Prediction of Penalties or Compensation Payments in Companies

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Corporate misconduct is a huge and widespread problem in the economy. Many companies make mistakes that result in them having to pay penalties or compensation to other businesses. Some of these cases are so serious that they take a toll on a company's financial condition. Several algorithms were to create and evaluate which can predict whether a company will have to pay a penalty and to discover what financial indicators may signal it.

Keywords: machine learning ; supervised learning ; classification ; corporate finance ; financial analysis ; financial indicators

1. Introduction

The assessment of activities in an enterprise is especially important, not only from the point of view of management but also counterparties or investors ready to invest their capital as well as other interdependent companies. Before deciding to grant a loan, many financial institutions, such as banks, are obliged to confirm the credibility of both individual and corporate customers. To support the analysis of company activities, advanced credit scoring algorithms are created. Their main objective is to streamline the evaluation process and minimize potential losses for business entities resulting from erroneous and costly decisions.

The evaluation of companies has been an important and widely studied topic for decades. A vast number of algorithms have been proposed (Beaver 1966; Altman 1968; Ohlson 1980; Zmijewski 1984; Betz et al. 2014; Mselmi et al. 2017; Pisula 2017; Shrivastav and Ramudu 2020). Nowadays, given the recent growth of big data, the most popular method is the implementation of machine learning techniques (Barboza et al. 2017; Le and Viviani 2018; Petropoulos et al. 2020; Jabeur et al. 2021; Pham and Ho 2021). In creating evaluating algorithms, it is also important to discover the reasons why one company is riskier than another and which variables have an impact on the final prediction results. Using advanced machine learning methods, it is difficult to obtain such information directly. Model explainability is a significant aspect of modelling. Many researchers focus only on the effectiveness of models, not their explainability. This approach makes the models more effective, but not easily interpretable.

Companies are evaluated in many ways, but most often this is through the analysis of the probability of events such as bankruptcy or losses (Jabeur et al. 2021; Pham and Ho 2021; Pisula 2017), which has been proven in the literature. The main purpose was to present an original solution for the evaluation of companies in terms of predicting a negative event—the payment of penalties or compensation. An in-depth analysis of the methods used to assess companies led to the development of the following hypothesis: the values of financial indicators signal, one year in advance, the occurrence of a negative event in the form of penalties or compensation, which is reflected in the financial situation of the business entity. Financial problems may translate into delays in the delivery of products and services, which in turn leads to sanctions. For example, in 2018 and 2019, the Polish company Elektrobudowa SA had to pay large penalties and compensation to another Polish company because of delays in the fulfilment of a contract. Consequently, this was one of the factors that contributed to the drop in the company's financial indicators and its financial collapse, which eventually led to its bankruptcy[1]. To verify this hypothesis, machine learning methods were used. The problem under investigation is related to classification and thus supervised learning methods were implemented. Another goal was to propose a solution to point out financial indicators which signal the occurrence of an analyzed negative event. The final results could support firms in decision-making processes.

2. Current Views

Methods for evaluating the probability of entities experiencing a negative occurrence have already appeared in the literature in the twentieth century. One of the first models, which is still used, was created by Altman, and is known as the

Z-score (Altman 1968). It was created using discriminant analysis, and nowadays it is used to predict corporate bankruptcy. Out of the initial twenty-two variables, five were selected for its construction (Altman 1968). The model is constantly in development and is used to predict the insolvency of companies. Almamy et al. (2016) used the Altman model to estimate the probability of such an event among British companies during the financial crisis. Despite the passage of years, it has been proven to still be precise. The Altman model encouraged other researchers to raise the issue of evaluating selected aspects of business activities. Over time, more and more advanced analytical methods were developed. This in turn, attracted more interest in the use of algorithms to assess entities.

In the twenty-first century, machine learning has played an increasingly important role in the construction of such algorithms. Colloquially, machine learning is defined as the ability of machines to learn without being programmed directly. This definition was coined by Arthur Samuel in 1959 (Awad and Khanna 2015). In the case of evaluation algorithms, they are based on a branch of machine learning known as supervised learning, which is similar to learning with the help of a teacher. This method consists of the computer model learning how to assign labels to input data that contain labels previously classified by humans (Chollet 2018). However, this does not exclude the use of other methods in scoring algorithms, such as unsupervised learning. The main purpose of unsupervised learning is to discover dependencies and patterns in data (Chollet 2018). Such methods are the basis for the segmentation and construction of recommendation systems. An example of the use of unsupervised learning methods in the assessment of taxpayers is a publication by Colombian researchers (de Roux et al. 2018). They analyzed the declarations of the Urban Delineation tax in Bogota to detect under-reporting taxpayers and based their calculations on a sample of 1367 tax declarations. They divided them into smaller groups using a spectral clustering technique. Then, they marked the declarations that stood out from other declarations in each of the created clusters. Finally, they submitted the selected declarations for expert verification (in-depth analysis).

Among supervised learning methods, a very popular trend in entity evaluation models is the use of the logistic regression (Barboza et al. 2017; Mselmi et al. 2017; Le and Viviani 2018; Zhou 2013; Zhao et al. 2009; Zizi et al. 2020) and support vector machine (Barboza et al. 2017; Geng et al. 2015; Harris 2015; Mselmi et al. 2017; Xia et al. 2018; Zhou 2013; Shrivastav and Ramudu 2020) models. Additionally, neural networks are also used. Tsai and Wu (Tsai and Wu 2008) followed this path in their research. They used neural networks to predict bankruptcy and evaluate creditworthiness using credit data from three countries: Germany, Japan and Australia. Neural networks also appeared in (Zhou 2013), except that the focus was on American (years 1981–2009) and Japanese (years 1989–2009) non-financial companies. In recent years, however, there has been an increase in the use of ensemble classifiers, such as random forests (Ala'raj and Abbod 2016; Barboza et al. 2017), as well as boosting-based methods, such as gradient boosting (Tian et al. 2020; Pham and Ho 2021), adaptive boosting—AdaBoost (Sun et al. 2020; Marqués et al. 2012; Pham and Ho 2021), extreme gradient boosting—XGBoost (Chang et al. 2018; Xia et al. 2018), or the increasingly popular categorical boosting—CatBoost (Jabeur et al. 2021). To construct the abovementioned methods, several weaker classifiers are combined. As a result, the most powerful classifier is created, which, by definition, increases accuracy (Bequé and Lessmann 2017). Similar methods have been used to assess both types of entities—companies and individuals. In both cases, the effectiveness of the models was satisfactory. Regarding the increasing attention on the assessment of companies, advanced machine learning methods have recently grown in importance.

In the literature, the use of datasets from different parts of the world can be observed, which shows that this topic is a global one. Pisula (2017) used and compared different ensemble classifiers to assess the phenomenon of production companies going bankrupt in a Polish region, based on a sample of 144 records. In his work (Harris 2015), Harris decided to compare the results of machine learning methods using two historical credit scoring datasets. In both cases, the information concerned credit applicants with and without creditworthiness. The researchers used a sample of 1000 observations from Germany with 20 variables and a credit union dataset from Barbados with 21,620 observations and 20 variables. In their empirical studies, Spanish researchers (Marqués et al. 2012) used six datasets. In a similar way to the aforementioned Tsai and Wu, they used credit datasets from Germany, Japan and Australia and also supplemented their calculations with information from the United States, Iran and Poland.

The common denominator of the analyzed publications is the use of financial indicators to predict the occurrence of negative events in companies (Sahin et al. 2013; Pham and Ho 2021; Patel and Prajapati 2018; Park et al. 2021; Monedero et al. 2012; Harris 2015; Zizi et al. 2021). Individual customer scoring was instead built based on information about a person's life, such as their gender, marital status and location, etc.

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