction model using the CART decision tree approach.

The purpose of the paper is to identify potential financial risks considering Slovak economic conditions. The research problem includes the formation of a business failure prediction model based on the significant financial indicators identified in the decision tree growing algorithm CART.

The remainder of this paper is divided into four main parts. Literature review briefly describes of background and most important related works. The primary aim and description of CART algorithm and data are described in the Methodology section. Section Results is focused on the description of the developed model, which identifies the business failure situation and thus eliminates financial risks. Discussion compares and analyses the studies and researches of other authors in the field of business failure prediction models and compares the results of the realized study with results of other studies based on different methods.

2 Literature review

In 1993, Altman defined failure as the situation where "the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates of similar investments", which did not indicate the discontinuity of a company. (Pozzoli and Paolone, 2017)

Various statistical techniques have been commonly used for business failure prediction. Multivariate discriminant analysis was the most frequently used method before the 1980s (Altman, 1968). This approach has been criticized for its unrealistic assumptions (multivariate normal distribution, equal variance-covariance matrices among groups, absence of multicollinearity). These assumptions are often not satisfied in real-world applications. Ohlson (1980) pioneered using logit in business failure prediction with an assumption of variation homogeneity of data and the sensitivity to multicollinearity. Some other techniques have been applied to solve this problem, e.g., probit analysis (Zmijewski, 1984; Kasgari et al., 2012). Nowadays, other statistical methods are not popular in business failure prediction because they require more computations or do not acts so accurate. (Dimitras et al., 1996)

Using machine learning methods based on artificial intelligence, research methods for business failure prediction advanced. Researchers developed different types of intelligent techniques to solve this problem, but artificial neural networks have been the most commonly used technique (Ravi Kumar and Ravi, 2007; Jones et al., 2016). Other data mining techniques included decision trees (Abellan and Castellano, 2017; Tsai et al., 2014; Zięba et al., 2016), case-based reasoning (Li and Sun, 2009), genetic algorithms (Lin et al., 2018; Chou et al., 2017; Shin and Lee, 2002), Kohonen map (Du Jardin, 2018; Du Jardin and Severin, 2012), rough sets (Xu et al., 2014; Kasgari et al., 2012), simulation analysis (Cohen et al., 2012), and support vector machines approach (Gogas et al., 2018; Alaminos et al., 2016; Zhao et al., 2016).

Many reviews of business failure or bankruptcy prediction models were published. In 2018, Alaka et al. published a systematic review of 49 journal articles published between 2010 and 2015. This review shows how eight popular and promising tools (multiple discriminant analysis, logistic regression, artificial neural network, support vector machines, rough sets, case-based reasoning, decision tree and genetic algorithm) perform based on key indicators within the bankruptcy prediction models research area.

Convolutional neural networks were used to business failure prediction of Japan listed companies in Hosaka (2019). This trained model achieves much higher prediction ability compared to models created by other methods (decision trees, support vector machines, etc.). The study of Doumpos et al. (2017) examines the development of corporate failure prediction models for European firms in the energy sector, using a large dataset from 18 countries. The results indicate that country-level data related to the economic and business environment, as well as data about the energy efficiency policies of the countries and the characteristics of their energy markets and networks, have high discriminating power and add valuable information compared to the traditional financial variables.

Barboza et al. (2017) tested machine learning models (support vector machines, bagging, boosting, random forest, and neural networks) commonly used to predict of business failure one year prior to the event, and compare their performance with results from classical methods (discriminant analysis, and logistic regression). For analyzing, authors used more than 10,000 North American firm-year observations. Machine learning models show, on average, approximately 10% more prediction ability in relation to traditional models.

In 1985, Frydman et al. were the first to use a decision tree (DT) approach to business failure prediction. They found their decision tree to be a better predictor compared with multiple discriminant analysis. Since then, many DT-based models have been created in this field. Kim and Upneja (2014) used DTs and AdaBoosted DTs to predict the financial distress of US restaurants. To form a model, publicly listed restaurant companies from food services and drinking places of the North American Industry Classification System from 1988 through 2010 were selected. The total number of companies was 826. Of the 826 observations, 42 observations from 21 companies were categorized as financially distressed, and the other 784 observations from 121 companies were sorted into non-distressed firms. The DTs classification methods (C5.0, CART, and CHAID) and logistic regression techniques were used to implement the financial distress prediction model for Taiwan listed companies (Chen, 2011). The data about 2006-2012 annual series of 25 financial ratios of 155 banks in the Eurozone were used to create a bank financial distress prediction model for Poland and Slovak banks (Brozyna et al., 2016). Geng et al. (2015) predicted business failure for 107 listed Chinese companies. To prediction, they used 10 different approaches including decision trees C5.0, CART, QUEST and CHAID. In their paper, Popescu and Dragotă (2018) identify the business failure predictors for 5 post-communist countries (Bulgaria, Croatia, the Czech Republic, Hungary and Romania) using CHAID decision tree and neural networks.

Of course, in the last years, several prediction models have also been created in Slovakia. Gurcik (2002) and Chrastinova (1998), created a model for agricultural companies using multiple discriminant analysis. These models are still used to predict the financial distress of Slovak companies in various industries. Slovak Logit models were introduced by Hurtosova in 2009 and Gulka in 2016. Kovacova and Kliestik (2017) developed models for bankruptcy prediction of Slovak companies by using logit and probit method and provide the comparison of overall prediction ability of the two developed models. Karas and Reznakova (2017, B) developed a CART prediction model for Slovak companies operating in the construction industry. Gavurova et al. (2017) developed a new model for Slovak companies by using the

DT technique. Mihalovic (2016) developed models for Slovak companies; the first one was estimated by multiple discriminant analysis, and the second was a logit model.

None of these aforementioned prediction models, developed in Slovakia, uses such a large database of companies as we have and often are created only for selected sectors of economic activity. For this reason, we consider it is necessary to create a new prediction model based on a large data sample of Slovak companies from the period of the last two or three years.

3 Methodology

The main aim of our research is to create a model using decision tree generating algorithm CART that reflects Slovak national economic conditions. For this reason, data on real Slovak companies was employed. This data was obtained from database Amadeus: A database of comparable financial information for public and private companies across Europe. Data contains values of financial ratios and indicators of more than 100,000 real Slovak companies. Based on financial statements (balance sheets and profit-and-loss statements) from the year 2016 and 2017 financial indicators values were calculated.

The initial set of predictors includes values of 37 financial indicators (see Table 1). These set of indicators contain not only the most frequently used predictors (Korol, 2013) but also contain some other indicators that can reflect Slovak national economic conditions.

Table 1: Financial indicators used as predictors

ID	Method for calculation
X1	Sales / Total Assets
X2	Current Assets / Current Liabilities
X3	Gross Profit / Total Assets
X4	Net Income / Equity
X5	EBITDA / Sales
X6	Liabilities / EBITDA
X7	Net Income/ Total Assets
X8	Working Capital / Total Assets
X9	Operating Profit / Total Assets
X10	Total Liabilities / Total Assets
X11	Current Assets / Total assets
X12	Cash & Cash Equivalents / Total Assets
X13	Cash-flow / Total Assets
X14	Cash-flow / Total Liabilities
X15	Current Liabilities / Total Assets
X16	Current Assets / Sales
X17	Operating Profit / Interest Paid
X18	Stock / Sales
X19	Cash-flow / Sales
X20	Net Income / Sales
X21	Non-current Liabilities / Total Assets
X22	Cash & Cash Equivalents / Current Liabilities
X23	Cash-flow / Current Liabilities
X24	Working Capital / Sales
X25	Current ratio
X26	Liquidity ratio
X27	Return on Assets
X28	Return on Equity
X29	Shareholder Liquidity Ratio
X30	Solvency ratio (Liability based)
X31	Cash-flow / Operating Revenue
X32	Net Assets Turnover
X33	Interest Paid
X34	Gross Margin
X35	Profit Margin

ID	Method for calculation
X36	Net Current Assets
X37	Working Capital

Source: compilation by authors

In 2016, the institute of "a company in crisis" was introduced by Slovak legislative. According to the §3 of Act no. 7/2005 Coll. on Bankruptcy and Restructuring as amended, financial distress is the state when a company is indebted or unable to pay. This means that it has more than one creditor and the value of its liabilities exceeds the value of its assets (i.e. has negative equity) or is unable to pay at least two financial obligations to more than one creditor for 30 days after the due date. We have approximated this fact by computing the current ratio (X25 in Table 1) and determining the breakpoint of this indicator at level 1. Companies are at risk of business failure if the solvency ratio (X30 in Table 1) is less than 0.06 (this value was valid in 2017). If at least one of the above conditions was not met, the company was considered to be non-failure. Therefore, based on data from 2017, companies were initially divided into two groups: failure companies and non-failure companies. Table 2 shows the absolute and relative frequencies of these groups. These frequencies reflect a real business failure situation of companies in the Slovak economy.

Table 2: Frequencies of failure and non-failure companies

Failure	Frequency	Percent
No	80,920	77.9
Yes	22,921	22.1
Total	103,841	100.0

Source: authors calculation

For the formation of the business failure prediction model, algorithm CART generating decision tree was employed. This algorithm can be used to detect optimal criteria for classification the individuals of a population into two or more predetermined classes (in our case into two groups: a group of failure companies and a group of non-failure companies). CART generates binary DT, thus, it grows by choosing the variable (financial indicator) which provides the best separation of the companies in, so-called, parental node into two sub-populations (child nodes). Then, each child node contains the largest possible proportion of individuals in a single class. This operation is then repeated until no further separation of the companies is possible or desirable (according to stop criterion). Terminal nodes (or leaves) and the set of splitting rules for all the leaves forms the classification model. In the final DT, its quality is considered by the purity of terminal nodes. In CART, the Gini index is used as the function of impurity.

The following conditions were considered as a stop criterion. Separation in some node was stopped, if the tree depth has reached a fixed limit of five separation levels, or the node is pure (all individuals belong to the same class), or the frequency of cases in node is less than 100, or the best results to child note with less than 50 cases, or the quality of the tree is no longer increasing significantly.

Because of the final DT can be over-fitted or over-trained, after generating maximum tree it can be pruned by the optimal pruning threshold. Another way to solve this problem is the creation of a test sample, separately from a training sample. Therefore, the initial sample was randomly divided into training and test samples in a ratio of 80:20. The test sample can be used to test each sub-tree of the maximum tree, and the subtree giving the lowest error rate in testing is then considered to be the best-pruned tree.

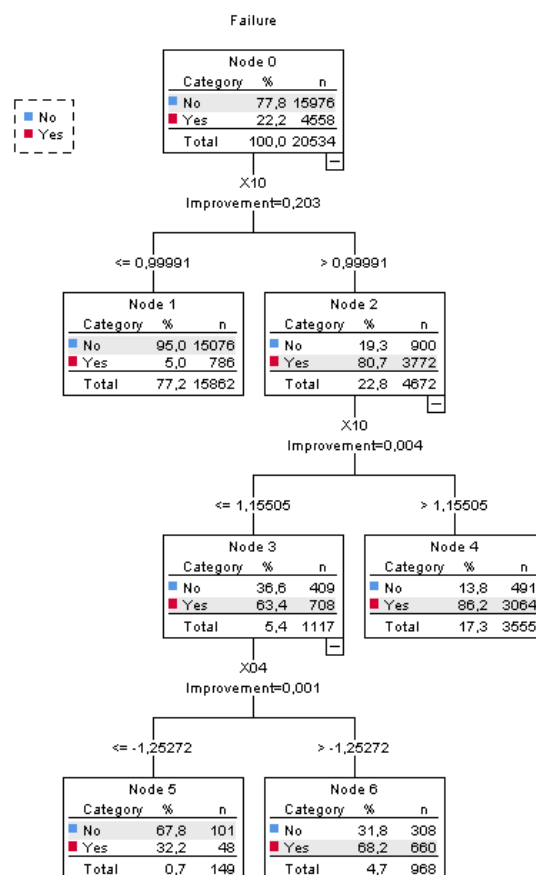
We measured the performance of the models in terms of their prediction ability (the ratio of a number of correctly predicted records including to group of failure companies and non-failure companies to the total number of records according to the common machine learning evaluation metrics). The random division of the training and test data might have some impact on the analysis. So we conducted 10 times repeated random sub-sampling validation based on the same data set. The average predictive performance of the 10 trials is regarded as a final prediction result for each model.

The AUC (Area Under Curve) is an another frequently used criterion for assessment of prediction ability of the created model. The maximum value of AUC is 1, i.e. 100%. Thus, if the size of the AUC is close to 1, then the created model has an excellent classification ability. If the size of the AUC is close to 0.5, the classification ability of the model is not good.

4 Results

Korol (2013) claims that DT business failure prediction models usually outperform similar models based on conventional tools, including multiple discriminant analysis approach or sophisticated artificial neural network. According to this and many advantages of CART, CART-based financial distress prediction model was created.

Figure 1: Final decision tree classification on test sample



Source: authors calculation

Slovak business failure prediction model was created based on a dataset of 103,841 companies, among them 80,920 non-failure companies and 22,921 failure companies (Table 2). In 2017, the state of business failure was considered. Growing algorithm CART was set up for the maximum tree depth of 5 levels of separations; a minimum number of companies was

set up to 100 in parental nodes and 50 in the child nodes. According to this, the algorithm grows the maximum tree. Initial dataset was 10 times repeated random sub-sampling to training sample (80% of the initial dataset) and testing samples (the remaining 20%). After that, in all of these sub-samplings, algorithm prunes the tree to avoid overfitting with respect to achieved maximum prediction ability. The overall prediction ability of the final model was assessed by the analysis of values in the classification table and the AUC value. These values represent an arithmetical average of all reached values in all 10 random sub-samplings.

From the initial set of 37 potential predictors (financial indicators in Table 1), only values of 35 of these predictors were used to grows the maximum trees by CART algorithm. However, after the pruning process of this maximum tree, final DT (see Figure 1) uses values of 2 predictors only. These predictors *X10* (Total Liabilities to Total Assets) and *X04* (Net Income to Equity) belong to the most frequently used ratios in prediction models (Korol, 2013).

Figure 1 illustrates how the final DT-based model classifies the companies in the test sample. The tree model is relatively simple. This is because, the model consists of 3 levels of nodes, 3 non-terminal nodes and 3 terminal nodes. Although the final business failure model is really simple, its classification ability is high. Table 3 illustrates the prediction ability of the model on both, training and test sample. For the test sample, the overall prediction ability is 92%. Moreover, 95% of non-failure companies in the test sample were classified correctly. In a group of failure companies, prediction ability was nearly 82%.

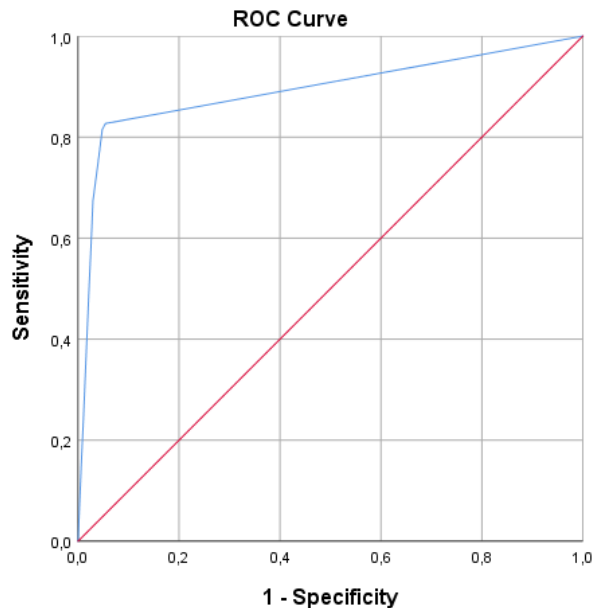
Table 3: Classification table

Sample	Observed	Predicted		Percent Correct
		No	Yes	
Training	No	61,845	3,099	95.2%
	Yes	3,395	14,968	81.5%
	Overall Percentage	78.3%	21.7%	92.2%
Test	No	15,177	799	95.0%
	Yes	834	3,724	81.7%
	Overall Percentage	78.0%	22.0%	92.0%

Source: authors calculation

Since the model is simple, the ROC curve also has a simple shape. Figure 2 shows the ROC curve of the best of all models that were created by 10 times repeated random sub-sampling to training sample (80% of the initial dataset) and testing samples (the remaining 20%). The shape of this ROC curve confirms high prediction ability of the created model. The AUC values varied between 0.87 and 0.91. An average AUC value of 0.893 is relatively close to 1, which confirms the fact that developed has pretty high prediction ability.

Figure 2: ROC curve



Source: compilation by authors

5 Discussion

In recent years, many models have been created using various commonly used methods in Slovakia. In 2016, Gulka created a Logit-based business failure prediction model with an overall prediction ability of less than 80%. Kovacova and Kliestik (2017) also used logistic regression to development of business failure prediction model under Slovak national economic conditions. This model classifies companies with an overall prediction ability of 86.6%. Business failure prediction models developed by Mihalovic (2016) using multiple discriminant analysis and Logit have overall prediction ability of 64.4% and 68.6%, respectively. All of the above-mentioned models were designed to predict threatening business failure situation of Slovak companies one year in advance. These models achieved a lower overall prediction ability than our model with an overall accuracy of 92%.

Boda and Uradnicek (2016) verify of Altman Z-score model usability in the Slovak business environment. Authors test three variants of the Z-score model and assess their prediction ability using a data set of real Slovak companies. The first one was the original 1968 Z-score model (Altman, 1968) and the second one was revised 1983 Z-score devised for the US economic environment (Altman, 1983) are compared with the Z-score model re-estimated to the Slovak data copying the methodological procedure of Altman. The results indicate that these models, especially in 1983 revised Altman model, are useful for business failure prediction of Slovak companies. This is because the highest overall prediction ability between 79% and 83% was achieved by the 1983 revised Altman model. By comparing these results we get our model which identifies business failure situation a little bit better.

In Slovakia, several prediction models were created using DTs. Gavurova et al. (2017) created models predicting financial distress one and two years in advance, respectively. These models were created using multiple discriminant analysis and the CHAID decision tree. Among them, models generated sing CHAID algorithm achieved a little bit higher overall prediction ability. Both, the one-year and the 2-year model, have achieved overall prediction ability of less than 87%. The overall prediction ability of our model, predicting business failure situation one year in advance, is higher by 5%.

Karas and Reznakova (2017, A; 2017, B; 2018) created two versions of CART-based financial distress prediction model for Slovak companies. For failure companies, the classification accuracy of these models is 94.9% and 91.5%, respectively. However, only 61% or 62.6% of non-failure companies was classified correctly. Compared to our model, the situation is reversed. This is because our model better classifies non-failure companies (95% of these companies were classified correctly). The prediction ability of our model is 81.7% for failure companies. However, the overall prediction ability of our model is higher by more than 26% (92% vs. 65.6%).

6 Conclusion

However, in recent decades the issue of financial distress prediction has been discussed by many authors and researchers, so far there is no generally accepted bankruptcy prediction model considering the specific economic conditions and legislation of Slovak Republic. To fill this gap, new business failure prediction models based on the CART decision tree algorithm were designed in this study. The proposed model was developed for business failure prediction in Slovak national economic conditions one year in advance. For its creation, data of more than 100,000 real Slovak companies covering the period of the years 2016 and 2017 was used. In 2017, if the financial ratios of the company met the conditions identified by the Slovak legislation, it was considered as a failure company.

Despite the fact that the final model classified companies on the basis of two ratios (Total Liabilities to Total Assets and Net Income to Equity), the model achieved pretty high overall prediction ability. On the other hand, such simple models are very easy to interpret and are also very easy applicable for business failure prediction also for companies for which we do not have complete accounting data. The final model providing high overall prediction ability of 92%. Nearly 82% of failure companies and 95% of non-failure were classified correctly.

As a further direction of this research, we suggest to verify this model on the data from new financial statements (balance sheets and profit-and-loss statements) of Slovak companies from 2018 (and later newer data) to find out possibilities for construction of the financial distress prediction model generally accepted in the national economic conditions of Slovakia. Further direction of the research could also lead to the formation of prediction models specific to individual sectors of economic activity of the company or for individual regions of Slovakia.

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