Evaluation model of college English teaching effect based on particle swarm algorithm and support vector machine

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Abstract

This paper studies the evaluation model of Higher Vocational English teaching effect based on particle swarm optimization and support vector machine classification. Based on the relevant theories, the model constructs a multi-index evaluation system of English teaching effect in higher vocational colleges, which takes teachers and students as the main body. This model improves the accuracy and efficiency of English teaching evaluation in Higher Vocational Colleges and meets the requirements of English teaching evaluation in higher vocational colleges. The experimental results show that this method has a good effect on the evaluation of English Teaching in higher vocational colleges. The average evaluation accuracy is 97.1%, the evaluation time is short, and the test time is as low as 6 ms.

Key words: Particle swarm algorithm; Support vector machine; Evaluation model

1. Introduction

At present, higher vocational English teaching evaluation is an important research topic in college education evaluation. According to the evaluation results, teachers can know the teaching effect in real time, adjust the teaching plan and progress in time, and personalize teaching methods [1-6]. According to the evaluation results, the school management can also comprehensively grasp the teaching situation of English subjects, which is convenient for teaching management. A scientific and reasonable evaluation model is used to comprehensively evaluate teachers' Comprehensive English teaching level in Higher Vocational Colleges [8], so as to make the evaluation objects more excellent. Relevant studies show that there are many problems in the current evaluation of College English teaching effect [3]. For example, the earliest evaluation methods mainly relied on the experience and judgment of evaluators. The subjective factors of the evaluation subject have a great influence on the evaluation results. Therefore, there is an urgent need for objective and quantitative evaluation methods in the evaluation of English teaching effect in higher vocational colleges. Relevant studies are also emerging. For example, Fan et al. [9] used BP neural network to optimize the evaluation model parameters and proposed a college English teaching quality evaluation model. However, in the process of College English teaching effect evaluation, this method ignores some factors that affect the teaching quality, resulting in the inaccuracy of this model in the evaluation of College English teaching quality. In addition, Wang [10] proposed a teaching evaluation method based on category weighted grey objective decision-making. The calculation process of this model is relatively complex, which leads to its low efficiency in College English teaching quality evaluation. In view of this, this paper attempts to put forward a model for evaluating the effect of Higher Vocational English teaching based on particle swarm optimization algorithm and support vector machine to evaluate the quality of Higher Vocational English teaching.

1.1. Construction of College English Teaching effect Evaluation System

There are many theories for college English teaching effect evaluation system. According to the relevant theories, a multi-index system with teachers and students as the main body is constructed. The evaluation index system of college English teaching effect is shown in Figure 1.
In Figure 1, it shows the evaluation index system of English teaching effect in higher vocational colleges. The system is composed of two sub-systems: student teaching evaluation and teacher teaching evaluation. Among them, teachers' sense of responsibility and English achievements are important evaluation indicators of English teaching effect in higher vocational colleges. By inputting the index data in the system as samples into the model, the evaluation of teaching quality is realized.

1.2. Evaluation principle of least squares support vector machine

Evaluation principle of least squares support vector machine: Set a group of training sample sets with description, where 
\[ s = \{x_i, y_i\} \quad i = 1, 2, \ldots, l \]. The input data of the least squares support vector machine are described by \( x_i \). The number of training samples was described by \( l \); Output data is described \( y_i \). The linear regression function in dimensional space is Equation (1).

\[
y = \omega^T x + b
\]  

(1)

where, the amount of deviation is described by \( b \); Weight vector is described by \( \omega \).

The regression function in the high-dimensional feature space is Equation (2).

\[
f (x) = \omega^T \varphi (x) + b
\]  

(2)

Where, \( \varphi (x) \) is the nonlinear mapping from the input space to the high-dimensional feature space.

The optimization objective function of least squares support vector machine is Equation (3).

\[
\min = \frac{1}{2} \| \omega \|^2 + \frac{1}{2} c \sum i \epsilon_i^2
\]

(3)

The constraint condition is Equation (4).
\[
\text{s.t. } \omega^T \varphi(x_i) + b + e_i = y_i, i = 1, 2, \cdots, l
\]
(4)

Where, \( c \) is the regularization parameter control representing the penalty degree of error; \( e_i \) is the error variable.

By introducing Lagrange multiplier, the constrained optimization is transformed into an unconstrained optimization problem and the solution of the optimization problem is realized, namely, Equation (5).

\[
\min J = \frac{1}{2} \| \omega \|^2 + \frac{1}{2} c \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \lambda_i \left( \omega^T \varphi(x_i) + b + e_i - y_i \right)
\]
(5)

Where, Lagrange multiplier uses description by \( \lambda_i \).

The calculation of the optimal value is obtained under KKT optimization conditions. The optimal value is solved as Equation (6).

\[
\begin{aligned}
\frac{\partial J}{\partial \omega} &= 0 \rightarrow \omega = \sum_{i=1}^{l} \lambda_i \varphi(x_i) \\
\frac{\partial J}{\partial b} &= 0 \rightarrow \sum_{i=1}^{l} \lambda_i = 0 \\
\frac{\partial J}{\partial e_i} &= 0 \rightarrow \lambda_i = ce_i, i = 1, 2, \cdots, l \\
\frac{\partial J}{\partial \lambda_i} &= 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0, i = 1, 2, \cdots, l
\end{aligned}
\]
(6)

The \( \omega \) and \( e \) in Equation (6) are eliminated, and the quadratic optimization problem is replaced by the calculation problem of solving linear equations. The calculation result is Equation (7).

\[
\begin{bmatrix}
0 \\
y
\end{bmatrix}
= 
\begin{bmatrix}
0 & Q^T \\
Q & \Omega + c^{-1}I
\end{bmatrix}
\begin{bmatrix}
b \\
\lambda
\end{bmatrix}
\]
(7)

Where, \( \lambda = [\lambda_1, \lambda_2, \cdots, \lambda_l]^T \); \( Q = [1, 1, \cdots, 1]^T \); \( I \) denotes the identity matrix; \( \Omega \in \mathbb{R}^{l \times l} \) and \( \Omega_y = \varphi(x_i)^T \), \( \varphi(x_i) = K(x_i, x_j) \); \( K(\cdot, \cdot) \) denote the function. The kernel function in the original space is used to obtain the regression function of least squares support vector machine, which is Equation (8).

\[
y = \sum_{i=1}^{l} \lambda_i K(x_i, x_j) + b
\]
(8)

In order to avoid the occurrence of dimensional disaster. The kernel function with radial basis, which is commonly used in least squares support vector machine, is introduced to replace the inner product operation of high-dimensional feature space. The radial basis kernel function is shown in Equation (9).

\[
K(x_i, x_j) = \exp\left(-\frac{\|x - x_j\|^2}{\sigma^2}\right)
\]
(9)

Where, the kernel parameter width is \( \sigma \).

Two parameters \( c \) and \( \sigma \) are optimized and represented to enhance the generalization ability of least squares support vector machine. Particle swarm algorithm is used to optimize the parameters of least squares support vector machine.
The process of implementing the college English teaching effect evaluation model with least squares support vector machine is as follows.

Step 1: Input the sample of evaluation data.

Step 2: Solve the optimal kernel function parameters $\sigma$ and regularization parameters $c$, and implement the particle swarm algorithm.

Step 3: Select the appropriate kernel function.

Step 4: Solve the optimization problem, and calculate the optimal solution by description, as in Equation (10).

$$\alpha = (\alpha_1^*, \alpha_2^*, \alpha_3^*, ..., \alpha_c^*)^T$$  \hspace{1cm} (10)

Step 5: Construction of decision function, construction process, as shown in Equation (11).

$$y = \sum_{i=1}^{c} (\alpha_i^* - \alpha_i)K(x_i, x) + b$$  \hspace{1cm} (11)

Step 6: Implement model evaluation through decision function.

### 1.3. Particle swarm algorithm search for least squares support vector machine parameters

It is set that a population is composed of $m$ particles, and in the search space of one dimension, the optimal position of the first particle in the search space is described by $p_1$; Velocity $v_1$ is described by description; The position of the second particle in the dimensional space is described $x_1$; The definition vector is described by $x_1 = (x_{11}, x_{12}, ..., x_{1d})$, $v_1 = (v_{11}, v_{12}, ..., v_{1d})$, $p_1 = (p_{11}, p_{12}, ..., p_{1d})$ $i = 1, 2, ..., m$. The optimal position searched by the whole population is described $p_g = (p_{g1}, p_{g2}, ..., p_{gd})$; The equations of particle position and velocity of particle swarm algorithm are updated as (12) and (13).

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}$$  \hspace{1cm} (12)

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id} - x_{id}^k) + c_2 r_2 (p_{gd} - x_{id}^k)$$  \hspace{1cm} (13)

Where, $\omega$ is the inertia weight coefficient; $c_1$, $c_2$ are the acceleration constants; $k$ is optimization algebra; $v_{id}^k$ and $x_{id}^k$ are search speed and position of particles in $d$ dimensional space when $k$ time; $r_1$, $r_2$ is a random number.

The process of particle swarm algorithm to optimize the parameters $c$ and $\sigma$ of support vector machine is as follows.

Step 1: Normalized pre-processing of college English teaching effect evaluation data.

Step 2: Set the value of parameters (the maximum number of iterations $T_{max}$, acceleration constants $c_1$ and $c_2$, the inertia weight coefficient $\omega$, the search range of population particle number $m$, $c$, $\sigma$ and the dimension of individual particles $d$).

Step 3: Initialize the parameters of particle swarm algorithm.

Step 4: Set individual extremum $P_{ibest}$ and global extremum $g_{best}$, and calculate the adaptation value of each particle according to the current position of the particle. The compute process is shown in Equation (14).

$$f = \sum_{i=1}^{N} |y_i - y_i'|$$  \hspace{1cm} (14)

Where, $y_i'$ is the predicted value; $N$ is the number of training samples; $y_i$ is the actual value.
Step 5: In order to generate a new population, Equation (12) and Equation (13) are updated according to the particle position and velocity.

Step 6: Solve the fitness value $f$ of each particle in the new population.

Step 7: Compare the optimal speed and position of the previous population. If the excellent particle is convertible, otherwise, no adjustment is made.

Step 8: If the end condition of optimization is not met, the number of iterations should be set $t = t + 1$ and Step 4 should be returned to find the optimal solution.

Step 9: If the optimal solution of the kernel function parameters $\sigma$ and regularization parameters $c$ of the least squares support vector machine is found, the search is completed.

1.4. Evaluation process of college English teaching effect based on particle swarm algorithm and support vector machine

Combining with the evaluation index system of English teaching effect in higher vocational colleges, this paper proposes an evaluation model of English teaching quality in Higher Vocational Colleges Based on particle swarm optimization algorithm and support vector machine. First, the data sample of English teaching effect evaluation in higher vocational colleges is taken as the sample of evaluation model, and particle swarm optimization algorithm is used to solve the kernel function parameters and regularization parameters of least squares support vector machine, find the optimal solution of the model, and realize the evaluation process of least squares support vector machine. If the obtained parameters are not the optimal solution of the model, the particle swarm optimization algorithm needs to be used again to adjust the parameters until the optimal solution is obtained. Through the above process, the optimization model is solved to achieve the evaluation of English teaching quality in higher vocational colleges.

2. Experimental results and analysis

Select a university computer professional English classroom teaching effect as the research object, according to the college English teaching effect evaluation index to collect sample data, through the actual situation of college English teaching effect on college English teaching evaluation and expert at the university of English class teaching quality level value, and it is concluded that the test of 300 data samples, and can be divided into 10 groups of data sets, There are 30 data samples in each group. Among them, the effect of college English teaching is described by $y$; English performance is described by $x_1$; The number of modified assignments and substitute lessons was described by $x_2$, and the number of English class suspensions was described by $x_3$. The experimental comparison method uses the method in this paper and literature [6] to optimize the BP neural network teaching quality evaluation model, and the teaching evaluation method based on category weighted grey target decision in literature [7] to carry out the comparison test of college English classroom teaching effect. Three methods were used to test the experimental data set, and the accuracy calculation results of the three methods were obtained, as shown in Table 1.

| Data set Number | This paper % | Optimize BP neural network % | Category weighted grey target Decision method % |
|-----------------|--------------|------------------------------|-----------------------------------------------|
| 1               | 96.30        | 90.00                        | 75.60                                         |
| 2               | 97.90        | 89.45                        | 77.70                                         |
| 3               | 95.71        | 88.67                        | 78.87                                         |
| 4               | 97.67        | 87.23                        | 75.76                                         |
| 5               | 96.90        | 89.45                        | 76.89                                         |
| 6               | 95.76        | 90.83                        | 78.34                                         |
| 7               | 96.77        | 89.12                        | 79.19                                         |
| 8               | 96.54        | 88.37                        | 78.58                                         |
| 9               | 95.25        | 90.01                        | 77.60                                         |
| 10              | 96.44        | 91.06                        | 79.54                                         |

According to Table 1, the average evaluation accuracy of the proposed method is 97.1%, which is 10% and 21% higher than the average evaluation accuracy of the teaching quality evaluation model method optimized by BP neural network.
and the teaching evaluation method based on category-weighted grey target decision, respectively. Therefore, the evaluation accuracy of the proposed method is the highest.

3. Conclusion

The quantitative non-linear functional relationship between College English teaching effect and each evaluation index is complex, which leads to the subjectivity of the evaluation scores obtained and affects the objectivity and fairness of the evaluation. In order to accurately evaluate the effect of College English teaching and improve the overall level of College English teaching, this paper studies the evaluation model of College English teaching quality based on particle swarm optimization algorithm and support vector machine. The experimental results show that this method has the highest evaluation accuracy, shorter evaluation time and the best evaluation effect. This method can improve college students' English learning achievements and has important practical significance for improving college English teaching level.

Reference

[1] Zhang Wei. An Exploration of Methods to Improve the effect of English Teaching: A review of College English Teaching Exploration and Practice [J]. Journal of Chinese education, 2018,307 (11): 135.
[2] Zhao Y, Jiang L J, Huang R. Experience perception of teachers and students and reform of graded College English teaching [J]. Higher education development and evaluation, 2018,34 (6): 98-107.
[3] Liang Jing. A Review of English Teaching Research Methods and Case Studies [J]. Chinese journal of education, 2018,306 (10): 130.
[4] Liu, S. Teaching evaluation system design based on the improved algorithm of grey relational analysis. 2012. Bulletin of Science and Technology.
[5] Hu, J. L., Deng, J. B., & Chang, H. An improved classification algorithm on teaching evaluation. 2012. IEEE International Conference on Granular Computing. IEEE.
[6] Zhang, X., Yang, X., & Yang, J. Teaching evaluation algorithm based on grey relational analysis. 2021. Complexity.
[7] Tian H, Wang Y, Han Y H. The teaching and effect of ESP for English majors in Physical education colleges [J]. Journal of Beijing university of sport, 2018,41 (6): 76-83.
[8] Dong Jindi. A study on the Construction of a multi-evaluation System for Hierarchical College English Teaching -- A case study of China University of Petroleum (East China) [J]. Fujian tea, 2019,41 (8): 123-124.
[9] Fan Y, Ma L P. Optimization of BP neural network teaching quality evaluation model in colleges and universities. Statistics and decision, 2018,34 (2): 80-82.
[10] Wang H Y. Research on teaching evaluation based on class-weighted grey target decision making [J]. Journal of henan agricultural university, 2018,52 (5): 733-737.