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Financial distress prediction based on SVM and MDA methods: the case of Chinese listed companies

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Abstract How to accurately predict financial distress is an important issue for enterprise managers, investors, creditors and supervisors. In this paper we develop SVM models (Support Vector Machine) and MDA (Multivariate Discriminant Analysis) models, using Chinese listed companies as our sample. The empirical results show that the prediction ability of SVM models outperforms the MDA models. Additionally, internal governance and external market variables, as well as macroeconomic variables are added as the predictive variables. The results indicate that these variables have theoretical and empirical linkage with the financial distress of Chinese listed companies.

Keywords Financial distress prediction · Support vector machine · Multivariate discriminant analysis · Financial variables · Non-financial variables

1 Introduction

Financial distress is a condition where a company cannot meet or has difficulty paying off financial obligations to its creditors, which may lead to bankruptcy of an enterprise, so accurate financial distress prediction models exert a critical influence on various corporate stakeholders in the process of decision-making. In the study of financial distress prediction, the methodologies and the predictive variables have attracted a lot of attention from scholars and practitioners.

On the one hand, the methodologies can be divided into two categories: parametric models and non-parametric models. Early researches focus on the parametric models (Fitzpatrick 1932; Beaver 1966; Altman 1968; Altman et al. 1977; Ohlson 1980). Multivariate Discriminant Analysis (MDA), LPA, Logistic models are widely used to predict financial distress of an enterprise, and Z score model and Zeta model (Altman 1968; Altman et al. 1977) become the paradigms of the MDA. Parametric methods have the advantage of convenience and they

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are easy to apply, but it is assumed that the sample has to follow a certain distribution which is often the normal distribution, while the real financial data is usually not normally distributed, consequently, this strict assumption may lead to mathematical inaccuracy.

Recently, with the development of the artificial intelligence, some literatures explore non-parametric models, such as Neural Network (NN), Rough Set, CBR, and SVM for financial distress prediction. These methods have no restrictions on the distribution of the input data, so the shortcomings of the parametric models can be overcomed to some degree. Odom and Sharda (1990) firstly attempts to use NNs for bankruptcy prediction. They explore a model which has five input variables used in the study of Altman (1968). NNs correctly classified 81.81% of the hold-out sample while MDA only achieved 74.28%. Later, Tam and Kiang (1992), Altman et al. (1994) and Yang et al. (1999) apply different NNs to prediction. These researches show that NNs have good prediction ability. Tam and Kiang (1992) compares the methods of MDA, Logistic and BPNN, and finds that BPNN outperforms in fitting the sample data, but loses in the testing accuracy. The similar result is also demonstrated in Bell (1997), thus the generalization ability of BPNN is widely doubted. Generally, it is accepted that the poor performance in testing is due to over-fitting when training the sample, the empirical risk minimization principle that seeks to minimize the training error can not guarantee good generalization performance (Shin et al. 2005). Meanwhile, other non-parametric methods such as Rough Set, DEA, and CBR are developed by different literatures (Tay and Shen 2002; Cielen et al. 2004; Bose 2006; Chun and Park 2006). Similar to NNs, their applications are limited due to the two major shortcomings: (1) the models are sensitive to changes in data and have poor generalization ability, which are caused by over-fitting. (2) The models are 'black-box' systems which can't provide economic explanation for the results.

Scholars are continuously improving the prediction models. Recently, a new approach, Support Vector Machine (SVM) has attracted attention because its structural risk minimization principle can guarantee a good generalization performance of the model. Hui and Sun (2006) and Hua et al. (2007) applies SVM to financial distress prediction, and empirical results show that SVM outperforms logistic regression models.

Because of the superiority of SVM, we are curious about whether the SVM can reach a highly predictive result when the research objects are listed companies in China, So the initial purpose of this paper is to empirically examine the performance of the MDA and SVM models, so that the practitioners in China, such as commercial banks, stakeholders can select appropriate approaches to evaluate their financial risk.

On the other hand, to detect more informative indicators becomes a new trend in the field of financial distress prediction. Earlier studies suggest that financial indicators have a direct impact on the formation of the financial distress, while little attention is paid to non-financial variables. Besides the widely observed financial statement-based determinants, Shleifer and Vishny (1997) and Elloumi and Gueyie (2001), find that shares concentration, the equity ratio of executives, board size, CEO duality, liquidity of the stock, cumulative annual return, auditors' qualified opinions and other corporate governance factors as well as the external market factors are closely connected with financial distress. Recently, more and more attention has been paid to macroeconomic factors. Carling et al. (2007) estimates a duration model to explain borrowers' survival time of a Swedish bank over the period 1994–2000, the empirical results show that the output gap, the yield curve and consumers' expectations for future economic development have significant explanatory power for the default risk of firms. Hunter and Isachenkova (2006) shows that shocks in the nominal interest rate and the real exchange rate are the key factors in causing large firms to fail.
Pesaran and Hashem (2006) and Nguyen (2007) also indicate that macroeconomic factors have an impact on the financial distress of the enterprises.

Based on the previous literatures, the second purpose of this paper is to examine if the non-financial variables are informative to predict financial distress of Chinese listed companies. The remainder of the paper is organized as follows: Sect. 2 introduces the sample, variables adopted in the predicting models and the methodologies. In Sect. 3, different models are designed, and the parameters of models are calculated. Section 4 compares the performance of the models. The conclusions are given in Sect. 5.

2 Samples, variables and methodologies

2.1 Sample

In Shanghai Stock Exchange and Shenzhen Stock Exchange, some listed companies are specially treated (ST) by China Securities Supervision and Management Committee (CSSMC). In this paper, the sample companies are grouped into two categories according to whether the company is ST or not. The distressed companies are ST companies which have had negative net profit in two consecutive years; healthy ones are those that never have been ST.

The sample consists of 260 Chinese listed companies in Shanghai stock market and Shenzhen stock market. To eliminate the industry effects, the samples are all from manufacturing industry. Among them, 130 companies are distressed which were firstly ST in 2005, 2006 and 2007. Correspondingly, 130 healthy ones are randomly selected in manufacturing industry. The samples are divided into 2 subsets: one is training set consisting of 65 ST companies and 65 healthy ones; the other is test set consisting of 65 ST companies and 65 healthy ones.

In this study, financial data is collected 3 years before the company is ST. Let the year when a company is ST be denoted as the benchmark year t, then, $(t-1)$, $(t-2)$ and $(t-3)$ respectively represents 1, 2 and 3 years before the event of ST. Whether a company is treated as a ST company or not is determined by the financial public report of year $(t-1)$, so it is meaningless to use the data of year $(t-1)$. If a company has a negative net profit in year $(t-2)$, there is a high possibility that the net profit still be negative in year $(t-1)$, thus the performance of the model will be over valued if the data of year $(t-2)$ is used. To ensure the effective predicting performance of the model, the data of year $(t-3)$ is used to develop the model in this paper.

All financial data of the listed companies in our study are collected from Tiny Software Database and Stockstar Website (http://www.stockstar.com).

2.2 Variables

2.2.1 Financial variables

In the past, most of the literatures utilize financial indicators to study financial distress early-warning. Financial ratio indicators should be scientific, systematic, timely and sensitive. Existing literatures build the prediction model mostly using the variables from the aspects of the operation capacity, profitability, solvency, asset management capacity and growth capacity. In this paper, financial variables are selected based on Zhang et al. (2005), specific variables in this paper are shown in Table 1.

Table 1 Financial variables

Categories	Variables	Description
Profitability indicators		
X_1	Return on assets	Net income/average total assets
X_2	Gross return on assets	Earnings before interest and assets/average total assets
X_3	Return on equity	Net income/average stockholders' revenue
X_4	Net profit margin	Net income/total operation revenue
X_5	Gross profit ratio	(Sales of main operation-cost of main operation)/sales of main operation
X_6	Earnings per share	Net income-preferred dividends/weighted average of common shares
Solvency indicators		
X_7	Current ratio	Current assets/Current liabilities
X_8	Quick ratio	Current highly liquid assets/current liabilities
X_9	Working capital over total assets	Net working capital/total assets
X_{10}	Working capital over Prime operating revenue	Working capital/Prime operating revenue
X_{11}	Cash flow from operations	Cash flow from operations/Current liabilities
X_{12}	Cash flow over financial cost	Cash flow/financial cost
X_{13}	Interest coverage ratio	Earnings before interest and taxes/Interest expense
X_{14}	Debt-to-equity ratio	Total liabilities/total equities
X_{15}	Debt ratio	Total liabilities/total assets
Operation indicators		
X_{16}	Total asset turnover	Total operating revenues/average total assets
X_{17}	Inventory turnover	Cost of sales/average total inventory
X_{18}	Accounts receivable turnover	Total operating revenues/average accounts receivable
X_{19}	Fixed asset turnover	Total operating revenues/average fixed assets
X_{20}	Average debts cost ratio	Financial cost/average total debts
Sustainable development indicators		
X_{21}	Growth rate of income	Net income of current year income/net income of last year
X_{22}	Growth rate of net income	Net income of last year/the absolute value of net income of last year
X_{23}	Growth rate of total assets	Total assets of current year/total assets of last year
X_{24}	Growth rate of sales revenues	Sales of main operation of current year/sales of main operation of last year
X_{25}	Retention ratio	Retained earnings/net income
X_{26}	Retained earning over total assets	Retained earning/total assets
Cash flow indicator		
X_{27}	Net cash flow from operation per share	Net cash flow from operation/weighted average of common shares
X_{28}	Growth rate of net cash flow	Net cash flow of current year/net cash flow of last year

Table 2 Independent sample t-test for of financial variables of distressed companies and health companies

		t-Test for equality of means			
		t	df	Sig. (2-tailed)	Mean difference
X_1	Return on assets	−1.676	127	0.046	-0.81070
X_5	Gross profit ratio	−2.854	127	0.005	-7.88531
X_9	Working capital over total assets	−2.838	127	0.005	-0.21360
X_{10}	Working capital over Prime operating revenue	−1.933	127	0.055	-1.45825
X_{11}	Cash flow from operations	−3.846	127	0.000	-0.18962
X_{14}	Debt-to-equity ratio	−2.141	127	0.034	-1.30015
X_{16}	Total asset turnover	−3.609	128	0.000	-0.19143
X_{19}	Fixed asset turnover	−2.796	127	0.006	-0.75209
X_{21}	Growth rate of income	−3.087	127	0.002	-0.76564
X_{26}	Retained earning over total assets	−2.367	127	0.019	-0.30010
X_{27}	Net cash flow from operation per share	−2.736	127	0.007	-0.17026

Not all above financial variables are significantly informative in predicting. An independent sample t-test is applied to compare the means of the two group companies. Test results are displayed in Table 2.

The means of the variables shown in Table 2 are significantly different between distressed companies and healthy companies, thus they are critical variables in predicting financial distress.

2.2.2 Internal governance and external market variables

The internal governance and external market variables adopted in this paper are as follows:

(1) *Shares concentration*. Under centrated ownership, conflicts of interests arise between minority shareholders and controlling shareholders. The more concentrated, the stronger the incentives of ultimate owners to expropriate minority's interest, and the expropriation may be realized through various ways, such as embezzlement by major shareholders and resources transferration to the benefits of the controlling shareholders, and these behaviors may worsen the financial condition or performance of the companies (Elloumi and Gueyie 2001).

(2) *The equity ratio of executives*. Managers may manipulate firms' resources to realize their own interests and if they own a certain amount of the shares, the interests of the outside shareholders and insider managers may be converged. Firms with higher proportion of equity ownership by executives have higher probability of experiencing financial distress (Shleifer and Vishny 1997).

(3) *Board size. Board as the linkage between the owners and managers represents the benefits of the shareholders*. The function of the Board may have an influence on the agent cost and further affect the financial performance. A proper board size helps the board execute its function and further affect the financial condition of the companies.

(4) *CEO duality. CEO may not separate personal interests from shareholder's benefit*. The dual CEO/Chairman of the Board probably has significantly increased power over the Board

Table 3 Internal governance and external market variables

Categories	Sign	Variables	Description
Corporate governance factor	Y_1	Shares concentration	The top ten shareholders/the company's total share capital
	Y_2	The equity ratio of executives	Executives holdings/company's total share capital
	Y_3	Board size	The number of Board
	Y_4	CEO duality	Chairman and CEO unity is $Y_4 = 1$, or equal to 0
External market information	Y_5	Liquidity of the stock	Turnover of A-share annually/A-share circulation
	Y_6	Cumulative annual return	The stock market prize yield − the market mean yield
	Y_7	Qualified auditors' opinion	Auditors hold opinions with no reservation: $Y_8 = 0$, the remaining equal to 1

Table 4 Independent sample t-test for of financial variables of distressed companies and health companies

		t-Test for equality of means			
		t	df	Sig. (2-tailed)	Mean difference
Y_1	Shares concentration	−0.83620	127	0.046	−1.1463
Y_7	Qualified auditors' opinions	1.2229	127	0.005	0.0859

and corporation, which may reduce the efficiency of controlling mechanism of governance structure and do harm to the financial condition.

(5) *Liquidity of the stock*. A liquid stock market reduces larger shareholder's incentives to monitor because it allows them to sell their stock more easily and provide convenience to purchase additional shares (Maug 1998).

(6) *Cumulative annual return*. In an efficient market, the market price contains the distressed information of a firm (Shumway 2001). Thus if a firm experiences financial distress, the stock price will be accepted at a lower level by investors.

(7) *Auditors' qualified opinions*. Information from external supervisors is also an indicator of the financial distress. As an important representation of operation, it can reflect the financial condition in some degree. If an auditor provides a report with reserved opinions, this may contain manipulation or fake (Pompe 2005).

Not all above financial variables are significantly informative in predicting (Table 3). An independent sample t-test is applied to compare the means of the two group companies. Test results are displayed in Table 4.

The means of the variables shown in Table 2 are significantly different between distressed companies and healthy companies, thus they are critical variables in predicting financial distress.

2.2.3 Macroeconomic variables

Macroeconomic factors have attracted more and more attention. In this paper, the following macroeconomic variables are taken into consideration:

(1) *Overall economic environment*. Generally, during the period of the economic recession, the cash flow of the enterprises will be reduced for the following reasons: firstly, surplus product in the market and decrease of the personal disposable income will lower the operating income of the enterprise; secondly, due to the pro-cyclicality, banks will level down their credit loan to the companies (Koopman et al. 2005), thus a reduction in cash flow may increase the possibility of the financial distress.

(2) *Money supply*. A change in money supply may affect the financing ability of the enterprises. After the easy-money policy is applied, the willingness of a commercial bank to issue loan will increase, consequently, the possibility of the enterprises trapped into financial distress will decrease. Meanwhile, if the easy-money policy is applied, investment will rise, and this will actually broaden the financing channel of the enterprises.

(3) *Inflation rate*. The rising of inflation level means a significant increase in production cost (including material cost and human resource cost), under the circumstance of high inflation, the pressure of operation capital rises dramatically, and if the company can't handle this problem, it will be trapped in financial distress condition. Meanwhile, during the period of the inflation, the assets evaluation system will be in disorder, there is a high possibility that a company bear a total loan exceeding its actual ability.

(4) *Interest rate*. Interest rate is an important variable that affects the corporate finance (Vickery 2008). Firstly, it is the main cost of the financing; a high cost will burden the enterprises. Secondly, when the actual interest rate rises, the discount factor increases, thus the Net Present Value of the project invested will decrease.

(5) *Exchange rate*. Unexpected changes in foreign exchange rates can result in a violation of the cash flows of a corporation (Bartram 2008). Exchange exposures may result from the effect that unexpected foreign exchange rate changes have on sales prices and quantities, production costs, market share (Bartram 2004). If the company cannot deal with the risk of exchange exposures of the cash, the company may face the risk of financial distress, for example, the bankruptcy of Peregrine Investments Holdings Limited is due to the exchange rate risk.

Basically, the macroeconomic environment is identical for all companies, why some companies are trapped into financial distress, while others remain financially healthy? Generally, healthy companies can adopt appropriate policies to react to the economic changes. In our paper, we utilize correlation coefficients between net profit of a company and the macroeconomic indicators to measure the sensitivity of companies to macroeconomic changes, all macroeconomic variables and profit data are semi-annual (Table 5).

Not all above financial variables are informative in predicting. An independent sample t-test is applied to compare the means of the two group companies. Test results are displayed in Table 6.

The means of the variables shown in Table 6 are significantly different between distressed companies and healthy companies, thus they are critical variables in the process of predicting financial distress.

2.3 Methods

Two methods are selected to predict financial distress of Chinese listed companies. One is support vector machine, and the other is multivariate discriminant analysis.

Table 5 Macroeconomic variables

Variables	Description
Economic environment variables	
Z_1	Correlation coefficient between net profit and Gross Domestic Production
Z_2	Correlation coefficient between net profit and Fixed asset investment
Z_3	Correlation coefficient between net profit and Value Added of Industry
Money supply	
Z_4	Correlation coefficient between net profit and $M0$
Z_5	Correlation coefficient between net profit and $M1$
Z_6	Correlation coefficient between net profit and $M2$
Inflation rate	
Z_7	Correlation coefficient between net profit and Consumer Price Index
Z_8	Correlation coefficient between net profit and Retail Price Index
Interest rate	
Z_9	Correlation coefficient between net profit and actual interest rate
exchange rate	
Z_{10}	Correlation coefficient between net profit and CNY/USD exchange rate

Table 6 Independent sample t-test for of financial variables of distressed companies and health companies

	t-Test for equality of means			
	t	df	Sig. (2-tailed)	Mean difference
Z_1	−8.456	128	0.000	−0.53652
Z_2	−9.144	128	0.000	−0.53616
Z_3	−8.111	128	0.000	−0.52461
Z_4	−7.506	128	0.000	−0.47958
Z_5	−7.720	128	0.000	−0.49258
Z_6	−7.785	128	0.000	−0.49847
Z_7	−6.087	128	0.000	−0.35038
Z_8	−6.672	128	0.000	−0.40334
Z_9	6.971	128	0.000	0.28981
Z_{10}	−8.094	128	0.000	−0.51951

2.3.1 Support vector machine classifier

Support vector machine (SVM) develops from the linear separable case. For a training pattern of 2 cases, given a training set of n pairs of observed sample $(x_i, y_i),\ i = 1, 2, \ldots, n$ (where y_i is a category signal, and $y = 1$, or $y = -1$), the SVM aims at finding the optimal hyperplane which can separate two different classes and maximum the margin of separation.

Subject to $y_i(w^T x_i + b) \geq 1$, finding the optimal hyperplane can be converted to an optimal problem:

$$\min \phi(w) = \frac{1}{2}\|w\|^2 \tag{1}$$

Constrained optimization problem with lagrangian, Eq. 1 changes to a dual problem. Subject to: $\sum_{i=1}^{m} a_i y_i = 0$ and $a_i \geq 0$, the purpose is to find the maximum value of the following function:

$$Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j x_i \cdot x_j \tag{2}$$

where a_i^* is the lagrangian multiplier of each sample. Equation 2 is a quadratic programming (QP) problem. It is proved that there is a single solution to the Eq. 2. Samples with non-zero a_i^* are support vectors (SV). Finally, the optimal classifier is as Eq. 3:

$$f(x) = \operatorname{sgn}\left[(w^*)^T \phi(x) + b^*\right] = \operatorname{sgn}\left(\sum_{i=1}^{n} a_i^* y_i (x_i \cdot x) + b^*\right) \tag{3}$$

where b^* is a threshold value, which can be calculated by SV.

For linear non-separable cases, the hyperplane can't classify two groups, therefore, a positive slack variable ξ_i $\left(\xi_i \geq 0, i = \overline{1, n}\right)$ is generally introduced to make the hyperplane $w^T x + b = 0$ satisfy:

$$y_i\left(w^T x_i + b\right) \geq 1 - \xi_i \tag{4}$$

When $0 < \xi_i < 1$, x_i is classified correctly, and if $\xi_i \geq 1$, x_i is misclassified. Thus the objection function becomes:

$$\psi(w, \xi) = \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \tag{5}$$

C is the penalty parameter of the error term. The solution of SVM can be converted to a QP problem. In order to map the primary input space into a higher dimensional spaces, kernel functions $K(x_i, x_j)$ is introduced to substitute the dot product $x_i \cdot x_j$, thus, the optimal function becomes:

$$Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{6}$$

Kernel functions $K(x_i, x_j)$ can be designed according to the Mercer Theorem (Vapnik 1995). Thus, the final classifier or the discriminant function becomes:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} a_i^* y_i K(x_i, x) + b^*\right) \tag{7}$$

There are several common kernel function types of SVM, such as linear kernel, polynomial kernel, and radial basis function. Vapnik (1995) and Keerthi and Lin (2003) prove that radial basis function (RBF) can handle the nonlinear relationships between independent variables and dependent variables without increasing the complication of the solution. Therefore, RBF is chosen as the kernel function to develop the model. Substitute the $K(x_i, x_j)$ with RBF, classifier becomes:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} a_i^* y_i \exp(-\gamma(x - x_i)^2) + b^*\right) \tag{8}$$

If $f(x)=1$, the company belongs to distressed group, otherwise, it is a financial healthy one. From Eq. 8: we need to determine two parameters, penalty parameter C and kernel parameter γ when using RBF kernel function.

2.3.2 Multivariate discriminant analysis

Multivariate Discriminant Analysis is concerned with the classification of distinct sets of observations and it tries to find the combination of variables that predicts the group to which an observation belongs. The combination of predictor variables is called as a linear discriminant function, and this function can then be used to classify new observations whose group membership is unknown. The linear discriminant function is as follows:

$$Z = B_0 + B_1 X_1 + B_2 X_2 + \cdots + B_n X_n \tag{9}$$

where Z is a discriminant score, B_0 is an estimated constant, B_n are the estimated discriminant coefficients, and X_n are input variables or predictors. In our paper, the input variables consist of financial variables, internal governance and external market variables, and macroeconomic variables. By judging the discriminant function score, an observation is classified into the appropriate group (Canbasa et al. 2005).

3 Modeling

By using above two methods, four models are designed: (1) Model I: SVM model with all predictive variables; (2) Model II: SVM model with only financial variables; (3) Model III: MDA model with all predictive variables; (4) Model IV: MDA model with only financial variables.

3.1 SVM modeling

To develop the SVM model, a hyperplane to classify the distressed companies and healthy companies is required to map. According to the financial condition of each company, let (-1) denote the distressed companies, and (1) denote healthy ones. The process of developing the SVM model can be converted to searching the optimal parameter (C, γ) by using predicting variables.

3.1.1 Scaling

The main purpose of scaling is to avoid attributes in greater numeric ranges dominate those in smaller numeric ranges. Furthermore, it can avoid numerical difficulties during the calculation of hyperplane. In this study, primary data is scaled to $(0 \sim 1)$. Scaling formula is as Eq. 10. v is primary data, and $v\prime$ is the scaled data. $\min_a$, $\max_b$ denotes the minimum value and the maximum value e of the primary data.

$$v' = (v - \min_a)/(\max_b - \min_a) \tag{10}$$

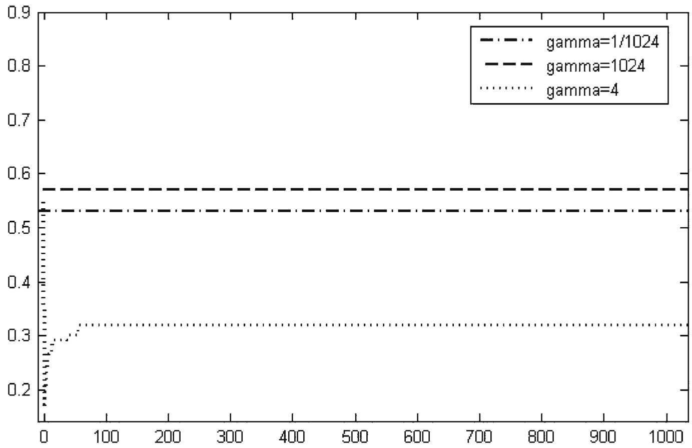

Fig. 1 Accuracy of training set varies with the change of C

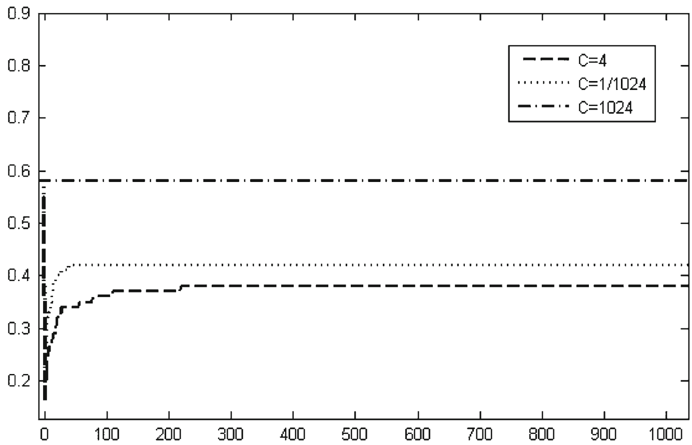

Fig. 2 Accuracy of training set varies with the change of γ

3.1.2 Influence of parameters C and γ on prediction ability

The parameters C and γ have influence on the Prediction ability of the SVM with RBF kernel function. This paper intends to provide a guideline on the parameter selection for SVM models. The calculation process is finished via The MATLAB SVM toolbox. Figures 1 and 2 shows different result when one parameter is fixed and other parameter increases.

Penalty parameter C balances the algorithm complication and the misclassification proportion. In a certain feature space, a smaller C is corresponding to a weaker penalty on empirical error. Although the learning machine has a low degree of algorithm complication, and the model may be poor in generalization ability. The model with a high training set accuracy can't promise a high accuracy in test set. Figure 1 shows the variation of training set accuracy with the increasing of Penalty parameter C when γ is fixed at the value of 4, 1,024 and 1/1,024. Given $\gamma = 4$, error firstly turns smaller to the lowest and then gradually increases to about 0.3, and after C reaches to a certain value, error stays at a fixed level.

Table 7 Parameter matchup and cross-validation accuracy of Models I and II

Model I			Model II		
Parameter matchup	Cross-validation accuracy (%)	nSV	Parameter matchup	Cross-validation accuracy (%)	nSV
(4, 0.250)	85.39	35	(8, 0.0625)	81.54	37
(128, 0.088)	84.62	35	(32, 0.177)	80.77	38
(128, 0.125)	83.85	36	(4, 0.1204)	80.77	38
(90.509, 0.044)	82.31	37	(2.828, 0.25)	80.00	38

Meanwhile, Fig. 1 also shows that the model with γ equals to 4 has better generalization ability than the model with Gamma equals to 1,024 and 1/1,024, and this result indicates that a model with good generalization ability can be acquired by carefully choosing the penalty parameters.

Kernel parameter γ actually changes the mapped function impliedly, thus changes the complication degree of feature space. Figure 2 shows the variation of training set accuracy with the increasing of Kernel parameter γ when C is fixed at the value of 4, 1,024 and 1/1,024. Given $C=4$, error firstly turn smaller to the lowest and then gradually increase to 0.5. After C reaches to a certain value, error stays at a fixed level. Meanwhile, the model with C equals to 4 has better generalization ability than the model with C equals to 1,024 and 1/1,024. This result also indicates that a model with good generalization ability can be acquired by carefully choosing the kernel parameters.

3.1.3 Optimal parameter matchup identification

There is a parameter matchup (C, γ) need to be determinated while using RBF kernel function. Li and Zhang (2007) points out that SVM classifier can get a high learning accuracy while adopting Grid-search method. In our study, Grid-search method is adopted to identify the optimal parameter. There are $M \times N$ pairs of parameters when C and γ are separately picked. Thus different SVM classifiers are formed. Finally, according to the accuracy of the classifiers, an optimal parameter matchup with the highest accuracy is identified.

To evaluate the accuracy, this paper uses 5-fold cross-validation. The training set is firstly divided into five subsets, A_1, A_2, A_3, A_4, A_5. In the ith iteration, the ith set is used to evaluate the performance of the classifier trained on the remaining four sets. Total error is the misclassified numbers in all iterations. Combined with Grid-search method, pairs of (C, γ) are tried and the one with the highest accuracy is picked up as the optimal parameters.

When $C = 1{,}024$, the cross-validation errors are high and stay at the fixed level with the increasing of γ, thus C is tried following a exponentially growing sequences from 2^{-10} to 2^{10}, similarly, γ is also tried following a exponentially growing sequences from 2^{-10} to 2^{10}, each step is $2^{-0.1}$.

After the searching of parameter matchup, the optimal parameters are calculated. Table 7 shows four pairs of (C, γ) with the first high accuracy to fourth high accuracy. As the Table 7 shows, $(4, 0.250)$ is the optimal parameter pair of Model I, the accuracy is 84.62%, $(8, 0.0625)$ is the optimal parameter pair of Model II, the accuracy is 81.54%.

Table 8 Prediction accuracy of Models III and IV

	Group	Predicted group membership		Total
		0	1	
Model III				
Count	0	58	7	65
	1	13	52	65
%	0	89.23	10.77	100.00
	1	20.00	80.00	100.00
Model IV				
Count	0	54	11	65
	1	16	49	65
%	0	83.08	16.92	100.00
	1	24.62	75.38	100.00

3.2 MDA modeling

The construction of the MDA model is accomplished by discriminant tool of SPSS software (SPSS 13.5). After the stepwise discriminant analysis, Canonical Discriminant Function with five variables is estimated, and non-standardized Canonical Discriminant Function of MDA is as follow:

Model III (MDA model with all predictive variables):

$$Z = -2.253 + 0.863X_9 + 1.147X_{11} + 0.001X_{21} + 5.985Z_2 - 3.821Z_8 \tag{11}$$

Model IV (MDA model with only financial variables):

$$Z = -1.921 + 0.044X_5 + 1.535X_{11} + 2.447X_{16} + 0.001X_{21} \tag{12}$$

Model III shows that X_9 (Working capital over total assets), X_{11} (Cash flow from operations), X_{21} (Growth rate of income), Z_2 (Correlation coefficient between net profit and Fixed asset investment) and Z_8 (Correlation coefficient between net profit and Retail Price Index) enter the discriminant model. Using fisher's linear discriminant function, the means of Z scores of each group are -1.108490 and 1.108490. Following the rules of symmetry, the critical point is 0 which is the average value of two groups. Substitute the X_9, X_{11}, X_{21}, Z_2 and Z_8 in Eq. 11 with a predictive financial variable, and calculate each company's Z score, if Z score is above 0, then the company belongs to the healthy group, otherwise to distressed group. Similarly, Model IV shows X_5 (Gross profit ratio), X_{11} (Cash flow from operations), X_{16} (Total asset turnover), X_{21} (Growth rate of income) are critical financial variables. Using fisher's linear discriminant function, the means of Z scores of distressed group and health group are -0.6635 and 0.6635, and the critical point is 0 which is the average value of two groups. Applying the Models III and IV to predict the financial condition of the companies in training sample, and the results are shown in Table 8.

As shown in Table 8, the forecasting accuracy of Model III is 84.62%. For Model IV, the accuracy is 79.23%. The results show that the macroeconomic variables can enhance the forecasting ability of the MDA models.

Table 9 Prediction ability of different methods

Methods	Sample	Type I errors (%)	Type II errors (%)	Forecasting accuracy (%)
Model I	Training set	9.23	20.00	85.39
	Test set	10.77	23.08	83.08
Model II	Training set	15.38	21.54	81.54
	Test set	18.46	24.62	78.46
Model III	Training set	10.77	20.00	84.62
	Test set	12.31	21.54	83.08
Model IV	Training set	16.92	24.62	79.23
	Test set	21.54	26.15	76.15

The parameters of Models I and II are (4, 0.250) and (8, 0.0625) respectively

4 Prediction performance comparison

A comparison is conducted among Models I–IV by taking test sample. Prediction ability of each model 3 years prior to financial distress happened is reported in Table 9.

A type I error occurs if the firm suffers financial distress but is misclassified as non-distressed firms. A type II error occurs if the firm is non-stressed but is misclassified as distressed firms. Judging by type I and type II errors, SVM methods get a lower error as a whole. Although SVM models can't provide economic explanation, the test results suggest that the SVM models have some advantages over MDA models. SVM methods are non-parametric methods which is unrestricted to the sample distribution. Meanwhile, SVM models can handle the non-linear relationships between independent (input) and dependent (output) variables. While MDA methods require that the sample follows a normal distribution which is unnecessarily true in real economic world and can only deal with the linear relationships. Because of above statistical superiority of SVM, SVM models can lower the type I and type II errors.

The forecasting accuracy of SVM models are higher compared to MDA models. Meanwhile, a good generalization ability of SVM model is showed in the table. Compared to forecasting accuracy in training sample, a dramatically decreasing of the forecasting accuracy is not appeared in test sample. This result can be attributed to the generalization ability of SVM. SVM models can generate a hyperplane which can classify two groups. This classification mechanism can avoid the over-fitting problem, thus lead to high prediction accuracy in test sample.

Additionally, models using all predictive variables outperform models with only financial variables. This result implies that non-financial variables, especial macroeconomic variables are informative to predict financial distress, in Model III, Z_2 (Correlation coefficient between net profit and Fixed asset investment) and Z_8 (Correlation coefficient between net profit and Retail Price Index) significantly explain financial distress.

5 Conclusion

In this paper, we apply SVM and MDA modes to predict financial distress of Chinese listed companies in manufacturing industry using financial variables, internal governance and external market variables as well as macroeconomic variables. From our study, we can draw the following conclusions:

(1) SVM methods and MDA methods are respectively developed. The exciting results show that the accuracy of SVM model exceeds 80% three years prior to the occurrence of the ST event. Additionally, SVM has the advantage of good generalization. Unfortunately, similar to the NNs methods, it is difficult to capture the critical variables using SVM methods. While MDA methods can select the critical variables and make a reasonable economic explanation. The advantages and disadvantages of two classes of models suggest that an efficient model should combine the features of different models.
(2) Some sensitive variables which value significantly different between healthy groups and distressed groups are identified by conducting independent sample t-test. These variables are: X_5 (Gross profit ratio), X_9 (Working capital over total assets), X_{10} (Working capital over Prime operating revenue), X_{11} (Cash flow from operations), X_{14} (Debt-to-equity ratio), X_{16} (Total asset turnover), X_{19} (Fixed asset turnover), X_{21} (Growth rate of income), X_{26} (Retained earning over total assets), X_{27} (Net cash flow from operation per share), Y_1 (Shares concentration), Y_7 (Qualified Auditors' opinions), and all macroeconomic variables.

These sensitive variables are further detected by using stepwise MDA method to discriminate the financial distress. Three years prior to the occurrence of the distress, X_5 (Gross profit ratio), X_9 (Working capital over total assets), X_{11} (Cash flow from operations), X_{16} (Total asset turnover), X_{21} (Growth rate of income), Z_2 (Correlation coefficient between net profit and Fixed asset investment) and Z_8 (Correlation coefficient between net profit and Retail Price Index) are the critical variables which contain platitudinous information of financial distress.

The above findings are supplementary for the prediction of the financial distress of Chinese listed companies. Unfortunately, there are some limitations in this paper, which future researches can aim at solving:

(1) The criteria of the financial distress. Because of the lack of bankruptcy data in China, Special Treated companies are considered as the distressed companies. ST event is a sign of financial distress, but this criteria is not precise. Two consecutive years' negative profits do not necessarily mean a bankruptcy. In fact, some ST companies are back to normal through improved management. So, a more scientific criteria need to be studied.
(2) The limitation of the SVM. There is no guideline for choosing Kernel function. Better function can be constructed in the future. In this paper, SVM only deals with two-class case while multi-classes or SVM regression need to be further studied to satisfy practical needs.

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References

Altman, E.: Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Financ. **23**(9), 589–609 (1968)

Altman, E., Haldeman, R.G., Narayanan, P.: ZETA ANALYSIS, a new model to identify bankruptcy risk of corporations. J. Bank. Financ. **1**, 589–609 (1977)

Altman, E., Marco, G., Varetto, F.: Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks. J. Bank. Financ. **18**, 505–529 (1994)

Bartram, S.M.: Linear and nonlinear foreign exchange rate exposures of German nonfinancial corporations. J. Int. Money Financ. **23**(4), 673–699 (2004)
Bartram, S.M.: What lies beneath: foreign exchange rate exposure, hedging and cash flows. J. Bank. Financ. **32**(8), 1508–1521 (2008)
Beaver, W.: Financial ratios as predictors of failure. J. Acc. Res. **4**, 71–111 (1966)
Bell, T.B.: Neural nets or the logit model? A comparison of each model's ability to predict commercial bank failures. Int. J. Intell. Syst. Acc. Financ. Manag. **6**, 249–264 (1997)
Bose, I.: Deciding the financial health of dot-coms using rough sets. Inf. Manag. **43**, 835–846 (2006)
Canbas, S., Cabuk, A., Kilic, S.B.: Prediction of commercial bank failure via multivariate statistical analysis of financial structures: the Turkish case. Eur. J. Oper. Res. **166**(2), 528–546 (2005)
Carling, K., Jacobson, T., Linde, J., Roszbach, K.: Corporate credit risk modeling and the macroeconomy. J. Bank. Financ. **31**(9), 845–868 (2007)
Chun, S.-H., Park, Y.-J.: A new hybrid data mining technique using a regression case based reasoning: application to financial forecasting. Expert Syst. Appl. **30**(2), 329–336 (2006)
Cielen, A., Peeters, L., Vanhoof, K.: Bankruptcy prediction using a data envelopment analysis. Eur. J. Oper. Res. **2**, 526–532 (2004)
Elloumi, F., Gueyié, J.P.: Financial distress and corporate governance: an empirical analysis. Corp. Gov. **1**(1), 15–23 (2001)
Fitzpatrick, W.: A comparison of ratios of successful industrial enterprises with those of failed firms. Certif. Public Acc. **6**(10), 727–731 (1932)
Hua, Z., Wang, Y., Xu, X., Zhang, B., Liang, L.: Predicting corporate financial distress based on integration of support vector machine and logistic regression. Expert Syst. Appl. **33**(2), 434–440 (2007)
Hui, X.-F., Sun, J.: An application of support vector machine to companies' financial distress prediction. Lect. Notes Artif. Intell. **5**, 274–282 (2006)
Hunter, J., Isachenkova, N.: Aggregate economy risk and company failure: an examination of UK quoted firms in the early 1990s. J. Policy Model. **4**, 911–919 (2006)
Keerthi, S.S., Lin, C.J.: Asymptotic behaviors of support vector machines with Gaussian kernel. Neural Comput. **15**(7), 1667–1689 (2003)
Koopman, S.J., Lucas, A., Klaassen, P.: Empirical credit cycles and capital buffer formation. J. Bank. Financ. **29**(12), 3159–3179 (2005)
Li, L., Zhang, X.-l.: Optimization of SVM with RBF Kernel. Comput. Eng. Appl. **29**, 190–194 (2007)
Maug, E.: Large shareholders as monitors: is there a trade-off between liquidity and control? J. Financ. **53**, 1–40 (1998)
Nguyen, P.: Macroeconomic factors and Japan's industry risk. J. Multinatl. Financ. Manag. **17**(6), 173–185 (2007)
Odom, M., Sharda, R.: A neural network for bankruptcy prediction. In: IJCNN International Conference on Neural Networks, San Diego, CA, 1990
Ohlson, J.A.: Financial rations and the probabilistic prediction of bankruptcy. J. Acc. Res. **18**, 109–131 (1980)
Pesaran, M., Hashem, S.: Macroeconomic dynamics and credit risk: a global perspective. J. Money Credit Bank. **38**(5), 1211–1262 (2006)
Pompe, B.: The prediction of bankruptcy of small and medium sized industrial firms. J. Bus. Ventur. **20**(6), 847–868 (2005)
Shin, K.-S., Lee, T.S., Kim, H.-j.: An application of support vector machines in bankruptcy prediction model. Expert Syst. Appl. **28**, 127–135 (2005)
Shleifer, A., Vishny, R.W.: A survey of corporate governance. J. Financ. **52**(2), 737–783 (1997)
Shumway, T.: Forecasting bankruptcy more accurately: a simple hazard model. J. Bus. **74**, 101–124 (2001)
Tam, K.Y., Kiang, M.: Predicting bank failures: a neural network approach. Decis. Sci. **23**, 926–947 (1992)
Tay, F.E.H., Shen, L.: Economic and financial prediction using rough set model. Eur. J. Oper. Res. **141**, 641–659 (2002)
Vapnik, V.: The Nature of Statistical Learning Theory. Springer, New York (1995)
Vickery, J.: How and why do small firms manage interest rate risk. J. Financ. Econ. **87**(2), 446–470 (2008)
Yang, Z.R., Platt, M.B., Platt, H.D.: Probability neural network in bankruptcy prediction. J. Bus. Res. **44**, 67–74 (1999)
Zang, H., Chen, H., Hsu, C., Chen, W., Wu, S.: Credit rating analysis with support vector machine and neural networks: a market comparative study. Decis. Support Syst. **37**, 543–558 (2004)
Zhang, L., Chen, S., Zhang, X.: Financial distress early warning based on MDA and ANN technique. Syst. Eng. **23**(11), 49–56 (2005)