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A PARAMETER ASSESSMENT OF TEACHING QUALITY INDICATORS BASED ON DATA CLASS MINING FUZZY K-MEAN TYPE CLUSTERING

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Abstract. This paper proposes a data-based mining and hesitant fuzzy C-canopy-K mean clustering degree algorithm and uses it in the parameter assessment model of teaching quality indicators. Simulation and training are carried out through data class mining, and information input, followed by combining the hesitant fuzzy K-mean classification assessment method, which involves a hesitant fuzzy type evaluation system, a neural network identification and prediction system, and an application system for module identity verification. The simulation results show that the results of the six simulation conditions are consistent with the actual results, with only slight differences in some amplitudes, and a high degree of consistency in the overall trend, the change rule, and the average peak value. Through the prediction model processing in this paper, the teaching quality index parameter assessment has high accuracy and can reach more than 95.0%, in addition, the development of the law also fits very well. a, b, c, d four kinds of teaching quality parameter assessment of the average calculation of the assessment speed increased by 52.5%. In addition, the assessment test after the integrated design of the module shows that the system can effectively identify the four clustering identification processes that can be seen as excellent, good, medium, and poor; at the same time, the test data show that the system class effectively for teaching quality indicator parameter assessment.

Key words: fuzzy K-clustering; C-anopy-K mean; data class mining; teaching quality; indicator parameter assessment

1. Introduction. With the rapid development of Internet technology, people's lives have become closely related to the Internet. In the context of the rapid popularization of the Internet, the behavioral analysis of Internet users has now become an advantageous means of gaining insight into users' teaching quality and other preferences, learning ability, etc. [1]. The analysis of user Internet behavior provides more diversified choices for intelligent network module authentication, but at the same time, it also puts forward more stringent technical requirements and specifications for intelligent network module authentication. The Internet behavior of network users is monitored by the data platform, while the platform understands the user's intention through data analysis, thus promoting the benign development of the network ecosystem [2, 3]. Currently, servers for certified billing, traffic line monitoring, and other applications are already widely used in the teaching quality management of major universities. These application servers provide management convenience for colleges and universities at the same time but also generate a large amount of log data, which is usually stored in the background database. Analysis shows that the log data contains a large number of user behavioral data on the Internet [4, 5]. Suppose the behavioral data in the logs can be scientifically and efficiently analyzed, and the deep-seated laws hidden in the data can be utilized. In that case, it will greatly improve the speed of network management assessment in universities, build effective support for network management in universities, and provide useful help for the scientific decision-making and management refinement. This paper takes a specific university as an example [6], analyzes the clustering of user online behavior data, mines the intrinsic laws, and helps the smooth implementation of university decision-making [8]. In traditional comprehensive indicators, raw data are usually given in the form of point values (real numbers). However, with the development of society, the evaluation environment is becoming more and more complex, and the evaluator is often affected by some of his own subjective and objective factors, such as knowledge structure [7], judgment level, and personal preference [9-10], and the evaluations made are largely imprecise or fuzzy [9]. In the evaluation of the level of impact of the resumption of production by enterprises on the recovery of the local economy after the epidemic, due to the existence of many uncertain factors, the learning parameters have a hesitant mentality when scoring

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[10], or multiple learning parameters have multiple different judgment results for them. Zadeh [13] proposed the concept of fuzzy sets in 1965, allowing the degree of affiliation of an element belonging to a set to be taken arbitrarily in the [0, 1]. The theoretical foundation of fuzzy sets was laid down by Torra et al [15, 14], who proposed the definition of hesitant fuzzy sets, where multiple values can be selected as the final degree of affiliation when the decision maker is hesitant. Xu Zeshui's team [16, 17] proposed a distance measure and a similarity degree measure formula between hesitation class fuzzy type sets and gave proof. Xia Meimei proposed a series of hesitant fuzzy distance and similarity degree formulas. [18] Clustering is the process of dividing a series of pairs of images, scenarios, events, etc., into several classes, where the characteristics of the objects in each class have a higher degree of similarity than the other classes. The analysis of clustering is the use of mathematical methods to classify objective things according to defined criteria, the degree of similarity of the samples as the principle of division, so that the selection of the appropriate degree of similarity becomes the key to clustering. Facing different fuzzy environments, various clustering degree algorithms have been proposed to deal with different types of fuzzy data, such as the intuitionistic fuzzy clustering degree algorithm [19], the two-type fuzzy clustering degree algorithm [20], etc. In 2015, Chen Na [21] proposed an algorithm to cluster hesitant fuzzy-type information based on the fuzzy information integration operator and the measure of the distance. In 2008, many scholars and others [22, 23, 24, 25, 26] applied the K-mean algorithm to fuzzy clustering. In the traditional K-mean clustering degree algorithm, due to the initial clustering center being random, sometimes needs to iterate several times to get the final clustering results, to a certain extent, affecting the speed of clustering evaluation. The c-anopy algorithm belongs to a kind of "coarse" clustering degree algorithm, through a simple, fast distance calculation can be hesitant fuzzy type set into several overlapable clusters. The fuzzy type set can be divided into several overlapping subsets by simple and fast distance calculation [29]. Moreover, compared with the traditional K-mean clustering degree algorithm, it does not need to formulate the number of clusters in advance. Therefore, to simplify the number of iterative approximations in the clustering degree algorithm, this paper proposes a K-mean hesitant fuzzy clustering degree algorithm based on the C-anopy algorithm [27]. Therefore, this paper develops a model of a new algorithm of prediction and assessment based on data class mining hesitant fuzzy K-mean type clustering for parameter assessment of teaching quality indicators, which can greatly improve the speed and accuracy of assessment based on the original model [28, 29, 30, 31].

2. Hesitant Fuzzy Assessment Model and Algorithm. The overall model architecture of this paper is shown in Figure 2.1, which involves a hesitant fuzzy type evaluation system, a neural network identification and prediction system, and an application system for modular identity verification. Through data class mining, information input, after that, combined with hesitant fuzzy K-mean type clustering method for simulation and training. A new algorithmic system for prediction and evaluation is developed by obtaining several predictions. Finally, the assessment of teaching quality and practical application is accomplished through the final component of the clustering degree algorithm. The specific kernel composition and calculation method are described in detail in the following.

2.1. Distance formula for hesitant class fuzzy type sets. In this given set, the occupation ratio, where is the occupation of the element in the set X and satisfies, let M be a hesitant class fuzzy type set defined on the set X. The measured (M, N) of the distance between M and N satisfies the following property.

1. 0 d (M, N) 1.
2. d (M, N) = 0 holds if and only if M = N;
3. d (M, N) = d (N, M)

Under the above-given conditions, the hesitant fuzzy weighted Euclidean degree distance formula is defined as:

$$d_{\mathrm{hw}}(M,N)=\left[\sum_{i=1}^{n} w_i\left(\frac{1}{l_{x_i}}\sum_{j=1}^{l_{x_i}}\left|h_M^{\sigma(j)}(x_i)-h_N^{\sigma(j)}(x_i)\right|^2\right)\right]^{\frac{1}{2}} \tag{2.1}$$

where $h_M^{\sigma}(j)$ and $h_N^{\sigma}(j)$ are the first largest element in the hesitant fuzzy degree number, respectively. To facilitate the calculation, the length of the paste number needs to be the same in each model, so it is necessary to add elements to the set with a short length of the hesitant ambiguity degree. In this paper, it is stipulated

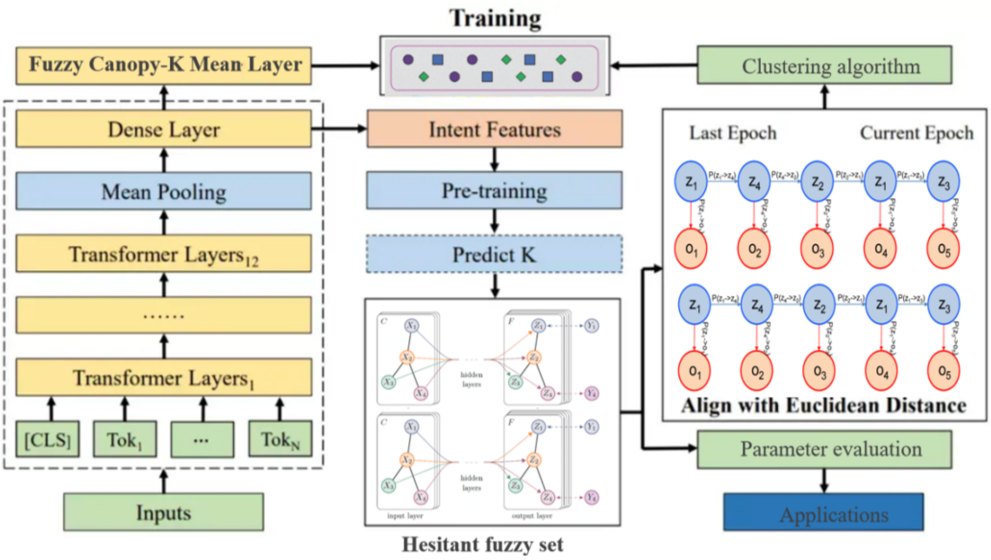

Fig. 2.1: Overall flowchart of the model

that the element with the smallest value in the set is added for the set that needs to be added. Then one of the hesitant fuzzy type sets can be written:

$$M_j = \{(x_i, h_{A_j}(x_i)) \mid x_i \in X\} \quad \text{for } j = 1, 2, \ldots, k \tag{2.2}$$

2.2. Recursive approximation for the assessment of teaching quality parameters. A quantitative recursive analysis method was used to analyze the big data information model for the assessment of comprehensive teaching competence.4 The control objective type function for constructing the predictive estimation of comprehensive teaching competence was:

$$\max_{x_{a,b,d,p}} \sum_{a\in A} \sum_{Ab\in B} \sum_{d\in D} \sum_{p\in P} x_{a,b,d,p} V \tag{2.3}$$

$$\sum_{a} \sum_{b} \sum_{d} x_{a,b,d,p} R_p^{bw} \leq K_b^{bw}(S), \quad b \in B \tag{2.4}$$

Quantitative recursive assessment of the level of comprehensive teaching ability using the gray degree model, assuming that the historical data of the distribution of comprehensive teaching ability is expressed as (x), and the probability density generalization of the predictive estimation of comprehensive teaching ability is obtained as with a certain initial value of the perturbation feature:

$$u_c(t) = K x_c(t) \tag{2.5}$$

In the high-dimensional characteristic type distribution space, the integrated teaching ability prediction estimation statistical model of the continuous function of u: IR→IR, after k-1 iterative approximation, k>1, integrated teaching ability assessment of the grayscale degree sequence to satisfy the N (k) < L, using quantitative type recursive analysis method, to get to the integrated teaching ability assessment of the output of the index distribution of the situation of big data information number of the K nearest-neighbor residue value is:

$$P_{1J} = \sum_{d_i \in \mathrm{KNN}} \mathrm{Sim}(x, d_i) \cdot y(d_i, C_j) \tag{2.6}$$

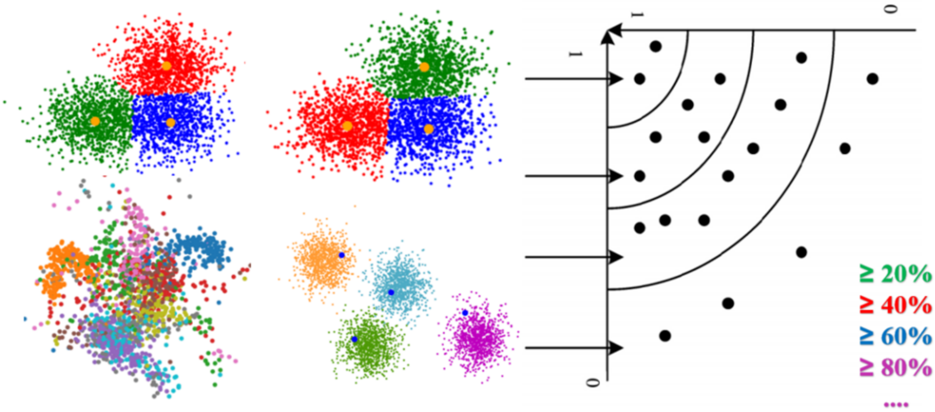

Fig. 3.1: Hesitant fuzzy algorithm clustering process schematic

The sequence of exponential correlation distributions (x) of the comprehensive teaching competence assessment of the large clustering degree data study was quantitatively analyzed and combined with the K-value optimization search method to obtain the quantitative recursive feature extraction results of the teaching competence assessment as:

$$x_n = a_0 + \sum_{i=1}^{M_{\mathrm{AR}}} a_i x_{n-i} + \sum_{j=0}^{M_{\mathrm{MA}}} b_j \eta_{n-j} \tag{2.7}$$

where α_0 is the amplitude of the sampling of the initial comprehensive teaching competency teaching assessment; x_n is the time series of the scalar; b_j is the oscillatory downward decay value of the comprehensive teaching competency assessment.

3. Parameter evaluation simulation program design. The K-mean hesitant fuzzy clustering degree algorithm based on the Canopy algorithm proposed in this paper uses Canopy clustering (Program 1) as a cluster to obtain the K-mean initial class centers, which are subsequently used to obtain the K-mean clusters by K-mean type clustering (Program 2) The final clustering results are obtained. The specific steps are as follows:

Step 1 Suppose k hesitant fuzzy type sets M, M2, ..., Mn

Step 2 Take an arbitrary class M, from which the distance D between the class M, and the remaining k-1 classes is calculated by Equation (1). set the values of the 2-distance kurtosis values T, T2 based on a priori knowledge, where T, > T2.
Here, T is chosen as the mean value after removing the minimum and maximum distances, and if T2<D<T, a weak mark is given to R to indicate that R belongs to that C-anopy, and R is added to it; if D<T2, a strong mark is given to R to indicate that R belongs to that C-anopy and is very close to the center of mass, and R is deleted from the set, and will not be a centroid in the future; if D>T, then R forms a new set of clusters and R is removed from the set.

Step 3 Repeat Step 2 until the elements within each set no longer change, at which point c Canopy (1<c<k) will be formed, each containing one or more hesitant class fuzzy type sets M. In this paper, we will denote each C-anopy as a hesitant class fuzzy type set M, (j=1, 2, c).

Step 4 From Eq. (3) combine M, (j = 1, 2, c) in the hesitant fuzzy type sets M are merged, and the class center of each M is calculated. The process of clustering is shown in Figure 3.1.

Step 5 Obtain the number of categories of clusters c and the initial cluster centers from Procedure 1.

Table 3.1: Indecisive fuzzy assessment information

mould	M1	M2	M3	M4	M5
X1	{0.1,0.4}	{0.4,0.7}	{0.45,0.5,0.6}	{0.3,0.5}	{0.8,0.9,1}
X2	{0.1,0.3}	{0.5,0.6,0.8}	{05}	{1}	{0.9}
X3	{0.4,0.5,0.6}	{0.5,0.6}	{0.1, 0.15, 0.2}	{0.5,0.7}	{0.7.0.8, 0.85}
X4	{0.4}	{0.15, 0.2, 0.35}	{0,0.1,0.2}	{0.4, 0.5, 0.65}	{0.6,0.8}
X5	{0.3,0.4,0.5}	{0.1,0.2,0.3}	{0.2,0.4}	{0.35}	{0.4, 0.5, 0.75}
X6	{0.2}	{0.6,0.7}	{0.5,0.6,0.8}	{0.4}	{0.3,0.35}

Step 6 Calculate the distance between the hesitant class fuzzy type set M and the class center by using Equation (1), and merge M into the class closest to the class center.

Step 7 Calculate the new class center from equation (3).

Step 8 Repeat steps 6 and 7 until the hesitant blur Can-copy-K iterative approximation reaches clarity and stability.

Step 9 Setting up under different working condition characteristics through the joint model, and evaluation application of subsequent equations (4-6), etc.

Considering that different learning parameters may give different assessment values for the attributes of the program, the hesitant fuzzy type set is used to represent the assessment information for the development status of the five teaching qualities. The specific data calculated by preliminary simulation are shown in Table 3.1.

4. Practical test analysis. To better illustrate the effectiveness and stability of the hesitant fuzzy C-anopy-K-mean type clustering degree algorithm proposed in this paper, the specific clustering process of the newly proposed algorithm is first given in combination with example data. Then, it is compared and analyzed with the K-mean type clustering degree algorithm based on hierarchical analysis. Matlab-2020 co-simulation analysis method was used to test the analysis performance under big data of comprehensive teaching ability assessment, statistical type analysis method was used to sample the data of comprehensive teaching ability assessment, the kurtosis value of decision making of teaching ability assessment was taken as D, $= 2$, the correlation parameter of the distribution of comprehensive teaching resources was set as $= 3/5$, $= 2/5$, $= 2/5$, $maxg1(d) = 6/5, maxg2(d) = 3/8$, $maxg3(d) = 1/10$, sampling frequency f=600 Hz, adaptive initial step size p=0.97, and the coefficient of correlation of the distribution of teaching resource characteristics is B=1.14. According to the above parameter settings, the big data reconstruction of the constraint parameters of the comprehensive teaching ability assessment is carried out, and the six time-domain waveforms of the big data distributions of the actual test are obtained as shown in Figure 4.1 shows.

After the fuzzification process through the above model, the waveforms of the six time-domain waveforms directly predicted by the parameters in the simulation model are shown in Fig. 4. It can be found that the results of the six time-domain waveforms predicted by the model in this paper are very similar to those of the original big data, and the peaks are comparable. Among them, the degree of conformity of condition 1 - condition 6 is consistent, only in some amplitude slightly different, which is due to the identification of the sampling frequency interval decided. Still, the overall trend, change rule, and average peak value have a high degree of consistency.

In the paper, four clusters A, B, C, and D are used in the application of K-Mean-s, and each of the four clusters accounts for 10%, 20%, 30%, and 40% of the total sample capacity. The overall parameters in the above model are made as the object of study, data clustering and information fusion processing are carried out and realized to achieve the assessment of teaching ability, and the results are shown in Figure 5. It can be found that through the above model parameters, the classification identification carried out and the prediction results are in good agreement. It shows that after processing through the prediction model in this paper, the assessment of teaching quality index parameters has high accuracy, which can reach more than 95.0%, in addition to the development law is also very suitable.

In addition, our model was compared with the traditional model in terms of computational assessment speed for the assessment of four teaching quality parameters, A, B, C, and D. The results are shown in

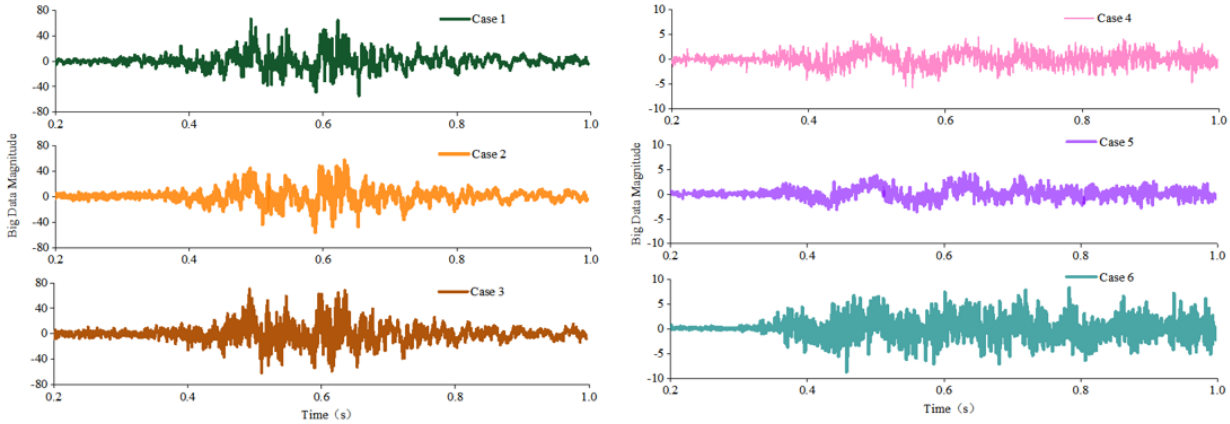

Fig. 4.1: Schematic representation of the six waveforms of big data on teaching quality

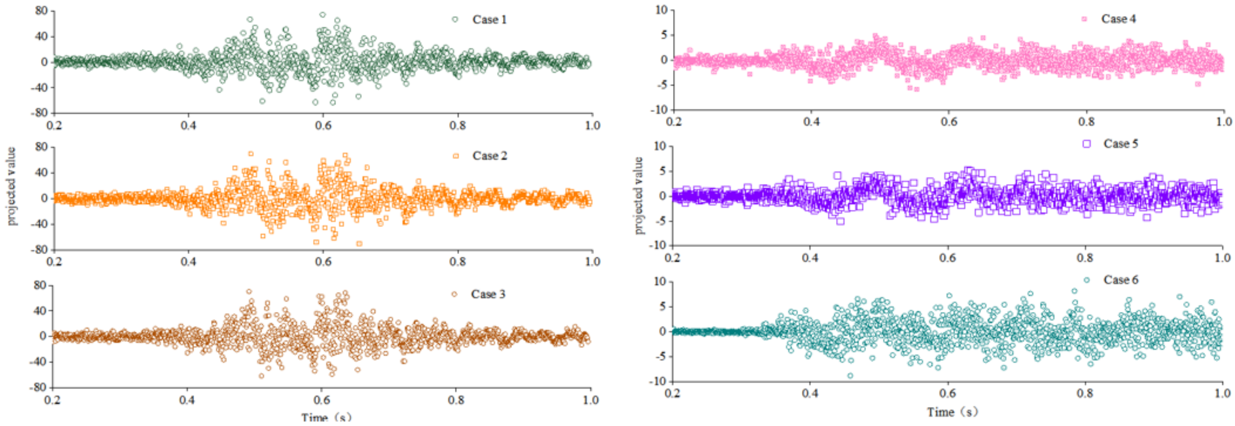

Fig. 4.2: Schematic of the six waveforms of the parameters predicted by the simulation of teaching quality

Figure 4.4. It can be found that all the methods proposed in this paper have high computational assessment speed. Among them, under the working condition A of teaching quality index parameter evaluation, the method of this paper improves by 59.0% compared with the traditional method, which is the highest among the four working conditions. In Case B, this paper's method is 56.2% faster than the traditional method, and in Case C, this paper's method is 49.2% faster than the traditional method. In condition D of the evaluation of teaching quality parameters, the method of this paper has improved by 45.6% compared to the traditional method. Summarizing the centralized conditions, the average speed of calculation and evaluation increased by 52.5%.

5. Integrated module design and evaluation of indicator parameters. Combining the fuzzy evaluation and data class mining methods mentioned above, this paper designs the module identity verification system shown in Fig. 5.1. In this system, there are six sub-functional modules, which are module identity verification module, evaluation basic information module, evaluation program design module, user online evaluation module, evaluation result statistical analysis module and system setting management module. The specific functions of each module are as follows:

1. Module authentication. The system designed in this paper is oriented to four categories of users:

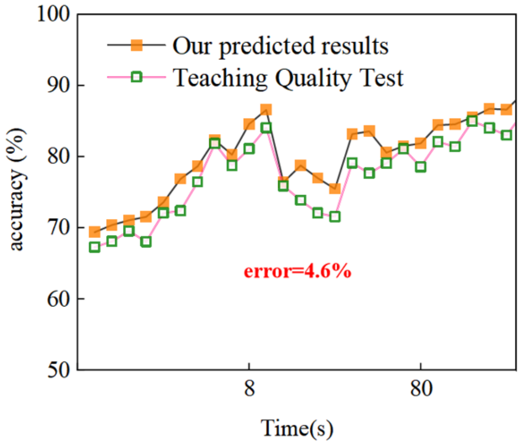

Fig. 4.3: Comparison of Simulation Results with Evaluated Parameters

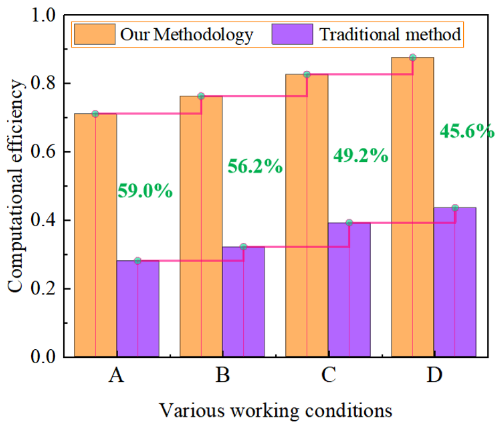

Fig. 4.4: Comparison of computational evaluation speeds for four working conditions A/B/C/D

students, teachers, experts, and system administrators, different categories of users have different user rights; different categories of users have different functional requirements in the system. Therefore, the system needs to distinguish user rights according to different user needs to ensure the smooth progress of the teaching evaluation workflow.

2. Evaluation of basic information settings. In the actual work of teaching evaluation, different users need to combine the specific needs of their information in the system to maintain it, and to determine the validity of the results of each evaluation. For student users, they need to browse the relevant evaluation information; for teachers and expert users, they need to browse and query the relevant evaluation information; for system administrators, they need to maintain all personnel information promptly.
3. Design of the teaching evaluation program. The users of this module are mainly experts who promote the work of teaching evaluation, and these experts, combined with the preliminary research, will add, delete, and distinguish the relevant evaluation indicators in the system's evaluation information setting module to occupy the final generation of the evaluation program.
4. Online evaluation of teachers by users. In this module, combining the different needs of different users,

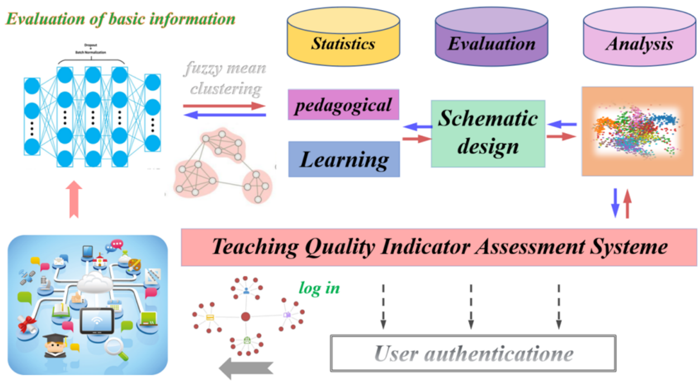

Fig. 5.1: Design and evaluation system for the modular system as a whole

Table 5.1: Indecisive fuzzy assessment information

Mould	excellent	very much	center	differ from
quality assessment	26.0%	13.0%	29.0%	32.0%

online evaluation of teachers' teaching content, teaching level, political level, scientific research level, and other dimensions is carried out, and this module can realize the evaluation of students on teachers, mutual evaluation among teachers, and the inspection and evaluation of teachers by experts.

5. Statistical analysis of evaluation results. This module combines the fuzzy evaluation and data class mining algorithms in the above section to carry out automated evaluation result statistics. Users can view and query the evaluation results with the help of this module, and at the same time, the historical evaluation results of each teacher will be saved in the database for all kinds of assessments.
6. System settings management. The main user of this module is the administrator of the system, which can be used for the allocation of user rights and responsibilities and the viewing of system operation logs.

After the final evaluation system of teaching quality index parameters is realized, according to the situation of the collected valid evaluation data, the actual evaluation test is carried out, and the results are shown in Figure 5.2, which shows that the four clusters of excellent, good, medium and poor are identified. By occupying the allocation, and then combining the K-M algorithm to obtain the parameter evaluation ratio of each teacher's teaching quality indicators, the evaluation results of all teachers can be obtained. Comprehensive pilot test calculations are shown in Table 5.1, which shows that 26.0% of the teachers in the school received excellent, 13.0% good, 29.0% moderate, and 32.0% poor in a teaching evaluation.

6. Conclusion. In this paper, a data class mining and hesitant fuzzy C-canopy-K mean clustering degree algorithm based on data class mining and information input, followed by simulation and training test combined with hesitant fuzzy K-mean classification evaluation method is proposed. Specific results are shown. The results of the six simulation conditions are consistent with the actual results, only slightly different in some amplitude, and the overall trend, change rule, and average peak value are highly consistent. After processing through the predictive model of this paper, the parameters of teaching quality indicators are assessed with high accuracy, which can reach more than 95.0%, in addition to the law of development fits well. The average computational assessment speed of the four teaching quality parameters assessment of A, B, C, and D increased by 52.5%. In addition, the assessment test after the integrated design of the module showed that the system can effectively identify the four clustering identification processes that can be seen as excellent, good, moderate, and poor; at the same time, the test data showed that the system class effectively assesses teaching quality indicator

Fig. 5.2: Schematic representation of the results of the data clustering assessment

parameters.

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