



MACHINE LEARNING MODELS FOR PREDICTING FINANCIAL DISTRESS

FİNANSAL KESİMİN GİDERİLMESİ İÇİN MAKİNA ÖĞRENME MODELLERİ

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Abstract

Difficulties in business liquidity and the consequent financial distress are usually an extremely costly and disruptive event. For this reason, this study attempts to provide a set of features that can help us predict the sustainability of a company. This study involves the building of a financial prediction system which after training on a set of companies' historical final accounts (ranging over a period of 3 to 5 years), the models built are then capable of evaluating the nature of another companies' financial data. Consequently, the company's financial position in the following financial period is predicted (whether a company is active or failing). After predicting firm financial health, the outputs of the Decision Tree, the Naïve Bayes classifier and the Artificial Neural Net are evaluated to see which algorithm is the most accurate in finding a set of features for this problem. The research findings over a real-life datasets confirmed the strength and ability of the proposed model in predicting eminent business failure. Moreover, Base-year and year-over-year comparison both produce good results, therefore both techniques can be used for financial analysis. The optimal feature set included ratios from all categories, meaning, company profitability, liquidity, leverage, management efficiency, industry type and company size are all crucial to distress prediction. The prototype implemented in this study attempts to answer open questions, such as whether ML techniques are capable of predicting financial distress and whether financial ratios and industry variables are indicative of financial sustainability.

Keywords: Financial Distress, Financial Ratios, Set of Final Accounts, Decision Trees, Naïve Bayes, Artificial Neural Networks, Base-Year Comparison, Previous-Year Comparison, Accuracy.

JEL Classification: M40, C80.

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Öz

İş likiditesindeki zorluklar ve bunun sonucunda ortaya çıkan finansal sıkıntı genellikle aşırı maliyetli ve yıkıcı bir olaydır. Bu nedenle, bu çalışma bir şirketin sürdürülebilirliğini tahmin etmemize yardımcı olabilecek bir dizi özellik sunmaya çalışmaktadır. Bu çalışma, bir dizi şirketin tarihi kesin hesapları (3 ile 5 yıl arasında değişen) üzerinde eğitim aldıktan sonra, diğer modellerin finansal verilerinin niteliğini değerlendirebilecek bir finansal tahmin sisteminin oluşturulmasını içermektedir. Sonuç olarak, aşağıdaki finansal dönemde şirketin finansal durumu tahmin edilir (firmanın aktif olup olmadığı). Firmanın mali sağlığı tahmin edildikten sonra, Karar Ağacı, Naïve Bayes sınıflandırıcı ve Yapay Sinirsel Ağ'ın çıktıları, bu problem için bir dizi özellik bulmakta en doğru algoritmanın hangileri olduğunu görmek için değerlendirilir. Gerçek hayattaki veri kümeleri üzerindeki araştırma bulguları, önerilen modelin seçkin iş başarısızlığını tahmin etmedeki gücünü ve kabiliyetini doğrulamıştır. Ayrıca, baz yıl ve yıldan yıla kıyaslama hem iyi sonuçlar verir, hem de finansal analiz için her iki teknik de kullanılabilir. Optimal özellik seti, tüm kategorilerden alınan oranları, anlamı, şirket karlılığını, likiditesini, kaldıracı, yönetim verimliliğini, endüstri tipini ve şirket büyüklüğünü, zorlama öngörüsü için çok önemlidir. Bu çalışmada uygulanan prototip, ML tekniklerinin finansal sıkıntıyı tahmin edip edemeyeceği ve finansal oranların ve sektör değişkenlerinin finansal sürdürülebilirliğin göstergesi olup olmadığı gibi açık soruları yanıtlamaya çalışmaktadır.

Anahtar Kelimeler: Finansal Sıkıntı, Mali Oranlar, Kesin Hesaplar, Karar Ağaçları, Naïve Bayes, Yapay Sinir Ağları, Baz Yıl Karşılaştırması, Önceki Yıl Karşılaştırması, Doğruluk.

JEL Sınıflaması: M40, C80.

I. Introduction

Due to changes in markets and the economy in itself, financial distress prediction is of major importance. Lenders and shareholders, lawmakers, central banks, auditors and managers value timely information regarding a firm's financial health. The ability to predict financial distress is significant to the companies themselves, to increase their potential, maintain and/or increase the number of current investors and to maximise the stock value.

From numerous research studies, it has been established that severe financial distress undermines the financial sustainability of enterprises (Hu and Sathye, 2015; Mahama, 2015; Balcaen and Ooghe, 2006). The detection of corporate failure can promote the financial sustainability of enterprises. Several definitions have been attributed to financially unstable companies, such as corporate or business failure, illiquidity, insolvency or bankruptcy. Financially distressed firms are companies that are experiencing difficulty in coping with their daily management tasks. In the worst case scenario, these companies are prone to take bankruptcy measures (Baharin and Sentosa, 2013). If an algorithm can gain the same experience from past data to improve the prediction for the future, it can result in businesses identifying red flags early enough, or at least just in time, to take appropriate remedial action. Studies regarding corporate failure prediction generally aim to determine one or several variables that make it possible to discriminate between failing and healthy businesses (Refait, 2004). The prediction largely focuses on financial data (Altman, 1968; Bunn and Redwood, 2003). The pioneers, Beaver (1966) and Altman (1968)

used univariate and linear discriminant analyses respectively. More recent studies have used different statistical techniques such as Logit (Ohlson, 1980) and Probit models (Zmijewski, 1984). Statistical methods, however, depend on restrictive hypotheses. In the nineties, thanks to the developments in computer sciences, some authors resorted to Machine Learning algorithms (ML) such as neural networks (Odom and Sharda, 1990; Altman et al., 1994; Platt et al., 1999; Hu and Tseng, 2010; Kim and Kang, 2010) to predict financial distress.

The approach taken for the current study involves the implementation of three Machine Learning techniques, namely Artificial Neural Networks, Naïve Bayes and Decision Trees. These techniques will then be used in the attempt to predict the sustainability of a firm through the provision of a set of features from firms' accounting. The models created in this study use the differences between calculated ratios (their evolution between periods), rather than the raw ratios themselves as it is usually the case for prediction models. Moreover, in order to eliminate data overfitting, the evaluation is performed on sets of data which are not used for training. The scope of this study is to build a financial prediction system which, after training on a set of companies' historical final accounts (ranging over a period of 3 to 5 years), applies the generated models to evaluate the nature of another companies' financial data. This paper treats this challenge as a classification problem rather than a regression problem. This means that the actual values of the final accounts will not be predicted, but rather attempts to determine whether a company is active or failing in the following financial period.

The three machine learning algorithms were trained and tested using the SEC EDGAR dataset of 1,848 US companies. The algorithms were compared to determine which algorithm is the most viable to predict corporate distress. In addition to financial ratios, information such as activity sector, company size, fraud detection and industry seasonality were integrated into the models.

The rest of the report is organised as follows. In the next section, we develop the theoretical framework underpinning our study: the business failure prediction models and refinements. In section 3, we discuss the data and the methodology employed, while in section 4 we present the results from our analysis. We conclude with a discussion of the findings.

2. Literature review

Corporate failure prediction models can be classified in two: statistical-based or algorithm-driven using Machine Learning (ML) techniques. As mentioned in the introduction to this paper, pioneers of bankruptcy prediction used statistical methods (Beaver, 1966; Altman, 1968; Ohlson, 1980; Zmijewski, 1984) to discriminate between failing and healthy businesses (Refait, 2004). Nevertheless, and although statistical methods are still used, in the nineties, some authors adopted Artificial Intelligence algorithms (or Machine Learning) techniques such as neural networks (Odom and Sharda, 1990; Altman et al., 1994; Hu et al., 1999; Platt et al., 1999; Hu and Tseng, 2010; Kim and Kang, 2010) for company failure prediction.

Machine Learning (ML) is “the science of getting computers to act without being programmed”. This process attempts to detect meaningful patterns between the inputs and autonomously build a model that can describe these patterns without human intervention. ML tools are concerned with providing programs with the ability to learn and adapt to different patterns. Following the footsteps of intelligent beings, many skills are obtained or refined through learning at different instances, as opposed to following explicit instructions (Shalev-Shwartz and Ben-David, 2014). ML may also be defined as the complex computation process of automatic pattern recognition and intelligent decision-making based on a training sample data (Dua and Du, 2016). Consequently, ML techniques have to be evaluated empirically because their performance are heavily dependent on the training dataset. The features selected for modelling a problem play a crucial role in the prediction. There are many aspects to consider when discussing financial distress. The prediction largely focuses on financial data (Altman, 1968; Bunn and Redwood, 2003). Financial ratios can be classified as asset management ratios, leverage ratios (assessing the ability of a firm to meet financial responsibilities), liquidity ratios (assessing the ability of a firm to meet its debt responsibilities), and profitability ratios.

Company Profitability

Company profitability ratios use financial ratios to evaluate a firm’s ability to generate income during a financial period. Overall, higher profitability ratios are indicative of a more profitable company. The following profitability ratios are considered in this study: Gross Profit rate, Return on Sales, Return on Assets, return on stock-holders’ Equity, Turnover Ratio and Return on Capital Employed (ROCE) ratio.

Company Liquidity

Company Liquidity ratios use financial ratios to evaluate the ability of a company to pay off debts when due. Generally, the higher the liquidity ratios, the higher the margin of safety the company possesses to meet its Current Liabilities. The following liquidity ratios are considered in this study: Current ratio, Acid Test ratio, Cash ratio and Working Capital rule.

Company Management Efficiency

Company Management Efficiency ratios use financial ratios to measure how well companies utilize their assets to generate earnings. These ratios are either used by management to help improve the company, or by investors and creditors to observe the profitability of the firm. The following efficiency ratios are considered in this study: Days Sales Outstanding, Inventory Turnover, Days Inventory Outstanding and Operating Cycle.

Company Leverage

Company Leverage ratios use financial ratios to look at how much capital comes in the form of debt, such as loans; and assess the ability of a company to meet the corresponding financial dues. More often than not, the more debt a company has, the riskier its stock is, since debt-holders have first claim to a company's assets. The following efficiency ratios are considered in this study: Debt Ratio, Equity ratio, Debt-Equity ratio, Times Interest Earned and Retained Earnings to Total Assets. In addition to financial ratios, this study takes account of the following features:

Industrial Sector

The industrial sector refers to the industry which the company operates in: it has been shown in literature (Sayari and Mugan, 2017), that the industry a particular company operates in plays a significant role in the prediction of the firm's sustainability. The following sectors have been considered in this study: agriculture, mining, construction, manufacturing, transportation, wholesale, retail, finance, services, public administration and others.

Company size

Company size: All companies included in the datasets are Public Limited Companies (PLCs), i.e., companies whose stock is traded on a stock exchange and can be bought and sold by anyone and where owners have a limited liability. Furthermore, these companies may then be categorized further into small, medium and large markets. Adopting the definition provided by the National Center for the Middle Market (2017), a company forms part of the median market if its revenues range from \$10 million to \$1 billion. As may be assumed, companies having less than \$10 million in revenue, are classified as part of the smaller markets. Similarly, firms generating more than \$1 billion in revenue, form part of the larger market.

Financial statements — Fraudulent Activity red flags

Literature shows that fraud cases have led the way for bankrupting firms (Mahama, 2015; Peng et al., 2011). Financial statement fraud red flags provide a general analysis of the warning signs of fraud. They do not necessarily indicate a certain occurrence of fraud, but merely warn that additional research must be conducted to determine the validity of the financial statements. On this account, the following checks have been included in the implementation for these cases:

- A company increasing its earnings but has declining revenues and increasing costs; sales are much easier to manipulate than cash flow but the two should be quite consistent over time;
- Unusual levels of returns suggest obsolete inventory items for which the firm is recording fictitious future sales;

- Increased or excessive past due accounts;
- Unexpected overdrafts or declines in cash balance;
- Increase in purchasing inventory but no increase in sales;
- Recurring negative cash flows while reporting earnings or earnings growth.

Finally, financial ratios on their own give little or no meaningful information but when used in conjunction with trend analysis, can prove to be insightful (Koonce and Lipe, 2010). The following two comparison techniques were implemented to improve the patterns found in the data:

Year-Over-Year Comparison

Year-over-year (YOY) is a method of assessing two or more measured events to analyze the results of a time period with those of the previous time period on an annualized basis. In this case, YOY will be used to determine whether a firm's financial status is improving or deteriorating. YOY comparisons are popular when analyzing a company's performance because they help alleviate seasonality, a determinant that can influence most businesses. Sales, profits and other financial metrics change during different periods of the year due to the fact most lines of business have peak and low-demand seasons.

Base-Year Analysis

Base-year analysis is an evaluation of economic trends in relation to a specific base year, thus allowing for a comparison between current performance and historical performance. This analysis expresses economic measures in base-year values to eliminate the effects of inflation. Base-year analysis of a company's financial statements is important to be able to determine whether a company is growing or failing. If, for instance, a firm is profitable every year, the fact that its expenses are increasing drastically year-over-year may go unnoticed. By comparing financial metrics to those of a base year, the larger picture can be analysed. It is important to note that negative values are accepted by this technique and thus check whether the company is performing well or under-performing in the subsequent years. Three machine learning models, namely Artificial Neural Networks, Naïve Bayes and Decision Trees, were tested using the metrics described previously.

3. Data and methodology

3.3. Data

The dataset used in this study is the SEC EDGAR (2017) dataset. The SEC's EDGAR (2017) database provides free public access to corporate information pertaining to the USA. It contains quarterly financial data spanning over a number of years for each company. For each company, the EDGAR dataset classifies the companies as either Failed or Active.

Data falling within scope consists of records containing at least three years of financial data between 1996 and 2016. Our final sample is made of 1,848 US companies (461 active and 1,387 failed). The 1,848 useful records are divided into the training and testing datasets for evaluation purposes. The training dataset contains 369 active and 1,110 bankrupt companies. Similarly, the testing dataset contains 92 active and 277 failed companies.

Data regarding financial ratios, company industry and size were obtained or calculated the SEC's EDGAR database and are used in the ML models.

3.2. Methodology

Russell and Norving (1995) define Neural Networks as the components of dynamic systems, which process experimental data and transfer the knowledge or the hidden laws into the network structure. In fact, the general principles are obtained through calculations on numerical data and samples. Artificial Neural Networks (ANNs) have the ability of extracting the relationship between data analysis and estimations of their applications, eventually capable of applying it to new data. Hence, the main purpose of ANNs is to predict of nonlinear functions.

Naïve Bayes is a categorisation technique based on Bayes' Theorem. 18th-century British mathematician Thomas Bayes devised the formula for determining the conditional probability. The theorem provides a way to revise existing predictions or theories given new or additional evidence — with the added assumption of independence among predictors. In simple terms, a Naïve Bayes classifier assumes that the presence of a particular input is completely unrelated to the presence of any other feature. Even if in real life these features rely upon each other or upon the presence of the other characteristics, all of these components individually contribute to the probability of an event being true; hence known as Naïve (Berend and Kontorovich, 2015).

Decision trees are simple predictive models which map input features to a target output using conditional rules. A decision tree takes as input a situation described by a set of attributes, and outputs a probabilistic decision. Each internal node in the tree corresponds to a test of the value of one of the properties, and the branches from the node are labeled with the possible values of the test. Each leaf node in the tree specifies the decision to be returned if that leaf is reached (Shalev-Shwartz and Ben-David, 2014). The tree structure is produced through recursive partitioning. Accord.NET Framework (2017) is a .NET machine learning framework, fully written in C#, which was used for the application of the ML techniques.

4. Results and discussion

The proposed system compares the three machine learning techniques described in the previous section. All three techniques are tested with the same datasets. Each technique uses a history span from three to five years. In order to avoid data over-fitting, training and testing samples from the datasets were ensured to be mutually exclusive.

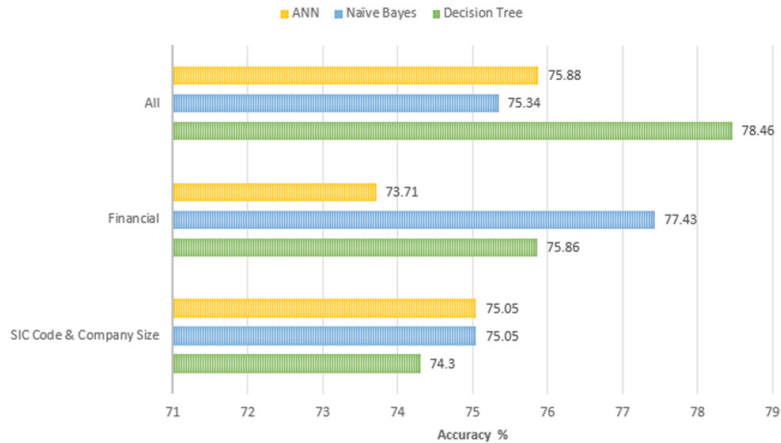
The aim of the study is to identify an effective pattern analysis technique for the prediction of corporate distress. From existing empirical research, base-year and year-over-year analysis were performed on the datasets. Overall performance scores, such as accuracy, help stakeholders to compare the performance of the different classifiers. Consequently, accuracy was chosen as one of the pivotal characteristic on which techniques will be compared. Table 1 shows the accuracy of the techniques when the whole feature set was tested on the algorithms.

Table 1: Accuracy across ML techniques

Technique	Comparison	Accuracy
Decision Tree	YOY	78.46%
	Base-Year	74.15%
Naïve Bayes	YOY	75.13%
	Base-Year	74.19%
ANN	YOY	75.88%
	Base-Year	73.66%

Source: Authors' own calculations.

First, we can conclude that the indicators chosen as inputs in the ML techniques were in fact effective in predicting a firm's status because the accuracy rate is comparable to previous studies. The results in table 1 show that despite each technique uses different model representations to classify previously unseen company records, the resulting values are very close to each other. A particularly interesting result which can be seen from above is that the base-year and the year-over-year comparison both produce encouraging results. Zheng and Yanhui (2007) used decision trees for financial distress prediction in their study. Their study focused on 48 failed and active Chinese listed companies in the period 2003 to 2005. Their results (Zheng and Yanhui, 2007) showed that decision trees were a valid model to predict financial distress in China, with an 80% probability of correct prediction. This shows that this study has quite a comparable result when compared to the literature, while also taking into account the economical factor which weighs in on a company's performance. Figure 1 compares the accuracy of the three models, with all the inputs, with financial inputs only and with industry-related factors only.

Figure 1: Accuracy of the ML models (YOY analyses)

Source: Authors' own calculations.

The combination of unrelated aspects of a company actually perform better than just focusing on one aspect. The results have shown that most techniques and analyses have improved prediction results when including financial factors along other indicators (industry-related factors). The exception is the Naïve Bayes classifier, which identified YOY financial values as the most indicative. This result reflects the results obtained by Hernandez Tinoco et al. (2015), who explored the role of accounting, market and macroeconomic variables with respect to financial distress predictions. Hernandez Tinoco et al. (2015) reported that model performance statistics show a substantial increase in the goodness-of-fit of the model taking into consideration all the variables, as opposed to the finance only models and the industry niche only model. Results have also shown that the Decision Tree outperforms the other two techniques, especially in previous-year comparison. This result is also confirmed by literature (Chen, 2011; Olson et al., 2012). One issue to note is that the nature of the model created in this study that is dealing with the differences between calculated ratios, rather than the raw ratios themselves, has provided reliable results with an acceptable accuracy rate.

5. Conclusion

Companies have to terminate operations for diverse reasons. The financial failure of a company affects various participants such as investors, owners, employees, creditors, clients and even the relevant authorities. Within this context, predicting financial failure attracts the interest of researchers. This study uses Decision Trees, Naïve Bayes classifier and an Artificial Neural Network. These techniques attempt to predict the status of companies as failed or active based on their financial capabilities, as well as a number of other industry-related variables. Thus,

the output of the classification process consists of two classes: Active or Failed. Two methods of pattern analysis were implemented, year-over-year and base-year comparisons, and both of which provided encouraging results.

The input vector set for this study consisted of 96 indicators, dealing with financial ratios indicative of company profitability, liquidity, management efficiency and leverage. The input vector also includes a number of fraud checks, as well as the industry code and company size. Results have shown that the optimal subset of indicators are made up of features from all categories. Results show that the proposed models are able to predict firm sustainability, at a comparable level with literature. One important result which emerged was that the industry a company forms part of highly affects the financial stability of the firm. Therefore, whilst some markets may be performing well and boosting company growth, other industries may be the cause of company status deterioration. The results also showed that most techniques and analysis have improved prediction results when coupling financial factors to other indicators, such as industry-related factors.

Of the methods that were tested, the Decision Tree was shown to outperform the other two ML Techniques. Further research is required to determine if a meta-predictor that combines the three methods could produce improved results. During the study, some limitations were identified which may have affected the final outcome. Even though an attempt was made at understanding the relationships between indicators in the input vector, further study is required to determine how the different features affect the overall outcome. This can, however, be addressed by adding a metaheuristic search. This involves an iterative generation process which guides a partial search algorithm by intelligently coupling different concepts for exploring and exploiting the search space (Zäpfel and Braune, 2010). This can then be used to find an optimal feature subset. These changes would be the basis for predicting the degree to which a company is failing. This would be quite advantageous as it would indicate the extent firms have to go to improve their financial status.

Future investigations will also include an assessment for optimal categorisation values, such that a better representation of the categories that can be obtained. The investigation will follow by evaluating the effect of different types of data records on the generated models, for instance comparing three-year versus four-year financial records. It can be concluded that the results have shown that the proposed decision support system using differences between calculated ratios rather than the raw ratios can become a practical solution for predicting companies' financial stability.

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