Evaluation Method of Agricultural Talent Education and Training Effect Based on AHP-Entropy Weight Method

Qi Wang[1], Guanghai Li[2,*] and Yang Liu[1]
[1]*Shenyang Urban Construction College, School of Management, Shenyang, 110167, China*
[2]*Guangxi Normal University, School of Education, Guilin, 541004, China*

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Abstract: In recent years, agricultural higher education has mostly focused on the quality of education and the efficiency of resource allocation, often ignoring the systematic study of the development level of agricultural education, and lacking a comprehensive measurement of the effect of agricultural education on personnel training. This paper constructs the evaluation system of the talent education and training effect in agricultural colleges and universities. According to the construction of teaching and scientific research, it applies the analytic hierarchy process-entropy weight method to give weight to the index, which reduces the error caused by subjective factors. The method of entropy weight and data envelopment analysis is adopted to evaluate the training quality and efficiency in colleges and universities. It enriches the research on the evaluation of the final effect of education, makes up for the shortcomings of traditional methods, and makes the evaluation results more objective and reasonable. From a practical point of view, it can not only understand the actual situation of input and output of higher education, but also provide a reference for the allocation of talent training resources or the improvement of governance efficiency in Colleges and universities.

1 INTRODUCTION

With the increasingly prominent role of education informatization and the increasing investment of the state, the teaching environment of agricultural education has been greatly improved. The level of professional education has been effectively improved. However, in the process of talent education construction and application in the agricultural field, due to the mismatch between some factors such as personnel, technology and system and the current development, a large number of equipment, digital resources and funds have not been able to play their maximum role. There is a significant difference between the actual results of informatization and the expected goals (Kaur, 2018). Therefore, it is very necessary to analyze the existing informatization training effect of agricultural education and evaluate the informatization governance effectiveness of colleges and universities.

The effect of educational personnel training is a long-term accumulation process with multiple inputs and outputs, and the effective evaluation of its governance effectiveness is more conducive to the school to achieve good economic and social benefits. However, at present, there are few evaluations on the effectiveness of personnel training in China and abroad. Relevant studies have been conducted on the input-output of the effectiveness of personnel training from the perspective of performance (Schlichtkrull, 2018). DEA (Data Envelopment Analysis) method can effectively deal with the problem of performance evaluation of educational personnel training effect. Thus, according to different evaluation objects, the methods of different fields are introduced, and a series of educational personnel training effect performance evaluation models with strong operability based on DEA theory is constructed (Ali Derakhshan,2020).

The TOPSIS model mainly evaluates the development level of the sample unit according to the degree of proximity (distance) between the evaluation unit and the positive (negative) ideal

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solution (Aikens, 2020). The core of this decision is to calculate the closeness degree between each evaluation scheme and the ideal scheme, which is used to represent the development level of the evaluation object, and to reflect the development level of provincial higher education through the closeness degree of each evaluation object. When using the TOPSIS model, we should focus on the determination of the index weight. When objectively calculating the index weight, the following two methods are favored: one is the principal component analysis (PCA) method (Xu, 2020). The PCA method is to integrate a number of indicators through dimensionality reduction, and to retain the original information as much as possible. Its disadvantage is that PCA is aimed at cross-sectional data and can not compare the original indicators, which happens to be the main focus of this paper. The other is the entropy weight method, which is mainly based on the variability of indicators to determine the objective weight. This method not only eliminates human subjective factors, enhances the discrimination significance and difference of indicators, avoids the difficulty of analysis caused by the small difference of selected indicators, but also comprehensively reflects the information of research objects (Conijn, 2018).

In the multi-base model experiment, this paper establishes a multi-layer combination capacity prediction model, and compares the prediction results with other models in terms of indicators. The results indicate that the algorithm in this paper has a certain improvement in performance compared with other models in terms of different indicators. From MAE, MSE, the multi-level combination model of RMSE performs the best, which illustrates that the predicted value of the model is closer to the actual value, and its residual distribution is also the smallest, which proves that the research content of this paper is the optimal choice for the evaluation scheme. Besides, it also provides technical support for the quality evaluation of agricultural personnel training.

2 HIERARCHICAL INDEX OF AGRICULTURAL EDUCATION

The purpose of agricultural talent education and training effectiveness evaluation is not to get the evaluation results, but to help colleges and universities improve their governance effectiveness and bring convenient services to every teacher, student and staff. The formulation of the evaluation index of higher education training efficiency can evaluate the input-output results of higher education, so that colleges and universities can understand the current problems of low efficiency, and ultimately solve the problems and improve the quality of education (Wilson, 2021). The establishment of evaluation index of the higher education informatization can also provide evaluation data and information for researchers in the direction of education, and provide a reference for them to carry out relevant research.

The quality of education summarizes the relevant evaluation contents of educational effectiveness according to colleges and universities, as displayed in Table 1.

Table 1: Educational effect evaluation index.

Level 1 indicator	Level 2 indicator	Level 3 indicator
Input	Infrastructure	Number of network access points
		Total amount of management information system data
	Digital source	Input quantity of electronic journals
		Dissertation input quantity
	Teaching and research construction	Teaching and scientific research per student
		New teaching and scientific research
Output	Personnel training	Number of students
		Competition awards
	Teacher development	MOOC Courses
		Virtual simulation experiment teaching project
	Science research	patent
		Core thesis
		Subject
		Social Services
		Science and Technology Award

3 EDUCATIONAL QUALITY ASSESSMENT ALGORITHM

The influence of different dimensions is removed, so that the index value after treatment falls in the interval [0,1]. In addition, in the case that a few indicators are 0 after the indicators are processed. In order to make the subsequent calculation meaningful, it is necessary to translate the dimensionless data to the right with a minimum unit value of 0.0001 (Adejo, 2018).

The global spatial auto-correlation is generally measured by the Moran 'sI, and its calculation formula is:

$$\lambda = \frac{\sum_{i=1}^{n} \theta_{ij} \left(c_i - c'\right)}{\sum_{i=1,j=1}^{n} \theta_{ij}} \tag{1}$$

Where λ is the spatial weight matrix, θ_{ij} is the distance between region *i* and region *j*, and C_i is the deviation mean of region *i*.

If the comparison result between the development level of higher education in two adjacent provinces and the mean value is one big and one small, the product of deviation is negative, that is, when the province with high development level of higher education is interlaced with the province with low development level, the Moran 'sI is negative. When the development level of provincial higher education is randomly and uniformly distributed, the Moran'sI is equal to 0. In addition, the value of Moran'sI after variance normalization will fall on the interval [-1,1]. The more the higher education development level C_i and C_j of adjacent provinces deviate from the mean value C, the greater the value of Moran'sI (C. Kiu, 2018).

After the Moran 'sI has been calculated, a significance test is performed with the standardized normal statistic IZ, whose standardized form is:

$$\mu_{(i)} = \frac{\sum \phi_n(i)}{\sqrt{Var_n(i)}} \tag{2}$$

4 ANALYSIS OF EXPERIMENT

4.1 Experimental Scheme

The fusion method first trains the base model, then takes the output results of the base model as the features of the new data set. Then, it adopts linear model fitting to calculate the optimal weight coefficients of different features, and applies the weights to represent the relative importance of each base model. In this paper, random forest, XGBoost and AHP-entropy method are chosen as examples. The paper takes the output value y_1, y_2, y_3 of the three basic models as the new features of the input, and uses the linear model to fit, so as to obtain the weight coefficient $\lambda_1, \lambda_2, \lambda_3$ corresponding to the three new features. Then, it calculates the final result by the weighted fusion through Formula 3 (Riestra-Gonz, 2021).

$$Y = y_1\lambda_1 + y_2\lambda_2 + y_3\lambda_3 \tag{3}$$

4.2 Weight Determination

In the linear weighted fusion, it is a key step to obtain the weight coefficient. The main weighting methods adopted are subjective weighting methods, such as expert investigation method, AHP, etc., which are set subjectively according to the recognition degree of experts or relevant decision makers in some fields for different attributes. There are also objective weighting methods, such as principal component analysis, entropy weight method, etc. The weight of the attribute is given according to the difference degree of the face value under different attributes (Javier, 2021).

The AHP-entropy weight method is adopted in the experiment. This method can effectively compress the data dimension and reduce the complexity of the original data while minimizing the loss. After taking the optimal prediction results of the base model random forest, XGBoost and the algorithm in this paper as new features, three weights corresponding to the base model are obtained, which are arranged from high to low as displayed in Table 2.

Table 2: Weight of base model.

Model	Weight value
Random forest	0.328
XGBoost	0.268
AHP-entropy weight method	0.404

Linear weighting formula:

$$Y = 0.328y_1 + 0.268y_2 + 0.404y_3 \tag{4}$$

Where, y_1, y_2, y_3 represent the respective predicted values of the three models, respectively.

4.3 Analysis of Prediction Results

In this paper, the weights obtained by the principal component analysis method and the optimal results of the three base learners are linearly weighted and fused according to Formula 3. The prediction effect of the final test set is displayed in Figure 1.

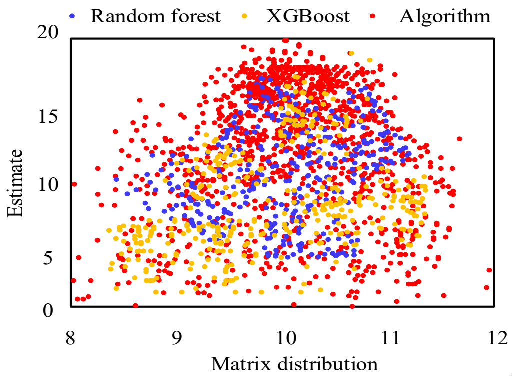

Figure 1: Model test set fitting.

By calculating the evaluation index of the model, the error results of the linear weighted fusion model are obtained as indicated in Table 3.

Table 3: Evaluation index of the linear weighted fusion model based on PCA.

Model	MSE	MAE	RASE	MAPE
Random forest	1.43	1.82	2.63	4.47
XGBoost	2.35	2.14	2.68	6.32
Algorithm	8.25	7.38	7.89	8.46

Compared with other models, the proposed algorithm performs best. The MSE (RMSE) of the linear weighted fusion model based on PCA decreases a little, but the MAPE (MAE) has a certain degree of improvement, which is the smallest linear weighted error after fusion. The predicted value is closer to the actual value in comparison.

5 CONCLUSION

In this paper, the collected education data are cleaned and integrated, and the key factors affecting the effect of agricultural talent education are explored by using the multi-layer linear model. The weighted model of entropy weight is applied to evaluate the development level of higher education. Through the experimental analysis, it is proved that the algorithm has the advantages of low data requirements and small amount of calculation, which is not only suitable for the comparison between horizontal multi-units, but also suitable for the vertical time series analysis, and further improves the stability of the spatio-temporal pattern.

In this paper, the dynamic efficiency analysis is carried out, and the effect evaluation of agricultural talent education informatization is studied. However, the output has a certain lag, and some colleges and universities may not see the results soon after investing in a lot of information resources. Thus, it is biased to judge the governance effectiveness of colleges and universities by the results of specific time nodes. In the follow-up study, we should collect the data over a longer period and establish the DEA-Malmquist index method to measure the dynamic efficiency of time series data.

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