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AdaBoost based bankruptcy forecasting of Korean construction companies

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ABSTRACT

A lot of bankruptcy forecasting model has been studied. Most of them uses corporate finance data and is intended for general companies. It may not appropriate for forecasting bankruptcy of construction companies which has big liquidity. It has a different capital structure, and the model to judge the financial risk of general companies can be difficult to apply the construction companies. The existing studies such as traditional *Z*-score and bankruptcy prediction using machine learning focus on the companies of non-specific industries. The characteristics of companies are not considered at all. In this paper, we showed that AdaBoost (adaptive boosting) is an appropriate model to judge the financial risk of Korean construction companies. We classified construction companies into three groups – large, middle, and small based on the capital of a company. We analyzed the predictive ability of the AdaBoost and other algorithms for each group of companies. The experimental results showed that the AdaBoost has more predictive power than others, especially for the large group of companies that has the capital more than 50 billion won.
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1. Introduction

In recent times, bankruptcy of construction companies has rapidly increased due to the recession in the real estate sector. Since 2008, a continuously decreasing profit ratio in the construction industry has had a negative influence on the liquidity of construction companies. According to the economic outlook report of 2013, it is predicted that the liquidity crisis experienced by construction companies will persist due to the continuing recession in the housing construction business [1]. While the construction industry has bigger social ripple effects caused by bankruptcy than other industries, due to the nature of its capital structure, debt-to-equity ratio and cash flow are different from other industries, bankruptcy predictions for construction corporations become more difficult.

The ratio of the construction industry to GDP in Korea is 5.9%, which is higher than the average ratio of other OECD countries, 5.1%. Investment in construction attempts to increase economic growth with large amounts of capital. While the USA shows a notable recovery trend, Korea is hindered by a significant decrease in investment in the construction industry due to the recession in the real estate business.

The construction industry has high leverage and debt-to-equity ratios. Positive cash flow in the construction business is highly concentrated in the latter parts of the projects. Construction companies are highly sensitive to economic cycles and bankruptcy rapidly increases in an economic downturn. Because the construction industry requires high leverage, increased bankruptcies of construction companies will be a big burden to creditor banks which provided the construction loans. Nevertheless, bankruptcy forecasting models mainly focused on financial institutions, and construction-specific studies have rarely been carried out.

Increases in bankruptcies of construction companies create a big burden on the banks that provide loans to the companies. In fact, some savings banks that were primarily dedicated to real estate project financing went bankrupt recently along with the bankruptcy of their borrowers, the construction companies. Not only savings banks, but also commercial banks could not avoid the impact. These banks should secure significant amounts of capital to cover losses for the possible risk of borrower bankruptcy. As the construction business is entwined in a complicated system involving numerous subcontractors, bankruptcy of a single construction company triggers a chain reaction of bankruptcies of other companies. Furthermore, since the construction industry is closely related to raw material industries such as cement and steel, its recession has huge influence on other industries. The construction industry also has a big employment-inducing effect, its bankruptcy has greatly affected ordinary households. Notwithstanding the fact, bankruptcy forecasting models so far have mainly focused on

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financial institutions, and few studies are conducted with construction industry-specified models.

Studies of bankruptcy forecasting models based on financial statements of a company have been conducted in diverse ways for long time. The subjects of the model, however, were the general firms, and the models may not be proper for accurately forecasting companies having large liquidity issues such as construction companies. The construction industry is a capital-intensive industry that requires long-term project periods, huge investment, and takes a long time to receive returns from the investment. Therefore, it has a different capital structure from other industries, and the same criteria used for other industries cannot be applied to effectively evaluate its financial risk [2].

Altman's *Z*-score has been commonly used as a bankruptcy forecasting model [3] so far. *Z*-score was first published in 1968 and it forecasted the likelihood of a company going bankrupt by using a simple formula. *Z*-score classified the results into three categories and evaluated the corporate status as dangerous, moderate or safe. When a company falls in the "dangerous" category, it has a high likelihood of bankruptcy within two years, while in the "safe" category, it has a low likelihood of bankruptcy. When the company falls in the "moderate" category, it is not easy to forecast the risk. Many of the construction cases in this study fell in the "moderate" category, which made it hard for us to forecast its risk.

Along with the development of machine learning by using a computer, studies of forecasting corporate bankruptcy have been active recently based on machine learning. Pattern recognition, which is a representative application area of machine learning, is applied in forecasting corporate bankruptcy. Patterns were analyzed based on financial information of a company and then we judged whether the pattern belongs to the bankruptcy risk group or safe group. The representative machine learning models used in the bankruptcy forecasting are Artificial Neural Networks [13,14,7] and Adaptive Boosting (AdaBoost) [2]. Some research used Support Vector Machine (SVM) [15,16,5,6]. There are also diverse hybrid studies that combined these models [17,8]. All the previous work used financial statements as an input in their forecasting models. These works are characterized by the machine learning algorithm and company's country. They all classified the financial statements as capital, assets, sales, income, and liability. The data was transformed into ratio because the scale is very different for each company. For example, the liability data was transformed into total liability to total assets.

Previous studies of bankruptcy forecasting models using *Z*-score and machine learning were carried out using general companies. Therefore, the specific characteristics of each industry have not been considered. This study compared the predictive ability of each model according to the size of the construction companies and verified that Adaptive Boosting has the best predictive ability.

This study classified construction companies into three classes according to the size of capital. It analyzed predictive ability of the AdaBoost for each class. For relative performance measurement of AdaBoost, we conducted comparative analysis with other machine learning models such as Artificial Neural Networks, SVM and Decision Tree. Predictive ability of each model was measured with financial data from the companies that went bankrupt in the period from 2008 to 2012 with those in normal operation as of 2012. As a result, it was found that AdaBoost had good predictive ability compared to other models. In particular, for companies of which capital was more than 50 billion won, it showed outstanding predictive ability.

The contribution of our work is that we have selected 12 variables for the model of bankruptcy forecasting and come to the conclusion that AdaBoost with a decision tree is more appropriate for the model that other machine learning algorithms, especially for Korean construction companies.

The structure of this study is as follows. Section "Description of the research issues" explains the issue of bankruptcy forecasting and Section "Descriptions on the data" describes the data of construction companies used in this study. Section "Adaptive Boosting" explains AdaBoost, the major machine learning method of this study. Section "Experiment" shows the experiment results and final section contains the conclusion.

2. Description of the research issues

Forecasting bankruptcy of a company is an important issue in business management. The goal is to discern sound companies from the companies having a likelihood of going bankrupt. That is, its goal is to construct a risk forecasting model of a company and make proper decisions accordingly based on the predictions. In order to forecast bankruptcy risk of a company, it is essential to know the current financial status of the company. As this information may have great difference in values depending on the size of the company, ratios are usually used in bankruptcy forecasting models [4]. For example, to indicate current assets, the ratio obtained from dividing by the total assets is used.

Although everybody acknowledges the importance of bankruptcy forecasting models, there are different opinions regarding the point in time a company is judged to be in a bankrupt state. In this study, all the cases of workout, receivership, and bankruptcy are considered as bankruptcy. When a company is in financial hardship, many stakeholders including shareholders, creditors, and employees face significant difficulties. Since all three types of financial hardship of a company can create huge damage and loss to its economic stakeholders, it is considered reasonable to define companies in such state as bankrupt.

Diverse kinds of financial data variables can be used for a bankruptcy forecasting model. Forecasting is an act which attempts to predict the state of the future based on current data. In this study, we intend to forecast the likelihood of bankruptcy of a company based on one year of its financial data. In order to set a model and verify the predictive ability of the model, this study used the financial data from bankrupt companies one year prior to the point of bankruptcy and that of a normal company for comparison.

3. Descriptions on the data

The financial data to be applied to the bankruptcy forecasting models is based on the financial statements of the companies for the past 5 years. We used the data from 5-year time periods regardless of the actual time because we need to exclude the effect of the economy in a given year. This study extracted the following financial data from the NICE DnB [9] which retains the financial data for all construction companies in Korea.

We classified companies into two categories: bankrupt and normal. The bankrupt companies are those that went into workout, receivership, or bankrupt during the period from 2008 to 2012. The normal companies are those that were not in bankrupt state as of December 2012. Eventually, we selected 1381 bankrupt companies and 28,481 normal companies. Then we collected the financial data of the bankrupt companies and normal companies. As for the financial data of the bankrupt companies, we used the financial data one year prior to bankruptcy. As for the financial data of normal companies, we used their 2011 financial data. That is, we applied the financial data one year prior to bankruptcy for bankrupt companies and the financial data of the previous year of the normal companies to the forecast models to see the level of bankruptcy after one year had passed.

Based on the collected financial data, we produced the following variables and applied them to the model.

Table 1
Descriptive analysis of the model variables of all construction industry companies.

	Mean	Median	Std. Dev		Mean	Median	Std. Dev
WC/S	−13.06	−0.02	298.03	S/TA	1.40	1.02	1.62
C/CL	0.58	0.03	5.45	EBT/CAP	−1.67	0.08	75.77
S/CA	3.45	2.34	6.01	S/CAP	116.41	9.85	4671.31
EBIT/TA	−0.14	0.03	0.96	lnTA	9.46	9.44	1.67
CA/TA	0.52	0.52	0.27	C/TA	0.06	0.02	0.10
WC/TA	−0.29	−0.02	6.65	CA/CL	2.78	0.96	16.81

Table 2
Correlation matrix on the model variables of all construction industry companies.

S/CAP	EBT/CAP	0.82	WC/TA	S/CA	−0.58
CA/CL	C/CL	0.68	WC/TA	EBIT/TA	−0.51
S/TA	S/CA	0.52	S/TA	WC/TA	−0.32
C/TA	C/CL	0.32	lnTA	S/TA	−0.29
C/TA	CA/TA	0.32	C/TA	lnTA	−0.27
S/TA	CA/TA	0.30	CA/TA	S/CA	−0.24
EBT/CAP	WC/S	0.26	lnTA	CA/TA	−0.18
C/TA	S/TA	0.19	lnTA	C/CL	−0.11
EBIT/TA	S/CA	0.14	CA/CL	lnTA	−0.11
CA/CL	C/TA	0.14	lnTA	S/CA	−0.09
CA/CL	CA/TA	0.10	CA/CL	S/CA	−0.04
...	...	...	...	...	...

- EBIT/TA: Earnings before interest and taxes/Total assets
- EBT/CAP: Earnings before taxes/Capital
- WC/TA: Working capital/Total assets
- WC/S: Working capital/Sales
- CA/TA: Current assets/Total assets
- CA/CL: Current assets/Current liabilities
- C/TA: Cash/Total assets
- C/CL: Cash/Current liabilities
- lnTA: Value of natural logarithm of the total assets
- S/CAP: Sales/Capital
- S/CA: Sales/Current assets
- S/TA: Sales/Total assets

Each variable was calculated as a ratio so that they could be applied regardless of the capital size or sales of the company. For example, CA/TA and CA/CL, which are the variables related to current assets, the values divided by total assets and current liabilities are used, respectively.

Tables 1 and 2 illustrate the descriptive analysis of the model variables of all construction industry companies and the correlation matrix.

As for the classification by size, construction companies are classified into small, medium, and large companies according to the size of their capital. Small construction companies refer to the companies of which capital is less than 500 million won. Medium construction companies have capital of 500 million won to 50 billion won. Large construction companies have capital of 50 billion won or more.

Table 3 shows the ratio of bankrupt companies according to the size of the capital.

Table 3
Bankruptcy ratio according to the size of the capital.

Size of capital	Bankrupt companies	Normal companies	Bankruptcy ratio
Less than 500 million won	181	10,762	1.7%
500 million won or more and less than 50 billion won	1164	17,203	6.3%
50 billion won or more	36	516	6.5%
Total	1381	28,481	4.6%

As shown in Table 3, though the number of large construction companies is not many, the bankruptcy ratio is relatively high. As for small-sized construction companies, the number of companies is numerous, but the bankruptcy ratio is very small. As for the large-sized construction companies, the bankruptcy ratio is high and the overall loss caused by the bankruptcy is far greater. This suggests that forecasting bankruptcy of large-sized construction companies is especially important.

4. Adaptive boosting

Adaptive boosting (AdaBoost) is one of the machine learning algorithms formulated by Freund and Schapire [10]. It can be used by combining other learning algorithms to make a more improved learning algorithm. AdaBoost combines with weak classifiers to build a learning algorithm with stronger classifiers. Weighted average method is used for combination. The following shows the algorithm that determines the weighted value and classification method that were used in this study.

In this study, Decision Tree is used as a weak classifier algorithm and the depth is set to 1. That is, 12 decision tree algorithms perform classifier learning for each variable. So, each decision tree algorithm uses a single variable. As the depth is 1, the bankruptcy predictive ability is very low. Let's call a set of 12 weak classifiers, H.

Assuming that m number of training samples are:

$(x_1, y_1), \ldots, (x_m, y_m)$

Herein, x indicates the features of the subjects for classification and y is a class having the value of -1 or 1. In this study, a set of model variables of a company is x. The bankrupt companies can be classified as -1, and normal companies are classified as 1. That is, x is a feature vector that can be represented as x = (EBIT/TA, EBT/CAP, WC/TA, WC/S, CA/TA, CA/CL, C/TA, C/CL, lnTA, S/CAP, S/CA, S/TA). Each weak classifier attempts classification on feature x with a single value. The distribution of weighted value is initialized through $D_1(i) = 1/m$.

Followings are repeated a total of T times from $t = 1$ to T.

- Suppose that the weak classifier with the lowest error is h_t. Herein, errors are set according to the distribution of weighted value.
- $h_t = argmax_{h_t a??H}|0.5 - e_t|$, where $e_t = \sum_{t=1}^{m} D_t(t) I(y_t \neq h_t(x_t))$. Function I has the value of 1 when the variable is true while it returns to 0 when the variable turned out to be false.
- The loop is ended when $|0.5 - e_t| \leq \beta$. The constant β is a predetermined threshold and when the error is dropped below the threshold, the training is terminated.
- α_t is calculated as follows. $\alpha_t = (1/2)\ln((1 - e_t)/e_t)$
- The m number of weight distribution D can be changed as follows.

$$D_{t+1}(i) = \frac{D_t(i)e^{\alpha_t(2I(y_i \neq h_t(x_i))-1)}}{\sum_i D_t(i)e^{\alpha_t I(y_i \neq h_t(x_i))}}$$

The final classifier is calculated as follows.

- $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$
- Herein, the sign function is +1 when the variable is positive number (normal companies), while returns to -1 when the variable is negative number (bankrupt companies). In this study, T is set to 1000. That is, 12 weak classifiers are calculated with the sum of 1000 weighted values and are classified into normal (+1) and bankrupt (-1).

Table 4
Bankruptcy forecasting experiment result by capital size.

	Successful forecasting	Failed forecasting	Forecasting suspended	Failed forecasting	
				Type-I error	Type-II error
(a) Less than 500 million won (training samples:288, test samples:74)					
AdaBoost	55	19	0	5	14
ANN	56	18	0	9	9
SVM	51	23	0	6	17
Decision-Tree	53	21	0	7	14
Z-score	40	7	27	3	4
(b) 500 million won and more and less than 50 billion won (training samples: 1862, test samples: 466)					
AdaBoost	358	108	0	43	65
ANN	350	116	0	57	59
SVM	332	134	0	61	73
Decision-Tree	343	123	0	57	66
Z-score	230	96	140	78	18
(c) 50 billion won and more (training samples: 56, test samples: 16)					
AdaBoost	15	1	0	1	0
ANN	13	3	0	1	2
SVM	10	6	0	0	6
Decision-Tree	14	2	0	2	0
Z-score	8	5	3	5	0
(d) The whole (training sample: 2208 s, test samples: 554)					
AdaBoost	435	119	0	48	71
ANN	427	127	0	57	70
SVM	406	148	0	59	89
Decision-Tree	405	149	0	60	89
Z-score	284	102	168	80	22

5. Experiment

It is necessary to adjust the number of companies that went bankrupt similar to the level of normal companies for the experiment, because the number of companies that went bankrupt are overwhelming. Because the bankruptcy forecasting models for normal companies may vary depending on the sampling method, it is necessary to select a fair sampling method. Therefore, we applied a random sampling method to adjust the number of normal companies to the number of companies that went bankrupt.

After classifying the companies into normal and bankrupt according to the size of capital, we selected normal companies by random sampling to equal the number of the bankrupt companies to make the number of both sample groups identical to each other. Each number of normal and bankrupt companies is 1381, respectively. Summing up the two sample groups, the number of companies in total is 2762. We used 80% of them, which was 2208 for training samples and the remaining 20%, which was 554, for test samples. In the training and test samples, there are the same number of normal and bankrupt companies, respectively. In the experiment according to the size of the capital, 80% were used for training samples and 20% were used for test samples.

This study used other machine learning algorithms and tested Artificial Neural Networks, SVM, and Decision Tree in order to compare the relative performance compared to AdaBoost. *Z*-score was tested as a traditional model. We used Neurolab [11] for neural networks, and Scikit-learn [12] for SVM, decision tree, and AdaBoost. Both Neurolab and Scikit-learn are implemented as a Python module.

We used Decision Tree as a weak classifier for AdaBoost. We also carried out other experiments with the model that used Decision Tree in order to compare the performance with the simple Decision Tree. We used Gini impurity for criterion and entropy for the information gain for the Decision Tree. As for the artificial neural networks model, all of the variables were used as input variables. The types of neural networks were multi-layer feed forward perceptron. The number of hidden layer nodes was 10 and the number of output was set to 1. As for SVM, model variables are used as features and radial basis function (RBF) was applied as a kennel function. In all machine learning-based models, the target value of bankrupt companies was −1, and that of normal companies was 1.

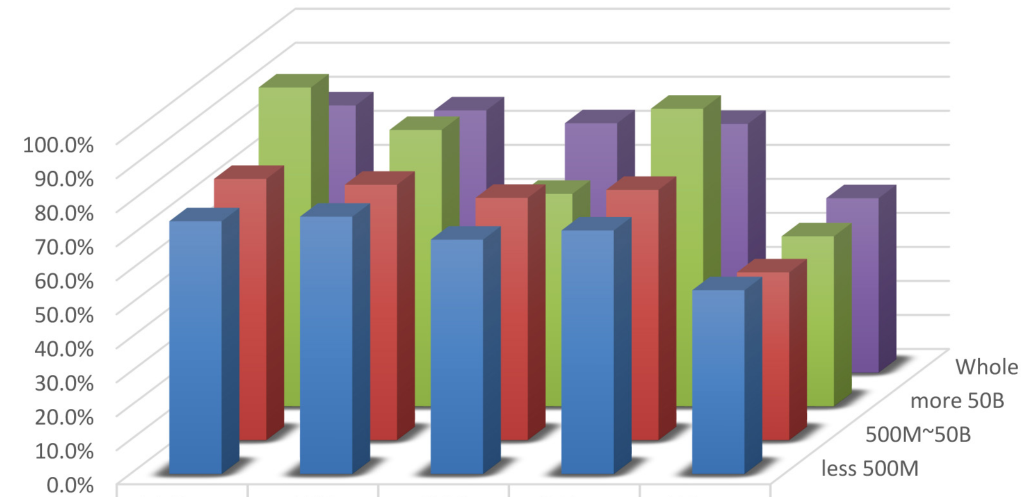
Z-score was used for the models of a private firm, because there were a significant number of unlisted companies among samples. In that case, the *Z* value can be calculated as follows.

$$Z\text{-score-private} = 0.717\mathrm{T1} + 0.847\mathrm{T2} + 3.107\mathrm{T3} + 0.420\mathrm{T4} + 0.998\mathrm{T5}$$

Herein, T1 = (Current assets − Current liabilities)/Total assets, T2 = Retained earnings/Total assets, T3 = Earnings before interest and taxes/Total assets, T4 = Book value/Total liabilities, and T5 = Total sales/Total assets. In the T4, book value was used instead of capital from the collected data. From the calculation result, if *Z*-score-private value exceeds 2.9, it is classified as a normal company, if it is less than 1.23, it is classified as a bankrupt one. If the value falls into the middle scope, forecasting is suspended.

The forecasting results by the size of capital and model are shown in Table 4. Forecasting is suspended when the *Z*-score falls in the normal company category, but belongs to the scope from which bankruptcy cannot be judged. In that case, it does belong to neither successful nor failed forecasting. Since the samples of normal companies were selected randomly in order to coincide with the same number of bankrupt companies in each experiment, the sum of companies in the test by capital size may not be the same as the sum of total companies used in the experiment. To complement the difference, the experiments were repeated 10 times and the median values of each model were selected. The standard deviation of the number of successful forecasts was less than 1 for each capital size. This means that each experiment generated similar results. We repeated the experiments 20, 30, and 40 times to confirm these results. As we expected, the results were not significantly different from the experiment repeated 10 times.

Success ratio of forecasting by model and capital size was calculated based on the results in Table 4 and it was shown in Fig. 1. The success ratio of forecasting is obtained by dividing the number of successful forecasting by the number of test samples.



	AdaBoost	ANN	SVM	D-Tree	Z-Score
less 500M	74.3%	75.7%	68.9%	71.6%	54.1%
500M~50B	76.8%	75.1%	71.2%	73.6%	49.4%
more 50B	93.8%	81.3%	62.5%	87.5%	50.0%
Whole	78.5%	77.1%	73.3%	73.1%	51.3%

Fig. 1. Success ratio of forecasting of each model by capital size.

As for traditional *Z*-score, the success ratio of the model is notably lower than the machine learning-based models due to the forecasting suspension segment. Furthermore, it does not mean that forecasting error would not happen due to the suspension segment. That is, the predictive ability of the *Z*-score algorithm is far lower than machine learning-based models.

As shown in Fig. 1, AdaBoost has the highest forecasting success ratio by capital size among the models. In particular, for large-sized construction companies of which capital is 50 billion won or more, AdaBoost showed a relatively high success ratio. As for the Artificial Neural Networks (ANN) model, in the case of small-sized companies, ANN has a slightly better predictive ability than AdaBoost, but it is not significant. As for SVM, it is considered that SVM is not proper for bankruptcy forecasting model. Decision Tree has a better predictive ability than a simple algorithm, and showed excellent predictive ability for large-sized construction companies. AdaBoost can provide more accurate bankruptcy forecasting by taking decision tree as a weak classifier.

6. Conclusion

In the previous section, we compared and analyzed the results of bankruptcy forecasting models with various bankruptcy forecasting models and AdaBoost applied to construction companies. Such results suggest important implications. In recent times, bankruptcy of construction companies rapidly increased due to the impact of the recession in the real estate sector, which produces economic and social problems accordingly. Bankruptcy of construction companies creates immense hardship for various economic subjects including shareholders, creditors and employees. Therefore, the need for bankruptcy forecasting models is very high, especially those customized for construction companies.

What we have found from the research results is that machine learning-based algorithms show far greater predictive ability than Altman's *Z*-score, which is a traditional statistical regression analysis method. Although the over-fitting problem that often occurs in machine learning leads to a decrease in predictive ability, machine learning methods show better predictive ability than *Z*-score method overall, which is noteworthy. AdaBoost model showed the best predictive ability among the models. For large-sized companies this was especially true with the model showing excellent predictive ability which provides useful suggestions for AdaBoost in its practical application.

This study proves the usefulness of the bankruptcy forecasting model using AdaBoost, especially in the construction industry. We hope this study is helpful in making sound decisions to forecast bankruptcy likelihood of a company and minimize the damage to related stakeholders including shareholders, creditors and employees. In addition, we expect active research to be carried out in other industries on top of the construction industry.

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