

Bankruptcy Prediction through Artificial Intelligence

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INTRODUCTION

Bankruptcy prediction or corporate failure is considered a classic issue in both, academic and business communities. Bankruptcy risk is one of the most important factors (if not the most important one) to be considered when credit requests are screened or even existing debtors are evaluated. On the other hand, all potential stakeholders (shareholders, suppliers, customers, employees, creditors, auditors, etc.) have potential interest to identify if a company is on a trajectory that is tending towards failure. Commercial banks, public accounting firms and other institutional entities (e.g., bond rating agencies) appear to be the primary beneficiaries of accurate bankruptcy prediction, since they can use research results to minimize exposure to potential client failures. In addition to avoiding potentially troubled obligors, the research can also benefit in other ways. It can help in accurately assessing the credit risk of bank loan portfolios. Credit risk has been the subject of much research activity, since the regulators are acknowledging the need and are urging the banks to assess the credit risk in their portfolios. Measuring the credit risk accurately also allows banks to engineer future lending transactions, so as to achieve targeted return/risk characteristics. The other benefit of the prediction of bankruptcies is for accounting firms. If an accounting firm audits a potentially troubled firm, and misses giving a warning signal then it faces costly lawsuits (Atiya, 2001).

A series of techniques have been applied in literature. Econometric / statistical methods have first appeared in literature: In late 1960's (multiple) discriminant analysis (DA) was the dominant method; during the 1980's logistic analysis. In the 1990's artificial intelligence starts appearing in financial literature with neural networks (Odom & Sharda 1990) serving as an alternative to statistical methods demonstrating promising results.

The goal of this chapter is therefore two-fold: First, it intends to give an overview of the artificial intelligence techniques successfully applied to the problem, ranging from the first neural network applications to recent applications of biologically inspired algorithms, such as genetic algorithms. Then, two kernel based methods, namely the Radial Basis Function Neural Networks and the Support Vector Machines are applied to the bankruptcy problem.

BACKGROUND

Early statistical studies in bankruptcy prediction (e.g., Beaver, 1966) adopted a univariate methodology identifying the accounting ratios having the highest classification accuracy in separating failing and non-failing firms. Beaver investigated the predictability of 14 financial ratios. Altman (1968) examined simultaneously a series of financial ratios, enriching the single ratio approaches. A multiple discriminant function was calculated, the so-called Z-score composed of five financial ratios:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_4 + .999X_5, \quad (1)$$

where

X_1 = Working Capital / Total Assets. (Measures liquidity)

X_2 = Retained Earnings / Total Assets. (Measures profitability)

X_3 = Earnings Before Interest and Taxes / Total Assets. (Measures operating efficiency)

X_4 = Market Value of Equity / Book Value of Total Liabilities. (Adds market dimension)

X_5 = Sales / Total Assets. (Standard measure for turnover)

Z-Score model was modified by Altman, Haldeman, and Narayanan (1977). Their ZETA model was composed from seven financial ratios. Since these early studies, a vast range of statistical methodologies have been applied for the purposes of corporate failure prediction including logistic regression (Martin, 1977), logit (Ohlson, 1980), Kolari, Glennon, Shin, and Caputo (2002), probit and maximum likelihood models (Zmijewski, 1984).

Literature review reveals that a series of financial ratios has been examined. Stability indicators, industry-specific indicators, macroeconomic factors, firm's particular features have been examined. However, there is no agreement on the features that carry significant predictive power. According to Courtis (1978) and Dimitras (1995) the applied ratios should adequately cover three fields: profitability, management efficiency, and solvency.

AI FOR BANKRUPTCY PREDICTION

The statistical methods described above have some restrictive assumptions such as linearity, normality and independence among predictor or input variables. Considering that violation of these assumptions for independent variables frequently occurs with financial data (Deakin, 1976) these methods have limitations to obtain effectiveness and validity. Artificial intelligence (AI) methods have been proven to be less vulnerable to these assumptions.

In the following paragraphs we present a brief description of AI techniques employed and a short review of research attempts applying AI techniques and approaches in the bankruptcy prediction problem. Specifically, three types of methods are analyzed: (1) artificial neural networks, (2) approaches based on decision trees, and (3) genetic algorithms.

Artificial Neural Networks

Artificial neural networks (ANNs) are based on the behavior of the biological neurons of the brain and are used to mimic the performance of a system. They consist of a set of elements that start out connected in a random pattern, and, based upon feedback, are modelled into the pattern required to generate the required results. When the problem is bankruptcy prediction, neural networks create a function of the predictors, mapping to a specified outcome; in our case bankruptcy or not.

As ANNs are capable of identifying and representing non-linear relationships in the dataset they were the first AI technique applied in the bankruptcy prediction problem and the most studied one. Odom and Sharda (1990) were the first to use NNs for bankruptcy prediction. They used the five financial ratios used in Altman's Z-score. A series of other applications can be identified where criteria / predictors'

number varied from Altman's original 5 to 41 (Leshno & Spector, 1996). Various ANN based models, with different architectures and training algorithms have been employed. In some applications an extra dimension reduction stage was added, such as Principal Components Analysis (Ravi & Pramodh, in press) in order to reduce the dimensionality of the input feature vector of the ANNs.

The creation of additional indicators or features has been also tested. Atiya (2001) developed and employed novel indicators for his ANN. Lam (2004) followed a different approach incorporating macroeconomic variables as well as financial ones. Recently, ensemble neural networks classifiers that combine a number of single NN classifiers into one multiple classification system have gained ground (Tsai & Wu, 2008).

Decision Trees

Decision tree induction is a technique which is widely used for predictive/classification tasks. Decision trees employ mathematical formulations in order to detect the most important predictors and create a tree structure for deriving the classification decisions. An advantage of the decision trees is their ability to provide interpretation for their automated decisions. Still, their linearity limits their performance.

Marais, Patel, and Wolfson (1984) proposed recursive partitioning algorithm and bootstrapping techniques for inducing the decision tree. Frydman, Altman, and Kao (1985) employed recursive partitioning and compared decision trees to the DA, which was found inferior.

Genetic Algorithms

More recently Genetic Algorithms (GAs) have been applied in the bankruptcy prediction problem. GAs are stochastic search techniques that can search large and complicating spaces and mimic the ideas of natural evolution and the survival of the fittest.

As GAs are effective in searching large spaces, they are particularly effective for multi-parameter optimisation problems under several constraints. For this reason, in the bankruptcy prediction problem, they have been mainly applied for optimisation of the classification process either by selecting the most discriminant financial ratios (Sai, Zhong & Qu, 2007) or by optimising the classifier parameters (Back, Laitinen & Sere, 1996). Shin (2002) also uses GAs for the extraction of classification rules.

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