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Research on the Evaluation System of English Teaching Effect in Colleges and Universities Based on Data Mining Algorithm

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Abstract The in-depth promotion of education informatization has put forward the demand for specialization and systematization in the assessment of English teaching effectiveness in colleges and universities. This paper introduces the adaptive CS algorithm (ACS algorithm) to optimize the clustering center, makes up for the defects that the original K-means clustering algorithm is easily affected by the initial clustering center and easily falls into the local optimum, and proposes the K-means clustering algorithm based on the improved cuckoo search algorithm (ACS-Kmeans). Applying this algorithm to deal with the data related to English teaching in colleges and universities, combining the characteristics of English teaching in colleges and universities, designing the corresponding programming algorithm and fitness function, and establishing the clustering algorithm for English teaching data in colleges and universities. According to the teaching data clustered by the algorithm, the evaluation indexes of teaching effect of English in colleges and universities are initially proposed. Combined with the opinions of experts, the evaluation system of English teaching effectiveness in colleges and universities is finally established, which contains 4 first-level indicators and 12 second-level indicators. Calculating the weights of the index system, the weight of “teaching plan” in the first-level index is 0.4181, which means that the improvement and optimization of English teaching effectiveness in colleges and universities should pay more attention to the design and arrangement of the teaching plan.

Index Terms ACS-Kmeans clustering algorithm, English teaching effectiveness assessment, fitness function, data mining

I. Introduction

With the continuous progress and wide application of big data technology, teaching assessment methods based on students' performance and participation in college English classroom have attracted great attention. Traditional English teaching assessment methods are relatively single, usually obtaining assessment results by grade comparison and practical teaching completion [1], [2]. This assessment method relies heavily on teachers' subjective assessment and limited student input, although it can accomplish the expected assessment effect, but in the actual processing process, it is very susceptible to the influence of external teaching factors, and the final results of the assessment of the effectiveness of English teaching are not accurate and reliable [3]-[6].

The emergence of big data analytics provides a new method for assessing the effectiveness of English teaching in the higher education environment [7]. The use of big data technology can collect, process and analyze a large amount of educational data to reveal potential patterns and influencing factors in the teaching process, providing a scientific basis for improving teaching quality [8]-[10]. In addition, the use of big data analysis allows for a nuanced exploration of the multifaceted factors that influence student performance and engagement, thus providing a solid foundation for teaching management and improvement [11], [12]. Using student performance and engagement as assessment indicators allows for an objective assessment of students' academic achievement and attitudes, providing educators with valuable feedback on teaching and learning, which helps to make timely adjustments to teaching strategies and methods [13]-[15]. In conclusion, the use of big data-driven assessment methods not only simplifies the assessment process and reduces resource expenditures, but also stimulates new ideas and benchmarks for the future development of teaching assessment methods.

This paper firstly briefly outlines the principle of ACS-Kmeans clustering algorithm, the coding method and the formula of the fitness function, and then discusses the implementation steps of ACS-Kmeans clustering algorithm. The ACS-Kmeans clustering algorithm is introduced into English teaching in colleges and universities, and the programming algorithm and fitness function characterization containing the characteristics of English teaching in colleges and universities are designed to propose the clustering algorithm process of English teaching data in colleges and universities. Then, by synthesizing the experts' opinions and teaching practice, the preliminary evaluation indexes of English teaching effectiveness in colleges and universities are proposed. Using the expert consultation method, the content of the indicators is screened to establish the final assessment system of English teaching effectiveness in colleges and universities. Subsequently, based on this assessment system, we carry out student assessment and cluster the characteristics of assessment data. By analyzing the categories of students who evaluate teaching, it reflects the characteristics of teachers and teaching effectiveness. Finally, the weights of the indicators are determined, and the evaluation system of college English teaching effectiveness is applied to actual teaching.

II. Design and application of ACS-Kmeans clustering algorithm

II. A.K-means clustering algorithm based on ACS algorithm

The original K-means clustering algorithm is easy to fall into the local optimal solution, resulting in unstable clustering results. Therefore, some improved algorithms of K-means clustering algorithm appear one after another, such as K-means clustering algorithm based on Genetic Algorithm (GA), K-means clustering algorithm based on Particle Swarm Optimization (PSO) algorithm and so on. However, due to the limitations of these optimization algorithms themselves, the clustering accuracy and time complexity of these improved K-means algorithms are not ideal. In this paper, the ACS algorithm is applied to the K-means clustering algorithm, and the ACS-K-means clustering algorithm is proposed in order to be able to optimize the results of clustering more effectively.

II. A. 1) Coding methods and fitness functions

Let the original sample data need to be clustered into k classes, each sample has d dimensional features, then the algorithm is encoded by selecting k sets of coordinates as a solution of a bird's nest, here the location of each bird's nest consists of k clustering centers, and since the dimensionality of the sample vectors is d, the location of the bird's nests is a $k\times d$ dimensional matrix, which is encoded as in Eq. (1):

$$A=\begin{bmatrix} nest_{11} & nest_{12} & \cdots & nest_{1d} \\ nest_{21} & nest_{22} & \cdots & nest_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ nest_{k1} & nest_{k2} & \cdots & nest_{kd} \end{bmatrix} \tag{1}$$

where: $nest_{11},nest_{12},\cdots,nest_{1d}$ denotes the clustering center of the first class. $nest_{21},nest_{22},\cdots,nest_{2d}$ denotes the clustering center of the 2nd class. The $nest_{k1},nest_{k2},\cdots,nest_{kd}$ denotes the clustering center of the k th class. The closest distance is used in the K-means clustering process to determine the class to which the samples belong.

A clustering criterion function is usually used to evaluate the quality of a clustering result, and the sum-of-squares function of error is one of the commonly used functions, which is expressed as in equation (2):

$$G=\sum_{j=1}^{k}\sum_{i=1}^{n_j}\left\|x_i^{(j)}-m_j\right\|^2 \tag{2}$$

where: $m_j\left(j=1,2,\cdots,k\right)$ represents each cluster center. x_i is the sample data. The value of G depends on the k cluster centers when the sample set D is given. G describes the sum of squares of the errors generated when n samples are clustered into a single k class. Obviously, the smaller the value of G, the better the clustering is. In this paper, Eq. (2) is used as the fitness function of the ACS-K-means clustering algorithm.

II. A. 2) Realization steps

On the basis of giving the coding method and the definition of the fitness function of the ACS-K-means clustering algorithm, the steps for the implementation of the algorithm are as follows:

(1) Given the samples to be clustered and the number of clusters k.

(2) Randomly initialize the positions of n nests and other parameters in the feasible solution space.

(3) Perform cluster partitioning, calculate the fitness value of each nest according to Eq. (2) and retain the optimal nest.

(4) Update the other bird nests according to the improved cuckoo search algorithm.

(5) Perform cluster partitioning and find the new fitness value according to the updated nests, compare the updated nests with the previous generation's nests, and replace them if they are better.

(6) Discard the bird's nest and rebuild it according to the discovery probability p_α.

(7) Perform clustering division and calculate the fitness of the bird nest, select the best bird nest, compare it with the optimal bird nest obtained so far, and if it is better, place this bird nest as the optimal bird nest.

(8) If the maximum number of iterations is not reached or the optimal value does not satisfy the condition then return to (4) to continue. Otherwise output the optimal cluster centroids, intra-cluster distances and inter-cluster distances.

II. B.ACS-Kmeans based clustering of English language teaching data

In order to better accomplish the evaluation of English online and offline hybrid teaching effectiveness, a series of indicators for hybrid English teaching effectiveness evaluation are designed and used in the process of English teaching effectiveness evaluation. In order to make the collected data better serve the evaluation of hybrid English teaching effectiveness, the collected English teaching effectiveness data are clustered by applying the parallel K-means (ACS-Kmeans) clustering algorithm with adaptive cuckoo search.

II. B. 1) Programming algorithms and fitness functions

If q represents the dimensionality of the sample vectors of data related to the effectiveness of English language teaching and the requirement of data clustering is to cluster the data by clustering algorithm into having k categories. The essence of the encoding algorithm in the operation of the parallel K-means clustering algorithm for adaptive cuckoo search is to vectorize the coordinates of k sets of vectors. Using the k data clustering centers of the ELA data to represent the locations of the bird's nests in the algorithm, then in fact the locations of the bird's nests in the ELA data set are matrices about $k \times q$. The specific encoding can be expressed as equation (3):

$$A = \begin{bmatrix} nest_{11} & nest_{12} & \cdots & nest_{1q} \\ nest_{21} & nest_{22} & \cdots & nest_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ nest_{k1} & nest_{k2} & \cdots & nest_{kq} \end{bmatrix} \tag{3}$$

where the q-dimensional vectors of the 1st clustering center, the 2nd clustering center and the k th data clustering center are represented by $nest_{11}, nest_{12}, \cdots, nest_{1q}$, $nest_{21}, nest_{22}, \cdots, nest_{2q}$, and $nest_{k1}, nest_{k2}, \cdots, nest_{kq}$ representatives.

Using the Euclidean distance to confirm the category of the sample, using x and y to represent two vectors respectively, the Euclidean distance between x and y can be expressed by the formula as equation (4):

$$D_{xy} = \sqrt{\sum_{i=1}^{q} (nest_{xi} - nest_{yi})^2} \tag{4}$$

In the formula, the difference obtained by subtracting the vectors x and y in the i th dimension is represented by $nest_{xi} - nest_{yi}$ and satisfies $1 \le x \le k$ and $1 \le y \le k$.

In the parallel K-means clustering algorithm for adaptive cuckoo search, the level of fitness value can evaluate the degree of goodness of an individual, and the magnitude of its value is positively related to the degree of goodness of an individual. Usually, the distance within the class and the number of clustering points are used to represent the fitness function, but this leads to the number of iterations and the degree of goodness or badness of the individual in the process of solving the fitness is not good enough, in order to change this situation, in the use of adaptive cuckoo search of parallel K-means clustering algorithm for clustering the data of the effectiveness of English language teaching the fitness function is expressed by the formula for the formula (5):

$$Fit(i) = \frac{CN_i}{DS_i}, i = 1, 2, \cdots, k \tag{5}$$

In the formula, the number of data points of English teaching effectiveness samples in the i th cluster and the sum of distances between each data point in the i th class and the center of clustering y are represented by CN_i and DS_i, respectively, and DS_i satisfies the formula $DS_i = \sum_{x \in y} D_{xy} \left(x = 1, 2, \ldots, CN_i; x \ne y \right)$; CN_i In the case of obtaining the class by sample clustering, the average distance of all the points to the center of the class is represented by $Fit(i)$, and the value of $Fit(i)$ is used as a fitness function of the parallel K-means clustering algorithm for the adaptive cuckoo search of the size is positively correlated with the effect of clustering the data on

English teaching effectiveness. The fitness values of k classes are summed up to get the value of total fitness G, and similarly, the magnitude of its value is positively correlated with the clustering effect. The total fitness G can be expressed as equation (6) using the formula:

$$G=\sum_{i=1}^{k}Fit(i) \tag{6}$$

II. B. 2) Clustering Algorithm Flow for English Teaching Data

Combining the discussion on programming algorithms and fitness functions in the previous subsection, the algorithmic flow of the parallel K-means (ACS-Kmeans) clustering algorithm for adaptive cuckoo search can be summarized as follows:

(1) Use $Iterator_{max}$, P_a to represent the maximum number of iterations and discovery probability. $step_{\max}$ and $step_{\min}$ represent the maximum and minimum step size. The input operations are performed sequentially on the English teaching effectiveness sample dataset to be clustered, the number of clusters, $Iterator_{\max}$, P_a, $step_{\max}$ and $step_{\min}$.

(2) Perform an initialization operation on the locations of the bird nests with number k.

(3) Perform the cluster division operation using K-means clustering algorithm to solve for the optimal bird's nest locations for each English teaching effectiveness sample data.

(4) Determine the most suitable location of the bird's nest by solving the value of each bird's nest adaptation according to equation (3).

(5) Find the total fitness G by Eq. (4).

(6) Keep the bird's nest locations from the previous iteration process and update the other bird's nest locations.

(7) In the update operation of other bird's nest locations, r and P_a are obtained. Where r represents a random number satisfying $r\in[0,1]$. The value of r is compared with the value of P_a. Return (6) when $P_a>r$, and vice versa discard the nest and perform a new nest construction operation.

(8) After constructing a new bird's nest, perform operations (3) to (5), compare its G value with the value of G of the previous generation, if the G value of the new bird's nest is greater, determine the bird's nest combination as the updated bird's nest combination, and vice versa return to step (7).

(9) The algorithm ends when the number of iterations is maximum, and vice versa return to (6).

III. Evaluation System of English Teaching Effectiveness in Colleges and Universities

III. A. Predefined evaluation indicators

Through the survey and analyze, research and read the literature related to the evaluation of English classroom teaching in colleges and universities, research on college and university English experts, combined with the practical experience of teaching English courses, the evaluation indexes of English teaching in colleges and universities are preset, and the specific indexes are shown in Table 1.

III. B. Indicator screening

By extracting the evaluation indexes of English classroom teaching in colleges and universities, the expert evaluation indexes are integrated. In the selection of each index, the index that occupies a smaller proportion is found through experimentation, and the index is sifted out to get the expert evaluation index.

In this study, the preset indicators were screened through the expert consultation method, and the questionnaires were mainly distributed in the form of E-mail after the class, and a total of 100 expert questionnaires were distributed. By counting the 100 questionnaires distributed, the statistic is that there are 6 responses that are not valid, 3 responses that are abstained from voting, and the rest there are 91 responses that are valid, and the response rate is 91.00%. Therefore, in response to the information to complete the statistical analysis, we were able to obtain the key research statistics of the expert evaluation indicators are shown in Table 2.The screening indicators used are key, and are divided into four levels: (K1) extremely key (3 points), (K2) key (2 points), (K3) not key (1 point), and (K4) extremely not key (0 points).

Table 1: Expert evaluation index preset system

<table>
<tr><th>The overarching goal</th><th>Primary index</th><th>Secondary index</th></tr>
<tr><td rowspan="15">U: Evaluation of English Teaching Effect in Colleges and Universities</td><td rowspan="2">U1: Teaching programme</td><td>U11: Classroom teaching is scientific and reasonable</td></tr>
<tr><td>U12: Moderately adjust the teaching plan to ensure timely completion</td></tr>
<tr><td rowspan="4">U2: Teaching method</td><td>U21: Utilize multimedia for teaching and explanation</td></tr>
<tr><td>U22: Help students broaden their horizons in English classroom teaching</td></tr>
<tr><td>U23: The teaching is meticulous, easy to understand, and full of examples</td></tr>
<tr><td>U24: Emphasize students' abilities in listening, speaking, reading and writing</td></tr>
<tr><td rowspan="4">U3: Teaching attitude</td><td>U31: The teaching content in middle school English classes should be fully prepared</td></tr>
<tr><td>U32: Strictly manage classroom discipline</td></tr>
<tr><td>U33: Provide timely feedback on the questions raised by students</td></tr>
<tr><td>U34: Arrange class time reasonably. Don't be late or leave early</td></tr>
<tr><td rowspan="5">U4: Classroom performance</td><td>U41: Clarity of spoken English</td></tr>
<tr><td>U42: The proportion of Chinese and English in spoken language</td></tr>
<tr><td>U43: The approximate proportion of new words in spoken language</td></tr>
<tr><td>U44: Students' enthusiasm in answering questions</td></tr>
<tr><td>U45: The ratio of oral statements in Chinese and English when students answer questions</td></tr>
</table>

Table 2: Key research and statistics on expert evaluation indicators

Index	(K1)	(K2)	(K3)	(K4)
U1	73	16	2	0
U11	60	31	0	2
U12	64	23	2	21
U2	70	18	2	36
U21	1	8	46	0
U22	58	33	0	5
U23	0	11	75	0
U24	59	31	1	0
U3	88	3	0	0
U31	78	13	0	0
U32	73	18	0	1
U33	66	22	2	10
U34	6	18	57	0
U4	78	13	0	0
U41	63	23	5	0
U42	83	8	0	0
U43	63	26	2	0
U44	65	24	2	0
U45	73	18	0	0

According to the expert evaluation of key research statistics, the total score of each indicator was calculated, and the detailed scores of each indicator are shown in Table 3.

Table 3: Expert evaluation index scores

Index	Total points
U1	253
U11	242
U12	240
U2	248
U21	65
U22	240
U23	97
U24	240
U3	270
U31	260
U32	255
U33	244
U34	111
U4	260
U41	240
U42	265
U43	243
U44	245
U45	255

Based on the scores for each indicator, a plot indicating the relationship between the indicator item and the total score is shown in Figure 1.

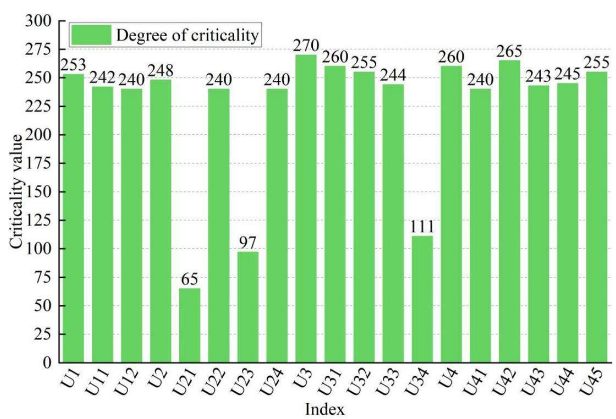

Figure 1: Experts evaluate the criticality of indicators

As can be seen from Figure 1, the horizontal coordinate X-axis represents the indicator items, and the vertical coordinate Y-axis represents the total score of the indicators. The analysis of the results shows that most experts agree that some indicators have higher total scores and the scores are basically distributed above 240, but there are also some indicators with lower scores, all below 120, so the indicators distributed above 240 are chosen as the reserved indicators, resulting in the following indicators: U1:Teaching plan, U11:Classroom teaching is scientific and reasonable, U12:Moderately adjusting the teaching plan to Ensure regular completion, U2:Teaching means, U22:Helping students expand their horizons in English classroom teaching, U24:Focusing on students' listening, reading and writing skills, U3:Teaching attitudes, U31:The content of secondary school English classroom lectures should be well-prepared, U32:Strictly managing the classroom discipline, U33:Providing timely feedback to the problems raised by students, U4:Classroom performance, U41:Clarity of spoken English, U42:the ratio of Chinese and English in spoken English, U43:the approximate ratio of vocabulary in spoken English, U44:the degree of students' enthusiasm in answering questions, and U45:the ratio of students' oral English and Chinese in answering questions. According to the expert evaluation index score in Table 3, it can be seen that the evaluation of U1: teaching program, U3: teaching attitude, U4: classroom performance of these three aspects of the development of the evaluation, and experts through these evaluation factors, the screening of indicators through the results of the experiment to come up with, the expert evaluation index system is shown in Table 4.

Table 4: Expert evaluation index system

The overarching goal	Primary index	Secondary index
U: Evaluation of English Teaching Effect in Colleges and Universities	U1: Teaching programme	U11: Classroom teaching is scientific and reasonable
		U12: Moderately adjust the teaching plan to ensure timely completion
	U2: Teaching method	U22: Help students broaden their horizons in English classroom teaching
		U24: Emphasize students' abilities in listening, speaking, reading and writing
	U3: Teaching attitude	U31: The teaching content in middle school English classes should be fully prepared
		U32: Strictly manage classroom discipline
		U33: Provide timely feedback on the questions raised by students
	U4: Classroom performance	U41: Clarity of spoken English
		U42: The proportion of Chinese and English in spoken language
		U43: The approximate proportion of new words in spoken language
		U44: Students' enthusiasm in answering questions
		U45: The ratio of oral statements in Chinese and English when students answer questions

IV. Establishment and Application of the Evaluation System of English Teaching Effectiveness in Colleges and Universities

IV. A. Results and analysis of the confidence grading experiment

In order to eliminate the influence of the scale between the indicators, data normalization is required. The data clustering method after normalization is used here.PCA reduces the data into two dimensions to provide data for data visualization.The first ten data before and after data reduction are shown in Table 5.The data features before reduction are (D1) variance of differentiation, (D2) number of index scores, (D3) indicator fluctuation extreme deviation, (D4) ratio of maximal identical scores of the indicators, (D5) ratio of maximal identical scores, and (D6) amount of information of rubrics, (D7) ratio of different rubrics, (D8) number of different rubric items.

Table 5: Data before and after dimension reduction

	Number	0	1	2	3	4	5	6	7	8	9
Before dimension reduction	D1	0.006	0.000	0.019	0.733	0.689	0.000	0.000	0.000	-0.191	-0.082
	D2	0.021	0.501	0.101	0.909	0.715	0.000	0.000	0.000	0.007	-0.063
	D3	0.004	0.000	0.030	0.960	0.874	0.000	0.000	0.000	-0.417	-0.068
	D4	0.012	0.501	0.119	0.685	0.511	0.000	0.000	0.000	0.242	-0.078
	D5	0.357	1.000	0.113	0.365	0.170	0.000	0.000	0.000	0.956	-0.086
	D6	0.059	0.501	0.058	0.694	0.430	0.000	0.000	0.000	0.294	-0.081
	D7	0.000	0.000	0.019	1.000	1.000	0.000	0.000	0.000	-0.516	-0.061
	D8	0.004	0.000	0.030	0.960	0.874	0.000	0.000	0.000	-0.417	-0.068
After dimension reduction	PCA Picture1	0.301	1.000	0.230	0.326	0.239	0.000	0.000	0.000	0.926	-0.083
	PCA Picture2	0.024	0.501	0.119	0.475	0.348	0.000	0.000	0.000	0.449	-0.090

The confidence feature data of students' evaluation of teaching was downscaled by PCA data and K-means clustering, and the clustering results are shown in Fig. 2.

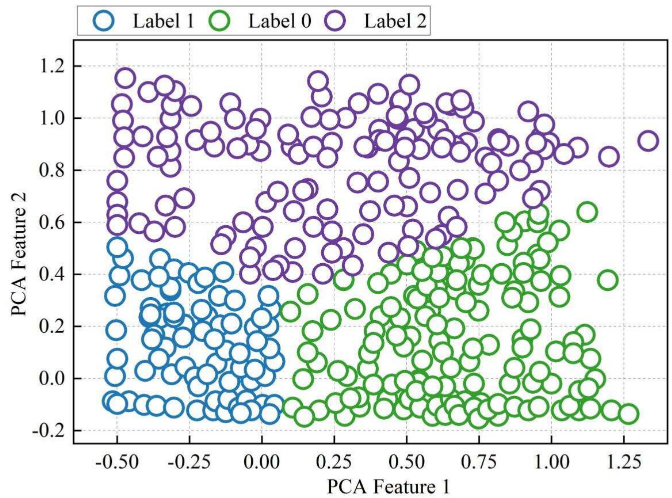

Figure 2: The clustering results of student evaluation of teaching reliability

The distribution of students in different categories can be visualized in Figure 2. After PCA processing can carry out data compression while minimizing the loss of information, student assessment credibility data for eight-dimensional data, eight-dimensional data distribution is difficult to represent, after the dimensionality reduction can intuitively see the clustering distribution of the data, but also able to reduce the computational resources. After mapping the clustering center of gravity after dimensionality reduction to the original space, the clustering center of gravity results are shown in Table 6.

Table 6: Cluster centroids

Label	0	1	2
D1	3.825	61.601	38.082
D2	0.88	0.453	0.675
D3	2.056	3.04	2.575
D4	0.251	0.268	0.267
D5	0.746	0.534	0.643
D6	0.104	0.075	5.047
D7	0.01	0.014	0.928
D8	0.055	0.077	2.964

The group of students labeled 0. From an objective scoring perspective, this group of students had the lowest differentiation of evaluation scores across teachers, gave the greatest share of the same scores to different teachers, used the fewest subcategories, fluctuated the least, and had the greatest share of the same sub-scores. From a subjective textual perspective, students in this category had fewer valid words in their comments, the most identical comments, and the fewest number of comments. This shows that students in this category make little contribution to both the grading and comment sections, and the assessment data is less informative.

The group of students labeled 1, from the perspective of objective scoring, this category has the greatest differentiation between the evaluation scores of different teachers, the smallest share of giving the same scores, the largest number of categories using minor scores, the largest fluctuation, and the smallest share of using the same minor scores. From a subjective textual point of view, the number of valid words in this category of student ratings is smaller, the proportion of giving the same ratings is larger, and the number of giving different ratings is smaller. This shows that students in this category are serious about evaluating teaching in the rating section, but there are fewer words and repetitive comments in the comment section. This group of students is objective in the rating part of the data and perfunctory in the comments part of the data.

The group of students labeled 2, from the perspective of objective scoring, this group of students has a greater differentiation between the evaluation scores of different teachers, a smaller proportion of the same scores given to different teachers, uses more subcategories, fluctuates more, and the proportion of the same sub-scores is smaller. From a subjective textual point of view, this category of students had the highest number of valid words in their rubrics, fewer identical rubrics, and the highest number of different rubrics. This shows that students in this category are serious about evaluating teaching in both the grading and rubric sections, and the evaluation data are more objective.

IV. B. Determination of the weights of the indicator system

The judgment matrix for constructing the level 1 indicators is shown in Table 7.

Table 7: First-level indicator judgment matrix

	U1	U2	U3	U4
U1	1	1/2	1/2	1/3
U2	2	1	2	1/2
U3	2	1/2	1	1/2
U4	3	2	2	1

When calculating the weights of the second-level indicators, the weights of the first-level indicators to which they belong should be taken into account, along with the weights of the first-level indicators to which they belong in the calculation of the weights of all the indicators. Therefore, by multiplying the weight value of each secondary indicator with the weight value of its corresponding primary indicator, the sorting weight can be obtained. The weights of the indicators for evaluating the teaching effectiveness of English in colleges and universities are shown in Table 8.

Table 8: Evaluation index weight

Primary index	Weight	λmax	Secondary index	Weight	Ranking weight	λmax	CR
U1	0.4181	4.0711	U11	0.4935	0.2063	3.0537	0.0517
			U12	0.5065	0.2118		
U2	0.1905		U22	0.5065	0.0965		
			U24	0.4935	0.0940		
U3	0.2708		U31	0.3109	0.0842		
			U32	0.1959	0.0530		
			U33	0.4932	0.1336		
U4	0.1206		U41	0.2304	0.0278		
			U42	0.1856	0.0224		
			U43	0.2079	0.0251		
			U44	0.2034	0.0245		
			U45	0.1727	0.0208		

IV. C. Analysis of evaluation results

College Y is selected as the experimental object, and the questionnaire is formed based on the designed college English teaching evaluation system, and the evaluation of the basic courses, the core courses and the professional development courses of English majors in this college is carried out. Through the questionnaire evaluation, the results of the fuzzy comprehensive evaluation of the specialized basic courses, specialized core courses and specialized extension courses are shown in Tables 9-11, and the evaluation grades are chosen as (a) good, (b) good, (c) medium, (d) poor, and (e) poor.

Table 9: The fuzzy comprehensive evaluation results of professional basic courses

Primary index	a	b	c	d	e	Evaluation
U1	0.4566	0.4168	0.1266	0.0000	0.0000	a
U2	0.4239	0.4473	0.1288	0.0000	0.0000	b
U3	0.4282	0.3663	0.1432	0.0587	0.0036	a
U4	0.3142	0.3280	0.2378	0.1200	0.0000	b
Total	0.3726	0.4002	0.1687	0.0573	0.0012	b

Table 10: The fuzzy comprehensive evaluation results of the core professional courses

Primary index	a	b	c	d	e	Evaluation
U1	0.4457	0.3657	0.1626	0.0260	0.0000	a
U2	0.3804	0.3657	0.1637	0.0640	0.0262	a
U3	0.5036	0.3969	0.0631	0.0364	0.0000	a
U4	0.3047	0.4273	0.2325	0.0355	0.0000	b
Total	0.4199	0.3754	0.1555	0.0423	0.0069	a

Table 11: Fuzzy Comprehensive Evaluation of Professional Expansion courses

Primary index	a	b	c	d	e	Evaluation
U1	0.2849	0.3148	0.2665	0.0975	0.0363	b
U2	0.2679	0.2936	0.2567	0.1564	0.0254	b
U3	0.1429	0.2374	0.3158	0.2465	0.0574	c
U4	0.1355	0.2256	0.3334	0.2685	0.037	c
Total	0.1881	0.2563	0.3009	0.2146	0.0401	c

First of all, in terms of professional basic courses, the evaluation results of "teaching preparation", "resource preparation", "teaching process" and "learning effectiveness" were "good", "good", "good" and "good", respectively, and the overall fuzzy evaluation was "good". This is mainly due to the relatively mature construction of professional basic courses, the course content changes are small, mainly based on knowledge explanation, after-class homework, tests and simple skills training, and online teaching has little impact on such courses, so the overall teaching effect is rated as "good".

Secondly, in terms of professional core courses, the evaluation results of "teaching preparation", "resource preparation", "teaching process" and "learning effectiveness" were "good", "good", "good" and "good", respectively, but the overall evaluation was "good". This results show that although the core curriculum of international trade major is relatively stable, online teaching has a certain impact on the teaching effect due to the large number of practical training links.

Finally, in terms of professional development courses, the evaluation results of "teaching preparation", "resource preparation", "teaching process" and "learning effectiveness" were "good", "good", "medium" and "medium", respectively, and the overall evaluation was "medium". Since professional development courses mainly focus on job skills practice, competition training and other courses, which usually require students to train independently, online teaching will inevitably lead to limited interaction between teachers and students, and the efficiency of dealing with temporary problems is low, so the teaching quality evaluation results of professional development courses are relatively average.

V. Conclusion

In this paper, ACS-Kmeans clustering algorithm, which has the advantages of high-precision search capability and faster convergence speed, is used as a data mining method to design the clustering process of English teaching data in colleges and universities. At the same time, a college English teaching effectiveness evaluation system with 12 secondary indicators is established from four levels: teaching program, teaching methods, teaching attitude, and classroom performance. By adopting the college English teaching effect evaluation system to evaluate the teaching effect and using ACS-Kmeans clustering algorithm to organize and mine the evaluation data, the college English teaching effect evaluation system is formed.

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