Proceedings of the 4th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/46/20241319

Administrative punishment likelihood forecasting based on deep learning

Chunyi Zhang

Faculty of Business Administration, University of Macau, Macau SAR, China

mc14452@um.edu.mo

Abstract. As the economic situation becomes increasingly complex, the need for investors to avoid risks grows rapidly. For instance, the investors may encounter companies that have potential to incur violations. Once the violation is exposed, companies may face fines, warnings, or even expulsion from the stock market. Such punishments damage the company's reputation and erode trust from stakeholders and investors. This paper proposes a deep learning-based model to predict the likelihood of a company facing administrative penalties in the future, aiming at assisting investors in making informed decisions. This study considered both financial and linguistic variables. To counter data imbalance, the under-sampling and normalization methods were employed to the dataset. For modelling, a Neural Network model was applied due to its competence in hierarchical learning. The fully connected layer incorporated a rectified linear unit activation function to address gradient explosion, while the output layer utilized the sigmoid activation function for binary classification to forecast potential violations. The model achieved a final testing accuracy of 0.9701.

Keywords: Deep learning, Text analytics, Neural network, Administrative punishment.

1. Introduction

In recent years, as the economic situation varied, the stock market had experienced great turbulence as well. To minimize the risks, the investors preferred to choose portfolios with higher stabilization. Apart from focusing on basic financial statistics, the ethical values of the companies and the company's features are also noteworthy, such as integrity and honesty. The untrustworthy behaviors of companies may lead to significant impacts to the capital market, which not only erodes investors' confidence in the company or even the whole market, but also attracts regulatory scrutiny and legal consequences. According to CSMAR database statistics, in China, since 2011, 7.848 administrative penalties had made to 1,206 listed companies for financial frauds and other violations by the China Securities Regulatory Commission (CSRC) [1]. The common violations include delayed disclosure, significant omittance, insider trading, misleading statements, etc. Companies that incur penalties may be subjected to fines, warnings, or, in severe cases, stock market expulsion. The announcement of punishments leads to reputational damage to the companies and a loss of trust from stakeholders, investors, and the public, and eventually ruins the market value and results in stock price crash [2]. The loss of confidence from investors can have significant consequences, such as reduced investment flows, increased volatility, and a general downturn in market activity [3]. Restoring investor confidence requires implementing stricter

© 2024 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/46/20241319

regulations, enhancing transparency, and appropriately punishing perpetrators to rebuild trust and ensure the stability and credibility of the capital market.

The likelihood of a company's violations is influenced by several factors. If the board structure of a company weakens, it can lead to a decline in the effectiveness of corporate governance and a subsequent impact on audit quality, which potentially creates incentives for the company to engage in fraudulent activities or other violations. As the deceptive actions may be undetected, the company would choose to take the risk of engaging in such violations [4]. Also, the top management may conceal unfavorable information intentionally from public for personal interest or other reasons. When the bad news accumulates excessively, it leads to stock crash and capital market turmoil as well [5]. To mitigate the potential investment risk, enhancing corporate transparency and reducing information gap between firms and investors is significant. Previous literatures have proved that high quality and high frequency of disclosures enable to alleviate information asymmetry and increase the average information level of investors [6, 7]. When the quality of disclosures is high, the investors are less motivated to seek private information [8].

The lack of information disclosure can significantly contribute to investors' growing distrust, particularly when it comes to financial frauds. After a series of accounting scandals of Enron, WorldCom, Tyco and Global Crossing during the period of 2001 to 2002, to compensate the distrust of investors in the corporate financial reporting and the trustworthiness of the management, the Securities and Exchange Commission (SEC) published Sarbanes-Oxley Act of 2002 to refine the existed auditing standards, strengthen the oversight of accounting firms and refine the quality and transparency of company's financial reporting and disclosures [9]. Through these measures, regulators aim to level the playing field, promote fair competition, and enhance market efficiency in the financial sector. In terms of China, to strengthen information transparency and enhance the reliability of financial reporting, the CSRC required all listed companies to disclose any significant risks that are noxious to the company's future development in the mandatory section of annual financial reports, Management Discussion and Analysis (MD&A). Furthermore, the companies are required to interpret these risks' causes, impacts on the firms, the measures to cope with the risks, and the outcome of implementing the corresponding strategies. If the analysis indicates that relevant changes have, are currently, or are possible to pose considerable threats to the operational performance and the financial condition of the company, it should provide management's fundamental assessment of these changes and conduct a detailed analysis of their effect on the company.

As essential reporting that is required to be disclosed regularly and mandatorily by listed companies, the annual financial report contains significant and necessary statistical and textual information that enables outsiders to learn the operating status and profitability level of the firm. Previous literature has extensively explored the use of financial factors in analyzing annual financial reports, which serve as crucial mandatory disclosures for listed companies [10]. These reports contain a wealth of statistical and textual information that allows outsiders to gain insights into the firm's operations and profitability. However, in addition to examining the financial figures, recent studies have started to place increased emphasis on the textual information within these reports. Researchers have explored various features such as tone, similarity, and readability to elucidate how these specific characteristics can serve as indicators of the firm's performance [11, 12]. By incorporating both financial and textual factors, these studies have provided a more comprehensive understanding of annual financial reports and their implications for assessing a company's status quo and financial viability. It is found that when the financial report indicates an ambiguous tone and low readability, the firm might experience a stock price crash and an increase in borrowing costs [13]. Also, the complexity of reporting text could influence analyst's behaviors and forecasting accuracy, which might affect investor's decisions as well [11]. Furthermore, Qian and Zhu [14] found that the similarity and readability of MD&A in annual financial reports were positively correlated with the probability of administrative penalties. On the contrary, the firms with higher similarity in non-MD&A section had lower probability of being punished by the regulators.

DOI: 10.54254/2755-2721/46/20241319

In order to further verify and apply the empirical results, this paper is based on the discovery of Qian and Zhu's study [14] and adopts a comprehensive approach by considering both financial and non-financial variables, along with a time element, to suggest a deep-learning-based model to forecast the likelihood of company's future administrative punishment. This study endeavors to offer a holistic perspective on the factors influencing administrative penalties by integrating multiple factors. The deep learning approach ensures a robust analysis and enhances the forecast accuracy of the study, ultimately contributing to an improved understanding of the administrative punishment condition.

2. Related works

2.1. Background knowledge

Nowadays, deep learning methods concerning annual report analysis have been widely applied in various fields, primarily focusing on Natural Language Processing (NLP) and financial fraud detection. Hajek and Henriques [15] tested various machine learning approaches to detecting financial fraud in the U.S. based on both financial and linguistic features. The linguistic variables in their study evaluated the tone of MD&A section, including positive/negative tone, uncertainty, frequency of litigious words, strong/weak tone, and frequency of constraining words. To ensure the reliability and robustness of each algorithm, they employed cross-validation techniques. The results revealed that the Interpretable Naïve Bayes-based models outperformed other algorithms. Matin et al. [16] applied Convolutional and Recurrent Neural Network (CNN and RNN) to capture the contextual information in audit reports and statements of top management and forecast Denmark company's financial distress. The results show that the incorporation of textual data enhances the accuracy of the risk prediction model. Feng et al. [17] employed CNN to predict the probability of company bankruptcy based on text analysis of MD&A section. To accomplish binary classification task, they conducted a comparison between CNN, Random Forests, Support Vector Machine and other machine learning approaches. The results indicated that CNN exhibited superior performance over the alternative approaches. Craja et al. [18] employed a hierarchical attention network to analyze the textual characteristics of annual reports. This model enabled comprehensive analysis of text grammar, structure, semantics, and context of a sentence in the report, which concentrated on preserving the logical content of the text. It extracted red flag words from MD&A and generated warnings, improving the correct rate of fraud detection model in financial area.

2.2. Data sources and sample selection

This essay aims to construct an administrative punishment forecasting model by integrating financial and non-financial variables. Since the causes and conditions of a company's violations are various, this essay implements a neural network approach to address these complexities. Additionally, this study considers the influence of time factors, equity nature, and audit quality, further enhancing the efficacy and comprehensiveness of the predictive model.

The samples contain data from 3,463 A-share listed companies in China from 2010 to 2021. Based on the initial data, the dataset has been processed as follows: (1) The firms from the financial industry have been excluded due to the specificity of accounting standards applied to this industry; (2) The samples that have missing value have been eliminated. The final dataset consists of 25,740 records with 658 violation records. The distribution of violation records is as Figure 1.

DOI: 10.54254/2755-2721/46/20241319

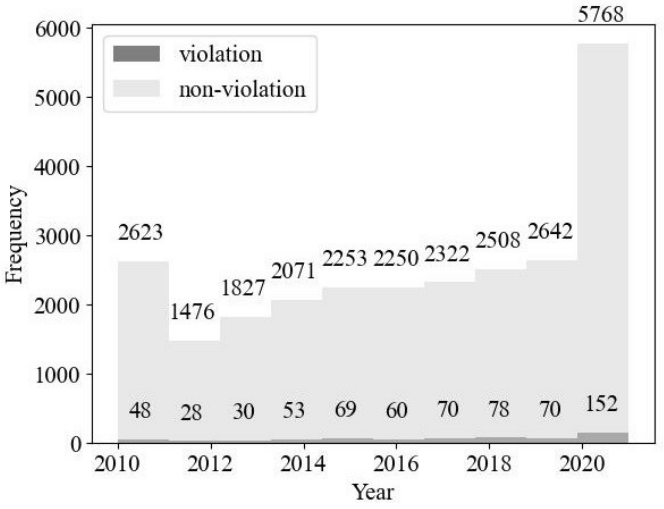


Figure 1. The distribution of violation records

Due to the significant class imbalance in the dataset (2.56% of violation records compared to 97.44% of non-violation records), this paper used under-sampling to solve the problem. By randomly sampling records from the non-violation dataset, the ratio of non-violation records to violation records is adjusted to 10:1. To prevent overfitting caused by the limited sample size, in terms of dataset splitting, the training set and the testing are set in a 1:1 ratio.

The financial statistics, the equity nature of the company, audit information and the datasets of administrative penalties are retrieved from CSMAR database [1]. The textual features of annual financial report are based on the MD&A of annual financial report and retrieved from Wingo database, including tone, similarity, readability and risk [19].

2.3. Variable definition

Since the annual financial reports are released during the period of January 1 to April 30 every year, to forecast the likelihood of administrative punishments, this paper used violation records from the next period, May 1, 2011, to December 31, 2022. The records were set as binary variables. The variable is set to 1 if the company received a punishment from CSRC in the given year. Conversely, if the company did not face any punishment, the variable is assigned a value of 0.

As for financial variables, based on the previous studies [11, 19], this paper chose 7 representative financial ratios to implement the forecasting, including Market to Book Ratio (MB), gearing ratio, leverage, current ratio and Return on Assets (ROA).

Furthermore, this study takes into account the distinct characteristics of the Chinese capital market, which gives rise to significant disparities between State-Owned Enterprises (SOE) and private enterprises. These disparities encompass differences in business objectives, resource acquisition, and regulatory supervision. To capture this distinction, companies are categorized as either state-owned or non-state-owned using a binary variable. Additionally, the evaluation of audit quality is based on whether the company underwent an audit by international Big 4 firms or national Top 10 audit companies. Both of these variables are classified as binary variables as well.

In terms of non-financial variables, 4 variables were incorporated into the analysis, including tone, risk, readability, and similarity. By considering tone, the study aimed to gauge the overall sentiment conveyed in the MD&A section. The tone evaluation is computed by the basis of Loughran and McDonald's sentiment dictionary and the expansion of Wingo database. After conducting segmentation of word, the computation of tone is defined by dividing the difference of the frequency of two type of sentiment words by the sum of these words plus one. As for risk the calculation of risk-related words frequency is based on Wingo risk vocabulary, and the index is measured by risk-related words frequency

DOI: 10.54254/2755-2721/46/20241319

divided by total words of MD&A section. The readability is measured by the logarithmic mean of the product of each sentence generation's probabilities. The computation of similarity starts with calculating the TF-IDF value of the text, then uses cosine function to compute the similarity index. Time factors are incorporated in analysis since text components from previous years might contain clues or evidence of past violations.

Figure 2 show the distribution of linguistic variables one year before the announcements of administrative punishments in the original dataset. As can be seen in the charts, most of companies tend to show an aspiring sentiment in MD&A section. Also, the risk index of most of companies is relatively low, accounting for approximately 0.01. The similarity of MD&A section compared to last period seems to have large discrepancy among investigated companies, while most of the companies have a readability index at around -20 to -30.

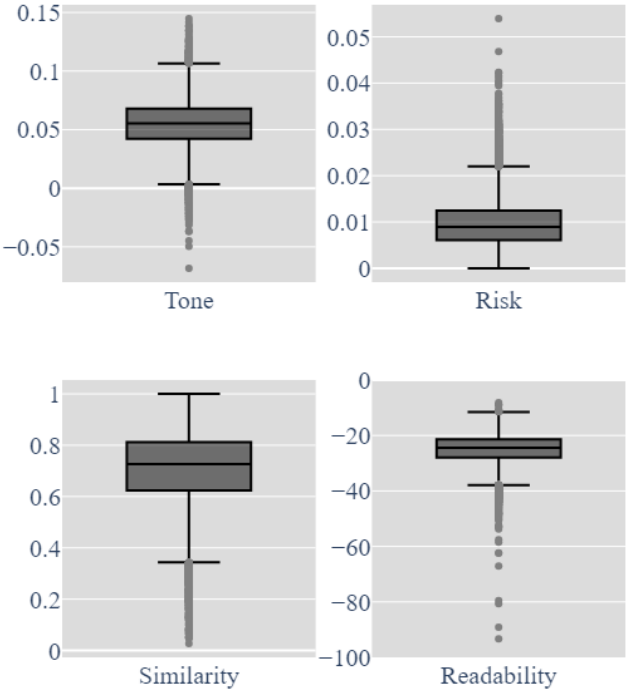


Figure 2. The distribution of violation records

To account for the varying scales of the variables, this essay employed a normalization technique. Specifically, the statistics were normalized by subtracting the minimum value of each variable within the variable group and dividing it by the result of maximum value minus minimum value. The normalization process keeps the data range at [0, 1].

3. Method

3.1. Administrative Punishment Forecasting Model

Deep learning, a subarea of machine learning, centers on the training of artificial neural networks to acquire knowledge and generate predictions by processing extensive volumes of data. It draws inspiration from the intricacies of the human brain in terms of structure and functionality. To process and analyze data, deep learning algorithms utilize artificial neural networks consisting of multiple interconnected layers of neurons.

One type of layer commonly used in neural networks is the fully connected (FC) layer, also known as the dense layer, which provides the final classification or regression output. In a FC layer, each neuron

DOI: 10.54254/2755-2721/46/20241319

from the last layer is connected to a neuron in the subsequent layer. These layers effectively learn intricate relationships between the extracted features and utilize them to generate accurate predictions.

The Sigmoid function is a non-linear activation function that is commonly used in the output layer of binary classification models. By taking the reciprocal of the sum of 1 and the exponential term, the sigmoid function compresses the output to a range between 0 and 1. Furthermore, the Sigmoid function provides a smooth gradient, ensuring that the network can learn effectively during the training process. It enables efficient backpropagation of errors, which allows the neural network to update its weights and improve its performance. However, for the input values that have large absolute values, the Sigmoid function tends to saturate, resulting in outputs reaching close to 0 or 1. This could lead to extreme small gradients during backpropagation, slowing down the learning process. Consequently, Rectified Linear Unit (ReLU) is applied to solve the problem.

ReLU is an activation function that transforming negative input values to zero while leaving positive values unaffected, possessing simplicity and computational efficiency. It does not suffer from the vanishing gradient problem as it only applies non-linearity to positive values and enables efficient gradient flow during backpropagation.

This paper employs ReLU and Sigmoid as activation functions to implement binary classification. The model structure is as Figure 3:

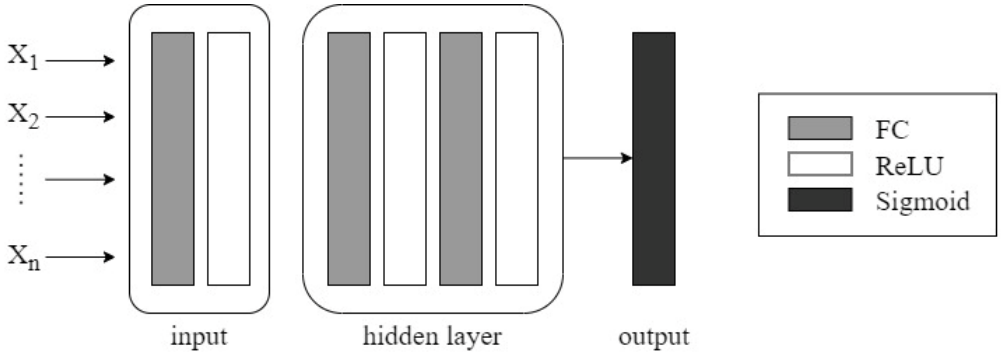


Figure 3. Structure of the model

The model begins with concatenating financial and non-financial variables into a comprehensive dataset. To ensure consistent scaling, the statistical values of the dataset has been normalized, ranging from 0 to 1. Subsequently, the dataset is fed into the FC layer, where each neuron is interconnected with every element in the input data. The purpose of this layer is to capture the patterns and relationships inherent in the data. In order to introduce non-linearity and improve the network's ability to express complex concepts, the output of the FC layer undergoes activation via the ReLU function. Finally, in the output layer, the Sigmoid function is applied to generate a probability value between 0 and 1.

3.2. Experiment result

The aim of this model is to forecast the probability of administrative punishments of the company. The model is optimized using Adam. The learning rate is set at 0.001 and the training batch size is 16. In terms of loss function, Binary Cross-Entropy is used in this essay. During the training phase, the model achieved a training accuracy of approximately 0.9121. This indicates the model's competence to correctly classify entities within the training dataset. In the testing phase, the model performed even better, achieving a testing accuracy of around 0.9701. The difference of accuracy between training set and testing set indicates an overfitting in the model. It may be due to the deficiency of dataset.

4. Conclusion

With the continuous fluctuations in the economic situation, it is imperative for investors to navigate the increasing risks associated with investments, for instance, identifying the companies that are likely to acquire administrative punishments. The companies with violation records shared similar features in

DOI: 10.54254/2755-2721/46/20241319

operation, such as the deficient corporate governance structure, weak internal control, and lack of information disclosure. The administrative punishments to company's violations can result in significant reputational damage and loss of trust from stakeholders and investors. This paper proposes a deep neural network-based model that incorporates financial and linguistic features to predict the likelihood of a company being penalized.

The selection of variables in this study is determined on the basis of a broad review of existing literatures, including 7 representative financial ratios, 3 binary variables to determine the audit quality and equity nature of the companies, 4 variables concerning the textual features of MD&A section in the annual financial reports. In the data preprocessing phase, missing data is eliminated to ensure data integrity. Additionally, the under-sampling method is employed to mitigate data imbalance. Random sampling is conducted from the non-violation group, creating a ratio of 10:1 between companies with non-violation and violation records. In consideration of the small sample size, a 1:1 ratio is employed to the datasets for training and testing. To mitigating the impact of varying statistical scales, the dataset is normalized before processing.

In terms of modelling process, neural network is adopted in this essay for its capability of processing and analyzing structured data. In the FC layer, ReLU activation function is employed to address the problem of gradient explosion. In the output layer, the Sigmoid activation function is applied to derive binary classification to implement forecasting of potential violations. The model exhibits an accuracy at 0.9701 in testing set, which is higher than that of training set accounting for 0.9121. The result indicates a potential issue of overfitting.

To overcome this problem, several adjustments can be considered in future work, including implementing regularization techniques such as dropout or L1/L2 regularization to control model complexity and enhance generalization performance. Also, increasing the size of the training dataset could potentially alleviate overfitting and further enhance the model's predictive capabilities.

By addressing these concerns and refining the model, it is possible to improve the effectiveness and robustness of the proposed model in forecasting violation risks for listed companies, providing valuable insights to investors in making informed decisions. Through combining advanced deep learning techniques with comprehensive utilizing the financial and textual features in annual financial reports, the model offers investors a valuable tool for assessing and managing risks associated with their investment decisions.

References

[1] CSMAR Database. Retrieved from: https://cn.gtadata.com/

[2] Karpoff J, Lee D and Martin G 2008 The consequences to managers for financial misrepresentation *Journal of Financial Economics* 88 193-215

[3] Lee W, Jiang X and Indro D 2002 Stock market volatility, excess returns, and the role of investor sentiment *Journal of Banking & Finance* 26 2277-99

[4] Rezaee Z 2005 Causes, consequences, and deterrence of financial statement fraud *Critical Perspectives on Accounting* 16 277-98

[5] Jin L and Myers S C 2006 R2 Around The World: New Theory and New Tests. *Journal of Financial Economics* 79(2) 257-92

[6] Kothari S P, Li X and James E 2009 The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis *The Accounting Review* 84(5) 1639–70

[7] Buskirk A 2012 Disclosure frequency and information asymmetry *Rev Quant Finan Acc* 38 411–44

[8] Brown S and Hillegeist A 2007 How disclosure quality affects the level of information asymmetry *Rev Acc Stud* 12 443–77

[9] Gleason C A, Jenkins N and Johnson W B 2008 The contagion effects of accounting restatements *Accounting review* 83 (1) 83 – 110

DOI: 10.54254/2755-2721/46/20241319

[10] Kaminski K A, Sterling Wetzel T and Guan L 2004 Can financial ratios detect fraudulent financial reporting? *Managerial Auditing Journal* 19 15-28
[11] Lehavy R, Li F and Merkley K 2011 The effect of annual report readability on analyst following and the properties of their earnings forecasts *The Accounting Review* 86(3) 1087-115
[12] Lang M and Stice-Lawrence L 2015 Textual analysis and international financial reporting: Large sample evidence *Journal of Accounting and Economics* 60 110-35
[13] Ertugrul M, Lei J, Qiu J and Wan C 2017 Annual Report Readability, Tone Ambiguity, and the Cost of Borrowing *The Journal of Financial and Quantitative Analysis* 52(2) 811-36
[14] Qian A and Zhu S 2019 Financial report similarity and the likelihood of administrative punishment: based on the empirical evidence of textual analysis *China Journal of Accounting Studies* 7:2 147-69
[15] Hajek P and Henriques R 2017 Mining corporate annual reports for intelligent detection of financial statement fraud – A comparative study of machine learning methods *Knowledge-Based Systems* 128 139-52
[16] Matin R, Hansen C, Hansen C and Mølgaard P 2019 Predicting distresses using deep learning of text segments in annual reports *Expert Systems with Applications* 132 199-208
[17] Feng M, Shaonan T, Chihoon L and Ling M 2019 Deep learning models for bankruptcy prediction using textual disclosures *European Journal of Operational Research* 274 743-58
[18] Craja P, Kim A and Lessmann S 2020 Deep learning for detecting financial statement fraud *Decision Support Systems* 139
[19] Wingo Database. Retrieved from: http://www.wingodata.cn/