

# Corporate Bankruptcy Forecast Using RealAdaBoost

Tadaaki Hosaka\*

Yuta Takata

*School of Management, Tokyo University of Science,  
500 Shimokiyoku, Kuki, Saitama 346-8512, Japan, E-mail\*: hosaka-t@rs.tus.ac.jp*

## Abstract

Critical elements in the process of predicting corporate bankruptcies are selection of financial indicators and construction of a forecast model. Many traditional methods implement these two tasks separately, and do not guarantee the optimality on the whole process. This study uses the RealAdaBoost algorithm so that the selection of indicators and the construction of a model can be realized within a single coherent framework in the process of forecasting bankruptcies. RealAdaBoost iteratively chooses a financial indicator and the weight of learning samples that are mistakenly classified by the indicator increases in the next iteration step, and because of this, a combination of indicators that complement each other is naturally extracted. Setting financial ratios generated from the balance sheets and profit-and-loss statements of 150 failed firms and 150 continuing firms as candidates of indicators, our proposed method selects the following four ratios in most cases: 1) Net income before taxes and other adjustments / Current liabilities, 2) Total investments and other assets / Capital stock, 3) Total liabilities / Fixed assets, and 4) Owned capital / Capital stock. Discrimination of RealAdaBoost with four financial ratios shows an identification rate of 0.893 under the leave-one-out cross validation.

**Key Words:** Bankruptcy prediction, AdaBoost, Financial ratios

## 1. Introduction

In order to generate profit in trading securities, it is important to forecast the future of a company from its current financial health. A typical way to do this is to forecast corporate bankruptcies. Many studies of bankruptcy prediction have been reported by using statistical analysis, such as pattern recognition and machine learning.

Crucial factors in studies of bankruptcy forecasting are the selection of financial indicators for use in the analysis and the construction of a forecast model. These two factors correspond to the feature extraction and the derivation of discriminant functions in machine learning. Many previous studies of bankruptcy forecasting set the indicators manually based on accounting perspectives and on the results of past studies, and focused on the evaluation of accuracy of the proposed forecast models. Those studies do not necessarily guarantee good chemistry between the financial indicators and the forecast model. On the other hand, some researches focused on the selection of financial indicators using statistical methods such as the decision tree. Many of those studies applied classifiers in the later stage, such as the linear discriminant analysis. These

two processes are separately implemented, and therefore, the selected financial indicators are not necessarily appropriate for the forecast models.

With this as the backdrop, the purpose of this study is to perform the selection of financial indicators and the construction of a forecast model within a single framework in corporate bankruptcy prediction. For this purpose, we look to AdaBoost [1], which has been occasionally used for feature vector selection in the field of machine learning, and we utilize in this study RealAdaBoost algorithm [2], an advanced version of AdaBoost. RealAdaBoost sequentially chooses a financial indicator and the weight of learning samples that are mistakenly classified by the indicator increases in the next iteration step. Because of this, indicators that can handle “difficult” samples will naturally be selected in the later steps. Furthermore, the process of the construction of a discriminant function (forecast model) with the selected indicators can be carried out in a single framework.

## **2. Previous Studies on Bankruptcy Forecasting**

While studies on bankruptcy forecasting include ones with non-financial approaches, such as the work by Argenti [3], many are based on corporate financial information. The pioneering work of bankruptcy forecasting based on statistical approach is the one by Beaver [4]. The criteria for selecting financial indicators used by this study were 1) often quoted in the literature; 2) provide good results in the past studies; and 3) based on cash flow. Under these criteria, 30 financial ratios were picked through the analysts’ subjective insights and the performance of distinguishing failed companies from continuing companies by each one of them was investigated. Consequently, the one with the highest distinguishing capacity was the cash flow-to-total liability ratio followed by the net income-to-total assets ratio.

The first research that tried to simultaneously handle multiple financial ratios was Altman [5]. This study used the financial information of 33 failed manufacturers that filed for bankruptcy during the period from 1946 to 1965 and that of 33 continuing companies of a comparable size. The ratio-selection criteria were 1) can be interpreted by either viewpoint of liquidity, profitability, leverage, solvency, and turnover rate; 2) has been addressed in past studies; and 3) suits the purpose of bankruptcy forecasting. In this study, 22 financial ratios were selected also through the analysts’ subjective insights, and classification performance of various combinations among those ratios was examined based on the linear discriminant analysis. Finally, the following bankruptcy prediction model was formulated with five financial ratios:

$$Z = 0.012x_1 + 0.014x_2 + 0.033x_3 + 0.006x_4 + 0.999x_5, \quad (2.1)$$

where

- $x_1$ : Working capital / Total capital,
- $x_2$ : Retained earnings / Total assets,
- $x_3$ : Earnings before interests and taxes / Total assets,
- $x_4$ : Market value of equity interests / Total assets,
- $x_5$ : Amount of sales / Total assets.

When the value of the discriminant function (2.1) called the Z-score is equal or less than 2.675, the company in question is judged as “failed” while, if it is over 2.675, “continuing.” On other 25 companies not used in the learning of the forecast model, the identification rate turned out to be 0.96.

Later, statistical approaches were also introduced in the process of selecting the financial indicators. Edmister [6] selected seven financial ratios by using the sequential variable selection method though the candidates of the indicators were limited to the 19 financial ratios used in previous studies. Sung [7] used the decision tree algorithm to select financial indicators effective for the bankruptcy forecast of Korean companies. Shirata [8] also prepared 65 ratios based on the effectiveness in the past studies or from accounting perspectives, and eventually selected four ratios using the decision tree algorithm and the stepwise method.

In order to improve the credibility of the analysis, Shirata [9] substantially increased the number of data samples which had consisted of tens or hundreds of company data previously. The study used the financial information of 1436 failed companies during the period of 1992 to 2000 and that of 3435 continuing companies. Seventy-two financial indicators, including some indicators in her previous study [8] and new ones on cash flow, were prepared as possible choices. Excluding the indicators that are vulnerable to economic environmental changes and lacking in accounting suitability leaves 42 financial indicators. Then, the following four financial ratios were chosen by using the CART (Classification and Regression Tree) algorithm, a kind of decision trees:

- $x_6$ : Retained earnings / Total assets,
- $x_7$ : Net income before taxes / Total assets,
- $x_8$ : Inventory ( $\times 12$ ) / Amount of sales,
- $x_9$ : Interest expenses / Amount of sales.

Finally, the following discriminant function was induced using these indices:

$$\text{SAF} = 0.010x_6 + 0.027x_7 - 0.066x_8 - 0.024x_9 + 0.71. \quad (2.2)$$

This forecast model is called SAF (Simple Analysis of Failure) 2002 and has been widely used as a benchmark in subsequent research studies. If the value of SAF in Eq. (2.2) falls below the threshold which differs from one industry to another, the company in question is judged as failed. An evaluation of 67 companies that failed or filed for bankruptcy during the period from January 2001 to December 2005 showed the correct identification rate of 0.940.

On the other hand, many studies focused on improving the accuracy of forecast models using non-linear discriminators without emphasizing the selection of financial indicators. Examples are the research by Ohlson [10], which used the logistic regression model, the one by Altman [11], which proposed bankruptcy forecast using neural network, or the study by Shin [12], which applied the support vector machine to bankruptcy forecasting. AdaBoost, which will be used in our study, appeared in the literature [13] not to select financial indicators but only to construct a forecast model.

We believe that the suitability or chemistry between selected financial indicators and the forecast model (classifier) greatly influences the final accuracy of the prediction. Therefore, if the indicators are manually chosen based on analysts' intuition, there is no guarantee that the discrimination accuracy is optimized. Also, as in the case of previous researches [7-9], even if the decision tree is utilized to select financial ratios for bankruptcy forecasting, there is no guarantee that financial indicators optimal for the final discrimination can be found by the decision tree. Because of such reasons, we believe that it is worth examining the effectiveness of an algorithm capable of conducting the selection of financial indicators and construction of a forecast model within a coherent single framework.

Based on the background mentioned above, this study utilizes RealAdaBoost algorithm which is occasionally used in the field of machine learning for the purpose of feature extraction, to conduct the selection of financial indicators effective in forecasting bankruptcies and the construction of a forecast model within a coherent framework.

### **3. Proposed Method**

#### **3.1 Financial data of this study**

While there is no clear-cut legal definition of bankruptcy in Japan, it is typically regarded as the status of "not capable of settling the liabilities due." Based on this understanding, failed companies as the subjects of this study are defined as the companies that delisted their shares

from the Tokyo Stock Exchange, the Osaka Stock Exchange, former NASDAQ Japan Standard, former Hercules Standard, and former JASDAQ in or after 2002. In addition, in view of forecasting bankruptcies, the list was narrowed down to 150 de facto bankrupt companies (reasons of the delisting are negative net worth, suspension of bank transaction, bankruptcy / revitalization / reorganization process, and termination of business activities except for a merger). Therefore, this study may be regarded to be forecasting delisting from stock exchanges as the prior step of bankruptcy. Financial institutions, including banks, are not covered in the study due to non-availability of their financial information. On the other hand, the subject continuing companies in this study are the randomly chosen 150 companies from the score sheet for the 2014 Awards for Excellence in Corporate Disclosure by The Securities Analysts Association of Japan.

The balance sheets and profit-and-loss statements for those 150 failed companies and 150 continuing companies are obtained from the Nikkei NEEDS Financial QUEST. The financial information on failed companies is the data released right before delisting (in most cases, within one year prior to the delisting), and the data for continuing companies are as of October 2014.

This study focuses on forecasting an individual company's bankruptcy and use unconsolidated financial statements, not the consolidated ones. Each data set of a company consists of 187 items of balance-sheet-related data and 106 items of profit-and-loss-statement-related data.

Generally, financial statements include many missing values due to the fact that specific items do not exist depending on the industry. This study, therefore, excludes any items missing from any one company's financial statements. As the result, 10 items from the balance sheets and 7 items from the profit-and-loss statements remain.

### **3.2 Generation of candidate financial ratios**

Using the obtained complete data, we generate candidate financial ratios. This study chooses arbitrary two items from the balance sheet and profit-and-loss statements (including cases where one item from each financial statement is selected) and calculates the ratio. Since replacing the numerator with the denominator generates an essentially identical ratio, we deal with either one of them. An item whose value is zero for even a single company will be treated so that it does not become the denominator of the ratio.

The notation is specified here. Defining the number of generated ratios and subject companies as  $M$  and  $N(=300)$ , respectively, the financial ratio for each company is expressed as  $\mathbf{x}_i \in \mathbf{R}^M$  ( $i=1,2,\dots,N$ ), and the class label as  $y_i \in \{1,-1\}$ . In this article,  $y_i = 1$  indicates a continuing company while  $y_i = -1$ , a failed company.

We will not narrow down the number of financial ratios from the accounting perspective or knowledge in previous studies. Some previous studies exclude indicators that are difficult to interpret from the accounting point of view. However, we believe that if the use of those excluded ratios brings about the improvement of the discrimination accuracy, positive consideration should be given to them. Also, Shirata pointed out in [9] that generating numerous indicators artificially can produce many indices with similar meanings. However, in the RealAdaBoost feature selection, indicators with a different quality from previously chosen ones are selected iteratively by reweighting mechanisms to learning samples, as we will discuss below. Therefore, even when multiple ratios with similar meanings coexist, it should not at least have any adverse impact on discrimination accuracy.

### 3.3 Selection of financial indicators and construction of forecast model

It is difficult to derive the optimal combination of indicators from many generated financial ratios. This study will overcome this difficulty by conducting the whole process from selecting financial indicators to constructing a forecast model in a single framework of RealAdaBoost. How RealAdaBoost makes the selection of financial indicators (feature extraction) and derivation of discriminant functions will be explained below.

AdaBoost [1] or RealAdaBoost [2] was not originally proposed for feature extraction. These are kinds of ensemble learning algorithms aiming at the creation of a single classifier with high accuracy (termed a strong classifier) by combining multiple classifiers with low accuracy (termed weak classifiers). This study applies the algorithm to the selection of financial indicators.

Below is the sequence of selecting financial indicators using RealAdaBoost:

- 1) Prepare a learning data set  $(\mathbf{x}_i, y_i)$  ( $i=1,2,\dots,N$ ).
- 2) Set weights  $w_i$  ( $i=1,2,\dots,N$ ) to each sample (data of each company) equally as follows:

$$w_i = \frac{1}{N} \quad (i = 1, 2, \dots, N). \quad (3.1)$$

- 3) Repeat the following procedures 4)–7)  $T$  times.
- 4) Calculate the weighted probability distribution with respect to  $k(=1,2,\dots,M)$ -th dimension of the financial indicator vector  $\mathbf{x}$ ,  $P_k^+(x), P_k^-(x)$  for each positive and negative example. These distribution functions are defined as follows, when the  $k$ -th dimension of a vector  $\mathbf{x}_i$  ( $i=1,2,\dots,N$ ), is represented as  $x_{ik}$ :

$$P_k^\pm(x) = \sum_{i=1 \text{ such that } y_i = \pm 1}^N w_i \delta(x - x_{ik}). \quad (3.2)$$

Here,  $\delta(\cdot)$  is the Dirac's delta-function.

- 5) As for the financial indicator  $k(=1,2,\dots,M)$ , calculate the distance  $d_k$  between the weighted probability distribution for positive examples and negative examples by the Bhattacharyya distance:

$$d_k = -\ln \left( \int_{x=-\infty}^{x=+\infty} \sqrt{P_k^+(x) \cdot P_k^-(x)} dx \right). \quad (3.3)$$

- 6) Select the index with the largest distance as the one with the highest identification capacity at  $t(=1,2,\dots,T)$ -th step:

$$k_t^* = \operatorname{argmax}_k d_k. \quad (3.4)$$

The discriminant function (weak classifier) corresponding to the financial indicator  $k_t^*$  is expressed as below:

$$h_t(x) = \frac{1}{2} \ln \frac{P_{k_t^*}^+(x) + \varepsilon}{P_{k_t^*}^-(x) + \varepsilon}. \quad (3.5)$$

Here,  $\varepsilon (\ll 1)$  is a minutely small figure introduced to avoid a zero divide. The class is categorized according to whether the discriminant function  $h_t(x)$  is positive or negative.

- 7) The weights of the samples  $w_i$  ( $i=1,2,\dots,N$ ) are renewed by the following formula:

$$w_i \leftarrow w_i \exp\{-y_i h_t(x_{ik_t^*})\}. \quad (3.6)$$

By this, the weights of the samples that can be correctly categorized by the selected financial indicator  $k_t^*$  decrease while the weights of the samples that are mistakenly categorized increase. The weights of each sample are eventually normalized so that the sum of the weights becomes one.

By completing the procedures above,  $T$  weak classifiers  $h_t$  ( $t=1,2,\dots,T$ ) are obtained. With RealAdaBoost, the weights of the samples that are mistakenly categorized by the selected financial indicator increase and in the later iteration step, financial indicators that enable the discrimination of such “difficult” samples will become easier to select. Note that the weights of correctly categorized samples will not become zero and will maintain a certain influencing power. Therefore, financial indicators that depend on a small number of samples will become difficult to select, which is an advantage compared to the traditional decision tree algorithm.

With RealAdaBoost, not only the selection of financial indicators but the forecast of new data  $\mathbf{z} = (z_1, z_2, \dots, z_M)$ , whose class label  $y_z$  is unknown, can be implemented by the following formula (corresponding to a strong classifier):

$$y_z = \text{sign} \left[ \sum_{t=1}^T h_t(z_{k_t^*}) \right], \quad (3.7)$$

where the function  $\text{sign}(\cdot)$  is defined as  $\text{sign}(x) = \begin{cases} +1 & (x \geq 0) \\ -1 & (x < 0) \end{cases}$ . The whole process from selecting financial indicators to constructing a forecast model is done within a single framework, and the optimal set of financial indicators are naturally selected. This is what differentiates our proposed method from traditional ones conducting both processes separately.

On a different note, a famous example of feature extraction by AdaBoost is the research on face detection [14], which is a study in image processing. In that work, feature vectors effective for face detection are derived from millions of the Haar-like features with AdaBoost.

### 3.4 Evaluation with the leave-one-out cross-validation

Leave-one-out cross-validation is used to evaluate the proposed method. With the leave-one-out method, the following procedures are applied: 1) the selection of financial indicators is conducted with RealAdaBoost by using corporate data of 299 companies out of 300 as learning samples, and 2) assuming the remaining one data to be the new data for the test, whose class label is unknown, the discrimination for this sample is performed by using Eq. (3.7). By changing the combination of learning samples and a test sample, the total of 300 patterns will be examined. We define the identification rate as the ratio at which discrimination is correctly made against the 300 test samples.



## 4. Evaluation Experiments

In this section, we will discuss the evaluation experiments. First of all, discrimination accuracy of the forecast model will be quantitatively verified on the basis of the leave-one-out cross-validation. Then, qualitative validity of selected financial ratios will be examined.

### 4.1 Verification of discrimination accuracy

The total number of financial ratios generated with the procedure in section 3.2 was 136. Fig.1 shows the discrimination accuracy obtained by RealAdaBoost (proposed method) as well as that of the original AdaBoost [1]. The horizontal axis indicates the number of financial ratios taken into the forecast model, which is equal to the number of times AdaBoost repeats the process, i.e. the value of  $T$ . The vertical axis shows the identification rate obtained by the leave-one-out cross-validation; the number of times the correct discrimination is made in 300 evaluations.

The overall trend is that as the number of financial ratios increases, discrimination accuracy improves. Especially until the number of financial ratios reaches 4 (identification rate of 0.893), the degree of improvement is high. When that goes beyond 5, the improvement becomes gradual and when the number of ratios is 10, the identification rate is 0.907, and at 20, 0.920. Forecasting

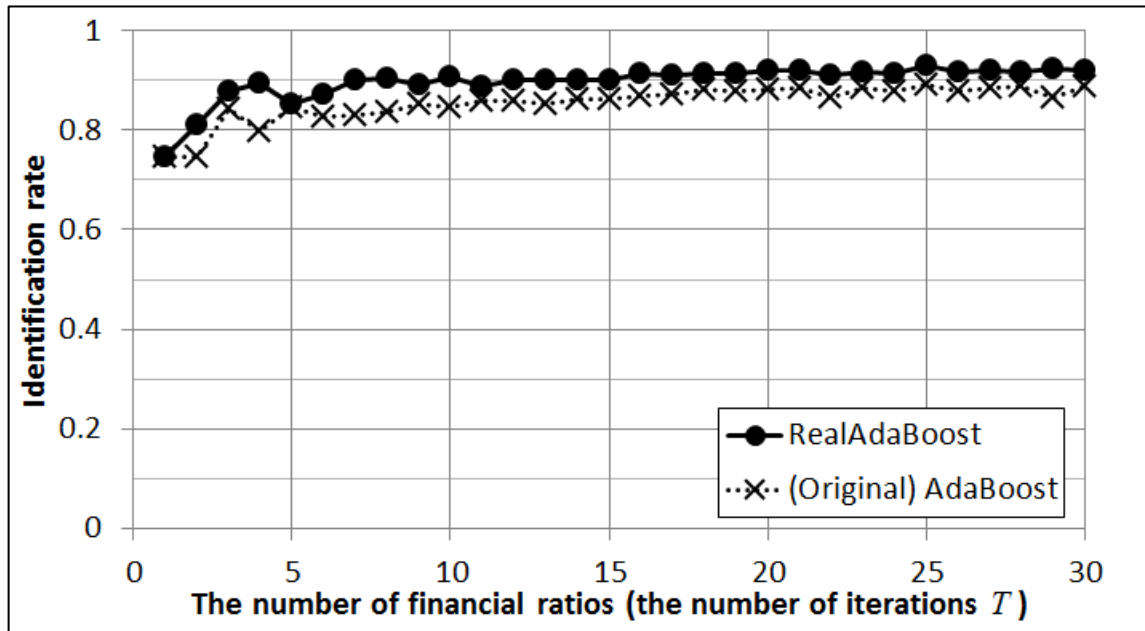


Fig. 1. The precision of the discriminant function with respect to the number of selected financial ratios.

Table 1. Combination of the most frequently extracted financial ratios

1	Net income before taxes and other adjustments / Current liabilities	[0.35 / -0.39]
2	Total investments and other assets / Capital stock	[2.17 / 0.076]
3	Total liabilities / Fixed assets	[0.92 / 7.13]
4	Owned capital / Capital stock	[9.24 / 1.09]

accuracy with RealAdaBoost is improved by the average of 0.0414 over the range of  $1 \leq T \leq 30$ , compared with the original AdaBoost.

#### 4.2 Discussion on selected financial ratios

We examine the financial ratios selected as effective for forecasting bankruptcies by the proposed method. As the identification rate increases drastically up until the first four financial indicators are extracted, here we examine those four financial ratios picked up by RealAdaBoost. Table 1 shows the combination of the first four financial ratios most frequently appearing in the 300 trials with the leave-one-out cross-validation. The numbers in parentheses in the table indicate the average value of financial ratios for 150 continuing companies (left) and for failed companies (right) used in this study.

The interpretation of each financial ratio is discussed below:

(1) Net income before taxes and other adjustments / Current liabilities

This ratio is often selected in the first step of RealAdaBoost and it is the indicator with the highest discrimination accuracy as a single financial ratio. The situation where net income before taxes and other adjustments, which is the disposable profit of the company, is greater than the liabilities payable within a short period of time by certain percentage is very important from the point of the soundness of a business. This ratio shows how efficiently a company is making profit by borrowing and, in this sense, it is close to financial leverage in meaning. Also, we consider that it can be a better index in judging whether a company fails or not, than ROA or ROE, which are typical financial indices representing high profitability of a business.

(2) Total investments and other assets / Capital stock

This ratio is often selected in the second step of RealAdaBoost. Total investments and other assets, the numerator, are fixed assets other than tangible fixed assets (land, plants and others)

and intangible fixed assets (software, patents and others), and mostly consist of securities for investment, shares in affiliated companies, and the stake in the company. As the business performance worsens, we can assume that they are likely to be sold. Capital stock, the denominator, plays a role as the normalization factor with respect to the size of the company. The ratio tends to show small numbers for failed companies and thus enables one to judge whether the business is experiencing difficulty.

### (3) Total liabilities / Fixed assets

This ratio often shows up in the third step of RealAdaBoost. As the business performance of a company deteriorates, liabilities typically grow larger, i.e., the numerator becomes larger. Further worsening forces the business to sell its fixed assets or be foreclosed, i.e., the denominator becomes smaller. Therefore, if this ratio shows a big figure, it indicates that the business is in bad condition.

### (4) Owned capital / Capital stock

This ratio often appears in the fourth step of RealAdaBoost. Owned capital, the numerator, is almost equal to net assets which include capital stock (the denominator) and earnings retained as the savings of the company. As the retained earnings is usually a positive figure as long as the business performance of the company is stable, this ratio is larger than one. However, when the business performance deteriorates, the retained earnings can be negative and this ratio becomes less than one. Actually, most failed companies in this study have this index around or below one.

Above discussion shows both qualitatively and quantitatively that the four financial ratios selected by the proposed method are effective in distinguishing failed companies from continuing companies.

Based on these four financial ratios, the activities of companies going bankrupt can be assumed as follows:

1. Sales fall and it becomes harder to pay down the debts. (The decrease of financial ratio 1)
2. The retained earnings decrease and the capital reduction advances. (The decrease of financial ratio 4)
3. The amount of liabilities further increases and the fixed assets and securities for investment are sold. (The decrease of financial ratio 2, the increase of financial ratio 3)

It should be noted that these events may not necessarily occur in the above order and other factors may have an impact for corporate bankruptcy.

In the 37 leave-one-out trials out of a total of 300 times, combinations other than the four above are selected. For those 37 combinations, we examined how many ratios are different from the most frequent ones, and its results are as follows:

Only one ratio is different: 4 times,

Two ratios are different: 25 times,

Three ratios are different: 8 times,

All four ratios are different: 0 times.

Thus, it is not the case that completely different ratios are selected and there is some tendency as to which ratios are extracted. This implies the robustness of the selection of financial indicators by RealAdaBoost.

## 5. Summary

In this study, we have proposed a coherent framework for the selection of financial ratios and the construction of a forecast model in bankruptcy prediction by using RealAdaBoost. Generating ratios from arbitrary two items in the balance sheets and profit-and-loss statements of 300 subject companies, we have evaluated the performance of the proposed method based on the leave-one-out cross-validation. As the result, the identification rate of 0.893 was achieved with four financial ratios. Out of 300 trials, the following combinations were selected with a probability of approximately 87.7%:

- 1) Net income before taxes and other adjustments / Current liabilities,
- 2) Total investments and other assets / Capital stock,
- 3) Total liabilities / Fixed assets,
- 4) Owned capital / Capital stock.

Shown below are the issues and areas for improvement of this study in the future. First, we have some issues about the data. In this study, financial statements just before the delisting were used for the failed companies. However, it is useful to forecast the failure at an earlier stage. Therefore, it seems significant to investigate the performance of our method by using the data which failed companies had disclosed two (or more) fiscal years ahead of the delisting. Furthermore, improving the discrimination accuracy by using financial statements for multiple

fiscal years is another challenge. Other future works include the use of information that is related with cash flow and non-financial matters.

Second, there are issues concerning the methods of evaluation. In this study, the evaluation by industry was not conducted. In reality, the trends in financial ratios differ substantially from one industry to another. Thus, implementing evaluations by industry may improve the accuracy and may bring about the discovery of more effective financial ratios. Also, as the performance of a business is influenced by external factors including the economic environment, it is unlikely that specific financial ratios are always effective in forecasting bankruptcies in any given period. Accordingly, the evaluation by year may lead to a discovery of new knowledge.

Third, enhancement of the algorithm is promising. Other than RealAdaBoost used in this study, some improvements to AdaBoost have been proposed (e.g. LogitBoost [15]). The application of such an algorithm is a future work.

## **Acknowledgements**

This research was supported by JSPS KAKENHI Grant Numbers 15K21395.

## **References**

- [1] Freund, Y., and R. E. Schapire, A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting, *Journal of Computer and System Sciences*, 55(1) (1997), 119–139.
- [2] Schapire, R. E., and Y. Singer, Improved Boosting Algorithms Using Confidence-rated Predictions, *Machine Learning*, 37(3) (1999), 297-336.
- [3] Argenti, J., Corporate Collapse: The Cause and Symptoms, McGraw-Hill Book Company (1976).
- [4] Beaver, W. H., Financial Ratios as Predictors of Failure, *Journal of Accounting Research*, 4 (1967), 71-111.
- [5] Altman, E. I., Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *The Journal of Finance*, 23(4) (1968), 589-609.
- [6] Edmister, R. O., An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction, *Journal of Financial and Quantitative Analysis*, 7(2), (1972), 1477-1493.
- [7] Sung, T. K., N. Chang, and G. Lee, Dynamics of Modeling in Data Mining: Interpretive Approach to Bankruptcy Prediction, *Journal of Management Information Systems*, 16(1), (1999), 63-85.

- [8] Shirata, Y., Formation of Bankruptcy Prediction Information (in Japanese), Chu-o Keizaisha, (1999).
- [9] Shirata, Y., Bankruptcy Prediction Model (in Japanese), Chu-o Keizaisha, (2003).
- [10] Ohlson, J. A., Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research*, 18(1), (1980), 109-131.
- [11] Altman, E. I., G. Marco, and F. Varetto, Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience), *Journal of Banking & Finance*, 18 (1994), 505-529.
- [12] Shin, K., T. S. Lee, and H. Kim, An Application of Support Vector Machines in Bankruptcy Prediction Model, *Expert Systems with Applications*, 28 (2005), 127-135.
- [13] Ramakrishnan, S., M. Mirzaei, and M. Bekri, Corporate Default Prediction with AdaBoost and Bagging Classifiers, *Journal Teknologi (Sciences & Engineering)*, 73(2) (2015), 45-50.
- [14] Viola, P., and M. Jones, Robust Real-Time Face Detection, *International Journal of Computer Vision*, 57(2) (2004), 137-154.
- [15] Friedman, J., T. Hastie, and R. Tibshirani, Additive Logistic Regression: A Statistical View of Boosting, *Annals of Statistics*, 28(2) (2000), 337-407.

\*Corresponding author: Tadaaki Hosaka, Ph.D.

School of Management,

Tokyo University of Science,

500 Shimokiyoku, Kuki-shi, Saitama, 346-0033 Japan

E-mail: hosaka-t@rs.tus.ac.jp