Research on the Evaluation Model of the Effectiveness of Teaching Civics Based on AutoEncoder

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Abstract. The comprehensive evaluation of big data on teaching effectiveness of Civics courses in colleges and universities is a powerful manifestation of the networked, digital and interactive teaching of Civics courses. This paper uses expert analysis method to model and analyze 500 Civics courses in 60 universities. Through the encoding and decoding process of self-encoder, 42 indicators of 500 Civics courses are analyzed, and then input into a multi-layer perceptron model to fit and train different course grades to get the final model evaluation prediction. Finally, AE_MLP is compared with PCA_MLP, GLM and AHP algorithms to verify that the AE_MLP algorithm used in this paper has the minimum error effect. The current recognition error of the model is only 0.1457, which is 46.34% more accurate compared to the traditional GLM algorithm, and can to a certain extent assist ideological and political educators in making certain decisions on the effectiveness of teaching Civics classes.

Keywords: Civics · AE_MLP · GLM · Encoding · Decoding

1 Introduction

In November 2021, the Ministry of Education issued the "Construction Standards for Ideological and Political Theory Classes in Higher Education Institutions (2021 version)" [1], which states, "Reform the examination and evaluation methods, establish a sound scientific and comprehensive and accurate examination and assessment evaluation system, and focus on process assessment and teaching effect assessment." The evaluation of higher education Civics courses has developed from scratch with the progress of the times and society, and has undergone profound changes, from coarse to fine, from single and standardized to multi-dimensional and comprehensive. The evaluation content is comprehensive with realizing the transformation from a single evaluation content based on students' examination results to examining students' comprehensive literacy ability, teaching management, quality of teaching work and other aspects. The evaluation subjects are diversified with realizing the transformation from students as the main

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evaluation subject to the implementation of multi-subject evaluation of teachers, peers, supervisors and other teaching staff and administrative personnel; and the evaluation method is scientific, gradually realizing the unification of qualitative and quantitative evaluation, process evaluation and result evaluation [2].

Teaching of college Civics is a networked, digital and interactive data trajectory process, and the development of big data comprehensive evaluation of teaching effect of college Civics is precisely in line with the current trend of development of college Civics, which provides background support for the effective implementation of big data comprehensive evaluation.

2 Evaluation Index System

The big data comprehensive evaluation of the teaching effect of college Civics class is based on information data to build the evaluation index system, and in the whole process of evaluation, information technology is inseparable from the data collection, analysis and integration, while information technology and big data have the advantageous characteristics of whole process, whole time and space, comprehensiveness and precision, which can not only drive the education evaluation towards scientific, professional and precise, but also be used to collect the information The data can be interpreted, calculated, deduced and predicted to provide technical support for the smooth promotion of the comprehensive evaluation of big data on the teaching effectiveness of college Civics courses.

Under the guidance of the OBE education concept [3], the article adopts the CIPP education evaluation model to conduct research on the big data comprehensive evaluation of the teaching effectiveness of the university's Civics and Political Science class. It is an effective method to realize the unification of teachers' teaching and students' learning, combine process evaluation and outcome evaluation and strengthen students' subject status and learning outcomes. It uses continuous improvement as the basic principle throughout the evaluation process for providing decision support for those involved in the evaluation process.

OBE education concept can help continuously optimize the implementation plan and construct a comprehensive evaluation index system for the effectiveness of developmental classroom teaching. Four primary indicators, such as background evaluation, input evaluation, process evaluation and result rating. 15 secondary indicators such as teaching environment and 42 tertiary indicators will now be constructed, as shown in Table 1. Using expert analysis method, modeling analysis will be conducted for 500 Civics courses in 60 universities. This table has three levels with 4 tertiary indicators in Level 1 and 15 tertiary indicators in Level 2, and the 42 tertiary indicators in Level 3 almost covers all evaluation factors on ideological and political education.

3 Mathematical Model of Multi-layer Perceptron Based on Self-coding

This paper uses a self-coder to analyze 42 indicators for 500 Civics courses, and obtain new 7-dimensional reconstructed indicators through the coding and decoding process, and then input a multi-layer perceptual machine model to fit and train different course

Table 1. Three-tier evaluation system

Level 1	**Level 2**	**Level 3**
Background Evaluation	Educational Environment	Strength of campus publicity
		Evaluation Effectiveness
	Teaching objectives	Clear objectives
		Alignment with training objectives
	Teaching needs	Need to enhance competence
		Teachers' ability to upgrade
		Schools promote building
Enter rating	Faculty	Number of teachers
		Academic qualifications
		Teachers' titles
		Teachers' quality
	Funding	Dedicated funding
		Usage norms
	Infrastructure	Equipped with facilities
		Intelligent equipment
		Practice base
	System construction	Well-developed system
		Effective system
Process evaluation	Teaching methods	Combining theory and theory
		Individualized teaching
		Modern educational technology
	Content of courses	Integration and optimization
		Scientific standardization
		Integration of current affairs
	Teaching process	Respect for students
		Innovative formats
		Good atmosphere
	Learning process	Student Attitude
		Attendance on time
		Active discussion
		Attention to politics

(*continued*)

Table 1. (*continued*)

Level 1	Level 2	Level 3
	Practical teaching	Teacher practice
		Student participation
Assessment of results	Student Development	Knowledge acquisition
		Enhancement of literacy
		Competence enhancement
	Teacher development	Teaching Enhancement
		Scientific Research
		Quality Enhancement
	Social Impact	Demonstration and promotion
		Outreach activities

grades to obtain the final model assessment predictions, and verify the accuracy and validity of the algorithm by calculating the predictions on a test set with the actual expert scoring MSE. Comparing AE_MLP with PCA_MLP, GLM and AHP algorithms can demonstrate the higher accuracy of the AE_MLP algorithm in the prediction task.

3.1 AutoEncoder

AutoEncoder, is an unsupervised learning model [4]. The algorithm model contains two main parts: Encoder (encoder) and Decoder (decoder), as shown in Fig. 1.

The role of the encoder is to encode the high-dimensional input X into a low-dimensional hidden variable h, thus forcing the neural network to learn the most informative features. The role of the decoder is to reduce the hidden variable h in the hidden

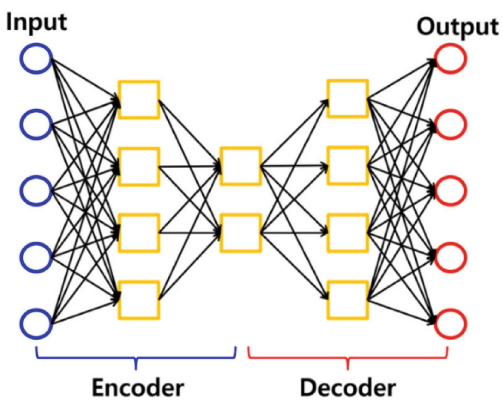

Fig. 1. Self-encoder structure

layer to its initial dimension. Ideally, the output of the decoder is a perfect or approximate recovery of the original input, i.e. $X^R \approx X \cdot X^R$ is a reconstructed output.

The process of encoding the original data x from the input layer to the hidden layer:

$$h = g\theta_1(x) = \sigma(W_2 \cdot \sigma(W_1 x + b_1) + b_2) \tag{1}$$

Decoding process from hidden layer to output layer:

$$\bar{x} = g\theta_2(x) = \sigma(W_3 \cdot \sigma(W_4 x + b_4) + b_3) \tag{2}$$

Then the optimization objective function of the algorithm is written as:

$$Min\_Loss = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left(x_i - x_i^R\right)^2 \tag{3}$$

3.2 Multilayer Perceptron (MLP)

In this paper, the multilayer perceptron hidden layers are set to 2 and the output layer dimension is 1.

For each hidden layer [5], the mathematical representation of the hidden layers is:

$$\mathrm{h} = \mathrm{f}\left(\mathrm{W_h h_{prev}} + \mathrm{b_h}\right) \tag{4}$$

where h is the output of the hidden layer, $\mathrm{h_{prev}}$ is the output of the previous layer (the input layer), $\mathrm{W_h}$ is the weight matrix of the hidden layer, $\mathrm{b_h}$ is the bias vector of the hidden layer and $\mathrm{f}(\cdot)$ is the activation function.

The activation function uses the ReLU function that,

$$f_{ReLU} = max(O, X) \tag{5}$$

The output layer is,

$$\mathrm{O} = \sigma(\mathrm{W_o h} + \mathrm{b_o}),\ \sigma(\mathrm{x}) = \frac{1}{1 - \mathrm{e}^{-\mathrm{x}}} \tag{6}$$

Using the mean error loss, the loss function is,

$$\mathrm{Loss} = \frac{1}{2}\|\mathrm{y} - \dot{\mathrm{y}}\|_2^2 \tag{7}$$

3.3 Principal Component Analysis Algorithm (PCA)

Principal component analysis is a common multivariate statistical analysis method which is used for dimensionality reduction, data compression, data visualisation and noise removal from data [6]. PCA allows the projection of high-dimensional datasets into a new space of lower dimensions, retaining the most important features in the data and describing the overall structure of the dataset by means of a linear combination. The following is the theoretical formulation of PCA:

It raises the assume that there are m sample points, each with n features, and form them into an m x n matrix x, where the i-th row represents the i-th sample point. In this paper m = 500 and n = 42. First we need to centralise each feature, i.e. the mean of each feature becomes 0, which can be expressed as,

$$\overline{x}_j = \frac{1}{m}\sum\nolimits_{i=1}^{m} x_{ij} \tag{8}$$

where $\overline{x}_j$ denotes the mean of the jth feature and x_{ij} denotes the jth feature at the i-th sample point.

We then need to calculate the covariance matrix S for the sample points, which can be expressed as,

$$\mathrm{S} = \frac{1}{\mathrm{m}-1}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{m}} (\mathrm{x_i} - \overline{\mathrm{x}})(\mathrm{x_i} - \overline{\mathrm{x}})^{\mathrm{T}} \tag{9}$$

where $\mathrm{x_i}$ denotes the i-th sample point and $\overline{\mathrm{x}}$ denotes the mean of all sample points.

The eigenvalue decomposition of the covariance matrix S is next required to obtain the eigenvalues and the corresponding eigenvectors, which can be expressed as,

$$\mathrm{Sv} = \lambda v \tag{10}$$

where v is an eigenvector and λ is the corresponding eigenvalue.

This paper sorts the eigenvectors by the corresponding eigenvalue magnitudes and then take the top k eigenvectors and form them into an n × k matrix V. Finally, we multiply the original data set X with the eigenvector matrix V to obtain a new m × k matrix Y, which can be expressed as,

$$\mathrm{Y} = \mathrm{XV} \tag{11}$$

The matrix Y is the new dataset after dimensionality reduction, which projects the original dataset into the k-dimensional space.

3.4 Analysis of Results

The features of the five hundred Civics courses were taken as 80% as the training set and 20% as the test set, and the training set was fed into the self-encoder for the encoding and decoding training process, using the mean square error (MSE) to represent the loss function of the self-encoder. After the training is completed the 42 evaluation indicators for various Civics courses can be encoded into 7 reconstructed indicators using the encoder. As shown in Fig. 2, the loss function stabilised at a smaller value after 40 rounds as training progressed, indicating that the self-encoder had converged. The final comparison with the three algorithms, PCA_MLP, GLM and AHP can prove the higher accuracy of the self-encoder.

In the comparison of the PCA and AE algorithms, Fig. 3 shows the 3D data after reconstruction by dimensionality reduction. In the left panel of the PCA algorithm, it can be observed that the three metrics are mixed with each other and poorly differentiated. In contrast, in the right panel of the AE algorithm, the reconstructed 3D data shows a

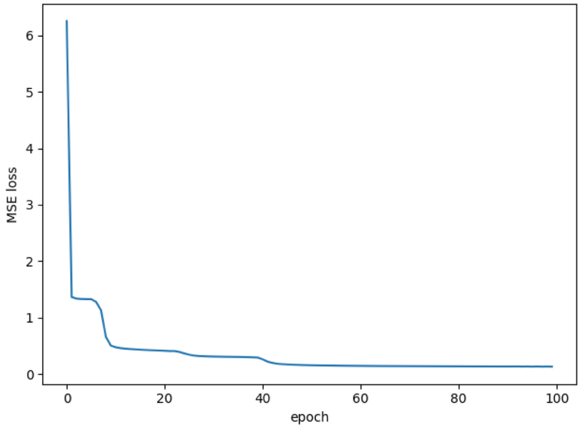

Fig. 2. Graph of the self-encoder iterative loss function

strong degree of differentiation and linearity. This suggests that the AE algorithm can achieve better performance when dealing with 42 evaluation metrics, while the PCA algorithm may suffer from poor performance due to the confounding of the metrics.

The Fig. 4 shows the prediction accuracy of the assessment results on the test set using the AE_MLP model. The x-coordinate is the normalization of the actual expert assessment results, and the y-coordinate is the prediction result using the AE_MLP algorithm. It can be seen that the predicted data fit around a straight line at y = x which indicates that the prediction scoring task for different courses is better accomplished using this algorithm.

To analyze the accuracy of AE_MLP algorithm, this paper compares the AE_MLP algorithm with three algorithms, PCA_MLP, AHP and GLM by analyzing the MAE error of the four algorithms (as shown in Fig. 5), it can be seen that the AE_MLP algorithm has the minimum MAE error and the highest accuracy.

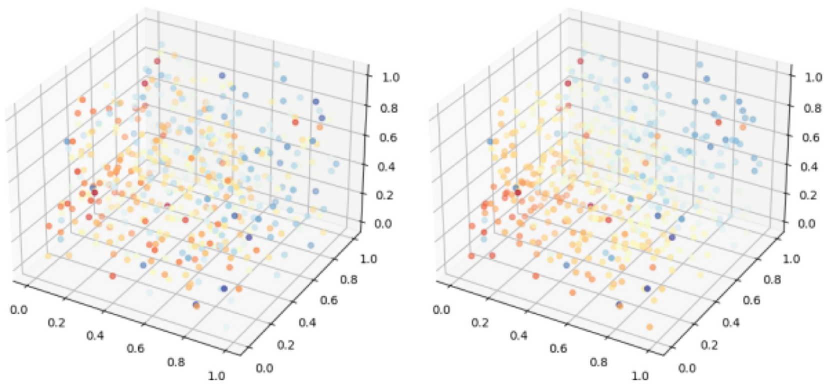

Fig. 3. (left) 3D data visualisation after PCA downscaling, (right) three-dimensional data visualisation after AE downscaling

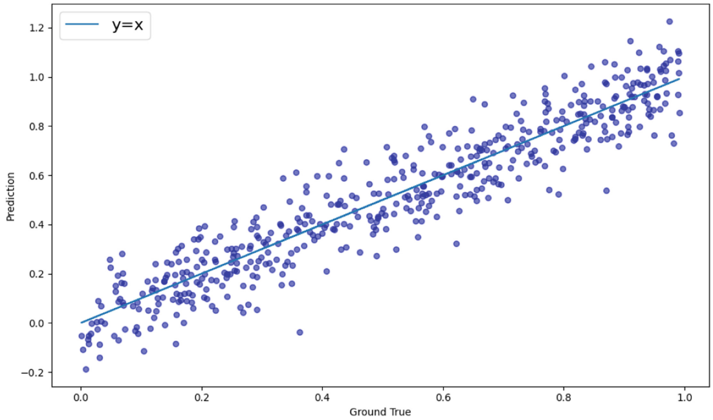

Fig. 4. Graph of predicted accuracy of assessment results for 500 courses

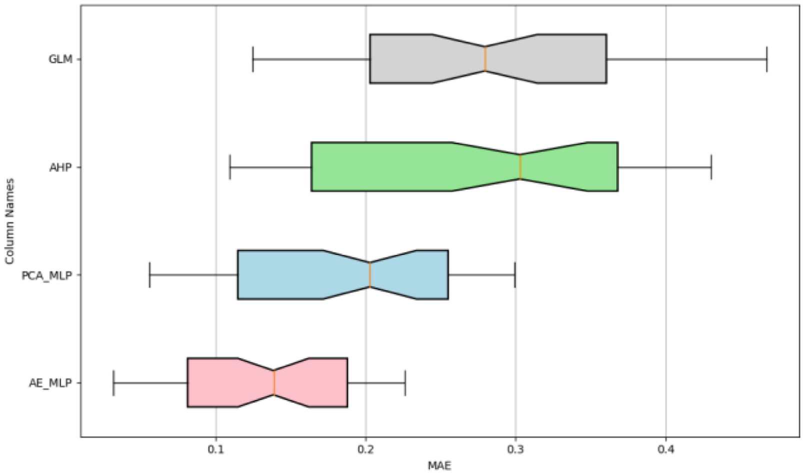

Fig. 5. MAE error box plot for the four algorithms

This paper calculates and compares the MAE, RMSE and MAPE of the four algorithms. The formulae for the three parameters are as follows, and the results are shown in Table 2. It can be seen that the error value of AE_MLP is minimum, verifying that the algorithm in this paper outperforms the other three algorithms.

Mean absolute error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum\nolimits_{i=1}^{n} \left|\overline{y}_i - y_i\right| \tag{12}$$

Root Mean Square Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} \left(\overline{y}_i - y_i\right)^2} \tag{13}$$

Table 2. Error analysis

	MAE	RMSE	MAPE
GLM	0.2715	0.3007	29.78%
AHP	0.3091	0.3201	32.16%
PCA_MLP	0.2132	0.2263	17.89%
AE_MLP	0.1457	0.1598	13.51%

Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left|\frac{\overline{y}_i - y_i}{y_i}\right| \times 100\% \tag{14}$$

where n is the total number of courses in the test set, i is the course index for the different courses, $\overline{y}_i$ is the predicted value of the score for course i, and y_i is the expert score for course i.

4 Summary

This research is based on this paper's comprehensive evaluation of big data based on the teaching effectiveness of college Civics courses, using a self-encoder to analyse 42 indicators of 500 Civics courses, and by recodeing the 42 indicators to obtain new 7 dimensional reconstructed indicators. The final model evaluation predictions were obtained by inputting into a multi-layer perceptron model, and the accuracy of the algorithms was verified by comparing the predicted values with the actual expert averages. Finally, the error analysis of the four algorithms are compared and the AE_MLP algorithm used in this paper was verified to have the least error effect. Based on the author's database, the current recognition error of the model is only 0.1457, which has 46.34% higher accuracy compared with the traditional GLM algorithm. To a certain extent, this model can help ideological and political educators make accurate judgments on teaching effectiveness of Civics courses.

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