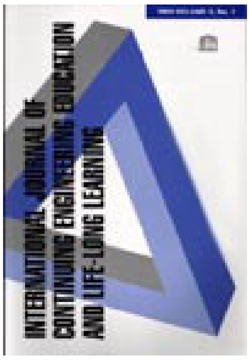

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A construction of online teaching quality evaluation model based on big data mining

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A construction of online teaching quality evaluation model based on big data mining

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Abstract: This paper designs an online teaching quality evaluation model based on big data mining. Firstly, the online teaching big data is preprocessed to improve data retrieval accuracy and save evaluation time. Then, a self-coding network is established to effectively represent data features and complete data reconstruction through data coding/decoding, so as to effectively mine teaching quality data. Finally, six first-level indicators and 16 second-level indicators are designed to complete the construction of online teaching quality evaluation model by setting the weight of each indicator. According to the simulation experiment, the evaluation time of model of this paper is 25 s–29 s, the retrieval accuracy of online teaching data is closer to 1, and the comprehensive evaluation accuracy is between 94% and 96%, indicating that the model has higher evaluation efficiency and reliability, and better application effect.

Keywords: big data mining; quality of teaching; index weight; self-coding network; quality evaluation.

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1 Introduction

In the popularisation of education, the quality of online teaching is widely concerned by all social strata. One of the key measures to improve online teaching quality is to evaluate online teaching quality (Xiao and Wang, 2020; Li et al., 2019). But how to establish a reasonable and effective evaluation model is a systematic and complicated task. In the evaluation of online teaching quality, there are many influencing factors, and the influence degree of each factor is not the same, so it is difficult to express the evaluation result by ordinary mathematical analytical expression (Wang and Wang, 2019; Yang, 2019).

In the neural network model, Wu et al. (2020) evaluated the quality of Internet teaching based on evidence theory, and constructed evaluation indexes of online teaching quality including teacher level, student performance, and environmental support degree, and uses BP neural network model and D-S evidence theory to evaluate online teaching quality. However, it is found in practical application that the model needs a long time to evaluate teaching quality. Yue and Wen (2019) used entropy method to screen indicators of teaching quality evaluation system and determine the weight values of indicators at all levels. Then, based on the initial evaluation results, the parameters of BP neural network are optimised by adaptive mutation genetic algorithm, so as to complete the evaluation of teaching quality. However, it is found in the practical application that the model has the problem of low accuracy of online teaching data retrieval. Li (2020) firstly analysed the relevant historical data of teaching quality, and established the impact factor set of the evaluation process, and then the data of influencing factors of teaching quality and learning samples of the evaluation process are collected. Finally, the samples are trained in the multi-level network and the final evaluation result is obtained through continuous iteration. However, it is found in the practical application that the model has the problem of low comprehensive evaluation accuracy.

In view of the above mentioned problems of long evaluation time and low accuracy of comprehensive evaluation, a new design is carried out in this study to effectively improve the effect of teaching quality evaluation. The design ideas are as follows:

1 Education collection is used as the data base to improve data retrieval accuracy and save evaluation time through discrete and normalised processing of online teaching big data.

2 In the coding in the network, to effectively represent data by data encoding/decoding characteristics, using activation function, bias, and output the activation values to stack multiple since the encoder, formed from coding space, thus in the input data online teaching to effective said that after making teaching data retrieval precision is improved.

3 In the coding space, design index of 6 one class and 16 secondary index as the constraint index, improve the comprehensive evaluation of accuracy through multiple angle of evaluation. Then, the importance of different indicators is measured by setting index weights, so that the effective evaluation can be completed in the self-coding space after the activation value is output.

2 Big data mining for online teaching

In this section, the online teaching big data is preprocessed to improve data retrieval accuracy and save evaluation time. Then, a self-coding network is constructed to effectively represent data features and complete data reconstruction through data encoding and decoding, so as to complete accurate mining of teaching data.

2.1 Data preprocessing

Online teaching big data has various structural characteristics and its data also has a variety of attributes including continuity and discontinuity. Therefore, the mining accuracy can be effectively optimised by unifying the structural features of the data. Before mining data features and reconstructing data, this study preprocesses online teaching big data. The pretreatment in this paper can be divided into two ways, which are discretisation and normalisation respectively.

1 Discrete processing.

In this paper, NaiveScaler algorithm is used to discretise any attribute q in the original education collection dataset X:

Step 1 Sort the data in online teaching dataset X according to attribute q in order from smallest to largest (Liu and Yang, 2019);

Step 2 x_a and x_b are respectively used to represent the two adjacent data in dataset X, and the top to bottom scanning is completed. If $q(x_a) = q(x_b)$, the scanning continues. When there is no $q(x_a) = q(x_b)$, the data breakpoint $p = \frac{q(x_a) + q(x_b)}{2}$ is obtained.

2 Normalised processing.

Although online teaching data has been discretised in the above process, there are still differences among different data value domains, resulting in the influence of data attributes after discretisation (Fu and Luo, 2019). Therefore, the effect of data range difference on mining results is weakened by normalisation processing.

In this paper, singular distance function is used to normalise online teaching big data. x_a and x_b are still used to represent any two data points in the dataset. Where, the j^{th} attribute of x_a is x_{aj}, and the j^{th} attribute of x_b is x_{bj}. Let $d(x_{aj}, x_{bj})$ represent the distance function between x_{aj} and x_{bj} on the j^{th} attribute, and it exists:

$$d\left(x_{aj}, x_{bj}\right) = \sqrt{\sum_{m=1}^{M} \left| \frac{n'_a}{n_a} - \frac{n'_b}{n_b} \right|^2} \tag{1}$$

where M represents the categories of online teaching datasets, n_a represents the total number of x_{aj} in the online teaching sample data, and n_b represents the total number of x_{bj} in the online teaching sample data. n'_a represents the number of samples of category m that are output in the sample data. If the values of x_{aj} and x_{bj} cannot be determined, then the distance between x_{aj} and x_{bj} is represented by one (Zhang, 2020).

Based on the distance function $d(x_{aj}, x_{bj})$, the online teaching big data is normalised. The process is as follows:

$$\mathrm{X}' = \frac{d\left(x_{aj}, x_{aj,\min}\right)}{d\left(x_{aj,\max}, x_{aj,\min}\right)} \tag{2}$$

where X′ represents the online teaching data after normalised processing, $x_{aj,\max}$ is the maximum attribute value in the dataset, and $x_{aj,\min}$ is the minimum attribute value in the dataset.

2.2 Feature mining and reconstruction of online teaching big data

In teaching data discretisation and normalised processing, on the basis of complete and effective online teaching big data mining, and according to the data characteristics of the case for reconstruction, and then re-use activation function, bias, and output the activation values to stack multiple since the encoder, formed from coding space, thus in the input data online teaching to effective after said, The accuracy of teaching data retrieval can be improved.

This study uses self-coding network to reconstruct online teaching big data. The encoding stage in the self-encoding network can effectively represent the data features, while the decoding stage is based on the obtained data features to complete the reconstruction of the original data (Zhao et al., 2018).

Assuming that $x_1, x_2, \ldots, x_n$ is a continuous input sample and sigmoid activates the function, then the forward propagation expression from the encoder is as follows:

$$H = \text{sigmoid}(\mathrm{W} + \mathrm{B}) \tag{3}$$

where sigmoid represents the activation function, B represents the offset term, and W represents the output activation value. On this basis, multiple self-encoders are stacked and combined with constraints to realise efficient representation of online teaching data at all levels. Then input the online teaching big dataset into the self-coding network, and complete the data mining according to the following process:

Step 1 Firstly, determine the Gaussian kernel similarity matrix $R^{n\times n}$ of the online teaching data samples.

Step 2 Use spectral clustering method to process n online teaching data samples to obtain clustering results K_n.

Step 3 Judge the average distance between the cluster centre and the data points according to the clustering results, select representative data points according to the calculation results, and delete the edge points in the dataset as much as possible;

Step 4 The pre-c data points with the smallest mean distance between the data points in the clustering results were extracted to build a new sub-dataset.

Step 5 Input the new sub-dataset into the self-coding network. In the same data space, make the parameters of the self-coding network consistent with the parameters of the Gaussian kernel similarity matrix $R^{n\times n}$.

Step 6 The classification interface is obtained through the above process to complete data reconstruction.

3 Online teaching quality evaluation model

Based on the data mining results, get online teaching on the basis of summarising the principle of online teaching quality evaluation, the screening index of 6 one class and 16 secondary indexes, and by setting the index weight to measure the importance of different indicators, so as to activate in output value, the evaluation modelling is completed in the self-coding space.

3.1 Online teaching quality evaluation principle and index setting

By setting a number of indicators on multiple perspectives, all aspects of the process of online teaching evaluation, so as to help people accurately analysis and judge the quality of online education, provide power for online teaching fundamentally. Under this research background, this paper sets up the following principles of online teaching quality evaluation:

1 Comprehensive: comprehensive the meaning of this principle is in the screening of online teaching quality evaluation indicators, to fully consider the comprehensive and comprehensive analysis of the premise condition, make the selected evaluation index to scientific and reasonable feedback out online relationship between various influencing factors in the process of teaching, so as to make the final evaluation results more comprehensive (Dong, 2020). At the same time, in order to avoid the complicated evaluation process, the evaluation indexes should be independent of each other.

2 Scientific: science is the meaning of this principle in building an online teaching quality evaluation model, the indicators should be scientific, reasonable and cautious when selecting, should be accurate excavated online teaching each link and the characteristics of generality, thus forming a kind of horizontal comparison, so as to help people more accurately and timely find the insufficiency of online teaching, provide maximum support for its development in a better direction (Feng and Shi, 2020).

3 Feasibility and generality: the significance of the principle of feasibility and generality lies in ensuring that all the indicators can effectively, intuitively and without exaggeration present the current development status of online teaching career when screening the evaluation indicators of online teaching quality. No matter it is worth promoting the aspects or the existing problems, the selected evaluation indicators can have a considerable comment on it.

4 Indicative: the significance of the principle of indicative lies in the fact that when selecting indicators and determining their weight values, the current development status of online teaching should be fully taken into account, and based on this, it plays a certain indicative significance for the development of online teaching (Tang et al., 2020).

Therefore, the following evaluation indicators are set:

a teaching content level, including: content source, content design rationality, content organisation and coordination;

b the level of teaching resources, including: rationality of resource arrangement, availability and abundance of resources

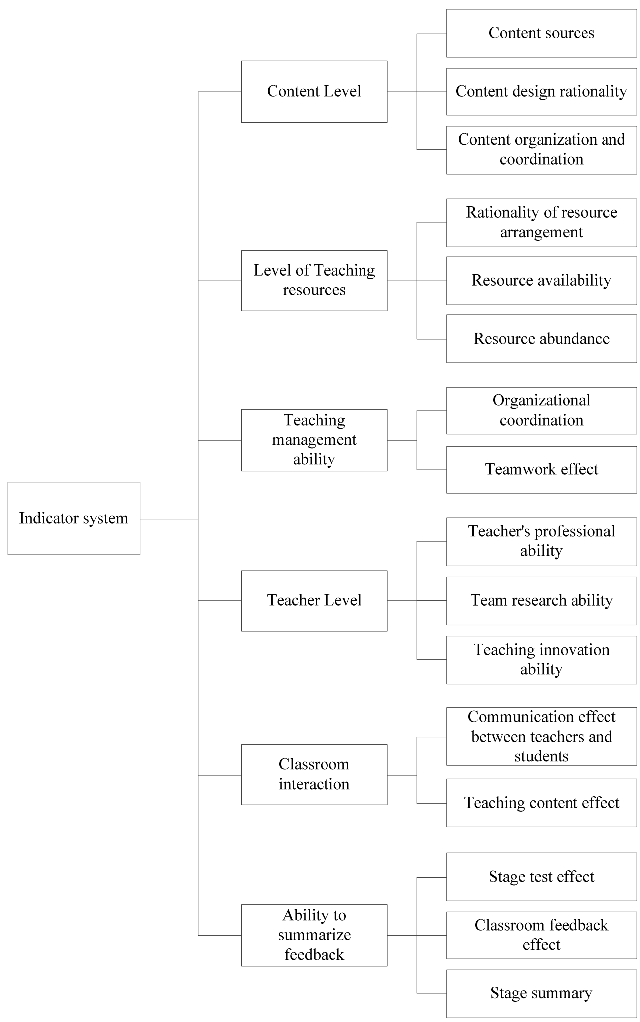
c teaching management ability, including organisational coordination and teamwork effectiveness

d the level of the teaching staff, including teachers' professional ability, team research ability and teaching innovation ability e classroom interaction, including the effectiveness of teacher-student communication and teaching content

f ability to summarise feedback, including: stage test effect, classroom feedback effect, stage summary.

To sum up, the construction of the index system is shown in Figure 1.

Figure 1 Illustration of index system



3.2 Generative evaluation model

After the evaluation indexes are screened, the importance of different indexes is measured by setting index weights, and then the evaluation results of indexes are summarised to complete the comprehensive evaluation.

a Teaching content level index Z_1: this index is the primary content to measure the quality of online teaching, mainly reflected by content source Z_{11}, content design rationality Z_{12}, content organisation and coordination Z_{13}. The calculation process is as follows:

$$Z_1 = \gamma Z_{11} + \delta Z_{12} + \varepsilon Z_{13} \tag{4}$$

where γ, δ and ε respectively represent the weight value of the subordinate index of the teaching content level index (Gu, 2020).

b Teaching resource level Z_2: this index analyses and evaluates the quality of online teaching from three perspectives: rationality of resource arrangement Z_{21}, availability of resources Z_{22} and abundance of resources Z_{23}. The calculation process is as follows:

$$Z_2 = \epsilon Z_{21} + \theta Z_{22} + \vartheta Z_{23} \tag{5}$$

where ϵ, θ and ϑ respectively represent the weight values of subordinate indexes of teaching resource level indexes.

c teaching management ability index Z_3: this index analyses the guiding ability of teachers and related principals in the process of online teaching from two perspectives: Z_{31} of organisational coordination and Z_{32} of team cooperation:

$$Z_3 = \alpha Z_{31} + \beta Z_{32}$$

where α and β respectively represent the weight value of subordinate indexes of teaching management ability index.

d Teacher level index Z_4: this index analyses the teaching ability of teachers in the online teaching system from three perspectives: teacher professional ability Z_{41}, team scientific research ability Z_{42} and teaching innovation ability Z_{43}. The calculation process is as follows:

$$Z_4 = \mu Z_{41} + \rho Z_{42} + \sigma Z_{43} \tag{7}$$

Among them, μ, ρ and σ respectively represent the weight values of subordinate indexes of teachers' level indexes.

e Classroom interaction indicator Z_5: this index analyses the classroom teaching effect in the process of online teaching from two perspectives: teacher-student communication effect Z_{51} and teaching content effect Z_{52}. The calculation process is as follows:

$$Z_5 = \tau Z_{51} + \varphi Z_{52} \tag{8}$$

Among them, τ and φ respectively represent the weight value of the subordinate index of the classroom interaction indicator.

f Feedback summary ability index Z_6: this index analyses the after-class and phased teaching effects of online teaching system from three perspectives: stage test effect Z_{61}, classroom feedback effect Z_{62} and stage summary situation Z_{63}. The calculation process is as follows:

$$Z_6 = \omega Z_{611} + \partial Z_{62} + \psi Z_{63} \tag{9}$$

where ω, ∂ and ψ respectively represent the weight value of the subordinate indexes of the feedback summary capability index.

And on that basis, 6 first-level indicators and 16 second-level indicators designed above are used in combination with the big data mining result G obtained above. On the basis of measuring the importance of different indicators by setting index weights above, the online teaching quality evaluation modelling is completed in the self-coding space after the activation value is output, and the final online teaching quality evaluation model is as follows:

$$Z = \propto \sum_{i=1}^{6} Z_i \times G \tag{10}$$

In Formula (10), ∝ represents the weight value of the teaching quality evaluation index set.

4 Simulation research

4.1 Project design

The feasibility and practicability of this model are analysed through the following simulation experiments.

The experimental host processor is i9-9900XE. The data used in the experiment came from the dataset of education collection, from which relevant online teaching data were obtained. Based on the obtained data, MATLAB software was used to establish the simulation environment. Before the experiment, the data was unified into int type through normalisation processing and stored as 01010101 binary.

In the experiment, model of Wu et al. (2020) and model of Yue and Wen (2019) were used as comparison models to complete performance check together with the model in this paper.

4.2 Build experimental indexes

1 Time required for teaching quality evaluation: this index can reflect the evaluation efficiency of different evaluation models. The less time required for teaching quality evaluation indicates that the evaluation efficiency of the evaluation model is higher, and the evaluation results can be obtained quickly in a short time.

2 Accuracy of online teaching data retrieval: this index can reflect the evaluation reliability of different models. The accuracy of online teaching data retrieval ranges from 0 to 1. The closer the accuracy of online teaching data retrieval is to 1, the higher the reliability of evaluation model method is. The accuracy of online teaching data retrieval is calculated by the adaptive degree of evaluation index and information recall rate. The specific calculation method is as follows:

$$W = \frac{2pq}{p+q} \tag{11}$$

In formula (11), W represents the retrieval accuracy of online teaching data, p represents the information recall rate, and q represents the self-fitness of evaluation indexes.

3 Comprehensive evaluation accuracy: this index can intuitively reflect the application effects of different evaluation models. The higher the accuracy of the comprehensive evaluation, the better the application effect of the evaluation model, the more it can help people to accurately analyse and judge the quality of online education, and provide power for online teaching career.

Using the above designed experimental environment and indicators, the application performance of model of this paper, model of Wu et al. (2020) and model of Yue and Wen (2019) was compared and verified.

4.3 Experimental results and analysis

First, Table 1 is used to reflect the time required for evaluation of different models.

Table 1 Time required for teaching quality evaluation of different evaluation models (s)

Number of experiments/time	*Model of Wu et al. (2020)*	*Model of Yue and Wen (2019)*	*Model of this paper*
5	73	51	26
10	75	52	28
15	74	55	27
20	72	49	29
25	76	53	27
30	74	52	25

In Table 1, it can be found that after the application of model of Wu et al., (2020), the time required for teaching quality evaluation varies between 72–76 s. After the application of model of Yue and Wen (2019), the time required for teaching quality evaluation varies between 49–55 s. The evaluation time of this model varies between 25 s and 29 s. Therefore, model in this paper requires less evaluation time, indicating that it is more efficient.

According to the adaptive degree and information recall rate of evaluation indexes of model of this paper, model of Wu et al., (2020) and model of Yue and Wen (2019), the retrieval accuracy of online teaching data of different evaluation models is calculated by using formula (11). The comparison results are shown in Table 2.

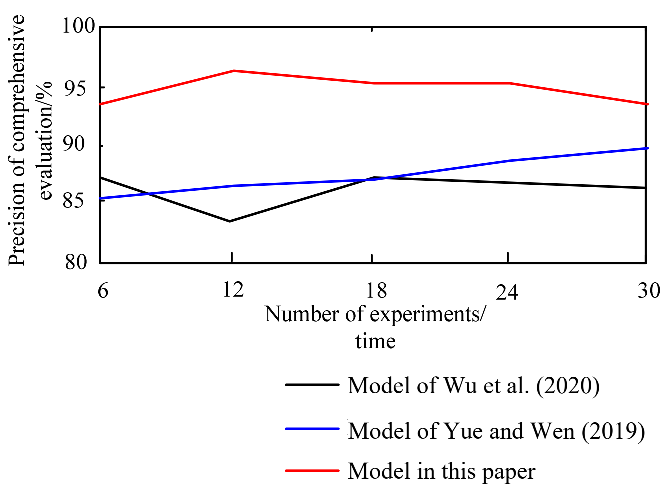
It can be found that the online teaching data retrieval accuracy of model of Wu et al. (2020) is between 82.9% and 85.7%, and that of model of Yue and Wen (2019) is between 83.5% and 89.6%. The retrieval accuracy of online teaching data of model of this paper is between 92.7% and 95.6%. Compared with the two traditional evaluation models, the online teaching data retrieval accuracy of model of this paper is closer to 1.

Finally, the application effect of model of this paper, model of Wu et al. (2020) and model of Yue and Wen (2019) is compared and tested by taking the comprehensive evaluation accuracy as the index. The results are shown in Figure 2.

Table 2 Statistical results of data retrieval accuracy (%)

Number of experiments/time	*Model of Wu et al. (2020)*	*Model of Yue and Wen (2019)*	*Model of this paper*
5	82.9	83.5	92.7
10	83.6	84.2	93.8
15	83.8	85.0	95.0
20	84.4	87.3	95.1
25	84.7	88.6	95.3
30	85.7	89.6	95.6

Figure 2 Comparison of comprehensive evaluation accuracy of different evaluation models (see online version for colours)



By comparing and observing the results in Figure 2, the comprehensive evaluation accuracy of model of Wu et al. (2020) varies between 83% and 87%, its comprehensive evaluation accuracy varies between 83% and 87%. After the application of model of Yue and Wen (2019), its comprehensive evaluation accuracy varies between 85%-90%. The comprehensive evaluation accuracy of the model in this paper varies between 94% and 96%.

Through the above comparison, model in this paper can help people accurately analyse and judge the quality of online education more effectively, and provide impetus for the cause of online teaching. This is because the model in this paper accurately mines the relevant data after constructing the self-coding network, which improves the retrieval accuracy of teaching data, and implements pre-processing to improve the data retrieval accuracy and save the evaluation time.

5 Conclusions

1. In order to effectively improve the effect and quality of online teaching, and timely evaluate and feedback the teaching effect, this study designed a new online teaching quality evaluation model based on the results of big data mining. On the basis of discretisation and normalisation of the data, self-coding network is used to reconstruct the data, and then the relevant evaluation indexes are designed, and then the modelling is completed by setting the weights of each index.
2. The time required for evaluation of the model of this paper varies between 25–29 s indicating that the evaluation efficiency of this model is higher; the accuracy of online teaching data retrieval is closer to 1, which proves that its evaluation reliability is higher. The comprehensive evaluation accuracy varies between 94% and 96%, which proves that the model achieves the design expectation.
3. Although the model in this paper has been successfully applied to a certain extent, it still has some deficiencies due to the constraints of research time, research conditions and other factors. Therefore, in the following research stage, we will consider adding the perspective of model evaluation, so as to further improve the application value of the model presented in this paper.

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