# Quality evaluation of university teaching, based on an improved least squares support vector machine

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ABSTRACT: A core mission of higher education is teaching, and so improving teaching quality is the key to promoting the reform and development of universities. The establishment of a scientific teaching quality evaluation system is an important means by which to strengthen the management of teaching and improve teaching quality in universities. In the research reported in this article, a systematic and comprehensive university teaching quality evaluation system was developed using a new method of teaching quality assessment: a grid search of a least squares support vector machine. The grid search is used to optimise the regularisation and kernel width parameters of the least squares support vector machine. A teaching quality evaluation model based on the proposed algorithm was built. Case results analysis showed that the mean absolute percentage error of the evaluation method was 0.44%. Hence, the method can be applied to evaluate the teaching quality of teachers at universities.

## INTRODUCTION

After several years of large student enrolments at universities, a series of related problems has appeared, i.e. a shortage of teachers, inadequate sources of students, a lack of teaching equipment and poor logistical services [1]. These problems cause widespread concern in society and the quality of university education has become a focus of discussion and reflection.

The evaluation of class teaching at universities is an important means of managing teaching quality. The construction of a scientific, systematic and effective teaching quality evaluation system would have great significance for managing teaching quality and for improving the quality of class teaching.

University teaching quality is a complex issue that includes a variety of factors, such as teaching conditions, the difficulty of the curriculum and the effect of the teachers' teaching. Currently, there is no generally accepted teaching quality evaluation system. Existing research focuses on three aspects: the first is the evaluation methodology, the second is the content of the evaluation system and the third is the rating method used in the evaluation [2][3].

The work reported in this article concerns further research on the first of the aspects mentioned above, viz. the evaluation methodology. After reviewing the literature, a comprehensive and systematic teaching quality evaluation system was developed. This introduces an improved least squares support vector machine (LSSVM) methodology for evaluating the quality of university teaching. Cases have been used to verify the validity of the proposed model.

## TEACHING QUALITY EVALUATION IN UNIVERSITIES

According to the accepted view, the following principles should be followed during the construction of a teaching quality evaluation system [4][5]:

- Objective principle: the evaluation must be objective and based upon the facts, with evaluation objects being treated equally.
- Totality principle: the evaluation must include a comprehensive collection of information on the teaching process and teaching environment.
- Incentive principle: the teaching evaluation is a measure and judgment of the teaching not only as a summary of knowledge, but also how it affirms progress, diagnoses problems, taps into students' potential and continuously improves the quality of education.

Based upon the above principle, a teaching quality evaluation system was constructed, as shown in Table 1. It contains four first-level indicators, 15 second-level indicators and the weight of each indicator.

First-level indicators	Weight	Second-level indicators	Weight
Droporation (D)	0.1	Pre-class preparation (C <sub>1</sub> )	0.4
Preparation ( <b>B</b> <sub>1</sub> )	0.1	Second-level indicatorsPre-class preparation (C1)Quality of lesson plans (C2)Teaching attitude (C3)Teaching content (C4)Teaching organisation (C5)Teaching media (C6)Teaching method (C7)Innovation (C8)Practice (C9)Proof of concepts (C10)Student performance (C11)Lesson reflection (C12)The degree of compliance (C13)Homework arrangement (C14)After-class summary (C15)	0.6
		Teaching attitude (C <sub>3</sub> )	0.1
Process (B <sub>2</sub> )	$0.5 \qquad \begin{array}{c} \mbox{Teaching content (C_4)} \\ \mbox{Teaching organisation (C_5)} \\ \mbox{Teaching media (C_6)} \\ \mbox{Teaching method (C_7)} \\ \mbox{Innovation (C_8)} \\ \mbox{Practice (C_9)} \\ \mbox{Proof of concepts (C_{10})} \\ \mbox{Student performance (C_{11})} \\ \mbox{Lesson reflection (C_{12})} \end{array}$	Teaching content (C <sub>4</sub> )	0.1
		Teaching organisation (C <sub>5</sub> )	0.15
		Teaching media (C <sub>6</sub> )	0.15
		Teaching method (C <sub>7</sub> )	0.2
		Innovation (C <sub>8</sub> )	0.1
		Practice (C <sub>9</sub> )	0.1
		0.1	
		Student performance (C <sub>11</sub> )	0.3
Effect (B <sub>3</sub> )	0.2	Lesson reflection (C <sub>12</sub> )	0.3
		The degree of compliance $(C_{13})$	0.4
Completion (R.) 0.2		Homework arrangement (C <sub>14</sub> )	0.5
	0.2	After-class summary (C <sub>15</sub> )	0.5

Table 1: Teaching quality evaluation system for university teachers.

The weights of the indicators were obtained by expert scoring. The experts were academics at a university in Hebei province of China. Five experts scored each level indicator and the weight was the average of the values of the experts. For example, the values of second-level indicators,  $C_1$  and  $C_2$ , belonging to Preparation (B<sub>1</sub>) as scored by experts are shown in Table 2.

Table 2: The weights of  $C_1$  and  $C_2$ .

Indicators	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
C1	0.4	0.5	0.3	0.5	0.3
C <sub>2</sub>	0.6	0.5	0.7	0.5	0.7

Taking the average yields, the weights of  $C_1$  and  $C_2$  are 0.4 and 0.6, respectively. The other weights were similarly calculated, and the results are shown in Table 1.

## TEACHING QUALITY EVALUATION MODEL

Least Squares Support Vector Machine (LSSVM)

The least squares support vector machine (LSSVM) model is an improvement of the support vector machine (SVM). It modifies the inequality constraints of traditional SVM to equality constraints, and sets the squared error and loss function as the loss experienced by the training set. This transforms the quadratic programming problem into a linear problem, which improves speed and convergence [6][7].

Set *n* samples and their values as  $D = \{(x_i, y_i) | i = 1, 2, \dots, l\}, x_i \in \mathbb{R}^l, y_i \in \mathbb{R}$ , in which  $x_i$  represents the input data and  $y_i$  represents the output data.

The function estimation problem in weight space  $\omega$  is defined as:

$$\min \quad \frac{1}{2}\omega^{T}\omega + \frac{1}{2}C\sum_{i=1}^{l}\xi_{i}^{2}$$
(1)

s.t. 
$$y_i = \omega^T \varphi(x_i) + b + \xi_i, \ i = 1, 2, \cdots, l$$
 (2)

Where  $\varphi(\cdot)$  is defined as the nonlinear mapping function, i.e. the training data are mapped into a high dimensional linear feature space through this function; *C* represents the regularisation parameter;  $\xi \in R$  represents the error variable; and *b* represents the offset.

According to Formulae (1) and (2), the Lagrange function is defined as:

$$L(\omega, b, x, a) = \frac{1}{2}\omega^{T}\omega + C\sum_{i=1}^{l} \xi_{i}^{2} - \sum_{i=1}^{l} a_{i} \left[ \omega^{T} \varphi(x_{i}) + b + \xi_{i} - y_{i} \right]$$
(3)

Where  $a_i (i = 1, 2, \dots, l)$  represents the Lagrange multiplier.

Using the Karush-Khun-Tucker (KKT) condition, calculate the partial derivatives of  $\omega$ , b,  $\xi_i$  and a, and set them equal to zero.

$$\omega = \sum_{i=1}^{l} a_i \varphi(x_i), \ \sum_{i=1}^{l} a_i = 0, \ a_i = C\xi_i$$
$$\omega^T \varphi(x_i) + b + \xi_i - y_i = 0$$
(4)

In the light of Formula (4), the optimisation problem is transformed into a set of linear equations:

$$\begin{bmatrix} b \\ a_1 \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1, x_1) + \frac{1}{C} & \cdots & K(x_1, x_l) \\ 1 & \vdots & \vdots & \vdots \\ 1 & K(x_1, x_l) & \cdots & K(x_l, x_l) + \frac{1}{C} \end{bmatrix} \times \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix}$$
(5)

Finally, the LSSVM model is obtained as follows:

$$y(x) = \sum_{i=1}^{l} a_i K(x, x_i) + b$$
(6)

Where  $K(x_i, x_j) = \varphi(x_i)^T \cdot \varphi(x_j)$  is the symmetric function that satisfies the Mercer condition, commonly referred to as the kernel function. This work used the radial basis function (RBF) as the kernel function, i.e.

$$K(x,x_i) = e^{-\frac{(x-x_i)}{2\sigma^2}}$$
(7)

Where  $\sigma^2$  is defined as the kernel width parameter.

For the RBF kernel function of LSSVM, the parameters include regularisation and kernel width. The regularisation parameter is a compromise between structural risk and sample error, whose value is related to tolerable error. For example, the larger the value, the smaller the error, and *vice versa*. The kernel width parameter is related to the input space and the width range of the learning sample. For example, the larger the spatial extent of the input sample, the larger the value, and *vice versa*. Grid search was applied in this work to optimise these two parameters [8].

## Grid Search Optimisation

## Cross Validation (CV)

Cross Validation is a statistical method used to verify the performance of a classification. The basic idea is to divide the original data into a training set and a testing set. First, the training set is used to train the classifier. Then, the testing set is used to test the trained model, which evaluates the performance of the classifier. In the general K-fold CV, the original data are divided into K groups (usually equal). Each group, in turn, is treated as the testing set and the K-1 remaining groups as the training set. This, therefore, yields K models. The average classification accuracy of these K models is used as the performance of the K-CV classifier. The K is generally greater than two and the actual operation generally involves at least three models. Only when the original data set is small, will K be chosen as two. The K-CV can avoid over-learning and produces a persuasive final result [9][10].

#### Grid Search (GS)

The basic principle of the GS method is to select parameters needed to optimise a grid divided over a range and to consider all the values in the range. For the obtained parameters, the K-CV method is used to compute the classification accuracy of the testing set and, hence, obtain the best set of parameters to achieve the highest classification accuracy.

Model for Teaching Quality Evaluation of University Teachers

#### Sample Set Data

Assume that the teaching quality indicators' values and the teaching quality values for *n* teachers are known. This determines the sample set  $(x_i, y_i)$ ,  $i = 1, 2, \dots, n$ . The model for the teaching quality evaluation of university teachers is based on GS-LSSVM.

The independent variables and dependent variables of the sample set are normalised according to the following formula:

$$x_{il} = \frac{x_{il} - \min_{i=1,2,\cdots,n} x_{il}}{\max_{i=1,2,\cdots,n} x_{il} - \min_{i=1,2,\cdots,n} x_{il}}, \ i = 1, 2, \cdots, n, \ l = 1, 2, \cdots, 6$$
(8)

$$y_{i} = \frac{y_{i} - \min_{i=1,2,\cdots,n} y_{i}}{\max_{i=1,2,\cdots,n} y_{i} - \min_{i=1,2,\cdots,n} y_{i}}, \ i = 1,2,\cdots,n$$
(9)

So, all the data are in the range [0, 1].

## The LSSVM Model

Select *m* samples as the training sample and the remaining *n* - *m* samples as the testing sample. For the training sample, select RBF as the kernel function and build the LSSVM model according to Formula (7). The regularisation parameter *C* and kernel width parameter  $\sigma$  of LSSVM are obtained using GS and CV. Split the range value of  $\log_2 C$  and  $\log_2 \sigma$  into several grids, and split all samples into K groups, and use K-fold CV.

For the parameters set (C,  $\sigma$ ) on the grid, take the k - 1 samples, in turn, as the training sample. Hence, train the model and obtain the optimisation and regression function. Then, put the rest of the sample into the regression function, output the fitted values, and calculate the error from the actual values and the mean square error (MSE) of the K samples. The formula for the MSE is shown as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (R_i - P_i)^2$$
(10)

Where  $R_i$  represents the actual value;  $P_i$  represents the calculated value.

Search for the parameter set in the grid that has the minimum MSE, and regard it as the optimal parameter set ( $C^*$ ,  $\sigma^*$ ). Train the LSSVM model using the optimal parameter values  $C^*$  and  $\sigma^*$ .

This completes the development of the trained teaching quality evaluation model.

#### Determining the Independent Variables

The normalised independent variables  $x_i$  of the testing sample can be determined according to Formula (8). These yield the output result  $y_i^0$ , when put into the trained teaching quality evaluation model. Unnormalisation gives:

$$\hat{y}_{i} = y_{i}^{0} \cdot \left( \max_{i=1,2,\cdots,n} y_{i} - \min_{i=1,2,\cdots,n} y_{i} \right) + \min_{i=1,2,\cdots,n} y_{i}$$
(11)

Where  $\hat{y_i}$  is the evaluated value of teaching quality.

## CASE STUDY

#### Teaching Quality Data Collection

This study considered 30 teachers at a university in Hebei Province of China as the research objects. Experts were used to score the teaching quality of these teachers. The evaluation score interval was [0,10], with higher scores indicating better performance, i.e. teaching quality is higher.

The teaching quality score A is obtained by using the following formula:

$$A = \sum_{i}^{4} B_i \times w_{B_i} \tag{12}$$

Where  $B_i$  represents the *i*<sup>th</sup> first-level indicator calculated according to Formula (13);  $w_{B_i}$  represents the weight of the *i*<sup>th</sup> first-level indicator.

$$B_i = \sum_{j=m}^n C_j \times w_{C_j} \tag{13}$$

Where  $C_j$  is the *i*<sup>th</sup> second-level indicator scored by experts;  $w_{C_j}$  represents the weight of the *i*<sup>th</sup> second-level indicator; *m* and *n* represent the starting number and the ending number respectively for second-level indicators belonging to a first-level indicator.

The teaching quality values for the 30 teachers are shown in Table 3.

No.	Value	No.	Value	No.	Value
1	8.14	11	8.37	21	8.14
2	8.43	12	8.08	22	7.72
3	7.99	13	8.42	23	8.39
4	8.21	14	8.65	24	8.63
5	8.21	15	8.17	25	8.38
6	8.31	16	8.09	26	8.22
7	7.97	17	7.52	27	8.74
8	8.45	18	8.31	28	8.18
9	8.36	19	7.95	29	8.33
10	8.30	20	8.44	30	7.93

Table 3: The teaching quality value of the 30 teachers.

## Parameters Optimisation

Select all the second-level indicator values scored by the experts as input to the LSSVM model, and the teaching quality values as the output of the LSSVM model. Implement the normalised process for 30 samples. Select 22 samples as training samples and the remaining eight samples as testing samples. The range of parameters  $\log_2 C$  and  $\log_2 \sigma$  are both set as [-10,10]. The grid width is set as 0.4. Implement 5-fold CV for the training samples. The contour map of the GS process is shown in Figure 1.



Figure 1: The contour map for the GS process.

As can be seen from Figure 1, the optimisation values for C and  $\sigma$  are, respectively, 64 and 0.39, and the MSE of the CV is 0.0040171.

## Training and Testing

Set the parameters for LSSVM as C = 64 and  $\sigma = 0.39$ . Use 22 groups as training samples to train the LSSVM model. Then, take the remaining eight groups as testing samples to test the trained LSSVM model. The testing results are shown in Table 4.

Sample No.	Actual value	GS-LSSVM testing value	Relative error %
23	8.39	8.3211	-0.82
24	8.63	8.5995	-0.35
25	8.38	8.3478	-0.38
26	8.22	8.2741	0.66
27	8.74	8.6993	-0.47
28	8.18	8.1615	-0.23
29	8.33	8.3013	-0.34
30	7.93	7.9511	0.27
Mean absolute percentage error (MAPE) %		0.44	

## Table 4: Testing results.

## **Results Analysis**

As can be seen from Table 4, the minimum relative error of the testing samples was 0.23%, and the difference between the testing value and the actual value was only 0.0185. The maximum relative error of the testing samples was 0.82%, and the difference between the testing value and the actual value was just 0.0689. The MAPE of testing samples is only 0.44%, which indicates that the accuracy of the teaching quality evaluation model based on GS-LSSVM is satisfactory. These results can provide guidance and a reference for teaching quality research in the future.

## CONCLUSIONS

To address the teaching quality evaluation problem, a comprehensive and systematic teaching quality evaluation system was established through this research. This included four first-level and 15 second-level indicators. Current, widely used artificial intelligence algorithms were introduced. A model for teaching quality evaluation based on GS-LSSVM was built. The case study indicated that the proposed model is effective, and can provide guidance and a reference for teaching quality research in the future.

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