Growth Enterprise Value Assessment Based on RF-BP Neural Network

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Abstract. Enterprise value assessment is an important prerequisite for company activities including listings, mergers, and acquisitions. In order to overcome the limitations of the methods including income method, market law, and to improve the accuracy of enterprise value assessment, this research has used the historical data of 164 growth/developing companies listed on the Growth Enterprise Market (GEM) to conduct neural network training, so as to explore the accuracy and applicability of the evaluation methods of enterprise value based on deep learning. The most important five types of indicators from many indicators were firstly selected with the random forest (RF) algorithm, then used as neural network input neurons. Meanwhile, in order to improve the learning ability of the neural network, this study has used RMSProp algorithm to rectify the node weights and offsets, which reduces the problem that the neural network may fall into the local minimum. The results gained from the training and testing of the data show that the method has high accuracy.

1. Introduction

Enterprise value assessment is an important prerequisite for corporate listings, mergers and acquisitions and other activities. It aims to assist investors and companies in performing effective portfolio management, M&A decision making, financial decision making, and performance management by investigating and calculating the overall value of the company, the value of the shareholders' total or partial equity. The enterprise value assessment methods mainly include the income method, the market law, etc., which all have certain limitations. Within the income method, there are many hypothesis/assumption premises and forecasting components, and the subjective factors have a greater impact on the evaluation value; furthermore, the growth enterprise is often small in scale, the performance is not outstanding, and the income may be negative. In the market law, there are too many parameters, and the correction is relatively difficult; furthermore, in China, there are few growth enterprises with the same functions, similar comparable capabilities, and similar development trends, so the rationality of the market law assessment is restricted. On this basis, in order to avoid the limitations of the existing methods, some scholars use independent learning to explore the value of enterprises [1]. They use computers to learn and test the complex nonlinear relationship between various indicators and market capitalization of listed companies, and subsequently to judge the feasibility of neural network-based evaluation methods in enterprise value assessment and market value prediction [2].

Existing methods for correcting neural networks mainly start with indicators or neural networks themselves. For the correction of the indicators, mostly the variables are selected with dimensionality reduction methods including principal dimension analysis, so as to improve the learning accuracy of the neural network [3]. For the correction of the neural network itself, mostly the optimization algorithm such as PSO is used to reduce the possibility the BP neural network falling into the local minimum [4].

The premise of using principal component analysis is that KMO is at least greater than 0.7, but the actual degree of correlation may not be strong in the selection of enterprise value indicators. Therefore, this research used the random forest algorithm to rank the selected indicators in importance [5], then used them for neural network learning and training.

2. Data selection

China's high-growth listed companies are mainly concentrated in the GEM, so this research used the GEM data to analyze the value of growth companies. There are 754 listed companies on the GEM in China. This study randomly selected 400 companies and used the CSMAR database to select indicators. Since the data of some enterprises have not been updated, in order to avoid the deviation of neural network training results due to lack of indicators, this research selected the data as of December 31, 2017 as the research object. After eliminating the missing data, there were 164 companies left. Among them, the data of 159 enterprises were used for learning, and the data of the remaining five enterprises were used to test the accuracy of the neural network.

In terms of indicator selection, this research mainly screened the data for indicators from the following six aspects. (1) The profitability of the company, which is mainly reflected by the return on equity (ROE), operating profit margin and cost and profit margin. (2) The solvency of the company, mainly reflected by the quick ratio and the asset-liability ratio; (3) The operating capacity, mainly determined by the inventory turnover rate and the total asset turnover rate; (4) The development capability, mainly reflected by the growth rate of net profit, the growth rate of total assets and the growth rate of operating income; (5) The innovation capability, mainly reflected by the amount of R&D investment and the net value of intangible assets; (6) The capital structure, mainly reflected by financial leverage and operating leverage. Therefore, a total of 14 independent variables were selected as the input layer of the neural network, and the market value of the enterprise was used as the output layer for learning and training.

3. Feature index selection based on random forest algorithm

3.1. Research design

Random forest is an integrated technique for training CART decision trees by re-selecting K new data sets with a bootstrap sample on the original data set. It classifies the new sample through the set of trained regression classification trees, and then uses the majority vote or the average of the output to count the classification results of all classifiers, which are then used as criteria for feature selection.

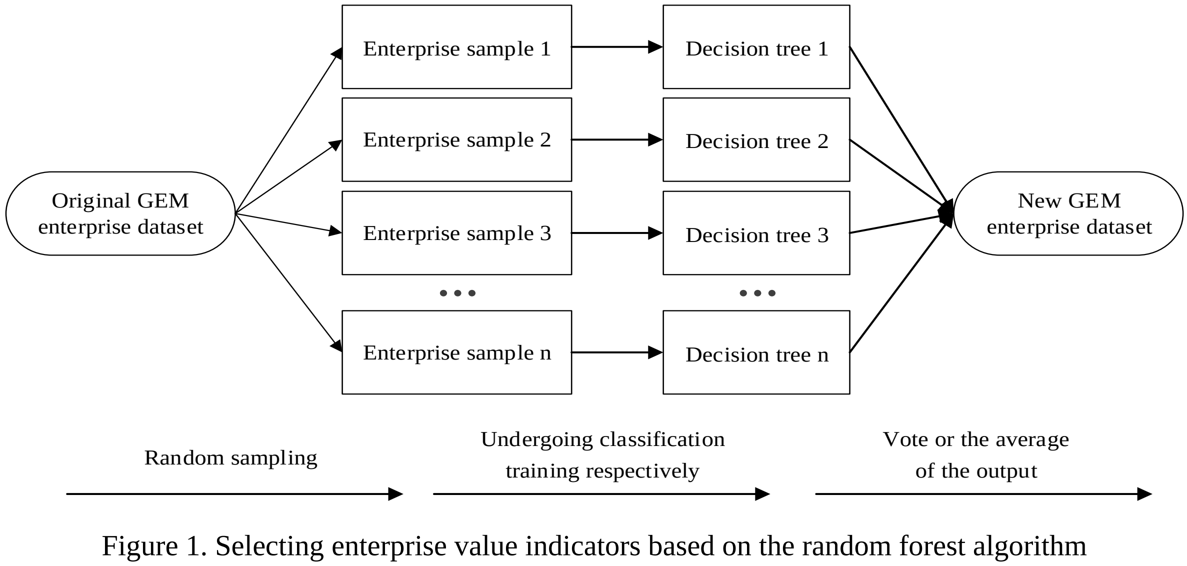

Figure 1. Selecting enterprise value indicators based on the random forest algorithm

In each round of random sampling of enterprise data, the random forest selects the same number of samples as the training sample number N, and appropriately retain some unsampled out-of-bag data (OBB) for detecting the generalization ability of the model. In the CART decision tree based classifier, the main basis for feature selection is the $Gini$ coefficient. The following is the selection criterion: when all observations in the sub-nodes of the decision tree represented by an enterprise value indicator belong to the same class, and the smaller the $Gini$ coefficient is, the smaller the uncertainty of the indicator becomes, then the indicator can be selected as a characteristic indicator for subsequent analysis. For a general decision tree, if there is a Class K enterprise sample, then the probability that the sample belongs to the Class K is P_k, and the $Gini$ coefficient it represents is:

$$Gini(\mathrm{p}) = \sum_{K=1}^{K} P_k(1-P_k) = 1-\sum_{K=1}^{K} {P_k}^2 \tag{1}$$

For the CART decision tree, since it belongs to the binary tree algorithm, its $Gini$ coefficient can be expressed as:

$$Gini(\mathrm{p}) = 2\mathrm{p}(1-\mathrm{p}) \tag{2}$$

When each of the enterprise value indicators traverses each division point, if the feature A = a is used, and D_n enterprise data samples are split into two portions according to a binary tree (i.e., a part D_n D_{n1} satisfies A = a set of samples, another portion D_{n2} does not satisfy A = a set of samples), then the $Gini$ coefficient of the sample D_n under this condition is:

$$Gini(\mathrm{D},\mathrm{A}) = \frac{|D_{n1}|}{|D_n|}Gini(D_{n1}) + \frac{|D_{n2}|}{|D_n|}Gini(D_{n2}) \tag{3}$$

Every decision tree in a random forest seeks the feature point with the smallest $Gini$ coefficient by traversing all possible cut-off points similar to the feature value a, and divides the enterprise sample data continually into two subsets until the indivisible conditions are met.

3.2. Feature indicator selection

This research used the random forest algorithm to select the value impact indicators of 14 enterprises. First, the 14 categories of indicators of 154 companies were normalized. The formula is:

$$\mathrm{x}^* = \frac{\mathrm{x}-\mathrm{x}_{\min}}{\mathrm{x}_{\max}-\mathrm{x}_{\min}} \tag{4}$$

Then the code calculation was used to obtain the top five indicators with the smallest $Gini$ coefficient, as shown in Figure 2.

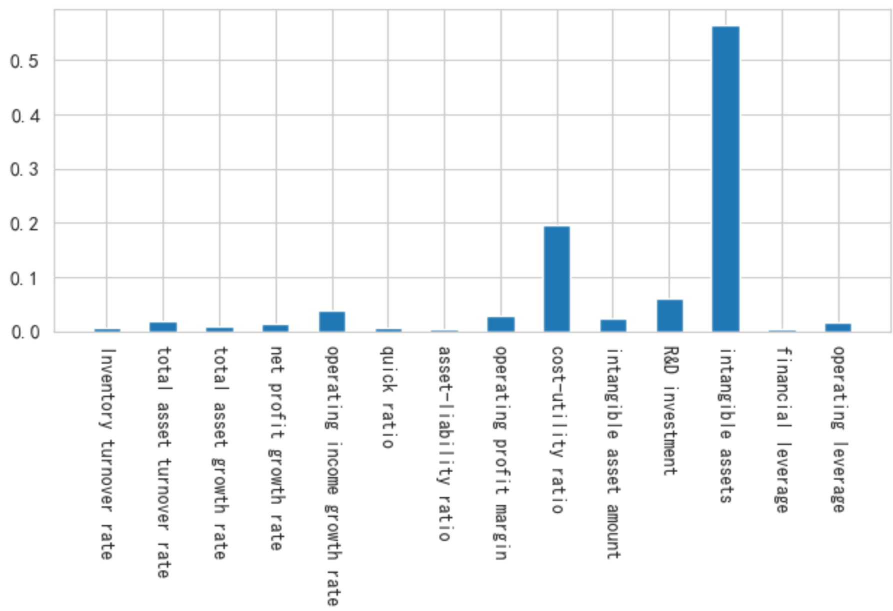

Figure 2. Importance of feature indicators

As can be seen from the above analysis, the smaller the coefficient $Gini$, the smaller the uncertainty was and the greater the importance was. It can be seen from Figure 2 that the R&D investment amount, operating profit margin, return on equity, net profit growth rate and asset-liability ratio were the top five most important indicators, and their corresponding $Gini$ coefficients were also relatively small. Therefore, this research used these five types of indicators for subsequent neural network training. Due to the large amount of data, this study only listed the five companies used for testing (the unit of R&D investment and market value: million yuan).

Table 1. Enterprise test set after indicator selection

Stock code	R&D investment	Operating profit margin	Return on equity	Net profit growth rate	Assets and liabilities	Market value
300419	33.21	0.119977	0.036442	0.581197	0.168468	3842.38
300304	47.27	0.25888	0.079078	0.188529	0.117871	6660.44
300359	47.07	-0.078424	-0.011683	-4.324277	0.267636	6759.01
300221	114.37	0.025504	0.01189	-0.874644	0.162944	8963.00
300115	629.11	0.026673	0.059917	-0.316977	0.470486	23, 674.28

4. Enterprise value assessment based on BP neural network

4.1. Enterprise value assessment structure

In the neural network-based enterprise value assessment process, the most important goal is to determine the node weights and offsets of each layer of neurons so that the output value of the network is as close as possible to the expected output. The neural network input layer nodes in this research are the following: R&D investment amount(X_1), operating profit margin (X_2), return on equity (X_3), net profit growth rate (X_4), and debt ratio (X_5). Y_{li} represents each neuron node starting from the second layer; l represents the number of layers of neurons and i represents the number of nodes. Therefore, Y_{li} can be seen as node i of layer l neurons. The weight of each neuron for a neuron in the next layer can be expressed asW_{li}^{mi}, wherein $\mathrm{m} = \mathrm{l} - 1$, that is, the weight of node i on layer m in relation to node i on layer l (two is may not be the same). In this example, there are five input layers and only one output layer is market value. Therefore, the following enterprise value assessment structure based on BP neural network was constructed.

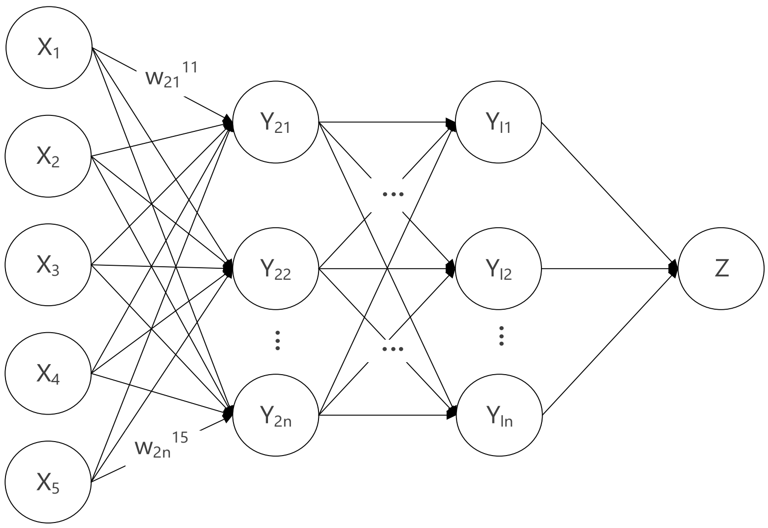

Figure 3. Enterprise value assessment structure based on BP neural network

The five enterprise indicators X_1-X_5 were input to the neural network input layer, and weight w and offset b were randomly generated for training. In the figure, the value of Y_{21} was actually obtained in this way: multiply the five enterprises input indicators by their corresponding input weights, and then add them up:

IOP Conf. Series: Earth and Environmental Science **310** (2019) 052043 doi:10.1088/1755-1315/310/5/052043

$$Y_{21} = X_1W_{21}^{11} + X_2W_{21}^{12} + X_3W_{21}^{13} + X_4W_{21}^{14} + X_5W_{21}^{15} + b_{21} \quad (5)$$

Other neurons were extracted in a similar way. In actual training, the weight and offset of each node were constantly adjusting, so in order to reduce the total error, node weight and offset b_{li} need to be constantly corrected by back propagation and gradient descent algorithms to minimize errors. At this point, the enterprise test set data could be incorporated for testing.

4.2. RMSProp optimization

As mentioned previously, to minimize the error, it is necessary to constantly correct the weight w and the offset b so as to find the most suitable value. However, the Prop weight updating algorithm in the BP neural network can only adjust the learning step length dynamically and in isolation, not suitable for mini-batch learning. But in fact, mini-batch can increase the learning speed of the model by introducing randomness. Therefore, the RMSProp optimization algorithm was used in this research to modify the gradient descent algorithm, so as to address the problem of the error function having over-large swing amplitude in the update.

The optimization of RMSProp mainly lies in calculating the differential squared weighted average of the gradient of the weight w and the offset b. It does not update in a single update step, but updates in contact with each previous gradient change.

Suppose training has gone through t iterations, RMSProp w is optimized as follows:

$$W_c = W - \alpha \frac{dw}{\in + \sqrt{S_{dw}}} \quad (6)$$

In the formula, dw is the gradient momentum of the weight w, S_{dw} is the cumulative gradient momentum of the t-1 iteration, α is an adjustment value, ∈ is a small value for model smoothing. And the optimization function for b is to replace W and W_c in the above formula with b and b_c.

4.3. Enterprise parameter training based on BP neural network

When conducting neural network learning, one needs first to determine the number of hidden layers. Because the nonlinear relationship between the various indicators of enterprise value and market value was strong, and they underwent repeated adjustments, this research finally chose three layers of hidden layers. The next was choosing hidden layer nodes. Since there is no good solution to the determination of the number of hidden layer nodes in the theoretical circle, this research selected the number of hidden layer nodes from the experimental results.

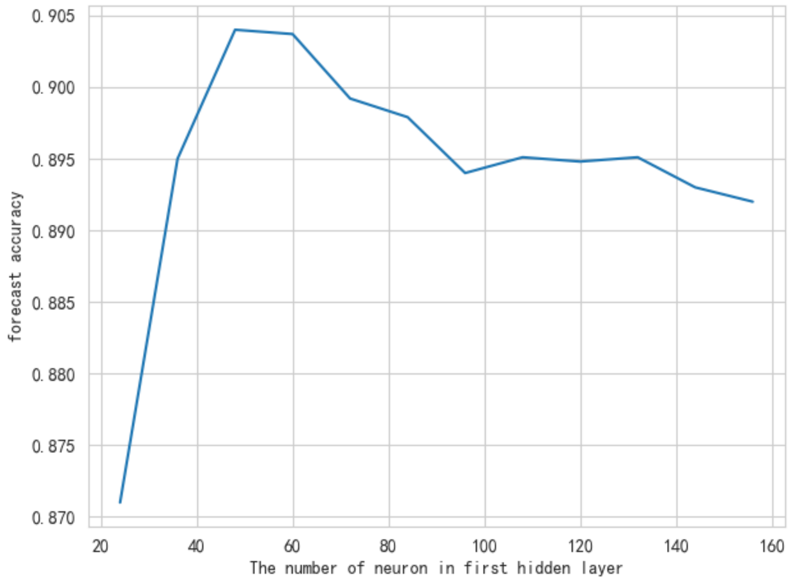

Figure 4. The effect of the number of nodes in the first layer of hidden layers on prediction accuracy

It can be seen from Figure 4 that as the number of nodes in the first layer of hidden layers increased, the prediction accuracy showed a general trend of rising first and then decreasing. When the number was nodes is 48, the prediction accuracy was maximized. Similarly, when the number of nodes in the second layer was 32; the number of nodes in the third layer was 16, the prediction accuracy was the largest. Therefore, the following numbers of hidden layer nodes were chosen respectively: 48, 32, and 16. In addition, the maximum training number of the neural network was set to 150, the batch size was set to 4, and the learning rate and momentum factor were the same as the default value in python keras framework.

The neural network was trained using the set parameters and six enterprise value indicators. The training error is shown in Figure 5.

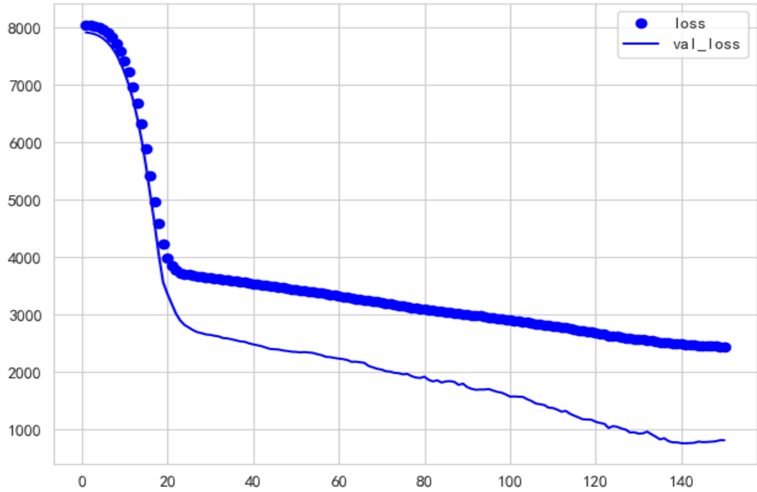

Figure 5. Training loss and verification loss

The loss in the figure was the error of the sample training, and the val_loss was the error of the sample verification. It can be seen from the above figure that as the number of training samples increased, both the training error and the verification error showed a downward trend, and the loss value of the verification sample was smaller than the training sample.

4.4. Enterprise value test based on BP neural network

After solving the nonlinear relationship between the enterprise index and the market value, verification is needed to judge the accuracy of the model learning. This research used the relevant data of the above five high-growth GEM listed companies to verify the results. The verification results are shown in Figure 6.

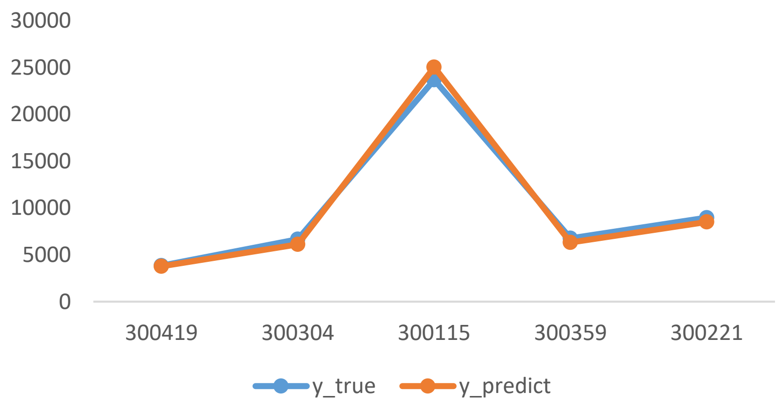

Figure 6. Forecast value and actual value of each company’s market value

As can be seen from the figure 6, the predicted value and the actual value of each enterprise were not equal. Therefore, the error level between the two needs to be considered. The market value error level is shown in Table 2 below.

Table 2. Neural network predicted and actual values (million yuan), and relative error

Stock code	Actual market value	Forecast market value
300419	3842.38	3770.32
	Relative error	-1.875%
300304	6660.44	6110.66
	Relative error	-8.254%
300115	23, 674.28	25022.48
	Relative error	5.6948%
300359	6759.71	6314.25
	Relative error	-6.59%
300221	8963.00	8505.94
	Relative error	-5.099%

It can be found from Table 2 that the error between the predicted value and the actual value does not exceed the maximum $\pm$10%, and the smallest error is only 1.875%. In terms of distribution, the error is between 5% and 6%. It thus can be seen that the accuracy of the neural network in the evaluation of the growth enterprise value is significant. It is feasible to use the neural network model for enterprise value assessment in relatively developed capital markets.

5. Conclusions

This research used RF-BP neural network to assess the value of China's high growth enterprises, based on the continuous improvement and development of China's capital market. Because the indicator data brought into the neural network for learning was generated in the past, the market conditions and corporate development trends it reflects are historical. Therefore, only when the capital market is relatively developed, the future value and trend of the enterprise predicted by historical data are effective. The random forest was used to conduct a dimensionality reduction analysis on the indicators, and the most important five types of indicators were selected. After putting them into the neural network training and testing, we found that the method had high accuracy in enterprise value assessment. Nevertheless, the method has one shortcoming: the relevant indicators of some enterprises have not been updated, and in the ever-changing Chinese stock market, it is necessary to use the latest data for verification.

References

[1] Leigh, W., Purvis, R., & Ragusa, J. M. (2002). Forecasting the NYSE composite index with technical analysis, pattern recognizer, neural networks, and genetic algorithm: a case study in romantic decision support.
[2] Christian Hake. (1996) Neural networks in the capital markets: An application to index forecasting. J. Computational Economics, 9(1):37-50.
[3] Wang, Jie,Wang, Jun. (2015) Forecasting stock market indexes using principle component analysis and stochastic time effective neural networks. J. Neurocomputing,156(May.25):68-78.
[4] H.S. Wang,Y.N. Wang,Y.C. Wang. (2013) Cost estimation of plastic injection molding parts through integration of PSO and BP neural network. J. Expert Systems with Application, ,40(2):418-428.
[5] Booth, Ash, Gerding, Enrico, Mcgroarty, Frank et al. (2015) Performance-weighted ensembles of random forests for predicting price impact. J. Quantitative finance,15(11):1823-1835.