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ORIGINAL RESEARCH ARTICLE

Enhancing online Chinese language education through intelligent computing and data clustering—A case study on personalized teaching for international students in Shanxi Province

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ABSTRACT

Providing users with high-quality personalised services in an online environment has become a research hotspot due to the rapid growth of Internet technologies. Personalized online teaching for international Chinese teachers takes domain knowledge as the core, computer and other information technologies as the support, and the network as the communication channel. It is an application system that integrates pedagogy, computer science, psychology and behavioral cognition to achieve better online teaching for international Chinese teachers. This paper focuses on the construction and analysis of student models for online teaching of international Chinese teachers, deeply studies and analyzes the advantages and disadvantages of various traditional student models, and improves the student model for online learning. The existing data mining clustering algorithms are studied and analyzed in detail to provide relevant technical support for analyzing learners' learning characteristics. The experiment shows that the student model and M-Kmeans algorithm proposed in this paper have certain significance and potential application value in personalized online teaching for international Chinese teachers.

Keywords: online teaching; intelligent computing; data clustering algorithms; educational data mining

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1. Introduction

Online learning is a way to quickly study new material and distribute it using the Internet and information technology[1,2]. With the development of Internet technology, online learning has become a way for people to quickly access the best educational resources thousands of miles away and improve themselves without being constrained by location and time. The online learning mode of "Internet + Education" provides learners with ways to broaden their knowledge, highlight their personality and develop their hobbies, and make it possible for learners to improve their quality in all aspects. Online learning has become one of the main ways of continuing education and lifelong learning[3]. More and more Internet product developers and educational technology researchers are concerned with the close collaboration between teachers and students, the construction of learners' knowledge, personalised learning guidance, the full development of learners' abilities and characteristics, and the selection of optimal learning paths that reflect the ideal online learning environment of intelligent international Chinese teachers' online teaching. Intelligent online education's primary objective is to "teach students in accordance with their aptitude" by implementing personalised coaching that is both adaptive and targeted for each individual online learner[4]. The partition method, hierarchical method, density-based method, grid-based method, model-based method, neural network method based on computational intelligence, evolutionary computing method, fuzzy method, etc.[5,6], and semi-supervised clustering method that is currently under consideration are the classical methods of cluster analysis[7].

Recently, a new area of clustering analysis research focus has emerged: the novel clustering ensemble approach. To provide clustering results that are more reliable and of higher quality, a clustering ensemble is used to combine the output of several clustering algorithms. One of the most rapidly evolving techniques in recent times is the graph theory-based approach[8]. It is a clustering technique that makes use of graphics and graph theory concepts. This technique can converge to the global optimal solution and handle more complex cluster configurations, such as non-convex structures, than standard algorithms. At present, the research on computational intelligence is a hot spot. This kind of technology is widely used in various fields. Computational intelligence (CI) is a general term for a class of algorithms. This kind of algorithm is inspired by human wisdom and natural wisdom. First of all, after studying many existing online teaching platforms for international Chinese teachers, this paper finds that the research on providing different teaching strategies for different learners' personalized characteristics, such as differences in learning basis, learning ability, learning characteristics, and changes in hobbies, is still very weak, and has great development space and potential. Second, there is a lot of data generated by online learning that should be fully utilised[9].

Data mining technology is advancing rapidly, making it possible to thoroughly mine the "knowledge" contained in these educational datasets. This paper uses the clustering technology in data mining to "develop" educational data, cluster various learning characteristic data generated by learners' learning behaviors on the network, divide students into several groups with similar characteristics, and then suggest flexible lesson plans and instructional techniques based on the unique qualities of each group. By grouping the knowledge that students have mastered, it is possible to determine their knowledge mastery, which offers useful information for determining the students' future course of study and career. This study employs technology and data mining clustering techniques to assist in resolving the students' personalised learning issues in the online instruction of foreign Chinese teachers.

The remaining organization of this article is shown in **Figure 1**:

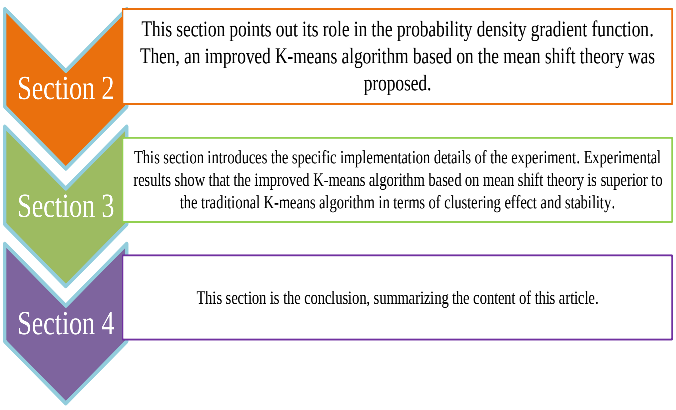

Figure 1. Article organization structure.

2. Methodology

2.1. Theory of mean shift

Fukunaga introduced the notion of mean shift, which pertains to the mean vector of offset, in a 1975 essay on the gradient function of probability density. Initially, mean shift is just a vector; but, as mean shift theory advances, mean shift algorithms also emerge. As seen in **Figure 2**, choose point A as the starting point initially, determine point A's offset mean value, obtain point B, proceed to point B, take point B as the new starting point, and keep moving until the predetermined end condition is satisfied. The mean shift theory gained popularity in 1995 thanks to Yizong Cheng[10,11]. In order to establish a link between the offset vector's contribution and the sample's distance from the offset point, he first proposed a kernel function. Secondly, he established a weight coefficient pertaining to the sample point's significance. In the *d*-dimensional space, given *n* data sample points x_i, where $i = 1, ..., n$. Any point *x* in the space can have its mean shift vector defined as:

$$M_h(x) = \frac{1}{k}\sum_{x_i \in S_h}(x_i - x) \tag{1}$$

where *h* is the area of a high-dimensional sphere satisfying the set of points given in Equation (2) with radius *h* (*d* may be more than 2). *K* denotes the zone that k points in n samples fall inside.

$$S_h(x) = \{y: (y-x)^T(y-x) < h^2\} \tag{2}$$

To put it simply, any one of n points can be represented as the solid point 1, as seen in **Figure 1**. Making a high-dimensional ball with this point as the centre and *h* as the radius, *k* points fall into the ball and create *k* vectors with the centre. Then, as indicated in Equation (1), determine the mean value of the *k* vectors, which is the mean shift vector, and correlate to the thick arrows in **Figure 2**. Next, create a high-dimensional sphere by ending the vector at a new point. The mean shift vector will converge to the area with comparatively high density if the previous stages are repeated.

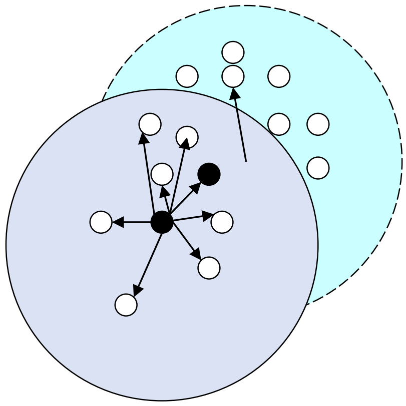

Figure 2. Schematic diagram of mean shift.

The most widely used density estimate technique is kernel density estimation, often known as the Parzen window in pattern recognition technology. The following is the definition: Each point in the *d*-dimensional space, where $i = 1, ..., n$, is represented by a column vector, given n data sample points. In the event that *x* is any of the points, then *x*'s module is.

$$K(x) = k(x^2) \tag{3}$$

In this scenario, $K(x)$ is a piecewise continuous function, if $a < b$, then $K(a) \geq K(b)$, and *k* is a nonnegative number.

$$\int_0^\infty k\,(r)\mathrm{d}r < \infty \tag{4}$$

If the above conditions are met, $K(x)$ defined in Equation (4) is a kernel function. Two unit kernels are frequently employed in mean shift: the unit Gaussian kernel function and the unit uniform kernel function. The following defines two functions: uniform kernel function in a unit:

$$F(x) = \begin{cases} 1 & \text{if } \|x\| < 1 \\ 0 & \text{if } \|x\| \geq 1 \end{cases} \tag{5}$$

Unit Gaussian kernel function:

$$N(x) = e^{-x^2} \tag{6}$$

It can be seen from Equation (5) that as long as point *x* is in a high-dimensional sphere with radius *h*, regardless of its distance from the center point, it is treated equally. There is no weighted value, and the contribution of M x h is the same when calculating. Nonetheless, we are aware that estimating the statistics surrounding the centre point is generally more relevant the closer the point is to the centre point. In order to solve this problem, Yizong Cheng introduced the kernel function into mean shift in 1995. At the same time, it is also considered that the importance of points i x in the dataset is different, so a weight value representing their importance is introduced for each point[12]. Equation (7) thus displays the extended version of mean shift:

$$M(x) = \frac{\sum_{i=1}^{n} G_H\,(x_i - x) w(x_i - x)}{\sum_{i=1}^{n} G_H\,(x_i - x) w(x_i)} \tag{7}$$

Including: $G_H(x_i - x) = |H|^{-1/2} G\left(|H|^{-1/2}(x_i - x)\right)$, $G_H(x)$ is a unit kernel function, and the weighted value of each point is defined as $w(x_i)$, and $w(x_i) \geq 0$. H is $d \times$ Diagonal matrix of d $H = diag\left[h_1^2, h_2^2, \dots, h_d^2\right]$. The simplified form is often used in mean shift, this form requires a coefficient h to be set. This form is adopted later in this article. Therefore, Equation (8) can be rewritten as follows:

$$M_h(x) = \frac{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i) w(x_i - x)}{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i)} \tag{8}$$

If the weight value $w(x_i)$ of all sampling points xi is the same, set it to 1, Equation (8) degenerates into the fundamental mean shift Equation (1) when the unit kernel function is utilised to apply the mean unit kernel function 4. Make some changes to Equation (8) to simplify the iteration steps of mean shift algorithm. Equation (8) is changed into Equation (9) as follows:

$$M_h(x) = \frac{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i) x_i}{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i)} - x \tag{9}$$

And make the first item as $m_h(x)$, namely:

$$m_h(x) = \frac{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i) x_i}{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h}\right) w(x_i)} \tag{10}$$

Then $mh(x)$ is modified by Equation (11):

$$mh(x) = mh(x) - x \tag{11}$$

2.2. Improved algorithm MKmeans

It can be seen from the above analysis that the initial cluster center selected randomly leads to unstable clustering, which is sensitive to noise and easy to enter local extreme points, and has a great impact on the clustering quality. In view of these shortcomings and deficiencies, this paper proposes an improved Kmeans algorithm based on mean shift theory—MKmeans algorithm. By focusing on high-density regions during the initial cluster centre selection process, this technique improves clustering stability and lowers the likelihood that the algorithm would enter local optimisation[13,14]. There is a coefficient h in the mean shift algorithm that needs to be set. This paper's experiment demonstrates how the degree of variation between dataset properties and the magnitude of h are related. H can be set to a lower value when the difference degree is smaller and to a higher value when the difference degree is larger. The following are the steps of the updated algorithm: (1) Set the coefficient h, calculate $mh(x)$, and randomly select a point. (2) Assign $mh(x)$ to x. (3) If, end the cycle, get m points; If not, continue with (1). (4) Select the point with the maximum sum of k distances from other points among m points. (5) Find k points most similar to these k points in dataset D, and make the initial center. (6) Sort the sample points into the cluster with the highest similarity by calculating how similar each remaining data sample point is to the k cluster centres. (7) Recalculate each of the k clusters' respective centres in the new cluster by taking the average of all the cluster's data samples. (8) Reclassify each element in D using the new centre as a guide. Until the number of iterations is reached or the cluster centre of the previous two times does not move, repeat steps (6) through (8). In **Figure 2**, the flow chart is displayed.

The *m* points selected by mean shift are all in places with relatively high density, as shown in **Figures 3** and **4**. **Figure 3** is the result of mean shift algorithm of iris dataset with $h = 0.65$ to get 7 points with relatively high density. **Figure 3** shows that when $h = 100$, eight points with relatively high density are obtained from the mean shift algorithm of the Wine dataset.

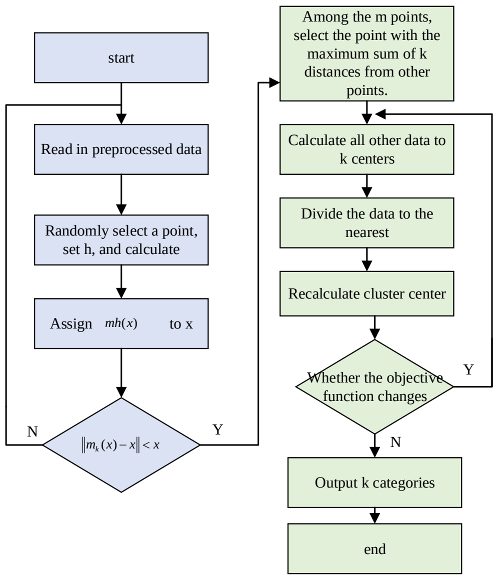

Figure 3. Example diagram.

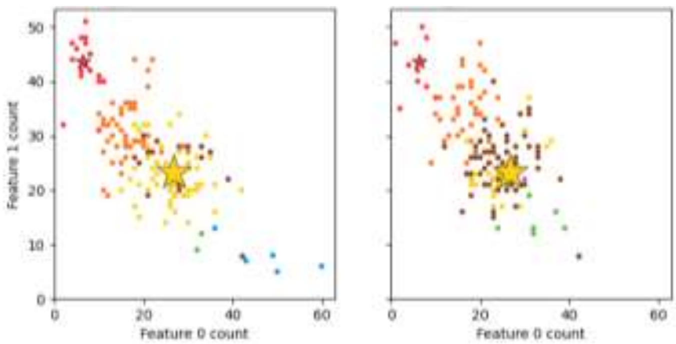

Figure 4. Wine dataset $h = 100$.

3. Experiments

3.1. Implementation details

All experiments in this paper share three experimental tools MATLAB, SPSS and Weka. Using MATLAB integrated hierarchical clustering, Kmeans clustering, FCM clustering, SOM clustering and other clustering algorithms to do comparative experiments; SPSS was used to analyze the characteristics of the experimental data set; The comparison experiment is made with Weka integrated Xmeans algorithm. The mathematical calculations involved in clustering algorithms are relatively complex and tedious, so professional scientific computing tools should be used. MATLAB is a mathematical software developed by American mathwork for data analysis, algorithm development and numerical calculation[15,16]. Its statistical tools provide several clustering methods: (1) hierarchical clustering, (2) Kmeans clustering, (3) fuzzy C-means clustering FCM: the membership degree of sample attribution in FCM algorithm is set to 2. (4) SOM Clustering of self-organizing feature maps. In this study, the Euclidean distance is utilised to quantify sample similarity when the hierarchical clustering technique is applied. In the SOM algorithm, this paper uses a one-dimensional array of SOM network to become a one-dimensional SOM (1-D SOM). There are many parameters that can be selected in the SOM algorithm, and different parameters have a great impact on the results. The training parameters in this paper are shown in **Table 1**:

Table 1. SOM training parameters.

SOM training parameters	Parameter value
Initial value of learning rate in sorting stage	60
Steps in sorting stage	100
Initial value of learning rate in adjustment stage	0.02
Other	Default

In order to analyze the data characteristics of iris and wine, which are used for experiments, mainly mean value, variance, peak value and frequency, etc. This paper uses its statistical analysis function, and finally outputs the desired results with clear and intuitive tables. The Waikato intelligent analysis environment is called Weka (Waikato environment for knowledge analysis). The Xmeans algorithm is one of the many data mining methods integrated by the open and free platform Weka[17].

3.2. Datasets

UCI is a database used exclusively for testing machine learning and data mining methods. Since the database's data sets are clearly categorised, external standards can be utilised to objectively and intuitively assess how well clustering algorithms perform. Two global data sets, Iris and Wine, show two distinct testing vantage points. In order to demonstrate the efficacy of the novel algorithm that is presented in this research, this paper examines and evaluates these two data sets. Iris includes 150 samples in three categories, namely, 1-setosa, 2-versicolor, 3-virginia. Each category includes 50 samples, namely, 1–50 is the first category, 51–100 is the second category, and 101–150 is the third category. The data contains four attributes, namely, calyx length, width, and petal length and width. The data are of numerical type. This article does not do any data processing for this, because after the data is normalized, it may destroy the relationship between the attributes of the data itself, using the most original data. Win includes 178 samples, which are divided into 3 categories. There are 13 attributes describing the samples, including 59 samples from 1–59 for the first category, 71 samples from 60–130 for the second category, and 48 samples from 131–178 for the third category. Like Iris dataset, it is numerical data, excluding name attribute and class attribute. This article also uses the most original Wine data set without any processing to test[18,19]. Because, different clustering algorithms have very different clustering effects for data sets with different characteristics. Therefore, it is necessary to analyze the mean, variance and other characteristics of the dataset. This paper uses SPSS data analysis software to analyze the mean, variance, peak and other parameters of Iris and Wine data sets, as shown in **Tables 2** and **3**. It is found that the difference between the average value and variance of the Iris data set is not very large, indicating that the Iris data set is intensive data, that is, the dispersion is small. The difference between the attribute values of the Wine data set, whether the average value or variance is large, is hundreds of times the smallest, and the variance is tens of thousands of times. For example, the variance of attribute 13 is 99167, while the variance of attributes 3, 8, 9, 11 is as low as 0, This indicates that the Wine dataset is decentralized, that is, highly dispersed.

Table 2. Iris data analysis.

Statistic					
		One	**Two**	**Three**	**Four**
N	Valid	150	150	150	150
	Defect	0	0	0	0

Table 2. (*Continued*).

Statistic				
	One	**Two**	**Three**	**Four**
Mean value	5.8433	3.0567	3.7508	1.1993
Standard deviation	0.82807	0.4358	1.7653	0.7624
Variance	0.6860	0.1900	3.116	0.581

Table 3. Wine data aggregation analysis.

Statistic							
		One	**Two**	**Three**	**Four**	**Five**	**Six**
N	Valid	178	178	178	178	178	178
	Defect	0	0	0	0	0	0
Mean value		13	2	2	19	100	2
Standard deviation		1	1	0	3	14	1
Variance		1	1	0	17	204	0

3.3. Examination of test findings

According to the analysis and test results of iris and wine datasets, the total F-measure value of MKmeans algorithm on both datasets has been improved. As shown in **Figure 5**, the MKmeans algorithm is stable on both iris datasets with small dispersion and Wine datasets with large dispersion. The total Fmeasure value is above 93%, which is 8–20 percentage points higher than the original Kmeans algorithm. From the comparison of operation efficiency, as shown in **Figure 6**, the improved algorithm MKmeans consumes an average of 0.01–0.06 s more time than the Kmeans algorithm, but the total F-measure value increases by 8–20 percentage points, so it is worth the extra time.

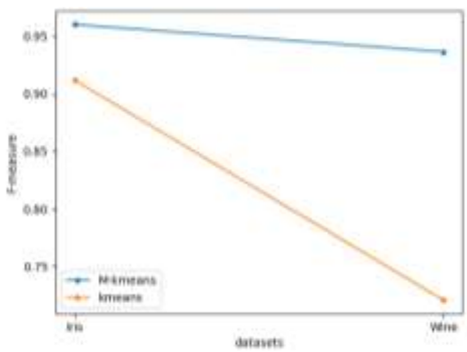

Figure 5. Comparison of total F-measure values.

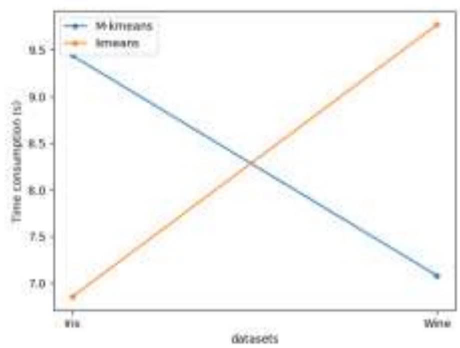

Figure 6. Time consumption comparison.

3.4. Application of MKmeans algorithm in teaching model

First, use Xmeans to get the optimal k value of 4. After that, the final dataset was clustered using MKmeans, Kmeans and two classical improved algorithms of Kmeans, K-mediums and Xmeans, respectively, Finally, as seen in **Figures 7–10**, the contour coefficient was used to analyse the clustering effect. Finally, the recognition ability grouping was analyzed using the clustering results.

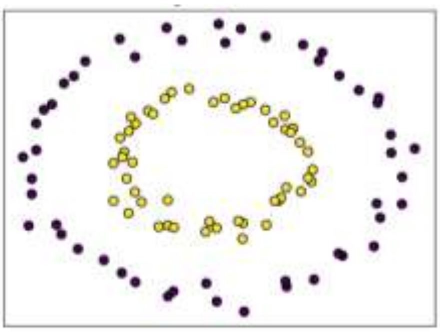

Figure 7. Profile coefficient of MKmeans.

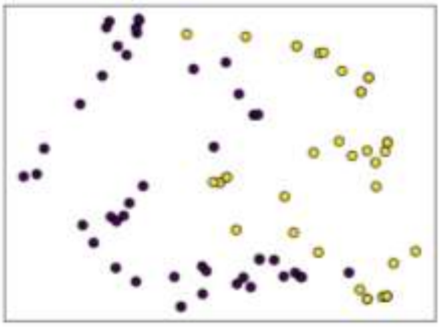

Figure 8. Profile coefficient of Kmeans.

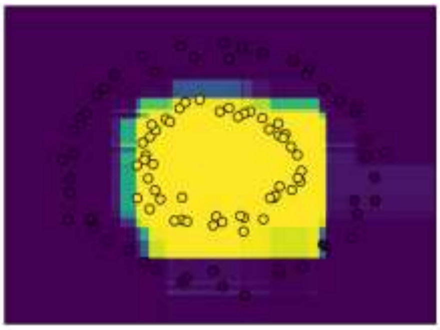

Figure 9. Profile coefficient of Xmeans.

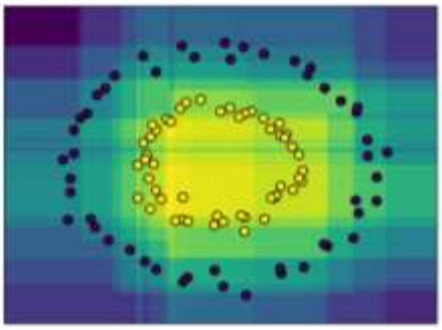

Figure 10. K-profile coefficient of medoids.

To sum up the contour coefficient graphs of MKmeans, Kmeans, Xmeans, K-medoid algorithms, it can be found that the contour coefficients of all categories obtained by the new MKmeans algorithm proposed in this paper are close to 1, and there is no category that tends to −1. Other algorithms more or less have the contour coefficient values of partial data of some categories tend to −1, indicating that some data are not classified into the optimal category. As a result, the MKmeans method presented in this study has a better clustering effect than the Kmeans algorithm and its two classically modified algorithms. **Table 4** displays the final clustering centre determined by the MKmeans method. SPSS is utilised to analyse the clustering outcomes.

Table 4. Cluster Center of MKmeans in fmal.

	Memorizing	Understand	Application	Comprehensive	Analysis	Evaluate
Class 1	0.504941	0.504941	0.504941	0.437103	0.421745	0.305882
Class 2	0.70075	0.70075	0.68657	0.6525	0.661923	0.66
Class 3	0.25465	0.255655	0.219964	0.151078	0.15066	0.0597
Class 4	0.895926	0.895926	0.891228	0.902546	0.930484	0.912346

As shown in **Figures 11–14**, the analysis of four cluster centers obtained by MKmeans algorithm can explain the learning characteristics of learners. It can be seen from **Figures 5** and **6** that the cognitive abilities of category 1 are below 0.5, that of category 2 in **Figure 12** are between 0.65–0.70, that of category 3 in **Figure 13** are below 0.25, and that of category 4 in **Figure 14** are between 0.89–0.93. The aforementioned four categories allow learners' characteristics to be easily separated into four learning groups of varying degrees, which can greatly increase learning efficiency based on many aspects of targeted training and improvement.

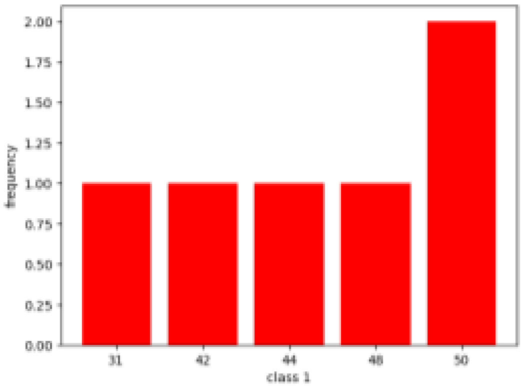

Figure 11. Cluster center of class 1.

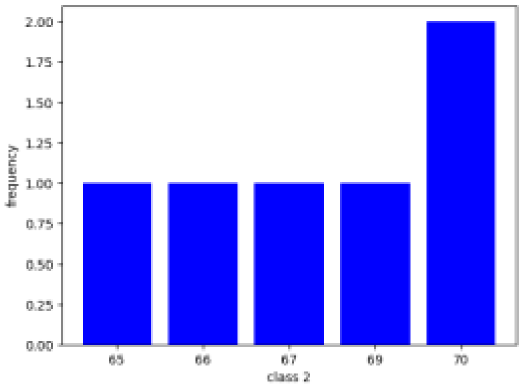

Figure 12. Cluster center of class 2.

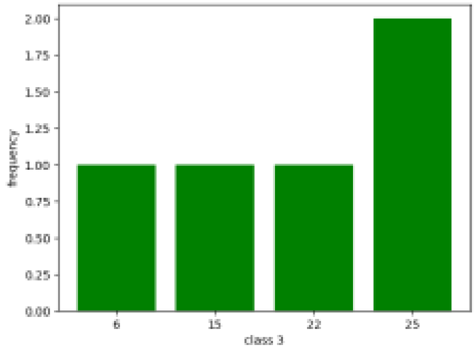

Figure 13. Cluster center of class 3.

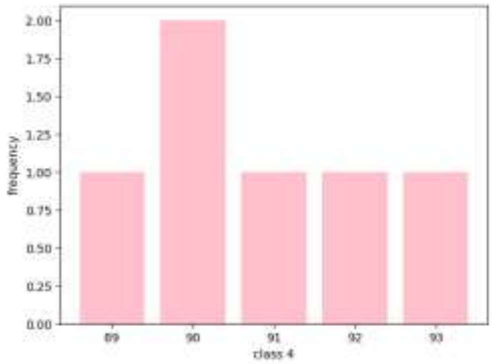

Figure 14. Cluster center of class 4.

4. Conclusion

This essay is based on Chinese instructors from abroad who teach online. This article builds an appropriate student model for online teaching of international Chinese teachers, and then examines the personalisation of online instruction by using the clustering algorithm theory in data mining. A traditional clustering technique built on the partition concept is the Kmeans algorithm. In order to create a student model appropriate for online instruction for foreign Chinese teachers, this paper applies the clustering algorithm to the personalised realisation of online instruction. Additionally, it makes improvements to the Kmeans algorithm to increase its efficiency, while also confirming the algorithm’s superiority. The improved algorithm MKmeans is verified with the international classic datasets Iris and Wine. The final clustering result quality uses the F-measure value as the evaluation standard. It is found that MKmeans performs better than the algorithms of Kmeans, FCM, and SOM, indicating the value of MKmeans. Finally, MKmeans and other algorithms are applied to the student feature data set corresponding to the student model, and learner groups with different levels of cognitive level and cognitive ability groups are obtained, as well as knowledge mastery level groups. It fully proves the value of cognitive model and knowledge model in student model.

Author contributions

Conceptualization, JZ and QL; methodology, JZ; software, JZ; validation, JZ and QL; formal analysis, JZ; investigation, JZ; resources, JZ; data curation, JZ; writing—original draft preparation, JZ; writing—review and editing, QL; visualization, QL; supervision, QL; project administration, JZ; funding acquisition, QL. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

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