FINANCIAL DISTRESS MODELLING IN SLOVAK SMALL AND MEDIUM ENTERPRISES USING SHINY AND MICROSOST EXCEL

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Abstract

The financial health of a company is one of the crucial factors that define whether the company will survive in today's rapidly evolving and volatile world, or not. As a consequence, it drives interest of researchers and practitioners in financial distress prediction modelling. Although many corporate financial prediction models were developed over the years, a big gap between theoretical research in this area and its practical utilization is still widely opened, especially in the case of small and medium enterprises (SMEs). There are many factors influencing negatively adoption of corporate financial distress prediction models making it quite infeasible for SMEs to deploy such models on their own. Non-existent free and/or open source software solutions allowing a quick and simple application of the fitted models are one of them. In our paper, we present applications for corporate financial distress modelling focusing on Slovak SMEs. The presented applications incorporate various statistical models, are based on Shiny and Excel and provide users with simple decision making support.

Key words: *financial distress, prediction, application, small and medium enterprises.*

1. Introduction

Small and medium enterprises (SMEs) are a crucial part of economy. According to Eurostat (2015), they represent around 99% of all enterprises. In Slovakia it is unbelievable 99,9%. If we have a closer look at the statistics of SMEs, we can see that the number of SMEs employees is increasing. In comparison with large enterprises that create a higher proportion of value added in the 'high and medium/low tech manufacturing' sector, small and medium enterprises create a higher proportion of value added especially in the services sector.

One of the key factors that defines whether a company will be able to succeed in today's rapidly evolving and volatile world is the financial health of the company. As explained by Lesáková (2008, p. 607) "Small and medium enterprises (SMEs) are faced with the need for a strategic response to the changes in global business environment." The same author also pointed out the impact of globalization on businesses sector, which is indisputable Lesáková (2008, p. 607): "The future success of small and medium enterprises in the new world of global economics will be determined by

a) implementation of new businesses types in SMEs sector,
b) implementation of innovation, information and communication technologies by SMEs,
c) implementation of strategic management by SMEs."

We suppose the point b) in previous statements involves also implementation of innovative theoretical ideas developed by academicians and the equivalent research outputs, e.g.

prediction models, into simple, but still powerful, managerial decision support systems utilizing various data sources and up to date software solutions.

In our article we focus on Slovak small and medium enterprises and we further discuss this point illustrating it in the case of supervised corporate financial distress (bankruptcy) prediction models represented for example by (in)famous Altman's bankruptcy formula (Altman, 1968), well known as Altman's Z-score, and its later modifications and extensions (Altman et. al., 1977; Altman 1983). It was explained also by Boďa and Úradníček (2016a, p. 70) that innovative approaches can emerge in corporate financial analysis, also in the case of Slovak economic environment. One of the main lasting problem is how to implement these methods into decision making processes in SMEs. The well-known and long existing financial distress and/or bankruptcy models still fully dominate their recent modifications or new counterparts, even though decision makers in SMEs are aware or should be aware of the possibility that assumptions used for fitting the original models are often not valid anymore due to changes in economic environments, law frameworks, incomparability of populations of interest etc.

As it was pointed out by Bieliková et al. (2014, p. 38), because of the dynamics and uncertainty of the current economics, the number of studies that focus on financial situation diagnostics by using various statistical and data mining methods increases. Unfortunately, without paying sufficient attention to accurate definition of risky company state. As a result, recently proposed modifications or new models can be only partially compatible or even worse, completely incompatible with the original ones.

In the case of SMEs, there are also many other factors influencing negatively adoption of corporate financial distress (bankruptcy) prediction models including employees lacking adequate data analytic skills, unavailable data and non-existent free software solutions allowing simple application of fitted models. These factors can make it quite infeasible for SMEs to construct and interpret such models on their own.

The presented obstacles are further amplified if SMEs decide to apply some current models presented in various research papers because of almost non-existent research reproducibility (non-public data sets, private source codes) and small to none attention of authors to deployment of their own research outputs.

The above mentioned reasoning leads us straightforwardly to the main aim of the paper, a proposal of a free, open source, modern, scalable and yet easily applicable software solution for deployment of supervised corporate financial distress (bankruptcy) prediction models focusing on SMEs. This software solution is designed in Shiny, a web application framework for R (R Core Team, 2016). Shiny and R are both open source and free, even for commercial activities, thus easily available for Slovak SMEs. Moreover, the main principles of friendly user graphics interface are applied to design the application as simple as possible to use in order to meet the needs and preferences of today's users.

To fulfil the aim of the paper the structure is outlined as follows. In section 2 we describe the basic requirements on an application for financial distress modelling in case of SMEs. In section 3 we characterize our application concept and solutions. In section 4 we explain the underlying statistical and data mining models and data sets serving as a basis for our application.

2. Basic Requirements

In this part of our paper we summarize basic requirements on an application for financial distress modelling in case of SMEs. The main aim of the application is to enable employees in SMEs to analyze financial distress of a company.

Graphic user interface (GUI) of any computer application is crucial factor of its future success. Users desire friendly looking, highly interactive, dynamically visualized and naturally controlled user interfaces (UI) that allow smooth navigation (Kurdi et al., 2014, p. 148). Science called Human Computer Integration (HCI) deals generally with user interface of computers, tablets, smartphones and similar devices. HCI integrates knowledge from fields such as psychology, computer science, sociology, design and ergonomics. The aim is to provide a user-friendly interface that will allow him to not only control the applications, but also provide adequate feedback.

Design of a GUI should be based on human characteristics. People differ in many aspects, but there are also some common characteristics important for design of a GUI. The most significant character in this case, just visual perception. Optimal design of a GUI should arrange all objects on the screen and thus facilitate the visual perception of information from the user. Success of a GUI does not hide only in deployment of graphical objects, but it is important to respect the following principles of interactive design specified by Nielsen (2005):

1. Visibility of system status: The system should always keep users informed about what is going on, through appropriate feedback within reasonable time.
2. Match between system and the real world: The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order.
3. User control and freedom: Users often choose system functions by mistake and will need a clearly marked "emergency exit" to leave the unwanted state without having to go through an extended dialogue. Support undo and redo.
4. Consistency and standards: Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions.
5. Error prevention: Even better than good error messages is a careful design which prevents a problem from occurring in the first place. Either eliminate error-prone conditions or check for them and present users with a confirmation option before they commit to the action.
6. Recognition rather than recall: Minimize the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate.
7. Flexibility and efficiency of use: Accelerators -- unseen by the novice user -- may often speed up the interaction for the expert user such that the system can cater to both inexperienced and experienced users. Allow users to tailor frequent actions.
8. Aesthetic and minimalist design: Dialogues should not contain information which is irrelevant or rarely needed. Every extra unit of information in a dialogue competes with the relevant units of information and diminishes their relative visibility.
9. Help users recognize, diagnose, and recover from errors: Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution.
10. Help and documentation: Even though it is better if the system can be used without documentation, it may be necessary to provide help and documentation. Any such information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.

In addition to well created GUI, there are also several other important aspects of an application used by SMEs (lack of statistical and analytical knowledge, lack of funds). Because of this an application for financial distress prediction must be as simple to use as possible and meet following requirements: simple inputs, easy to interpret outputs, no statistical or analytical knowledge is required, based on commonly used software, available for free.

In the following part of this paper, we describe our application concept and solutions.

3. Application Concept and Our Solutions

Based on requirements specified in previous section, we set following application concept:

- Prediction using statistical models: Application should be able to process statistical models and present results to the user.
- Usability: Simple UI without need of any special knowledge in the field of information technology or statistics. For simple usability it is crucial that user interface corresponds to the users` knowledge and experiences.
- Availability: Available for 24 hours in a day, 7 days in week without any restrictions.
- Free of charge: Available for free, without registration.
- Incorporation of subjective opinion: Subjective opinion of a user can be incorporated in process of calculation of corporate financial distress.
- Input: We use basic financial indicators as an input. All of the indicators must be easy to understand by representatives of small and medium size enterprises.
- Output: Results from our models are represented by probability of corporate financial distress. Results in form of probability may seems too simple from statistical point of view, but are very simple to interpret by end users.

We created two different application for two different purposes. First application is available online and is aimed on simple financial distress prediction using any device connected to the Internet. Second application is much more complex with advanced features.

3.1 Online Application Using Shiny Server

We decided to build online application because of ubiquitous internet access, standard users' experience with web browsers and cloud computing which is becoming more popular. The most important benefit of online version is that users can use it directly within web browser on any device connected to the Internet using. The only limitation of the application is that only one prediction model is included. But this tool should be used only for fast analysis and in this case is one model sufficient. Our application is available for free on https://efumb.shinyapps.io/deploy/. Figure 1 shows interface of the online application.

We described this solution in more details in another paper of ours; see Kollár et al. (2016).

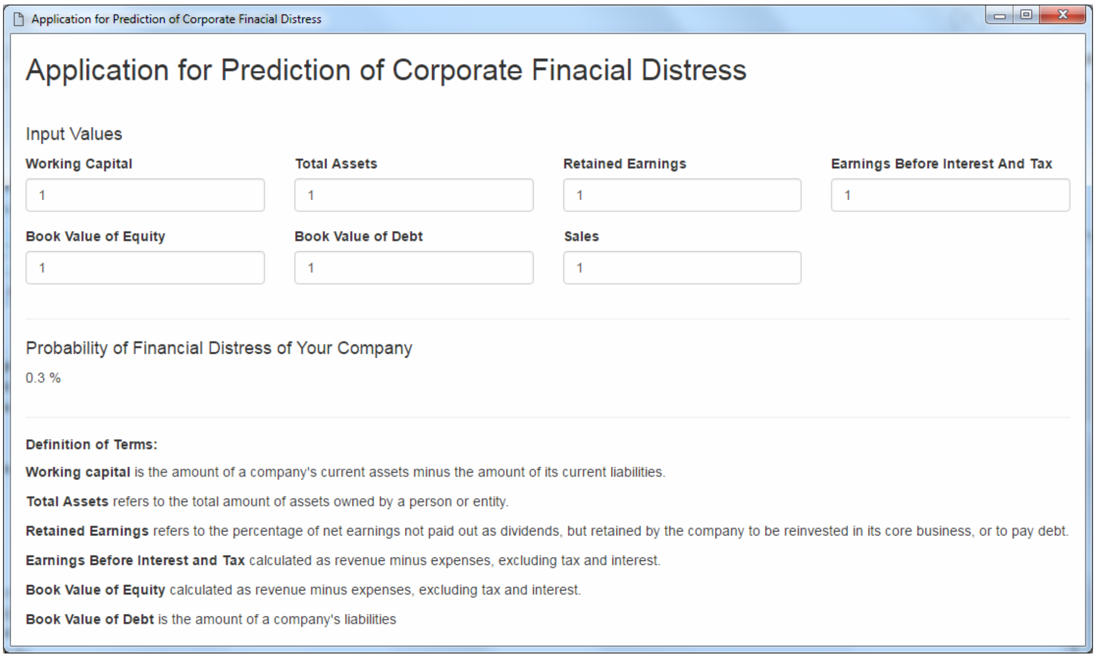
3.2 Offline Application Using MS Excel and R

Offline application is made for more complex financial distress prediction. Key characteristics of the application are:

- More prediction models: We included following models: Quadratic discriminant analysis, Altman 68', Altman 83', Linear discriminant analysis (Boďa and Úradníček, 2016b), Logistic regression, Decision tree, Random forest.
- More complex information: Each of specified models is described in more details including basic characteristics, confusion matrix, overall accuracy, ROC curve and AUC.
- Possibility to add custom models: Application enables users to add own custom models and use them for analysis. The only requirement is that custom model must use the same input values as included models.

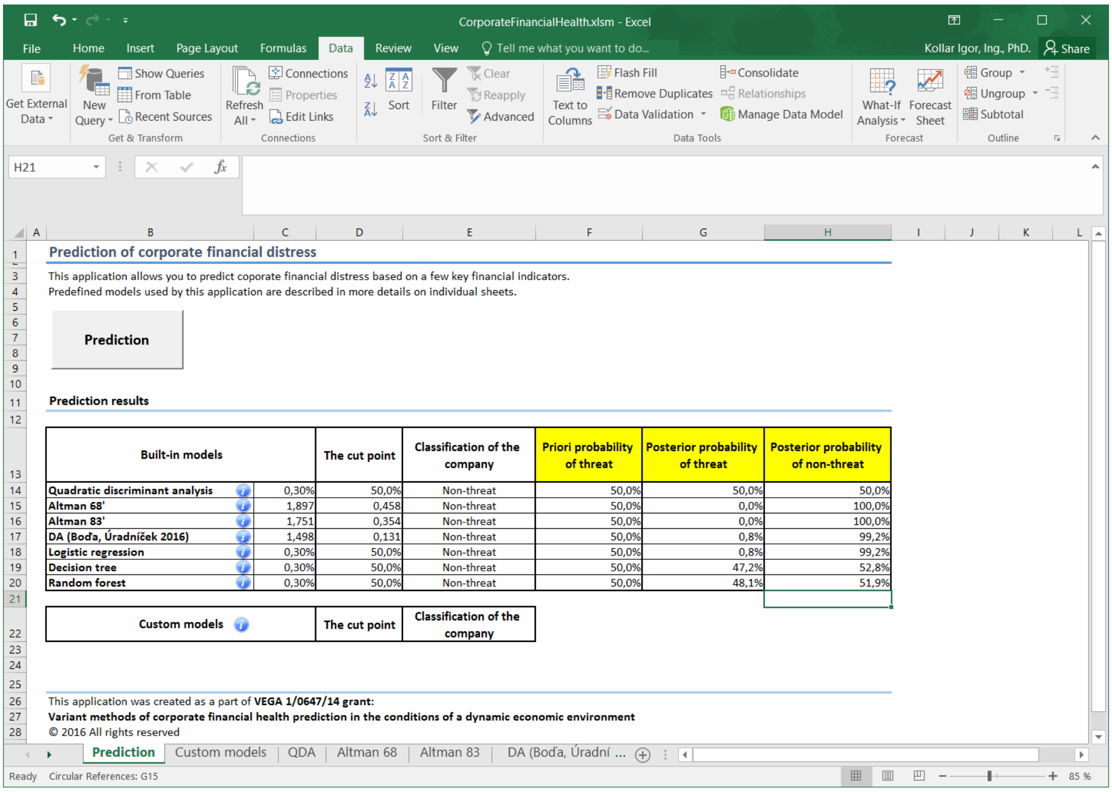
- Offline mode: Connection to the Internet is almost everywhere. But in some situations but in some situations local application can be very useful (for example internet access failure or lack of internet access due to security reasons).

Figure 1: Online application



Source: the authors.

Figure 2: Offline application

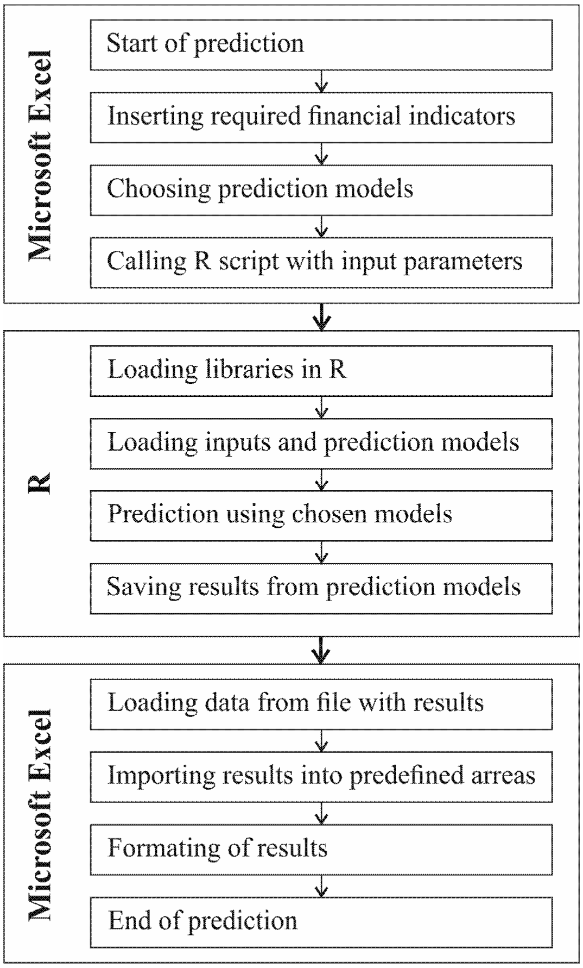


Source: the authors.

Our offline application is based on MS Excel and statistical program R (portable version). We decided to use MS Excel as an interface, because it is widely used by SMEs and working with known program is for end-users much more comfortable, than learning new program a new interface. Statistical program R is used to process analysis using statistical models. We use portable version of R, because we want to avoid local installation of any program by end-users. Screenshot of the offline application you can see in Figure 2.

The whole process of analysis is divided in the steps shown in Figure 3, realized in MS Excel or R.

Figure 3: Processes of analysis in prepared application



Source: the authors.

4. Data, Statistical Methods and Models

The core part of any application for financial health prediction is formed by prediction models incorporated in it. Without properly constructed and validated models the application would be useless despite satisfying all condition imposed on it with respect its graphical user interface and other related properties. The problem is that there are too many statistical, datamining and machine learning methods which can be utilized for construction of such models. Therefore we need to define criteria which allows us to choose the most suitable methods for creating portfolio of models to be included in our application. Having in mind our ultimate goal – to create an application which can be a useful support tool for practitioners lacking deep knowledge of quantitative methods, we could define quite naturally the following basic requirements for a method to be used to fit prediction models implemented in our application. We can say that a model based on a particular method is suitable for our application if

1. it has satisfactory prediction ability,
2. it has satisfactory stability over time,
3. it poses simplicity of interpretation,
4. it provides us with some insight how changes in financial ratios could affect the model prediction of the response, e.g. probability of being endangered by financial distress,
5. there exist a possibility to incorporate expert knowledge easily.

Let's discuss the above mentioned criteria in more details. First and foremost, if we would like to talk about satisfactory prediction ability it is necessary to define error measures which will be used to assess the prediction abilities of the model. The most common error measures used in this context are overall accuracy, true positive rate, true negative rate, false negative rate, false positive rate and AOC (area under the ROC curve). These models and their combinations are not used only for validation of the models but at the same time as optimization criteria (Úradníček et al., 2016) in model fitting. The most common technique used for estimation of these errors is some kind of cross validation which allows us to decrease the risk of ending up with an overfitted model (James et al., 2013).

Unfortunately, it is not enough if our models have adequate prediction ability when fitted. In order to get a usable application, prediction ability of our models has to be quite stable without updating these models during a longer period of time. In our opinion, the prediction ability of a model at hand shouldn't deteriorate significantly for about two years.

The next property, simplicity of interpretation, has the components. The first one means that we would like to have, in our application, models providing us with a simple output and granting us that by applying very simple decision rules to this output we can easily determine a state of a company. Such simplicity is mainly assured by the fact that we often prefer models which express the fact of possible financial distress of a company in the form of a single number - probability. The probability can be then interpreted as our believe that a company will encounter some kind of financial distress in the near future or, if we have a stable model, even in more distant future. The most common decision rule applied in this case is to identify a company as being in financial distress if this probability is greater or equal to 0.5 which is consistent with construction of a so called Bayesian classifier (James et al., 2013). This simple decision rule can be modified based on our preference, i.e. we can be more strict and lower the threshold below 0.5 or we can be benevolent and relax the threshold above 0.5. We can also identify threshold giving us the best classification ability of the model in hand.

The second component of interpretability is the possibility to identify the most influential predictors in the model which is closely connected to insight how changes in predictors can affect the output – probability of financial distress.

The last of our criteria, a possibility to incorporate to expert knowledge easily, can be met in different ways. We can utilize expert knowledge in modifying the default decision rules implemented in application. Assuming that all models implemented in our application output for a company its probability of being in distress, we can change the corresponding threshold. Moreover, the probabilistic character of the models allows us to combine our expert knowledge with the output of the models via the Bayes rule.

Following the above mentioned criteria, we decided to implement models based on linear and quadratic discriminant analysis, binary logistic regression, decision trees and random forest in our application. As a result we ended up with models having probabilistic character, straightforward interpretation and identification of the most influential variables. The data sets we used for model fitting were extracted originally for the paper (Boďa and Úradníček 2016b) from the data base purchased from the leading Slovak corporate analytical agency CRIF – Slovak Credit Bureau, s.r.o, consisting of various financial indicators and covering economic activities 1110 – 96060 according to SK NACE classification. More details about individual models can be found in (Kráľ et al., 2016). These models were also complemented by models published in (Boďa and Úradníček 2016b). Because the included models are based on methods with various requirements on data, we can see them as complementary and we can expect that our application could provide us with reliable and useful results even in cases where for some methods their basic assumptions would not be met. For simplicity, we restricted ourselves to a quite limited possibility to mix results of our models with some kind of expert knowledge. A user is able to modify the results of a model by adding, for a company, expert information about probability of being in financial distress and her/his believe that the model provides us with correct results. All these pieces of information are used to modify the probability of being in financial distress using the Bayes rule.

5. Conclusion

The main goal of our paper was to propose application providing a supervised corporate financial distress prediction model for SMEs. This goal was achieved as it was described in individual chapters. In chapter 2 we characterized the basic requirements on an application for financial distress modelling in case of SMEs. A user graphic interface was designed in order to provide high user experience and usability, e.g. interpretation of results is also included in the application. In chapter 3 we describe our application concept and solutions. It was designed in Shiny, a web application framework for R. This application was developed to run on commonly used technologies available for Slovak SMEs. We also developed offline version using MS Excel and R. In chapter 4 we explain the underlying statistical and data mining models and data sets used in our application. Finally, our application is available on the Internet for free.

In the future, we plan to:

- implement custom models including evaluation of prediction capability (using sample dataset),
- improve the user graphic interface in accordance with the user feedback,
- use the created tool to analyze the data available for Slovak companies to stratify them according to various criteria like sector or size.

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