

Research Article

Improve the Assessment Model of Personnel Develop Level in Higher Education Based on Machine Learning

Rui Zhu and Yong Li 

Chengdu University, Chengdu, Sichuan 610106, China

Correspondence should be addressed to Yong Li; liyong18@cdu.edu.cn

Received 28 July 2022; Revised 17 August 2022; Accepted 7 September 2022; Published 5 October 2022

Academic Editor: Hangjun Che

Copyright © 2022 Rui Zhu and Yong Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the ability to manage the quality constraint index parameters of higher education talent training, an evaluation model of higher education talent training quality based on improved machine learning is proposed. Combined with the characteristic analysis method of higher education talent training quality constraint index parameters, an autocorrelation feature matching model of higher education talent training quality constraint index parameters is established, and fuzzy association rule scheduling is used to realize the feature extraction and fuzzy clustering of higher education talent training quality constraint index parameters. The mutual information coupling parameter analysis of the quality constraint index parameters of higher education talent training, combined with the generalized association rules and periodic association rules, realizes the feature clustering and global candidate item set analysis of the quality constraint index parameters of higher education talent training and realizes the dynamic evaluation of the quality of higher education talent training according to the machine learning analysis results. The test results show that this method has good clustering of data characteristics, good reliability of the evaluation process, and good convergence of machine learning process, which improves the dynamic and quantitative management ability of talent training quality in higher education.

1. Introduction

With the country's emphasis on the cultivation of personnel in higher education, the quantitative assessment of the level of personnel cultivation in higher education has attracted people's attention. As an important part of teaching assessment, the level assessment of higher education personnel develop plays an important role in daily teaching management [1]. Effective level assessment of higher education personnel develop is conducive to understanding the actual operation of school teaching and supervising the normal and standardized operation of various teaching activities. With the continuous large-scale enrollment expansion of colleges and universities in China for many years, the level of personnel cultivation in higher education has increasingly become the focus of social attention [2]. How to improve the level of education and teaching, cultivate high-level personnel, and establish a scientific, reasonable, fair, and equitable assessment system of personnel cultivation level in higher

education, so as to discover, analyze, and solve problems in time and objectively, has great historical and practical significance for promoting the development of personnel cultivation in higher education [3].

By using big data analysis technology, the assessment model of higher education personnel cultivation level is established, the regression analysis of higher education personnel cultivation level assessment is realized by data mining technology, and the assessment model of higher education personnel cultivation level is constructed by multidisciplinary technology [4]. On this basis, the new technology of higher education personnel cultivation level assessment is developed, which integrates the knowledge of databases, information retrieval, statistics, algorithms, and machine learning [5]. To realize the level assessment of higher education personnel develop, machine learning algorithm is that it can find hidden and valuable information from databases or massive information, sometimes called exploratory data analysis, data-driven discovery, and inductive learning.

Generally speaking, data mining is a process of extracting potentially useful information and knowledge from a large number of incomplete, noisy, fuzzy, and random data, which people do not know in advance in the assessment of personnel cultivation level in higher education [6]. With the wide application of large database and network parallel parameter distribution and fusion technology, the scale of higher education personnel develop level constraint index parameters is increasing, so it is necessary to build an optimized personnel develop level assessment model [7]. Combined with the characteristic analysis and fusion processing of higher education personnel develop level constraint index parameters, a personnel develop level assessment model is built, and according to the characteristic distribution of higher education personnel develop level constraint index parameters, the dynamic assessment of higher education personnel develop level is realized, and the information management ability of higher education personnel develop level constraint index parameters is improved [8].

The assessment of personnel develop level is based on the analysis of the central characteristics of personnel develop level in higher education. Among the traditional methods, the integration methods of the constraint index parameters of personnel develop level in higher education mainly include the assessment method of personnel develop level based on fuzzy information clustering [9], the assessment method of personnel develop level based on fuzzy detection, and the assessment method of personnel develop level based on joint parameter identification. The fuzzy detection model of personnel develop level assessment is constructed, and the cluster of constraint index parameters of personnel develop level in higher education is realized through joint parameter distribution. Reference [10] puts forward a transient stability assessment method considering the cultivation of higher education personnel and combines the neural network model of message transfer graph to realize the data integration management of the cultivation level assessment of higher education personnel, but the storage cost of this method is large. Reference [11] puts forward an intelligent data mining-oriented personnel develop level model of higher education, which combines decentralized and coordinated robust optimal scheduling and data detection to realize the assessment and data analysis of personnel develop level of higher education. However, this method has high computational cost and poor real-time performance.

In view of the above problems, this paper proposes a talent training quality evaluation model based on improved machine learning to realize the mutual information coupling parameter analysis of higher education talent training quality constraint index parameters. The results show that the model has good performance, and the evaluation effect of talent training quality is good.

2. Improve the Theoretical Methods of Machine Learning

Machine learning is an interdisciplinary subject, involving probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory, and many other disci-

plines. Machine learning is the core of artificial intelligence and the fundamental way to make computers intelligent [12]. It is widely used in all fields of artificial intelligence, and it mainly uses induction and synthesis instead of deduction. Some information is provided to the learning part of the environment, and the learning part uses this information to modify the knowledge base, so as to improve the efficiency of the system execution part. The execution part completes the task according to the knowledge base and feeds back the obtained information to the learning part. There are many forms of knowledge representation, such as feature vectors, first-order logical statements, production rules, semantic networks, and frameworks. These representations have their own characteristics. When choosing representations, we should give consideration to strong expressive ability, easy reasoning, easy modification of knowledge base, and easy expansion of knowledge representation. Every learning system requires some knowledge to understand the information provided by the environment, analyze and compare, make assumptions, and test and modify these assumptions. The execution part is the core of the whole learning system, because the actions of the execution part are the actions that the learning part tries to improve. A learning system always consists of two parts: learning and environment [13]. The environment provides information, while the learning part realizes information conversion, memorizes it in an understandable form, and obtains useful information from it. In the process of learning, the less reasoning the learning part uses, the greater his dependence on the environment. Learners directly absorb the information provided by the environment without any reasoning or other knowledge conversion. The systematic learning method is to learn directly through preprogrammed and structured programs, and learners do not do any work or learn directly by receiving established facts and data, without any reasoning about the input information. The improved machine learning algorithm can be adjusted according to training examples, number of features, polynomial degree, and regularization parameters. By obtaining more training examples, the high variance can be solved. Relying on changing the number of features, reducing the number of features can solve the high variance, while increasing the number of features can solve the high deviation. High variance can be solved by changing polynomial degree to reduce polynomial degree, and high deviation can be solved by increasing polynomial degree [14]. Change the regularization parameter: reducing the regularization parameter can solve the high deviation, while increasing the regularization parameter can solve the high variance.

3. Data Structure Model and Feature Analysis

3.1. Higher Education Personnel Develop Level Constraint Index Parameter Structure Model. The assessment of higher education personnel cultivation adopts the principle of combining analysis with synthesis: the assessment of higher education personnel cultivation is a process. The assessment process must be analyzed first, and the effects and characteristics of each part of the teaching process should

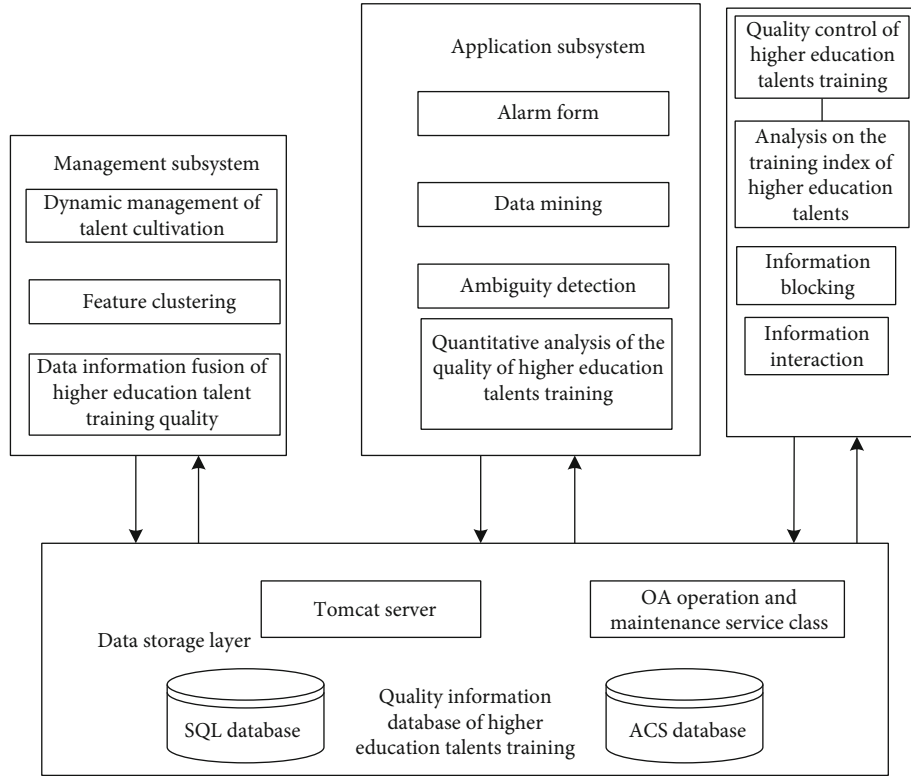


FIGURE 1: Overall structure of level assessment of personnel develop.

be analyzed. Then, on this basis, the overall analysis should be made to judge the level effect of higher education personnel cultivation, which must be synthesized. In this sense, the combination of analysis and synthesis, that is, the principle of combining partial assessment with overall assessment or combining individual assessment with comprehensive assessment with qualitative assessment and quantitative assessment: qualitative assessment is often based on certain observation or experience of teaching [15], which inevitably has subjective components or some one-sidedness, but it cannot be completely ignored. Quantitative assessment is to make a scientific analysis of observation or experience summary through a certain index or index system, in terms of quantity and under a certain confidence level. The quantitative assessment of personnel cultivation level in higher education is quite reliable, because teaching assessment is a complicated process, and it is absolutely reliable because of the selection of index or index system and the influence of systematic error and random error. Therefore, the combination of qualitative assessment and quantitative assessment, mutual reference, and complementarity will reduce the one-sidedness of teaching assessment. In order to realize the dynamic assessment of personnel cultivation level in higher education, this paper combines the heterogeneous reorganization of the big data characteristic distribution of the constraint index parameters of personnel cultivation level in higher education, establishes the big data information analysis model of the constraint index parameters of personnel cultivation level in higher education, and adopts information fusion and

characteristic clustering to realize data integration. The overall structure is shown in Figure 1.

According to the overall structure model of personnel cultivation level assessment in Figure 1, the fuzzy information clustering model of higher education personnel cultivation level constraint index parameters is obtained by using harmonic resonance disturbance characteristic analysis method, and the distribution results of characteristic attributes are obtained [16, 17]. The distribution sequence $A = \{a_1, a_2, \dots, a_n\}$, $B = \{b_1, b_2, \dots, b_m\}$, and the higher education personnel cultivation level constraint index parameters is optimized by online clustering design under the background of big data. The statistical quantization standard function of higher education personnel cultivation level constraint index parameters is as shown in the following formula:

$$\begin{cases} \dot{x} = -\sigma x + \sigma y, \\ \dot{y} = -xz + rx - y, \\ \dot{z} = xy - bz. \end{cases} \quad (1)$$

Wherein, x represents the horizontal component of higher education personnel cultivation level constraint index parameters, y represents the central component of higher education personnel cultivation level constraint index parameters, Z represents the three-dimensional characteristic quantity of higher education personnel cultivation level constraint index parameters, and σ is a fuzzy

membership parameter. Based on the transmission protocol design mode of higher education personnel cultivation level constraint index parameters, the formal characteristic grouping detection model of higher education personnel cultivation level constraint index parameters is obtained as shown in the following formula:

$$d_i = \sqrt{x_i^2 + y_i^2 + z_i^2}. \quad (2)$$

Wherein, x_i is the integration parameter of the i th distribution block of higher education personnel develop level, y_i is the autocorrelation characteristic matching coefficient of higher education personnel develop level, and $z_i^2 D$ is the fuzzy optimization parameter of higher education personnel develop level assessment. The statistical analysis model of parameter clustering of higher education personnel develop level constraint index is established. In the fuzzy grid area, the statistical analysis of parameter clustering of higher education personnel develop level constraint index is carried out, and the parameter structure distribution model of higher education personnel develop level constraint index is obtained.

3.2. Higher Education Personnel Develop Level Constraint Index Parameter Characteristic Analysis. Data structure feature is an important professional basic course for computer majors such as software technology and network technology. It is highly theoretical, practical, and comprehensive and can enable people to learn how to transform real-world problems into internal representation and processing of computers. The factors of higher education personnel develop level assessment are complex, and the workload is heavy, so it is necessary to have an appropriate number of experts and nonexperts, evaluators and evaluators, leaders and the masses, and necessary relevant personnel to participate in the assessment, so as to strengthen the democracy, representativeness, and comprehensiveness of higher education personnel develop level assessment. Establish the autocorrelation characteristic matching model of higher education personnel develop level constraint index parameters, adopt fuzzy association rule scheduling, realize the feature extraction of higher education personnel develop level constraint index parameters, and establish the interactive relationship model of higher education personnel develop level constraint index parameters, which is expressed as shown in the following formula:

$$d_{m+1}(m) = d_{k+1}(m) \pm \sqrt{(d_m(0)e^{\lambda_1} + 1)^2 - \sum_{i=1}^{m-1} [d_{m+1}(i) - d_{k+1}(i)]^2}. \quad (3)$$

Wherein, $d_{m+1}(m)$ is the predicted value of the parameter set of higher education personnel develop level constraint index at point, $d_{k+1}(m)$ is the interactive information of higher education personnel develop level constraint index parameters collected at point m , and $d_m(0)$ is the initial detection statistical characteristic quantity [18, 19]. Considering the equivalent semantic mapping, the fusion analysis

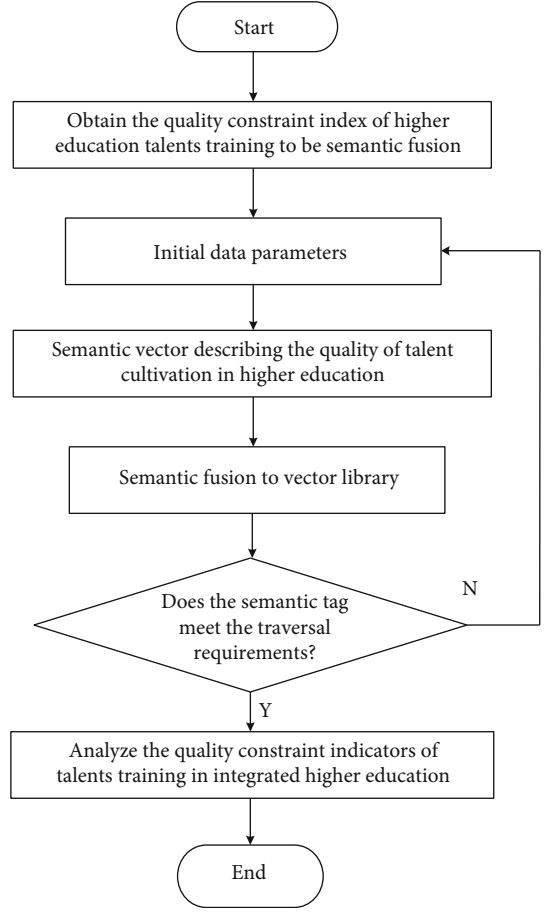


FIGURE 2: The process of parameter fusion of quality constraint indicators of higher education personnel training.

of the level constraint index parameters of higher education personnel develop is carried out. The specific operation process is shown in Figure 2.

Fusion distribution function of the evolution characteristics of the level constraint index parameters of higher education personnel develop is obtained as shown in the following formula:

$$D(d_i, d_j) = \frac{d_i \cdot d_j}{\|d_i\| \times \|d_j\|}. \quad (4)$$

Wherein, d_i represents the level deviation of higher education personnel develop, and d_j represents the adjustment parameter of the decline of higher education personnel develop level. Based on the estimation of virtual inertia frequency deviation, the weight preference of the parameter fusion of higher education personnel develop level constraint index is obtained, as shown in the following formula:

$$P(K = T | R = 1) = \frac{P(K = T)P(K = 1 | K = T)}{P(R = 1)}. \quad (5)$$

Wherein, $P(K = T)$, $P(R = 1 | K = 1)$, and $P(R = 1)$ are,

respectively, shown in the following formulas:

$$P(K = T) = \frac{|C|}{|S|}, \quad (6)$$

$$P(R = 1|K = 1) = \frac{N_B}{|C|}, \quad (7)$$

$$P(R = 1) = \frac{N_S}{|S|}. \quad (8)$$

Wherein, N_B is the recombination dimension of the constraint index parameters of higher education personnel develop level, N_S is the steady-state parameter value of higher education personnel develop level, and C is the dynamic parameter of higher education personnel develop data storage center.

4. Assessment and Optimization of Personnel Develop Level

4.1. Higher Education Personnel Develop Level Constraint Index Parameter Fusion. By using fuzzy association rule scheduling, the feature extraction and fuzzy cluster analysis of higher education personnel develop level constraint index parameters are realized, the cluster model of frequent item set concept tree of higher education personnel develop level constraint index parameters is constructed [20], and the transient feature quantity of broadband window of higher education personnel develop level constraint index parameters is obtained. The high-frequency feature parameters of higher education personnel develop level constraint index parameters are as shown in the following formula:

$$X = A \times S \times C + N. \quad (9)$$

Wherein, A is the regression analysis parameter of higher education personnel cultivation level, S is the modulation parameter of higher education personnel cultivation level assessment, N is the steady regression parameter, and C is the fuzzy parameter of higher education personnel cultivation level assessment. By analyzing the detection statistical characteristic quantity of higher education personnel cultivation level constraint index parameters, the state characteristic equation of higher education personnel cultivation level constraint index parameters is obtained in the maximum amplitude distribution domain within the time window by using fuzzy autocorrelation fusion scheduling method as shown in the following formula:

$$X = \left\{ \begin{array}{cccccc} r_{\{1\}} & r_{\{2\}} & r_{\{3\}} & r_{\{4\}} & r_{\{5\}} & r_{\{i\}} \\ x & ,x & ,x & ,x & ,x & , \dots, x \end{array} \right\}. \quad (10)$$

Wherein, $r_{\{1\}}$ is the initial sampling data time series, and $r_{\{i\}}$ is the final sampling time series for the assessment of personnel cultivation level in higher education. When the

frequency of the system returns to a steady state, the fuzzy clustering center of the constraint index parameters of personnel develop level in higher education is obtained by using the differential fusion matching interactive control method, as shown in the following formula:

$$A = \left\{ r_{a_M}^r(\theta_1), r_{a_M}^r(\theta_2), \dots, r_{a_M}^r(\theta_n) \right\}. \quad (11)$$

Wherein, $r_{a_M}^r$ represents the equivalent inertia of higher education personnel develop level assessment, θ_1 represents the associated dynamic distribution parameters of higher education personnel develop level assessment, $r_{a_M}^r$ represents the sampling frequency of higher education personnel develop level assessment, and θ_n represents that the system frequency returns to a steady state. In the spread spectrum transmission channel, the distribution is dynamically adjusted according to different intervals, and the spread spectrum sequence of constraint index parameters of higher education personnel develop level is obtained as shown in the following formulas:

$$C = \left\{ r_{c_1}^r, r_{c_2}^r, \dots, r_{c_n}^r \right\}, \quad (12)$$

$$S = \text{diag} \sqrt{p_i} g_i d_i(t). \quad (13)$$

Wherein, C represents the collection of database transactions, p_i is the probability density distribution of support degree, g_i is the fuzzy subset, and $d_i(t)$ is the distribution cluster of the cluster center for the assessment of personnel cultivation level in higher education [21].

Under the optimized control rules, the sparse scattered point parameter fusion model of higher education personnel develop level constraint index parameters is established, and the characteristic clustering and global candidate item set analysis of higher education personnel develop level constraint index parameters are realized by combining the analysis of generalized association rules and periodic association rules. The reference vector of higher education personnel develop level constraint index parameters retrieval is expressed as shown in the following formula:

$$E[N_{kl}^* N_{nm}] = \sigma^2 \times \delta_{km} \times \delta_{ln}. \quad (14)$$

Wherein, σ is the root-mean-square error of minimum support, δ_{km} is the regression steady-state parameter of higher education personnel develop level assessment, and δ_{ln} is the joint detection probability density. The transaction database is transformed into a transaction matrix, and the fuzzy retrieval and information clustering analysis of the constraint index parameters of personnel develop level in higher education are carried out through the feature extraction results [22].

4.2. Higher Education Personnel Develop Level Constraint Index Parameter Mining and Integration. In order to realize the fuzzy information integration of the constraint index

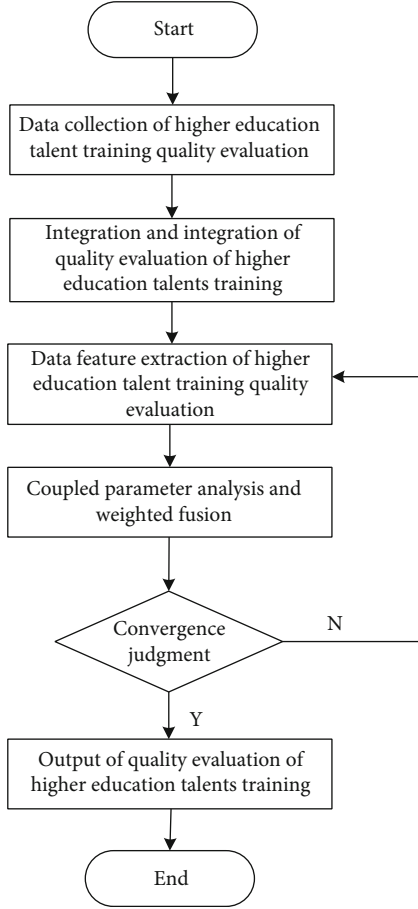


FIGURE 3: Implementation process of improved algorithm.

parameters of personnel develop level in higher education, the fuzzy sampling time series of each combination pair is taken as the constraint parameter, and the spatial distribution matrix of personnel develop level assessment is obtained as shown in the following formula:

$$X = [\vec{a}_1, \vec{a}_2] \begin{pmatrix} s_1 & 0 \\ 0 & s_2 \end{pmatrix} \begin{pmatrix} \vec{c}_1 \\ \vec{c}_2 \end{pmatrix}. \quad (15)$$

Wherein, \vec{a}_1 , \vec{a}_2 , \vec{c}_1 , and \vec{c}_2 are the direction vectors in the high-dimensional random matrix of higher education personnel develop level constraint index parameters. The regression analysis model of higher education personnel develop level constraint index parameters is constructed by using the steady-state regression analysis method, and the output of regression analysis is as shown in the following formulas:

$$H(S) = - \sum_{i=1}^n P_s(s_i) \log_2 P_s(s_i), \quad (16)$$

$$H(Q) = - \sum_{j=1}^n P_q(q_j) \log_2 P_q(q_j). \quad (17)$$

Wherein, $P_s(s_i)$ represents the probability that the concept set s_i of higher education personnel develop level constraint

TABLE 1: Descriptive statistical distribution of level constraint index parameters of higher education personnel develop.

Assessment sample	Practical parameters of teaching activities	Teaching objectives	Correlation test parameters	Assessment coefficient
1	9.154	4.617	74.385	8.886
2	5.776	8.685	6.355	8.745
3	7.838	0.424	8.997	9.961
4	5.854	6.667	9.812	7.137
5	5.372	8.752	7.163	6.993
6	3.584	2.768	6.685	5.066
7	1.417	5.200	6.910	9.216
8	9.629	9.692	9.454	3.081
9	5.607	7.094	3.639	0.122
10	4.129	7.642	8.167	0.949
11	3.428	0.158	0.987	3.037
12	8.410	6.111	6.389	2.387

index parameters appears in the fuzzy concept set S , and $P_q(q_j)$ has a similar definition. Using prior sample analysis, the integrated output of higher education personnel develop level constraint index parameters is obtained under differentiated integration, as shown in the following formula:

$$I(Q, S) = H(Q) - H(Q|S). \quad (18)$$

Wherein, the expression of $H(Q|s_i)$ is shown in the following formula:

$$H(Q|s_i) = - \sum_j \left[\frac{P_{sq}(s_i, q_j)}{P_s(s_i)} \right] \log_2 \left[\frac{P_{sq}(s_i, q_j)}{P_s(s_i)} \right]. \quad (19)$$

It represents the edge template matching degree of personnel develop level assessment under the satisfied conditions. According to the above analysis, a matched filter detection model of personnel develop level assessment and a sparse scattered point parameter fusion model of higher education personnel develop level constraint index parameters are constructed [23]. The characteristic clustering and global candidate item set analysis of higher education personnel develop level constraint index parameters are realized by combining the generalized association rules and periodic association rules analysis, and the dynamic assessment output function is expressed as shown in the following formula:

$$K_{wpg}(x, y, w_i) = \begin{cases} 1 & d(w_i, k) \leq r - r_u, \\ u \left(\frac{-\alpha_1 \theta \beta_1}{\theta_2 \beta_2} \right) + \alpha_2 & r - r_u < d(w_i, k) < r + r_u, \\ 0 & \text{else.} \end{cases} \quad (20)$$

In the above formula, r_u ($0 < r_u < r$) represents the difference operator of higher education personnel develop level

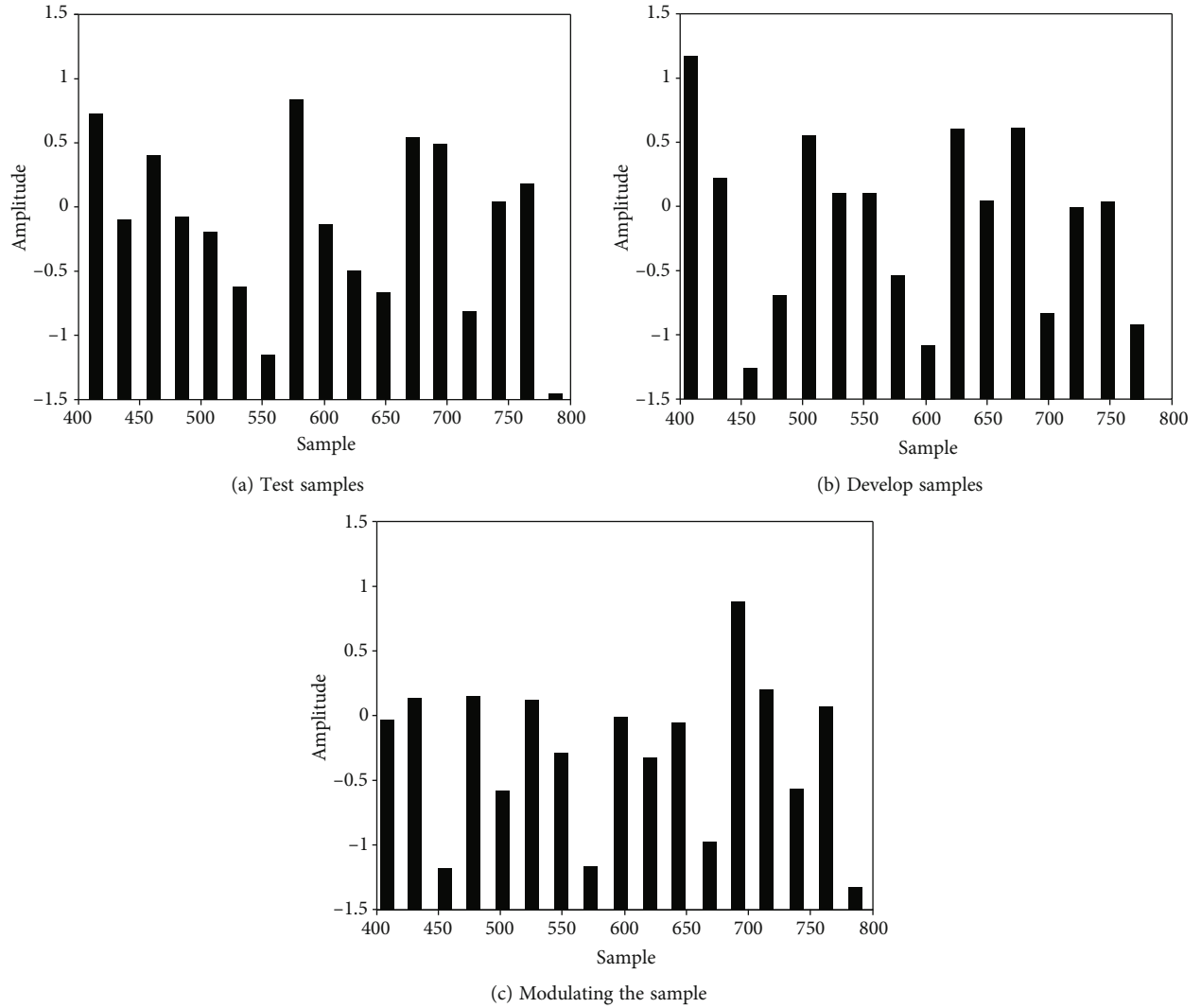


FIGURE 4: Time-domain distribution of constraint index parameters of personnel cultivation level in higher education.

constraint index parameter detection, β_1 is frequent set, β_2 is the basic data for assessment and analysis, α_1 is the matching degree of each nonempty subset of the final frequent item set, and α_2 is the parameter of support and confidence assessment system [24, 25]. Combining generalization association rules and periodic association rules analysis, the characteristic clustering and global candidate item set analysis of higher education personnel develop level constraint index parameters are realized [26], and data integration processing is realized according to the results of spectrum parameter clustering analysis. The realization process is shown in Figure 3.

5. Experimental Test

In order to verify the application performance of this method in the assessment of personnel develop level, the Matlab simulation tool is used for the test. First, all the students' usual scores and final exam scores are added to get a comprehensive score, which is sorted out in Excel, and the Excel file containing the comprehensive scores of several courses to be used is named MARK.xls. This paper applies

Weka, a tool commonly used in cluster analysis technology of personnel develop level assessment. Weka supports files in CSV and ARFF data formats. In data analysis, the earliest data is stored in EXCEL files, so we first need to convert the original data stored in Excel into CSV files or ARFF files. The specific operation is in Microsoft Excel software, open the file named "Mark.xls" and then select "Save As" in the "File" menu to save the file as the type with the suffix ".csv." Finally, we got the "Mark.csv" file open: the low frequency of the constraint index parameters of higher education personnel cultivation level is 49.40 Hz, the sampling rate of strong association rules is 124 kHz, the length of the sample data of personnel cultivation level is 12,000, and the adaptive adjustment coefficient is 0.854, see Table 1 for the descriptive statistical distribution of the constraint index parameters of higher education personnel cultivation level.

According to the parameter settings in Table 1, the time-domain distribution of the constraint index parameters of personnel cultivation level in higher education is shown in Figure 4.

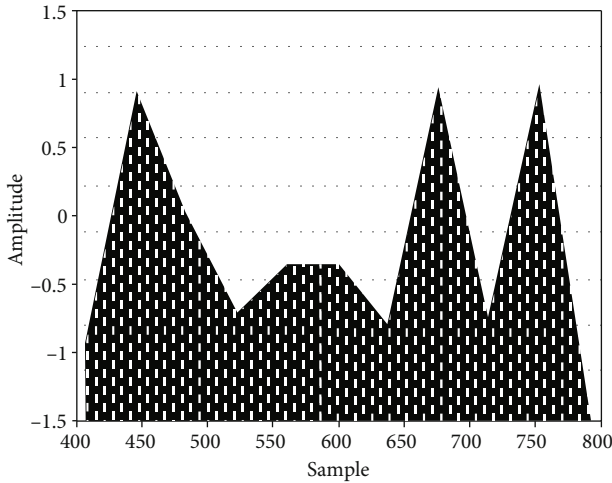


FIGURE 5: Output of level assessment of higher education personnel develop.

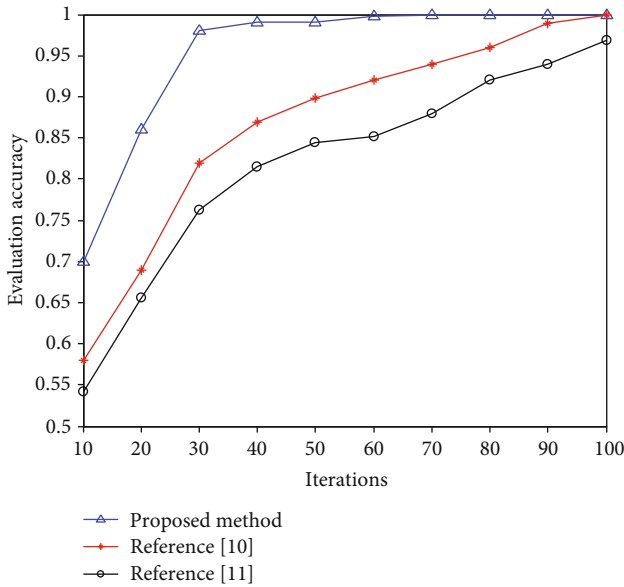


FIGURE 6: Comparative test of assessment reliability.

Take the data of test samples, training samples, and modulation samples in Figure 4 as the research object to evaluate the quality of talent training. In the evaluation process, based on improved machine learning, the output of evaluation results is shown in Figure 5.

According to the analysis of Figure 5, this method can effectively realize the dynamic assessment of higher education personnel cultivation level and improve the clustering performance of the constraint index parameters of higher education personnel cultivation level, the reason is that this method analyzes the evaluation process, analyzes the effects and characteristics of each part in the teaching process, and then makes an overall analysis on this basis to judge the quality effect of higher education talent training, which is conducive to enhancing the output results of higher education talent training quality evaluation.

And test the storage cost after the assessment of personnel cultivation level, as shown in Figure 6.

According to the analysis of Figure 5, comparing the methods of reference [4] and reference [5], this method compares the reliability of higher education talent training quality evaluation. The reason is that this method adopts fuzzy association rule scheduling to realize the feature extraction and fuzzy clustering analysis of higher education talent training quality constraint index parameters and build a frequent item set concept tree clustering model of higher education talent training quality constraint index parameters, and obtaining the transient characteristic quantity of the broadband window of the quality constraint index parameters of higher education talent training is conducive to improving the reliability of the evaluation to a certain extent.

6. Conclusions

In this paper, an assessment model of personnel develop level in higher education based on improved machine learning is proposed. Combining with the characteristic analysis method of higher education personnel develop level constraint index parameters, this paper establishes the autocorrelation characteristic matching model of higher education personnel develop level constraint index parameters, adopts fuzzy association rule scheduling to realize feature extraction and fuzzy cluster analysis of higher education personnel develop level constraint index parameters, constructs the concept tree clustering model of frequent item sets of higher education personnel develop level constraint index parameters, and adopts the association rule matching method. The mutual information coupling parameter analysis of higher education personnel develop level constraint index parameters is realized, and the sparse scattered point parameter fusion model of higher education personnel develop level constraint index parameters is established. The characteristic clustering and global candidate item set analysis of higher education personnel develop level constraint index parameters are realized by combining generalized association rules and periodic association rules analysis, and the dynamic assessment of higher education personnel develop level is realized according to the machine learning analysis results. The test results show that this method has good clustering of data features, good reliability of assessment process, and good convergence of machine learning process, which improves the dynamic and quantitative management ability of personnel develop level in higher education. This method is of great significance in improving the assessment ability of personnel cultivation level in higher education.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

Acknowledgments

This work supported by Talent Cultivation Quality and Teaching Reform Project of Chengdu University “From Emerging to First-class: An Exploration of the Educational Mode of” One Foundation, Three Yuan, Integration of Innovation and Integration “in Urban Universities under the Integrated Development of University and City” (CDJGB2022191).

References

- [1] Z. H. O. U. Lin and W. A. N. G. Shu, “Challenges and strategies of the talent cultivation of undergraduate education major[J],” *Journal of National Academy of Education Administration*, vol. 291, no. 3, pp. 46–55, 2022.
- [2] L. I. Xinhao, H. O. U. Ke, and G. U. O. Mingcheng, “Research on talent training mode of big data major[J],” *Journal of Yanqing Vocational & Technical College*, vol. 20, no. 3, pp. 47–52, 2021.
- [3] D. U. Lijuan, “Research on university education quality grading evaluation based on data mining[J],” *Modern Electronics Technique*, vol. 43, no. 15, pp. 101–104, 2020.
- [4] D. U. Jiayin, “Application of data mining in the training of technical network talents[J],” *Modern Computer*, vol. 27, no. 17, pp. 69–71+75., 2020.
- [5] X. Xiaoyun, Z. Xiaodong, W. Shuai, L. Jinming, C. Lulu, and Z. Zhiyang, “Improved EM algorithm of semi-supervised machine learning[J],” *Journal of Chinese Computer Systems*, vol. 41, no. 2, pp. 230–235, 2020.
- [6] Z. Yadi, S. Yue, L. Feng, and Z. Erzhou, “Study on density parameter and center-replacement combined K-means and new clustering validity index[J],” *Computer Science*, vol. 49, no. 1, pp. 121–132, 2022.
- [7] W. A. N. G. Lijuan and D. I. N. G. Shifei, “A spectral clustering algorithm based on ELM-AE feature representation[J],” *CAAI Transactions on Intelligent Systems*, vol. 16, no. 3, pp. 560–566, 2021.
- [8] Z. Erzhou, S. Yue, Z. Yuanxiang, G. Xin, M. Ruhui, and L. Xuejun, “Optimal clustering number determining algorithm by the new clustering method[J],” *Journal of Software*, vol. 32, no. 10, pp. 3085–3103, 2021.
- [9] L. I. Huirong, Z. H. Lin, Z. H. Pengjun, and L. I. Chao, “Semi-supervised concept factorization algorithm with local coordinate constraint[J],” *Journal of Frontiers of Computer Science & Technology*, vol. 15, no. 2, pp. 379–388, 2021.
- [10] T. A. N. G. Hanqiao and S. H. E. N. Lei, “Construction of university education informatization benefit evaluation model using cloud model data mining algorithm[J],” *Modern Electronics Technique*, vol. 43, no. 13, pp. 25–27,31, 2020.
- [11] L. I. U. Weijun and L. I. Xiaohui, “Research on terminal online education data mining technology based on model driving[J],” *Modern Electronics Technique*, vol. 43, no. 16, pp. 112–114,118, 2020.
- [12] J. I. Shouling, D. U. Tianyu, L. I. Jinfeng et al., “Security and privacy of machine learning models:a survey[J],” *Journal of Software*, vol. 32, no. 1, pp. 41–67, 2021.
- [13] L. Zhouzhou, Y. Wenxiao, Z. Qianyun, and P. Han, “Sensor cloud intrusion detection based on discrete optimization algorithm and machine learning[J],” *Journal of Jilin University(Engineering and Technology Edition)*, vol. 50, no. 2, pp. 692–702, 2020.
- [14] H. A. N. Gaofeng and Z. H. O. N. G. Yuanquan, “Application of improved machine learning algorithm in network data security risk prediction[J],” *Journal of Inner Mongolia University for Nationalities(Natural Sciences)*, vol. 35, no. 1, pp. 30–35, 2020.
- [15] L. I. U. Peng and J. I. A. Wenya, “The teaching quality evaluation model of the RBF neural network based on particle swarm optimization[J],” *Modern Computer*, vol. 27, no. 19, pp. 12–15, 2020.
- [16] X. Zhuoyu, H. Pei, C. Guo, X. Yunbiao, and G. Jie, “Design pattern classification mining with feature metrics constraints[J],” *Journal of Shandong University(Engineering Science)*, vol. 50, no. 6, pp. 48–58, 2020.
- [17] G. Jinliang, C. Tao, Z. Yanfei, and L. Yubin, “An improved interframe differential target detection and tracking algorithm based on multi-region information fusion constraints[J],” *Journal of Jiangsu University(Natural Science Edition)*, vol. 43, no. 3, pp. 302–309, 2022.
- [18] L. I. U. Zhongbao and Z. H. A. O. Wenjuan, “Research on cross-media correlation analysis by fusing semantic features and distribution features[J],” *Journal of the China Society for Scientific and Technical Information*, vol. 40, no. 5, pp. 471–478, 2021.
- [19] C. Bo, X. Jun, M. Duoqian, W. Yuzhu, and X. Xinying, “Chinese text sentiment feature analysis based on rough set and multi channel word vector[J],” *Journal of Chinese Information Processing*, vol. 34, no. 8, pp. 94–104, 2020.
- [20] C. H. E. N. Tong, F. A. N. Beibei, and C. H. E. N. Dongping, “Intuitionistic fuzzy vector association rules mining based on dual fuzzy simulation[J],” *Computer Integrated Manufacturing Systems*, vol. 26, no. 7, pp. 1875–1886, 2020.
- [21] B. I. A. N. Chen, X. I. U. Weirong, and Y. U. Jiong, “A data skew correction scheduling strategy of heterogeneous spark cluster[J],” *Computer Engineering and Science*, vol. 44, no. 4, pp. 620–630, 2022.
- [22] H. E. Dengping, Z. H. A. N. G. Weiyi, and H. U. A. N. G. Hao, “A hybrid recommendation algorithm based on multi-source information clustering and IRC-RBM[J],” *Computer Engineering and Science*, vol. 42, no. 6, pp. 1089–1095, 2020.
- [23] Z. H. A. O. Yuming, S. H. U. Hongping, W. E. I. Peiyang et al., “Clustering algorithm for sparse data set[J],” *Science Technology and Engineering*, vol. 20, no. 2, pp. 659–663, 2020.
- [24] F. A. N. G. Jiayan and L. I. U. Qiao, “Iterative tighter nonparallel hyperplane support vector clustering with simultaneous feature selection[J],” *Acta Electronica Sinica*, vol. 48, no. 1, pp. 44–58, 2020.
- [25] W. E. N. Mingyao and L. I. A. O. Weiguo, “Incremental mining algorithm for uncertain data based on machine learning[J],” *Computer Simulation*, vol. 38, no. 11, pp. 290–294, 2021.
- [26] Y. A. N. G. Yun and L. I. U. Yanrong, “An efficient algorithm for mining high average utility term set[J],” *China Computer & Communication*, vol. 32, no. 5, pp. 67–69, 2020.