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Predicting the removal of special treatment or delisting risk warning for listed company in China with Adaboost

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Abstract

Most previous research focuses on the problem of financial distress prediction or bankruptcy prediction for an ordinary listed company in China. However, few research discuss the problem of predicting the removal of special treatment or delisting risk warning for the listed companies having already receiving risk warning by stock exchange. This problem is also very important for stock investors. In this study, the Adaboost method is employed to construct the model for the prediction of the removal of special treatment or delisting risk for the listed company in China. The empirical results show that Adaboost method is a better alternative when compared to other popular classification techniques and the problem of prediction of the removal of special treatment or delisting risk warning is more challenge than the problem of financial distress prediction.

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Keywords:removal of special treatment; prediction; Adaboost;listed company

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1. Introduction

In 1998, Shanghai and Shenzhen Stock Exchanges in China implemented a new stock listing rule that they would give special treatment (ST) or delisting risk warning to the stocks of the listed companies with abnormal financial conditions or other abnormal conditions in order to indicate the risk of the stock to investors. The short name of a stock receiving special treatment or delisting risk warning will be prefixed with "ST" or "*ST". Accordingly, the company will be called ST company or *ST company if its issued stock receive ST or *ST respectively.

In July 2012, Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) released "Rules Governing the Listing of Stocks on Shanghai Stock Exchange" and "Rules Governing the Listing of Stocks on Shenzhen Stock Exchanges" respectively, in which they listed similar conditions for the implementation of special treatment or delisting risk warning. The conditions about the abnormal financial situations are as follows:

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(1) The audited net profit of the company was negative in the last two consecutive fiscal years.

(2) The audited net worth of the company was negative in the last fiscal year.

(3) The audited operating income of the company was less than 10 million Yuan in the last fiscal year.

(4) The financial statements for the last fiscal year receiving adverse opinion or disclaimer opinion from the auditing company.

(5) The company has been commanded to correct the serious errors and false record by the China Securities Regulatory Commission (CSRC), but fails to mend within the specified time limit, and the company's stocks have been suspended from trading for two months.

(6) The company fails to disclose its annual report or semi-annual report within the statutory time limit and the company's stocks have been suspended from trading for two months.

In terms of rules in China stock market, a normal stock can receive special treatment or delisting risk warning, while a ST or *ST stock can have the opportunity to get the prefix of special treatment or delisting risk warning removed if the financial status of the corresponding company has been improved or the company has correct their errors in above item (5) and (6) and then the rules for giving the company special treatment or delisting risk warning do not hold.

In China stock market, the limit of the increase and decrease of a ST stock's price is 5% within one trading day while the limit is 10% for ordinary stocks. If the ordinary stock receives special treatment or delisting risk warning, the stockholders will suffer a great loss due to the decrease of the stock price for the increase of its delisting risk. On the other hand, if the ST or *ST stock gets its special treatment or delisting risk warning removed, the stockholders will make a great profit due to the increase of the stock price for the decrease of its delisting risk or improvement on financial status. Therefore it is important for investors to predict if a normal company receive ST or *ST or if a ST or *ST stock recover to ordinary status.

Since firms receiving ST or *ST are mainly due to their financial distress, the problem of predicting if a normal company receive ST or *ST can be taken as a problem of bankruptcy prediction or financial distress prediction. There is a lot of research on bankruptcy prediction or financial distress prediction. Ravi and Ravi reviewed 121 papers about bankruptcy prediction published during 1968-2005 from the aspect of quantitative techniques applied for modeling, source of data sets, financial ratios used, country of origin, time line of study, and comparable performance of techniques in terms of prediction accuracy if available [1]. None of them used China data set. Zhang, Altman and Yen developed a model called ZChina score which is similar to the Z-score model proposed by Altman to predict financial distress of firms in China. Chen, et. al. use four prediction models to examine the usefulness of financial ratios to predicting business failure in China [2]. Zhou, Lai, and Yen investigated more than 20 different quantitative models and six feature ranking strategies to determine the proper quantitative model and features selection strategy [3]. The empirical result on China data set shows that most models can achieve more than 90% prediction accuracy on the 184 testing sample. Although the performance of some models has no significant difference, Adaboost model shows consistently good performance and keeps in the top3 position in terms of the average ranking on area under ROC curve (AUC) for China data set and USA dataset.

The problem of predicting if an ordinary listed company in China stock market receive ST or *ST, denoted as O2ST, has been widely studied, however the problem of predicting if a ST or *ST company can recover to better financial status or to an ordinary company which is denoted as ST2O has seldom been studied by researchers. These two problems O2ST and ST2O have different characteristics. O2ST focuses on ordinary company and predicts if the financial status of this ordinary company turns worse. There are a large number of ordinary companies in market and their financial characteristics are easy to identify. ST2O focuses on unusual company who have fall into financial distress and predicts if they can recover or turn worse. If the *ST company turns worse, it will be delisted. If the ST company turns worse, it will receive delisting risk warning and will be identified as *ST company. However, both of the two problems are essentially classification problem in statistics.

A formal description of the prediction of removal of special treatment and delisting risk warning can be given as follows:

Suppose $x = (x_1, x_2, L, x_m)^T$ is a set of m explanatory variables that describe an ST or *ST company's financial information of the most recent fiscal or other potential information that can be used for prediction, such as macroeconomic data, market data. The value of the m variables for a particular company k can be denoted by $\boldsymbol{x}_k = (x_{k1}, x_{k2}, \cdots, x_{km})^T$. A function $f(\cdot)$ can be constructed from a group of selected ST or *ST companies with observed status (recovered or worsen), which maps the information of a company to the probability of its recovery. Change of status of a ST or *ST company, denoted by y, is determined by the value of $f(\boldsymbol{x})$, and a cutoff value F_c. Suppose $y = +1$ means the company recovered and $y = -1$ means that the company worsens; then the value of y can be determined as follows:

$$y = \begin{cases} +1 & \text{if } f(\boldsymbol{x}) \geq F_c \\ -1 & \text{otherwise} \end{cases} \quad (1)$$

Formula (1) shows why the ST2O problem becomes a classification problem. The main processes of model classification model construction are shown in Fig 1.

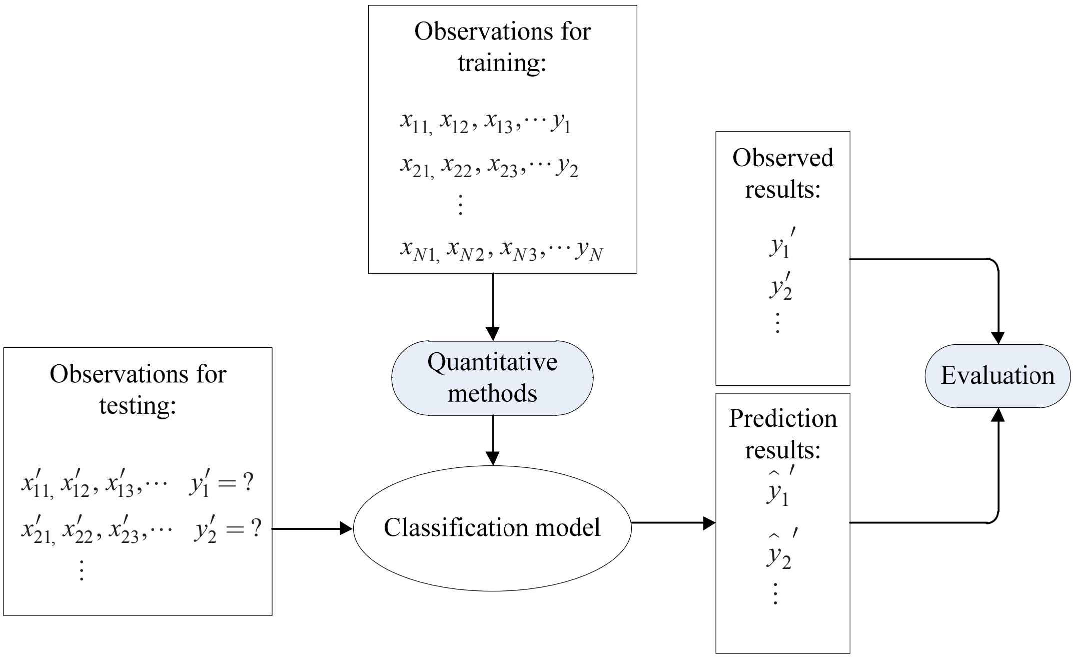

Fig 1. The mechanism of bankruptcy prediction model construction and evaluation

As shown in Fig 1, during the construction of model for the prediction, there are many issues, such as the selection of features, selection of observations for training and testing, selection of quantitative models and the selection of evaluation measures, etc. This paper has no intention to discuss all these issues and it just focus on the employment of Adaboost method which showed good performance in the financial distress prediction test in our previous work [3]. Peng, et. al. [4] presented a framework for the field of data mining and knowledge discovery, which discussed the processes in Fig 1. The features which has been widely used and shows good performance from Altman [5] and [6] along with additional market features are used in this paper.

The rest of this paper is organized as follows: Section 2 is a brief introduction to Adaboost method. The result of empirical study is presented in section 3. Section 4 gives the conclusion and a short discussion.

2. Adaboost Method

AdaBoost is a kind of ensemble algorithm which constructs a composite classifier by sequentially training classifiers while putting more and more emphasis on certain patterns [7]. There are several methods for combining results from many weak learners into one high–quality ensemble predictors, such as uniform voting, distribution summation, Bayesian combination, etc. The elements for construction of AdaBoost include: input features and responds, ensemble method, base learners and number of base learners in ensemble. Different combination of these elements will make different AdaBoost models.

For the prediction of removal of ST or *ST for listed company, we are given a training data set S = $\{\boldsymbol{x}_n, y_n\}_{n=1}^{N}$, where input data $\boldsymbol{x}_n \in R^m$ and its corresponding output $y_n \in R$ and $y_n \in \{1, -1\}$.

2.1. AdaBoost.M1

AdaBoost.M1 is a very popular boosting algorithm for binary classification problems. It was initially proposed by Freund and Schapire [8]. The main idea of AdaBoost.M1 is to assign a weight to each observation in the training set. Initially, each sample in training set *S* is assigned an equal weight of 1/N, which means that each sample has the same opportunity to be selected at the first step. Generating AdaBoost model need *T* rounds of training base learners with *T* different training sample groups S_t (t=1, 2, …, T). In round *t*, the function to determine the weight of observation *k* is denoted by $D_t(n)$. In each round after the construction of learner C_t which provides a function F_t to map $\boldsymbol{x}$ to {1, -1}, the value of $D_t(n)$ is adjusted in terms of how they are classified by the classifier C_t and the training sample group S_t+1 is then generated in term of D_t on *S* with sample replacement.

The detail of AdaBoost.M1 is described as follows in pseudo-code:

Input:

S, a set of samples for training with size *N*;

T, the number of rounds to construct the Adaboost model;

Settings for training the base classifiers;

Output: Adaboost model

Algorithm: AdaBoost.M1 (AB.M1)

Step 1: initialize the weight of each sample in S to 1/*N*, i.e. $D_1(n) = 1/N$, n=1, 2,…N, t= 1;

Step 2: repeat

2.2 build classifier Ct using base learner and distribution D_t

2.3 compute the weighted error ε_t from model C_t on S as Formula (2):

$$\varepsilon_t = \sum_{n=1}^{N} D_t(n) \times err_t(\boldsymbol{x}_n) \tag{2}$$

where $err_t(\boldsymbol{x}_n)$ is the misclassification error of $\boldsymbol{x}_n$ by model C_t, it is defined as following:

$$err_t(\boldsymbol{x}_n) = \begin{cases} 1 & \text{if } F_t(\boldsymbol{x}_n) \neq y_n \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

2.4 if $\varepsilon_t > 0.5$, then
    $T = t$ -1;
    exit Loop.
  end if

$$2.5\ \ \beta_t = \frac{\varepsilon_t}{1-\varepsilon_t} \tag{4}$$

update the weights:

$$D_{t+1}(n) = \begin{cases} D_t(n) \times \beta_t & \text{if } F_t(\boldsymbol{x}_n) = y_n \\ D_t(n) & \text{otherwise} \end{cases} \tag{5}$$

2.6 Normalize D_t+1 to be a proper distribution

$$D_{t+1}(n) = \frac{D_{t+1}(n)}{\sum_{n=1}^{N} D_{t+1}(n)} \tag{6}$$

2.7 $t = t + 1$
until $t > T$

Following above method, we have a set of base learners C_t which actually defines a set of functions $\{F_t \mid t=1, 2, \ldots, T\}$ and the final decision from this set of functions (AdaBoost models) is defined as (7):

$$\hat{y}(\boldsymbol{x}) = \underset{y\in\{1,-1\}}{\arg\max}\left(\sum_{t:F_t(\boldsymbol{x})=y} \log\frac{1}{\beta_t}\right) \tag{7}$$

In this study, decision tree is selected as the base learner.

3. Empirical Study

3.1. Data set

Initially, a total of 872 observations are retrieved from CSMAR databases. The observations cover the period of years from 1999 to 2012 in which the ST or *ST companies recover to ordinary company or turn worse. The risk of the listed companies can be categorized into four ordered lever: normal, ST, *ST, delisting. In this data set, the change to better or worse status of a ST company or *ST company is defined as follows: (1) better status including ST→Normal, *ST→ST,*ST→Normal; (2) worse status including ST→*ST, ST→delisting, *ST→delisting. The change to better status of a listed company is denoted by 1, while the change to worse status is denoted by -1.

The ST or *ST companies always get their special treatment removed after their release of the financial statements of the previous fiscal year. However, the prediction always needs to be conducted before the release of the financial statement of the previous fiscal year; therefore, the available information that can be used for prediction is the financial statements of the fiscal year before last year and the most recent market information of the corresponding stock. For example, it is January, 2013. To predict if a current ST company gets its ST removed or receives delisting risk warning or delisting treatment, only the financial statements of year 2011 and all available market information can be used.

Many different features have been used to predict the financial distress or bankruptcy. It is reasonable to assume that the features having been proved to be effective in the prediction of financial distress or bankruptcy have good capability to discriminate the good or bad financial status of a company. Therefore, in this study, the features that have been tested to be effective are employed. The employed features are from the work of Altman [5] and Shumway [6]. The five financial ratios used by Altman are working capital/total assets (WCTA), retained earnings /total assets (RETA), earnings before interest and tax/total assets (EBITTA), market equity/total liabilities (METL), and sales/total assets (STA). Shunway [6] used net income / total assets (NITA), total liabilities / total assets (TLTA), the excess annual return over index return (EAROIR), log(stock market capitalization /total market capitalization (LSMCOTMC), and the stock's volatility for the concerned year. In this study, a new market variable the β of stock, a good indicator of market risk of the stock, is introduced.

3.2. Experimental setting

The number of observations with change to better status and with change to worse status is different in the original data set. A research from Zhou [9] discussed the effect of sampling methods on the performance of quantitative bankruptcy prediction models on real highly imbalanced dataset. The results showed that the difference of performance of models measured by imbalanced test sample and balanced test sample is slight and is not significant. Consequently, in this study, a balanced data set is used to test the performance of Adaboost method in the prediction of removal of ST or *ST for the listed ST companies. The final dataset contains 206 observations with change to better status and 206 observations to worse status. The number of observations in each year is shown in Fig 2. All the 412 observations are randomly selected from the original 872 observations. The 322 sample in or before year 2007 are used for training the models and the other 90 sample after year 2007 are used for testing the models.

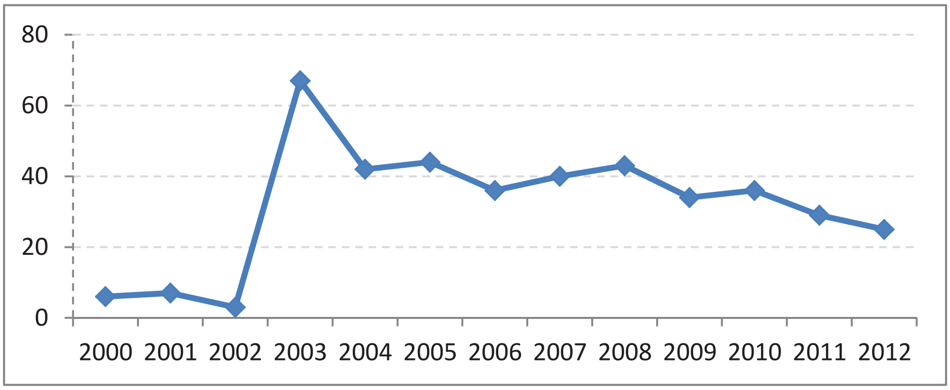

Fig. 2. The number of observations in years from 1998 to 2010.

The performance of Adaboost is also compared to other five popular classification techniques, such as linear discrimiant analysis (LDA), logistic regress (LR), decision tree C4.5 (DC4.5), neural network (NN) and least square support vector machines (SVM). All these models except DC4.5 are implemented by matlab. DC4.5 is implemented by Weka.

The following popular measures are used to evaluate the performance of the models:

(1) Sensitivity (Sen) = $\frac{BB}{BB+BW}$

(2) Specificity (Spe)= $\frac{WW}{WW+WB}$

(3) Accuracy (Acc) = $\frac{BB+WW}{BB+BW+WW+WB}$

Where *B* indicates change to better status, *W* indicates change to worse status. BB: change to better status classified as change to better status, BW: change to better status classified as change to worse status, WW: change to worse status classified as change to worse status, WB: change to worse status classified as change to better status.

3.3. Experimental results

Table 1, Table 2, and Table 3 show the average performance of models on 30 groups of randomly selected 412 observations with features group from Altman [4], Shumway [2], and the combination of features from above two works along with β of the stock.

Table 1. Performance of models with features from Altman [5]

Models	Sen	Spe	Acc
LDA	0.7074	0.3652	0.5363
LR	0.6926	0.3785	0.5356
DTC4.5	0.5800	0.5341	0.5570
NN	0.5881	0.5096	0.5489
SVM	0.6681	0.4578	0.5630
Adaboost	0.6200	0.5178	0.5689

Table2. Performance of models with features from Shumway [2]

Models	Sen	Spe	Acc
LDA	0.8689	0.1296	0.4993
LR	0.8593	0.1541	0.5067
DTC4.5	0.3830	0.8207	0.6019
NN	0.7156	0.2785	0.4970
SVM	0.6437	0.3622	0.5030
Adaboost	0.7059	0.5644	0.6352

Table 3. Performance of models with combined features from Altman [5] and Shumway [2] and β

Models	Sen	Spe	Acc
LDA	0.8304	0.1311	0.4807
LR	0.8207	0.1259	0.4733
DTC4.5	0.6244	0.4748	0.5496
NN	0.7630	0.1904	0.4767
SVM	0.6978	0.3052	0.5015
Adaboost	0.6422	0.5600	0.6011

From above tables, it can be observed that Adaboost model constantly obtains the best performance in terms of accuracy in the test with different features set. Adaboost model combined with features from Shumway can achieve 63.52% accuracy which is the best among all the results. However, the accuracy of 63.52% is very low when compared to the performance of these models in the prediction of financial distress for normal companies in China [3]. It indicates that the problem of predicting the removal of special treatment or delisting risk warning for the listed companies having received special treatment is more challenge than the problem of predicting the financial distress of an ordinary listed company.

4. Conclusion

This study uses Adaboost method to predict if a ST or *ST listed company will have its special treatment or delisting risk warning removed. The results show that Adaboost method combined with Shumway's features achieves the best predictive accuracy. The employed popular models tested in this study have excellent performance on the problem of financial distress prediction; however, their performance for the problem in this study is not satisfactory. What make the prediction of the removal of special treatment or delisting risk warning more difficult will be our further research.

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