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Research article

Application of deep learning in recognition of accrued earnings management

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ABSTRACT

We choose the sample data in Chinese capital market to compare the measurement effect of earnings management with Deep Belief Network, Deep Convolution Generative Adversarial Network, Generalized Regression Neural Network and modified Jones model by performance. We find that Deep Belief Network has the best effect, while Deep Convolution Generative Adversarial Network has no significant advantage, and the measurement effect of Generalized Regression Neural Network and modified Jones model have little difference. This paper provides empirical evidence that neural networks based on deep learning technology and other artificial intelligence technologies can be widely applied to measure earnings management in the future.

1. Introduction

Earnings management, as a hot issue of financial information disclosure and corporate governance, attracts wide attention. Scholars have given different definitions about the concept of earnings management. Two of the most representative definitions are as follows: ①Earnings management is actually a kind of "disclosure management" in which managers control the process of external financial reporting in order to obtain some private interests [1]. ② Earnings management refers to the behavior that maximizes managers' own interests or the company's market value by choosing accounting policies within the allowable scope of accounting standards [2]. Under the accounting rules of accrual basis, the accounting surplus of an enterprise includes two parts: net operating cash flow and accrued profit. Because cash flow is real and difficult to manipulate, earnings management can only be operated through accrued profit. According to the controllable degree of the total accrued profit, it can be divided into two parts: discretionary accrued profit and non discretionary accrued profit. Measuring the degree of earnings management can be transformed into measuring discretionary (abnormal) accrued profit. Management can manipulate earnings for many purposes, such as achieving performance appraisal, reducing tax burden, catering to analysts' earning forecast, avoiding loss, smoothing earnings and so on [3]. Seeking accurate measurement of earnings management has always been the goal of academic and practical circles. It not only affects the accuracy of empirical research, but also plays an important role in supervising listed companies, and improving audit quality and investors' decision-making.

Academic circles have never stopped exploring new models for measuring abnormal accrued profit. Early studies mention many well-known accrued profit models [4–7], such as Healy model, Deangelo model, Jones model, modified Jones model and so on.

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Dechow & Sloan [7] and Dechow et al. [8] respectively use time series data and cross-sectional data to test the detection ability of accrual profit model. They compare and analyse five accrual profit models to measure earnings management, and find that the modified Jones model is considered to be better than other earnings management models to measure abnormal accrual profit. Subsequently, Kothari et al. [9] find that the modified Jones model by corporate performance in the previous year is better than other modified Jones models, that is, the modified Jones model is the optimal tool to detect earnings management. Therefore, the modified Jones model is widely used in the empirical study of earnings management.

However, Jones model and other linear abnormal accrual models are based on the following assumption: the Accruals Generation Process does not change with time, is stable [6], and industry-consistent [10]. However, many scholars study the Accruals Generation Process and find a nonlinear relationship [8,9,11]. Moreover, Dopuch et al. [12] prove that there is a strong multicollinearity problem between the determinants of accrued profit, which makes it difficult to establish the estimation model of abnormal accrued profit by using linear regression. However, Jones model and so on all rely on the linear regression. Using a linear method to measure accruals will inevitably get a lower detection rate of earnings management. The advanced evaluation method negates the Jones model on the measurement of earnings management. Nam and Park [13] use a comprehensive simulation method to evaluate the effect of various models, and find that the average detection rate of the modified Jones model is only 49.1%, which is not significantly different from coin tossing (50%). This conclusion makes many scholars study more superior earnings management measurement model than Jones model [14–18].

Because the poor detection rate of linear abnormal accruals models such as Jones model and the Accruals Generation Process is nonlinear, it needs nonlinear models to estimate abnormal accruals. But so far, only a few suggestions are about nonlinear models. In a study of Detienne et al. [19], the performance of neural networks is compared with linear regression models. They mention four advantages of neural networks. First, neural networks can be used to model nonlinear relationship. Second, contrary to linear regression, neural networks do not need to specify the model in advance, because neural networks are completely data-driven. Third, compared with linear regression, neural networks are less sensitive to extreme values and missing data. Last, Detienne et al. [19] mention that linear regression models have strict assumptions on multicollinearity and error distribution, and these assumptions are not needed in neural network models. Therefore, when the relationship between variables is complex and nonlinear, neural network models are better than linear regression models [19–21].

Neural networks are successfully applied in financial research by some scholars [22,23]. Other researchers in the field of accounting also use neural network technology. In early studies, Tsai and Chiou [24] develop neural networks and decision tree models to predict accrued income management level. Höglund [21] compares the Self-Organizing Map (SOM), Multilayer Perceptron (MLP) and Generalized Regression Neural Network (GRNN) with modified Jones model, and finds that the three neural network models are better than linear Jones model, and GRNN is the best one. Later, Höglund [18] uses the Self-Organizing Map again to estimate abnormal accrued profit, with various determinants of accrued profit proposed by Dechow et al. [25] and Dopuch et al. [12]. They find that the performance of Self-Organizing Map is better than modified Jones model. However, the above neural networks are only based on machine learning. At present, there is no literature on deep learning neural network model to estimate abnormal accruals.

With the development of artificial intelligence, machine learning has made great progress. Deep learning is the development and extension of machine learning. As an important part of artificial intelligence, its effect on data learning, recognition and processing is far greater than machine learning. Therefore, deep learning has been widely used in such areas as driverless cars, intelligent medical, financial services, intelligent education, biometrics and so on. Based on deep learning technology, this paper attempts to use more complex neural networks to identify earnings management of listed companies, which can provide reference for supervisors to supervise financial behavior of listed companies, protecting the interests of investors. This paper also provides reference for audit units to allocate resources and improve audit quality, and enrich the literature on the application of artificial intelligence.

The innovations of this paper are as follows: (1) Neural networks based on deep learning technology are proposed to identify accrual earnings management for the first time, which fills the gap of related research. Traditional neural networks, such as Self-Organizing Map (SOM), Multilayer Perceptron (MLP), Generalized Regression Neural Network (GRNN), Back Propagation Neural Network (BP), etc., are shallow learning models. They usually have only input layer, hidden layer and output layer, which easily leads to over fitting and poor generalization ability. Shallow structure has a good effect on the data with uncomplicated internal structure and weak constraints. However, when dealing with the data with complex internal structure in the real world, these models will have the problem of insufficient representation ability. Different from shallow learning, deep learning is to transform the data original features into a feature representation through multi-step feature transformation, which can effectively capture the internal hidden structure of the data. When the training data has enough diversity and complexity, the deep learning model can truly show the powerful modeling ability of massive data, and use the powerful modeling ability to represent the data. The basic idea of deep learning is to abstract features by using the structure of multilayer neural networks. One layer is used as the input of the next layer to realize the hierarchical expression of the input information. The expression of data in the original feature space can be transformed into a new feature space through multiple nonlinear mapping of the network, and more data distribution characteristics can be found. It ultimately makes the classification and prediction easier. At present, the mainstream network models in the field of deep learning include: Deep Belief Network (DBN), Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Generative Adversarial Network (GAN) and Recurrent Neural Network (RNN) and so on. Deep Belief Network is a typical representative of the earlier deep probability generation model. It is composed of multilayer neurons, and has better feature learning ability and faster model training ability. Deep Convolution Generative Adversarial Network is a common deep learning algorithm. It is also one of the most representative neural networks in the field of deep learning technology, and a deep neural network of supervised learning. In this paper, Deep Belief Network and Deep Convolution Generative Adversarial Network are selected as representatives of deep learning to identify accrual earnings management.

(2). This paper uses the sample data of China, which is an emerging power. The quality of accounting information is influenced by accounting standards, investor protection system, corporate governance structure, audit supervision and management reporting motivation [26,27]. As a transitional economy country with big government, small market and imperfect legal system, China has an imperfect investor protection system. The dominance of state-owned shares has existed for a long time. The corporate governance structure is poor. Audit and manager market do not provide a good supporting environment for the effective implementation of the standards, which lead to the widespread existence of earnings management in Chinese listed companies [28,29]. The motivation of earnings management in Chinese listed companies is significantly different from that in developed countries. It not only has the motivation to achieve performance appraisal, avoid performance decline and avoid loss, but also has the motivation to evade the regulation of China Securities Regulatory Commission, obtain the qualification of financing and refinancing, and maintain the qualification of listed company. Wang et al. [29] use the method of earnings distribution to draw the conclusion that the average proportion of Chinese companies turning loss into profit through earnings management is 64.4%. Earnings management in Chinese capital market is more common and more serious than that in developed institutional environment, which makes the samples in Chinese capital market not only more representative, but also more convincing.

(3). We put forward a new idea to identify earnings management. Earnings management is common in Chinese listed companies [28,29]. If we use the previous method [18,21], the learning target value will be systematic biased in the samples with systematic earnings management, and the obtained model will be inappropriate. Therefore, the neural network model with wrong learning value has great deviation. This paper uses a new recognition idea of accrual earnings management. There are n companies in an industry. We use n-1 companies to train the deep neural network, and then predict the remaining one. We will get a residual value, and continue to select n-1 companies to train and predict. Such repeated cycle, we will get n residual values. Each residual value is the proxy variable of earnings management. We think that the data relationship should be similar in the same industry, and the deviation from the data relationship with comparable companies is likely to be abnormal.

(4). We use a new method to compare the models' effect. Based on the characteristics of earnings management in Chinese listed companies, this paper uses a new efficiency evaluation scheme to compare the identification effect of models on earnings management. According to the existing research, the motivation of earnings management in Chinese stock market is in order to keep earnings and avoid the decline of performance [28,29]. This paper selects two measurement variables of marginal ROE, and uses the method of linear regression to compare the models' effect on earnings management.

(5). This paper shows that earnings management has deep and complex nonlinear characteristics. We find that Deep Belief Network has the best measurement effect on accrual earnings management. Deep Convolution Generative Adversarial Network has no obvious advantages, while the effect difference between Generalized Regression Neural Network and modified Jones model by performance is small. Earnings management fits well with Deep Belief Network. It shows that the formation process of earnings management has deep and complex nonlinear characteristics. Management use a variety of means to manage earnings, which change with time, and also use some masking means. The finding is helpful to understand earnings management.

The structure of this paper is as follows: The second part is the theoretical background and analysis. The third part is the research design. The fourth part is model design and results. The fifth part compares the effect of models. The sixth part is the conclusion, and the last part is the implications.

2. Theoretical background and analysis

2.1. Theoretical background

Deep learning is different from the traditional neural network. It is a general term for a class of methods to train model with deep structure. It adopts the multilayer nonlinear transformation method to extract information and train a group of network parameters. Deep learning can extract rich content of data through unsupervised or supervised training. Finally, it is used for feature extraction, transformation, pattern classification and other tasks. Deep learning can summarize the general rules from the limited samples, and can be applied to new unknown data. Through learning algorithm, deep learning makes the model automatically to learn good feature representation from low-level feature to middle-level feature, and then to high-level feature. Through multilayer feature transformation, the original data is transformed into the higher level and more abstract representation, so as to ultimately improve the accuracy of the prediction model. The data processing flow of deep learning is shown in Fig. 1. Deep Belief Network and Deep Convolution Generative Adversarial Network are two common deep learning algorithms. They are also very representative neural networks in the field of deep learning technology. Their measurement effect on earnings management will be better.

2.1.1. Deep belief network

Deep Neural Network (DNN) is a multilayer perceptron with multiple hidden layers. The two adjacent layers are fully connected.

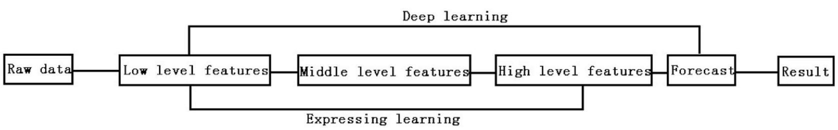

Fig. 1. Data processing flow of deep learning.

Usually, unsupervised pre-training method is used to initialize the connection weight, and Soft-max network is formed between the last hidden layer and the output layer. Finally, the network parameters are tuned by supervised training. In order to solve the problem of training multilayer neural networks, Hinton et al. [30] first propose a special multilayer neural network named Deep Belief Network (DBN) based on deep learning theory. Its structure is shown in Fig. 2. DBN and traditional multilayer neural networks have both similarities and differences. The common point is that DBN is still a multilayer neural network in essence. After the initial value of the network is determined, BP algorithm is still used to fine tuning. The difference is that the essence of traditional neural network is decision-making model, while DBN is a hybrid model combining generation model and decision-making model. DBN can obtain the joint probability distribution of observation data and label, which is convenient to estimate prior probability and posterior probability, while the decision-making model can only estimate posterior probability. In addition, in the training phase, DBN needs to use unsupervised method to determine the initial value after pre-training, which reduces the requirements of input data. DBN consists of a series of Restricted Boltzmann Machine (RBM). The training of RBM is a key to the successful application of deep learning. By combining a large number of bottom-up RBM, DBN can be constructed. It is proved that the layer by layer learning procedure improves the lower bound of likelihood probability of training data based on the hybrid model. In other words, this greedy algorithm is similar to maximum likelihood learning. Such learning is unsupervised and does not require label sample, but the generalization ability of the model is strong. The training process of RBM is called pre-training in the whole DBN training process, which adopts unsupervised learning method. After the whole DBN is constructed, the supervised learning method can be used to callback the whole network from back to front, which is similar to the traditional BP neural network. Finally, Deep Belief Network can be established. The reason why DBN is effective is that it uses unsupervised learning to get the initial value of the whole network. Compared with the neural network with randomly selected initial value, it can effectively avoid the problem of falling into local optimum.

2.1.2. Deep Convolution Generative Adversarial Network

Generative Adversarial Network is a network that lets the machine to understand the data and generate the model. Generative Adversarial Network introduces the concept of adversarial, and uses the model to generate data. Then another model is used to judge the generation effect. In this way, the two models are iterated and modified repeatedly to achieve the dynamic balance and the understanding of real samples. Generative Adversarial Network introduces adversary mechanism into machine learning. Discriminant model can be regarded as supervised learning, while generative model can be regarded as unsupervised learning. Through the adversarial training of discriminant model and generative model, the new samples can be generated effectively. Because neural network is used as the structure of discrimination model and generation model, Generative Adversarial Network also has the ability to generate high-dimensional data. In the process of model training, the adversarial network is generated and model parameters are trained by back propagation. The training process does not depend on the repeated sampling of Markov chain, nor does it need approximate reasoning. Generative model trains and optimizes the parameters by using the gradient of the backward transmission of discriminant model, rather than directly using the real sample data for parameter optimization. Generative adversarial network can be combined with other neural networks, thus giving many advantages to generative adversarial network..

Radford et al. [31] introduce deep convolution into the generative adversarial network, and find a set of better network topology to form Deep Convolution Generative Adversarial Network (DCGAN). Its structure is shown in Fig. 3. Deep Convolution Generative Adversarial Network also includes discriminant model and generative model, in which the objective function is the same as that of generative adversarial network. In addition to introducing convolution layer into the generation adversarial network, the optimization points of Deep Convolution Generative Adversarial Network for model structure include adding regularization layer, replacing pooling layer, selecting specific activation function, etc. (1) Adding regularization layer. Regularization is used in both the discriminant model

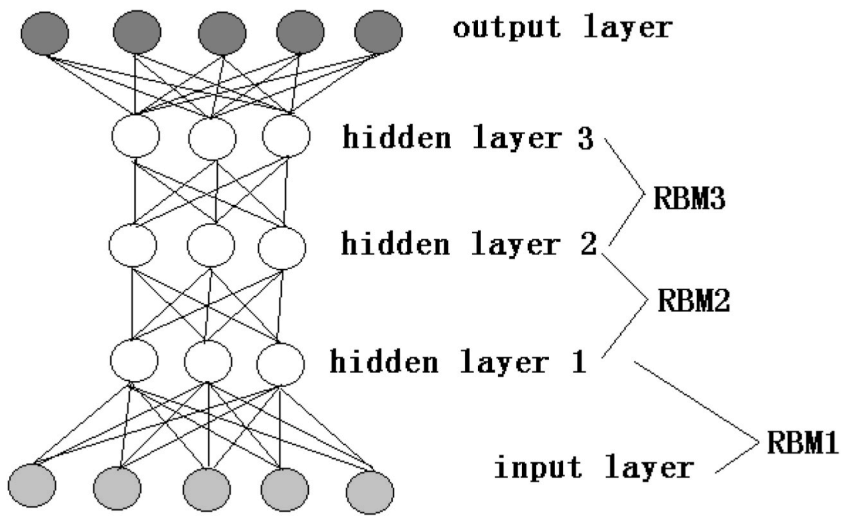

Fig. 2. Deep belief network.

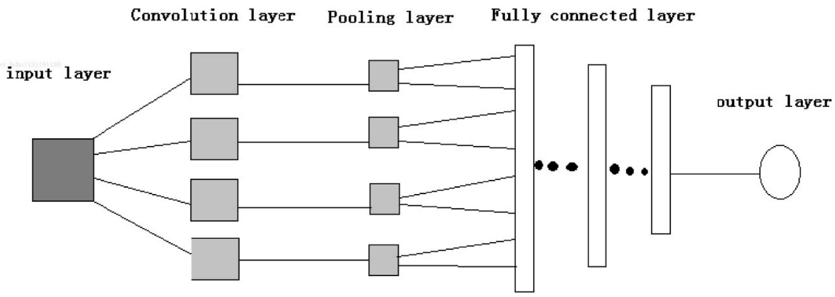

Fig. 3. Deep convolution generative adversarial network.

and generative model, which can prevent generative model from converging all the newly generated samples to one point, resulting in the diversity of the generated samples, and can also transfer the gradient to the next layer to speed up the training. But the regularization method can not be applied to input layer of discriminant model and output layer of generative model, because if regularization is applied to all layers of the discriminant model and generative model, the stability of the model will be affected. (2) Replacing pooling layer. In discriminant model, it uses convolution kernel with step size instead of pooling layer to learn downsampling. In generative model, it uses deconvolution to learn upsampling. The purpose of pooling layer in convolution neural network is mainly to speed up training, while DCGAN uses regularization and convolution kernel with step size, so the training speed has been improved and pooling layer is not necessary. (3) Selecting specific activation function. Leaky ReLU is used as activation function in all layers of discriminant model. In addition to output layer, generative model uses ReLU as the activation function, while output layer uses Tanh as the activation function.

2.2. Theoretical analysis

Earnings is the sum of operating cash flow and accruals which non discretionary accruals and discretionary accruals can be separated from. Discretionary accruals is the size of earnings management. There is a nonlinear relationship in the Accruals' Generation Process (AGP) [8,9], and the Accruals' Generation Process (AGP) is unstable, changing with time, and has industry differences [11]. The Accruals' Generation Process will inevitably affect the process of earnings management. We can infer that earnings management has similar characteristics. Managers don't want their earnings management behavior to be found, because once it is found, earnings management will damage the management's reputation among shareholders and potential employers, and the reputation mechanism in the market will make management's value decline in the professional manager market. In addition, if the company's earnings management is found, the company's financial information will not be trusted by investors. It will reduces the company value. Therefore, in the process of earnings management, managers will use a variety of means to manipulate accrued profit, changing with time, and also use some masking methods. These make earnings management to have complex nonlinear characteristics. According to the matching principle, the complex nonlinear network model should be better than the general neural network model and linear regression model to measure earnings management. Our hypothesis (in alternative form) is as follows:

The recognition effect of Deep Belief Network and Deep Convolution Generative Adversarial Network on earnings management may be significantly better than that of general neural network model and modified Jones model.

3. Research design

3.1. Model selection

Höglund [21] studies and compares the measurement effect of Self-Organizing Map (SOM), Multilayer Perceptron (MLP) and Generalized Regression Neural Network (GRNN) and modified Jones model on accrual earnings management. He finds that the three neural network models are better than linear model, while GRNN is the best one. Kothari et al. [9] find that Jones model modified by performance in previous year is better than other modified Jones models. Considering comprehensively, this paper finally selects four models to identify and measure accrual earnings management, which are Deep Belief Neural Network, Deep Convolution Generative Adversarial Network, Generalized Regression Neural Network and Jones model modified by corporate performance.

3.2. The way of estimating accrued earnings management

There are n companies in an industry. We use n-1 companies to train the deep neural network, and then predict the remaining one. There will be a residual value between the predicted value and the actual value, and then continue to select n-1 companies to train and predict. Such repeated cycle, we will get n residual values. Each residual value is the proxy variable of earnings management. The data relationship should be similar in the same industry, and large deviation from the data relationship with comparable companies is likely to be abnormal. In this way, we use Deep Belief Neural Network, Deep Convolution Generative Adversarial Network, Generalized Regression Neural Network and modified Jones model to estimate earnings management respectively. For Generalized Regression

Neural Network and modified Jones model, using the idea of this paper and the previous idea [19,21], the residual values have no significant difference. Deep Belief Neural Network and Deep Convolution Generation Adversarial Network have stronger ability to learn information and absorb information more fully. Matching with this way, the measurement effect of earnings management is higher.

3.3. Selecting sample

This paper selects Chinese A-share listed manufacturing companies (industry code C13–C43) as samples in 2015 and 2016. All data are from China Research Data Service Platform. The industry classification standard of listed companies comes from the «Guidelines for Industry Classification of Listed Companies » issued by China Securities Regulatory Commission in 2012, which takes the audited business income of listed companies in recent years as the classification standard. It is scientific and authoritative. Company whose absolute value of total accruals is equal to or greater than lagged total assets will be removed from the data set. In addition, all five variables used in the models are winsorized at the 1st and 99th percentile. According to these criteria, the total number of companies included in the final data set is 2173. Descriptive statistics for data set is shown in Table 1.

4. Model design and results

4.1. Jones model modified by corporate performance

According to the research of Kothari et al. [9], we use Jones model modified by the performance in previous year to estimate earnings management. Specifically, we run the following regression model on the sample and use the residual values as our measurement of earnings management:

$$TAC_t = Earn_t - CFO_t \tag{1}$$

$$TAC_t / TA_{t-1} = \beta_0 + \beta_1(1 / TA_{t-1}) + \beta_2(\Delta SALES_t - \Delta AR_t) / TA_{t-1} + \beta_3(PPE_t / TA_{t-1}) + \beta_4 ROA_{t-1} + \varepsilon \tag{2}$$

In equation (1), *TAC* variable is the total accrued profit item. *Earn* is the net profit excluding non sustainable operation and extraordinary items. *CFO* is the net operating cash flow. In equation (2), *TA* is the total assets at the beginning of the year. Δ*SALES* is the change of sales revenue in this year compared with the previous year. Δ*AR* is the change of accounts receivable in this year compared with the previous year. *PPE* is the plant, equipment and other fixed assets. *ROA* is the rate of return on assets in the previous year, which is calculated by the ratio of net profit excluding non sustainable operation and extraordinary items to total assets. ε_t is the residual value, which is the measurement data of earnings management. Table 2 shows the regression results of Jones model modified by corporate performance.

4.2. Introduction to the characteristics of network model

This paper uses matlab2018 software for data processing. According to Occam's Razor, a simple model has better generalization ability, so the selected model is relatively simple.Considering that this paper is only for academic discussion, not for the application of system engineering, the models used are representative and simple.Considering that this paper is only for academic discussion, not for the application of system engineering, the models used are representative and simple. An overview of the neural network models used is as follows: (1) Deep Belief Neural Network adopts a neural network model containing three hidden layers. The network parameters of the first hidden layer are obtained by RBM training, and the input of RBM is the original information. RBM trains the network parameters of the second hidden layer, and the input is the output of the first hidden layer. RBM trains the network parameters of the third hidden layer, and the input is the output of the second hidden layer. Then, Deep Belief Neural Network is constructed, and the initial parameters are the parameters trained by RBM. Finally, the deep network is trained by BP and tested by the trained deep network. (2) In this paper, a simple 1 + N structure of Convolution Generative Adversarial Network is adopted here, that is, one

Table 1
Descriptive statistics for data set.

n = 2173	*Earn*	*CFO*	*TA*	Δ*SALES*	Δ*AR*	*PPE*	*ROA*
Mean	303.8	410.1	6582	488	109.1	1926	6.259
Median	99.89	110.3	2081	107.2	27.28	469	5.570
St. dev.	1372	1495	20,520	1556	342.8	6334	8.125
Min	6.925	6.866	45.869	−2069	−622.9	0.111	−68.66
Max	43,960	26,700	511,600	11,170	2326	118,100	56.45

Note: *Earn* is the net profit excluding non sustainable operation and extraordinary items. *CFO* is the net operating cash flow. *TA* is the total assets at the beginning of the year. Δ*SALES* is the change of sales revenue in this year compared with the previous year. Δ*AR* is the change of accounts receivable in this year compared with the previous year. *PPE* is the plant, equipment and other fixed assets. The unit of the above variables is million. *ROA* is the rate of return on assets in the previous year, calculated as the ratio of net profit excluding non sustainable operation and extraordinary items to total assets. The unit is %.

Table 2
The regression results of Jones model modified by corporate performance.

Variable coefficient	TAC_t/TA_{t-1} Coef	Std. Err	t	P>|t|
intercept	−0.010	0.004	−2.23	0.026
$(\Delta SALES_t - \Delta AR_t)/TA_{t-1}$	0.075	0 .009	8.41	0.000
PPE_t/TA_{t-1}	−0.028	0.011	−2.59	0.010
ROA_{t-1}	0.016	0.033	0.47	0.640
F statistical value	27.32 (0.000)			
$Adjusted.R^2$	0.0462			

convolution layer (including pooling layer) and N fully connected layers. Convolution layer: no padding, stride set to 1, and the activation function selecting ReLU function. Pooling layer: no padding, and pool type only implementing the “average” method. Spread layer: the layer designed for convenient calculation, which belongs to the preallocation memory space and is used as the input of the full connection layer. Full connection layer: the activation function is Sigmoid function. Output layer: Softmax function is selected for classification function, and cross entropy cost function and L2 regularization are selected for cost function. (3) Generalized Regression Neural Network model is composed of four layers: input layer, mode layer, summation layer and output layer. The number of neurons in the output layer is equal to the dimension of input vector in the learning sample. Each neuron is a simple distribution unit, which directly transfers input variables to the mode layer. The best spread value is obtained by using the method of cyclic training to ensure that the model is well trained. We use the above three neural networks to learn, predict and record the residual values. Due to the large number of learning and prediction times and the huge amount of technical details information, the specific parameters of each learning result of three neural networks and other technical details are omitted here.Due to the large number of learning and prediction times and the huge amount of technical details information, the specific parameters of each learning result of three neural networks and other technical details are omitted here.

4.3. *Descriptive statistics for the results obtained*

It can be seen from Table 3 that the average value of abnormal accruals obtained by the four models is not zero, which is consistent with the conclusion that earnings management generally exists in Chinese listed companies [28,29]. The standard deviation obtained by DBN model is the largest and the average value is the smallest. These show that DBN model has the highest accuracy in earnings management identification. Comparing the maximum value of abnormal accruals, it is found that the maximum value obtained by DBN model is the smallest, followed by DCGAN model. The maximum value of abnormal accruals obtained by GRNN model and modified Jones model is larger. At the same time, considering the degree of symmetry of the maximum and minimum, we can see that the result of Deep Belief Network model is most consistent with the reality. So the effect of DBN is the best.

5. Compare the effect of models

5.1. *Literature about comparing the effect of models*

If the behavior of earnings management can be observed, then the evaluation of earnings management measurement model only needs to directly compare earnings management estimated by each model with the actual earnings management. However, it is difficult for researchers to observe earnings management behavior itself. Therefore, we can only use indirect methods to evaluate the effect of earnings management measurement model. For example, Guay et al. [32] test the relationship between stock price and abnormal accruals or normal accruals based on efficient market theory, and use the relationship to test the recognition effect of earnings management measurement model. Bartov et al. [16] believe that if audit quality is relatively high, the company with earnings management is more likely to be issued with non-standard unqualified audit opinion. So they test the relationship between earnings management and audit opinion to evaluate the effect of earnings management measurement model. But Chinese stock market has not yet formed an effective market, and the audit quality of Certified Public Accountants is not very high [33]. Therefore, the methods used by Guay et al. [32] and Bartov et al. [16] are not applicable in Chinese capital market. Höglund [21] think that the mean and median of residuals obtained from random samples are closer to 0, and the model is the better. However, earnings management is prevalent in

Table 3
Descriptive statistics for the results obtained.

	Statistics of earnings management calculated by various models （DA）				
Model	Obs	Mean	Std. Dev.	Min	Max
Modified Jone Model	2173	−0.0129	0.0583	−0.7219	1.0654
GRNN Model	2173	0.0113	0.0643	−0.1993	1.8096
DCGAN Model	2173	0 .0010	0.0568	−0.4521	0.8822
DBN Model	2173	−0.0025	0.0730	−0.2131	0.2389

Chinese capital market [28,29]. The mean and median of residuals close to 0 do not mean a better model. This evaluation method is biased. Some scholars use the method of simulating dirty companies to evaluate the effect of earnings management model [8,17,18]. They artificially create dirty companies by simply adding additional accruals, which may violate company's financial dynamics. Moreover, companies that do not add extra accruals are regarded as cleaning companies. In the sample of universal earnings management, even if there is no added accrued profit, it may be a dirty company. Therefore, there is the possibility that mistakes the dirty company for the cleaning company. This evaluation method is not reliable. Nam & Park [13] adopt a comprehensive method to simulate the company, but their company is far from the real company. So the evaluation method is also not credible. This paper uses and improves the method adopted by Xia [35], and tests the relationship between abnormal accruals estimated by each model and the marginal ROE of listed companies to evaluate and compare the effect of earnings management measurement models.

According to the existing research, information asymmetry is serious between management and shareholders in Chinese stock market [36]. As insiders, management hold company's private information. As outsiders, shareholders have the right of ownership and residual income, but they know little about the internal information of the company. Under the background of the separation of ownership and management rights, the interests of shareholders and management are not consistent, and the first kind of agency problem is serious [34]. Managers have the decision-making power of the company, which is not always based on the maximization of shareholder value. They have self-interested opportunistic behavior. Managers may conduct earnings management in order to avoid loss and performance decline for their own interests such as reputation or compensation [3]. There is a significant phenomenon of earnings management in listed companies, which specifically shows that companies with marginal ROE are more frequently than other companies [29]. Fig. 4 shows the distribution of samples in each ROE interval, listing the ROE interval distribution of 2173 sample companies. As can be seen from the figure, there are only 16 companies with ROE in (- 1%, 0], while 209 companies with ROE in (0, 1%]. It forms a great change in the number distribution of listed companies, and shows obvious signs of earnings management. This is consistent with the conclusion that managers conduct earnings management to avoid loss [29,37]. Therefore, we can test the relationship between abnormal accruals estimated by each model and the marginal ROE of listed companies to evaluate the effect of earnings management measurement models. If abnormal accruals calculated by earnings management measurement models are positively correlated with company's marginal ROE, then these models can reveal earnings management.

5.2. Empirical design of comparing model effect

$$DA = \beta_0 + \beta_1 Tests1 + \beta_2 Test2 + \beta_3 No - Tests + \beta_4 Loss + \beta_5 Time + \varepsilon \tag{3}$$

In equation (3), DA is the abnormal accruals estimated by the above four earnings management measurement models. β_0 is the intercept, $\beta_{1\sim5}$ are the regression coefficients, and ε is the residual. *Tests*1 is the test variable, representing earnings management motivation of avoiding loss. When the company's ROE is in (0,1%], we define *Tests* as 1, and the other case is defined as 0. $No-$ *Tests* is the control variable. When the company's ROE is in $(-1\%, 0]$, we define $No - Tests$ as 1, and the other case is defined as 0. According to the above analysis, the sample companies with ROE in [0, 1%) have obvious signs of earnings management, while those with ROE in $[-1\%, 0)$ have no obvious signs of earnings management. Therefore, if the tested earnings management measurement model can reveal earnings management, there should be a significant positive correlation between DA and *Tests*1, and no significant positive correlation between DA and $No - Tests$. Chinese listed companies also conduct earnings management to avoid performance decline [29,37], so *Tests* 2 is used as a tested variable here. If the result of company's ROE in 2016 minus ROE in 2015 is in (0,1%], that is, ROE2015 $= <$ ROE2016 $<$ 1% $+$ ROE2015, we define *Tests*2 as 1, and the other case is defined as 0. If the tested earnings management measurement model can reveal earnings management, then DA should be significant positive correlation with *Tests*2 *Loss*.is the control variable. When the sample company loses in the current period, we define *Loss* as 1, and the other case is defined as 0. There is a significant positive correlation between the company's accruals and performance, and loss making companies have the earnings management motivation of Big Bath [8]. Therefore, we add the control variable *Loss* to the test model, which represents the performance loss. *Time* is the control variable, representing the company's listing time. Its value is calculated as the number of days between the listing date of the company and December 31, 2016 divided by 360. Because the value is large, normalization is carried out here. Aharony et al. [38]

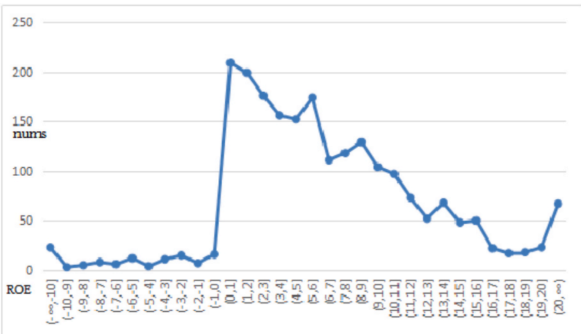

Fig. 4. Distribution of samples in each ROE interval.

show that Chinese listed companies have significant earnings management behavior in the IPO process, which will lead to the gradual reversal of accruals after IPO. Therefore, we add the control variable *Time* to the test model, which represents the listing time of the company.

5.3. The effect of earnings management measurement model

It can be seen from Table 4 that the significance of intercept items is very high, indicating that there are other factors that significantly affect earnings management. Comparing the coefficients of *Tests*1, it is find that DBN model has the best effect, which is significant at the level of 1%, and the absolute value of the coefficient is the largest. But DCGAN model has poor effect, which is not significant, and the absolute value of the coefficient is the smallest. The coefficients of *Tests*1 are little difference between GRNN model and modified Jones model. Comparing the coefficients of *Tests*2, DBN model is significant at the level of 1%, while DCGAN model is significant at the level of 5%. There is little difference between general regression neural network model and Jones model. The coefficients of *Tests*2 are little difference between GRNN model and modified Jones model. The coefficients of $No-Tests$ are not significant, which accords with expectations. The coefficients of *Loss* are significantly positive, which indicate that listed loss making companies have the motivation of earnings management of Big Bath. From the absolute values of coefficients of $No-Tests$ and *Loss*, DBN model shows the best result, and the absolute value of the coefficient is the largest. The coefficients of *Time* are not significant, which are not consistent with the previous research [38]. Because most sample companies have been listed for a long time in 2016, earnings management is no longer significantly correlated with the listed time. By comparing the regression results of the above models, we can conclude that DBN has the best effect, DCGAN has no obvious superiority, and the effect between GRNN and modified Jones model have little difference.

6. Conclusion

In this paper, Deep Belief Network and Deep Convolution Generative Adversarial Network are selected to estimate earnings management of listed companies by using deep learning technology. These two models have stronger ability of information mining and recognition, which are better than the traditional neural network model and modified Jones model in theory. The empirical analysis shows that Deep Belief Network has the best measurement effect on accrual earnings management. Deep Convolution Generative Adversarial Network has no obvious advantages, and the effect difference between Generalized Regression Neural Network and modified Jones model by performance is small. These show that the formation process of earnings management has deep and complex nonlinear characteristics, which fits well with Deep Belief Network. This finding is helpful to understand earnings management. The sample data selected for empirical research comes from the growing Chinese capital market. Because earnings management in Chinese capital market is more common and its motivation is more complex, the empirical results are not only representative, but also more convincing.Generally speaking, the deep learning neural network model used in this paper is not unique. Due to the different network parameters and learning methods, the results may have some differences, and we can not verify all cases. However, neural networks based on deep learning technology have many advantages over the traditional neural networks, and its robustness has been widely confirmed.Generally speaking, the deep learning neural network model used in this paper is not unique. Due to the different network parameters and learning methods, the results may have some differences, and we can not verify all cases. However, neural networks based on deep learning technology have many advantages over the traditional neural networks, and its robustness has been widely confirmed. This paper also puts forward a new way to measure earnings management. We suggest that there are n companies in a certain industry, use n-1 companies to train the neural network model, and then predict the remaining one. We will get a residual value, and continue to select n-1 companies to train and predict. Such repeated cycle, we will get n residual values. Each residual value is the proxy variable of earnings management. This idea to identify earnings management is more suitable for the capital market where there is a wide range of earnings management, such as emerging countries (eg: China and Brazil), and can also be used in the mature capital market such as developed countries.

Implications

In view of the advantages of Deep Belief Network, investors, creditors, auditors and analysts can use deep belief network model based on deep learning technology to test the accrual earnings management of listed companies. In practical application, it is a very complex system engineering to use deep learning neural network model to measure accrual earnings management. The selection of parameters and learning mode need to be constantly tried (No Free Lunch Theorem). With the development of artificial intelligence and big data resources, neural network model based on deep learning technology and other artificial intelligence technologies will be widely used in the identification process of earnings management in the future. Industry practitioners and regulators should learn to use relevant technologies to gain opportunities in the market economy.

Author contribution statement

Jia Li: Conceived and designed the analysis; Wrote the paper
Zhoutianyang Sun: Analyzed and interpreted the data; Contributed analysis tools or data

Table 4
The regression coefficients of the test model.

The explained variable is abnormal accruals : *DA*				
coefficient	MJM with ROA	GRNN Model	DCGAN Model	DBN Model
intercept	0.0037***	0.0037**	0.0035**	0.0079***
*Tests*1	0.0092**	0.0093**	0.0010	0.0162***
*Tests*2	0.0390**	0.0400**	0.0400**	0.0470***
No − Tests	0.0016	0.0014	0.0019	0.0041
Loss	0.0520***	0.0525***	0.0480***	0.0580***
Time	0.0054	0.0039	0.0015	0.0066
Adjusted.R^2	0.0330	0.0260	0.0270	0.0270

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Data availability statement

Data associated with this study has been deposited at “China Research Data Service Platform” under the accession number [industry code C13–C43].

Declaration of interest’s statement

The authors declare no competing interests.

References

[1] Katherine Schipper, Commentary on earnings management, Account. Horiz. 3 (4) (1989) 91.
[2] R. Scott William, Discussion of‘Two models of auditor-client interaction, Tests with United Kingdom Data 14 (2) (1997) 51–53.
[3] P. Healy, J. Wahlen, A review of the earnings management literature and its implications for standard setting, Account. Horiz. 13 (1999) 365–383.
[4] P.M. Healy, The effect of bonus schemes on accounting decisions, J. Account. Econ. 7 (1985) 85–107.
[5] L. Deangelo, Accounting numbers as market valuation substitutes: a study of management buyouts of public stockholders, Account. Rev. 61 (1986) 400–420.
[6] J. Jones, Earnings management during import relief investigations, J. Account. Res. 29 (1991) 193–228.
[7] P. Dechow, R. Sloan, Executive incentives and the horizon problem: an empirical investigation’, J. Account. Econ. 14 (1991) 51–99.
[8] P. Dechow, R. Sloan, A. Sweeny, Detecting earnings management, Account. Rev. 70 (1995) 193–225.
[9] S. Kothari, A. Leone, C. Wasley, Performance matched discretionary accrual measures, J. Account. Econ. 39 (2005) 163–197.
[10] M.L. Defond, J. Jiambalvo, Debt covenant violation and manipulation of accruals, J. Account. Econ. 17 (1994) 145–176.
[11] D.C. Jeter, L. Shivakumar, Cross-sectional estimation of abnormal accruals using quarterly and annual data. Effectiveness in detecting event-specific earnings management, Account. Bus. Rev. 29 (1999) 299–319.
[12] N. Dopuch, C. Seethamraju, W.H. Xu, The pricing of accruals for profit and loss firms, Rev. Quant. Finance Account. 34 (4) (2010) 505–516.
[13] G. Nam, J.W. Park, A new approach to evaluating earnings management models, Int. J.Managerial and Financial Accounting 8 (3/4) (2016) 247–269.
[14] S. Young, Systematic measurement error in the estimation of discretionary accruals: an evaluation of alternative modelling procedures, J. Bus. Finance Account. 26 (7–8) (1999) 833–862.
[15] J. Thomas, X.J. Zhang, Identifying unexpected accruals: a comparison of current approaches, J. Account. Publ. Pol. 19 (2000) 347–376.
[16] E. Bartov, F. Gul, J. Tsui, Discretionary-accruals models and audit qualifications, J. Account. Econ. 30 (2001) 421–452.
[17] P. Dechow, A. Hutton, J. Kim, R. Sloan, Detecting earnings management: a new approach, J. Account. Res. 50 (2012) 275–334.
[18] H. Höglund, Uniform accrual generating process grouping with self-organizing maps, Expert Syst. Appl. 42 (2015) 554–561.
[19] K.B. Detienne, D.H. Detienne, S.A. Joshi, Neural networks as statistical tools for business researchers, Organ. Res. Methods 6 (2) (2003) 236–265.
[20] H.A. Abdou, A. Kuzmic, J. Pointon, R.J. Lister, Determinants of capital structure in the UK retail industry: a comparison of multiple regression and generalized regression neural network, Intell. Syst. Account. Finance Manag. 19 (2012) 151–169.
[21] H. Höglund, Detecting earnings management with neural networks, Expert Syst. Appl. 39 (10) (2012) 9564–9570.
[22] A. Vellido, P.J.G. Lisboa, J. Vaughan, Neural networks in business: a survey of applications (1992–1998), Expert Syst. Appl. 17 (1) (1999) 51–70.
[23] M. Paliwal, U.A. Kumar, A study of academic performance of business school graduates using neural network and statistical techniques, Expert Syst. Appl. 36 (4) (2009) 7865–7872.
[24] C.F. Tsai, Y.J. Chiou, Earnings management prediction: a pilot study of combining neural networks and decision trees, Expert Syst. Appl. 36 (3) (2009) 7183–7191.
[25] P.M. Dechow, S.P. Kothari, R.L. Watts, The relation between earnings and cash flows, J. Account. Econ. 25 (2) (1998) 133–168.
[26] R. Ball, L. Shivakumar, The role of accruals in asymmetrically timely gain and loss recognition, J. Account. Res. 44 (2) (2006) 207–242.
[27] N.S. Soderstrom, K.J. Sun, IFRS adoption and accounting quality: a review, Eur. Account. Rev. 16 (4) (2007) 675–702.
[28] Q. Yu, B. Du, Q. Sun, Earnings management at the rights issues thresholds: evidence from China, J. Bank. Finance (30) (2006) 3453–3468.
[29] Y. Wang, S.K. Chen, B. Lin, L. Wu, The frequency and magnitude of earnings management in China, Appl. Econ. 40 (13) (2008) 3213–3225.
[30] G.E. Hinton, Osindero Simon, Y.W. Teh, A fast learning algorithm for deep belief nets, Neural Comput. 18 (2006) 1527–1554.
[31] Alec Radford, Metz Luke, Soumith Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks, in: a conference paper at ICLR, 2016.
[32] W. Guay, S. Kothari, R. Watts, A market-based evaluation of discretionary accrual models, J. Account. Res. 34 (1996) 83–105.
[33] M.L. DeFond, T.J. Wong, S.H. Li, The impact of improved auditor independence on audit market concentration in China, J. Account. Econ. 28 (3) (2000) 269–305.
[34] M.C. Jensen, W. Mecking, Theory of firm: managerial behavior, agency cost, and capital structure, J. Financ. Econ. 3 (4) (1976) 305–360.
[35] L.J. Xia, Application of earnings management measuring models in the Chinese stock market, China Accounting and Finance Review 5 (2) (2003) 94–122.

[36] J. Li, Z.Y. Luo, A quasi-natural experiment: product market competition and stock price crash risk, Global Econ. Rev. 51 (1) (2022) 18–42.
[37] S.K. Chen, B. Lin, Y. Wang, L. Wu, The frequency and magnitude of earnings management: time-series and multi-threshold comparisons, Int. Rev. Econ. Finance 19 (4) (2010) 671–685.
[38] J. Aharony, C.J. Lee, T.J. Wong, Financial packaging of IPO firms in China, J. Account. Res. 38 (2000) 103–126 (Spring).