Research on online evaluation method of MOOC teaching quality based on decision tree-based big data classification

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Abstract: In order to improve the online evaluation ability to massive open online course (MOOC) teaching quality, an online evaluation method of MOOC teaching quality based on decision tree-based big data classification is proposed. First, a big data statistical analysis model is built to identify fuzzy degree parameters. Then, the quality index system is obtained to realise big data fusion and cluster analysis. It is concluded that this method has high accuracy in online evaluation. In this paper, the method shows that the accuracy as high as 0.996 when the number of iterations reaches 500. Its innovation lies in the analysis of the global optimal solution of online evaluation of distance MOOC teaching quality by using the big data decision tree model, which improves the information management of MOOC online evaluation.

Keywords: big data statistical analysis; decision tree-based classification; MOOC teaching quality; online evaluation method; information fusion and clustering.

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1 Introduction

As the massive open online course (MOOC) teaching method is continuously applied in the remote education system, the MOOC teaching mode is adopted to optimise teaching reform to better evaluate the MOOC teaching quality, and both quantitative statistical analysis and quantitative analysis are adopted to construct a quantitative regression analysis model for online evaluation of MOOC teaching quality. The online evaluation and quantitative estimation of MOOC teaching quality are carried out based on the sampling results of previous big data information, so as to build an online evaluation model of MOOC teaching quality. Effective evaluation of MOOC teaching quality is of great significance to the optimisation of MOOC teaching reform (Chen et al., 2019), and relevant research on online evaluation model and algorithm design of MOOC teaching quality has attracted great attention.

Conventional online evaluation methods of MOOC teaching quality mainly include the fuzzy statistical feature analysis method, regression analysis method, detection statistical feature analysis method, and online evaluation method of MOOC teaching quality based on PID adaptive learning, and so on (Yu et al., 2014; Berriri et al., 2012). MOOC has brought impact on the traditional classroom teaching mode, teaching curriculum, teaching concept and the relationship between teachers and students, and has played a promoting role in the teaching reform of universities. Universities should take MOOC as an opportunity to carry out teaching reform from the aspects of innovating teaching methods, constructing core courses, and giving active guidance to teachers, so as to further utilise the advantages of MOOC and strengthen the university's social service function improving the quality of education. In these methods, a big data information analysis model for online evaluation of MOOC teaching quality is constructed, Through quantitative recursive analysis and statistical analysis, MOOC online teaching quality evaluation is realised. In Khil et al. (2016), an online evaluation method of MOOC teaching quality based on the scheduling of clustering attributive character is proposed to carry out the fusion scheduling and classification identification of the online evaluation system of MOOC teaching quality, And then improve the ability of online evaluation and statistical analysis of MOOC teaching quality. However, this method is highly complex in computation and performs not well in fusion. In Youcef and Arnaud (2019), an online evaluation method of MOOC teaching quality based on support vector machine learning is proposed. In this method, online evaluation of MOOC teaching quality is implemented based on the results of big data mining and adaptive learning, which improves the convergence of learning. However, this method is poor in anti-interference ability and redundancy elimination of big data. In Wang and Wang (2019), an online evaluation method of MOOC teaching quality based on fuzzy information clustering and FCM is proposed, which adopts fuzzy C-means clustering analysis to realise big data feature clustering for online evaluation of MOOC teaching quality. This method has problems of large coupling and poor information classification and recognition ability.

In order to solve the above problems, an online evaluation method of MOOC teaching quality based on big data classification of decision tree is proposed. First, aiming at the online evaluation of MOOC teaching quality, a big data analysis model is proposed. On this basis, the auto correlation feature matching method is used to realise big data fusion and information management of MOOC teaching quality online evaluation, and fuzzy fusion and cluster analysis are realised. With the big data decision classification model for online evaluation of MOOC teaching quality, the online evaluation ability to MOOC teaching quality is improved and the design of online evaluation is optimised. Finally, the experimental results show that this method has certain advantages in improving MOOC teaching quality and online evaluation ability.

2 Data analysis for online evaluation of remote MOOC teaching quality

2.1 Statistical analysis of big data for online evaluation of MOOC teaching quality

Online evaluation of MOOC teaching quality based on decision tree classification big data, application of Ig data fusion and cluster analysis in the evaluation of distance MOOC teaching quality, establishing data mining model of distance teaching quality. Using the method of multi index joint analysis and modelling, the index system of online evaluation of distance teaching quality is constructed (Yang and Wei, 2019). The clustering centre $F(x_i, A_j(L))$, $k = 1, 2, \ldots, m$, $w = 1, 2, \ldots, k$ represents the preliminary processing of MOOC online teaching quality evaluation data classification, and the rough set of online evaluation of remote MOOC teaching quality is extracted, and it is $n_m(t)$. Finally, the associated information fusion model for evaluation of remote MOOC teaching quality is obtained as follows:

$$x_m(t) = \sum_{i=1}^{j} F\left(x_i, A_j(L)\right) + n_m(t), -p+1 \le m \le p \tag{1}$$

Assuming that the number of nodes for collection of the information of remote MOOC teaching quality characteristics is $N = n - (m - 1)\tau$, the statistical characteristic quantity for online evaluation of remote MOOC teaching quality is calculated as follows:

$$\gamma_i = \frac{\frac{1}{N}\sum_{l=0}^{N-1}\left[x_i(k-l)-\mu_i\right]^3}{\left(\frac{1}{N}\sum_{l=0}^{N-1}\left[x_i(k-l)-\mu_i\right]^2\right)^{3/2}} \tag{2}$$

$$\kappa_i = \frac{\frac{1}{N}\sum_{l=0}^{N-1}\left[x_i(k-l)-\mu_i\right]^4}{\left(\frac{1}{N}\sum_{l=0}^{N-1}\left[x_i(k-l)-\mu_i\right]^2\right)^{2}} - 3 \tag{3}$$

where $x_i(k - l)$is the statistical collection of MOOC teaching quality information and μ_i is the proportional coefficient of information of MOOC teaching quality characteristics.

Big data analysis and statistical modelling for remote MOOC teaching quality mining are carried out using the big data fusion method. With the corresponding optimisation learning algorithm (Zhang and He, 2019), big data mining for online evaluation of MOOC teaching quality is realised. Through statistical sample regression analysis, the decision tree function of online evaluation of distance MOOC teaching quality is expressed as follows:

$$S(k, w) = \frac{\sum_{u \in U_{ij}} (V_{u,i} - 3)(V_{u,j} - 3)}{\sqrt{\sum_{u \in U_{ij}} \left(V_{u,i} - \overline{V_{.i}}\right)^2} \sqrt{\sum_{u \in U_{ij}} \left(V_{u,j} - \overline{V_{.j}}\right)^2}} \tag{4}$$

where the index system of online evaluation of remote MOOC teaching quality is $(V_{u,i} - \overline{V_{.i}})$, and the data information samples of MOOC teaching quality are $V_{u,i}$ and $V_{u,j}$. The fuzzy degree parameter of big data for online evaluation of MOOC teaching quality is analysed (Li, 2018), and the statistical analysis function $\delta_{ik}(t)$ for big data of online evaluation of MOOC teaching quality is as follows:

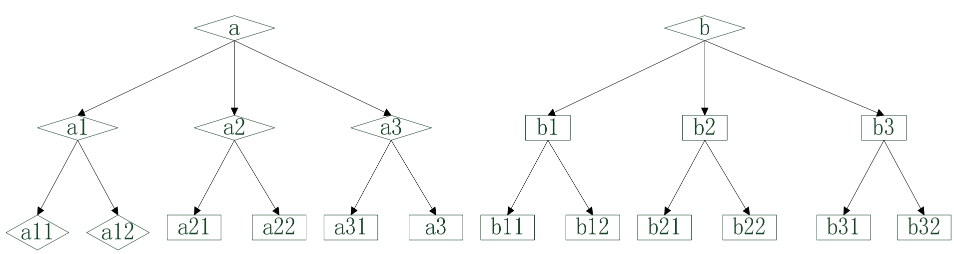
$$\delta_{ik}(t) = \{x(t_0 + i\Delta t)\} + N(S(i, j)) \tag{5}$$

where the data sampling sequence of online evaluation of remote MOOC teaching quality is $i = 0, 1, \cdots, N - 1$, and the vector length of data information flow is N. Big data mining and information detection for online evaluation of MOOC teaching quality is carried out by semantic segmentation.

2.2 Fuzzy parameter identification for online evaluation of MOOC teaching quality

With the block region fusion method, big data statistical analysis is carried out for online evaluation of MOOC teaching quality (Bin et al., 2020), and the centre distance between the big data clusters of online evaluation of remote MOOC teaching quality M_i and M_j is $Clustdist(M_i, M_j)$. When $(i \neq j, 1 \leq i \leq q, 1 \leq j \leq q)$, a fuzzy decision tree model for online evaluation of remote MOOC teaching quality is constructed as shown in Figure 1.

Figure 1 Fuzzy decision tree for online evaluation of MOOC teaching quality



According to the distribution of the decision tree in Figure 1, the quantitative evaluation parameter model of remote MOOC teaching quality is obtained as follows:

$$\Psi(\omega) = Clustdist(M_i, M_j) + \sum_{k=1}^{n} M_i + M_j \tag{6}$$

The semantic features of big data for online evaluation of MOOC teaching quality are extracted, and done with segmented sample detection (Yin and Zhang, 2020). Then the sub-mode of the distributed state model T for online evaluation of remote MOOC teaching quality is obtained, and it is $X = I_1 I_2, \ldots, I_k$. The decision tree optimisation model for remote MOOC teaching quality distribution is constructed as follows:

$$\begin{cases} f_i(t) = \dfrac{k}{t_0 - t} = \dfrac{k / t_0}{1 - t / t_0} = \dfrac{f_{\max} f_{\min}}{f_0}\left(1 + \dfrac{t}{t_0} + \dfrac{t^2}{t_0^2} + \cdots\right) \\ |t| \le \dfrac{T}{2} \end{cases} \tag{7}$$

where k is the given positive integer; the semantic features of $f_{\max}$, $f_{\min}$ are the maximum and the minimum respectively; t time for detecting segmented samples.

The weight $W_e = (\omega_j^{(e)}, 0)$ of decision tree-based classification optimisation is used as the adjustment coefficient to implement evaluation of remote MOOC teaching quality and feature information fusion, and the reliable fuzzy parameter identification function for online evaluation of MOOC teaching quality is obtained as follows:

$$Q = \frac{C_1 \sum_{i=1}^{k} \exp\left[-S_2\left(f_i(t) - \Psi(\omega)\right)^2\right]}{1 + \exp\left[-S_1 \sum_{i=1}^{k} w_i\left(\Psi(\omega)\right)\right]} \tag{8}$$

where C_1, S_1, and S_2 are all constants. According to the quantitative feature set analysis and decision tree model construction for online evaluation of remote MOOC teaching quality, evaluation of remote MOOC teaching quality and fuzzy parameter identification are realised using attribute clustering analysis (Zeng et al., 2019).

3 Optimisation of evaluation of remote MOOC teaching quality

3.1 Fuzzy fusion clustering for evaluation of remote MOOC teaching quality

The big data semantic feature decomposition model of MOOC online teaching quality evaluation is established by using the related feature matching method, and the big data fusion and information management of MOOC online evaluation are realised. Using block information clustering (Lin et al., 2020), the online evaluation quality index system of distance MOOC teaching quality is obtained and expressed as:

$$x_n = a_0 + \sum_{i=1}^{M_{AR}} a_i x_{n-i} + \sum_{j=0}^{M_{MA}} a_i \eta_{n-j} \tag{9}$$

where a_0 is the information distribution amplitude of big data about remote MOOC teaching quality; a_i is the characteristic distribution amplitude of the big data; x_{n-i} is the scalar time series of remote MOOC teaching quality; η_{n-j} is the index information sequence of MOOC teaching quality. The big data decision tree model is used to analyse the global optimal solution of online evaluation of remote MOOC teaching quality (Li, 2019), and the optimal solution distribution is obtained as follows:

$$f\left(x_{k-1}\right) = \frac{1}{2} x_n + a_0 \sum_{i=1}^{n}\left(x_{n-i} + \eta_{n-j}\right) \tag{10}$$

Full sample regression analysis based on MOOC teaching quality evaluation optimisation results, the descriptive statistical characteristics in the online evaluation of distance MOOC teaching quality are described as follows:

$$\omega_k = x_n - \sqrt{f\left(x_{k-1}\right)} \tag{11}$$

A statistical analysis model for big data detection for online evaluation of MOOC teaching quality is established, and the fuzzy state function for evaluation of remote MOOC teaching quality is obtained by the auto-correlation feature matching method:

$$\tilde{u}_{e|v,k} = \tilde{u}_{e,k} + \sum \sum\nolimits_{e,k}^{-1} \left(\omega_k - \tilde{u}_{e,k}\right) \tag{12}$$

where the fuzzy functional parameter for online evaluation of MOOC teaching quality is $\tilde{u}_{e,k}$. Construction of scalar time series for MOOC teaching quality remote evaluation, the iterative function for optimising the evaluation is as follows:

$$x\left(t_{n+1}\right)' = X_{m+1}(m) + \tilde{u}_{e|v,k} \tag{13}$$

where *m* represents the scalar time series number of teaching evaluation.

The association degree information of big data for online evaluation of MOOC teaching quality is extracted, and the fuzzy fusion clustering model for online evaluation is obtained as follows:

$$CPC_{a,b} = \left[\sum \left(d_{a,i} - \overline{d}_a\right) \times \sqrt{\frac{\left(d_{b,i} - \overline{d}_a\right)}{x\left(t_{n+1}\right)'}}\right]^2 \tag{14}$$

where $\overline{d}_a$ is the similarity clustering characteristic of evaluation of remote MOOC teaching quality, and $d_{a,i}$ and $d_{b,i} \in [1, 5]$ are fuzzy correlation constraint coefficients. The structural model of the online evaluation system of remote MOOC teaching quality is constructed. According to the results of fuzzy fusion and clustering analysis, the big data decision classification model for online evaluation of MOOC teaching quality is constructed. MOOC online evaluation of teaching quality has high reliability and can be used to evaluate the original data effectively.

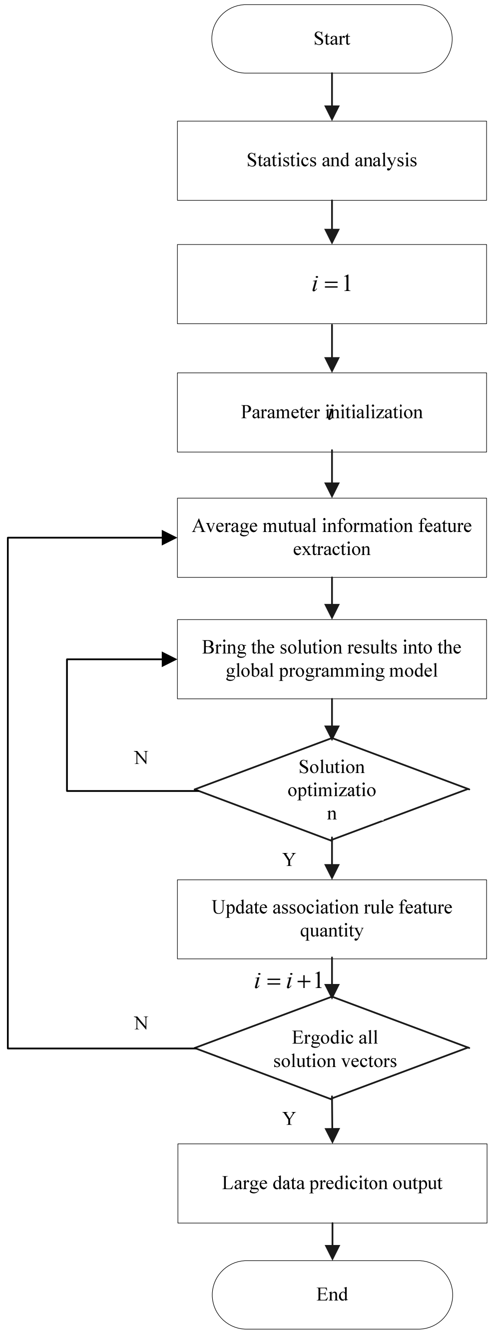
3.2 Convergence control for online evaluation of MOOC teaching quality

The horizontal distribution sequences of online evaluation index samples of MOOC teaching quality are grouped and ordered. The fuzzy parameter identification method is used to implement online evaluation of MOOC teaching quality. With the quantitative regression analysis method, the mathematical description of the fuzzy constraint index distribution for online evaluation of MOOC teaching quality is obtained as follows:

$$\min F(x) = CPC_{a,b} \sum_{x \neq 0} f_1(x) + f_n(x) + \int_0^{\infty} \frac{h_j(x)}{g_i(x)} dx \tag{15}$$

where $f_i(x)$ $(i = 1, 2, \ldots, n)$ is the statistical characteristic function for online evaluation of MOOC teaching quality; $g_i(x)$ is the cost function for online evaluation of MOOC teaching quality; $h_j(x)$ is the statistical constraint condition of the correlation.

Figure 2 Optimisation process of the model



The constraint cost factor is used as the horizontal feature distribution state parameter for online evaluation of remote MOOC teaching quality (Yang et al., 2019). In the decision tree model, the correlation state factor between X_i and X_j is obtained, and the reliability distribution state parameter for online evaluation of remote MOOC teaching quality is obtained as follows:

$$l(X_i, X_j) = \|X_i - X_j\| + \frac{f_i(x)}{2} \tag{16}$$

where $\|X_i - X_j$ indicates the differentiation of online evaluation of MOOC teaching quality. Through local convergence learning, the optimised weight subset of online evaluation of MOOC teaching quality is obtained and it is $\{W_O\}_{i=1}^{N-m-a}$. The fuzzy parameter distribution subset of online evaluation of MOOC teaching quality is $\{W_{final}\} = \{\{W_H\}, \{W_C\}, \{W_O\}\}$. Based on the above analysis, the control function for online evaluation of MOOC teaching quality is obtained.

$$C = \{W_O\}_{i=1}^{N-m-a} + \frac{\{W_{final}\}}{l(X_i, X_j)} \tag{17}$$

The expression of convergence control equation for online evaluation of MOOC teaching quality is:

$$K_{\min} = \frac{\beta}{C} K_{poly} + (1-\beta) K_{RBF}, \quad \beta \in (0,1) \tag{18}$$

where $K_{poly} = [(x \cdot x_i) + 1]^2$ is the control function for MOOC teaching quality; $KRBF = \exp(-\gamma\|x - x_i\|^2)$ is the adaptive function for MOOC teaching quality control; β is the adjustment weight coefficient. The flow chart 2 shows the optimisation.

4 Simulation test and analysis

To test the reliability and effectiveness of MOOC teaching quality online evaluation method, the MATLAB is used for simulation test and analysis. Experimental methods: the sample size of big data for online evaluation MOOC teaching quality is set to 2,400; the experimental evaluation index: the number of test samples is set to 120; the correlation degree is set to 0.34; the similarity coefficient is set to 0.56. For online evaluation MOOC the minimum window threshold of teaching quality is $W_{\min} = 0.4$; the maximum window threshold is $W_{\max} = 0.9$; the characteristic component of fuzzy correlation is $C_{\min} = 1.5$; the normalised processing model of evaluation information is $z_i = \frac{x_i}{\max(x_i)}, \quad i = 1, 2, \cdots, 5$. Based on the above index parameter settings, the method proposed in this paper was tested in teaching quality evaluation. Table 1 shows the results of online descriptive statistical analysis of MOOC teaching quality.

Based on the results of the above statistical analysis, The method introduced in this paper is an experimental group, and the methods proposed in Khil et al. (2016), Youcef and Arnaud (2019) and Wang and Wang (2019) are set as the control group. Then, the reliability, response time, and accuracy of them in online evaluation of teaching quality are compared and analysed.

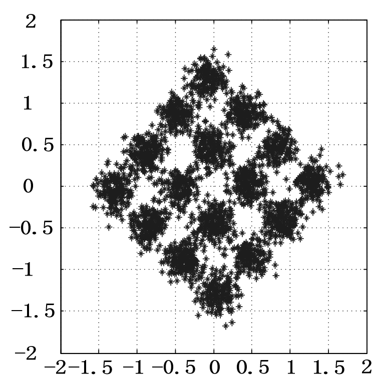
1 Comparative analysis of reliability

Comparison of different methods in online evaluation of MOOC teaching quality is shown in Figure 3.

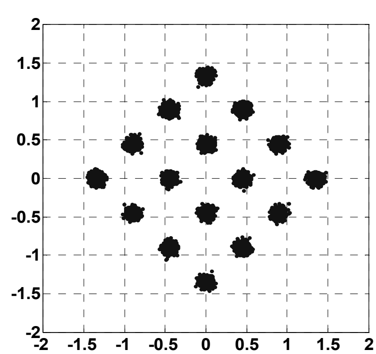
Table 1 Descriptive statistical analysis results of online evaluation of MOOC teaching quality

Experiment time	*Input of teaching resources*	*Classroom teaching effect*	*Students' satisfaction*	*Reliability analysis value*
2011	0.356	0.377	0.332	0.477
2012	0.323	0.743	0.387	0.433
2013	0.589	0.488	0.543	0.477
2014	0.653	0.422	0.476	0.544
2015	0.468	0.347	0.654	0.433
2016	0.321	0.765	0.433	0.486
2017	0.348	0.443	0.486	0.544
2018	0.554	0.334	0.644	0.872
2019	0.578	0.336	0.422	0.357

Figure 3 Comparison of online evaluation results of MOOC teaching quality, (a) raw data (b) the method proposed in this paper (c) the method proposed in Khil et al. (2016) (d) the method proposed in Youcef and Arnaud (2019) (e) the method proposed in Wang and Wang (2019)

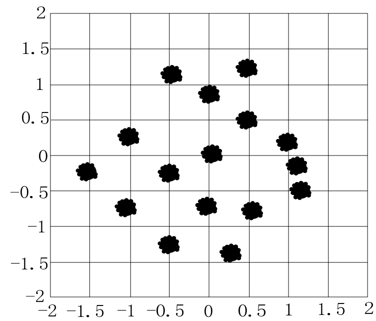


(a)

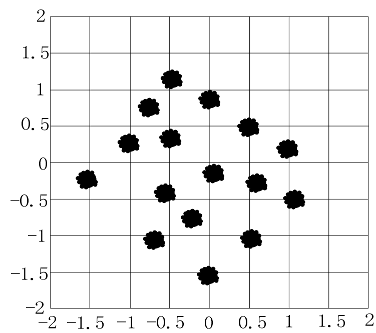


(b)

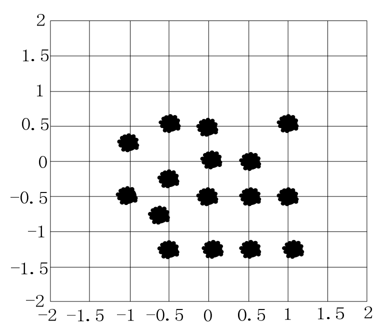
Figure 3 Comparison of online evaluation results of MOOC teaching quality, (a) raw data (b) the method proposed in this paper (c) the method proposed in Khil et al. (2016) (d) the method proposed in Youcef and Arnaud (2019) (e) the method proposed in Wang and Wang (2019) (continued)



(c)



(d)



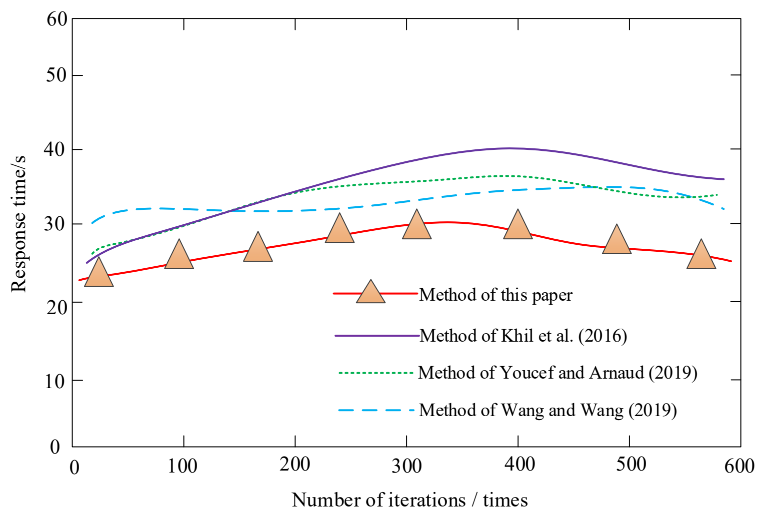
(e)

Analysis of Figure 3 clearly demonstrates that the reliability of evaluation results obtained by the methods proposed in Khil et al. (2016), Youcef and Arnaud (2019) and Wang and Wang (2019) is low, while the method proposed in this paper has high reliability in big data classification for online evaluation of MOOC teaching quality. The circle in the graph represents the cluster centre. According to the experiment, the data provided by the experimental group is more accurate, and can be used to effectively evaluate the raw data.

2 Comparative analysis of response time

The response time of different methods in online evaluation of MOOC teaching quality was tested, Figure 4 shows the results of the comparison.

Figure 4 Response time comparison results of online evaluation (see online version for colours)



Analysis of Figure 4 shows that the response time of the methods proposed in Khil et al. (2016), Youcef and Arnaud (2019) and Wang and Wang (2019), there are many methods used in MOOC teaching quality online evaluation. Therefore, This method can effectively improve the effect of MOOC online teaching quality evaluation.

3 Comparative analysis of accuracy

The accuracy of different methods in online evaluation of MOOC teaching quality was tested, and the comparison results are obtained as shown in Table 2.

Table 2 Comparison of online evaluation accuracy of MOOC teaching quality

Number of iterations	*The method proposed in this paper*	*The method proposed in Khil et al. (2016)*	*The method proposed in Youcef and Arnaud (2019)*	*The method proposed in Wang and Wang (2019)*
100	0.932	0.873	0.822	0.823
200	0.977	0.893	0.845	0.835
300	0.989	0.901	0.884	0.894
400	0.991	0.923	0.892	0.903
500	0.996	0.944	0.912	0.914

The analysis in Table 2 shows that the evaluation accuracy of the method described in the Khil et al. (2016), Youcef and Arnaud (2019) and Wang and Wang (2019) is low. The evaluation accuracy of this method is generally above 93%. Therefore, this method has a high accuracy for the online evaluation of MOOC teaching quality.

5 Conclusions

The online evaluation methods of MOOC teaching quality are studied to optimise the evaluation of MOOC teaching quality. Explanation of this paper, Application of big data classification based on decision tree in MOOC teaching quality online evaluation. Establishing data mining model of distance teaching quality, Using the method of multi index joint analysis and modelling, the online evaluation index system of distance MOOC teaching quality is constructed. With the block region fusion method, big data statistical analysis is carried out for online evaluation of MOOC teaching quality. According to the quantitative feature set analysis and decision tree model construction for online evaluation of remote MOOC teaching quality, Through the establishment of big data decision tree model, this paper analyses the global optimal solution of MOOC online teaching quality evaluation, and uses fuzzy parameter identification method to evaluate MOOC online teaching quality.. With the quantitative regression analysis method, the fuzzy constraint index distribution for online evaluation of MOOC teaching quality is obtained. Analysis reveals that in online evaluation of MOOC teaching quality, this method has the advantages of high precision, good reliability and short response time.

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