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Research article

A rational resource allocation method for multimedia network teaching reform based on Bayesian partition data mining

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Abstract: In order to improve the application of teaching resources and reduce delays in the integration process of multimedia network, a rational resource allocation method for multimedia network teaching reform based on Bayesian partition data mining is proposed. Bayesian partition is used to preprocess the multimedia network teaching resources (MNTR), adjusting the recognition probability of MNTR in each partition based on its attributes. By performing Bayesian quantitative classification using samples of MNTR, the prior probability is adjusted through maximization analysis. The partitioned resources undergo sample data mining to obtain the data category collection of all MNTR. A prediction model is then built to forecast the demand for teaching resources at specific times in the future. MNTR can be rationally allocated based on the prediction results. Experimental results demonstrate that this method reduces delays in MNTR application and improves the accuracy and utilization of teaching resources.

Keywords: Bayesian; partition data mining; multimedia network; teaching reform resources; rational allocation; resource forecast

1. Introduction

Under the condition that the reform of the educational system is gradually strengthened and the computer technology is becoming more mature, the construction and application of multimedia network teaching resources (MNTR) has become a key symbol of the teaching level and school image of colleges and universities [1]. Therefore, all colleges and universities have set the construction of MNTR as the focus of their work and put a large amount of human, material and financial resources into it, which has also led to significant changes in the school structure of colleges and universities, and the school running structure has a decisive impact on the allocation of educational resources [2]. At present, there are some unreasonable problems in the structure and operation mechanism of higher education in China. It is precisely because of these problems that the rational allocation of resources in the multimedia network teaching reform has become the focus of the current teaching system reform [3].

The main purpose of teaching resource allocation is to improve the applicability and application efficiency of multimedia network teaching reform resources [4], while the use of MNTR needs to identify MNTR [5], and the identification of MNTR requires a priori analysis of the characteristics and categories of teaching resources, so as to provide a basis for the determination of MNTR. On this basis, the classification of MNTR is determined by the analysis algorithm. To complete the above-mentioned process, it is necessary to perform probabilistic analysis on the features of MNTR through the features in the recognition model, so as to realize high-precision recognition of MNTR. Based on the identified different types of MNTR, it adopts scientific methods to promote the rationalization of the allocation of MNTR.

Scholars at home and abroad have done a lot of research on the allocation of MNTR and other related issues. For example, Bayat and Khalili proposed a multi-objective resource allocation method for Device to Device (D2D) and enabling multi-carrier non-orthogonal multiple-access (MC-NOMA) networks based on the Tchebycheff method. While considering the relevant standards, they used the weighted Tchebycheff method to transform the multi-objective optimization problem into a single objective optimization problem. On this basis, they used the monotone optimization method to solve the single objective optimization problem [6]; However, in the practical application of this method, due to the huge amount of data of teaching resources, there is a high probability of local optimization. Sun [7] proposed a resource allocation method of a vocal music teaching system based on mobile edge computing, and realized the optimal allocation of teaching resources through iterative optimization; this method has a certain bias to the classification of resources in the practical application process, and has a large probability to affect the identification of new resources. Ao et al. [8] proposed a hybrid grey wolf-symbiotic search algorithm (MRSSOS) based on the multi role optimization strategy in view of the shortcomings of the symbiotic search algorithm, such as easy to fall into local optimization and search stagnation, to improve the standard SOS algorithm from many aspects, reduce invalid search while maintaining population diversity and further balance the exploration ability and mining ability in the iterative process of the algorithm; this method cannot meet the requirements of rationality and real-time in the process of resource allocation in practical application.

The above-mentioned study is limited by the diversity of resources and convergence speed, resulting in increased transmission delay and energy consumption. In order to enhance the utilization of educational resources and reduce latency in the multimedia network integration process, we propose a Bayesian partition-based data mining method for rational allocation of multimedia network educational reform resources. The data mining algorithm includes several data classification methods; thus, it can be essentially understood as a data classification algorithm [9]. Moreover, this type of algorithm has good compatibility and can be combined with other data processing algorithms for application. By applying Bayesian partitioning to preprocess MNTR and using the data mining process to classify them into different categories, the MNTR can be reasonably allocated based on the host load prediction results. This allocation aims to satisfy the resource requirements while minimizing the host load, thereby improving system efficiency and performance, and achieving rational allocation of MNTR.

2. Resource allocation of multimedia network teaching reform

2.1. Framework of the rational allocation method of MNTR

By constructing a reasonable resource allocation method architecture, the transmission distance and path of resources can be reduced, thereby reducing transmission delay and energy consumption, and providing a faster, more efficient and stable network teaching environment. Figure 1 shows the structure of the method for rationalizing the allocation of MNTR, which mostly involves the document library, controller, hub accelerator, hub, application terminal and other parts of multimedia network teaching reform resources. Each part uses star connection to build NOVELL Network [10].

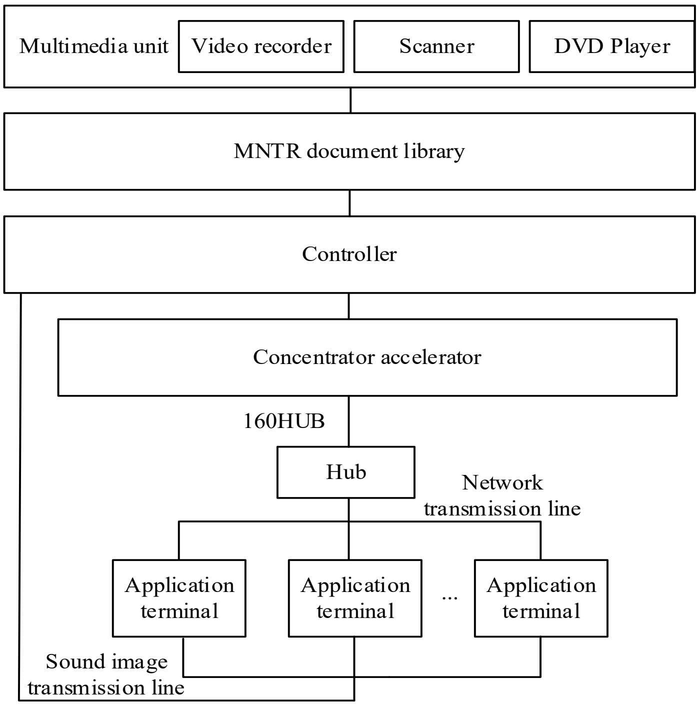

Figure 1. Architecture of the multimedia network teaching resource platform.

In the framework of the rational allocation method of MNTR [11], teachers record MNTR using video recorders, scanners, Video Compact Discs (VCDs) and other equipment, store MNTR in the resource library of multimedia network teaching reform and divide the categories of MNTR through Bayesian partition data mining algorithm; the task scheduling model in the controller rationally configures the MNTR, and the configured MNTR are transmitted to different application terminals through the hub for use by users.

2.2. Processing of MNTR

2.2.1 Resource partitioning based on the Bayesian classification algorithm

The Bayesian classification algorithm is a Statistical classification method, which assumes the independence of observation data and calculates Posterior probability through Prior probability and Conditional probability for classification [12]. In the classification task of MNTR, the Bayesian classification algorithm can be used to calculate the probability according to the actual data, so as to partition the resources and make the resources in each area more similar. Using this algorithm, it is possible to better understand the classification and partitioning results of resources, know the probability distribution of each category and classify them accordingly. A pair of random variables in the MNTR are represented by X and Y, thus the Bayesian theory can be described by formula (1):

$$P(Y|X)=\frac{P(X|Y)P(Y)}{P(X)} \tag{1}$$

In the actual process of classification of MNTR, if X and Y are defined as the characteristic variables and category variables of the classification object (MNTR), $P(Y|X)$ can describe the correlation between the characteristics of MNTR and their categories from the perspective of probability, define it as the posterior probability of Y and define $P(Y)$ as the prior probability of Y. The judgment of $P(X|Y)$ should be emphasized in the calculation of $P(Y|X)$. If the MNTR contain m categories of teaching resources, $Y=\{L_1,L_2,L_3,\cdots,L_m\}$ represents the category mark set and the feature X can be described by P indicators, that is, $X=\{X^{(1)},X^{(2)},X^{(3)},\cdots,X^{(p)}\}$. In the process of judging $P(X|Y)$, it is generally set that the features have category independence characteristics, that is, the proportion of the features of the multimedia network teaching resource samples marked as the same category is independent [13], which can be described by formula (2):

$$P(X=x|Y=L_k)=\prod_{j=1}^{P}P\left(X^{(j)}=x^{(j)}|Y=L_k\right) \tag{2}$$

where, $k=1,\cdots,m$.

Based on formula (1), formula (2) and the full probability formula, the posterior probability that the MNTR belong to class $L_k\ (k=1,\cdots,m)$ can be described by formula (3):

$$P(Y=L_k|X=x)=\frac{P(Y=L_k)\prod_{j=1}^{P}P\left(X^{(j)}=x^{(j)}|Y=L_k\right)}{\sum_{k=1}^{m}P(Y=L_k)\prod_{j=1}^{P}P\left(X^{(j)}|Y=L_k\right)} \tag{3}$$

The maximum a posteriori criterion in the classification of MNTR by the Bayesian algorithm is to determine that formula (3) reaches the upper limit [14], that is, to determine the category of MNTR as formula (4):

$$y = f(x) = \arg\max_{L_k} \frac{P(Y = L_k)\prod_{j=1}^{p} P\left(X^{(j)} = x^{(j)} \middle| Y = L_k\right)}{\sum_{k=1}^{m} P(Y = L_k)\prod_{j=1}^{p} P\left(X^{(j)} \middle| Y = L_k\right)} \tag{4}$$

Moreover, the denominator in formula (4) is consistent with all L_k, so it can be transformed into formula (5):

$$y = \arg\max_{L_k} P(Y = L_k)\prod_{j=1}^{p} P\left(X^{(j)} = x^{(j)} \middle| Y = L_k\right) \tag{5}$$

In fact, the above posterior probability is infinite and the near-term risk is minimal [15]. Formula (6) is used to describe the 0–1 loss function:

$$S(Y, f(x)) = \begin{cases} 0, Y = f(X) \\ 1, Y \neq f(X) \end{cases} \tag{6}$$

In formula (6), $f(X)$ is the predicted classification result. The expected risk function is described by formula (7):

$$R(y) = E\left|S(Y, y)\right| = Wx\sum_{k=1}^{m}\left[S(Y, L_k)\right]P(L_k|X) \tag{7}$$

In order to minimize the expected risk, it is only necessary to minimize $X = x$, thereby obtaining formula (8):

$$\begin{aligned} f(x) &= \arg\min_{y} \sum_{k=1}^{m} S(y, L_k)P(L_k|X = x) \\ &= \arg\min_{y}\left(1 - P\left(y = L_k|X = x\right)\right) \\ &= \arg\max_{y} P\left(y = L_k|X = x\right) \end{aligned} \tag{8}$$

On this basis, according to the expected risk minimization standard, the maximum posterior probability criterion [16] can be determined as formula (9):

$$f(x) = \arg\max_{L_k} P(L_k|X = x) \tag{9}$$

Based on the above process, it can be seen that the process of classifying MNTR by the Bayesian classification method is relatively simple. However, this method also has some problems. For example, within the prior probability obtained through the multimedia network teaching resource sample, if a certain component has never appeared in any category of the overall multimedia network teaching resource sample, the final result of the entire test case will be zero. In order to prevent the elimination of attribute values that do not appear in the training set of the information contained in other attributes, smoothing processing is required in the process of determining the prior probability, and the commonly used processing method is Laplace correction [17]. Laplacian correction ensures that each category has a non-zero prior probability by adding a smoothing factor to the count value of each category, making the probability estimation smoother and more reasonable. To avoid the problem of encountering categories that do not appear in the training data or have very few samples during the classification process, it improves the performance and generalization ability of Bayesian classification algorithms.

The Bayesian classification prior probability smoothing process based on Laplace correction is described in detail as follows:

The training set of multimedia network teaching resource classification is represented by H, and the number of categories included in the training set is N. Therefore, the possible value number of the *i*-th attribute can be described by N_i, and the modified formula (10) can be obtained:

$$\begin{cases} P\left(C_k\right)=\dfrac{\left|H_c\right|+1}{\left|H\right|+N} \\ P\left(X\middle|C_k\right)=\dfrac{\left|H_{c,x_i}\right|+1}{\left|H_c\right|+N_i} \end{cases} \tag{10}$$

According to the above process, Laplace correction can avoid the phenomenon that the probability value is zero due to incomplete samples of MNTR in the process of classification of MNTR, and, under the condition that the training set of MNTR is gradually improved, the prior influence used in the correction process is gradually reduced, so that the prior probability gradually approaches the actual probability to get more accurate classification results of MNTR.

2.2.2 Data mining of MNTR

After the division of MNTR is realized using Bayesian theory, data mining is carried out on the MNTR samples that have been divided into four parts, namely, the feature data extraction of MNTR, the preprocessing of MNTR, the classification of MNTR and the model construction. The data mining process is described as follows:

1) Carry out the trend analysis on the category of MNTR for the determined zones, thereby dividing the big data format and the type category of different MNTR;

2) Implement probabilistic processing on MNTR [18], and superimpose the probabilistic attribute and probabilistic coefficient of MNTR;

3) Transform the probabilistic distribution of MNTR into feature vectors through Bayesian topological structures, thereby constructing the boundary conditions of data mining [19].

A and B respectively represent the set of MNTR and the mining feature parameters, and n and l, respectively represent the classification coefficient and probability coefficient of MNTR. Therefore, the calculation rule of partition data mining of MNTR conforms to formula (11):

$$\int \overline{P}=\left\{P\left(a_n\right)\sum_{i\in n}^{B_i} l\left(A_i,B^n\right)\forall\right\} \tag{11}$$

In order to enhance the constraint relationship between the accuracy of data mining and the mining efficiency [20], the initial massive MNTRs are partitioned by Bayes partition, so that the emphasis of the partitioned areas is also different in the process of data mining [21]. In view of the difference in the probabilistic values of the different MNTR, the mining depth and efficiency are optimized to prevent the mining process from failure. Thus, the efficiency of partition mining of MNTR is guaranteed.

The data set in any Bayes partition is represented by X, where the matrix form that can be converted into $n \times n$ corresponds to the multimedia network teaching resource sample set. Therefore, the probability correlation that conforms to the partition data mining can be described by formula (12):

$$X = \sum_{n \in N} \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{pmatrix} \tag{12}$$

In order to improve the classification accuracy and convergence efficiency of resource categories in MNTR, Bayesian partitions are introduced in the data partitioning process before mining MNTR, so that the recognition probability of multimedia network teaching resource categories in each partition can be adjusted according to the partition attribute, and the accuracy and convergence efficiency of category identification of multimedia network teaching resource can be improved. According to the above process, the data sets in each Bayesian partition can be iterated, thereby efficiently determining all the data category sets of multimedia network teaching resources.

2.3. Rational allocation of MNTR based on resource prediction

In the configuration process of different types of MNTR, the classified MNTR are stored in the document library and can be read at any time. These different types of teaching resources are the basis for rational configuration. The process of rational allocation of different types of MNTR can be divided into pretreatment, operation and ending.

In the preprocessing process, before the rationalization of different types of MNTR, it is necessary to obtain the relevant operation and environment information, so as to improve the implementation efficiency of the rationalization. The information required by this link includes the content request and the current load processing status transmitted by the application end to the document library of multimedia network teaching resources via the network. The content request data can be obtained by querying the relevant data record table, and the processing status data can be obtained by running the state space program. Based on the data obtained in the above process, the prediction model is used to calculate the future usage trend of the central processing unit (CPU) at the application end and the application prediction of the application end for different types of MNTR.

In the operation link, according to the prediction results of the preprocessing link, whether to operate the rationalization configuration program of different types of MNTR is determined. The prediction data obtained in the previous step will be compared with the preset startup threshold. If the threshold setting range is exceeded, the rationalization configuration program of different types of MNTR will begin, whereby more CPU resources will be allocated to the application with heavy load, thereby reducing the rationalization configuration load of different types of MNTR.

If the configuration program is started in the operation phase, the closing phase will be executed after the configuration is completed. In this link, the system transmits information to relevant components to enable different units to complete the configuration process of MNTR, reset relevant parameters and start the next rationalization configuration task after the reset is completed.

Figure 2 shows the flow of rationalization of MNTR based on resource prediction.

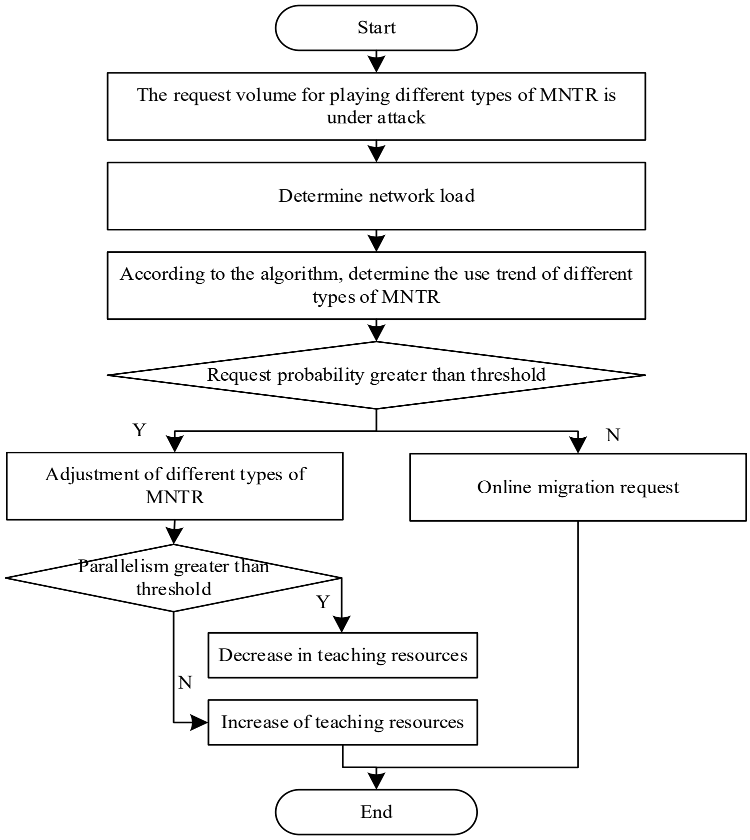

Figure 2. Flow chart of rational resources allocation of multimedia network teaching.

The processing performance of multimedia network resources in the preprocessing process has a major impact on the rationality of the final allocation of different types of MNTR. In the pre-processing process, the current operation information needs to be obtained during the operation of the multimedia network teaching platform, so as to build the prediction model for the application of different types of MNTR. Additionally, from the perspective of performance, the efficiency of data acquisition and the operation efficiency of prediction algorithms should be improved at the same time in the preprocessing process. The user's different operation data for the application of various MNTRs are stored in the controller. Furthermore, considering that the load data fluctuates rapidly in the rationalization process of different types of MNTR, the memory file technology is adopted in the rationalization process of various MNTRs, so as to obtain the high-speed transformed load information at a faster speed, improving the access efficiency of application data in different types of MNTR. The preprocessing process mostly includes data acquisition, data processing and prediction operation, among which the prediction operation process is the most critical.

There are three aspects that need to be focused on during the prediction operation, namely:

1) The application status of the CPU at the application end is because the streaming media resource service is mainly applied to different application terminals and is controlled to realize the configuration of different types of MNTR;

2) The application terminal is carried on the physical server node. Currently, the processing of the server node basically has the performance of multi-core and multi-threaded processing. Therefore, it is necessary to analyze the conditions for its parallel operation;

3) During the operation of different types of MNTR, not all resources are evenly distributed.

Under some conditions, the application of many types of MNTR is concentrated on a small number of resource files. Therefore, under the condition of insufficient service resources, if most of the resources are allocated to service requests with high application degrees, the service efficiency will be enhanced as a whole. Based on the above analysis, a demand prediction model for different types of MNTR is constructed. The model includes two major parts, as shown below.

1) Prediction of the CPU utilization of the application end in the corresponding time in the future.

The utilization rate of the CPU at time t is represented by $U_v(t)$, and the time slice during the operation of the CPU is divided into: the CPU consumption time and idle time (t_s and t_{idle}) in the system mode, the waiting time in the data input / output exchange process and the CPU consumption time (t_{io} and t_u) in the user mode, the internal soft interrupt processing time and the external interrupt processing time (t_{si} and t_{irp}) in the system. Whereby formula (13) can be obtained:

$$U_v(t) = \frac{t_s + t_{io} + t_u + t_{si} + t_{irp}}{t_{total}} = 1 - \frac{t_{idle}}{t_{total}} \tag{13}$$

The prediction model formula (14) can be obtained by processing formula (13) with collage quantitative and separate interpolation methods:

$$U_v(t) = \bigcap_{i=1}^{n} w_i(L) \tag{14}$$

In formula (14), w_i and L respectively represent the radiation transformation determined based on the statistical theory and the set of all data values on the time axis.

2) Probability prediction of application side's request for high application MNTR.

The homogeneous discrete Markov chain is used to construct the request probability prediction model. Based on the historical data of the application end, the transfer profile of the application end's requests for any type of MNTR in the adjacent period is determined by statistical theory, represented by $b_{ij}(i, j \in E)$. It is thus possible to determine the *k*-th transfer rate, which can be described by the matrix $b_k = b_1^{(k)}$. Based on this, the request probability vector formula (15) of any user terminal for any type of MNTR in the future time *t* can be described by formula (15):

$$B(t+k) = B(t)B_k = B(t)B_1^{(k)} \tag{15}$$

Based on the setting of the initial probability vector and the analysis of the historical application data in different types of multimedia teaching network resources, the formula (16) for the application status of different types of multimedia teaching network resources in the user terminal in the future time *t* can be obtained:

$$B(t) = B_1 \times B(t-1)W_1, B_1^{(2)} \times B(t-2)W_2, \cdots, B_1^{(n)} \times B(t-n)W_n \tag{16}$$

In formula (16), B_i and W_i respectively represent the transition probability matrix and the weight.

For $B(t)$, different dimensions in the matrix can describe the possible subsequent states of the application end, and the state with the largest probability value is the state with the largest probability of occurrence of the application end.

The core of this process is to build a probability matrix according to the request probability of different types of MNTR and the application frequency data of different types of MNTR at any application stage before any time point, and then determine the application probability prediction of this application node for any type of MNTR by numerical calculation based on the probability matrix. Combined with the threshold set by the system, it is determined whether to transfer different types of MNTR.

In summary, the process of rational allocation of multimedia network teaching reform resources based on Bayesian partitioned data mining is shown in Figure 3.

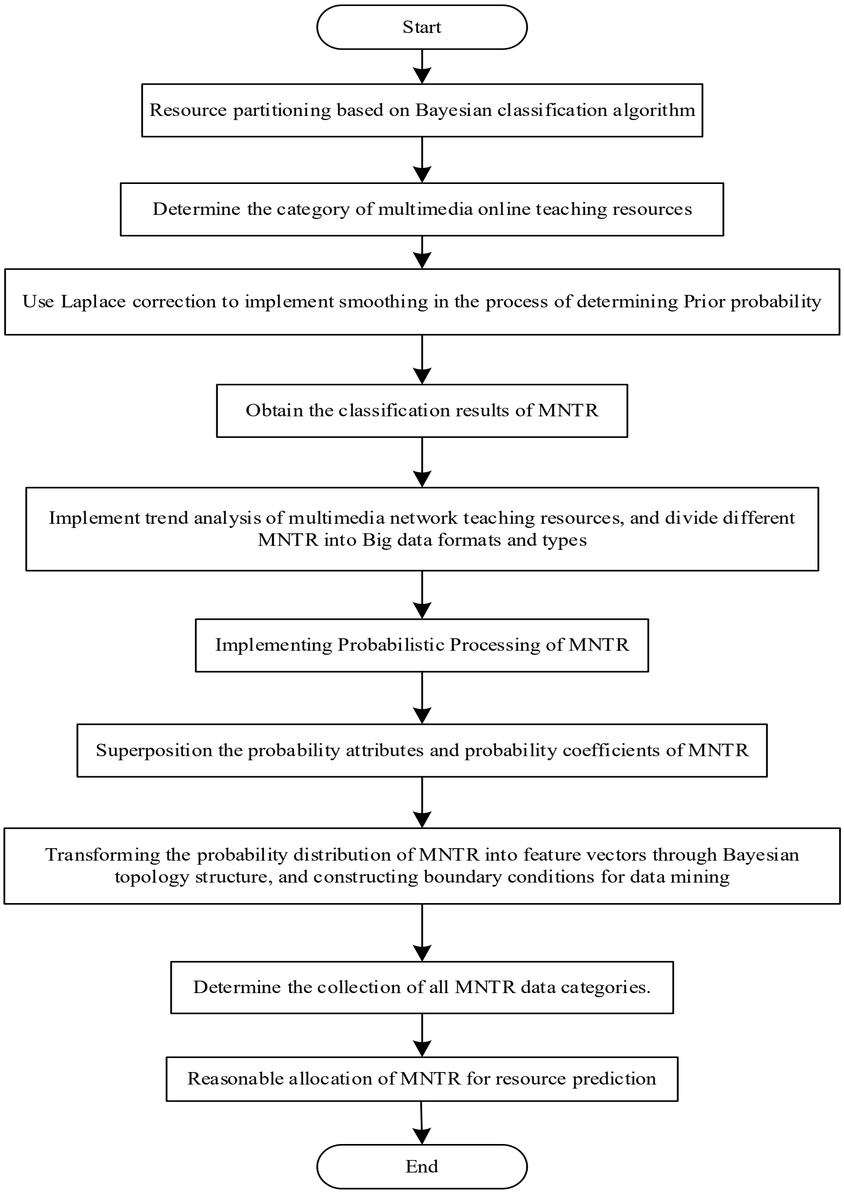

Figure 3. Flowchart of rational resource allocation for multimedia network teaching reform based on Bayesian partition data mining.

3. Experimental analysis

In order to verify the application effect of the rational resource allocation method for multimedia network teaching reform based on Bayesian partition data mining in the actual teaching resource allocation, based on the multimedia network teaching reform resources of a certain university, the application test environment of the proposed method is set as the actual operating environment, and the service platform of multimedia network teaching resource is built in the central computer room of the University as the research subject. It provides services such as classification of MNTR, rational allocation of resources and real-time load balancing. In the process of setting up the test environment, the major network connection devices are routers and switches, and the Gigabit network bandwidth is set. The application end is set as teacher machine and student machine, and the numbers are one and ten, respectively. In the test process of this method, the test cases are set according to the built platform, the test cases are run in the set test environment and the output results of the test cases are analyzed to verify the performance of this method.

3.1. Delay analysis of on-demand application of teaching resources

The method in this paper is tested with practicability as the test index. For the research subject, the delay state in the on-demand application of different types of MNTR (traditional course teaching plan and scheme resources, traditional audio-visual media resources, multimedia teaching courseware and software resources and network teaching resources) is determined by gradually increasing the number of concurrent users. The results are shown in Figure 4.

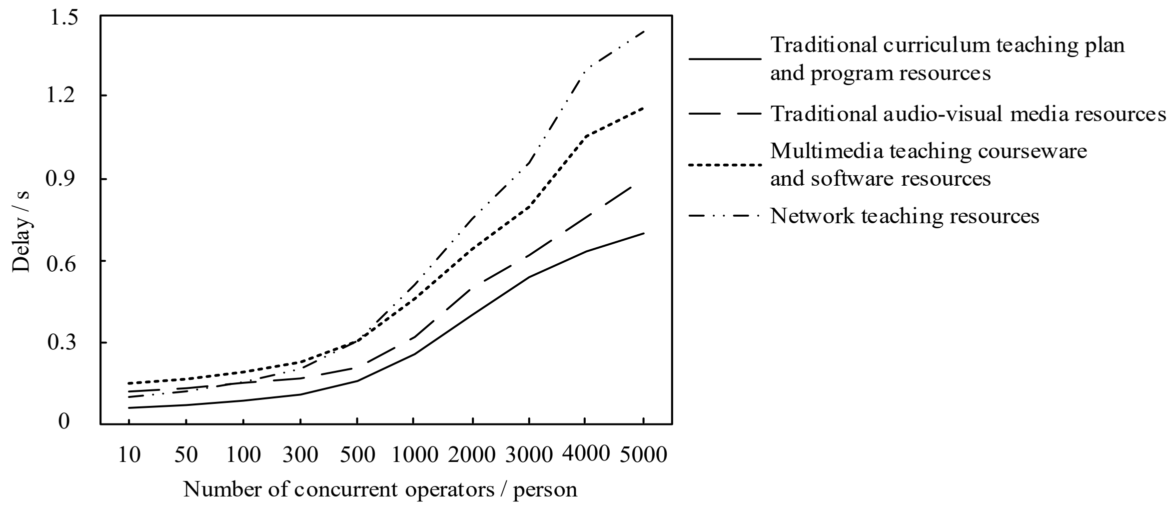

Figure 4. Delay recording results.

By analyzing Figure 4, it can be seen that under the condition that the number of concurrent users gradually increases, the time delay of playing different types of MNTR also gradually increases, but this increase does not have linear characteristics. Among them, the delay of traditional course teaching plan and scheme resources is the shortest, and the delay of network teaching resources application is the longest. However, under the condition of different concurrent operators, the application delay of different types of MNTR is less than 1.5s. This shows that the application of MNTR on demand has lower delay after adopting the method in this paper.

The performance of this method was tested using effectiveness as an indicator. Under the same experimental conditions and environment, under different concurrent population conditions, the average latency of on-demand video and audio of MNTR on the application end was tested using this method and without this method. The results are shown in Table 1.

Table 1. Average delay of MNTR on demand at application end.

Number of concurrent operators/person	Video Resources			Audio Resources		
	Adopting the method of this paper	Not using the method described in this paper	Delay difference/s	Adopting the method of this paper	Not using the method described in this paper	Delay difference/s
10	0.1	0.1	0	0.1	0.2	0.1
50	0.2	0.2	0	0.2	0.4	0.2
100	0.2	0.2	0	0.2	0.3	0.1
300	0.6	0.8	0.2	0.6	0.7	0.1
500	0.9	1.1	0.2	0.9	1.2	0.3
1000	1.5	3.3	1.8	1.5	2.3	0.8
2000	1.6	3.9	2.3	1.6	2.9	1.3
3000	1.7	4.7	3.0	1.7	3.6	0.9
4000	1.8	5.4	3.6	1.8	4.4	2.6
5000	1.9	6.0	4.1	1.9	5.0	3.1

By analyzing Table 1, it can be seen that, under the condition that the number of concurrent operators is gradually increasing, after starting the method in this paper, the research subject has implemented rational configuration of different types of MNTR, so the average delay of application end on-demand resources is small, and under the condition that the number of concurrent operators reaches 5000, the delay is less than 2s. Under the condition of closing the method in this paper, the research object has not rationally configured the MNTR, so the average delay of the application end on-demand resources has increased significantly. Under the condition that the number of concurrent operators reaches 5000, the delay of on-demand video reaches 6.0 seconds, which is 4.1 seconds compared to when the method in this paper is enabled; The delay of on-demand audio reaches 5.0 seconds, which is 3.1 seconds compared to the method used in this paper, This fully verifies the effectiveness of the method in this paper.

3.2. Bayesian classification accuracy test

In order to test the classification accuracy of different types of MNTR in the proposed method, the classification of teaching resources in this paper is adopted in the research object, and the results obtained by this method are compared with the actual teaching resources. The results are shown in Figure 5.

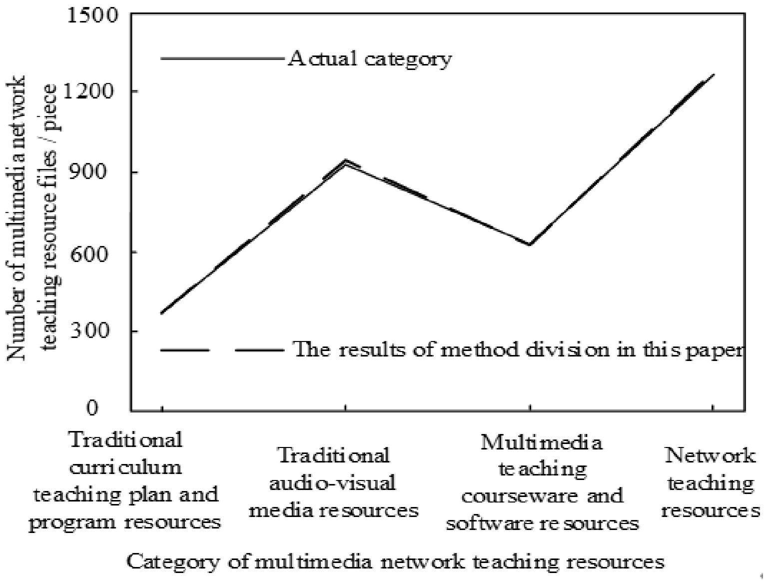

Figure 5. Classification accuracy of MNTR in the proposed method.

By analyzing Figure 5, it can be seen that after the classification of MNTR by the method in this paper, the number of traditional curriculum teaching plans and program resources and traditional audio-visual media resources are 371 and 984, respectively, and the number of multimedia teaching courseware and software resources and network teaching resources are 639 and 1334, respectively. The classification results of traditional curriculum teaching plans and program resources are consistent with the actual number. However, there is little difference between the classification results of the remaining three types of MNTR and the actual number. The above experimental results can show that this method has a good classification result of MNTR.

In the process of data mining of MNTR based on Bayesian partition, the probability coefficient has a direct impact on the final classification accuracy. The classification accuracy of MNTR of the method in this paper under different probability coefficient conditions is analyzed, and the results are shown in Figure 6.

According to the analysis of Figure 6, with the gradual increase of the number of multimedia network teaching resource files, the classification accuracy under the conditions of different probability coefficient values shows a gradual decline trend; with the gradual increase in the probability coefficient, the classification accuracy of MNTR shows a trend of first increasing and then decreasing. Under the condition that the probability coefficient value is 0.2 and 0.3 respectively, the average classification accuracy of MNTR is about 96.84 and 97.79%, showing a trend of gradual improvement. When the probability coefficient value is increased to 0.4, the classification accuracy of MNTR is significantly increased, and the average accuracy reaches 99.55%; When the probability coefficient value is increased to 0.5, the classification accuracy of MNTR decreases, and the average accuracy reaches 98.71%. The above data fully show that the classification accuracy is higher when the probability coefficient value is 0.4 during the use of the proposed method.

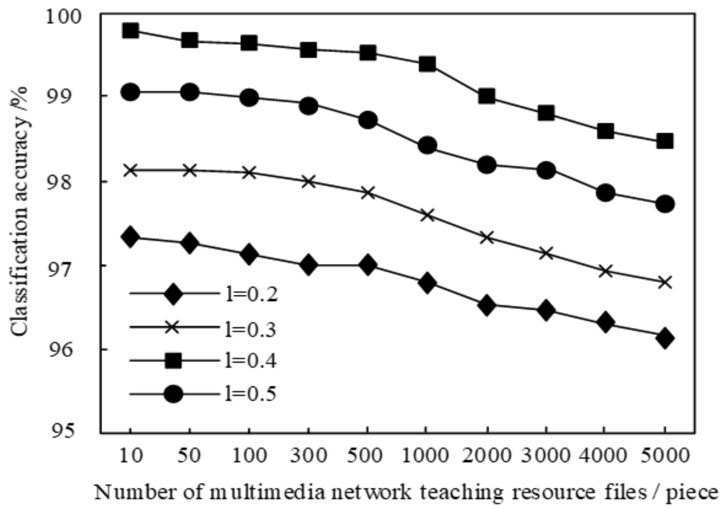

Figure 6. Classification accuracy of the method in this paper under different probability coefficient conditions.

3.3. Comparison of resource occupancy

In order to further verify the application performance of the method in this paper, from the perspective of resource occupancy rate, the method based on Tchebycheff in reference [6], the method based on mobile edge computing in reference [7] and the method based on symbiotic biological search algorithm in reference [8] are used as comparison methods. By comparing the methods in this paper and the comparison methods in the CPU occupancy rate and memory occupancy rate of human-computer interaction, Bayesian classification, data mining resource prediction and rational configuration, etc., the performance of this method can be verified. The results are shown in Table 2.

Table 2. Comparison results of occupancy rate of different methods in actual application.

Different methods		Treatment process				
		Treatment process	Human-computer interaction	Bayesian classification	Data mining	Rational allocation
Methods in this paper	CPU utilization rate /%	7.9	7.9	4.5	8.7	5.0
	Memory occupation rate/%	4.2	3.9	1.8	4.5	2.2
The method based on Tchebycheff in reference [6]	CPU utilization rate/%	15	13.8	12.4	16.6	12.7
	Memory occupation rate/%	9.2	8.4	4.6	8.5	5.9
The method based on Mobile edge computing in reference [7]	CPU utilization rate/%	8.7	7.5	14.2	18	6.9
	Memory occupation rate/%	4.0	4.7	6.1	8.5	8.5
Methods based on Symbiotic Organisms Search in reference [8]	CPU utilization rate/%	9.6	10.3	5.8	9.2	6.4
	Memory occupation rate/%	4.9	5.6	3.3	9.4	4.8

According to the analysis of Table 2, the CPU occupancy rate and memory occupancy rate of the rationalization configuration for MNTR using the proposed method are 34.0 and 16.6%, respectively, which are reduced by 21 and 68%, respectively, compared with the other three comparative methods. This shows that this method can effectively reduce the CPU occupancy rate and memory occupancy rate during the operation of the experimental object, and can improve the applicability of teaching resources.

4. Conclusions

Aiming at problems, such as the confusion of resource classification and the extension of on-demand time in the application of MNTR, we study the rational resources allocation method of multimedia network teaching reforms based on Bayesian partition data mining and effectively realize the classification of MNTR using Bayesian partition data mining, and rationally allocate different types of MNTR based on resource prediction. The experimental results show that this method has good application performance. In the follow-up study, the application efficiency of this method will be optimized in order to improve the application performance of this method.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflicts of interest.

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