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Research Article

Analysis and Countermeasure Research of Modern English Teaching Problems Based on Data Mining Technology

Shuang Yang

Foreign Languages School, Huanghuai University, Zhumadian 463000, China

Correspondence should be addressed to Shuang Yang; 20101164@huanghuai.edu.cn

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In order to improve the effect of English teaching reform, this paper combines data mining technology to analyze the modern English teaching process and formulate corresponding strategies. Moreover, this paper uses the parameter covariance moment drop as a performance indicator to evaluate the data points in the sample set and obtain the preliminary clustering of the data points. At the same time, this paper adjusts the initial accumulation of data points, including merging and deleting clusters, and this paper assigns missing data points and corrects data points that are incorrectly clustered. In addition, this paper adopts the LSVM method to segment the interval and constructs the system structure on the basis of this data analysis. Through the simulation teaching research, we can see that the problem analysis and countermeasure research system of modern English teaching based on data mining technology proposed in this paper meet the needs of modern English teaching reform.

1. Introduction

The development of the information age requires the cultivation of high-quality talents, which puts forward increasingly higher requirements for the development of education. As the foundation of education, colleges and universities are important places to improve core literacy and undertake the important task of cultivating talents for all-round development. Therefore, in order to stand out in the international competition and meet the needs of social development, the United States, the United Kingdom, China, and other countries have issued educational policies to improve schools and promote student development. However, various problems existing in the current school improvement restrict the pace of our improvement. Some scholars believe that the reason why the current improvement of English teaching in urban schools is in trouble is that it pays too much attention to the allocation of external resources of the school while ignoring the individual needs of students and the relationship between students' emotions. In addition, some scholars believe that the reason why the current college improvement is in trouble is that it ignores the internal needs of the school and pays too much attention to the interests of special groups. At the same time, there are improvement models that do not start from themselves and blindly imitate other schools, and there is a disconnect between improvement theory and improvement practice. Therefore, what and how to improve the school to achieve the goal of promoting the all-round development of each student has become a key issue that we need to consider. School improvement refers to efforts to focus on changes in English teaching and the conditions it supports to improve student performance and believes that school improvement is based on continuous English teaching improvement. Moreover, it affirms the importance of English teaching improvement for school improvement. Among the many ways included in school education, English teaching is the most basic, and its effect is the most lasting and profound. The quality of English teaching affects the quality of English teaching in schools to a large extent. Therefore, in school improvement, we should focus on the improvement of English teaching, establish its core position, and provide a series of supports for the improvement of English teaching.

The lack of pertinence in the improvement of English teaching makes it difficult for different teachers to find their own solutions to the problems that arise in the process of

English teaching. According to the practice survey, it is found that teachers in different occupational cycles encounter different perplexities in English teaching improvement, and even teachers of different genders encounter different perplexities. In-depth field investigation to understand the problems existing in the process of teachers' English teaching, on the one hand, can really understand the problems that teachers actually encounter and also explore the similarities and differences of teachers in different regions. On the other hand, the obtained real data can be provided to research organizations for research and discussion and to find scientific and effective solutions. The third aspect is that the problems encountered by teachers in the process of English teaching can be solved, which is conducive to improving teachers' professional quality and professional ability. From practice to practice, in-depth teachers' English teaching practice is conducive to a real understanding of teachers' confusion and has then put forward targeted solutions. These problems are solved, and it is more conducive to promoting the development of English teaching improvement practice.

In order to improve the effect of English teaching reform, this paper combines data mining technology to analyze the modern English teaching process, formulates corresponding strategies, and finds the problems existing in the current English teaching in colleges and universities, which provides a reference for the further improvement of English teaching in the future.

2. Related Work

The parameter setting plays an extremely important role in the solution effect of the intelligent optimization algorithm. Appropriate selection can greatly enhance the optimization efficiency of the algorithm. Parameters can be mainly divided into two types: control parameters and noncontrol parameters [1]. Parameters such as population size, decision variable dimension, and iteration termination conditions (usually the number of iterations or the maximum number of function evaluations) are called control parameters, no matter which intelligent optimization algorithm has control parameters, and parameters such as crossover rate and mutation rate are called noncontrol parameters. The noncontrol parameters are generally generated by the unique evolution mechanism of the algorithm [2]. In addition to the control parameters shared by the intelligent optimization algorithm, TLBO has only one parameter of the learning factor. In the improvement of parameter settings, the control parameters are mainly represented by the population size, indicating the number of individuals included. The population diversity in population evolution is high, and the evolution direction is not easily disturbed by individual individuals, but the increase in population size will lead to a substantial increase in computational complexity [3]. The smaller the population size, the fewer individuals contained in the population, the lower the population diversity, and the faster the convergence speed, but the population is easy to fall into the local optimum and the solution fails [4]. Among the noncontrol parameters, the learning factor plays an important role in the optimization performance of TLBO. Its value is 1 or 2, which means that the students either did not learn any knowledge from the teacher or accepted the teacher's teaching. This value method is not in line with reality. The information contained in the population is not fully utilized; in a sense, it has a negative impact on the efficiency of the algorithm [5]. In terms of evolutionary mechanism improvement, TLBO still has a broad research space [6]. Scholars have enhanced the performance of TLBO in certain aspects by introducing different mechanisms into the basic TLBO, thereby improving its optimization effect.

Taking advantage of the dominant role of elite individuals in the evolution of the population, a certain number of elite solutions are retained in each generation, and the poor solutions are replaced by elite solutions, and a detailed analysis of the influence of different numbers of elite individuals on the algorithm is carried out, which solves the complex optimization well [7]. Considering that teachers have a dominant role in the evolutionary process if teachers themselves have limited level, then as a leading individual, it is difficult to lead the population to approach the region where the global optimum is located. Literature [8] proposed an improved TLBO algorithm (ImprovedTLBO, ITLBO) changes the teaching method from one-person teaching to multi-person teaching and introduces adaptive learning factors and two new learning methods to coordinate algorithm exploration and development capabilities; The optimization problem, the literature [8] improves the TLBO evolution equation. In the learning stage, the individual learns not only from other individuals but also from the teacher individual. Other individuals randomly select from the neighborhood and the entire search area with a probability, and after the teaching stage, the self-study stage is introduced, so that individuals can update according to their own gradient information, or re-explore new positions according to the mean and variance information. The simulation results show that the algorithm has a very good performance in solving the global optimization problem. Literature [9] pointed out that to overcome the shortcomings of TLBO's easy precocity, it is necessary to take into account the convergence speed and the diversity of the population at the same time, so as to achieve a balance. A relatively elite teaching optimization algorithm is proposed, which effectively improves the solution accuracy of the algorithm. In order to improve the performance of ETLBO, the literature [10] proposes a feedback-based elite teaching optimization algorithm, considering that students will not only interact with classmates during self-study. At the end of the algorithm iteration, a new feedback stage is added to enable random students to communicate with teachers again. The experimental results show that the algorithm improves the understanding accuracy and robustness; in order to overcome the slow convergence and ease of TLBO, falling into the shortcomings of precociousness, literature [11] proposed an improved TLBO algorithm, in which the teaching factor is dynamically adaptive according to the teaching effect so that the teaching factor gradually decreases with the increase of the number of iterations. The population difference is large; the diversity is better; a larger learning factor is conducive to the rapid approach of the individual student to the individual teacher; in the later stage of population evolution, the individual difference is reduced; and the population diversity is reduced, and a smaller learning factor is conducive to the algorithm local search is carried out, and at the same time, the knowledge sharing between teachers and students is realized by using the trust weight, and the utilization of evolutionary population information is increased. Literature [12] proposes a dynamic grouping teaching optimization algorithm, which makes each individual contribute to the mean value of the group. Learning, using this process to replace the mechanism of individual learning from the average value of the entire class in the basic TLBO, strengthens the diversity of the population and effectively avoids the algorithm from falling into precociousness. Literature [13] proposed a teaching method based on the learning experience of other individuals. The optimization algorithm makes the individual learn from the teacher individual and other individuals at the same time in the teaching stage and, in the learning stage, makes the individual learn from two other individuals randomly. Simulation experiments show that the algorithm can obtain better quality when solving the global optimization problem.

3. Intelligent Teaching Information Data Processing Algorithm

Data mining is carried out for a variety of information existing in English teaching. This paper proposes an intelligent teaching information data processing algorithm.

F: $\chi \mapsto R^P$ is a nonlinear mapping defined on $\chi \subseteq R^n$. A sample set $S = \{(x(1), y(1)), \cdots, (x(N), y(N))\}$ is given where the data points satisfy

$$y(k) = F(x(k)) + \varepsilon(k), k = 1, \ldots, N, \quad (1)$$

where $\varepsilon(k) \in R^p$ is the interference term. The performance metric is given as $V_N = 1/N \sum_{k=1}^{N} [y(k) - f(x(k))]^2$, and the goal is to find a PWA map $f(\cdot)$ that minimizes the performance metric [14] as follows:

$$f(x) = \begin{cases} \theta_1' \begin{bmatrix} x \\ 1 \end{bmatrix}, if\ x \in \chi_1 \\ \vdots \\ \theta_s' \begin{bmatrix} x \\ 1 \end{bmatrix}, if\ x \in \chi_s \end{cases}, \quad (2)$$

where $\theta_i \in R^{(n+1)\times p}$, $i = 1, \ldots, s$ is the model parameter matrix, and $\{\chi_i\}_{i=1}^{s}$ is the face angle interval of X divided by the hyperplane. $\cup_{i=1}^{s} \chi_i = \chi$ is satisfied, and there is $\chi_i \cap \chi_j = \theta$ when there is $i \neq j$.

For the dynamic system identification problem, k in formula (1) represents the time series. $x(k)$ is the regression vector, which is defined as follows:

$$x(k) = [y(k-1), \ldots, y(k-n_0), u'(k-1), \ldots, u'(k-n_b)]', \quad (3)$$

where $u(k) \in R^m$ represents the input of the system and $y(k)$ is the output of the system. n_a and n_b are the order $n = n_a \times p + n_b \times m$ of the model. If the submodel in formula (2) adopts an input autoregressive (ARX) model, formula (2) is called a piecewise affine input autoregressive (PWARX) model.

For simplicity, this chapter only considers the identification problem of a MIMO PWARX system, that is, the case of $p = 1$. In fact, the identification method given in this paper can also be applied to the case of $p > 1$. In this paper, it is assumed that the structure of the submodel is known, that is, n, and n are known. However, the number s of submodels is unknown, and the extended regression vector $\varphi(k) = [x\prime(k), 1]'$ is recorded [15].

The PWARX system identification problem consists of two parts: the segmentation of the regression vector space and the identification of the submodel parameters. If the partition of the regression vector space is known, the PWARX system identification problem becomes s simple linear system identification problems, which can be easily realized by using the linear system identification method. However, the problem now is that we do not know how the regression vector space is divided or even how many submodels there are.

A PWARX system is [16]

$$y(k) = \begin{cases} [1, 2][u(k-1), 1]' + \varepsilon(k) \\ if\ u(k-1) = x(k) \in \chi_1 = [-4, -1] \\ [-1, 0][u(k-1), 1]' + \varepsilon(k) \\ if\ u(k-1) = x(k) \in \chi_2 = (-1, 2) \\ [1, 2][u(k-1), 1]' + \varepsilon(k) \\ f\ u(k-1) = x(k) \in \chi_3 = (2, 4) \end{cases}, \quad (4)$$

where there is $s = 3, n_a = 0, n_b = 1$, $\chi = [-4, 4], \varphi(k) = [u(k-1), 1]'$. Input $u(k) \in R$ is randomly generated according to a uniform distribution on X. The variance of noise $\varepsilon(k)$ is $\sigma^2 = 0.05$.

We assume that we are given a sample set of 50 data points, as indicated by the "+" in Figure 1. The three line segments in the figure represent the three real submodels on the three intervals, respectively. What we need to do is how to use these 50 data points to identify the PWARX system in example 1. We note from Figure 1 and (3.4) that there are two submodels with the same parameters, but they are defined at different intervals χ_1 and χ_3, respectively.

First, a data point (x_{j1}, y_{j1}) is selected from S, and $c-1$ data points $(x_{j1}, y_{j1})_c^2$ that are closest to (x_{j1}, y_{j1}) are found to form a cluster C_j, and these c data points are deleted from S. In this paper, the Euclidean distance 6 is used to measure the distance between data points, that is, $c-1$ different data points satisfy

$$\left\| x_{j1} - y_{ji} \right\|^2 \leq \left\| x_{j1} - \widetilde{x} \right\|^2, \forall (\widetilde{x}, \widetilde{y}) \in S. \quad (5)$$

We should note that c must satisfy $c > n + 1$; this is to ensure that a set of model parameters can be estimated from these c data points. Then, based on the c data points,

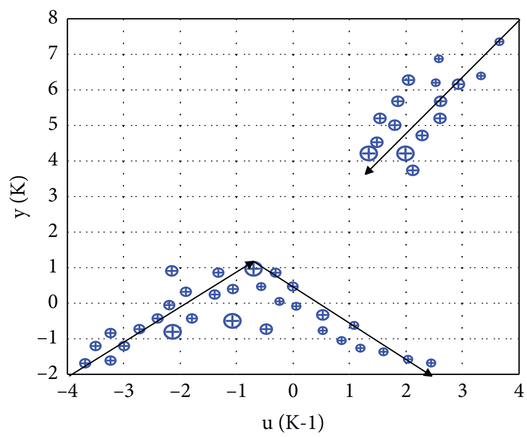

FIGURE 1: Algorithm example 1.

a set of model parameters is estimated by the least-squares method:

$$\widehat{\theta}_j = \left(\Phi_j'\Phi_j\right)^{-1}\Phi_j'Y_j, \tag{6}$$

where there is

$$\Phi_j = \begin{bmatrix} x_{j1} & x_{j2} & \cdots & x_{jc} \\ 1 & 1 & \cdots & 1 \end{bmatrix},$$
$$Y_j = \begin{bmatrix} y_{j1} & y_{j2} & \cdots & y_{jc} \end{bmatrix}. \tag{7}$$

At the same time, the empirical covariance matrix $V_j{}^*$ of the model parameter $\widehat{\theta}_j$ can also be calculated as follows [17]:

$$V_j = \frac{SSR_j}{c-(n+1)}\left(\Phi_j'\Phi_j\right)^{-1}.$$
$$SSR_j = Y_j'\left(I - \Phi_j\left(\Phi_j'\Phi_j\right)^{-1}\Phi_j'\right)Y_j, \tag{8}$$

where I is an identity matrix and V_j is a matrix of $(n+1)\times(n+1)$.

The evaluation of data points is carried out in a near-to-far manner, where the distance is still calculated according to the Euclidean distance. First, the center position of cluster C is calculated. If the current cluster C contains d data points, the center position is

$$x_{j0} = \frac{1}{d}\sum_{i=1}^{d} x_{ji}. \tag{9}$$

The distance of each data point in S to the center position x_{j0} is calculated, and the data point $(\tilde{x}, \tilde{y})$ with the closest distance is selected. We use all the data points included in the current cluster C_j plus the data point $(\tilde{x}, \tilde{y})$ to estimate a new set of model parameters $\widehat{\theta}_j^{new}$ according to formula (6) and calculate the corresponding empirical covariance matrix V_j^{new} according to formula (8). Then, we can judge whether the data point $(\tilde{x}, \tilde{y})$ belongs to the cluster C_j according to the new and old empirical covariance matrices and calculate as follows:

$$\Delta V = \sum_{l=1}^{n+1}\sum_{m=1}^{n+1}\left(\left|V_j^{new}(l,m)\right| - \left|V_j(l,m)\right|\right). \tag{10}$$

If the new empirical covariance matrix V_j^{new} is not greater than the original empirical covariance matrix V_j, that is, $\Delta V \le 0$, it is considered that the data point $(\tilde{x}, \tilde{y})$ belongs to the cluster. Data point $(\tilde{x}, \tilde{y})$ is added to cluster C_j, and this data point is removed from S. At this time, the center position of the cluster C_j has shifted, and the new center position needs to be recalculated according to formula (9). At the same time, the new empirical covariance matrix V_j^{new} is used as the empirical covariance matrix V_j of the current cluster C_j. If the new empirical covariance matrix V_j^{new} is larger than the original empirical covariance matrix V_j, it is considered that the data point $(\tilde{x}, \tilde{y})$ does not belong to this cluster. Therefore, cluster C_j still only includes the original data points, and the covariance matrix and the center position are unchanged. In order not to repeatedly judge the data point $(\tilde{x}, \tilde{y})$, it needs to be transferred from S to S_{Temp}. S_{Temp} represents a collection of data points that have been judged but do not belong to any cluster. This completes the evaluation of a data point.

For each cluster, its initial c data points must be carefully chosen because these c data points are picked from S. Therefore, for each data point $\{(x_{ji}, y_{ji})\}_1^c$ in S, according to formula (5), $c-1$ closest data point $\{(x_{ji}, y_{ji})\}_1^c$ of the data point is found, and a set of model parameters $\widehat{\theta}_1$ is estimated with these c data points. The average fit error of the model over these c data points is calculated and estimated as follows:

$$e\overline{r}_l = \frac{1}{c}\sqrt{\sum_{i=1}^{c}\left(y_{li} - \left[\, x_{li}' \;\; 1 \,\right]\widehat{\theta}_l\right)}. \tag{11}$$

If only the information of the covariance matrix is used to determine whether a data point belongs to a certain cluster, in some special cases, the correct interval segmentation cannot be achieved. The distance factor also needs to be considered when deciding whether a data point belongs to a certain cluster. Therefore, the algorithm introduces a distance parameter d, which is used to measure the distance between the data point and the cluster.

As shown in Figure 2, when the distance between data point $(\tilde{x}, \tilde{y})$ and cluster C_j is very far, that is, when $\min_{(x_{ji}, y_{ji})\in C_j}\|\tilde{x} - x_{ji}\|_2 > d_0$ is satisfied, it is considered that data point $(\tilde{x}, \tilde{y})$ does not belong to cluster C_j. In this way, the data points on the two intervals can be effectively separated even if the submodels on the two different intervals have the same parameters. Similarly, in step 3, the maximum distance $d_{\max}$ between the data point (x_{j1}, y_{j1}) and its $c-1$ neighbors is calculated. At the same time, the judgment by the if-then statement in step 4 is also to prevent the data points belonging to different intervals from being classified into the same cluster [18].

A data point $(\tilde{x}, \tilde{y})$ that should belong to cluster C_j is greatly affected by noise. It may happen that the inverse of the parameter empirical covariance matrix V_j^{new} after cluster C_j is added to the data point $(\tilde{x}, \tilde{y})$ is larger than the original empirical covariance matrix V_j of C_j so that

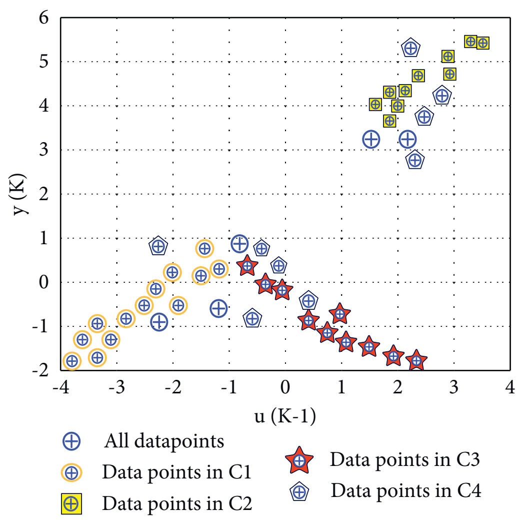

Figure 2: Algorithm example 2.

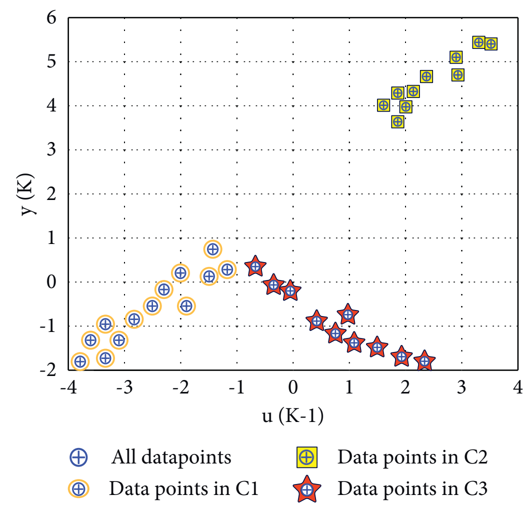

Figure 3: Algorithm example 3.

the data point $(\tilde{x}, \tilde{y})$ is not included in the cluster C_j. Of course, there may also be data points (,) that should not belong to cluster C_j. Due to the influence of noise, the new empirical covariance matrix V_j^{new} is less than or equal to the original covariance matrix V_j, and as a result, the data point $(\tilde{x}, \tilde{y})$ is misjudged into the cluster C_j. This situation is particularly prone to occur with data points where different clusters intersect. These cases will be corrected in subsequent adjustments to the clustering of data points.

Merging clusters C_k and C_l is only considered if the minimum distance between data points in clusters C_k and C_l is less than $d_{\min}$. That is, only when two clusters C_k and C_l are adjacent or their data points are partially or completely overlapped, they can be merged. When clusters C_k and C_l meet the distance condition, their model parameters θ_k and θ_l are compared. We define the difference between model parameters θ_k and θ_l as

$$V_\theta = \max\left(\left|\frac{\theta_k - \theta_l}{\max(\theta_k, \theta_l)}\right|\right), \quad (12)$$

where | represents dot division. Two clusters C_k and C_l are considered to be mergeable if $V_\theta \le \Delta\theta$ is satisfied. In the application of example 1, $d_{\min} = 0.5, \Delta\theta = 50$ is taken.

Then, the unclassified data points in S_0 are to be assigned to individual clusters. The assignment of data points in S_0 is based on the classification of its $c-1$ neighbors [19].

As shown in Figure 3, interval partitioning the regression vector space is actually a pattern classification problem given the known clusters of data points. Since the interval in the PWA system is divided by a hyperplane, although any two clusters may not be linearly separable due to the influence of noise, the linear support vector machine (LSVM) is still a better choice. The SVM function used in this paper comes from the spider software package ∗ based on the MATLAB simulation platform, and its core is realized by the LIBSVM software.

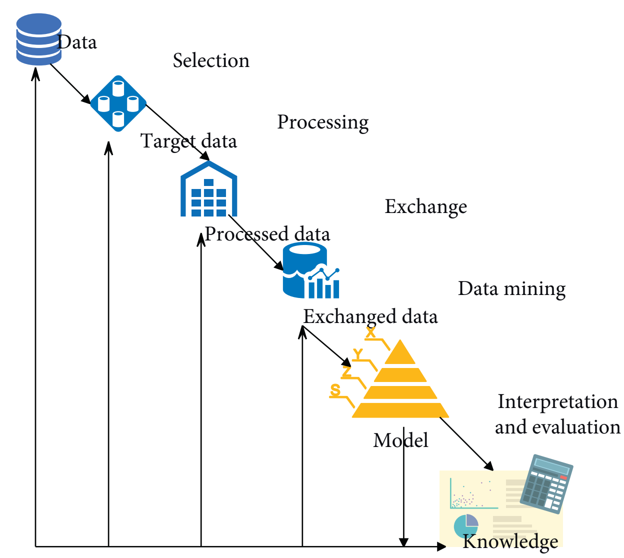

Figure 4: Schematic diagram of the KDD process.

Two of the clusters are arbitrarily selected, classified by the LSVM method, and their segmentation planes are obtained. This is repeated three times, resulting in the following interval division:

$$\begin{aligned} \chi_1 &= [-4, -0.995], \\ \chi_2 &= [-0.995, 1.975], \\ \chi_1 &= [1.975, 4]. \end{aligned} \quad (13)$$

After the interval segmentation is clarified, the system identification problem becomes multiple linear system identification problems. As long as the data points in each interval are used and the linear identification technology is used to obtain the respective submodel parameters, the entire system identification problem can be completed. The research on the identification of linear systems is relatively thorough, and there are many identification methods that can be used. The most commonly used method is the least-squares method. Of course, some improved algorithms, such as the weighted least-squares algorithm, can also be used.

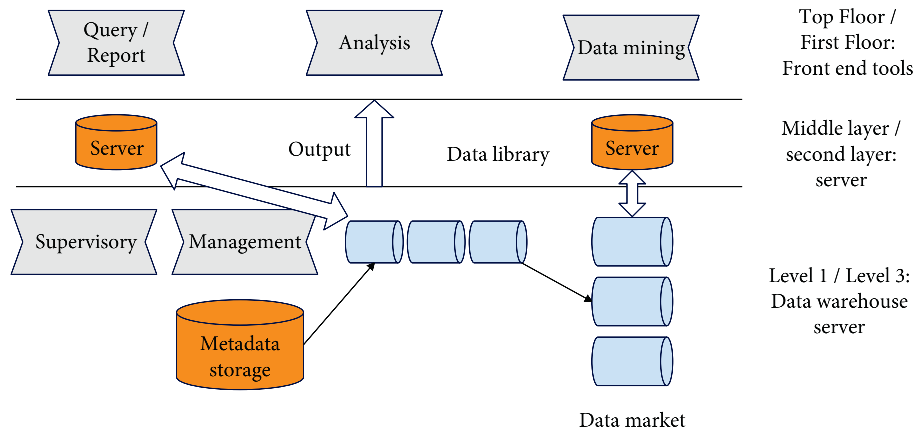

FIGURE 5: Architecture diagram of the system.

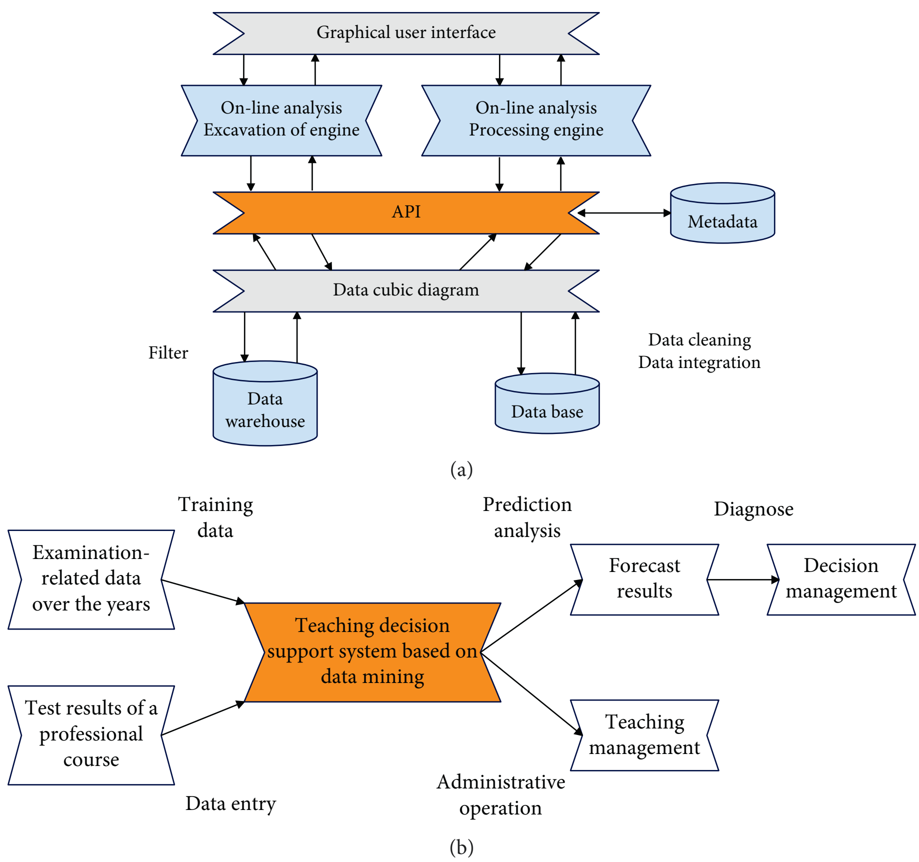

FIGURE 6: Teaching decision-making system based on data mining. (a) System diagram. (b) Design diagram.

The data points on each interval are weighted by the least squares method (6); the following model parameters can be obtained:

$$\begin{aligned} \chi_1&: \widehat{\theta}_1 = [0.950, 1.872],\\ \chi_2&: \widehat{\theta}_2 = [-0.990, 0.034],\\ \chi_1&: \widehat{\theta}_3 = [0.949, 2.130]. \end{aligned} \tag{14}$$

4. Analysis and Countermeasure Research of Modern English Teaching Problems Based on Data Mining Technology

Data mining is an iterative cycle of human-computer interaction. The process requires multiple steps and many decisions, many of which need to be provided by the user. However, from a macroscopic point of view, the KDD

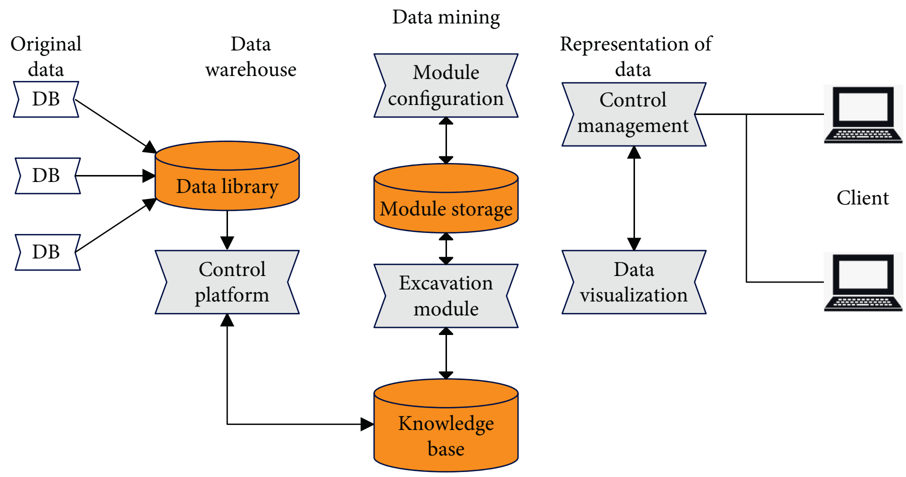

Figure 7: Structure diagram of teaching decision support system.

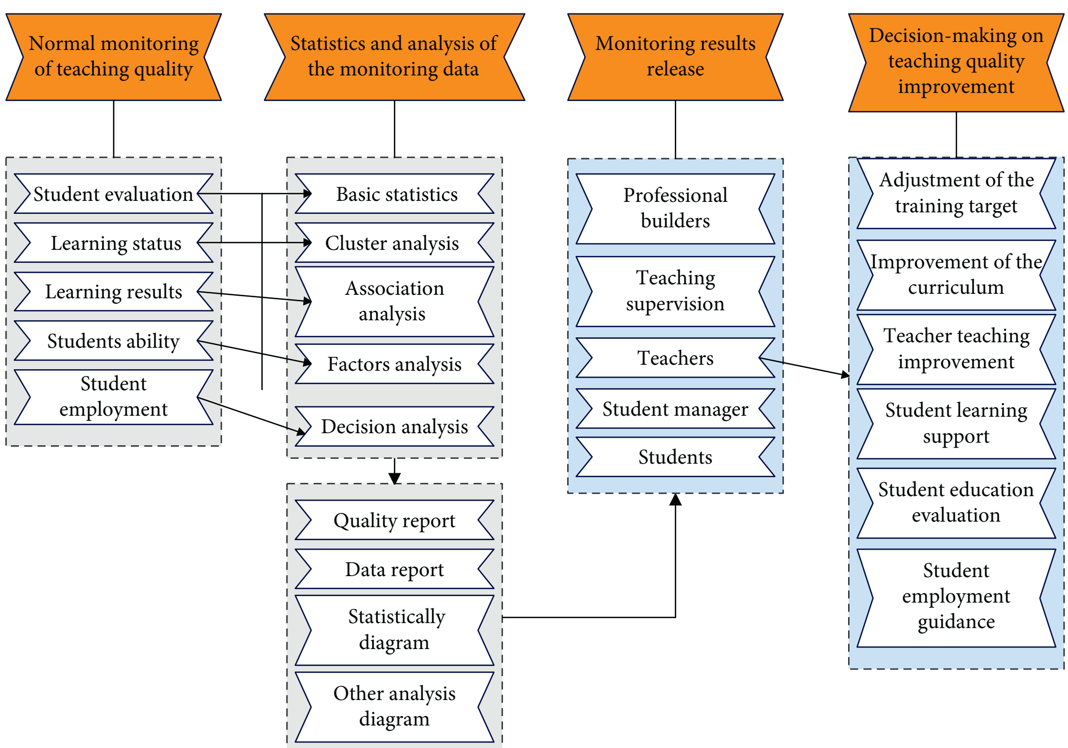

Figure 8: Technical route of teaching quality monitoring based on data mining.

process consists of three parts, namely, data sorting, data mining, and interpretation of evaluation results. See the steps illustrated in Figure 4.

The system development platform selects the VB.NET programming environment, which can directly present the analysis results of the system. For further WEB development and application, standard class calls can be used. The server-side SQL Server system itself has standard interface functions for remote access, which can query and retrieve, and some function plug-ins integrated with the SQL Server system have data mining functions. This kind of environment is simple, can flexibly query or call data according to data requirements, and can directly use some integrated functions, which reduces the communication overhead with remote data and improves system efficiency. The three-tier architecture diagram of the system is shown in Figure 5.

The organizational chart of the system is shown in Figure 6(a). From the organizational chart, it can be shown that the teaching decision support system finally shows the user a good graphical interface, which is easy to understand and use. After the data in the database is integrated and filtered, it is convenient for the system to analyze and process it, dig out the useful information hidden among this information and finally display it to the user. The design diagram of the data mining teaching decision-making system is shown in Figure 6(b).

Table 1: Analysis effect of modern English teaching problem and countermeasure research system based on data mining technology.

No.	Problem mining
1	78.9
2	84.9
3	85.6
4	78.7
5	85.7
6	83.1
7	78.9
8	86.2
9	86.9
10	78.0
11	82.2
12	78.8
13	86.4
14	86.9
15	85.9
16	78.1
17	84.0
18	85.8
19	81.5
20	85.9
21	83.1
22	81.1
23	86.2
24	78.2
25	86.4
26	81.1
27	83.8
28	85.9
29	78.4
30	78.0
31	83.5
32	85.2
33	84.5
34	78.8
35	80.3
36	79.6
37	86.1
38	85.4
39	86.0
40	83.9
41	82.2
42	86.4
43	84.5
44	78.8
45	83.1
46	81.0
47	79.5
48	82.7
49	86.5
50	83.2
51	82.3
52	84.6
53	83.0
54	85.6
55	85.1
56	78.6
57	82.9
58	79.0
59	84.3
60	85.1
61	87.0
62	82.2
63	81.6
64	84.9
65	80.2
66	81.9

From the design diagram of the data mining teaching decision-making system in Figure 6(b), the data of the school's students' test scores over the years are collected. Aiming at the scores of students in a certain professional course and whether the final grades are qualified or not, these data are imported into the teaching support system based on data mining through the SQL Server database management system. After that, through predictive analysis, the prediction results are obtained, and the basis for decision-making support is provided to decision-makers.

The structure diagram of the teaching decision support system is shown in Figure 7. The main module functions are as follows: (1) data source: it contains course information, student and teacher information, student achievement information, and so on, which are all taken from the college information management system. After the information is cleaned, extracted, transformed, loaded, and other processing operations, the data enter the data warehouse. (2) Model configuration: it can modify and add algorithms, mining models, graphical window configuration, and command line methods. (3) Data visualization: it can present and realize data from various angles, such as reports, graphics, and so on, and export and inventory mining results. (4) Data warehouse: after processing the data in the data warehouse, a data mining system is established, which is based on decision support. Finally, it is user-oriented and can be flexibly inquired, such as statistics and analysis of teaching and curriculum settings, which can be carried out in depth from various perspectives and finally guide decision-making. (5) Control management: it can query and set the configuration of the mining model. Complete the management of user registration and login rights, call the data visualization module, and finally display the mining results.

The internal teaching quality monitoring in colleges and universities can be monitored and managed around five aspects: teachers' teaching level, students' academic status, course learning effectiveness, students' ability and quality, and students' employment status. In order to effectively use the above-mentioned teaching-quality-monitoring factors to help colleges and universities make more scientific and rational management decisions, we need to use data mining technology. By using data mining techniques such as classification, clustering, and association, it can analyze teachers' teaching and students' learning behavior data and feed back the analysis results to teachers, students, and relevant managers, which can help improve teaching and learning

Table 2: The countermeasure research effect of modern English teaching problem analysis and countermeasure research system based on data mining technology.

No.	Intelligent decision
1	72.4
2	76.3
3	69.9
4	80.6
5	78.9
6	69.4
7	78.2
8	78.7
9	70.3
10	69.2
11	78.9
12	79.4
13	80.2
14	74.3
15	80.1
16	79.3
17	70.5
18	80.3
19	74.5
20	69.4
21	70.3
22	78.2
23	75.5
24	80.6
25	74.8
26	71.3
27	75.9
28	75.7
29	73.9
30	78.1
31	79.8
32	78.3
33	75.7
34	69.8
35	76.6
36	74.1
37	75.8
38	75.8
39	76.6
40	74.1
41	69.4
42	73.8
43	75.3
44	73.9
45	71.8
46	76.3
47	74.4
48	69.5
49	73.0
50	79.5
51	78.4
52	79.9
53	76.5
54	76.2
55	69.1
56	72.6
57	78.3
58	80.1
59	80.0
60	74.9
61	73.7
62	78.2
63	76.0
64	75.0
65	75.6
66	71.6

more effectively. Therefore, on the basis of the actual quality monitoring system of the school, combined with relevant research, this research designs a technical route of teaching quality monitoring based on data mining. The main idea is to find the problems and deficiencies in the relevant links in the process of talent training through the collection of teaching information from multiple channels, the statistics, analysis, and feedback of teaching quality information. At the same time, it provides a detailed basis for timely adjustment and improvement of professional training standards, curriculum settings, and curriculum content. The technical route of teaching quality monitoring based on data mining is shown in Figure 8.

On the basis of the above system structure, the system structure is constructed through MATLAB, and the system is applied to the analysis of English teaching problems, and the corresponding strategies are simulated and formulated, and the test results shown in Tables 1 and 2 are obtained.

Through the above research, we can see that the problem analysis and countermeasure research system of modern English teaching based on data mining technology proposed in this paper meets the needs of modern English teaching reform.

5. Conclusion

There is often a lack of scientific and targeted problems in the improvement of English teaching. On the one hand, lack of scientificity means that most of the English teaching improvement research is a summary of the practical experience of front-line teachers, lacking the guidance of scientific theory. On the other hand, it means that there is no deep understanding of the teachers' team to really understand the problems existing in the process of teachers' English teaching. This can easily lead to the proposed countermeasures that cannot really solve the problem; it is difficult to promote the development of teachers' professional level, and it is not conducive to promoting the all-round development of students. This paper combines data mining technology to analyze the modern English teaching process and formulate corresponding strategies. Through the simulation teaching research, we can see that the problem analysis and countermeasure research system of modern English teaching based on data mining technology proposed in this paper meet the needs of modern English teaching reform.

Data Availability

The labeled data sets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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