Based on Dynamic Weight Optimization and Machine Learning Study on the Value-added Evaluation of College Students' Comprehensive Quality

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Abstract: In order to further enhance the scientificity and adaptability of the value-added evaluation of college students' comprehensive quality, this study applies the machine learning algorithm model to realize the dynamic optimization of the weight on the basis of the initial weight determined by the analytic hierarchy process (AHP). By constructing a loss function with the goal of minimizing the value-added error of the comprehensive quality evaluation, the weight is used as a training parameter, and the gradient descent method is used to iteratively update the weight to realize the adaptive adjustment of the evaluation model. The dynamic weight optimization model can more accurately reflect the individual differences and group advantages of students' quality development, and can significantly improve the accuracy and feasibility of the value-added evaluation.
***Keywords*:** comprehensive quality of college students, value-added evaluation, dynamic weight optimization, gradient descent method

1. Introduction

The comprehensive quality evaluation of college students is an important part of the quality assurance system of higher education. The "Overall Plan for Deepening the Reform of Educational Evaluation in the New Era" issued by the Central Committee and the State Council in 2020 proposed "adhering to science and effectiveness, improving the evaluation of results, strengthening the process evaluation, exploring value-added evaluation, and improving the comprehensive evaluation"[1], emphasizing the "dynamic" and "adaptability" of the evaluation. Although the traditional value-added evaluation model quantifies the five-dimensional index weights of "moral, intellectual, aesthetic and labor" through the analytic hierarchy process (AHP) (30% moral education, 25% intellectual education, 15% physical education, 15% aesthetic education, and 15% labor education), this method has limitations: first, the weight is fixed and cannot respond to the dynamic changes of students' growth trajectory and multi-modal data; second, when the evaluation error is large, the static weight is difficult to adapt to the development differences of students in different majors and grades[2]. Therefore, based on the fusion model of AHP and machine learning, this study further proposes a dynamic weight optimization mechanism, which converts the weights into trainable parameters, and realizes the dynamic adjustment of the weights by constructing the optimization objective function, so as to realize a more personalized and time-sensitive comprehensive quality value-added evaluation[3].

2. Optimization of the value-added evaluation index system of college students' comprehensive quality

2.1 The composition of the indicator system

The comprehensive quality evaluation index system of college students is divided into 5 first-level indicators and 15 second-level indicators, as shown in Table 1.

Tabel 1. The comprehensive quality evaluation index system of college student

Tier 1 indicator (weight)	Tier 2 indicator (weight)
	Ideological and political literacy (12%)
moral education(30%)	Moral character (10%)
	Professional values (8%)
	Academic performance (8%)
Intellectual education(25%)	Practical ability (12%)
	Innovation ability (5%)

Tier 1 indicator (weight)	Tier 2 indicator (weight)
	Physical health (7%)
Physical education (15%)	Exercise habits (5%)
	Competitive spirit (3%)
	Artistic accomplishment (6%)
Aesthetic Education (15%)	Aesthetic ability (5%)
	Cultural heritage (4%)
	Labor practice (7%)
Labor Education (15%)	Volunteering (5%)
	Professional quality (3%)

2.2 Index system optimization principle

On the basis of the five-dimensional framework of morality, intelligence, physique, aesthetic and labor, the principle of "quantifiable, multi-modal and easy to collect" is followed to supplement the secondary indicators, solve the problem of single dimension of traditional model data, and provide rich training sample data for machine learning. The specific optimization ideas are as follows:

First, retain the core dimensions and maintain the five-dimensional first-level indicators of morality, intelligence, physique, aesthetic and labor to ensure consistency with the direction of education evaluation policies. Secondly, supplement the second-level indicators, add quantifiable second-level indicators under each first-level indicator to cover students' process performance and results; finally, expand the data sources and integrate multi-channel data such as the educational administration system, the student-worker system, and the training platform to form a multi-modal dataset.

2.3 Index data preprocessing

In order to eliminate the differences in the dimensions of different indicators, two-step preprocessing is carried out on the secondary index data:

Step 1: Data standardization, using Z-Score standardization to convert secondary indicators into standard values with a mean of 0 and a standard deviation of 1:

$$x_{ij}^{'} = (x_{ij} - \mu_j) / \sigma_j$$

The x_{ij} is the original value of the i-th student's j-th secondary index, the μ_j is the mean value of the index, and the σ_j is the standard deviation.

Step 2: The first-level index is synthesized, and the weighted average of the second-level indicators under each first-level index is taken to obtain the value-added of the five-dimensional first-level indicators for each student.

3. Value-added evaluation optimization model construction

3.1 Initial weight setting

Based on the five dimensions of "moral, intelligence, physical, aesthetic and labor", the initial weight vector is determined through the analytic hierarchy process. The steps are as follows:

Step 1: Construct a judgment matrix, and the education evaluation experts score the five-dimensional first-level indicators according to the "degree of importance" to form a judgment matrix;

Step 2: The consistency test, calculate the consistency index CI, look up the table to get the random consistency index RI, and then calculate the consistency ratio CR < 0.1 (CR is the ratio of CI to RI), then the judgment matrix passes the consistency test;

Step 3: The initial weight of the five-dimensional index is calculated by the eigenvalue method. The initial weight vector is [0.3, 0.25, 0.15, 0.15, 0.15], which is basically consistent with the weight of the traditional model and ensures the adaptability of the education evaluation policy.

3.2 Machine learning and dynamic weight optimization

The five-dimensional index weight is used as the model parameter, and the weight is dynamically updated by constructing the objective function and combining the gradient descent method.

3.2.1 Model assumptions and variable definitions

Input variables: The i-th student's five-dimensional normalized increment vector X_i .;

Model parameters: five-dimensional index dynamic weight vector recorded as $\omega = [\omega_1, \omega_2, \omega_3, \omega_4, \omega_5]$, subject to $\sum_{i=1}^{5} \omega_j = 1$ and $\omega_j \geq 0$;

Output variable: The predicted value of the i-th student is $y_i^{pred} = \sum_{i=1}^{5} \omega_j \cdot X_{ij}$;

True Label: The comprehensive value-added true value of the i-th student is y_i .

3.2.2 Construct the objective function

With the goal of "minimizing the mean error (MSE) between the predicted value and the true value", construct the objective function:

$$J(\omega) = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_i^{pred})^2 = \frac{1}{n} \sum_{i=1}^{n} (y_i - \sum_{i=1}^{5} \omega_j \cdot X_{ij})^2 ,$$

Where n is the number of samples.

3.2.3 Gradient descent method update weight

The weight ω is iteratively updated by the gradient descent method, the gradient of the objective function for each weight is calculated, and the parameters are adjusted in the negative direction. The specific steps are as follows:

Step 1: Initialization parameters. Set the initial weight ω_0, the learning rate λ is equal to 0.01, and the number of iterations uppercase T is equal to 1000;

Step 2: Calculate gradient. Object function $J(\omega)$ to find the partial derivative of ω_j (i.e. gradient), if gradient is positive, indicating that ω_j is too large and needs to be reduced, otherwise it needs to be increased;

Step 3: The weights are updated iteratively. Adjust the weights according to the gradient, and the formula is

$$\omega_j^{(t+1)} = \omega_j^{(t)} - \lambda \cdot \frac{\partial J(\omega)}{\partial \omega_j} ;$$

Step 4: Constraints are satisfied. After each iteration, the weights are normalized to ensure that the $\sum_{i=1}^{5} \omega_j^{(t+1)} = 1$, if a negative weight occurs, set it to 0 and then normalize;

Step 5: Terminate iteration. When the number of iterations reaches 1000, the iteration is stopped and the optimal dynamic weight is obtained.

3.3 Model validation and performance evaluation

In order to avoid model overfitting, the historical data is divided into training dataset and test set according to 4:1 for model training, and the optimal learning rate is selected by cross-validation, and then the performance of the model is evaluated.

4. Conclusion

Based on the integration of AHP and machine learning, this study further proposes a dynamic weight optimization model based on gradient descent, which realizes the individualization and automation of the value-added evaluation of college students' comprehensive quality. This method has strong practicability and promotion, and can provide scientific and technical support for personalized teaching and student development evaluation in colleges and universities.

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