AdaBoost-SVM Based Undergraduates Evaluations

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**Abstract.** The quality of undergraduates' training directly reflects the quality of university education. Therefore, the study on the evaluation of undergraduates' cultivation quality is of great significance to the improvement of college teaching and management. In this paper, the evaluation of undergraduates' cultivation quality was decomposed into three criteria (knowledge, quality and ability), 14 sub-criteria and 39 observation points. The calculation method of index weight was investigated, and the AdaBoost-SVM model was used to evaluate the cultivation quality and rank of college students. The experiments indicated that the method is reasonable and effective, and the evaluation results are consistent with the actual situation.

**Introduction**

At present, there are few studies on the quality evaluation of undergraduates' cultivation. Most of the research focus on the comprehensive quality evaluation of undergraduates while the indicator system of comprehensive quality assessment focuses on the quality of undergraduates, such as professional quality and ideological quality [1]. The quality of college students’ training is reflected not only by the quality but also by the evaluation of knowledge and ability. The application of Analytic Hierarchy Process (AHP) in comprehensive evaluation has been efficient [2,3]. The AHP constructs comparison matrix based on the decision maker’s pairwise comparisons of the criteria and the scale of relative importance. Then verify whether the comparison matrix is consistency adequate. However, the amount of calculation may be larger when too many criteria are introduced and the comparison matrix can not meet the standard. In addition, when there are a lot of students, the evaluation workload will be heavy. With its development, machine learning exhibits excellent performance in many fields. In comprehensive evaluations, neural network and Support Vector Machine have been exhibited excellent performance [4,5]. However, the neural network is highly demanded on the sample data, and the model training requires a large amount of data. In this paper we use SVM as the evaluation model, then utilize AdaBoost algorithm to embody the SVMs to improve the performance of the model.

Firstly, we use AHP to generate a weight for each evaluation criterion, and construct the training samples and test samples. Through the obtained samples, AdaBoost-SVM was trained to the model and to produce the evaluation results.

**Evaluation Indicators**

The cultivation quality evaluation of college students should be carried out in three aspects: quality, ability and knowledge. It consists of evaluation objective, 3 first-level indexes and 14 secondary indexes. The evaluation objective refers to the cultivation quality evaluation of college students (Q). The three first-level indicators are knowledge (B\(_1\)) ability (B\(_2\)) and quality (B\(_3\)). Secondary indexes are: knowledge of humanities and social science (C\(_11\)), knowledge of mathematics, physics and computer science (C\(_12\)), foreign language knowledge (C\(_13\)), professional knowledge (C\(_14\)),...
knowledge acquirement (C_{21}), application of knowledge (C_{22}), knowledge representation (C_{23}), communication (C_{24}), innovation (C_{25}), entrepreneurial capability (C_{26}), ideological quality (C_{31}), cultural quality (C_{32}), physical and psychological quality (C_{33}) and professional quality (C_{34}). They are quantified with 39 observation points. Listed as Table 1.

| evaluation objective                     | first-level indexes B | Secondary indexes C          |
|------------------------------------------|-----------------------|-----------------------------|
| Cultivate quality of college students Q  | knowledge B_1         | knowledge of humanities & social science C_{11} |
|                                          |                       | mathematics & physics & computer C_{12} |
|                                          |                       | foreign language C_{13}      |
|                                          |                       | professional knowledge C_{14}|
| ability B_2                              | knowledge acquirement C_{21} |
|                                          | application of knowledge C_{22} |
|                                          | knowledge representation C_{23} |
|                                          | communication C_{24}     |
|                                          | innovation C_{25}        |
|                                          | entrepreneurial capability C_{26} |
| quality B_3                              | ideological quality C_{31} |
|                                          | cultural quality C_{32}  |
|                                          | physical and psychological quality C_{33} |
|                                          | professional quality C_{34} |

**Indicator Quantification**

The value of the indicator C_{ij} is represented by S_{ij} where i\in\{1,2,3\}, j\in\{1,2,3,4,5,6\}. The observation points include course score, practice score and experiment score (G_1), awards score (G_2), papers score (G_3), reading book score (G_4), teacher-to-student appraisal and student mutual appraisal score (G_5). All items are graded by hundred-mark system.

- G_1 Obtained on the basis of students’ grades from the educational administration system.
- G_2 Obtained according to the level of awards. The awards include: national, provincial, municipal, and college levels. The scores are decreased according to the level of awards from high to low.
- G_3 Obtained according to the level of papers. The scores will be given according to the level of the papers, such as Science Citation Index, Engineering Index, Chinese core journals and so on. The higher the publication level of the paper, the higher the score.
- G_4=10\times n (n is the number of books, 0\leq G_4\leq 100)
- G_5 Obtained from teacher-to-student appraisal and student mutual appraisal and 0\leq G_5\leq 100.

\[ S_{ij}=\frac{\sum G_{ik}}{k}, (0\leq i\leq 5, l is an integer), \]  

where k is the number of items scored, students who do not get score at the corresponding observation point, no points will be added.

**Determination of Indicator Weight**

The weight reflects the importance of an indicator in the evaluation index system [6]. The higher the weight, the more important the corresponding criterion. Common weighting methods are Delphi method, entropy weight method and Analytic Hierarchy Process. This paper uses AHP to generate index weights, from the perspective of practical application.

The AHP generates a weight for each evaluation criterion [3]. Structure the decision model in a hierarchy first and then construct the comparison matrix according to several teachers and business managers’ pairwise comparisons of the options based on a fixed criterion. Finally, Calculate the weights and a consistency index. For detailed steps of the analytic hierarchy process can be referred to literature [2,3,6] and will not be described in this paper.

The weight of each second level criterion is w_{ij} where i\in\{1,2,3\}, j\in\{1,2,3,4,5,6\}. 

\[ w_{ij} \]
Evaluation Grade

It collects information about students' course score, practice score, awards and papers publication from the educational administration system, obtains the number of students reading books from the library management system, and gains the teacher-to –student appraisal and students mutual appraisal through questionnaires.

Calculate the student's final evaluation score \( S_Q \) by formula (2) and evaluation grade by formula (3) [7].

\[
S_Q = \sum S_{ij} w_{ij}. \quad (2)
\]

\[
\text{Evaluation Grade}= \begin{cases} 
A & 90 \leq S_Q \\
B & 80 \leq S_Q < 90 \\
C & 70 \leq S_Q < 80 \\
D & S_Q < 70 
\end{cases} \quad (3)
\]

Evaluation Algorithm Based on AdaBoost-SVM

From the perspective of machine learning, the evaluation of college students' training quality is a multi-classification problem. In this paper we use SVMs as the evaluation model, which are embodied by AdaBoost algorithm in order to improve the performance of the model.

Support Vector Machine

Support vector machines, and the different kinds of samples will be differentiated very well by finding a hyperplane in the sample space [8]. Support vectors are the data points that lie closest to the hyperplane. Sum of the distance from the hyperplane to the two closest data points from different classes is called "margin" (\( \gamma \)). The hyperplane equation is \( w^T x + b = 0 \) (w is a weight vector, b is bias, x is input vector) and \( \gamma = 2/\|w\| \).

The optimal values of w and b can be obtained by solving the following optimization problem:

\[
\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{n} \xi_i \quad \text{where } \xi_i \geq 0 \text{ is the } i\text{th slack variable and } C \text{ is the regularization parameter. According to the Wolfe dual form, the above minimization problem can be written as the next formula}
\]

\[
\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j, \quad (4)
\]

subject to: \( \sum_{i=1}^{n} \alpha_i y_i = 0, \ 0 \leq \alpha_i \leq C, \ (i=1,2,3\ldots,n) \).

Finally we can get the decision function of SVM show as Eq. 5.

\[
f(x) = \sum_{i=1}^{n} \alpha_i y_i k(x,x_i) + b, \quad (5)
\]

where \( k(x,x_i) \) is a kernel function. Input index data x and we can get the evaluation result. In this paper, we use “one-against-one” method [8] to solving support vector machines for multiclass classification.

AdaBoost-SVM

AdaBoost is adaptive in the sense that subsequent weak learners are adjusted in favor of those samples misclassified by previous classifiers. So that the performance of the model can be improved.

Construction of AdaBoost-SVM Evaluation Model [9].

1. Input: a set of training samples with labels \( D=\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\} \). ComponentLearn algorithm SVM, the number of cycles \( T \).
2. Initialize: the weights of training samples: \( D_1(x)=1/n \).
3. for t=1,2,\ldots,T do
4. Use the ComponentLearn algorithm to train a component classifier, $h_t$, on the weighted training samples.
5. Calculate the training error of $h_t: \epsilon_t = P_{x \sim D_t}(h_t(x) \neq f(x))$.
6. if $\epsilon_t > 0.5$ then break.
7. Set weight for the component classifier: $\alpha_t = \frac{1}{2} \ln \left( \frac{1-\epsilon_t}{\epsilon_t} \right)$.
8. Update the weights of training samples: $D_{t+1}(x) = \frac{D_t(x) e^{-\alpha_t f(x) h_t(x)}}{Z_t}$, where $Z_t$ is a normalization constant.
9. end for.
10. Output $H(x) = \text{sign} \left( \sum_{t=1}^{T} \alpha_t h_t(x) \right)$.

**Experiments**

The sample data will be constructed from marking students’ data according to the result of the equation (2). For SVM the kernel function is $k(x_i, x_j) = x_i^T x_j$ and $C=0.0032$ the accuracy of the model is 0.79. For AdaBoost-SVM the kernel function is $k(x_i, x_j) = \exp(- \frac{1}{2} \frac{||x_i - x_j||^2}{\sigma^2})$ $\sigma > 0$, $\sigma$ is the Gaussian width. $\sigma = 35$ and $C=1.4$, the number of component learner is 7, finally we can get the error rate is 0.09.

The AdaBoost-SVM evaluation model was tested with the data of students majoring in Agricultural Water Conservancy Engineering in a collage. We use four groups of data, and each group contains 25 samples. The results are shown in the contingency table, listed as Table 2.

| sample | sample size | evaluation result |
|--------|-------------|-------------------|
|        | A           | B     | C     | D     |
| A      | 25          | 21    | 2     | 2     | 0     |
| B      | 25          | 0     | 24    | 1     | 0     |
| C      | 25          | 0     | 1     | 23    | 1     |
| D      | 25          | 0     | 0     | 2     | 23    |

Accuracy on data set $T$, $\text{acc} = \frac{1}{|T|} \sum_{x \in T} I[\hat{c}(x) = c(x)]$ where $I[\cdot]$ is indicator function. The indicator function of an event is a random variable that takes value 1 when the event happens and value 0 when the event does not happen.

From the contingency table we can conclude the accuracy show as Eq. 6.

$$\text{acc} = \frac{1}{|T|} \sum_{x \in T} I[\hat{c}(x) = c(x)] = 0.91.$$  \hspace{1cm} (6)

It can be conclude that AdaBoost-SVM has a higher accuracy than SVM, and the accuracy is improved by 0.12. When the training is completed, the model can be easily used for college students’ cultivation quality evaluation.

**Conclusions**

AdaBoost-SVM creates model in “black box”, and gets the mapping relations between input data and evaluation of output by data training. It is simplified the evaluation process. Once the training of the model is completed, there is no need for further training and the model can be directly used for evaluation. When using the AdaBoost algorithm to integrate SVM, we should pay attention to the parameter settings. The parameters with good performance of SVM are not necessarily the optimal parameters with AdaBoost-SVM, so it is need to be adjusted to find the optimal parameters.
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