Dynamic Evaluation and System Coordination Study of Asset Valuation Based on Deep Learning

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With the rapid development of artificial intelligence, the information construction of the database plays a very important role in various industries, such as the field of asset appraisal. Therefore, we can use deep learning technology to carry out a dynamic evaluation of asset appraisal, simultaneously adjust, and improve the coordination degree for such system. In this paper, according to asset appraisal theory, we conduct a comprehensive scientific study on asset appraisal about the information construction of the database and the evaluation system, which is conducive to promote the self-improvement and development of the asset appraisal industry in terms of internal control construction. Experimental results show that our method using DL (deep learning) can well accomplish the dynamic evaluation of asset appraisal with competitive performance.

1. Introduction

It is clearly pointed out in the report of the 19th National Congress that accelerating the development of the modern service industry is the right thing to do to improve the market economy system of socialism with Chinese characteristics and should follow the international advanced standards to continuously improve its service level. Under the tide of the construction of the socialist market economy system, asset appraisal institutions, as important intermediary service institutions, have become an indispensable and important part of it. They should give full play to their fundamental role in value mining, value assessment, value anchoring, and value guarding to enhance the new dynamics of serving the economy and promote the construction of the socialist modernized economic system. The 5th National Members’ Congress of the CMA in 2016 proposed that asset appraisal is an important professional service support in the market economy, and there is an urgent need to promote the standardization of the development of the appraisal industry. In the new era, the appraisal industry should focus on serving market economy functions, leading the value orientation of the appraisal industry, and promoting the transformation and upgrading of the appraisal industry, thereby contributing to the construction of the modernization of the governance system and governance capacity.

As an independently operated and risk-bearing enterprise entity, asset appraisal organization is not only closely related to the external environment such as national policies and macro economy, corporate operations, the safety of corporate assets, and the reliability of financial information, so as to promote the implementation of corporate development strategies and further enhance the operational efficiency of the enterprise.

In April 2010, the Ministry of Finance, together with four major ministries and commissions, jointly issued the Supporting Guidelines on Enterprise framework, thus marking the government’s systematic regulation of the construction of internal control systems at the official level. In particular, the introduction of the Asset Appraisal Law and the Measures for Financial Supervision and Administration of the Asset Appraisal Industry elevated the importance of asset appraisal standards in the practice process and placed more
emphasize on the construction of the regulatory system of the asset appraisal industry, thus contributing to the reduction of internal risks of asset appraisal organizations. In 2017, the COSO committee revised and completed the latest version of the Enterprise RM Framework, strengthening the role and enterprise performance, embedding the kernel of prudential RM into strategy and performance management, laying the foundation for the true integration of prudential risk management (RM) into organizational governance, and enabling the level of enterprise RM to rise to a new level. Under the current complex and changing internal and external environment, the internal control system of asset appraisal organizations is also facing new changes and developments in the face of the trend requirements of the new framework and new standards.

Although asset appraisal organizations are playing an increasingly important role in the market, their internal controls are currently characterized by a lack of governance structure foundation, a weak awareness of practice risks, and a lack of quality control system, which, coupled with the current unevenness of asset appraisal in China, makes it difficult to determine an appropriate method to evaluate their internal controls. At the same time, it is difficult to obtain asset appraisal information. On the one hand, the information disclosure system of some asset appraisal institutions is not sound enough, and on the other hand, the operation of internal control of asset appraisal institutions lacks an effective supervision mechanism for supervision and management. These factors lead to the lack of necessary evaluation systems and institutional constraints, and this will become a major restriction on the transformation and upgrading of the asset appraisal industry. Therefore, how to systematically sort out the influencing factors and existing problems affecting the quality of internal control of asset appraisal institutions and build a clear and reasonable evaluation system of internal control quality.

2. Related Work

The research on asset valuation theory started late in China's academic circles, and the initial research on asset valuation was mainly focused on the financial and insurance industries, and then gradually expanded to other fields, such as strategic management, credit management, and financial management [1]. It was not until the 1990s that the combination of internal control and enterprise asset valuation gradually entered the academic circles, and the idea of comprehensive asset valuation was formed through development and improvement. In terms of the main contents of asset appraisal, work [2] stands on the perspective of system view that asset appraisal should include the basic components such as target principles, management procedures, and management countermeasures. From the perspective of contract economics, Zhao and Zheng [3] considered the uncertainty of the complex external environment, the imperfection of the contract entered into by the enterprise, and the limitation of the manager's knowledge as important factors affecting the asset valuation of the enterprise. 2006 Guidelines on Comprehensive Asset Valuation of Central Enterprises clearly classifies enterprise risk into pure risk and opportunity risk and points out that enterprise risk refers to the impact of future uncertainties on the achievement of business objectives. Elmaghrraby and Keskinocak [4] used insurance planning to achieve risk sharing from the perspective of risk loss compensation to improve asset valuation. On the other hand, Petruzzii and Dada [5] proposed a more operational management approach from a technical perspective in terms of processes such as developing asset valuation plans, identifying risk factors, and assessing enterprise risks. Buzacott and Zhang [6] measured enterprise risk from the perspective of overall enterprise portfolio risk, first analyzing the potential risk of each business unit, and then matching the residual enterprise risk with the enterprise risk appetite to ensure that the enterprise achieves its strategic business objectives from a holistic perspective.

Second is the elaboration of the enterprise prudent risk integration framework [7, 8], which comprehensively evaluates asset valuation in terms of target selection, risk assessment, risk response, and other elements, and puts forward relevant policy recommendations for the enterprise risk integration framework. Third, it argues for the key impacts of enterprise risk value management. Lewis [9] discussed modern enterprise risk value management from a management accounting perspective, and proposes proactive response and management of various risks and adjustment of the risk-return profile by integrating the value drivers of the enterprise. Fourth, there are many practical measures for enterprise risk assessment and internal control, such as [10] using various enterprise strategic analysis methods, combining with the modern risk oriented audit model, to identify and assess the operational risk and major misstatement risk of enterprises, so as to provide more applicable reference examples for enterprises to carry out asset assessment.

However, the construction of internal control evaluation indexes is still at a preliminary stage, and no unified quantitative evaluation standard has been formed [11, 12]. Broadly speaking, internal control quality evaluation mainly has the following methods of selection of evaluation criteria [13]. The identification criteria of internal control deficiencies have been determined in a qualitative or quantitative manner, thus taking internal control deficiencies as an important measure of internal control quality evaluation [14].

Another approach is used to measure asset valuation by constructing an internal control quality evaluation system, which can be broadly divided into two categories. The method of the first category is applied to obtain realistic data in various aspects in the form of questionnaires in a specific enterprise. For example, An et al. [15] took 136 real estate companies in Shanghai as a sample and designed questionnaires from various aspects [16]. The advantage of this approach is that it can directly understand the reality of the internal control system of enterprises, and it can reduce the time and cost spent on collecting information to a
the visual layer and the rest of the hidden layers in the DBN weight of the network. WY he joint probability distribution of traditional method is used to call back and optimize the DBN model belongs to the rational selection of the initial model is constructed. WY he unsupervised pretraining of the global learning methods, and finally, the complete DBN model.

3. Methods

A deep belief network model (DBN) is built, and the DBN model is constructed by supervised callback using traditional global learning methods, and finally, the complete DBN model is constructed. The unsupervised pretraining of the DBN model belongs to the rational selection of the initial values of the DBN model for the network, and then, the traditional method is used to call back and optimize the weights of the network. The joint probability distribution of the visual layer and the rest of the hidden layers in the DBN model is

\[ p(v, h^1, h^2, \ldots, h^s) = p(v|h^1)p(h^1|h^2) \ldots, \]

\[ p(h^{s-1}|h^{s-2})p(h^{s-2}|h^{s-3}) \ldots p(h|v^0) \]

When \( s = 2 \), it means that there are two Bernoulli-Bernoulli DBM stacked greedy layer-by-layer training process, and similarly, the training process of DBN model is obtained by the formula as

\[ p(h|v^0) \rightarrow h^0 \Rightarrow p(v|h^0) \rightarrow v^1, \]

\[ \Rightarrow p(h|v^1) \rightarrow h^1 \Rightarrow p(v|h^1) \rightarrow v^2, \]

\[ \ldots \]

\[ p(h|v^n) \rightarrow h^n \Rightarrow p(v|h^n) \rightarrow v^{n+1}, \]

\[ p(v, h^1, h^2; \theta) = p(h^1; v^1) p(h^2; W^2), \]

\[ p(h^1; W^1) = \prod_i p(v_i|h^1; W^1), \]

\[ p(v_i = 1|h^1; W^1) = f \left[ \sum_j W^1_{ij} h^1_j \right], \]

\[ p(h^1, h^2; W^2) = \frac{1}{Z(W^2)} \exp(h^1W^2h^2). \]

The initial state of the visual layer is \( v^0 \); the state of the visual layer reconstructed by the\( n \)th sampling is \( v^n \), that is, the state of the visual layer reconstructed by \( h^{n-1} \); the state of the hidden layer composed of \( v^n \) samples is \( h^s \); the random variable is \( Z \); the Sigmoid function is \( f \); the number of iterations is \( T \); the bias of each layer is set to 0, and the parameters of the DBN model can be simplified at this time.

The weights \( W^2 \) between the hidden layers are initialized to \( W^1 \), and the joint probability distribution \( p(v, h^1; \theta) \) of the deep learning network model is proved as joint probability distribution \( p(h^1, h^2; W^1) \) of the RBM using Equation (5), as follows:

\[ p(v, h^1; \theta) = \sum_{h^2} p(v, h^1, h^2; \theta) \times \sum_{h^1} p(h^1, h^2; W^2) \]

\[ = \prod_i \frac{\exp(v_i \sum_j W^1_{ij} h^1_j)}{1 + \exp(\sum_j W^1_{ij} h^1_j)} \]

\[ \times \frac{1}{Z(W^2)} \prod_i \left\{ 1 + \exp(\sum_j W^1_{ij} h^1_j) \right\}. \]

Equation (5) can be simplified to the following equation according to \( W^1_{ij} = W^2_{ij}, Z(W^1) = Z(W^2) \) two properties:

\[ p(v, h^1; \theta) = \frac{1}{Z(W^1)} \prod_i \exp(v_i \sum_j W^1_{ij} h^1_j) \]

\[ = \frac{1}{Z(W^1)} \exp(\sum_{ij} W^1_{ij} h^1_j), \]

\[ = p(v, h^1; W^1). \]

According to equation (6), the DBN model \( p(h^1; W^1) \) is \( p(v, h^1; W^1) \) of the RBM as well, therefore, the greedy layer-by-layer pretraining steps for the existence of \( s \) layer hidden depth belief network model, and the distribution matrix is

\[ l_0(x^i) = \begin{bmatrix} p(y' = 1|x^i; \sigma) \\ p(y' = 2|x^i; \sigma) \\ \vdots \\ p(y' = M|x^i; \sigma) \end{bmatrix} = \frac{1}{\sum_{j=1}^{M} e^{\sigma^T_{y,j} x^i}} e^{\sigma^T_{y,j} x^i}, \]

\[ \sigma = \left[ \begin{array}{c} \sigma_1^T \\ \vdots \\ \sigma_M^T \end{array} \right] \]

The cost function of Softmax regression is expressed as follows:

\[ f(\sigma) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{M} 1\{y^i = j\} \log \left( \frac{e^{\sigma_{y,j}^T x^i}}{\sum_{d=1}^{M} e^{\sigma_{d}^T x^i}} \right) = \frac{T}{2} \sum_{i=1}^{N} \sum_{j=0}^{M} \sigma_{ij}. \]

By minimizing the cost function through the SGD method, the expression of the gradient function is obtained as follows:
\[ \nabla_{\sigma} J(\sigma) = -\frac{1}{n} \sum_{i=1}^{n} \left[ x'(1|y' = j) - p(y' = j|x'; \sigma) \right] + \tau \sigma, \quad (9) \]

The model parameters are updated as follows:
\[ \sigma'_j = \sigma_j - \varepsilon \nabla_{\sigma} J(\sigma), \quad j = 1, \ldots, M, \quad (10) \]

where the learning rate is \( \varepsilon \).

In constructing 17 reliability indicators \( \{x_1, x_2, \ldots, x_{17}\} \), which may have redundancy, using 17 reliability indicators as the input of the machine learning model for reliability decisions may affect the accuracy of the machine learning model. Therefore, in this paper, the original reliability features are downsampled, and the downsampled reliability features are input into the neural network model and trained to obtain a nonlinear mapping relationship between reliability indicators and reliability. Stacked autoencoder (SAE) is a cascade of several symmetric 3-layer neural networks to build a deeper neural network and extract more effective features by stacking, as shown in Figure 1.

The full-volume reliability index obtained by hierarchical modeling is used as the features of SAE, that is, the input vector of SAE model \( \bar{x} = \{x_1, x_2, \ldots, x_n\} \), and the output vector \( \bar{y} = \{y_1, y_2, \ldots, y_m\} \) is made to reconstruct the input vector \( \bar{x} \) as much as possible by seeking the optimal parameter \((w, b)\), and the reconstructed vector \( \bar{y} \) is the reliability feature of the power communication network after dimensionality reduction extracted by SAE [21–25].

To make the reliability features of SAE output with,

\[ \frac{1}{m} \sum_{i=1}^{m} \frac{1}{2} \|y - \bar{x}\|^2. \quad (11) \]

Weight decay constraint is as follows:
\[ \frac{\delta}{2} \sum_{l=1}^{n-1} \sum_{j=1}^{s_l} \sum_{i=1}^{s_l} (W^{(l)}_{ji})^2. \quad (12) \]

Sparsity constraint is as follows:
\[ \beta \sum_{j=1}^{s_2} KL(\rho|\bar{p}_j). \quad (13) \]

where \( m \) denotes the number of samples; \( n_l \) denotes \( l \)-th layers of the SAE; \( s_l \) denotes #neurons in layer \( l \) of the SAE; \( W^{(l)}_{ji} \) denotes the connection weights of the neurons in layer \( l \) to the neurons in the previous layer; \( KL \) denotes the Kullback-Leibler scatter; \( \rho \) denotes the desired average activation, which is usually taken as a constant close to 0; \( s_2 \) denotes #hidden layer neurons; \( \bar{p}_j \) denotes the average activation of the \( j \) th hidden layer neuron over \( m \) samples; \( \delta, \beta \) are hyperparameters that denote the weights of the weight decay constraint and the sparsity constraint, respectively.

The lower layer autocoder is completed, the training of the higher layer autocoder is continued until all autocoders are trained, and the reduced-dimensional reliability features are finally output. Using the reduced-dimensional reliability features (reconstruction vectors) as the input of the neural network, the nonlinear mapping relationship between reliability index and reliability can be further trained.
4. Experiments

First, the research collected the required questionnaire information and then combined it with deep learning methods for model evaluation. The results are shown in Table 1. After excluding invalid questionnaires, the overall validity of the questionnaire increased to 93.78%. Furthermore, the overall validity of the questionnaire was tested, and it was found that the common factor variance extracted in the factor analysis results was greater than 50%, which further proved the good validity of the questionnaire [26–28].

Questions 1–30 in the questionnaire are an important part of the survey to study the factors affecting the quality of internal control of asset valuation and the problems that exist. This shows that the overall reliability of the research questionnaire has basically reached a reliable level, see Table 2.

Among the 488 valid questionnaires, 73.60% were with a bachelor degree or above, and 44.22% were with a post-graduate degree or above. The proportion of respondents who are above 35 years old reaches 48.62%, which indicates that most of the respondents have certain experience and related experience, which enhances the credibility of the questionnaire to a certain extent. The cross-sectional distribution of the respondents’ age and education is shown in Table 3, which shows that most of the respondents are teachers of asset appraisal and undergraduate and graduate students of asset appraisal in universities, and the composition of the respondents is appropriate, which effectively reflects the professionalism and academic nature of the survey results.

The correlation between the respondents’ educational level and their current job and asset valuation work is shown in Table 4.

Figure 2 shows the distribution of respondents’ knowledge about asset valuation institutions and institutional responsibilities.
In order to train the proposed deep learning model, the 2,000 run samples were divided into 4 equal subsets, and 4 identical deep learning models were instantiated. The mean-square error performance of the proposed deep learning model on the training and test sets is shown in Figures 3 and 4. The deep learning model can converge quickly and effectively on both the training and test sets, indicating that the model has a certain generalization ability.

The prediction errors of the deep learning models on different real reliability label data are counted in the form of box line plots, as shown in Figure 5. The horizontal coordinates represent the real label values for reliability levels 1–5, and the vertical coordinates represent the prediction values of the cascaded deep learning model. Deep learning has a small prediction error on data with reliability labels of 4 or 5, while it has a large prediction error on data with reliability labels of 1–3. Because the vast majority of the data collected are labeled 4 or 5 data, and a small percentage are low-reliability data labeled 1–3, the deep learning model is not sufficiently trained on labeled 1–3 data.

5. Conclusion

This paper studies the factors and indicators, which affect the asset appraisal, and further constructs a dynamic evaluation system of asset appraisal. The practical significance of this paper is reflected in the following aspects: first, this study systematically researches the influencing factors and problems of asset appraisal in China, and the information collected and summarized by the research has a certain reference value for the enhancement of the dynamic system of asset appraisal. Second, the asset appraisal dynamic evaluation system designed and constructed in this study is both scientific and generalizable. Such a system can be applied to different asset appraisal institutions in a more flexible manner, which can effectively improve the quality of asset appraisal.

Data Availability

The dataset used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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