A Machine Learning Approach for Selecting Directors of Chinese Listed Company

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Abstract. Contemporarily, the directors sever as a vital role in companies strategy decisions and daily operation. On this basis, it is crucial to select a suitable and appropriate directors of listed companies to fulfill the requirements and criteria of shareholders (at least most of them). In this case, this paper discusses a financial big data-based machine learning approach for board selection of Chinese listed companies. This approach achieves effective feature extraction through big data related to changes in boards of directors and successfully identifies the outstanding features of excellent boards. The empirical results show that machine learning models have a significant advantage over traditional methods, such as ordinary least squares (OLS) regression, for board selection by Chinese companies. According to the analysis, the model can extract important features of an excellent board of directors from big data related to the board's features, such as academic, research and development (R&D), and politician backgrounds. These results shed light on guiding further exploration of board selection in China.

Keywords: Corporate directors, director performance prediction, machine learning, big data.

1. Introduction

Boards of directors are elected by shareholders, act as representatives of shareholders to supervise and manage managers, approve important decisions made by companies, and are key components of modern corporate governance. However, according to many news reports, the role of the board of directors of Chinese companies has not been fully realized. On the one hand, corporate governance mechanisms fail to guarantee checks and balances among shareholders, boards of directors, management, and subsidiaries. On the other hand, the selection process of boards of directors fails to guarantee directors' ability and quality, implying that boards of directors fail to play their role.

Therefore, this paper explores how to use machine learning models to assist companies in better selecting their board of directors, aims to deepen the understanding of the optimal selection mechanism for boards of directors of Chinese companies and promote the development and application of fintech in the field of corporate governance. An important advantage of adopting a machine learning approach is that it can effectively address the diversity and complexity of big data related to a board's features. By using corporate performance as the evaluation criteria and introducing various factors that affect this performance (e.g., historical financial indicators) as the control variables, a machine learning approach comprehensively considers the impact of various board features on board performance, especially the background features of directors. This study combines the actual data before and after changes in boards of directors of Chinese listed companies between 2008 and 2016 to attempt to answer the following three main questions: 1) are machine learning models more effective than the traditional linear models for board selection? 2) do the important background features of directors, such as academic, research and development (R&D), and politician backgrounds, have a significant impact on corporate performance? 3) can the machine learning approach help improve the selection mechanism of boards of directors of Chinese companies?

The features of boards of directors considered in this study include the structure of the board and the features of individual differences among the directors. These features affect corporate performance by influencing the board's effectiveness in performing its due functions. It is found that the board of directors affected corporate performance by fulfilling the following three functions, i.e., resource dependency, supervision agency, and strategic role [1]. First, boards of directors with different features may have different effectiveness, which in turn affects corporate performance differently. For example, board size, fraction of independent directors, CEO duality, and others, may enhance the effectiveness of a board's supervisory function [2-4]. Second, directors' individual features, such as capacity and backgrounds, affect the effectiveness of the board in playing its role. Studies have shown that the impact of directors will offer important indicators for the company's successful operation [5-7]. Some scholars believed that the backgrounds of directors can affect whether they can successfully perform the functions of decision-making support and supervision [8].

An important advantage of machine learning models used in this study over traditional ordinary least squares (OLS) methods is that such models can comprehensively consider various factors. The mechanisms by which board features affect corporate performance are complex. In different types of companies, the roles of the boards of directors are also different [9], and many factors that may affect board performance should be considered. However, most previous studies only consider a single factor, possibly because the linear models used are limited by the structure and assumptions. Currently, a large number of studies take advantage of the comprehensiveness of machine learning models. For example, some researchers used a machine learning approach to comprehensively consider multiple features at the levels of director, board, and company to analyze the important factors affecting the shareholder approval rate of potential directors [10]. Other study used a machine learning approach to analyze the relationship between corporate governance and corporate performance and found a positive correlation between the existence of women on boards of directors and corporate performance [11]. In addition, many studies on credit risk have also applied machine learning models to comprehensively analyze various features of borrowers, account behavior, and credit reporting agencies [12, 13]. In general, machine learning models can better capture the complex feature interactions and nonlinearities [14, 15]. Therefore, the comprehensiveness and flexibility of the machine learning approach give it great application potential in the selection of boards of directors.

This study adopts a series of machine learning models, such as Lasso, Ridge, random forest, XGBoost, artificial neural network (ANN), and ensemble, to study the selection of boards. By dividing the sample data into in-sample and out-of-sample data, significant training on each machine learning model is conducted to optimize the selection of the hyperparameters to achieve optimal model performance. A comparison of the performances of the prediction models obtained after the training found that the performance of the traditional OLS model is significantly worse than that of machine learning models, whereas among machine learning models, the performance of the Random Forest and XGBoost models are relatively good, but the ensemble model performs even better. In contrast, the XGBoost model is the optimal machine learning model for board selection of companies in the United States [10], indicating that the selection of boards of directors of Chinese companies cannot directly use a model suitable for U.S. companies. In addition, the empirical analysis of the out-of-sample prediction ability of machine learning models finds that having more directors with academic, R&D, and politician backgrounds can promote corporate performance. Moreover, independent directors, foreigners, and sophisticated directors also have a significant positive impact on prediction performance. In summary, the results of this study indicate that the machine learning approach has great potential in solving the optimal selection mechanism of boards of directors of Chinese listed companies.

2. Machine Learning

Machine learning algorithms and models have begun to gain more attention and research in the field of fintech. Based on the study results of Ref. [10], this paper considers several major machine learning models, namely, Random Forest, XGBoost, and ANN. The preliminary analysis results of changes in boards of directors of Chinese listed companies are used to further construct a new ensemble model on the basis of the concept of ensembling. In addition, this paper uses traditional OLS and linear models, such as Lasso and Ridge, as benchmarks to analyze the effectiveness of machine learning models.

2.1. Random Forest

The Random Forest is an extension of the bagging algorithm proposed in the early era of machine learning [16] based on the basic procedure of the bagging algorithm [17]. Based on the bagging constructed by decision tree learners, Random Forest introduces the random attribute selection in the process of decision tree training. The Random Forest is simple and easy to implement, has low computational costs, and exhibits strong performance in many practical tasks.

2.2. XGBoost

Similar to the random forest, gradient boosting trees is a multitree fusion method. The key differences are that the final prediction is the sum of all trees, and the goal of each tree is to minimize the residual of the previous trees. The model uses all of the trees in the previous step to advance toward the direction of minimizing the given objective function, and then generates a new tree. The XGBoost algorithm is a highly efficient implementation of gradient boosting trees, is modified to improve accuracy, and can be extended in all scenarios [18].

2.3. ANN

ANN is designed to simulate the way the brain processes information. The simplest ANN has a hierarchical structure in which neurons in one layer are completely interconnected with the neurons in the next layer. No interlayer or cross-layer connection exists between the neurons. The neurons in the input layer receive the external inputs, the neurons in the hidden and output layers process the signal, and the neurons in the output layer output the results. In other words, the input layer only receives input without functional processing, and the hidden and output layers contain functional neurons.

2.4. Ensemble Model

In many predictions, researchers find that assembling different prediction methods perform better than one method alone [19, 20]. After having several powerful machine learning models, as previously mentioned, combining different models may bring advantages in statistics, calculations, and representation, and may improve generalization performance [21]. Some scholar studied panel data and found that, for different types of data structures present in empirical studies of economics, assembling is a practical and effective method that deserves more applications [22].

Generally, three ways exist to construct the ensemble model, the simple averaging method, the weighted averaging method, and the learning method, and the difference lies in the setting of weights. In the simple averaging method, each model has the same weight; in the weighted averaging method, the weight is generally learned from the training data; and in the learning method, the weight is learned using another learner. In this study, a simplified learning method is used. The training set has N samples, $i = 1, \dots, N$, and random forest, XGBoost, and ANN are trained on sample i of the training set to obtain the prediction results $\hat{Y}_i^{RF}$, $\hat{Y}_i^{XGB}$, and $\hat{Y}_i^{ANN}$. If the test set has M samples, $j = 1, \dots, M$, the weight of each model is as follows:

$$\min_{\theta>0} \sum_{i=1}^{N} (Y_{iT} - \theta_{RF}\hat{Y}_i^{RF} - \theta_{XGB}\hat{Y}_i^{XGB} - \theta_{ANN}\hat{Y}_i^{ANN})^2 \quad (1)$$

The following prediction results of the ensemble model on the test set can be obtained using the obtained weights:

$$\hat{Y}_j^{ENS} = \theta_{RF}\hat{Y}_j^{RF} - \theta_{XGB}\hat{Y}_j^{XGB} - \theta_{ANN}\hat{Y}_j^{ANN} \quad (2)$$

3. Empirical results

3.1. Data

This study adopts Chinese listed companies from 2008 to 2016 as subjects, samples each director from the boards of directors, and uses the average profit for the three years after the director took office as corporate performance. After eliminating the missing data, a total of 42,418 samples are obtained from 30,462 directors of 2,853 companies, all of which are obtained from the China Stock Market and Accounting Research (CSMAR) database. For the model, a total of 31,857 samples from 2008 to 2014 are used for in-sample training, and 10,561 samples from 2015 to 2016 are used to test its out-of-sample prediction ability.

3.2. Director Features and Descriptive Statistics

Table 1 shows the descriptive statistical results of this paper. All variables are winsorized at the 1% level at both tails of the distribution. Table 1 shows that the size difference between the sample firms is relatively large. The average firm has a size of 21.884 (the logarithm value of the total assets in RMB) and a board of 8 people (e^2.132=8.43). The average firm's shares are 6.3% owned by the Chinese government. From the perspective of equity concentration, the sample firms are held by the largest shareholder on average by 33.4%, up to 71.6%, which proves that the equity concentration of Chinese listed firms is relatively high. Regarding performance, on average, sample firms have a ROA ratio of 3.8%.

Table 1. Definition of variables

Variable	Definition
A: Individual features	
Background academic	Equals one if director has the professional background
Background finance	
Background Human Resource (HR)	
Background law	
Background manager	
Background marketing	
Background manufacturing	
Background R&D	
Background designer	
Background accounting	
Background politician	
Independent director	Equals one if director is an independent director
Duality	Equals one if director serves as both CEO and board chair
Foreign	Equals one if director's nationality is not China
Gender	Equals one if director is male
Age	Director age
Nb Boards sitting on	The number of other boards an individual serves on
Nb Listed Boards sitting on	The number of other listed boards an individual serves on
B: Board-level features	
Board size	Number of directors on the board
Nb foreign	Number of foreign directors
Nb of shares held	Number of shares held by directors on the board
Avg indep	Fraction of independent directors on the board
Avg indep comp	Average of independent directors' compensation
Avg tenure	Average board tenure of directors on the board
Avg age	Average board age of directors on the board

3.2.1. Director features

To investigate the effect of board features on corporate performance and the effect of different directors on a particular board of directors, the sample data include directors' background, board structure, and the company's relevant feature indicators. The individual director's background, gender, and age are used as his or her individual features, whereas board size, fraction of independent directors, and others are used as features of the board of directors. The main features are defined in Table 1. At the same time, many companies' financial indicators, such as annual return and leverage (the company-level features), are used as the control variables of corporate performance.

The descriptive statistics of the main variables find the following. For individual director features, manager background has the highest proportion (75%), and the HR and design backgrounds have the lowest proportion (2%); except for manager background, the proportions of other backgrounds are all less than 30%; 87% of directors are male, the average age of directors is 49.2 years old, the oldest age is 86 years old, the youngest is 19 years old, and the average number of other listed boards on which an individual serves is 0.46. At the board structure and company features level, the fraction of independent directors is 36%, and the average number of foreigners on a board is 0.15; on average, the annual return is 0.22, and leverage is 8%. The main features of the directors are shown in Table 2. Because of the length of this paper, other descriptive statistics are not listed but are saved.

Table 2. Descriptive statistics for individual variables

Variable	N	Mean	Std	Min	Max
Background academic	42418	0.29	0.45	0	1
Background finance	42418	0.15	0.35	0	1
Background HR	42418	0.02	0.15	0	1
Background law	42418	0.08	0.27	0	1
Background manager	42418	0.75	0.43	0	1
Background marketing	42418	0.12	0.32	0	1
Background manufacturing	42418	0.05	0.22	0	1
Background R&D	42418	0.14	0.35	0	1
Background designer	42418	0.02	0.13	0	1
Background accounting	42418	0.24	0.42	0	1
Background politician	42418	0.24	0.43	0	1
Independent director	42418	0.40	0.49	0	1
Duality	42418	0.02	0.15	0	1
Foreign	42418	0.02	0.13	0	1
Gender	42418	0.87	0.33	0	1
Age	42418	49.22	8.42	19	86
Nb Listed Boards sitting on	42418	0.46	0.97	0	8

3.2.2. Measure of performance

In this paper, the average profitability of the company within three years after the director takes office is used to measure corporate performance, which is basically consistent with the study by [10]. To be noted is that, given the special circumstances in China, the shareholder voting turnout rate cannot effectively distinguish board performance; therefore, using average profitability can better assess board performance. The specific calculation of profitability is based on return on assets (ROA) before interest, that is, profit/assets before interest and after taxes. The after-tax profit before interest equals the net profit plus after-tax interest. The ROA before interest is also the after-tax return on all invested capital. The profitability of each year corresponds to the average profitability of the following three years. In the last year of the sample period, the profitability of 2017 is used as the corporate performance of 2016, and the average profitability of 2016 and 2017 is used as the corporate performance of 2015. The descriptive statistics on the profitability data of each year show that the profitability of each year is not much different from the overall average of 4%, and the overall standard deviation is 6%. The 25th and 75th percentiles of the profitability distribution are approximately 0.02 and 0.06, respectively.

3.2.3. Comparison of model performances

Excellent boards of directors should be able to effectively improve corporate performance. Therefore, to study the optimal selection mechanism for boards of directors of listed companies, a series of advanced machine learning models is used. Using features such as director background, board structure, and corporate finance, the corporate performance (average profit for the subsequent three years) after the new board takes office is predicted. The corporate financial indicators are used as control variables to control the impact of historical financial factors on future corporate performance, thereby better identifying the impact of board features on corporate performance.

The prediction models used in this study include not only the Lasso, Ridge, random forest, ANN, XGBoost, and ensemble models but also the traditional OLS model (as a benchmark). Because every machine learning model basically contains some hyperparameters that need to be optimally adjusted, the in-sample data are further divided into training and verification sets. Through much training and multiple cross-validation, the hyperparameters of each machine learning model are optimized to achieve optimal model performance. Table 3 summarizes the goodness-of-fit and mean absolute error (MAE) of each prediction model obtained from the training. Among the machine learning models, random forest and XGBoost perform similarly, the out-of-sample prediction performance of ANN is relatively weak, and the ensemble model has the highest R^2 and the lowest MAE on the test set, showing the best performance. Overall, the prediction performance of the linear models is not as good as that of the machine learning models, whereas the overall differences among the machine learning models are not large, which is different from the conclusion in [10] that the XGBoost model has obvious advantages.

Table 3. Prediction performance of models

Model	R^2		MSE	
	in-sample	out-of-sample	in-sample	out-of-sample
Ensemble	0.280	0.253	0.00258	0.00291
Xgboost	0.261	0.238	0.00264	0.00298
ANN	0.285	0.122	0.00263	0.00346
Random forest	0.246	0.219	0.00270	0.00305
OLS	0.105	-0.02	0.00320	0.00398
Lasso	0.050	0.0185	0.00340	0.00383
Ridge	0.077	0.0391	0.00330	0.00375

3.2.4. Analysis of the main influencing factors of the prediction ability of machine learning models

One difference between machine learning and traditional econometric models is that machine learning models do not directly explain the impact of specific variables on performance. Therefore, according to the method of Ref. [10], this paper studies the out-of-sample prediction ability using the optimal ensemble model, ranks director features using prediction performance, and compares the top 10% with the last 10% of the director features to analyze the main influencing factors of board performance and to conduct statistical tests. Table 4 summarizes the averages of several features associated with low and high prediction performance when using the ensemble model and the significance test result (p-value) of the difference. Some features have a significant impact on board performance, for example, having more directors with academic, R&D, and politician backgrounds and fewer directors with HR and accounting backgrounds has a significant positive impact on future corporate performance. In addition, independent directors, foreigners, and sophisticated directors have a significant positive impact on future corporate performance. Many of the important influencing factors are not effectively identified by the traditional OLS approach, indicating that machine learning models can better identify important features that have a significant impact on board performance.

3.2.5. Comparison of empirical results between the United States and China

Several major differences exist between the empirical results of Chinese and U.S. companies. First, the results in Table 4 indicate that the academic, R&D, and politician backgrounds of directors have a significant positive impact on board performance. According to Ref. [10], the financial and management backgrounds of directors in the United States have a significant positive impact on board performance (the impact of these two features is not significant in Chinese companies). Therefore, in the Chinese market, the academic, R&D, and politician backgrounds of directors can effectively help companies better access important information and resources related to market, technology, and policy, thereby improving corporate performance. For example, it is believed that directors with technical expertise and R&D experience can establish a network of relationships with other technical experts and innovative enterprises [23]. This advantage not only enhances innovation collaboration among enterprises and reduces transaction costs but also mitigates the constraints of uncertainties on enterprises.

Table 4. Top vs. Bottom Decile of Predicted Performance

Variable	Mean		
	Bottom decile of predicted performance	Top decile of predicted performance	Difference p-value
Background academic	0.238	0.338	0.000
Background finance	0.141	0.148	0.304
Background HR	0.029	0.019	0.001
Background law	0.087	0.079	0.168
Background manager	0.733	0.752	0.039
Background marketing	0.119	0.132	0.071
Background manufacturing	0.055	0.049	0.138
Background R&D	0.114	0.167	0.000
Background designer	0.017	0.018	0.814
Background accounting	0.252	0.229	0.010
Background politician	0.212	0.250	0.000
Independent director	0.372	0.407	0.001
Duality	0.025	0.030	0.150
Foreign	0.013	0.026	0.000
Gender	0.868	0.860	0.278
Age	48.330	49.585	0.000
Nb Boards sitting on	0.790	1.404	0.000
Nb Listed Boards sitting on	0.364	0.517	0.000
Board size	8.865	9.393	0.000
Nb foreign	0.111	0.229	0.000
Avg indep	0.368	0.365	0.001
Avg indep comp	47201.561	59038.337	0.000
Nb of shares held	20007460.296	54710967.358	0.000
Avg tenure	20.464	16.643	0.000
Avg age	49.210	50.073	0.000

These changes are conducive to enterprises seeking to attract high-quality, innovative projects, thereby effectively improving corporate performance. It is argued that the relationship between a company and the government can reduce the risk and friction of operations while obtaining the maximum resources [24]. Second, in contrast to the results of U.S. companies, a study using Chinese data shows that having directors sitting on multiple boards is associated with better prediction performance, which supports the conclusion that social reputation has a significant promotional effect on corporate performance [25].

In addition, this paper also expands the study of Ref. [10] and adds some variables that are unique to Chinese companies. Table 4 reports differences in the effect of these variables on performance. At the individual level, independent directors, foreigners, and sophisticated directors are associated with better performance. At the board level, both the machine learning and linear models show that boards with high shareholdings are associated with better performance. This finding to a certain extent supports the conclusion that a significant correlation exists between the shareholding ratio of the board and performance indicators and indicates that the shareholding ratio of the board can motivate directors to pay attention to corporate performance [26]. In addition, boards with better prediction performance also have the following features: more substantial salary, higher average age, and more independent directors and foreigners.

3.2.6. Other results and discussion

To ensure the robustness of the results, the actual performances corresponding to the medians of the lowest and highest 10% predictions are ranked and compared, as shown in Table 5. The results show that the actual performance corresponding to the median of the lowest 10% ranks in the ninth percentile and that corresponding to the median of the top 10% ranks in the 84th percentile. In contrast, the performances of OLS, Lasso, and Ridge are close to the 30th, 30th, and 76th percentiles, respectively. Therefore, compared with the linear models, the prediction performance of the machine learning models is closer to the actual performance.

Table 5. Evaluating the predictions

	Median percentile of observed performance						
	OLS	Lasso	Ridge	Ensemble	XGBoost	ANN	Random forest
Bottom decile of predicted performance	29^{th}	31^{th}	30^{th}	9^{th}	9^{th}	16^{th}	9^{th}
Top decile of predicted performance	76^{th}	75^{th}	77^{th}	84^{th}	86^{th}	82^{th}	80^{th}

Table 6. The determinants of predictions: OLS regression

Background academic	0.002 (2.264)	Duality	-0.001 (-0.43)
Background finance	-0.000 (-0.78)	Foreign	0.002 (0.65)
Background HR	-0.002 (-0.87)	Gender	-0.001 (-0.9)
Background law	-0.002 (-2.22)	Age	0.000 (0.63)
Background manager	0.002 (2.18)	Nb Boards sitting on	0.001 (4.37)
Background marketing	0.001 (1.00)	Nb Listed Boards sitting on	0.001 (1.87)
Background manufacturing	-0.001 (-0.35)	Board size	0.001 (6.93)
Background R&D	-0.002 (-2.72)	Nb foreign	0.002 (2.79)
Background design	-0.002 (-0.83)	Avg indep	-0.019 (-3.07)
Background accounting	-0.002 (-3.24)	Avg indep comp	0.000 (0.48)
Background politician	-0.000 (-0.17)	Nb of shares held	0.000 (7.17)
Independent director	0.001 (1.66)	Avg tenure	0.000 (10.27)

To explain the main driving factors of the effectiveness of machine learning models from a different aspect and based on the method of Ref. [10], the interpretable linear model is used to regress the predictions of the machine learning models (Table 6), and results are compared with that of the machine learning models. Using the ensemble model as the representative, the regression results of predicted profitability explain the effects of most prediction differences at the board and company levels but only explain the effects of a small number of features at the individual level. For example, the regression coefficient of the variable “Nb Boards sitting on” is positive and significant at the 1% level. However, the regression coefficients of some individual features, such as a politician background, foreigner, and age, are not significant, and the regression coefficients of other individual features, such as R&D background, are significant but of the opposite sign. These insignificant and opposite regression coefficients may reflect factors that the linear model cannot identify, and the OLS results only show an R^2 of 26.9%. Previsou study considered that the feature interactions and nonlinearities that a machine on which a learning model relies to generate its predictions caused the differences [10]. It indicates that the interactions and nonlinearities between directors' individual features may drive the machine learning model to predict precisely the factors that the linear model has difficulty identifying.

4. Conclusions

Based on the AI (machine learning) algorithm, this study innovatively develops an effective selection method for boards of directors of listed companies, which is its main contribution. Through an empirical analysis, the following conclusions are reached. First, compared with the traditional OLS, Lasso, and Ridge models, machine learning models have significant advantages in selecting boards of directors and can further identify important influencing factors that are not effectively identified by linear models, thus helping to deepen the understanding of the optimal selection mechanism of boards of directors of Chinese companies. For example, by using machine learning models, this paper finds that, in China, the academic, R&D, and politician backgrounds of directors are helpful to improve future corporate performance. In the United States, these three directors' backgrounds cannot significantly promote corporate performance. A possible explanation for this difference is that, in China, directors with academic, R&D, and politician backgrounds can effectively help companies better access key information and resources related to the market, technology and policy, thereby playing a positive role in corporate performance. In the United States, because the institutions and markets that provide technical and market consulting services to the company are relatively well developed, the academic, R&D, and politician backgrounds of directors are not necessary to obtain relevant information and resources. Therefore, the design of the selection mechanism for boards of directors in Chinese companies cannot completely rely on the experience of U.S. companies. Moreover, thoroughly considering the differences between Chinese and U.S. markets to develop a broad selection mechanism suitable for China's national conditions is necessary. In addition, this paper finds that the XGBoost model, which is preferred by U.S. companies in selecting directors, is not necessarily applicable to Chinese companies. Therefore, the results of this study are helpful in promoting the further development and application of machine learning models in the field of corporate governance in China.

The research framework of this paper can be further extended to deepen the application of and research on machine learning models in the field of corporate governance. One of the most noteworthy points is that text analysis and machine learning can be combined to further deepen the research on the optimal corporate governance mechanisms. The importance of this possible future research is that financial and internal control reports and other documents also contain some important factors that affect corporate governance. Nevertheless, these factors need to be effectively extracted through appropriate text analysis methods to facilitate subsequent training and analysis of machine learning models. Therefore, a study on corporate governance that combines text analysis with machine learning models could be a challenging research topic worth exploring in the future. Overall, these results offer a guideline for board selection in China.

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