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Capability Assessment of Cultivating Innovative Talents for Higher Schools Based on Machine Learning

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ABSTRACT

The innovation capability largely determines the initiative for future development of a region. Higher school is the main position for training innovative talents. Accurate and comprehensive assessment of innovation cultivation capability is an important basis of higher schools for continuous improvement. Thus, this paper focuses on assessing innovative talent cultivation capability. First, by CIPP model (Context, Input, Process and Product Evaluation), an assessment indicator system is built, consisting of 89 indicators in 21 categories. Then, based on indicator characteristics, this paper uses public data statistics, database retrieving, student survey, teacher survey, support personnel and expert investigation, to collect indicator values. After this, by a powerful machine learning algorithm, gradient Boosting regression tree, a capability assessment model is established. And based on collected data, established model is compared with several regression models in innovative talent cultivation capability assessing. Results confirm the performance superiority of our solution.

KEYWORDS

Assessment, Cultivation, Evaluation, Higher Education, Innovation Talent

Innovation determines competitiveness of a country or region in all walks of life. Innovative talents are resources that must be strived for, which largely determines the initiative for future development of a country or region. Colleges and universities are the battlefield for cultivating innovative talents, and their capabilities to cultivate innovative talents affect the influence and competitiveness of a region or country where they are located. They can deliver a large number of innovative talents to the region or country and help to attract high-tech talents from surrounding neighborhoods and even all over the world (Labrianidis et al., 2022). This can further improve the cultivation capabilities and

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influences of local colleges and universities and may lead to a "winner-takes-all" scenario, which exacerbates imbalances in the distribution of talents across regions. For example, *Times Higher Education* reports as many as 36 universities in the United States in their "2024 World University Rankings," which lists the world's top 100 higher education institutions, while its neighbor, Canada, has only four universities on that list (*Times Higher Education*, 2023).

In order to improve the innovative talent cultivation capability, the first task of a university is to accurately have a clear sense of self-orientation and identify key factors that can enhance its cultivation capability, so as to make targeted improvements (Bond et al., 2020). In this regard, this paper focuses on the assessment of Innovative Talent Cultivation Capabilities of Higher Educational institutes (ITCCHE), which is to analyze the factors of ITCCHE, and find the relationship between these factors and ITCCHE.

There are several studies concerning ITCCHE assessment. Some works focus on how to increase innovative talents by improving or reforming traditional education and argue that ITCCHE assessment is one of the most important assessments (Li et al. 2023; Chen, 2022; Lu & Mei, 2022). But these works don't provide any assessment solution. Some other works present several ITCCHE assessment methods according to survey data on students' innovative abilities (Yang & Zhou, 2018; Li et al., 2022; Wang et al., 2022) or teachers' teachings and innovative abilities (Ismayilova & Laksov, 2022; Abibo et al., 2022). These works only take into account more one-sided factors of ITCCHE, leading to limited accuracy of their assessment solutions. In contrast, some works combined ITCCHE related data of students, teachers and higher educational institute to provide comprehensive factors for accurate assessment (Hu et al., 2020; Cancino et al., 2020; Wang & Fu, 2023). But these works use only quality or quantity of publications or outstanding alumni to quantify ITCCHE.

Existing assessment solutions for ITCCHE involve one-sided information, and many of them only consider the current output achievements of higher education institutions, leading to inaccurate ITCCHE assessment or development trend predictions. In practice, influencing factors of ITCCHE are complicated, not only do they depend on objective outcomes, but they are also influenced by teachers, resources, and surrounding environments of universities (Chakraborty & Biswas, 2020; Abu Talib et al., 2021; Rapanta et al., 2021). In addition, few works exploit powerful machine learning (ML) to build ITCCHE assessment, even though ML has excellent performance in data analysis and decision-making and widely applies in various fields (e.g., the food industry) (Chakraborty et al., 2023) and consumer behavior analysis in some networking platforms (Chakraborty, 2023; Patre et al., 2023).

In order to accurately and comprehensively assess ITCCHE, this paper focuses on solving the following research questions:

(1) What factors influence or even decide ITCCHE?
(2) What are the association relationships between these influencing factors and ITCCHE?
(3) Can ML accurately find these relationships?

To achieve this goal, this paper firstly utilizes the Context, Input, Process, and Product (CIPP) model evaluations (Dizon, 2022) to determine the influencing factors (i.e., ITCCHE indicators), in four aspects, context, input, process, and product. Secondly, we collected numerical information of these ITCCHE indicators from 52 Chinese higher education schools at various levels and in different regions, by public data retrieving, academic research database retrieving, questionnaire survey, specialist consultation, and self-assessment. Then, a ITCCHE assessment model is established by ML to learn relationships between indicators and ITCCHE. The ITCCHE assessment model can be used for analyzing the effect degree of each indicator on ITCCHE for higher education schools. In the end, the ITCCHE assessment model is evaluated based on collected data, and its performance superiority is verified.

The contents of this paper are organized as follows: The following section, "Related Work," reviews recent research on assessing ITCCHE. The third section, "Assessment Indicator System," illustrates the influencing factors, (i.e., ITCCHE indicators) derived by CIPP. Next, "Numerical Information Collection" includes data collecting methods based on different characteristics of indicators are introduced. Then, the "Assessment" section details the ITCCHE assessment model built based on Gradient Boosting Regression Tree (GBRT), and in subsequent section, "Performance Evaluation," explains how the model is evaluated based on data collected from 52 Chinese Higher educational institutes. In the last section, "Conclusion," our work is concluded.

RELATED WORKS

Due to the importance of innovative talent cultivation, extensive research has been done on improving ITCCHE in various aspects. Dai et al. (2023) and Michel-Villarreal et al. (2023) focus on how to apply generative artificial intelligence (AI) tools effectively and efficiently, (e.g., ChatGPT) on student-driven innovation, to enhance students' ability as well as their educational experiences and resources. Børte et al. (2020) identify prerequisites of student active learning by reviewing related articles. Alt et al. (2023) studies the benefits of future problem-solving for students' creativity and innovation. These works ignore the ITCCHE assessment that is the cornerstone for their applications.

There are many works that focus on the ITCCHE assessment to provide reference and basis for continuous improvement. Li et al. (2023) presents a case study of innovation and entrepreneurship experiences by the ecosystem idea. They analyze the innovation and entrepreneurship ecosystem of a Chinese university in four aspects: organizational communities, population relations, environmental elements, and governance mechanisms. Chen (2022) analyzes how to use blended teaching methods to improve innovative talents. They emphasize clarifying the major objectives, focusing on comprehensive ability cultivation, improving the assessment system, and constructing assessment indicators for blended teaching, but this work does not present measures to implement their propositions. Similarly, Lu and Mei (2022) list several ways to improve traditional education for a better ITCCHE. These works only focus on how to design or implement the cultivation of innovative and entrepreneurial talents but do not study quantitative assessment of ITCCHE. By only these works, it is difficult for higher education schools to find causes of poor implementation of cultivation methods, leading to unsustainability of their methods.

Students are objects of innovative talent cultivation in higher education schools; therefore, some works study assessing innovative abilities of students. Yang and Zhou (2018) list several indicators that can be used to assess students' innovation and entrepreneurship abilities but do not give the assessing method. Li et al. (2022) surveyed 498 students by questionnaire and discuss factors influencing innovation abilities of undergraduate students majoring in economics. This work is based on students' subjective data entirely and only considers three basic skill indicators, four innovation consciousness indicators, and three innovation ability indicators, leading to limitations of its used scheme and obtained conclusions. In order to accurately evaluate students' innovation and entrepreneurship abilities, Wang et al. (2022) first built an indicator system for assessing innovation and entrepreneurship abilities of students by in-depth interview, which included 18 indicators in four aspects: student background, professional skill, practical ability, and expanding ability. Then, they collected valid information of 1773 students by questionnaire and established a nonlinear assessing model through a backpropagation neural network.

Teachers are the main implementers of talent cultivation, so their teaching abilities greatly affect the innovative abilities of the students they cultivate (Chakraborty & Biswas, 2020). Therefore, Ismayilova and Laksov (2022) focus on analyzing influencing factors on teachers' perception of creative teaching. Through researching 14 university teachers, the literature argues that influencing factors include both teachers' characteristics and the supportive environment provided by the faculty.

Some works have been done to analyze or assess the innovative capacity of higher education schools. Abibo et al. (2022) utilizes panel data analytical frames to analyze the main factors affecting innovation capacity. Their data is collected from 24 Ethiopian public universities, including 10 categories of outcomes, such as patent, publication, and research funding. Based on analyzed results, they recommend improving the innovation capacity and research outcomes of Ethiopian public universities by increasing research budgets, strengthening international cooperation, and expanding the enrollment of PhDs.

The above works focus on assessing the innovative ability or analyzing influencing factors in perspective of students, teachers, and universities. Although these works are related to ITCCHE, they are concerned about only part of the products for ITCCHE. In contrast, some other works, and our work, aim to establish an accurate and comprehensive assessment solution for ITCCHE. Hu et al. (2020) constructed an indicator system for ITCCHE, consisting of 27 indicators in four aspects that are context, teaching links, teachers, and students. Then, they established an assessment model by using fuzzy the comprehensive evaluation method and illustrated the implementation of their proposed approach with the case of their own university. Cancino et al. (2020) analyzes the development of entrepreneurship and innovation research in each region of Ibero-America according to publication only. Wang and Fu (2023) employ data envelopment analysis methodology to analysis the effect of resources that universities, students, the government, platforms, and intermediary systems have on ITCCHE. This work employs the quantity and quality of outstanding alumni for quantifying the ITCCHE.

All of the above works take a single school as a case to study ITCCHE assessment based on one-sided subjective data or statistical information. On the contrary, our work takes into account as comprehensive information about ITCCHE as possible by combining extensive subjective and objective data related to ITCCHE, aiming at providing a ITCCHE assessment model that can be applied for all higher education schools considering cultivating innovative talents.

ASSESSMENT INDICATOR SYSTEM

In order to assess ITCCHE in an all-around way, following principles of subjective and objective information combination comprehensiveness, as well as easy accessibility, this paper adopts the CIPP evaluation model to construct an indicator system for assessing ITCCHE. CIPP model is used for evaluating the decision-making based on four different aspects of information: context, input, process, and product. Because of its effectiveness, the CIPP model has been widely used to guide the evaluation of education, programs, projects, systems, and so on. CIPP is well suited for programs that require long-term sustainable improvements (Stufflebeam & Zhang, 2017). The following contents illustrate the assessment indicator system constructed based on CIPP for assessing ITCCHE in this paper.

Context

The contextual factors affecting ITCCHE are mainly the development status, the attention degree, and support conditions of the region for the innovation cultivation, as well as the recognition degree of innovative talent cultivation goals by stakeholders (including students, families, governments, enterprises, educational experts, industry experts, and the regional public). Usually, if surroundings have good development statuses, innovative talent cultivation has a strong attention as well as good support conditions, and stakeholders have high recognition degrees, then higher education schools can cultivate a large quantity of innovative talents with high qualities. Therefore, this paper sets four categories of indicators, regional development status, attention degree, supporting environment, and recognition of innovation, in the context assessment. The specific secondary indicators are shown in Table 1.

Input

For assessing ITCCHE, the input factors include various resources and support conditions provided by higher education schools, themselves, for cultivating innovative talents. Thus, the input factors mainly consist of the scientific research environment, teaching environment, financial support, teachers,

Table 1. Assessment Indicators in Context

Category	Secondary indicator	Data source
(1) regional development status	1) GDP Per Capita	Public data
(1)	2) proportion of highly skilled	
(1)	3) talent net immigration	
(1)	4) revenue of high-tech industries	
(1)	5) approved scientific project quantity	
(1)	6) highly cited paper quantity	Database retrieving
(1)	7) SCI indexed paper quantity	
(1)	8) scientific paper quantity	
(2) attention degree	9) proportion of government official document about innovation and high-tech	Public data
(1)	10) investment in high-tech industries	
(3) supporting environment	11) investment for Higher educational institutes	
(1)	12) investment for school-enterprise joint cultivation	
(4) recognition degree	13) on-campus students	Survey
(1)	14) alumni	
(1)	15) governments	
(1)	16) families	
(1)	17) employers and related enterprises	
(1)	18) educational expert	
(1)	19) industry experts	
(1)	20) the public	

curriculum structure settings, teaching methods, practice teaching settings, and practice resource conditions provided by higher education schools. Therefore, this paper sets the input evaluation indicators as shown in Table 2.

Process

The results of cultivating innovative talents in higher education are largely influenced by the implementation of the cultivation. The effect of cultivation implementation mainly depends on the participation of various teachers (especially teachers with strong innovative ability and rich teaching experience) in innovative cultivation, the degree of innovation in course structure and content setting, classroom teaching methods, and quality assurance of course implementation, as well as the support of logistic management personnel. For this reason, this paper sets the process assessment indicators as shown in Table 3.

Outcome

Students are the object of innovative talents cultivation. So, the cultivation outcome is the innovation achievements obtained by students, specifically including the participation of students in innovation activity, the employment of recent graduates, and the development of former graduates. Thus, this

Table 2. Assessment Indicators in Input

Category	Secondary indicator	Data source
(5) research environment	21) satisfaction of teachers in research environment	Survey
(1)	22) satisfaction of students in research environment	
(6) teaching environment	23) satisfaction of teachers in innovation teaching	
(1)	24) satisfaction of students in innovation learning	
(1)	25) satisfaction of support personnel in innovation managing	
(7) financial support	26) expenditure proportion in innovation cultivation links	Public data and support personnel survey
(1)	27) expenditure proportion in innovation activities	
(1)	28) expenditure proportion in teachers' innovation teaching ability train	
(1)	29) expenditure proportion in building or operating platforms for innovation cultivation activities	
(1)	30) expenditure proportion in building or operating practical bases	
(8) teacher	31) student teacher ratio	
(1)	32) diversity of teachers' education experiences	
(1)	33) quantity of national outstanding teachers	
(1)	34) quantity of regional outstanding teachers	
(1)	35) proportion of teachers with working experience in Hi-tech enterprises	
(9) curriculum structure	36) ratio of theoretical course and practical hours	Public data
(1)	37) proportion of innovation teaching hours	
(1)	38) proportion of practice course hours	
(1)	39) systematization of the course system	Teacher survey and expert investigation
(10) teaching method	40) pioneering degree of teaching principle	
(1)	41) activated degree of students' innovative consciousnesses and abilities	
(1)	42) personalization degree in cultivation	
(11) practice teaching	43) proportion of real practical topics derives from Hi-tech enterprises in practice teaching links	
(1)	44) proportion of real practical topics derives from scientific project in practice teaching links	
(1)	45) proportion of interdisciplinary practical topics in practice teaching links	
(1)	46) degree of tracking needs of emerging industries in practice teaching links	
(12) practice resource	47) utilization of practice equipment	
(1)	48) upgrade frequency of practice equipment	
(1)	49) open degree of laboratories	
(1)	50) quantity of employees that work in high-tech enterprises and participate in innovation cultivation	

Table 3. Assessment Indicators in Process

Category	Secondary indicator	Data source
(13) teacher	51) proportion of coaching students in innovation activity	Public data of Higher educational institutes and Support personnel survey
(1)	52) proportion of teachers undertaking research projects	
(1)	53) proportion of teachers undertaking enterprise projects	
(1)	54) proportion of professors	
(14) course structure	55) rationality of restructuring implementation plan	Teacher survey and expert investigation
(1)	56) frequency of restructuring implementation plan	
(15) course content	57) degree of teaching contents tracking needs of emerging industries	
(1)	58) proportion of teaching contents blending with scientific achievements	
(1)	59) degree of interdisciplinary integration	
(1)	60) proportion of research-oriented teaching contents	
(1)	61) degree of teaching cases tracking needs of emerging industries	
(16) teaching	62) application degree of modern teaching technologies	
(1)	63) participation of students in group discussions and class interactions	Teacher and student survey
(1)	64) diversity of used teaching methods	
(17) course evaluation	65) evaluated course achievements by teachers	Teacher survey
(1)	66) evaluated course achievements by students	
(1)	67) recognition of students in teaching method	Student survey
(1)	68) recognition of students in teaching resources	
(1)	69) recognition of students in teaching platform and tool	
(1)	70) recognition of students in constructing world views by teaching	
(1)	71) implementation degree of continuous improvement of teaching	Teacher survey and expert investigation
(18) support personnel	72) diversity of teachers' education experiences	Support personnel survey
(1)	73) satisfaction of teachers for support personnel	Teacher survey
(1)	74) satisfaction of students for support personnel	Student survey

Table 4. Assessment Indicators in Output

Category	Secondary indicator	Data source
(19) innovation activity	75) proportion of students participating in scientific research	Teacher and student surveys
(1)	76) proportion of students participating in innovation and entrepreneurship projects	
(1)	77) proportion of students participating in academic competitions	
(1)	78) proportion of students participating in enterprise projects	
(1)	79) proportion of students participating in social practices	
(1)	80) quantity of students' research publication	Database retrieving
(20) employment	81) employment rate of graduates	Public data of Higher educational institutes and Support personnel survey
(1)	82) employment rate of professional counterparts	
(1)	83) retention rate of graduates in their own fields	
(1)	84) employment rate of graduates working in well-known institutions	
(1)	85) satisfaction of graduates in work	
(21) development	86) qualification of graduates in their work	
	87) satisfaction of employees to their hired graduates	
	88) degree of graduates in achieving career advancement objectives	
	89) recognition degree of the public in graduates' work	

paper designs the outcome assessment indicators as in Table 4, which are used as the basis for assessing ITCCHE.

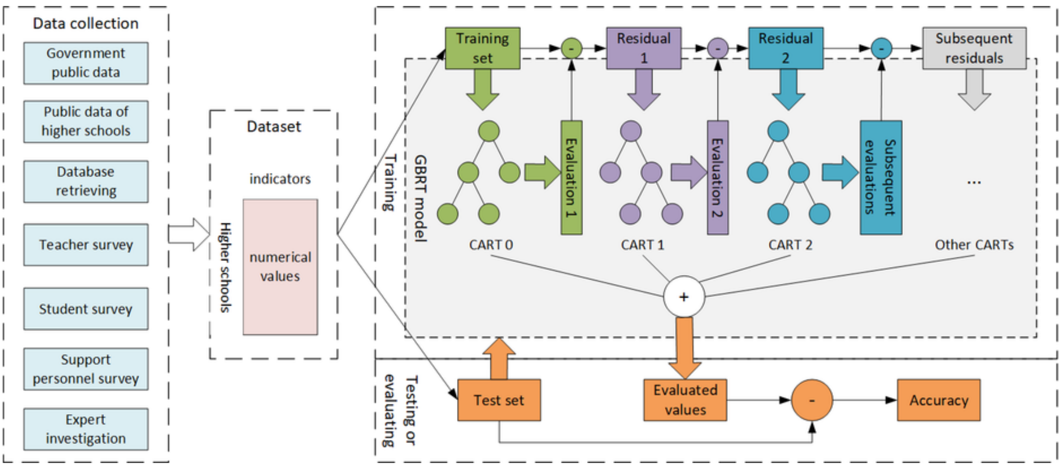
NUMERICAL INFORMATION COLLECTION

Given the comprehensive indicator system combining subjective and objective information obtained by the CIPP model, this section illustrates data acquisition technologies to collect numerical values according to different characteristics of various indicators. The data sources mainly include government public data, higher education schools' public data, and databases, as well as surveys or investigations of teachers, students, support personnel, and experts. The data acquisition methods for these data sources are as follows.

- **Government Public Data:** Every year, governments need to summarize and report their work to the public. The public data often include fiscal revenues and expenditures, including part of the context assessment indicators which are GDP (Gross Domestic Product) per capita, revenues from high-tech industries, capital investment in high-tech industries, and financial allocations to universities. At the same time, data on fiscal revenues and expenditures, as well as intellectual property rights in each region, are counted and publicized by the National Bureau of Statistics (NBS) and each local statistical office. The proportion of government official documents can be calculated by counting the number of web pages related to innovative talents on the official websites of the relevant governments (e.g., the Ministry of Education, the Ministry of Science and Technology, the State/Provincial Departments of Education, the State/Provincial Departments of Science and Technology, etc.) and calculating its ratio to the total number of web pages. Moreover, the honorary titles awarded by each agency are often publicized and published in the form of summarized news pages. In the case of regional governments, their higher-level achievements are often publicized on the respective government websites. Government-funded research platforms publish statistical information on the projects they fund, which can be used to count the number of research projects approved in each region.

- **Public Data of Higher Education Schools:** Each department of every higher education school conducts a year-end summary, which is publicized within its official website. These summaries include data on each item of financial income and expenditure, achievements, received honors, and so on. Also, for grants and honorary titles received (e.g., recipients of outstanding talent titles, graduation rates, high-quality graduation rates, etc.), higher education schools tend to publish news for publicity, as it helps to increase their influence and enroll high-quality students. For training programs and faculty information, higher education schools usually disclose these accomplishments on their official websites, so the values of some indicators, like faculty and course structure, can be obtained through the public data of higher education schools.
- **Database Retrieving:** Publication information of higher education schools can be retrieved by some databases (e.g., Web of Science and Engineering Village) and search engines (e.g., Google Scholar).
- **Survey of Teachers and Students:** The main subject and object of innovative talents cultivation in higher education schools are teachers and students. Therefore, teachers and students can directly experience the environment of cultivating innovative talents in higher education schools. For this reason, this paper uses questionnaires to obtain data on teaching and research, as well as learning environments, by teachers' and students' assessments in higher education schools. At the same time, students evaluate teachers' teaching quality based on their experiences. Teachers and students self-assess their own teaching skills and learning achievements, respectively. For each indicator surveyed by teachers/students or recent graduates/former graduates, this paper obtains the ratings of not less than 50/200/100 people and takes the average value as its value.
- **Survey of Support Personnel:** The efficient operation of all aspects of higher education schools cannot be separated from reasonable planning and management and affects the achievement of innovative talent cultivation in higher education schools. For evaluating the operation efficiency of higher education schools, teachers and students are surveyed, and the support personnel carries out a self-assessment, so as to obtain more comprehensive information. For every indicator of the operation efficiency, this paper surveys no less than 50 ratings and takes its average value as its value.
- **Expert Investigation:** The operational efficiency of cultivating innovative talents in higher education schools is often complex and has interrelated factors, and thus is difficult to quantify. Therefore, through questionnaires, interviews, visits, etc., we obtain the evaluation data from specialty-related and education-related experts on the efficiency and effectiveness of cultivation programs (curriculum structure, teaching methods and practical teaching, etc.). At the same time, through the expert survey, the overall evaluation of ITCCHE can be obtained and will be used for the following model establishment to learn the relationship between indicators and cultivation capacity. For each indicator rated by experts, this paper obtains the evaluation of no less than 20 experts and takes its average value as the value.

Figure 1. Framework of ITCCHE Model Establishment Based on GBRT



ASSESSMENT MODEL

After collecting the data related to ITCCHE by the data collection method explained in the previous section, we achieve numerical values of all indicators for several higher education schools that are all real numbers and can be organized into a table. In this table, each row is a higher education school, and each column is the value of an indicator for the higher education school. With this table, we intend to establish a regression model with indicators as independent variables and the cultivation capability as the dependent variable. However, there is not a simple linear relationship between indicators and the cultivation capability, and each indicator has a variety of value ranges. These lead to a poor effect of a single data analysis model, (i.e., linear regression). For this reason, this paper adopts the ensemble learning technology that provides an overall relationship model with good comprehensive effect by fusing multiple data analysis model (weak learner) with poor performance.

Specifically, GBRT is chosen in this paper. Its basic idea is to iteratively generate a Classification and Regression Tree (CART), fit the residuals, and train along the negative gradient direction of the loss function, as shown in Figure 1.

Ultimately, GBRT obtains a regression model that is a linear combination of multiple CARTs. The detailed steps of applying GBRT for training the assessment model of ITCCHE are described as follows.

Step 1: Collecting indicator values of n higher education schools, $\mathbf{X} = (X_1, X_2, \cdots, X_n)$, and their ITCCHE evaluated by experts, $Y = (y_1, y_2, \cdots, y_n)$, by the method presented in the previous two sections. Then the training set $T = \{(X_1, y_1), (X_2, y_2), \cdots, (X_n, y_n)\}$ is achieved. $X_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,89})$ $(1 \le i \le n)$ is a vector with 89 dimensions, where each dimension corresponds to the value of an indicator presented in the "Assessment Indicator System" section of this paper ITCCHE is represented by the scalar equivalent to y_i $(1 \le i \le n)$, a real number in the range between 0 and 100, where a greater value means stronger capability.

Step 2: By the training set T, training a CART, $y = f_0(X)$, with minimized loss accumulated by each sample of T. The loss is evaluated by mean square error, $L(y, f_0(X)) = (y - f_0(X))^2$.

Step 3: Iteratively executing following three steps M times. The current iteration time is denoted as m.

Step 3-1: Calculating accumulated negative gradient of the current trained model, $g_m = -\frac{\partial L(y, f_{m-1}(X))}{\partial f_{m-1}(X)} = y - f_{m-1}(X)$.

Step 3-2: By the training set T, training a CART, $y = f_m(X)$, with minimized $\sum_{i=1}^{N}(g_m(X_i, y_i) - f_m(X_i))^2$.

Step 3-3: Accumulating trained CART model function, $f_m(X) = f_{m-1}(X) + \alpha \cdot f_m(X)$, where $\alpha \in (0,1)$ is the hyper-parameter tuned for the algorithm convergence.

Step 4: After the iteration finishes, GBRT returns a regression model by the linear combination of multiple CART, $f_M(X)$.

PERFORMANCE EVALUATION

In this section, experimental comparisons will be conducted to demonstrate the performance advantages of the ITCCHE assessment model proposed in the previous section. The experimental data are the collected information from 52 Chinese higher education schools that are at different levels and spread in various regions. During the experiment, the information of 42 schools is randomly selected as the training set, and the information of the remaining 10 schools is used as the test set. Each set of experiments is repeated 10 times, and the average value is used as the performance metric value for comparison.

The comparison algorithms chosen for the experiments include Linear Regression (LR), Ridge Regression (Ridge), Multilayer Perceptron (MLP), Classification and Regression Tree (CART), Random Forest (RF), and Adaboost. During the experiments, for LR and Ridge, the data used for training and testing are normalized using zero-mean normalization in order to avoid the effect of different scales and units of indicators.

The performance metrics for comparison include Mean Squared Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2), which are calculated as in (1), (2), and (3), respectively. If an assessment model has smaller values in MSE and MAE and greater value in R2, then it has more accurate and thus better performance, compared with another.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - f(X_i))^2 \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - f(X_i)\right| \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f(X_i))^2}{\sum_{i=1}^{n}\left(y_i - \frac{\sum_{i=1}^{n} y_i}{n}\right)^2} \tag{3}$$

Figures 2-4 show the experimental results in these three performance metrics for each algorithm, respectively. From these results, it can be seen that GBRT obtains optimal MSE, MAE, and R2 values. Compared to other models, GBRT can obtain 13.1% to 51.3% lower MSE, 3.62% to 31.7% lower MAE, and 4.26% to 35.9% greater R2. The experimental results confirm the superior performance

Figure 2. Performance Comparison in MSE

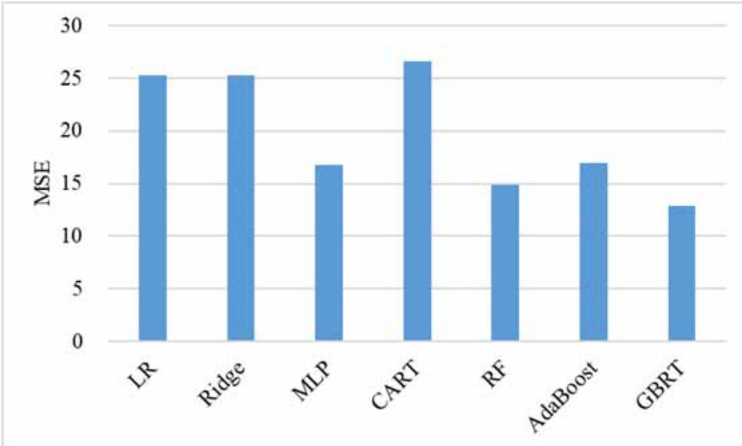


Figure 3. Performance Comparison in MAE

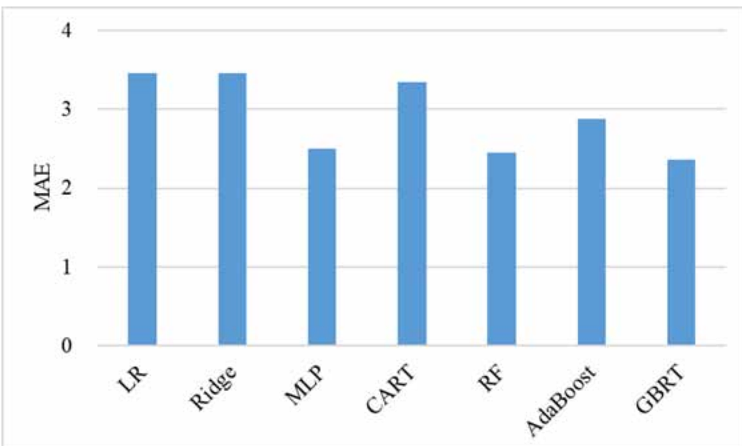
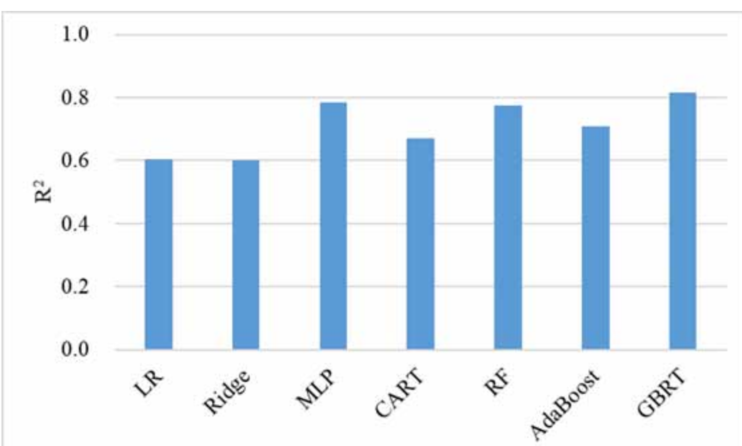


Figure 4. Performance Comparison in R2



of GBRT. This is mainly due to the basic idea of integrating multiple CARTs in GBRT. CART itself is an unstable learner, and a little fluctuation in the training data may bring a large impact on the results, resulting in a large variance of CART, which is prone to overfitting. So, it can be seen from Figure 2 that CART has the worst MSE. In practice, the characteristics that different CARTs' overfits bias may vary, so GBRT can fuse advantages of multiple overfitted CARTs to obtain an ensemble learning model with a strong generalization ability.

The performance of LR and Ridge is almost the worst, mainly because they are more suitable for regression problems with linear relationships. In contrast, the correlation between indicators in the ITCCHE assessment problem is much more complex and hidden, and thus cannot be described by using simple linear or polynomial relationships. At the same time, in this problem, there are not only continuous indicators but also discrete indicators. Therefore, LR and Ridge, which are good at fitting linear relationships, perform poorly in the experiment.

Similar to GBRT, AdaBoost is also a model that integrates CARTs. Their main difference is that AdaBoost strengthens the trained CART by increasing the misclassification weights in each iteration, whereas GBRT trains a CART that fits the residuals along the negative gradient direction in each iteration. AdaBoost is sensitive to anomalous samples, which may receive higher weights for these samples in training, affecting the prediction accuracy of the final strong learner. AdaBoost is more suitable for scenarios with balanced data distribution. For the small samples in this experiment, the possibility of abnormal indicator values is high, so AdaBoost is not as effective as GBRT.

RF is also an ensemble learning method that integrates multiple trees. The basic idea of RF is first to construct different training sets by random sampling (bagging and bagging), and then build a CART by each sampled training set separately. In the end, RF constitutes a forest consisting of trained CARTs, and uses the weighted average of the CART outputs as the final forest output. Sampling is done to reduce the correlation between weak learner models, which helps to reduce the variance of the integrated model, and thus improves the generalization ability. But this randomness can lead to an increase in the bias of the random forest. Also, in the case of only a few samples, the forest generated by RF may have multiple similar trees, leading to overfitting of the overall model. Therefore, it can be seen from Figure 2, Figure 3, and Figure 4 that RF performs not as good as GBRT, although it has better performance than CART and AdaBoost.

CONCLUSION

This paper studies the assessment of innovative talent cultivation capacities for higher education schools. In order to establish an improved assessment indicator system, this paper adopts the CIPP evaluation model, follows the principles of subjective-objective combination, comprehensiveness, and easy accessibility. This paper designs 89 indicators in the four aspects of context, input, process, and output of ITCCHE. These indicators are easily accessible through public data statistics, database retrieval and surveys. At the same time, this paper adopts GBRT to construct an assessment model for ITCCHE. And in the end, based on the collected data set from 52 Chinese higher education schools, this paper verifies the effectiveness and efficiency of the proposed assessment model through experiments.

The accuracy of the assessing model still needs to be improved, and we will improve the assessing in the following two directions. First, we will collect ITCCHE data from more higher education schools to expand the data set that can be used for analysis, so as to give full play to the advantages of data analysis technology and discover the concealing characteristics and rules of ITCCHE. The second is to seek more efficient data analysis techniques, such as integrating more diverse machine learning and deep learning, to build assessment models with better performance.

There is an essential problem when applying machine learning technologies, especially ensemble learning and deep learning, that is poor interpretability of trained models. This makes it difficult to study the influence degrees of different factors on ITCCHE, as it is hard to obtain the weights of indicators (dependent variables) from trained models. A simple and effective way to overcome this issue is to conduct very extensive experiments for studying the performance variations of methods training models with various combinations of indicators. This is also part of our future works.

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CONFLICT OF INTEREST

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