Research Article

Improvement of English Teaching Process Management Based on Intelligent Data Sampling

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In order to improve the management effect of English teaching process, this paper combines intelligent data to use technology to improve the management of English teaching process, improve the effect of English teaching, and construct an intelligent English teaching process management system. Moreover, this paper considers the interpolation problem of time series data in the metric space defined by dynamic time warping, and proposes an oversampling method for unbalanced time series data. In addition, this paper chooses to classify the Gaussian process model that is sensitive to unbalanced time series data to test the effect of the model. The experimental research results show that the English teaching process management system based on intelligent data sampling proposed in this paper can play an important role in English teaching management and can effectively improve the efficiency of English teaching.

1. Introduction

Inquiry-based English teaching is an important achievement in the development and reform of modern western science education and is known as a new milestone in the innovation and development of modern science education. With the development of science, people’s accumulation of knowledge continues to increase, and the contradiction between tradition and innovation has become increasingly prominent in the process of moving towards the Frontier of knowledge. In particular, the traditional English teaching, which is mainly based on knowledge transfer in educational English teaching, has to focus on the teacher in order to pursue the coherence, system, and integrity of knowledge. In this way, it is easy to evolve into a cramming education, and it is difficult to improve the subjectivity and innovation ability of students.

The new curriculum encourages students to experience the methods and processes of scientific inquiry. At the same time, in order to effectively construct the chemical inquiry classroom and improve the quality of chemical inquiry English teaching, we should also pay attention to improving the effectiveness of the implementation of chemical inquiry English teaching [1]. The effectiveness of the current inquiry-based English teaching needs to be improved, and there are many obstacles, which should be improved from many aspects. Through the investigation and analysis of the current influence of various obstacles, suggestions for improvement can be put forward. At the same time, by combining the design of inquiry-based English teaching cases and the implementation of improvement strategies, the effectiveness of inquiry-based English teaching can be effectively improved [2].

In order to improve the management effect of English teaching process, this paper combines intelligent data to use technology to improve the management of English teaching process, improve the effect of English teaching, and construct an intelligent English teaching process management system. Moreover, this paper considers the interpolation problem of time series data in the metric space defined by dynamic time warping, and proposes an oversampling method for unbalanced time series data. In addition, this paper chooses to classify the Gaussian process model that is sensitive to unbalanced time series data to test the effect of the model. The experimental research results show that the English teaching process management system based on intelligent data sampling proposed in this paper can play an important role in English teaching management and can effectively improve the efficiency of English teaching.
management and maintenance of the course, the supervision and management of the English teaching process, the evaluation and management of English teaching, and other complete course management systems. With the development of E-Learning (e-learning), the teaching and learning of teachers and students on the network platform has become more adaptable to the interaction between teachers and students, and it also reduces the burden on the management of educational administrators. At the same time, the sharing of English teaching resources for teachers, the creation of course forums, and the design of students’ communication environment have become more prominent; online examinations, online Q&A, online attendance, etc., can be incorporated into the English teaching process with the development of network learning. In the management system, the improvement of teachers’ English teaching ability requirements is also accompanied by comprehensive evaluation of teachers in various aspects such as breadth and depth, and the realization of a complete English teaching evaluation system can also better reflect the advantages of informatization development. The systematic and scientific statistical analysis and evaluation results can also play a great role in various aspects such as teachers’ English teaching level and teachers’ English teaching ability. Therefore, based on the existing design and implementation and the existing technical support, the design of a complete English teaching process management system can promote the development of informatization, improve the educational administration management system, and improve the scientific nature of educational administration management.

This paper combines intelligent data and technology to improve the English teaching process management, improve the English teaching effect, and construct an intelligent English teaching process management system, which provides a reference for the further improvement of the quality of English teaching in the future.

2. Related Work

Teaching quality monitoring is a process of purposefully monitoring, evaluating, and applying effectiveness to the teaching quality system in order to achieve the intended purpose of teaching quality [4]. Teaching quality monitoring is a management process of detecting, measuring, judging, and improving the deviation of predetermined teaching quality goals in the process of teaching quality management and teaching implementation to ensure the effectiveness of teaching goals. The formulation of professional training objectives is usually based on [5]. Teaching quality monitoring is to ensure that the quality of personnel training can achieve the predetermined goals and that school leaders and teaching quality management departments can timely regulate teaching work, correct deviations, coordinate relationships and fully stimulate the full potential of all aspects [6]. Teaching quality monitoring is a process of monitoring and regulating the teaching process according to the expected quality standards in order to meet the needs of customers and ensure that all the teaching process and the quality of student training can achieve the predetermined purpose and develop continuously [7]. Reference [8] defines teaching quality monitoring as follows: The teaching quality monitoring system in colleges and universities refers to a series of teaching quality management work systems and monitoring operation mechanisms that are used to ensure the teaching quality in the teaching operation process of colleges and universities. The monitoring organization uses certain methods and means to carry out detailed planning, inspection, evaluation, feedback, and adjustment of various influencing factors of teaching quality and each link of the teaching process, so as to improve the quality of teaching and personnel training. Teaching quality monitoring can be divided into two monitoring forms: external quality monitoring and internal quality monitoring according to the monitoring subject and scope. The practical activities or management behaviors that the organization or department outside the school (usually refers to the education administrative department, social group, etc.) supervises and evaluates the teaching quality of the school as a whole is the external monitoring of the teaching quality [8]. The monitoring and control practice activities or management behaviors carried out by the school’s teaching quality management department and teachers and students on teaching quality are called internal monitoring of teaching quality [9]. Teaching quality monitoring is an important means and link of teaching quality management in colleges and universities.

The teaching quality monitoring system refers to the use of corresponding methods and means by colleges and universities to ensure and improve their own teaching quality and to achieve the expected teaching quality goals under the guidance of scientific teaching concepts [10]. A stable and effective quality management mechanism and system is established by effective monitoring and regulation to ensure and improve teaching quality [11]. The teaching quality monitoring system is mainly composed of six elements: subject, object, purpose, standard, method, and system of teaching quality monitoring [12]. The links of teaching quality monitoring mainly include the following: establishing quality standards for teaching links, monitoring information on teaching process, sorting and analysis of relevant data, evaluation, feedback information, and regulation and rectification. Through the effective operation of the teaching quality monitoring system, various information can be fed back in a timely and accurate manner, and the problems and causes that deviate from the predetermined goals in the process of teaching and teaching management can be analyzed by sorting out various information the goal of [13].

In the existing educational administration system, there is no detailed design and implementation of the management of the entire teaching process in terms of architecture, course notifications, online exams, online Q&A, etc., designed for teaching tasks, and at the same time, there is no management record of each link in the teaching process. It
can achieve real-time and scientific teaching evaluation feedback for teachers and does not involve objective records in the teaching process and complete systematic analysis of student-teacher evaluation results [14]. Similarly, each university has its own teaching process management in its own educational administration system, but it is designed for the different teaching characteristics and school-running styles of each school. Most of the systems have evaluation systems that are not perfect and have no systematic details. Design and statistical analysis are not scientific enough to apply to the university’s established process management normative requirements. Therefore, proposing a feasible teaching process management scheme can play a huge role in the educational administration system [15].

3. Smart Data Sampling

In this paper, the interpolation problem of time series data is considered in the metric space defined by dynamic time wrapping (DTW). It proposes an oversampling method for unbalanced time series data and selects a Gaussian process model sensitive to unbalanced time series data for classification to test the effect of the model.

DTW uses the time warping function that satisfies the boundary, continuity, and monotonicity conditions, calculates the minimum distance between two sequences, and solves the time warping function corresponding to the minimum distance.

We are given two sequences \( A = (a_1, a_2, \ldots, a_i, \ldots, a_m) \) and \( B = (b_1, b_2, \ldots, b_j, \ldots, b_n) \), and we first define the dynamic warping path as [16]

\[
W = \{w_1, w_2, \ldots, w_K\}, \quad \max(m, n) \leq K \leq m + n - 1. \tag{1}
\]

Among them, \( w_k \) corresponds to the synchronization point \((i, j)\) \((k = 1, 2, \ldots, K)\), \( i \) represents the index of the element on the sequence \( A \), \( j \) represents the index of the element on the sequence \( B \), and the indexes of all the elements of the sequences \( A \) and \( B \) must appear on the regular path, and \( w_1 = (1, 1) \), \( w_K = (m, n) \). If it is known that the path has passed the synchronization point \( (i, j) \), the next synchronization point to pass through is only \((i + 1, j), (i, j + 1), (i + 1, j + 1)\), and the number of paths that satisfies the condition is exponential, the goal of dynamic time warping is to find the path that minimizes the cost of warping, and the mathematical expression is

\[
\text{DTW} (A, B) = \min_W \sum_{k=1}^{K} d(w_k). \tag{2}
\]

The minimum cost path can be calculated by accumulating distance, and the accumulative distance is defined as [17]

\[
y(i, j) = d(i, j) + \min \{y(i - 1, j - 1), y(i - 1, j), y(i, j - 1)\}. \tag{3}
\]

Among them, \( d(i, j) \) is the distance between \( a_i \) and \( b_j \). Different distance calculation methods can be used for distance, such as Euclidean distance and Manhattan distance. The most commonly used Euclidean distance is used in this paper. In order to find a regular path that satisfies the minimum cumulative distance, the cumulative distance corresponding to this path is the DTW distance of the two sequences.

Figure 1 shows the cost matrices of the two sequences and the path with the least normalized cost. DTW needs to calculate the value of each element in the cost matrix, and then search for the path with the least regular cost. The regular path in the figure is \( W = \{(1, 1), (2, 2), (3, 3), (3, 4), (3, 5), (4, 5), (5, 6), (7, 7), (7, 8), (8, 8)\} \), there are vertical lines and horizontal lines on the path, that is, there are vertical lines and horizontal lines on the path; that is, there are one-to-many and many-to-one, which originate from the stretch and offset of the sequence on the time axis.

Figure 2 is a schematic diagram of the two sequences. Sequence \( A \) and sequence \( B \) have position offset and scale scaling. Using DTW calculation, it is concluded that the distance between the two is extremely small and the similarity is high.

DTW can effectively measure the similarity between time series data. The time and space complexity is \( O(N^2) \), and it is usually used on small-scale time series datasets. Because of the high time and space complexity, it reduces the computational efficiency when applied to large-scale datasets.

FastDTW combines two methods of restriction and data abstraction to speed up the calculation of DTW (as shown in Figure 3), while avoiding the shortcomings of both methods. The specific algorithm is as follows:

① Coarse-grained: the algorithm abstracts the original time series data to obtain a coarse-grained dataset. Each coarse-grained data point represents multiple fine-grained data points (each coarse-grained data point can be an average of multiple fine-grained data points). The coarse-grained process can be performed iteratively multiple times, sequentially from \( 1/2^k \rightarrow 1/2^{k-1} \rightarrow \ldots \rightarrow 1/2 \rightarrow 1/1 \).

② Projection: the algorithm uses the standard DTW algorithm to calculate the regular path on the coarse-grained dataset after data abstraction.

③ Fine-grained: the algorithm adjusts the regular path obtained on the coarse-grained dataset in step ② to a finer-grained space through local adjustment. That is, on the neighbor cost matrix unit of the regular path in the coarse-grained space, the optimal path of the finer-grained space is found, and the size of the neighbor can be adjusted by the radius (similar to the window width of the restriction method) parameter.

In this paper, FastDTW is used to calculate the DTW distance and regular path, and the efficiency of this method is improved under the condition of ensuring the accuracy.

This paper considers the characteristics of time series data, draws on the interpolation idea and the adaptive advantage, and proposes an unbalanced time series data processing method based on DTW. For the convenience of description, the oversampling method proposed in this paper is abbreviated as SDTW, that is, sampler with dynamic time warping.
First, the total number of minority class samples to be generated is determined as follows [18]:

$$G = (N_+ - N_-) \times \alpha.$$  

(4)

Among them, $N_+$ and $N_-$ represent the number of minority class and majority class samples in the original data, respectively, and $\alpha (0 < \alpha \leq 1)$ is the adjustment degree, which is usually taken as 1.

For each minority class sample $x_i$, the DTW distance and regular path between it and other samples are calculated. According to the DTW distance ordering, the $k$ nearest neighbors of the sample are
found. Then, we calculate the ratio using the following formula:
\[
    r_i = \frac{k_i}{k},
\]
\[
i = 1, 2, \ldots, N_x.
\]

Among them, \(k_i\) is the number of samples belonging to the minority class among the \(k\) nearest neighbor samples.

- The threshold \(\theta(0 < \theta \leq 1)\) is set. The ratio \(r_i\) is divided into two numerical sets according to the threshold, corresponding to two different regions of the sample set: the noise set \(X_{\text{noise}}(r_i \in [0, \theta))\) and the safe set \(X_{\text{safe}}(r_i \in [\theta, 1])\). Considering that the noise set contains wrong sensitive information, it is not conducive to the learning process of the model. Therefore, the minority class samples belonging to the noise set do not participate in the artificial sample synthesis process.

- The ratio distribution of the samples of the normalized security set \(X_{\text{safe}}\) is obtained \(\tilde{r}_i\). Considering that the sample is over-ignored because the ratio is too small, the exponential function is used for smoothing correction:
\[
    \tilde{r}_i = \frac{\exp(r_i)}{\sum_{i=1}^{N_x} 1_{\{x_i \in X_{\text{safe}}\}} \cdot \exp(r_i)},
\]
\[
    \sum_i \tilde{r}_i = 1.
\]

Among them, \(1_A\) is an indicative function. If \(A\) is true, the indicator function takes the value 1, otherwise, it is 0.

- The number of sampling samples is determined: for each minority class sample \(x_i\), in the security set, the number of sampling samples is
\[
    g_i = \lceil G \cdot \tilde{r}_i \rceil.
\]

Among them, \([\cdot]\) means round up. It is worth noting that if the total number of samples obtained by sampling exceeds the set number of samples \(G\), the method of simple random sampling is used to eliminate the excess samples sampled.

- The sampling process is as follows: for each minority class sample \(x_i\) in the safe set, a minority class sample \(x_k\) among its \(k\) nearest neighbor samples is randomly selected. We assume that the dynamic time warping path of sample sequences \(x_i\) and \(x_k\) is \((w_1, w_2, \ldots, w_L)\). Among them, the synchronization point \(w_l = (w_{j1}, w_{j2})\), \(l = 1, 2, \ldots, L\), \(n \leq L \leq 2n - 1\), \(n\) is the sample sequence length (because the lengths of time series data samples in the UCR dataset used in this paper are all the same, for the convenience of understanding, it is assumed that the time series samples used are of equal length, and the case where the sample sequences are not of equal length is similar, that is, \(\max(m, n) \leq L \leq m + n - 1\)). The specific steps (as shown in Figure 4) are as follows:

Step 1: counting between synchronization points of the regularized path, new sample points are generated. However, due to the existence of one-to-one, one-to-many, and many-to-one situations in the regular path, when calculating the sample value of the sampling point, it is necessary to perform the same interpolation operation on the sampling time point for subsequent adjustment, that is,
\[
    x_p = x_{W_i} + \lambda_0(x_{W_i} - x_{W_k}),
\]
\[
    P = W_i + \lambda_0(W_k - W_i).
\]

Among them, \(x_p\) is the new sample sequence \(x_p = (x_{p1}, x_{p2}, \ldots, x_p)\) obtained by path interpolation, \(P\) is the sampling time point corresponding to the new sample sequence \(P = (P_1, P_2, \ldots, P_p)\), \(\lambda_0\) is a random number \((0, \lambda \leq 1)\) between \((0, \lambda)\), and \(x_{w1} = (x_{w1}, x_{w2}, \ldots, x_{wL})\) and \(x_{w1} = (x_{w1}, x_{w2}, \ldots, x_{wL})\) are the sample value sequences of the minority class sample \(x_i\), corresponding to the synchronization point on the DTW path and its nearest neighbor minority class sample \(x_k\), respectively. \(W_i = (w_{i1}, w_{i2}, \ldots, w_{iL})\) and \(W_k = (w_{k1}, w_{k2}, w_{kL})\) are the sequences composed of the points of the minority class samples \(x_i\) and \(x_k\) corresponding to the synchronization points on the DTW path, respectively.

Step 2: the sampling time point is adjusted. Due to the existence of one-to-one, one-to-many, and many-to-one situations in the regular path, this may lead to the situation that the sampling interval of the interpolation sample points is unequal and inconsistent with the sampling interval of the original sequence. Therefore, the sampling time point \(P = (p_1, p_2, \ldots, p_p)\) of the new sample sequence needs to be adjusted to be consistent with the sampling time point \(T = (t_1, t_2, \ldots, t_n)\) of the original data, and the adjusted sample value sequence \(x_{a \cdot d j} = (x_{i1}, x_{i2}, \ldots, x_{in})\) is given. For each \(t_j \in T\), then we have the following:

1. If there is \(p_j \in P\) such that \(p_j = t_j\), then the sample value corresponding to \(t_j\) is
\[
    x_{t_j} = x_{p_j},
\]

Among them, \(x_{p_j} \in x_p\).

2. If there is no \(p_j \in P\) such that \(p_j = t_j\), then \(P = \max\{p_i; p_i < t_j\}\) and \(\overline{P} = \min\{p_i; p_i > t_j\}\) are solved first, that is, \(p < t_j < \overline{P}\). In this paper, the linear interpolation method is used (other interpolation methods such as square interpolation and cubic interpolation can also be used, but the
The linear interpolation method is simpler and more efficient after trying, and the sample value corresponding to \( t_j \) the calculation is

\[
x_{t_j} = \frac{(t_j - p)}{(\bar{p} - p)}(x_{\bar{p}} - x_p) + x_p.
\]

Among them, \( x_{\bar{p}}, x_p \in x_p \).

Step 3: We repeat the first and second steps until \( g_i \) samples are generated.

The algorithm repeats step ⑥ until a specified number of samples are generated around each minority class sample in the safe set.

The Bayesian method is introduced into the Gaussian process model, which can accurately calculate the
posterior probability value, and the results are easy to interpret. It has the characteristics of adaptive acquisition of hyperparameters and flexible nonparametric inference. Moreover, the kernel function is adopted, so that the model can be used in nonlinear and high-dimensional problem processing. In the case of unbalanced data, the model is more inclined to the majority class, and the ability to identify the minority class decreases, that is, it is sensitive to unbalanced time series data. In this paper, GPC is used to classify the unbalanced time series data before and after sampling to test the effectiveness of the sampling method.

A Gaussian process refers to a set of random variables, and any finite number of random variables in the set obeys a joint Gaussian distribution. Any Gaussian process can be determined by the mean function $m(x)$ and the covariance function $k(x, x')$ of a random process $f(x)$:

$$f \sim GP(m(x), k(x, x')).$$

(11)

Among them, $m(x) = E(f(x)), k(x, x') = E((f(x) - m(x))(f(x') - m(x'))^T)$. The idea of the Gaussian process classification model is to replace the non-Gaussian real posterior distribution by a Gaussian approximate posterior distribution, and then we use the approximate posterior distribution to give test data to approximate the predicted distribution.

We give the training set $S = \{(x_i, y_i), i = 1, 2, \ldots, n\}, x_i$ is the input, and $y_i$ is the output. Given $x$, the conditional probability of $y$ is $p(y, x) = \Phi(f(x))$. Among them, $f(x)$ defines the mapping relationship between input data and output. When $x$ is given, $f(x)$ is the implicit function obeying the Gaussian process $f(x, \theta) \sim GP(0, K(\theta)), \theta$ is the parameter of the covariance function $K(\theta)$, and $\Phi(\cdot)$ is the cumulative probability density function of the standard normal distribution.

We give $f = [f_1, \ldots, f_n]^T, f_k = f(x_k)$, and we set $Y = [y_1, \ldots, y_n]^T, X = [x_1, \ldots, x_n]^T$. Since the observed data are independent of each other, there is a likelihood

![Diagram of English teaching calendar generation](image-url)
function $p(Y, f) = \prod_{i=1}^{n} p(y_i, f_i) = \prod_{i=1}^{n} \Phi(y_i, f_i)$, the prior distribution of the implicit function $f$ is $p(f, X, \theta) = N(0, K, k_{ij} = k(x_i, x_j, \theta), k(\cdot))$ is the covariance function. The Gaussian kernel function is commonly used as the covariance function $(k(\|x - x_c\|) = \sigma_f^2 \exp \{- (1/2d^2) (x-x_c)^2\}$, $x_c$ is the center of the kernel function, the parameter is $\theta = \{\sigma_f, d\}$, $d$ is the window width. The posterior distribution of the implicit function $f$ can be expressed as

$$p(f, S, \theta) = \frac{p(Y, f)p(f, X, \theta)}{p(S, \theta)} = \frac{N(0, K)}{p(S, \theta)} \prod_{i=1}^{n} \Phi(y_i, f_i).$$ (12)

It is worth noting that the posterior distribution is non-Gaussian. We predict the class $y_*$ given the sample $x_*$ to be classified. First, the conditional probability of its implicit function $f_*$ is calculated:

$$p(f_*, S, \theta, x_*) = \int p(y_*, f, X, \theta, x_*)p(f, S, \theta)df.$$ (13)

Using the conditional probability distribution of this implicit function $f_*$, the probability distribution of class labels $y_*$ is obtained as follows:

$$p(y_*, S, \theta, x_*) = \int p(y_*, f_*)p(f_*, S, \theta, x_*)df.$$ (14)

The conditional probability of $f_*$ is not a Gaussian likelihood. Therefore, it cannot be calculated directly using the integral. An alternative approach is to use a Gaussian-like approximate posterior distribution $q(f, S, \theta) = N(f, (\mu, \Sigma))$ to approximate the true posterior distribution $p(f, S, \theta)$. We substitute this approximate posterior distribution into the conditional probability calculation formula of the implicit function $f_*$, and after obtaining the approximate Gaussian test of the implicit function $f_*$, we finally verify it, as follows:

$$q(f_*, S, \theta, x_*) = N(f_*, (\mu_*, \sigma^2_*)).$$ (15)

Among them, $\mu_* = k_{x}^T K^{-1} \mu$, $\sigma^2_* = k(x_*, x_*) - k_{x}^T (K^{-1} - K^{-1} AK^{-1}) k_{x}$, $k_{x} = [k(x_1, x_1), \ldots, k(x_m, x_1)]^T$ is the prior covariance function between the sample $x_*$ to be classified.
and the training set $X$. Thus, the approximate prediction distribution of the samples to be classified is

$$q(y_*=1,S,\theta,x_*) = \Phi(f_*)N(\mu_*,\sigma_*)^2\) df$$

$$= \Phi\left(\frac{\mu_*}{\sqrt{1+\sigma_*^2}}\right).$$

(16)

Therefore, the parameter $\theta_* = \{\mu_*,\sigma_*^2\}$ of the approximate Gaussian posterior distribution can be solved by approximation algorithms such as maximum likelihood method and Laplace approximation.

4. Improvement of English Teaching Process Management Based on Intelligent Data Sampling

The overall design of the system starts from the stage of English teaching process management, improves the English teaching process management, optimizes the management mode, and improves the quality of English teaching. It mainly includes three aspects of demand analysis. The overall system demand analysis is shown in the overall demand diagram of English teaching process management in Figure 5.

At present, for the courses of theory plus experiment or theory plus computer in the system, when the execution task is generated, the experimental or computer part is stripped, and the execution task is set up separately, and then the English teaching calendar is generated. The main activity diagram of English teaching calendar generation is shown in the activity diagram of English teaching calendar generation in Figure 6.

In the management of the whole English teaching process, the maintenance and management of the English teaching calendar is a key step, and the good design and management of the English teaching calendar can have a direct impact on the management of the English teaching process. The maintenance of the English teaching calendar plays a paving role in the management of the subsequent English teaching process. The overall description of the maintenance and management of the English teaching calendar is shown in the activity diagram of the maintenance and management of the English teaching calendar in Figure 7.

The system use case analysis diagram of teaching staff and teachers is shown in Figure 8, the English teaching calendar maintenance and management use case diagram.

Figure 8 can visually show the main participants of the system in the maintenance of the English teaching calendar. Among them, the main role of each role can be clearly described.
defined through the description of the use case. The main use case for teaching staff includes generating executive tasks, generating English teaching calendars, and English teaching calendar updates. The main use case scenarios for teachers include the maintenance of the English teaching calendar and the grouping of the English teaching calendar. By analyzing the use cases of teachers and educational administrators, the main operating rights of system users are given according to their roles. Through the analysis of the above use case diagram, the main participants and the main demand use cases in the process of English teaching calendar maintenance and management can be clarified. In a word, the generation of the English teaching calendar is the foundation of the English teaching process management. Through the generation and maintenance of the English teaching calendar, it has laid the cornerstone for the realization of other main functions of the system. On the basis of performing tasks, the English teaching execution process is supervised, and an online management learning platform is established. On the basis of the English teaching calendar, the course evaluation is open, and the English teaching process is fed back through real-time evaluation conclusions.

Based on the demand analysis of the above online learning platform, the activity diagram of teachers in the platform is shown in Figure 9.
On the basis of the above research, this paper evaluates the English teaching process management system based on intelligent data sampling proposed in this paper, and explores its effect on the English teaching process management. The test results are shown in Table 1 and Figure 10.

It can be seen from the above research that the English teaching process management system based on intelligent data sampling proposed in this paper can play an important role in English teaching management and can effectively improve the efficiency of English teaching.

### 5. Conclusion

The study found that there are a series of factors hindering the effectiveness of inquiry-based English teaching. It is embodied in the factors of teachers, students and policy environment. Teachers are mainly influenced by their own educational beliefs and evaluation views. The second is the impact of technology, including teachers’ lack of effective English teaching strategies, insufficient knowledge and insufficient English teaching skills. The main factor of students is the lack of knowledge reserve and ability of students. The environmental aspects are mainly the lack of English teaching conditions, English teaching time and the level of attention of leaders. This paper combines intelligent data sampling technology to improve the English teaching process management, improve the English teaching effect, and construct an intelligent English teaching process management system. The research shows that the English teaching process management system based on intelligent data sampling proposed in this paper can play an important role in English teaching management and can effectively improve the efficiency of English teaching.

### Data Availability

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

### Conflicts of Interest

The author declares no conflicts of interests.

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