Design and Implementation of a Student Behavior Analysis System Based on the Kmeans Algorithm

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Abstract: Aims to deepen the application of digital teaching material in the teaching process and improve its quality, ensure the quality of digital teaching material continuous optimization, this study to "nursing management" this course as a research object, for 497 students in a semester of 36 kinds of different digital teaching materials use behavior data collection. After regularization processing, the classification of behavioral data is completed by K mean algorithm. On the basis of the classification results, this paper makes an in-depth analysis of different types of digital teaching materials, and puts forward a personalized optimization scheme. This method effectively solves the problem that cannot be accurately analyzed in the context of large data volume, and reduces the large errors that may be generated by manual analysis. The classification results of resources are used to determine the quality of digital teaching materials, which provides a solid analysis foundation for the continuous progress of the quality of teaching materials.

1 INTRODUCTION

The Blueprint for the Development of China's Digital Economy during the 14th Five-Year Plan Period clearly guides the direction of continuously promoting the healthy development of "Internet plus education", that is, the continuous radical reform and innovation activities of education modernization. The main position of teaching innovation is located in the classroom. With the rapid development of information technology, digital teaching materials are more and more used in daily classroom teaching. The so-called digital teaching resources refer to the educational materials that can be used in the multimedia computer system or network environment and can realize resource sharing after digital processing. In the process of digital teaching transformation, we need to collect, analyze and use data in the content of teaching plans, learning materials, teaching activities and many other levels, so as to promote the digitalization of teaching activities, create a ubiquitous network learning environment, and promote the extensive implementation of innovative teaching mode. In addition, the "Ministry of Education on the construction of first-class undergraduate curriculum guidance" also explained this. Teaching materials should keep up with the trend of The Times, and should have the characteristics of diversification. From this perspective, digital education resources have been widely respected in many institutions of higher learning in China, and have gradually evolved into important materials that cannot be missing in teaching activities, providing a solid foundation for the improvement and innovation of teaching methods.

With the popularization of e-learning materials, online learning students have produced a lot of behavior records, such as records of watching videos, interactive click logs, discussion courses and other (Zaky, Ahmed et al. 2023). These behavioral records reflect the students 'learning effectiveness (Li, 2023), which provides scientific research data support for the analysis of students' learning models. Many researchers have used this kind of data to carry out several studies, including analyzing the change of students 'online learning attitude (Deng, 2022) , grouping students into groups according to students' characteristics (Dolbier, Vanacore, et al. 2023) , and predicting students' performance.

Kmeans As a classic representative of partitioning clustering method, the algorithm (Wang, 2022) has been applied in many fields due to its efficient and simple and rapid convergence of implementation process, including the evaluation and analysis of

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student performance , the of daily temperature load mode and the identification of key edges in machining . The main advantage of this algorithm is that the output result is clear, which is easy to reveal the potential patterns. Based on the principle of student-oriented, this paper comprehensively considers students' learning feelings, so as to promote the reasonable allocation of digital teaching resources. By analyzing the behavioral data of students' interactive digital teaching resources, this study uses the Kmeans clustering algorithm in unsupervised learning to obtain the classification results. In-depth analysis of these classification results, and through continuous observation of the use of different categories of digital teaching resources, aims to ultimately promote the improvement of the quality of teaching resources.

2 DESCRIPTION OF THE RELATED PROBLEMS

2.1 Analysis of the Constraint Parameter Data of the Student Behavior Analysis System

Based on the Kmeans algorithm, the sampling model of the constraint parameters of the student behavior analysis system is established, and the nonlinear information fusion is combined with the time series analysis, so as to carry out the statistical analysis of the student behavior analysis system. The constraint index parameters of the student behavior analysis system belong to the non-linear time series. Establish the distribution model of the practice evaluation index of students' behavior analysis system. The constraint parameter model of differential equation expression system is expressed as:

$$x_n = x(t_0 + n\Delta t) = h[z(t_0 + n\Delta t)] + \omega_n$$

In the high-dimensional feature distribution space, the training subset of the evaluation characteristics of the student behavior analysis system is obtained to meet the following conditions:

$$\sum = diag(\delta_1, \delta_2, \cdots, \delta_T), \delta_i = \sqrt{\lambda_i}, \forall i \neq j \tag{1}$$

$$\bigcup_{i=1}^{L} S_i = V - v_s \tag{2}$$

$$x_{n+1} = \mu x_n(1 - x_n)$$
$$U = \{u(t) \mid u(t) \in X, \|u\| \leq d, t \in I\}$$

It is the solution of the statistical model of the effect evaluation of students' behavior analysis system, which meets the decomposition conditions of the initial characteristics. The information flow model of Kmeans algorithm practice based on the previous statistical measurement value is expressed as follows:

$$c_{1x}(\tau) = E\{x(n)\} = 0$$
$$c_{2x}(\tau) = E\{x(n)x(n+\tau)\} = r(\tau)$$
$$c_{kx}(\tau_1, \tau_2, \cdots, \tau_{k-1}) \equiv 0, k \geq 3$$

The teacher strength level of the student behavior analysis system and the distribution level of the resources of the student behavior analysis system need to meet the continuous functional condition, that is, the convergence solution of the student behavior analysis system evaluation, and the constraint condition is expressed as follows:

$$\Psi_x(\omega) = \ln \Phi_x(\omega) = -\frac{1}{2}\omega^2\sigma^2$$

According to the information flow model of the effect of student behavior analysis system, the data distribution model of sampling sequence is established to provide the data input basis for the practice method of student behavior analysis system.

2.2 Quantitative Recursive Analysis of The Student Behavior Analysis System Based on the Kmeans Algorithm

The data model analysis of the student behavior analysis system is conducted through quantitative recursive analysis, and the control objective function predicted by the student behavior analysis system is expressed as follows:

$$\max_{x_{a,b,d,p}} \sum_{a\in A}\sum_{b\in B}\sum_{d\in D}\sum_{p\in P} x_{a,b,d,p} V_p$$
$$s.t. \sum_{a\in A}\sum_{d\in D}\sum_{p\in P} x_{a,b,d,p} R_p^{bw} \leq K_b^{bw}(S), b \in B$$

The Kmeans algorithm is used to carry out quantitative recursive evaluation of students' behavior analysis system level. It is assumed that under the historical data of student behavior analysis system distribution in the initial value of disturbance characteristics, the prediction probability density functional of student behavior analysis system is expressed as follows:

$$u_e(t) = Kx_e(t)$$

All the K nearest neighbor sample values of the output index distribution data of the student behavior analysis system are expressed as:

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

The objective function of the distributed data flow of the student behavior analysis system is established by the data and information fusion, that is, the objective function of the data clustering is expressed as follows:

$$Jm(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}^{m} (d_{ik})^2$$

By expanding the distribution sequence of the student behavior analysis system index and combining with the K-value finding method, the results of quantitative recursive feature extraction of the student behavior analysis system are expressed as follows:

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

3 ANALYSIS OF THE EXPERIMENTAL RESULTS

Aiming at grasping the specific use of students 'digital teaching resources, this study selects a course on the online teaching platform of a college, and collects and analyzes the relevant behavior information of students' contact with the digital teaching resources on the platform during this period.

3.1 Acquisition of the Behavioral Data

In this study, we selected the required undergraduate "nursing management" as the survey object to make a community analysis of the collected student behavior information. This course has diversified teaching arrangements, including online self-study, classroom teaching, clinical operation and social application, etc., and integrates the education mode of "four-in-one type, double platforms and three steps", with massive digital teaching materials; many courses have been successfully held on the network platform, which can accommodate 400 to 500 students to register for study. The article examines in detail the five key teaching interaction data of students in the latest semester, such as video learning completion rate, discussion and interaction frequency, classroom learning frequency, after-school test scores and homework scores. The video material consists of 32 video learning content in different chapters. Specific behavioral information data are given in Table 1 in the text.

Table 1: Student behavioral data

1 Student ID	Video resources			
	Resources 1 (%)	Resources 2 (%)	...	Resource of 32 (%)
2019001	76.4	127.4	...	50.6
2019002	52.2	50.6	...	50.3
2019003	100.1	117.5	...	127.3
2019004	100.1	100.3	...	100.2
2019005	51.2	50.4	...	100.2
2019006	100.1	100.8	...	99.8
2019007	52.3	50.7	...	100.2
2019008	100.4	100.3	...	127.3
...	...	...	...	...

Here, by ij represents the specific values of students numbered i in the j th resource, with details given in Table 1. The video resources produced in 32 different chapters constitute the video textbook, which tracks the students 'learning behavior by recording the completion percentage of the material. The course interaction can be observed by the number of discussion topics students participate in the course. which reflects the learning enthusiasm and the difficulty of the course, and the chapter quiz and homework results directly demonstrate the students' learning results, which come from the students' scoring during the chapter examination and completing the course assignments.

3.2 Data Normalization

Chart 1 reveals that the student behavior data extracted from the network learning platform presents a heterogeneity. Given that the different categories of teaching resources are equally important, we standardized these data to a range of 0 to 100. Specific to each resource, its standardized computational flow is described below.

The digital identification of the learning progress of the film reflects the completeness of the viewing material, that is, when the value reaches or exceeds 100%, it can be considered to have mastered the learning material thoroughly.

The number of discussions, the learning frequency of each chapter, chapter testing, and job scores are standardized, in which the term max (yj) refers to the highest value of the j th type of resource.

3.3 Using Kmeans, the Algorithm for Clustering

After the collected data was standardized processing, the classification was implemented based on the Kmeans algorithm. The specific operation steps are as follows:

Algorithm input, namely the resource value set y.

The output obtained after the algorithm includes the conclusion of the cluster as well as the error squared and SSE of the cluster.

After normalization operation, dataset y was transformed into dataset X containing behavioral samples of n students.

The number of clusters k was determined, with the behavioral dataset X as input, following the algorithmic steps presented in Figure 1 to perform data aggregation.

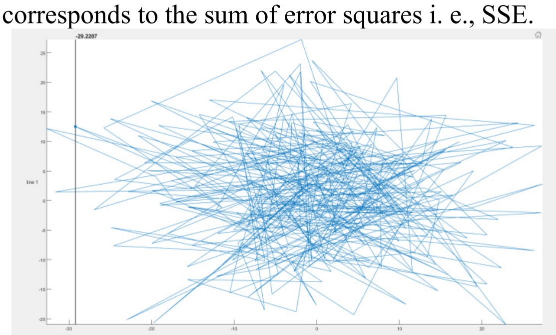
The results of the cluster analysis and its corresponding squared error sum SSE are provided as the resulting output.

Increase the cluster number k and recluster.

Outputs all the clustering results that satisfy the criteria.

3.4 K Value Determination and Most Clustering Results

Relying on the Kmeans algorithm to implement the cluster analysis of action data, which is shown in Figure 2. The horizontal axis in the graph represents the number of clusters k, while the vertical axis corresponds to the sum of error squares i. e., SSE.



1 Figure 1: Cluster error sum of squares

By analyzing the sum of error squares of each k option, we can observe a special turning point in the SSE change curve, that is, the "elbow" point, where the decrease slows down significantly at this point, so the k value corresponding to this point is determined to be the optimal solution. Based on this optimal k value, the student behavioral data can be effectively divided into 12 categories. When the number of selected clusters is 12, the cluster centers of each other category are presented according to the information in Table 2. With the number of clusters of 12, the mean versus standard deviations of each cluster center are detailed in Table 3. Meanwhile, when the number of clusters is set as 12, the proportion of students in different clusters and their distribution are shown in Table 4.

Table 2: Values of cluster center points 2

Cluster serial number	Video resources			
	Resource 1	Resource 2	...	Resources 32
1	100.00	96.67	...	25.10
2	98.57	97.63	...	75.89
3	32.90	9.88	...	10.08
4	69.95	58.85	...	48.06
5	95.49	92.33	...	93.87
6	97.40	97.49	...	9.73
7	97.38	98.00	...	97.71
8	87.79	90.30	...	64.84
9	96.78	93.72	...	90.13
10	99.43	99.69	...	99.00
11	97.49	97.17	...	6.32
12	83.48	76.91	...	83.81

Table 3: Mean and standard deviations of cluster central points 3

Numerical type	Video resources			
	Resource 1	Resource 2	...	Resources 32
mean	88.06	84.05	...	58.71
standard error	18.64	25.04	...	35.45

Table 4: Number of students in each cluster

Cluster serial number	1	2	3	4	5	6	7	8	9	10	11	12
Number of clusters	6	41	8	33	39	22	95	28	18	172	12	23

proportion (%)	1.21	8.25	1.61	6.64	7.85	4.43	19.11	5.63	3.62	34.61	2.41	4.63

4 CONCLUSION ANALYSIS

Student behavior data was adjusted to a range of 0 to 100 for all resources, and 60 points were used as the eligibility standard. Referring to Table 2 to Table 4, taking the course "Nursing Management" as an example, the Kmeans algorithm is used to analyze the behavior of students in digital teaching resources as follows.

4.1 Video Teaching Resources

By comparing the cluster center data in Table 2, the center values of three clusters with serial numbers 5,7 and 10 respectively are higher than 60, and the proportion of students corresponding to the fourth table) is 61.57%, while the center values of two clusters marked 1 and 3 are generally less than 60, and the resource value decreases significantly in some areas, and the proportion of these students is 2.82%. Such data show that most students hold a positive attitude towards video teaching resources, show a certain enthusiasm for learning, and can complete the task of video learning. Nevertheless, we still need to pay attention to the use of video resources in the two clusters of serial numbers 1 and 3, actively collect their feedback, and optimize and adjust the video resources according to the feedback, so as to improve the overall quality of teaching resources.

According to the center of figure three point data vertical research, we found that 28 and 32 resources related cluster center value of the average are not more than 60, at the same time the central numerical fluctuation is relatively high, this trend shows the students on the two resources, and the difference between students, so the research team need for the two teaching video appropriate modification and optimization.

4.2 Number of Discussions

According to table 2, table 3 data analysis, found that the core data are not break the boundaries of 60, at the same time the standard deviation performance is low, it shows that most students lack on the behavior of posts, course discussion enthusiasm is not enough, and these discussion frequency directly mapping the student initiative in course interaction, it became the key channel communication between time and space between teachers and students. Therefore, course makers need to reconsider how to set the discussion topic and how to plan the content of the topic discussion, enhance the role of teachers in the guidance of students' discussion and q & A, and enhance the activity of the teacher team in the q & A discussion page.

4.3 Number of Chapter Studies

After observing the details of Table 2 and Table 3, it is found that the average number of times that students use in the learning process of chapters is low, and the standard deviation of their distribution is relatively low, showing that learners can master the teaching resources with a small number of attempts. Students using the platform; however, whether the course resources are challenging, which may absorb the content and key points of the course without repeated learning, which indicates that teachers should consider the depth and difficulty of designing course resources.

4.4 Section Test

In Table 1 and Table 2, except for cluster 3, the chapter test scores of each central point exceeded 60 points, and the standard deviation showed a high degree of dispersion. This shows that most students have a good grasp of the chapters. However, for the eight students in Cluster 3, the should fluctuations,, should to particularly attention.

4.5 Homework

According to the data analysis of the second and third tables, the scores of all job nodes are generally above 60 points, and the score volatility is low, meaning that the standard deviation is small. This suggests that the performance assessment conducted through the submitted assignments reflects the students' relatively good mastery of the course. In addition, the digital education content provided by the platform plays a positive role in improving students' learning effectiveness.

5 CONCLUSIONS

In the course of "nursing management", we collected data on the use of digital teaching resources within a semester and standardized the data. Then, the Kmeans algorithm is used to cluster the data, and combine the error square sum SSE and the "elbow" point method to determine the most appropriate clustering number of clusters and the most optimal clustering effect. Through thorough analysis of clustering results, we find that the use of video resources is generally good, but the 28th and 32nd resources need to be further optimized; students 'participation in the discussion shows the lack of the course in encouraging students' communication and interaction; the challenge of the course content needs to be improved; and it can effectively reflect students' learning situation. The improvement proposed by the study aims to continuously improve the quality of digital teaching resources.

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