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Predicting corporate financial distress based on integration of support vector machine and logistic regression

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Abstract

The support vector machine (SVM) has been applied to the problem of bankruptcy prediction, and proved to be superior to competing methods such as the neural network, the linear multiple discriminant approaches and logistic regression. However, the conventional SVM employs the structural risk minimization principle, thus empirical risk of misclassification may be high, especially when a point to be classified is close to the hyperplane. This paper develops an integrated binary discriminant rule (IBDR) for corporate financial distress prediction. The described approach decreases the empirical risk of SVM outputs by interpreting and modifying the outputs of the SVM classifiers according to the result of logistic regression analysis. That is, depending on the vector's relative distance from the hyperplane, if result of logistic regression supports the output of the SVM classifier with a high probability, then IBDR will accept the output of the SVM classifier; otherwise, IBDR will modify the output of the SVM classifier. Our experimentation results demonstrate that IBDR outperforms the conventional SVM.
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1. Introduction

Corporate financial distress forecasting is an important and widely studied topic since it has significant impact on lending decisions and profitability of financial institutions. Therefore, accurate bankruptcy prediction models are of critical importance to various stakeholders (i.e., management, investors, employees, shareholders and other interested parties) as it provides them with timely warnings. From a managerial perspective, financial failure forecasting tools allow to take timely strategic actions such that financial distress can be avoided. For stakeholders, efficient and automated credit rating tools allow to detect clients that are to default their obligations at an early stage.

Financial failure occurs when the firm has chronic and serious losses and/or when the firm becomes insolvent with liabilities that are disproportionate to assets. Widely identified causes and symptoms of financial failure include poor management, autocratic leadership and difficulties in operating successfully in the market. The common assumption underlying bankruptcy prediction is that a firm's financial statements appropriately reflect all these characteristics. Several classification techniques have been suggested to predict financial distress using ratios and data originating from these statements, e.g., univariate approaches (Beaver, 1966), multivariate approaches, linear multiple discriminant approaches (MDA) (Altman, 1968; Altman, Edward, Haldeman, & Narayanan, 1977), multiple regression (Meyer & Pifer, 1970), and logistic regression (Dimitras, Zanakis, & Zopounidis, 1996; Ohlson, 1980; Pantalone & Platt, 1987). However strict assumptions of traditional statistics such as the linearity, normality, independence among predictor variables and pre-existing functional form relating the criterion variable and the predictor variable limit application in the real world.

To develop a more accurate and generally applicable prediction approach, data mining and machine learning

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techniques including decision trees, neural networks (NNs), fuzzy logic, genetic algorithm (GA), support vector machine (SVM), etc., have been successfully applied in corporate financial distress forecasting. Developed by Vapnik (1995), SVM is gaining popularity due to many attractive features and excellent generalization performance on a wide range of problems. Also, SVM embodies the structural risk minimization principle (SRM), which has been shown to be superior to traditional empirical risk minimization principle (ERM) employed by conventional neural networks. SRM minimizes an upper bound of generalization error as opposed to ERM that minimizes the error on training data. It has been shown by Min and Lee (2005) that SVM outperforms NNs, MDA and logistic regression in corporate bankruptcy prediction. However, the SRM embodied in SVM implies that the empirical risk of misclassification may be high, especially when a point to be classified is close to the hyperplane.

The purpose of this paper is to develop a new financial distress prediction approach to improve its prediction accuracy. The described approach provides an integrated binary discriminant rule (IBDR) by interpreting and modifying the outputs of the SVM classifiers. Since logistic regression analysis has also been used to investigate the relationship between binary response probability and explanatory variables, it can be integrated into the modifying process to decrease the empirical risk of the SVM outputs. That is, depending on the vector's relative distance from the hyperplane, if result of logistic regression supports the output of the SVM classifier, then IBDR will accept it; otherwise, modify it. The validity of IBDR has been verified by numerical results on several benchmark data sets, and tested on the prediction of financial distress of companies listed in Shanghai Stock Exchange (China) by comparing its accuracy with that of the conventional SVM.

The rest of this paper is organized as follows. The following section presents a brief review of SVM for binary classification. Section 3 describes the proposed IBDR approach. Sections 4 and 5 explain the experimental design and the results of the evaluation experiment. The final section ends the paper with some conclusion remarks.

2. A brief review of SVM for binary classification

In this section, we provide a brief review of SVM for binary classification. More details about SVM can be found in Huang, Nakamoria, and Wang (2005), Min and Lee (2005), and Vapnik (1995).

Given a training set $G = \{\bar{y}_i, \bar{x}_i\}_{i=1}^{N}$ with input vector $\bar{x}_i \in \mathbf{R}^s$ and corresponding binary class labels $\bar{y}_i \in \{-1, 1\}$, the support vector method aims at constructing a classifier of the form:

$$\bar{y}(\bar{x}) = \text{sign}\left[\sum_{i=1}^{N} \alpha_i \bar{y}_i K(\bar{x}_i, \bar{x}) + b\right], \tag{1}$$

where α_i are nonnegative real constants, b is a real constant, $K(\cdot,\cdot)$ is the kernel function that can be specified as linear, polynomial, radial basis function or sigmoid.

The classifier can be constructed as follows. Assume that

$$\begin{aligned} &w^{\mathrm{T}}\varphi(\bar{x}_i) + b \geqslant 1 \quad \text{if } \bar{y}_i = +1, \\ &w^{\mathrm{T}}\varphi(\bar{x}_i) + b \leqslant 1 \quad \text{if } \bar{y}_i = -1, \end{aligned} \tag{2}$$

which is equivalent to

$$\bar{y}_i[w^{\mathrm{T}}\varphi(\bar{x}_i) + b] \geqslant 1, \quad i = 1, \ldots, N, \tag{3}$$

where $\varphi(\cdot)$ is a nonlinear function which maps the input space into a higher dimensional space. However, this function is not explicitly constructed. In order to have the possibility to violate Eq. (3), in case a separating hyperplane in this higher dimensional space does not exist, variables $\xi_i\,(i = 1, \ldots, N)$ are introduced. According to the structural risk minimization principle, the risk bound is minimized by solving the following optimization model:

$$\begin{aligned} &\min_{w,b,\xi_i} \quad J(w, \xi_i) = \frac{1}{2}w^{\mathrm{T}}w + C\sum_{i=1}^{N}\xi_i \\ &\text{s.t.} \quad \bar{y}_i[w^{\mathrm{T}}\varphi(\bar{x}_i) + b] \geqslant 1 - \xi_i, \qquad \xi_i \geqslant 0, \quad i = 1, \ldots, N. \end{aligned} \tag{4}$$

The solution to model (4), (w, b) defines a hyperplane of equation $w^{\mathrm{T}}\bar{x} + b = 0$, and is named as the optimal separating hyperplane (OSH). The parameter C in model (4) is a regularization parameter. If we denote by ω the norm of w, the OSH tends to maximize the minimum distance $1/\omega$ for a small C and minimize the number of misclassified points for a large C. For intermediate values of C, the solution of model (4) trades errors for a larger margin.

By introducing Lagrange multipliers $\alpha_i \geqslant 0$ and $\upsilon_i \geqslant 0$ $(i = 1, \ldots, N)$ associated with the constraints in model (4), solving model (4) is equivalent to determining the saddle point of the Lagrangian function:

$$L = J(w, \xi_i) - \sum_{i=1}^{N} \alpha_i\{\bar{y}_i[w^{\mathrm{T}}\varphi(\bar{x}_i) + b] - 1 + \xi_i\} - \sum_{i=1}^{N} \upsilon_i\xi_i. \tag{5}$$

From the conditions of optimality, we obtain the Karush–Kuhn–Tucker (KKT) system, which leads to the solution of the following quadratic programming (QP) problem:

$$\begin{aligned} &\max_{\alpha_i} \quad Q(\alpha_i) = -\frac{1}{2}\sum_{i,j=1}^{N} \bar{y}_i\bar{y}_j K(\bar{x}_i, \bar{x}_j)\alpha_i\alpha_j + \sum_{i=1}^{N}\alpha_i \\ &\text{s.t.} \quad \sum_{i=1}^{N}\alpha_i\bar{y}_i = 0, \quad 0 \leqslant \alpha_i \leqslant C, \ \ i = 1, \ldots, N. \end{aligned} \tag{6}$$

In problem (6), $K(\bar{x}_i, \bar{x}_j) = \varphi(\bar{x}_i)^{\mathrm{T}}\varphi(\bar{x}_j)$, which is motivated by Mercer's Theorem (Vapnik, 1995). Problem (6) can be efficiently solved using the Lemke complementary pivot algorithm (Lemke, 1965).

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