SVM-Based evaluation model for college laboratory learning

Xiaoling Tan[1]*, Zefu Tan[1], Juan Qu[2], Guangwen Xi[3]

[1]*School of Electronic and Information Engineering, Chongqing Three Gorges University, Chongqing 404100, China*

[2]*School of Mathematics and Statistics, Chongqing Three Gorges University, Chongqing 404100, China*

[3]*Network Centre, Chongqing Three Gorges University, Chongqing 404100, China*

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Abstract

Evaluation for laboratory learning is based on different factors, while each factor is varied by individuals. Hence it is difficult to express the quantitative nonlinear functional relationship among the evaluation indexes. With limited sample, Support Vector Machine (SVM) could be generalized by compromising between model's complexity and learning ability. That is its advantage on the evaluation of small sample, nonlinear and multi-indexes. It is a good try to apply Support Vector Machine (SVM) to laboratory learning evaluation. With Support Vector Machine (SVM), the relationship between the learning quality and evaluation indexes could be revealed. Experiments show that Support Vector Machine (SVM) model is with high prediction accuracy, faster speed and simple algorithm. It is suitable and more reasonable for laboratory learning evaluation.

Keywords: Support Vector Machine (SVM), evaluation model, laboratory learning quality

1 Introduction

Being different from that of classroom teaching, the valuation of laboratory teaching consists of various factors. An objective, comprehensive, impartial and accurate evaluation is significant to the improving of teaching quality, motivating of learning, and even the optimizing of discipline construction. Evaluation on college laboratory learning combines theory with practice. It works under evaluation index system, while the system is guided by educational theories. Educational theories are the summary of educational practice, which reveal the law of education [1]. On the other side, laboratory learning evaluation is based on different factors, while each factor is varied by individuals. Students have to abide the rules and regulations at the laboratory as well as to be innovative and motivate to experiments. It is also a basic quality for the students to keep the laboratory tidy and safe when they are learning. That shows the laboratory learning is interacted with multi-factors, which should be taken into account at the evaluation [2, 3].

Being lack of approximation capability to nonlinear relationship, the use of multiple linear regression and partial least square method is restricted. As a new technology with the features of nonlinear mapping, learning classifying and real-time optimizing, artificial neural nets (ANN) opened a new way on pattern recognition, nonlinear classification and artificial intelligence. It also has been applied a certain into educational evaluation. However, the features of large calculation, continually local extremum, and low generalization impact the application of ANN [4]. SVM is a new machine learning method based on statistical learning theory. Its topological structure depends on support vector. Differs from that of ANN depended on designer's experience, it solve Ann's problem of high dimension, local minimum and small sample. It covers the advantages of neural network and gray-scale model. After revealing the relationship between the laboratory learning quality and influence factors by learning the existed sample, an accurate and objective evaluation on a specific laboratory learning could be realized by SVM.

Laboratory learning evaluation is essentially a classification by some decision-making mechanism and parameters. To the limited sample, SVM could be generalized by compromising between model's complexity and learning ability. That is its advantage on classification. SVM also overcomes the shortcomings of multi-layer feedforward neural network. It specially aims at the limited samples, not only for an optimal solution of infinite samples, but for the one of the current existed samples. It becomes a quadric form algorithm of optimization finally, which theoretically could achieve a global optimal solution. By the nonlinear transformation, SVM transfers the issue to a high dimensional feature space, and realizes the original nonlinear classification by constructing a linear classification function in the space. That ensures the category is with the ability of generalization, solves the curse of dimensionality and reduces the impact to the speed. To the classification, multi-layer feedforward neural network could realize the nonlinear classification, but the classifier would not be the best. SVM based on statistical theory ensures the optimality of classification theoretically, while the generalization ability of algorithm is further ensured [5]. On the other side, the laboratory learning evaluation is a typical multi-class problem. It is feasible to apply SVM to construct a multi-class model for the evaluation.

*** *Corresponding author*** e-mail: xltan023@hotmail.com

2 SVM

SVM (Support Vector Machine) is a pattern recognition proposed by Vapnik et al in 1995. It is good at solving the problem of small sample, nonlinear and high dimensional machine learning. Its basic idea is: to form an optimal hyper-plane at sample space or feature space to get a max distance between the hyper-plane and the sample sets, so that to gain the maximum generalization ability [6].

2.1 FUNDAMENTAL THEORY OF SVM

SVM is the youngest and most important part of statistical learning theory. It becomes a conventional tool on machine learning as it matures theoretically and practically. So far, it is on the highest performance on application to the text and image classifications of pattern recognition [7].

SVM realizes the following thought: it maps the input vector X to a high dimensional feature space by a nonlinear mapping selected in advance. An optimal classification hyper-plane is formed in the feature space. In order to get an optimal classification hyper-plane in the feature space Z, the display format of Z is not taken into consider, only the calculation of inner product of vectors of SVM and the feature space is needed.

According to functional theories, when kernel function $K(x_i,x_j)$ satisfies Mercer condition, an inner product in a transformation space is corresponded. The basic thought of nonlinear SV is mapping the input vector x_i to a high dimensional Hilbert space (feature space) by a nonlinear mapping selected in advance. An optimal classification hyper-plane is formed in the feature space. The inner product between any two points in the space could be reflected by the kernel function, which is corresponded to the input vectors in the original space.

Different inner product kernel functions of SVM form different classifiers. Here are the major 3 kernel functions.

Firstly, polynomial kernel function. See Equation (1).

$$K(x,x_i)=[(x,x_i)+1]^p . \quad (1)$$

Secondly, radial basis function (RBF), namely Gaussian kernel function. See Equation (2).

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\delta^2}\right). \quad (2)$$

The significant distinction between RBF classifier and traditional classifier is: the centre of each primary function corresponds to an SV, and its output weight is automatically determined by algorithm. RBF is the most effective kernel function so far.

Thirdly, sigmoid function. See Equation (3).

$$K(x,x_i)=\tanh\left[k(x\bullet x_i)-\delta\right]^q . \quad (3)$$

In this case, SVM acts as a multilayer perception with an implicit strata. The hidden node is automatically determined by algorithm. Moreover, in the algorithm, there is no local minimum, which perplexes neural network [8].

2.2 SVM SORTING ALGORITHM

At present, 3 methods have been proposed to solve SVM multiclass classification problem. They are: One-Against-Others, One-Against-One and Decision Directed Acyclic Graph (DDAG) [9].

2.2.1 One-Against-Others

It was proposed by Vapnik in 1998. The basic thought is: to construct several two-class classifiers and combined them together to accomplish the multi-class classification. Each classifier separates one class from the others, and infers the affiliation of an input *x*. It constructs k SVM two-class sub-classifiers for class k. The i^{th} SVM adopts training samples in the i^{th} class as the positive training samples, while adopting the others as negative ones. The unclassified samples are classified to the class with maximum classification function. Disadvantages: Firstly, every SVM classifier takes all the samples as training samples. When the quantity is large, the training time is long. Secondly, the two-class problems are asymmetric, which means the number of two-class samples are imbalanced.

2.2.2 One-Against-One

It was proposed by Knerr. It constructs all the possible k(k-l)/2 two-class classifiers in the training samples of class k. Each two-class classifier separates class *i* and class j by a simple classification rule. There is many two-class problems in it, so more classifiers are needed than that of One-Against-Others. However, the scale of each problem is much less than that of One-Against-Others. So the training speed is faster. But if k is too large, sub-classifiers will be more and the training speed would slow down.

2.2.3 Decision Directed Acyclic Graph

It was proposed by Platt etc. It is the same with One-Against-One at the training phase. But at the decision phase, DAG started from root node is used. Every internal node is a two-class classifier, and the leaf node is the final class. DDAG is faster at decision than that of One-Against-Others and One-Against-One. However, the result of classification is uncertain. Different classifier as the root node may lead to different classification result.

3 Laboratory learning evaluation model based on SVM

The evaluation includes the aspects of knowledge application, thinking innovation, experiment operation and safety, and experimental attitude. Knowledge application means students' ability of learning, principle theory grasping and practical application. Thinking innovation means innovation consciousness, independently thinking, cooperation, and exploring to solve problems. Experiment operation and safety means safety awareness, and sanity habit. Experimental attitude means initiative, responsibility, being truthful and practical, and spirit of teamwork [10].

3.1 EVALUATION INDEX SYSTEM OF LABORATORY LEARNING

The students in the laboratory class of Basis of Database at Chongqing Three Gorges University were taken as the sample. Each sample has 7 indexes. Evaluation on knowledge application is based on the experiments and lab reports of database *x1*, form *x2* and programming *x3*. *x4*, the evaluation on thinking innovation is based on comprehensive assessment on the experiment and lab report. *x5*, the one on experiment operation and safety is based on the average value of ordinary checks. *x6*, the one on experimental attitude is based on the comprehensive assessment to the experimental discussion and optional experiments. What's more, a network learning system has been founded to record students' network learning. The average value *x7* based on each online testing is taken as the other index.

According to the above index system, 100 samples in a grade were taken as the dataset of training and testing. The evaluation result was classified into 5 ranks: excellent (identified as 1), good (identified as 2), middle (identified as 3), pass (identified as 4) and failed (identified as 5). Each sample was composed by 7 inputs and 1 target output. To group the data into two, each group randomly consisted of data from all the 5 ranks. The first group with 60 samples was training dataset. The second one with 40 samples was testing dataset. The visualization figure of training data is showed as Figure 1. Its abscissa axis is student's number, the vertical axis is the classification result. Please see Figure 1.

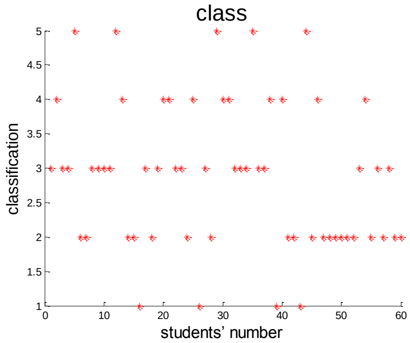

FIGURE 1 Classification of training samples

3.2 NORMALIZATION OF INPUT SAMPLES

It is important to normalize data before adopting SVM, which could eliminate the influence of dimension. Firstly, according to the features of the index data, the big index would weaken the influence of small index to the model if it is not normalized. Secondly, SVM needs to calculate inner product kernel function of sample point. Without normalization, the overlarge value will cause trouble on calculation. In order to reduce the complexity of calculation and shorten the time of training, every data was normalized to [0, 1].

There are many methods of normalization. The frequently-used are MinMax and Exponential Function. MinMax is a linear transformation, by which the original sense of the data could be preferably remained with fewer information loss after normalization. Hence MinMax was adopted to normalize the input samples to [0,1], which is showed as the following. See Equation (4).

$$x_i^{'} = \begin{cases} \dfrac{x_i - \min}{\max - \min}, & if \quad \min < x_i < \max \\ 0, & if \quad x_i < \min \\ 1, & if \quad x_i \geq \max \end{cases} . \tag{4}$$

The original data of evaluation on laboratory learning is showed as Table 1. Please see Table 1.

TABLE 1 Original data of evaluation on laboratory learning

No.	Database x1	Form x2	Programming x3	Thinking innovation x4	Laboratory specification x5	Experimental attitude x6	Network learning x7	classification
1	2	6	6	4	4	5	75	3
2	6	5	5	2	1	5	47	5
3	9	9	7	2	3	5	49	4
4	9	9	7	2	5	5	84	2
5	9	9	7	2	5	5	76	2
6	10	10	7	10	6	5	84	1
7	9	2	6	4	3	5	79	3
8	9	9	6	4	5	5	80	2
9	9	9	7	2	4	5	71	3
10	10	8	7	0	3	5	57	4

The normalized data is showed as Table 2. Please see Table 2.

TABLE 2 Normalized data

No.	Database x1	Form x2	Programming x3	Thinking innovation x4	Laboratory specification x5	Experimental attitude x6	Network learning x7	classification
1	0.6	0.5	0.375	0.2	0	1	0.274	3
2	0.9	0.9	0.625	0.2	0.4	1	0.306	5
3	0.9	0.9	0.625	0.2	0.8	1	0.871	4
4	0.9	0.9	0.625	0.2	0.8	1	0.742	2
5	1	1	0.625	1	1	1	0.871	2
6	0.9	0.2	0.5	0.4	0.4	1	0.790	1
7	0.9	0.9	0.5	0.4	0.8	1	0.806	3
8	0.9	0.9	0.625	0.2	0.6	1	0.661	2
9	1	0.8	0.625	0	0.4	1	0.435	3
10	0	0.8	0.625	0	0.4	0.5	0.661	4

3.3 DESIGN OF MULTI-CLASSIFIED SVM EVALUATION MODEL

The SVM-based laboratory learning evaluation is the classification of learning quality by the pattern classification of SVM.

The evaluation data is formed by the data of 5 ranks, so it is multi-classified. Because the classification patterns are not so many, so One-Against-One was selected. k(k-l)/2 SVM classifiers were constructed to the data of class K. Each classifier only classified two class. This model is simple and has well ability on classification. The well performed RBF kernal was adopted as SVM kernel function.

Two parameters have to be determined in SVM training process: penalty parameter C for mistaken classification, and RBF kernel control parameter. In order to reduce human influence, meanwhile the real-time requirement is not strict in the evaluation system, cross-validation was adopted to search for optimal parameter. It helped the system to be with some adaptivity. The working process of the system is showed on Figure 2. Please see Figure 2.

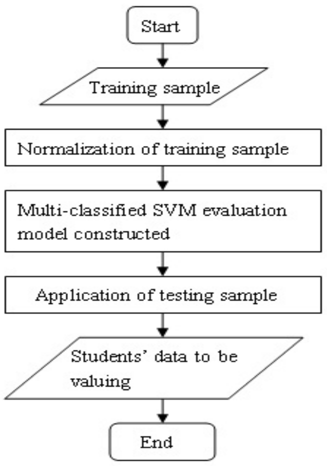

FIGURE 2 Process of evaluation system

4 Experimental result and analysis

The experimental result is showed on Figure 3. In the laboratory learning evaluation of the 40 students, only 6 are not fit the real one. The other 34 are in accordance to the reality. The accordance rate is 85%. It proves that the trained multi-classified SVM evaluation model could simulate teacher's evaluation thought. It could analysis the evaluation data rapidly and reduce the randomness of human evaluation from different teachers, which helps to rank the students more objectively and precisely. Please see Figure 3.

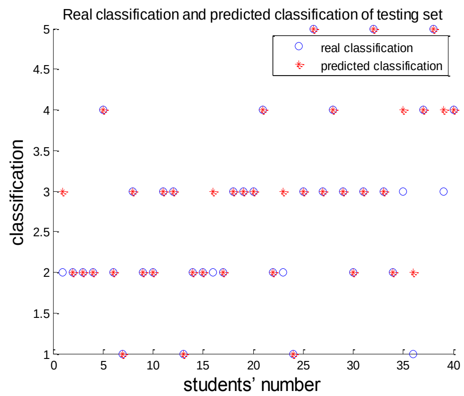

FIGURE 3 Real classification and predicted classification of testing set

5 Conclusions

Because it is difficult to show the quantitative nonlinear functional relationship among the evaluation indexes, the final evaluation rating is usually subjective and one-side. The founding of laboratory learning evaluation system makes the evaluation more logically and reasonably. SVM learning model, with the ability of approximating any nonlinear relationship between input and output, could seek out the relationship between learning quality and the evaluation indexes by learning the given sample. Experiment shows that SVM model is with high prediction accuracy, faster speed and simple algorithm. It is suitable to the laboratory learning evaluation. It is theoretically and practically significant to the development of laboratory teaching.

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Authors

Xiaoling Tan, born on April 22, 1969, China

Current position, grades: associate professor at Chongqing Three Gorges University, China.
University studies: majored in mathematical statistics at Nankai University, China in 1990. **Scientific interests:** data mining, intelligent computing and information security.
Publications: more than 20 research papers.

Zefu Tan, born on January 23, 1969, China

Current position, grades: professor at Chongqing Three Gorges University of China, and a master's supervisor of Chongqing University of Posts and Telecommunications of China.
University studies: Master degree in electromagnetic field and microwave technology from Beijing University of Posts and Telecommunications, China in 2002.
Scientific interests: mobile broadband communication techniques and electronic information technology.
Publications: more than 30 research papers.

Juan Qu, born on August 4, 1984, China

Current position, grades: lecturer at Chongqing Three Gorges University.
University studies: BS degree in 2006, and M.S. degree in Applied Mathematics from Shaanxi Normal University, China in 2009.
Scientific interests: Cryptography, information security, and authentication protocol.
Publications: more than 10 research papers.

Guangwen Xi, born on March 19, 1982, China

Current position, grades: lecturer at Chongqing Three Gorges University.
University studies: BS degree in 2005, and M.S. degree in computer science and technology from Chongqing University, China in 2011.
Scientific interests: computer network security and cloud computing.
Publications: more than 10 research papers.