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Enterprise Classification Based on BP Neural Network

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Abstract. In today's increasingly complex market environment, the competition among enterprises has become more and more intense, and more factors need to be considered in the formulation of strategies and behavioral decisions of enterprises. Through the sand table simulation experiment of enterprise operation and management, this paper simulates the management decision-making within the manufacturing enterprise and the competitive behavior between enterprises, and forms the experience data of the enterprise. Taking this as an example, the hierarchical classification method and BP neural network are used to classify the enterprise. , summarizes and describes the behavior characteristics of different types of enterprises through the classification results, provides a reference and strong support for the actual operation and management decision-making of enterprises, and helps enterprises to develop better in the fierce competition.

Keywords: business management, corporate strategy, hierarchical clustering, BP neural network

1. Introduction

1.1. Background Information

With the increasingly complex business environment and the increasingly fierce competition among enterprises, the formulation of corporate strategies and decision-making of behaviors have become more and more difficult. According to the decision-making behavior of competitors, the strategic decision of the enterprise can improve the comprehensive competitiveness of the enterprise in the complex business environment, which is of great significance to the development of the enterprise. With the development of science and technology, we have entered the era of big data, and business analysis based on big data plays an important role in the good development of enterprises. Business data analysis can organize, summarize, and analyze data to find out the potential laws of data, which can be used to support managers' decision-making behavior. The sand table simulation of business management can simulate the salient characteristics of the market environment through role-playing, case analysis, and diagnostic comments, and provide simulation data to provide a reference for the practical decision-making of enterprises. According to a survey by The Strategic and Competitive Intelligence Professionals, an enterprise that conducts high-level competitive intelligence activities will perform better than those that do not or less. [1]. It can be seen that in the actual market environment, the competitive intelligence information owned by the enterprise directly affects the performance of the enterprise. If an enterprise wants to develop in the industry, it must formulate its own strategy and make good decisions. In order to make a decision that is beneficial to its own development, it must not only understand the situation of the entire industry, but also learn about its competitors. Behavioral analysis to formulate strategies suitable for your own situation, so as to better be invincible in the competition.

This paper uses BP neural network to classify enterprises by using historical data of enterprises, and enriches and expands the research methods of enterprise classification. Through the sand table simulation of enterprise operation and management, the experience management decision within the enterprise and the competitive behavior between enterprises are simulated. Through the processing of the simulation data, the characteristics of different types of enterprise decision-making under commercial competition are analyzed, and the actual operation and management decision-making of enterprises can be provided. Reference and strong support.

1.2. Literature Review

Enterprise labeling classification refers to abstracting and labeling the specific behavior attributes of the enterprise, and obtaining an enterprise label classification through the processing and analysis of the decision-making behavior data of the enterprise. Through enterprise labeling and classification, enterprises can browse a full range of information about themselves and competitors at any time, and grasp their own development from a macro perspective.

Alan Cooper [2] proposed the concept of user portrait persona in 1999, which is a mapping of real users in terms of data, and a user model is extracted from user data to describe users. In terms of classification methods, Wang Qingfu [3] used Bayesian network to describe user portraits, completely constructed user portraits, and understood users' needs through user portraits, thereby improving user experience. Ma Chao [4] proposed a social network user portrait analysis model (UPTM) through statistical analysis of the completeness of user information in social platforms. The UPTM model can integrate the social information and incomplete user attribute information of users in the social network into a topic model framework, and then fine-tune the results generated by the UPTM model through the label propagation algorithm (Label Propagation), and finally generate a Semi-supervised user portrait analysis method based on topic model. Tian Juan et al. [5] extended user portraits and believed that users can also describe enterprise portraits based on data. Tian Juan and others conducted research on enterprise portraits, and on the basis of big data technology, proposed ideas and methods for building enterprise portrait models. The literature compares the advantages and disadvantages of feature extraction methods such as k-means, LDA, NB, and CNN. The literature gives a comparison of the advantages and disadvantages of KNN algorithm, SVM algorithm, and decision tree algorithm for classification and prediction. The literature believes that there are not many applications in the field of corporate portraits, and more experimental research is needed.

Yang and Zhang [6] introduced the important role of data in enterprise decision-making. Based on the background of big data, they established an enterprise rejection management system model, and proposed coping strategies for the dilemma of enterprise decision-making management. They believe that more and more enterprises begin to use enterprise management systems such as MIS, MRP, ERP, etc., which proves that the informatization level of enterprises is constantly improving. Facing the increasingly fierce market competition, more and more enterprises realize that data acquisition, analysis, screening and application play an important role in enterprise decision management.

It can be seen from the above analysis that although there are not many related research literatures on user and enterprise portraits, some scholars have begun to become interested in this field and conduct research, and have also used machine learning and neural network methods for classification and prediction. As part of the enterprise portrait, the enterprise labeling classification draws on the basic idea of the enterprise portrait, uses the behavior characteristic data of the enterprise to label and classify the enterprise, and uses the classification results to make corresponding countermeasures and decisions, which is also of great importance to the development of the enterprise effect.

2. Method

2.1. Hierarchical Clustering

Step1: Treat each sample as a category, at this time the distance between classes is the distance between objects;

Step2: Combine the two categories with the closest distance into one category, and subtract one from the total number of categories at this time;

Step3: Recalculate the distance between the new class and all old classes;

Step4: Repeat steps 2 and 3 until finally merged into one class.

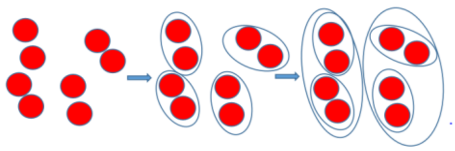

Fig. 1: Hierarchical clustering diagram.

2.2. BP Neural Network

The BP algorithm is a supervised learning algorithm. Its main idea is to input the learning samples, and use the back-propagation algorithm to repeatedly adjust and train the weights and biases of the network, so that the output vector is as close as possible to the expected vector. , when the sum of squared errors of the output layer of the network is less than the specified error, the training is completed, and the weights and biases of the network are saved.

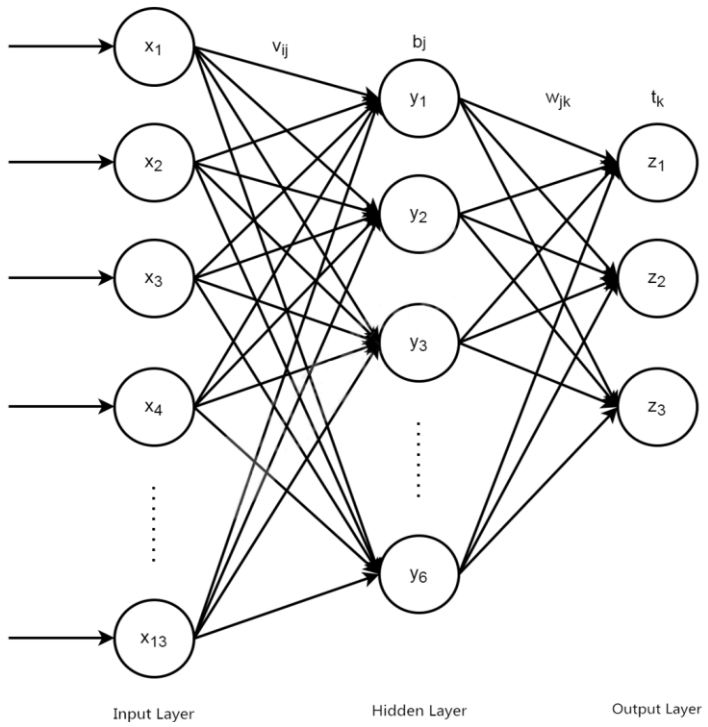

Fig. 2: BP neural network settings.

Step1 parameter definition and initialization: the input layer data is xi, the hidden layer value is yj, the output layer value is zk, the weight parameter from the input layer to the hidden layer is vij, the weight parameter from the hidden layer to the output layer is wjk, the hidden layer is biased The offset is bj, and the output layer offset is tk. Randomly assign weight parameters and offset parameters between [-1, 1].

Step2 Calculate the value of the hidden layer:

$$y_j = f(\sum_{i=1}^{13} x_i v_{ij} + b_j)$$

Among them, the activation function uses the Sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}}$$

Step3 calculates the value of the output layer:

$$z_k = f(\sum_{j=1}^{6} y_j w_{jk} + t_k)$$

Step4 calculates the error ak of the output layer:

$$e_k = z_k(1-z_k)(z_k^l - z_k)$$

where is z_k^l the desired output.

Step5 Calculate the error ei of the hidden layer during backpropagation

$$r_j = y_j(1-y_j)\sum_{k=1}^{3} w_{jk} e_k$$

Step6 Modify the weights between the output layer and the hidden layer:

$$\Delta w_{jk} = \alpha y_j e_k$$

$$\Delta w_{jk}(n+1) = \alpha y_j e_k + \gamma \Delta w_{ij}(n)$$

Where α is the learning rate and γ is a constant.

Step7 Modify the weights between the input layer and the hidden layer:

$$\Delta v_{ij} = \beta x_i r_j$$

where βis a constant controlling the learning rate.

Ste8 modified deviation:

$$\Delta b_j = \beta r_j$$

$$\Delta t_k = \alpha e_k$$

Step9 Repeat the second to eighth steps until the error of the output layer is small enough.

2.3. Evaluation Methods

$$FMI = \sqrt{\frac{a}{a+b} \cdot \frac{a}{a+c}}$$

Among them, a means that the sample pair is the same cluster in the calculated cluster division and the original model cluster division; b means that the sample pair is a cluster in the calculated cluster partition, but is not a cluster in the cluster partition of the original model ;c indicates that the sample pair is a cluster in the cluster partition of the original model, but not a cluster in the calculated cluster partition.

The value range of FMI is [0, 1], FMI represents the relationship of cluster label assignment, FMI close to 0 indicates that the label assignment between clusters is basically independent, and close to 1 indicates that the label assignment between clusters Significantly consistent, so the closer the FMI value is to 1, the better the clustering effect.

3. Case Study: Result and Discussion

3.1. Case Description

This paper uses the business management sand table to simulate real business competition. The specific settings are as follows: In order to obtain enterprise data, I will conduct several simulations. In each simulation, 6 manufacturing companies have to make decisions in various aspects. decision, will get their score and ranking. Through the reading and research of relevant literature on enterprise sand table simulation, this paper extracts and summarizes 6 dimensions of corporate investment, liabilities and equity, corporate assets, products, cash flow, and result evaluation, and designs 11 factors affecting corporate decision-making under the 6 dimensions. The index characteristics of , used for classification and forecasting, obtained the decision data of 612 different enterprises in different fiscal years and situations through simulation experiments.

Table 1: Characteristics of indicators that affect enterprise decision-making

Dimension	Indicator features
Business investment	Advertisement
	Equipment and plant
	Market development
	ISO Certification
	Product research
Liabilities and Equity	Liabilities and Equity
Corporate assets	Current assets
	Fixed assets
Product	Output
	Average unit price
Cash flow	Cash flow
Business results	Score
	Ranking

3.2. Clustering Results and Evaluation

After the hierarchical clustering algorithm, the obtained clustering results and clustering evaluation are as follows:

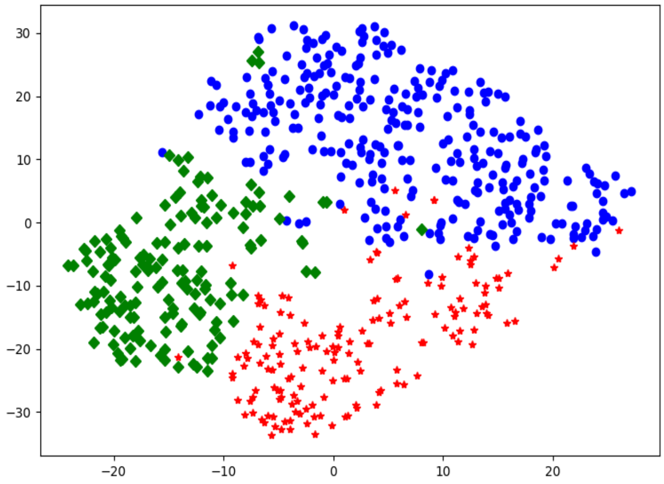

Fig. 3: Clustering results.

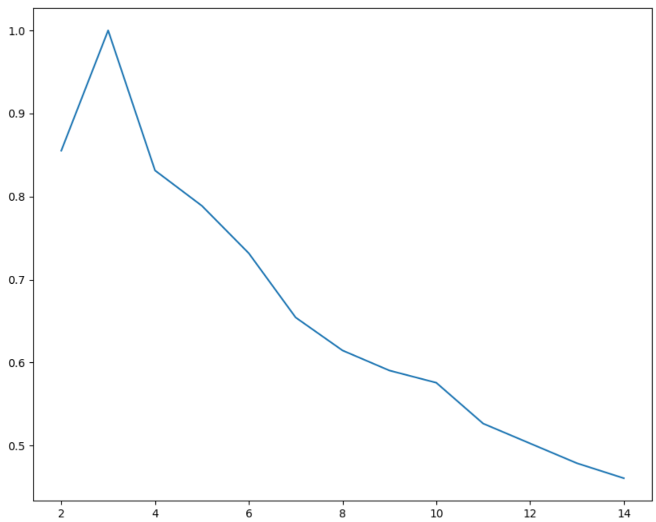

Fig. 4: Clustering result evaluation.

When the clustering category is 3, the calculated FMI value is significantly higher than the other cases. Therefore, according to the FMI value, it is considered that the clustering category of 3 is the best.

3.3. BP Neural Network Prediction Classification Results and Evaluation

In this paper, 75% of the data set is selected as the training set, and the remaining 25% is used as the test set. The random division algorithm is used to divide the training set and the test set, and the deviation standardization method is used to standardize the data. For training and testing, this paper counts the accuracy of the BP neural network under different Learning rates, Epochs and the number of hidden layer nodes, as follows:

Table 2: BP Neural network classification results

Epoch	Learning Rate	Hidden Nodes	Accuracy
500	0.1	6	0.980263158
1000	0.85	3	0.947368421
500	0.85	6	0.947368421
1000	0.1	5	0.940789474

1000	0.5	4	0.934210526
500	0.5	5	0.934210526
1000	0.5	3	0.927631579
500	0.85	5	0.927631579
1000	0.5	6	0.927631579
500	0.85	4	0.921052632
1000	0.85	5	0.921052632
500	0.1	4	0.914473684
500	0.5	6	0.914473684
1000	0.85	6	0.907894737
500	0.5	4	0.901315789
1000	0.85	4	0.901315789
500	0.1	5	0.901315789
1000	0.1	4	0.894736842
1000	0.5	5	0.894736842
500	0.5	3	0.888157895
1000	0.1	3	0.875
500	0.85	3	0.868421053
1000	0.1	6	0.868421053
500	0.1	3	0.861842105

When the Epoch is 500, the Learning Rate is 0.1, and the number of hidden layer nodes is set to 6, the prediction effect of the BP neural network is the most accurate.

4. Conclusion And Future Research Direction

4.1. Conclusion

Descriptive statistics are carried out on all indicators of different types of enterprises to analyze the characteristics of the decision-making behavior of enterprises, as follows:

Table 3: Descriptive statistics of enterprise characteristics of category 1

Category 1 —Descriptive Statistics					
	N	Min	Max	Mean	SD
Advertisement	295	2	49	9.60	5.448
Equipment	295	0	18	9.96	3.721
Market	295	0	2	.26	.475
ISO	295	0	2	.16	.440
Product research	295	0	12	.43	1.597
Liabilities	295	32	362	159.89	56.278
Current assets	295	8	252	91.47	41.721
Fixed assets	295	0	154	68.42	30.858
Output	295	5	150	16.39	9.518
Average price	295	4.67	10.18	7.4649	.88481
Cash flow	295	-17	495	145.27	87.462
Score	295	-193	205	47.64	53.403
Ranking	295	1	6	3.37	1.656

Table 4: Descriptive statistics of enterprise characteristics of category 2

Category 2 —Descriptive Statistics					
	N	Min	Max	Mean	SD
Advertisement	162	1	48	10.84	8.351
Equipment	162	1	16	5.93	2.619
Market	162	0	4	2.04	1.045
ISO	162	0	2	1.25	.827

Product research	162	0	18	6.63	4.590
Liabilities	162	65	254	126.13	30.797
Current assets	162	19	167	63.23	24.412
Fixed assets	162	19	125	63.09	18.386
Output	162	1	88	7.85	8.504
Average price	162	4.50	9.50	5.7022	.84529
Cash flow	162	-71	288	24.83	69.390
Score	162	-88	90	-4.36	30.606
Ranking	162	2	6	4.97	.987

Table 5: Descriptive statistics of enterprise characteristics of category 3

Category 3 —Descriptive Statistics					
	N	Min	Max	Mean	SD
Advertisement	155	1	29	8.47	5.457
Equipment	155	2	13	5.08	1.990
Market	155	0	4	1.82	1.125
ISO	155	0	4	1.18	.856
Product research	155	0	14	3.89	3.182
Liabilities	155	42	230	120.99	27.185
Current assets	155	16	139	59.95	21.177
Fixed assets	155	16	112	61.50	14.748
Output	155	1	90	8.56	10.994
Average price	155	4.50	8.30	5.6483	.80681
Cash flow	155	-56	254	22.66	51.829
Score	155	-40	133	26.17	26.857
Ranking	155	1	5	2.05	.935

According to the characteristics and differences of the above three types of enterprises, the above three types of enterprises are named. The first type of enterprise: the lowest investment, the most assets, the most production, the highest price, the most cash flow, and the highest score. This type of enterprise uses funds to purchase assets and expand production to create a larger cash flow, which meets the scoring criteria of the simulation. Therefore, with the highest score, such enterprises are named as conservative investment and production radical enterprises; the second type of enterprises: the highest investment, the least production, the lowest score and the lowest ranking; such enterprises pay more attention to the investment in advertising, marketing, production and research, etc. However, the importance of production is relatively neglected, no large cash flow and benefits are created, and the invested funds have not exerted the corresponding effect. Therefore, such enterprises have the lowest scores and rankings, and such enterprises are named as aggressive in investment and conservative in production. Enterprise; the third type of enterprise: the lowest asset, the lowest price, the lowest cash flow, and the highest ranking; this type of enterprise has purchased less assets and has the lowest product price. Although the cash flow is the least, this type of enterprise has created greater benefits. Although the score is not the highest according to the simulation rules, but the funds are sufficient and the profits are high, so such enterprises are ranked higher, and such enterprises are named as stable capital, product profit-oriented enterprises.

From the average ranking of the three types of enterprises, it can be seen that enterprises with conservative investment and aggressive production and enterprises with conservative capital and profit-oriented enterprises operate better, while enterprises with aggressive investment and conservative production operate poorly. Enterprises with conservative investment and aggressive production are significantly more aggressive in production and asset acquisition than the other two types of enterprises. These types of enterprises attach importance to assets and products and can generate larger cash flow. The investment in advertising, investment in equipment and workshops, liabilities, and cash flow of capital-conservative, profit-oriented enterprises are significantly lower than those of the other two types of enterprises. Such enterprises use funds rationally, control liabilities and assets to a more appropriate level, and attach importance to market share. And product research and development, reasonably produce products and set product prices according to demand. In actual situations, enterprises should pay attention to the situation of competitors when making decisions. When competitors increase investment and production, the enterprise can reduce the investment in advertising and equipment, control liabilities and assets within an appropriate range, and make reasonable production, price reduction and other measures to deal with, in order to enhance their competitiveness. When competitors are more conservative, the company can pay more attention to expanding production and seizing the market to ensure its own market share, so as to obtain good returns.

4.2. Future Research Direction

This paper conducts a sand table simulation experiment of enterprise management, simulates the competition of enterprise operation in a complex business environment, obtains enterprise operation data, then uses the hierarchical classification method to cluster the enterprises, and finally uses the BP neural network to predict the type of enterprises. 98.03%. In the last part, according to the classification results, the decision-making behavior of different types of enterprises and their performance are compared and analyzed, which provides certain directions and ideas for enterprise decision-making. Subsequent research can use the classification results, combined with the historical data of the enterprise, to predict the decision-making behavior of the enterprise, further improve the effectiveness of the enterprise's decision-making, and promote the development of the enterprise.

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6. References

[1] Zhao Wenchong, Chen Guang, & Yu Hao. (2018). Analysis of the impact of big data on corporate decision-making. Modern Management Science (9), 3.

[2] Cooper A. The Inmates Are Running the Asylum: Why High Tech Products Drive Us Crazy and How to Restore the Sanity. The Inmates Are Running the Asylum: Why High Tech Products Drive Us Crazy and How to Restore the Sanity (2nd Edition), 2004.

[3] Wang Qingfu. (2016). Research on Bayesian Networks in User Interest Model Construction. Wireless Internet Technology (12), 2.

[4] Ma Chao. (2017). An analysis method of social network user portrait based on topic model. (Doctoral dissertation, University of Science and Technology of China).

[5] Tian Juan, Zhu Dingju, & Yang Wenhan. (2018). A review of enterprise portrait research based on big data platform. Computer Science, 45(B11), 5.

[6] Yang, L. , & Zhang, J. J. . (2017). Realistic plight of enterprise decision-making management under big data background and coping strategies. 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA). IEEE.

[7] Ouyang, Y. , Guo, B. , Lu, X. , Qi, H. , Tong, G. , & Yu, Z. . (2018). Competitivebike: competitive analysis and popularity prediction of bike-sharing apps using multi-source data. IEEE Transactions on Mobile Computing, PP, 1-1.

[8] Liu Junshan, Zhang Lei, & Yin Yu. (2021). A prediction model of Chinese enterprises ofdi investment based on genetic algorithm optimization of bp neural network. Modern Computer (7), 8.

[9] Bae, J.. (2020). Price Competition, Capacity Decisions, and Information Asymmetry.

[10] Li Junzheng, Huang Hai, Huang Ruiyang, & Wang Kangli. (2017). Research on user search portrait technology based on chi-square test and svm. Electronic Design Engineering, 25(24), 5.