Research Article

Application of Cluster Analysis Algorithm in the Online Intelligent Teaching Art Resource Platform

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With the explosion of knowledge and the high-speed dissemination of information, people’s desire for knowledge and information is getting stronger and stronger. At the same time, the updating of knowledge and information is going on at an unprecedented speed. The traditional teaching mode is affected by time and space. Its limitations have become more and more prominent; the traditional classroom teaching has been unable to meet the existing teaching needs. At present, there are many methods for the analysis of network user behavior, such as statistical methods, association analysis methods, and clustering algorithms. Among them, clustering algorithms are more widely used in network user behavior analysis, which is closely related to the unsupervised and high efficiency of clustering algorithms. This paper combines the advantages of clustering algorithm in network user behavior analysis and, on the basis of the existing clustering algorithm research, proposes an improved algorithm for the analysis of online intelligent teaching art resources, so as to obtain the law of online behavior of student users in campus network. Provide some help for students’ Internet management and network optimization. Finally, summarize and put forward the concept of intelligent teaching and design and implement an online intelligent teaching art resource platform based on cluster analysis algorithm. Studies have shown that the average number of transactions processed by the platform per second is 65.21, which can well simulate real information query use cases. The transaction processing time of the platform will eventually stabilize between 30 s and meet the performance requirements.

1. Introduction

Since the rapid development of information technology, it has continuously affected all aspects of social life [1, 2]. In recent years, the application of information technology in education and teaching has led to changes in the teaching process that have attracted the attention of experts, scholars, managers, and front-line teachers, whether from the national level, industry level, or front-line education and teaching management departments. At present, there are many cases of teaching resource platform construction, but most of them are modified from the early resource management system. The single system has strong coupling, and the functions of resource collection, processing, retrieval, sharing, and reuse are insufficient [3, 4]. The application support ability of the business system is weak. At the same time, with the rapid development of multimedia and network technology and the popularization of Internet, remote online teaching has become a new generation of education combining computer network and multimedia technology because of its long-distance real-time interactive function and the characteristics of separation of time and space between teaching and learning. Technology: especially at the end of the twentieth century, the development and research of network-based teaching systems have quickly become an important subject for research in various countries.

Foreign research text classification is relatively early, and obvious academic research results have been obtained [5]. In the late 1950s, it was the first to apply statistical theory to text classification; IBM in the United States also carried out groundbreaking research in the field of text classification; Huang et al. first proposed to apply word frequency statistics to automatic text classification [6]; in the early 1960s, Lee and Chung published the first paper in the field of automatic
text classification [7]; subsequently, Kuo and many other scholars proposed to use factor analysis to study document classification [8]. Fang believes that online teaching quality evaluation refers to the process of using effective technical means to comprehensively collect, organize, and analyze teaching conditions and make value judgments to improve teaching activities and improve teaching quality [9]. However, it is not common to explore the application of text classification in intelligent teaching systems, and the research of text classification in this field is still immature. Compared with foreign countries, the domestic research on automatic text classification started late, and it mainly went through three stages of feasibility study, auxiliary classification system, and automatic classification system [10].

This paper attempts to design and implement an open online intelligent teaching art resource platform under the cluster analysis algorithm, realize the storage of basic resource data, meet the resource application support for other business systems, and provide the collection, processing, and retrieval of teaching resources, sharing, multiplexing, and other application functions [11]. This article analyzes the current situation of regional education resources; sorts out the needs of the service object, service content, and basic structure of the regional science art resource service cloud platform; formulates the overall goal of construction; and plans the hardware support infrastructure, application system structure, data business logic, and system deployment plan. Remote online teaching is a new generation of educational technology that combines computer network technology and multimedia technology. Using remote online teaching, the majority of educated people can break through the limitations of traditional education in educational resources and educational methods and can achieve excellence without the constraints of time and space. With the sharing of educational resources and educational methods, the educated can arrange their own learning plans and learning progress according to their own level and time situation, so as to realize the "autonomous choice education" that cannot be achieved by traditional education. Finally, the system test results of the online intelligent teaching art resource platform are given [12]. The clustering results are very satisfactory; at the same time, the individual characteristics belonging to different classes are also obtained. The system realizes targeted and differentiated personalized teaching according to the individual characteristics. The personalized intelligent learning system well implements “individualized” and “intelligent” learning services and can greatly improve the learning efficiency of students and enhance the intelligence of the embedded online intelligent teaching platform. It is used in theoretical research and practical applications. Both are of great significance. The article innovatively applies the improved clustering analysis algorithm to the embedded online intelligent teaching platform and realizes the personalized intelligent learning system of the embedded online intelligent teaching platform. The system integrates learning, testing, and guidance, which well embodies the concept of personalized and intelligent teaching, greatly enhances the intelligence of the embedded online intelligent teaching platform, and provides students with good personalized learning resources and adaptive guidance, and the application of the system also proves the effectiveness and practicability of the algorithm.

2. Clustering Analysis Algorithm of Online Intelligent Teaching Art Resource Platform

2.1. Online Intelligent Teaching Art Resource Platform Based on Cluster Analysis Algorithm

(i) The service objects of the online intelligent teaching art resource platform

Compared with the previous teaching resource service platform, the teaching network intelligent teaching art resource platform designed in this article emphasizes the openness of the system and the convenience of application. Application openness is to achieve resource support for other teaching-related business systems on the basis of meeting the national education resource standards, and convenience is to improve the application effect of users when using the teaching resource system. Specific service objects can be divided into two categories:

(1) Business applications

The business application system includes the user operation interface functions (including browsing, searching, uploading, downloading, and quoting functions) provided by its own resource system, teaching preparation, teaching research, teacher training, etc.

(2) Functional user class

The user design includes resource platform management users, ordinary teachers, ordinary students, ordinary parents, and education administrators. Provide teachers, students, and parents with the basic functions of retrieval, browsing, uploading, downloading, sharing, and quoting of teaching resources and, at the same time, push preferred teaching resources to users based on related algorithms; provide education managers with resource construction, use, and use of resource platforms. Cobuild and share data analysis; provide management functions such as system configuration, resource screening, and elimination for management users [13–15].

The “learning” mode of distance network teaching is mainly defined for the educated. The modes provided by general education websites can be divided into individual learning modes, discussion learning modes, and multiperson cooperation learning modes:

(1) Students can obtain knowledge through individual learning by consulting teachers or using teaching software

(2) A teaching mode in which multiple students learn through discussion with the help of the discussion support system
(3) Using the Internet, multiple students interact and cooperate with each other for the same learning content to complete learning tasks together.

(ii) The service content of the online intelligent teaching art resource platform

The online intelligent teaching art resource platform provides services for two types of service objects, provides access to the framework API interface for business application systems, and provides different user operation function interfaces for resource users, as shown in Figure 1.

(iii) The infrastructure requirements of the online intelligent teaching art resource platform

In order to meet the design requirements of the service object and service content of the smart teaching resource service cloud platform, the infrastructure of the entire platform must be different from the previous teaching resource platform, mainly including the following aspects:

(1) Constructed in the cloud computing mode, configure computing resources, and storage resources to achieve elastic expansion of basic hardware resources

(2) Both computing and storage adopt cluster architecture to achieve high availability of application and data access

(3) Open architecture, compatible with national education data standards, to achieve good access to business systems and resource data exchange

2.2. Design Goal of the Online Intelligent Teaching Art Resource Platform. The design goal of the online intelligent teaching art resource platform is based on the support of the underlying hardware structure of the clustering analysis algorithm, adopts an open structure design, is compatible with national education resource standards and specifications, and realizes the separation of the underlying resources, basic services, access frameworks, and upper-level functional application interfaces. Layer design to meet the access requirements of other business application systems related to teaching resources in the region, as well as the retrieval, operations of ordinary users to the teaching resources themselves, and finally, realize as a regional education cloud. The platform provides part of teaching resource management and services [16, 17].

Implement the “three chains and two platforms” regulations by building a regional education cloud service platform to accelerate the efficient development of regional education informatization [18].

2.3. Hardware Support Environment of the Online Intelligent Teaching Art Resource Platform. The design of the online intelligent teaching art resource platform consists of two parts, namely, the hardware support environment and the software application service system.

The hardware support environment of the online intelligent teaching art resource platform based on the clustering analysis algorithm is based on the clustering analysis algorithm data center, structured storage, unstructured storage, and resource underlying services composed of high-performance computing servers and high-performance storage devices, and resource service open access framework; the second part is the front-end business cluster supported by the virtual computing platform to provide users with access to the operation interface [19–22]. Follow the principles of completeness, clarity, understanding, query ability, and ease of operation. Provide students with retrieval mechanism, information network structure diagram, online help manual, preset or preview learning path, record learning path, and allow backtracking, use electronic bookmarks, etc.

Each node of the low-level high-performance computing server is equipped with 4 channels of 12-core CPUs, and 256 GB of memory can provide the resource service platform with powerful resource data processing capabilities. The high-performance storage using 8 G optical fiber connection provides the resource bottom platform with a high speed of over 800 MB/S. Reading and writing capabilities ensure the throughput of resource data. The 200 TB*2 storage
configuration provides a large storage space for resource data, which can meet the collection of high-quality resource data for a large number of users within a certain period of time. Virtualized computing provides multinode clusters for resource application front-end services, ensuring high availability while ensuring horizontal resource expansion under extreme pressure conditions [23, 24].

2.4. Software Service System of Online Intelligent Teaching Art Resource Platform

(1) The composition of the software service system of the online intelligent teaching art resource platform based on the clustering analysis algorithm

The intelligent teaching resource platform software service system is composed of two main parts as described above: one is the basic layer service of teaching resources; the second is the application layer of teaching resources.

The business application layer of teaching resources provides access and operation function interfaces for multiple users, including resource browsing, retrieval, uploading, downloading, sharing, quoting, optimization, elimination, resource evaluation activities, resource points, and resource management, to meet users’ needs for resources the routine application operation [6, 25, 26].

(2) Data application logic of online intelligent teaching art resource platform software service system

The intelligent teaching resource platform software service system is based on the design structure. The basic layer of teaching resources serves as the data collection and distribution center of teaching resources. Based on structured data storage and unstructured data storage software, it constructs resource data collection, processing, storage, access, and core functions such as indexing, word segmentation, and full-text retrieval, provides an open service framework for teaching resources to realize the operation of resource data at the business application layer of teaching resources, and at the same time, meets the resource data operation needs of other business applications under security control.

Teaching resource base layer services, provide structured storage of resource data, unstructured storage, resource collection, processing, access, indexing, word separation, full-text search, data security control, resource open framework API, etc.

The teaching resource business application layer is mainly used to implement user interaction, complete resource collection, display, and application-related resource logic, and provide users with a convenient and clear operation platform. It is an important source of teaching resource data and data export.

(3) Software deployment structure of online intelligent teaching art resource platform

The online intelligent teaching art resource platform software service system based on the clustering analysis algorithm is designed according to the hierarchical design, and the software deployment is also divided into two levels, the teaching resource basic layer and the teaching resource business application layer, as shown in Figure 2.

The basic layer of teaching resources is deployed in the basic environment of high-performance computing clusters and high-performance storage. File system and MongoDB are combined to realize unstructured data storage, Oracle database cluster mode provides structured data storage, Weblogic middleware is the platform, and JAVA language is used to construct the basic core of teaching resource data such as reading and writing, conversion, word segmentation, indexing, and full-text retrieval. The service program realizes the open service framework of teaching resources and provides support for the upper application system and data interaction [27]. The teaching resource business application layer is deployed on the computing node cluster provided by the cloud computing center virtualization platform.2.5 Cluster Analysis Algorithm

(1) Cluster analysis algorithm

Clustering analysis is an important task in data mining. Clustering is one of the most common techniques in the field of data mining. It is used to discover unknown object classes in the database. The basis for this classification of object classes is "things are clustered together," that is, to examine the similarity between individuals or data objects and divide individuals or data objects that meet
The relationship is:

\[ \text{ables (also called metrics or attributes) to represent different data sources, and classify data sources into different clusters. The specific algorithm is as follows:} \]

\[ G_i \cup G_j \cap G_k = X, \]

\[ G_i \cap G_j = \varnothing, i \neq j. \] (1)

The nodes in the clustering tree graphically represent a class or use the logical expression of sample attributes to represent the class [28].

(2) Data types

(i) Data matrix of calling object and variable structure

With the quantitative representation of data, the results can be sorted and analyzed more accurately. It uses \( p \) variables (also called metrics or attributes) to represent \( n \) objects. The relationship is:

\[
\begin{bmatrix}
  x_{11} & \cdots & x_{1j} & \cdots & x_{1p} \\
  \vdots & \vdots & \vdots & \vdots & \vdots \\
  x_{i1} & \cdots & x_{ij} & \cdots & x_{ip} \\
  \vdots & \vdots & \vdots & \vdots & \vdots \\
  x_{n1} & \cdots & x_{nj} & \cdots & x_{np}
\end{bmatrix}
\] (2)

(ii) Dissimilarity matrix (or object-object structure): stores the similarity between \( n \) objects in the form of an \( n \times n \) matrix

\[
\begin{bmatrix}
  0 & d(2, 1) & 0 \\
  d(2, 1) & 0 & d(3, 2) \\
  \vdots & \vdots & \vdots \\
  d(n, 1) & d(n, 2) & \cdots & 0
\end{bmatrix}
\] (3)

(3) Similarity measure

The similarity measure can be expressed as:

\[ \forall x', x \in X \forall x', x \in X. \] (4)

Generally speaking, the similarity metrics of clustering algorithms can be standardized as:

\[ 0 \leq s(x, x') \leq 1 \forall x', x \in X. \] (5)

However, it is common to use a measure of dissimilarity rather than a measure of similarity as a standard. The measure of dissimilarity is expressed as:

\[ d(x, x'), x \in X. \] (6)

Generally, we discuss that the variable describing the object is a continuous interval, and the degree of dissimilarity is usually called the distance. When \( x \) and \( x' \) are similar, the distance \( d(x, x') \) is small. If \( x \) and \( x' \) are not similar, \( d(x, x') \) is very large [29, 30].

Here, we only introduce the distance definition of the data object when the description attributes of the data object are all interval scaled metric attributes. The commonly used distance definitions are as follows:

(1) Manhattan (Manhattan) distance

\[ d(i, j) = |x_{i1} - y_{j1}| + |x_{i2} - y_{j2}| + \cdots + |x_{im} - y_{jm}|. \] (7)

(2) Euclidean distance

\[ d(i, j) = \sqrt{|x_{i1} - y_{j1}|^2 + |x_{i2} - y_{j2}|^2 + \cdots + |x_{im} - y_{jm}|^2}. \] (8)

(3) Minkowski distance

\[ d(i, j) = \left( |x_{i1} - y_{j1}|^q + |x_{i2} - y_{j2}|^q + \cdots + |x_{im} - y_{jm}|^q \right)^{1/q}, \] (9)

where \( q \) is a positive integer. When \( q = 1 \), Minkowski distance is Manhattan distance; when \( q = 2 \), Minkowski distance is Euclidean distance.

2.5. K-Means Clustering and Grid Clustering

(1) K-means clustering

K-means is an iterative clustering algorithm. In the process of iteration, the members of the cluster are constantly moved until the ideal cluster is obtained. Using the clusters obtained by the K-means algorithm, the calculation of the similarity between the members of the cluster is represented...
by the mean value of the objects in the cluster (which is regarded as the centroid of the cluster). Given cluster \( k_i = \{ t_{i1}, t_{i2}, \ldots, t_{im} \} \), its mean value is defined as:

\[
M_i = \frac{1}{m} \sum_{j=1}^{m} t_{ij},
\]

where \( M_i \) is the average value of the \( i \)th cluster, \( m \) is the number of objects in the cluster, and \( t_{ij} \) is the distance from the \( j \)th object to the centroid of the \( i \)th cluster.

(2) Grid clustering

The grid-based grouping method uses a multiresolution grid data structure to quantify the space in a limited number of cells. These cells form a grid structure, and all cluster operations are performed in the continuation of the grid operations [31].

2.6. GBKM. The algorithm has achieved impressive results by using iris and other data for testing and applying it to actual systems, satisfactory results [32].

Let \( A = (D_1, D_2, \cdots, D_n) \) be \( n \)-bounded domains, then \( S = D_1 \times D_2 \times \cdots \times D_n \) is an \( n \)-dimensional space. We regard \( D_1, D_2, \cdots, D_n \) as the dimensions of \( S \). The input of the algorithm is a point set in \( n \)-dimensional space, set as \( V = \{ v_1, v_2, \cdots, v_n \} \), where \( v_i = \{ v_{ij}, v_{i2}, \cdots, v_{in} \} \) represents the \( i \)th point, \( v_{ij} \in D_j \) which means the component of the \( j \)th dimension of the \( i \)th point.

(1) Grid unit

Suppose the value on the \( i \)th dimension is in the interval \([l_i, h_i]\), \( i = 1, 2, \cdots, n \). The length of the grid cell in the \( i \)th dimension is

\[
\delta_i = \frac{(hi - li)}{p}.
\]

The \( j \)th interval on the \( i \)th dimension can be obtained by:

\[
I_{ij} = [l_i + (j - 1)\delta_i, l_i + j\delta_i], \quad j = 1, 2, \cdots, p.
\]

(2) Clustering center of gravity

Given cluster \( K_i = \{ t_{i1}, t_{i2}, \cdots, t_{im} \} \), its mean value, the cluster center of gravity, is defined as:

\[
Z_i = \left( \frac{1}{n} \right) \sum_{x,y \in K_i} (x, y)^2.
\]

(3) Grid cluster analysis

For the determination of the density threshold in the GBKM algorithm, a new algorithm is proposed:

\[
\text{Minpts} = \left[ \frac{\sum_{i=1}^{N} \text{Den}(C_i)}{N} \right]^{1/2}.
\]

Among them, \( \text{Den}(C_i), i = 1, 2, \cdots, N \) is the density value of the \( N \) dense cells with the highest density. The value of \( N \) depends on the specific data. Generally, \( \text{Den}(C_i) \) is arranged in descending order. If \( \text{Den}(C_i) \) and \( \text{Den}(C_{i+1}) \) show obvious changes in density, then \( N = i \).

3. Application Experiment of Cluster Analysis
Algorithm in the Online Intelligent Teaching
Art Resource Platform

3.1. Lab Environment. Based on the .NET digital art education information system, there is only one server, which can make the system maintenance more convenient [8, 33]. The system does not use a dedicated server server, only a dual-purpose database [10]. However, because the system has to deal with all kinds of complex and complicated things, it will reduce the slow system speed and allocate some work to its customers. Based on the above reasons, this system uses C/S and B/S two operating modes to combine the system architecture. In this way, it not only utilizes the characteristics of B/S structure maintenance and simple operation but also uses the characteristics of C/S structure safety and high processing efficiency. Use ASP.NET Web database middleware technology to develop Web pages, and use ADO.NET (ActiveX Data Object.NET) technology and OLEDB to connect and access the database. The design, development, debugging, and deployment of the system share the same working environment, which improves the continuity and efficiency of system development.

The back-end database adopts SQLServer2019, while using JavaBean to realize database connection and data
query and update operations, and adopts advanced B/S (Browser/Server) architecture, and the page design adopts the current international popular webpage authoring tool Dreamweaver2017; both EditPlus are used for editing; the script language uses Java Script, and the page image processing uses Photoshop CS and Flash5.0.

3.2. Development Model. This system is a system composed of people and computers for information collection, storage, knowledge transfer, and use.

4. Application Experiment Analysis of Cluster Analysis Algorithm in the Online Intelligent Teaching Art Resource Platform

4.1. Performance Verification of GBKM Clustering Algorithm. This experiment uses Intel(R) Pentium(R) 4 CPU 2.80 GHz processor, 512 memory, Windows XP Professional (5.1, Build 2600) operating system. The code is written in java language.
Table 5: The clustering of GBKM.

<table>
<thead>
<tr>
<th>Category</th>
<th>Member of class</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>35, 37, 41, 43, 46, 48, 61, 65, 69, 74</td>
</tr>
<tr>
<td>1</td>
<td>8, 26, 30, 31, 32, 33, 34, 37, 38, 44, 46, 47, 49, 50, 51, 52, 54, 55, 56, 59, 60, 62, 64, 66, 69, 70, 71, 72</td>
</tr>
<tr>
<td>2</td>
<td>48, 75, 76, 77, 78, 79, 80, 82</td>
</tr>
<tr>
<td>3</td>
<td>16, 17, 18, 19, 53, 63, 73, 83, 93</td>
</tr>
<tr>
<td>4</td>
<td>7, 9, 10, 11, 12, 13, 14, 15, 20, 21, 22, 23, 24, 25, 27, 28, 29, 39, 40, 41, 57, 68</td>
</tr>
</tbody>
</table>

The sample data for the experiment uses the famous Iris dataset. Its dataset, also known as dataset, dataset or dataset, is a collection of data. Dataset (or dataset) is a collection of data, usually in the form of a table. Each column represents a specific variable. Each row corresponds to a question of a member’s dataset. It lists the values as a random number for each variable, such as height and weight of an object or value. Each value is called a data sheet. Corresponding to the number of rows, the data of the dataset may include one or more members. The dataset includes 4 characteristics of 3 types of flowers: sepal width, sepal length, petal width, and petal length, with a total of 150 records.

First, compare the clustering results of GBKM algorithm and grid clustering algorithm. Use the GB algorithm to cluster the data, and the result is shown in Figure 3.

From Figure 3, we can see that the result of grid clustering is missing many points, and the clustering result is not satisfactory. The low-density area of the grid cluster is discarded, and only the high-density area is processed, resulting in the loss of the cluster. However, the result obtained by using GBKM clustering is much better than the result of grid clustering, and the distribution is shown in Figure 4.

On the horizontal axis, the value in the range from 1 to 2 is setosa type, the grid line with value 5 is the watershed, the left is the versicolor type, and the right is the virginica type. The experiment proves that most of the points can be well clustered.

Next, compare the clustering results of the GBKM clustering algorithm with the clustering results of the K-means clustering algorithm. Using the GBKM clustering algorithm for many experiments, the clustering process has gone through intermediate clustering, postclustering, and clustering after one iteration, and the analysis results are quickly obtained. A total of 3 categories are obtained, and the value of the initial center of each category at each clustering stage is shown in Table 1.

Figure 5 shows the line chart of the clustering center changes during this clustering process. The clustering centers of each class in the figure do not change much at each stage, and they converge quickly. This shows that the GBKM clustering algorithm which obtains the dense unit of the dataset simulates the distribution of the dense area in the dataset, quickly determines the K initial clustering center points, then uses the K-means clustering to reclustering the free data, and finally, completes it quickly and effectively.

However, the results of multiple experiments on Iris data using K-means clustering vary greatly from the initial cluster center to the final cluster center. In this clustering process, the K-means algorithm randomly selected 3 points as the initial clustering center, and it could not capture the center of natural clustering well. The algorithm continued to find a better initial clustering center. It is the constantly changing clustering center that makes the algorithm unable to converge quickly, and the number of iterations of the algorithm has also increased significantly to 11 or more.

4.2. Purity Comparison. Using the Iris dataset, several experiments were performed, and the result values of the purity of the clusters obtained by the three different algorithms are shown in Table 2.

In order to see the difference between the three more intuitively, Figure 6 shows the purity comparison line chart.

Obviously, the GBKM algorithm is significantly better than other algorithms in terms of purity, and the polyline of the GBKM clustering shown in Figure 5 is more stable than the other two algorithms. Therefore, the GBKM algorithm is more stable and can reconstruct free data compared to other algorithms and finally complete clustering quickly and effectively.

4.3. Evaluation of Cohesion Degree and Separation Degree. After clustering, the data in the clusters should be as compact as possible, and the data gap between the clusters should be as large as possible, the aggregation degree should be as small as possible, and the separation degree should be as large as possible.

The Iris dataset is still used this time, and the K-means clustering and GBKM clustering algorithms are used for repeated experiments. The results obtained are shown in Table 3 and Table 4.
It can be seen from Table 3 that in the comparison of the aggregation degree of the 8 pairs of clustering results, the aggregation degree obtained by the GBKM clustering is much smaller than the aggregation degree obtained by the K-means clustering. The smaller the degree of aggregation, the tighter the objects in the cluster, and the better the clustering result. At the same time, it can be seen from Table 4 that in the comparison of the degree of separation of the 8 pairs of clustering results, the degree of separation obtained by the GBKM clustering is greater than the degree of separation obtained by the K-means clustering. The greater the degree of separation, the greater the object difference between clusters, and the better the clustering results. The maximum difference reached 270.9847.

### 4.4. Evaluation of Online Intelligent Teaching Art Resource Platform

In this online intelligent art education resource platform, GBKM generation was used as the basic performance analysis algorithm of the application, and the corresponding content in the database was successfully read, and the GBKM clusters other than the formed clusters were quickly and effectively analyzed. After analyzing and displaying the analysis results on the browser page, save the analysis results in the corresponding test history database table, and update the entries in the database table.

The clustering results are shown in Table 5.

Comparing the characteristics of each class, we can see that the members between the classes are very similar, and the differences between the classes are very large, and the cluster center of each class can represent the characteristics of each class. In the figure, it can be seen that the members belonging to category 0 have high scores in each chapter, especially the relatively low scores of chapter 3, so in the future learning, we must maintain the advantages of chapter 0 and strengthen the study of chapter 3.

### 4.5. Stress Test

The system was subjected to stress testing, and in the actual application process, an online intelligent teaching art resource platform based on cluster analysis algorithm was selected. Observe the performance of the system, and use the test sample of the full-text search of the survey information as the performance test.

As shown in Figure 7, analyze the results of the stress test, and the response time will increase or decrease with the number of visits. In the high-stress test, it can also maintain good performance and response time to meet the demand.

### 4.6. Platform Processing Performance

The system transaction performance of the platform is tested, and the results are shown in Table 6.

It can be seen from Figure 8 that the number of transactions processed by the platform per second is 65.21, which can well simulate real information query use cases. The platform processing transaction time will eventually stabilize between 30 s, which can well meet the performance requirements.

### 5. Conclusion

In recent years, with the rapid development of the Internet, the Internet has penetrated into all aspects of social life and has become an important part of human life. While the Internet is widely used, along with the explosive growth of network data, information that is of great significance to people’s lives and human development is hidden in the huge network data. How to capture hidden campus network behavior information from these data? It has become a hot spot and focus of current research. The application of clustering algorithm in campus user behavior analysis is quite mature and has achieved certain results. However, due to the diversity, dynamics, and relevance of network user behaviors, resulting in complex data structures, there is still no algorithm that can be universally applied to reveal the structural characteristics of various multidimensional network user behavior data. Therefore, by analyzing the advantages and disadvantages of different clustering algorithms, combining the advantages of the algorithm itself in different data structures to propose suitable improved algorithms is still the focus of clustering technology in the application of research. How to apply the GBKM algorithm to the embedded online intelligent teaching platform more widely is the subject of the next research, such as how to tap the learning habits of the majority of students, discover the habits of the majority of students to browse the web, and how to discover the laws and potentials of the students’ learning courseware demand. Due to the limited data, the results of the experiment are relatively one-sided and cannot represent the conclusion of all the data, but it can also reflect the problem from a certain aspect. First of all, although the article improves the traditional clustering analysis algorithm, proposes the GBKM clustering analysis algorithm, and has
achieved good results, the algorithm still has shortcomings, such as how to better choose the density threshold, which will affect the performance of the algorithm, and this is also the place that needs to be studied and improved in the future. Secondly, how to apply the GBKM algorithm to the embedded online intelligent teaching platform more widely is the subject of the next research, such as how to mine the study habits of the students, the habits of browsing the web, and the rules of the students learning coursework and potential needs.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References


