With the 2008 global financial crisis, there has been an increased number of corporate bankruptcies at a global level, becoming its prediction in one of the key tools in financial decision-making and the main driver for credit risk. Understanding and predicting company bankruptcy has been a widely studied topic, due to the importance for many institutions to identify key factors of a firm's repayment probability. From the first qualitative models back in 1800 from the rating agencies, there has been a progressive development of ever-evolving models.

As a result, bankruptcy prediction models research is gaining primary attention not only from the academia also by creditors, regulators and investors all over the globe. The first univariate models (Beaver, 1966) allowed to start using quantitative measurements to compare a company with itself through time, and with others of the same industry. This concept continued its sophistication towards multivariate discriminant or logit models (Altman, 1968) where 5 strictly financial variables were used to determine the probability of default, over a 66 companies database, but with such good results that this method and its variants are still a reference today. Next, structural models built upon Merton's proposals (Merton, 1974) appeared which are still in use, followed mainly by accurate and practically acceptable blended models called Z-Metrics (Altman et al., 2010) mainly used today together with classical approaches.

Over these years, models based in varying algorithms have been proposed, seeking to improve accuracy, the ability to foresee bankruptcy with enough anticipation, or stability in time. The main limitation of the initial models is the use of limited number and variety of variables, which could be enhanced with macroeconomic indicators, or non-financial data such as company performance data coming from the media and social networks. However, classical models are difficult to be extended with more variables and/or more complex relationships among them. To tackle these limitations, machine learning algorithms have been extensively analysed with plenty of different datasets, based on big data and/or non-traditional metrics (invoice analysis, payable history, social media data, attention to the news in media (FRISK Scoring System 2017')) and novel artificial intelligence-based techniques (Zheng and Yanhui (2007), Sun and Li (2012), Iturriaga and Sanz (2015), Barboza et al. (2017), Mselmi et al. (2017), Charalambakis (2017), Zelenkov et al. (2017), Qu et al. (2019), Le et al. (2019), Huang and Yen (2019)) such as Support Vector Machine (SVM), genetic algorithms, neural networks among others. These approaches have shown better results in terms of accuracy as compared with traditional discriminant or logistic regression models up to 10% improvement (Barboza et al., 2017). However, they have still considered ‘exotic’ approaches and their use still limited because of the lack of trust in ‘black box’ solutions (Altman, 2018). Precisely, to shed light into these ‘black boxes’ and, thus to make it possible to understand the rationale behind the results of those algorithms the eXplainable Artificial Intelligence (XAI) literature provides several techniques for that (Friedman (2001), Ribeiro et al. (2016), Apley and Zhu (2016), Lundberg and Lee (2017)). Some of these techniques have been applied to a similar case of bank distress to understand, not only the distress predictions themselves but also how the variables in the model play a role in the distress probability (Suss and Treitel (2019), Joseph (2019)).
Many studies have been focused on investigating AI models for corporate bankruptcy forecasting, however, few of them are offering explanations or trust behind those AI models or “black boxes”. Most of the studies have been based on financial data source published by third party such as data aggregators and requires much of data engineering before it can be used to train the model. Financial performance information available in structured and digital format such as XBRL can bring additional value in terms of providing good quality, comparable ready to use data. XBRL reports submitted in fulfilment of reporting obligations by the companies enhances the trust worthiness of data source.t. Our study introduces XAI models for corporate bankruptcy forecasting using more than 10 years of open data in XBRL format, concretely financial reports collected by the Spanish and Exchange Commission (CNMV) for Spanish listed companies and solvency reports. The objective of this study is twofold: 1) to construct an Explainable AI model with high transparency and trust capacity for bankruptcy prediction 2) to demonstrate the use of public XBRL filings as an efficient data source prediction. These findings are vital for driving greater transparency and trust on financial sustainability, as investors, policymakers, auditors and stakeholders of this market are looking for more accurate information about the chances of corporate bankruptcy.

References


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1 FRISK Scoring System 2017 http://www.creditriskmonitor.com