Research and Analysis of Data Modeling in Economic Management Based on the Background of Artificial Intelligence Technology

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Abstract: In the face of the massive amount of data constantly generated, people hope to reveal the potential patterns of things and discover knowledge with important value. However, the existence of missing data not only increases the difficulty of data mining, but also reduces the reliability of analysis results. Rational filling of missing values has become a very important part of current data analysis and mining. In this paper, we use data modeling to fill the missing values in incomplete data, and construct a model to mine the association relationship between data attributes, with the goal of improving the model's ability to approximate the association relationship between incomplete data attributes. The research in this paper completely combines big data context modeling and economic growth for application and research, and makes a new breakthrough and analysis in a new research area and a new research direction.

Keywords: Artificial intelligence; Economic management; Data modeling; Economic Growth

1 INTRODUCTION

Artificial neural network as an information processing technology, with the proposed BP algorithm, the rapid improvement of computer computing performance with the introduction of BP algorithm, the rapid improvement of computer computing performance and the rise of big data, it has received extensive attention and research in various fields [1]. Neural networks are very widely used in the work of reducing the incompleteness of data sets because of their flexible structure, outstanding nonlinear learning ability, and ability to uncover the hidden information carried in the data [2]. In order to be able to properly improve the modeling efficiency and model fitting accuracy, this paper investigates the neural network-based modeling method for incomplete data from two perspectives: network structure and training scheme [3]. In view of the simple structure and good learning ability of single-output subnets, this chapter adopts the subnet structure to build the attribute association model. In addition, to address the problem of incomplete model input caused by the presence of missing values, an iterative learning scheme is used to train the neural network, which enables all the present attribute values to participate in the model training, which not only effectively solves the problem of incomplete model input and thus improves the approximation performance of the

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model, but also increases the utilization of the information of the present attribute values in the data. In this paper, the bp neural network algorithm is studied and analyzed in the context of the change of economic model big data.

2 MULTILAYER PERCEPTRON MODEL FOR INCOMPLETE DATA

Multilayer perceptron is a classical feedforward neural network, and this section introduces the basic principles and processes of neural network-based regression modeling of incomplete data attributes, using multilayer perceptron as a representative [4].

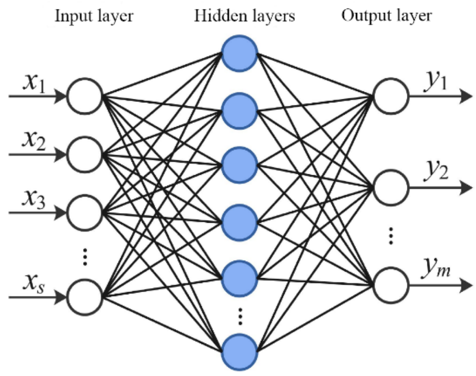


Figure 1: Single hidden layer multilayer perceptron

A perceptron is a simple linear classifier consisting of two layers of neurons, one for receiving input signals and the other for logical operations [5]. To solve the nonlinear separable problem, it is necessary to add functional layers to improve the learning capability of the model, so that a multilayer perceptron model is obtained [6]. The hidden and output layers are functional layers responsible for the accumulation, nonlinear transformation and output of the information coming from the previous layer [7].

Most methods for processing incomplete data based on multilayer perceptrons are divided into two phases: modeling and filling [8]. The missing value filling stage, on the other hand, is where the existing attribute values from incomplete samples are fed into the model after the modeling is completed and the missing attribute values are filled with the model output [9].

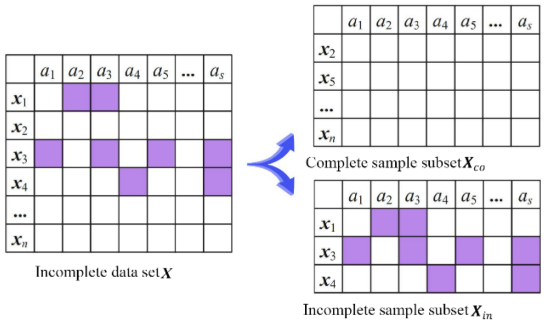


Figure 2: Data set division

As shown in Figure 2, the incomplete dataset $X = \{x_1, x_2, \dots, x_3\} \in \Re^s, x_k = [x_{k1}, x_{k2}, \dots, x_{ks}]^T$ Figure 222 represents the first dimensional attribute of the dataset. The white squares in the figure represent known attribute values at the corresponding locations, while the purple squares represent missing attribute values at the corresponding locations. Before modeling, the samples are divided in order according to the presence or absence of missing values to obtain a complete sample subset X_{co} and an incomplete sample subset X_{in} of the data set X.

The missing attribute combinations in the incomplete sample subset X_{in} are counted, and the number of models to be constructed is determined based on the number of combinations. The dataset shown in Figure 2 has $\{a_2, a_3\}, \{a_1, a_3, a_5, a_s\}, \{a_4, a_s\}$ three different combinations of missing attributes. A multilayer perceptron model with output attribute a_2, a_3 and remaining attribute $a_1, a_4, \dots, a_s$ as input attributes is created for the missing combination $\{a_2, a_3\}$, and the other two missing combinations are treated similarly.

2.1 Based on single output subnets

The problem of excessive number of models and complex modeling process is solved by the single output subnet structure. This scheme allows all incomplete samples to participate in the network training as well, and the missing data's get a dynamic adjustment after each training round, so the iterative learning based approach does not need to be divided into two phases of modeling and filling, and the filling of incomplete data is done simultaneously with the training of the model and completed simultaneously.

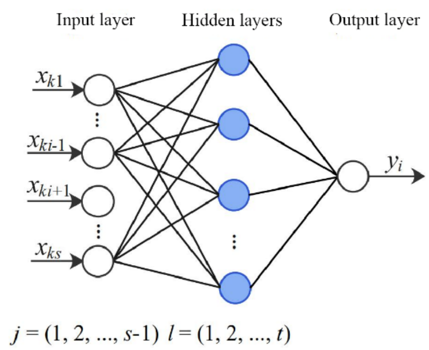


Figure 3: The i-th single output subnet of the subnet group

For an incomplete data set X with the number of samples n and the number of attributes s, the single output subnet iterative learning method requires the construction of s subnets to form a model group. The i-th single hidden layer subnet of the model group is shown in Figure 3, with s-1 input nodes in the input layer, t nodes in the hidden layer, and 1 output node in the output layer. Denote X_m as the subset of missing attribute values, and any sample in X is denoted as $x_k = [x_{k1}, x_{k2}, \dots, x_{ks}]^T, take\ x_k^` = [x_{k1}, x_{ki-1}, x_{ki+1,} \dots, x_{ks}]^T$ as the input vector of subnet i. The network parameters are randomly initialized with smaller non-zero values before the iteration and the missing value variables are initialized using the mean fill method. In each iteration, the network parameters are first updated by two processes of input signal forward propagation and error back propagation, and then the missing value variables are updated using the network output.

Suppose the output of the lth node of the hidden layer of subnet i is h_{kl} output node is y_{ki} then.

$$h_{kl} = f(\sum_{j=1}^{s-1} w_{jl}^{(1)} x_{kj}^` + b_l^{(1)} \tag{1}$$

$$y_{ki} = g(\sum_{l=1}^{n} w_{li}^{(2)} h_{kl} + b_i^{(2)} \tag{2}$$

where f(-) and g(-) are the activation functions of the hidden layer and the output layer, respectively, $w_{jl}^{(1)}$ is the connection weight between the jth node of the input layer and the lth node of the hidden layer, $w_{li}^{(2)}$ is the connection weight between the lth node of the hidden layer and the output node, $b_l^{(1)}$ is the threshold value of the lth node of the hidden layer, and $b_i^{(2)}$ is the threshold value of the output node. Denote L_i as the fitting error of subnet i.

$$L_i = \frac{1}{2}\sum_{k=1}^{n}(x_{ki} - y_{ki})^2 \tag{3}$$

Calculate the partial derivatives of L_i with respect to each network parameter separately according to the chain derivative rule:

$$\frac{\partial L_i}{\partial w_{li}^{(2)}} = \frac{\partial L_i}{\partial y_{ki}} \frac{\partial y_{ki}}{\partial w_{li}^{(2)}} \tag{4}$$

$$\frac{\partial L_i}{\partial b_i^{(2)}} = \frac{\partial L_i}{\partial y_{ki}} \frac{\partial y_{ki}}{\partial b_i^{(2)}} \tag{5}$$

$$\frac{\partial L_i}{\partial w_{jl}^{(1)}} = \frac{\partial L_i}{\partial y_{ki}} \frac{\partial y_{ki}}{\partial h_{kl}} \frac{\partial h_{kl}}{\partial h_{kl}} \tag{6}$$

$$\frac{\partial L_i}{\partial b_i^{(1)}} = \frac{\partial L_i}{\partial y_{ki}} \frac{\partial y_{ki}}{\partial h_{kl}} \frac{\partial h_{kl}}{\partial b_i^{(1)}} \tag{7}$$

If the above network parameter $w_{li}^{(2)}, b_i^{(2)}, w_{jl}^{(1)}, b_i^{(1)}$ is expressed in terms of θ, its update is given by:

$$\theta^{(r)} = \theta^{(r-1)} - \eta \frac{\partial L}{\partial \theta} + \alpha\left(\theta^{(r-1)} - \theta^{(r-2)}\right) \tag{8}$$

where η is the learning rate, a is the momentum factor, and r is the number of iterative learning. After the network parameters are updated, the missing value variables in the corresponding positions in the dataset are updated using the network output y_{ki}.

$$x_{ki} = y_{ki}, if, x_{ki} \in X_m \tag{9}$$

3 EXPERIMENTS AND ANALYSIS OF RESULTS

3.1 Comparative experiments of neural network methods

In order to verify the effectiveness of single-output subnetwork structure and iterative learning training scheme to improve the fitting effect of incomplete data attribute relationships, this experiment compares four neural network modeling and filling methods, and compares the model approximation performance and filling accuracy of the four methods using the dataset filling error MAPE as the evaluation index. Assuming that the number of attributes of the incomplete dataset is s, the four methods are implemented as follows.

(1) Modeling and filling method based on single output subnetwork (SONN): make the incomplete attributes of the data set as outputs in turn, and construct a subnetwork model group with s-1 input nodes and single output nodes, and the number of models is equal to the number of incomplete attributes.

(2) Modeling and filling method based on single output subnetwork iterative learning (SONN+IL): make the incomplete attributes of the data set as outputs in turn, and construct a subnetwork model group with input node s-1 and single output node, and the number of models is equal to the number of incomplete attributes.

(3) Self-encoder-based modeling and filling method (AE): construct a self-encoder model with both input nodes and output nodes s. The network is trained to solve the parameters of the self-encoder model based on complete samples, and incomplete samples are only input to the model to fill in the missing values after the modeling is completed. Attribute association modeling and missing value filling are performed in two stages, before and after.

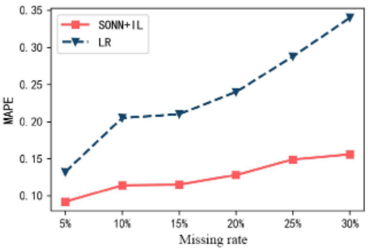
(4)Five complete data sets shown in Table 1 were used for the experiments, and for these five data sets, incomplete data were constructed by randomly removing attribute values at a given missing rate of 5%, 10%, 15%, 20%, 25%, and 30%, respectively.

Table 1: Experimental data set

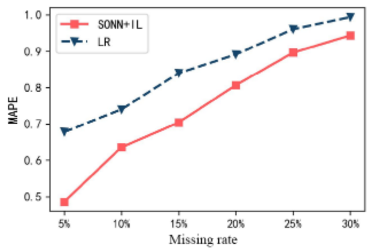
Data set name	Number of samples	Number of attributes
Iris	150	4
Blood	248	4
Seed	210	7
Glass	214	9
Wine	178	13

3.2 Experimental results

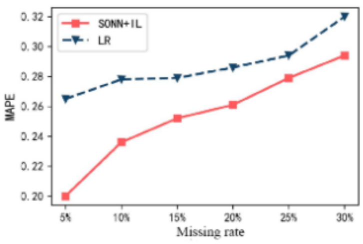
For each missing rate, five incomplete data sets were randomly generated for each complete data set, and the attribute association models were built for the incomplete data based on the subnet iteration method and the linear regression method, respectively, and the missing value filling error MAPE was calculated for the two methods, and the error was used to measure the fitting accuracy of the two models for the attribute relationships of the incomplete data. Figure 4 shows the filling results of both SONN+IL and LR methods at each deletion rate for the eight experimental data sets.



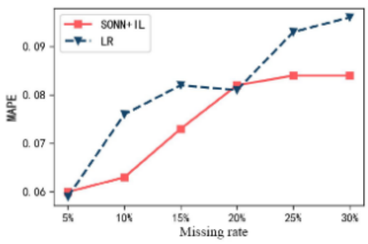
(a) Iris dataset



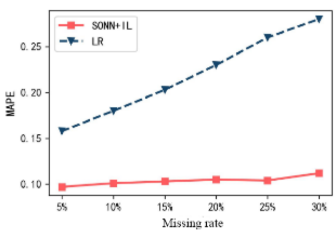
(b) Blood dataset



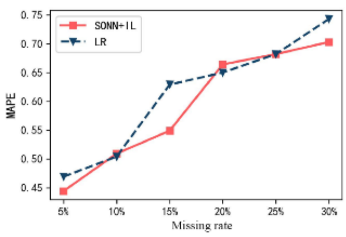
(c) Ecoli dataset



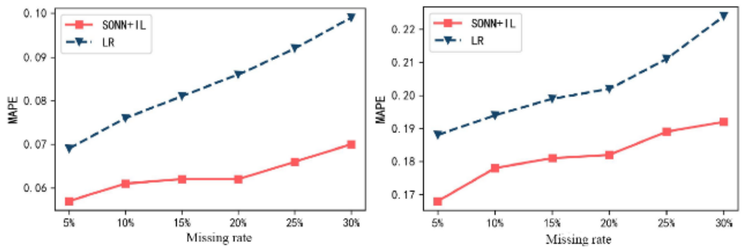
(d) Seed dataset



(e) Abalone dataset



(f) Glass dataset



(g) Stock dataset (h) Wine dataset

Figure 4: Filling results of single output subnetwork model and linear regression model

4 CONCLUSIONS

In view of the nonlinear characteristics of association relations of incomplete data attributes and the powerful nonlinear learning ability of neural networks, this paper investigates the modeling method based on neural networks and proposes a modeling and filling method based on iterative learning of single-output subnets, starting from the neural network structure and missing value processing. The single-output subnetwork structure has a more concise structure and good learning ability compared with the multi-output network structure, so this paper introduces the subnetwork structure into incomplete data modeling. To address the problem of incomplete inputs in modeling, an iterative learning scheme is used to treat the missing values as variables, so that incomplete samples also participate in model training. During the iterative learning process, the missing value variables are updated alternately with the network parameters, and the filling accuracy and the model fitting accuracy rise synergistically, which solves the input incompleteness problem and also realizes the dynamic filling of missing values. Finally, the effectiveness of the subnetwork iterative learning modeling approach is verified by the results of filling in the missing values.

REFERENCES

[1] An Hong. Discussion on the innovation path of intelligent new media based on artificial intelligence technology[J]. Network Security and Informatization,2023(03):16-18.

[2] Chen, H. P., Zheng, B. C., Huang, H. Hu. Thinking about the development of artificial intelligence technology in future equipment applications[J]. Total Aerospace Technology,2023,7(02):69-74.

[3] Du Hui,Zheng Yunmei,Tian Lu. Factors influencing the willingness of enterprises to adopt artificial intelligence technology based on TAM and the role model[J]. Hebei Enterprise,2023(03):62-64.DOI:10.19885/j.cnki.hbqy.2023.03.041.

[4] Long Fei. Thoughts and practices on using artificial intelligence technology to help cultural communication[J]. Foreign Communication,2023(03):68-71.

[5] Ma, Liang. Next-generation artificial intelligence technology and the modernization of national governance[J]. SAR Practice and Theory, 2023(01):45-50. doi:10.19861/j.cnki.tqsjyll.20230307.004.

[6] Song Shiyang,Zan Shengfeng. Exploring the application of artificial intelligence technology in natural risk management of sports tourism[J]. Liaoning Sports Science and Technology,2023,45(02):30-35.DOI:10.13940/j.cnki.lntykj.2023.02.020.

[7] Yu, W. X., Ma, L., Wang, T. L., Han, C., Xie, X. S., Ye, L., Wen, H.. "The application and regulation of ChatGPT, a new generation of artificial intelligence technology[J/OL]. Journal of Guangxi Normal University (Philosophy and Social Science Edition):1-23 [2023-03-31]. http://kns.cnki.net/kcms/detail/45.1066.c.20230315.1655.002.html
[8] Zhang Xiaheng. Next generation artificial intelligence technology (ChatGPT) and its impact and change on human society [J/OL]. Industrial Economics Review:1-14 [2023-03-31].DOI:10.19313/j.cnki.cn10-1223/f.20230310.001.
[9] Zhao HQ, Duan JF, Luo JL. Research on the use of artificial intelligence technology in big data network security defense[J]. Network Security Technology and Applications,2023(03):19-20.