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Optimization of Teaching Quality Improvement Path Based on Recursive Algorithm in the Construction of Higher Vocational English Gold Classes under the Background of Industry-Teaching Integration

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ABSTRACT

The integration of industry and education refers to the in-depth integration of industry and education, which emphasizes the cultivation of students' practical ability and vocational quality. The integration of industry and education brings a new development direction for higher vocational education, and at the same time puts forward higher standards and requirements for higher vocational English teachers. In this paper, a new recursive Bayesian network structure algorithm is proposed based on RAI algorithm and CS algorithm, which mainly learns the Bayesian network structure by calling two functions recursively. Then based on the application effect evaluation model of recursive Bayesian network, the index system of classroom teaching evaluation is given based on the characteristics of classroom teaching, and the application effect is evaluated. The experimental results show that the optimization of the Bayesian network model can significantly improve the classification recognition reliability of the classifier, and taking the appearance score as a random effect, it can be found that the teacher's appearance difference has a significant effect on the teaching evaluation. The results of the study are of great significance to the construction of scientific English classroom construction as well as teaching quality evaluation system.

Keywords: bayesian network, recursive algorithm, classroom construction, teaching pathway

1. Introduction

Higher vocational English course is to serve the goal of cultivating highly skilled talents for the needs of the front line of production, construction, service and management, and it is an important course to cultivate students' comprehensive quality and enhance their ability of career sustainable development, with the goal of cultivating students' basic ability to utilize English in the workplace environment [1-

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3]. The orientation of college English teaching should be service, and its function is to serve the school's purpose, the faculty's specialty, and the students [4]. It can be seen that the integration of industry and education is an important direction and goal for the reform and development of public English course teaching [5].

The three distinctive features of the gold course are innovative and challenging and high-order [6]. For the English teaching work in higher vocational colleges and universities, the primary task at present is that it needs to be unified with the actual needs of the country and society for talents [7-8]. So that the specialized non-general English can be taught in the teaching process, according to the needs of the students themselves and future positions in the teaching design [9]. It is necessary to strengthen the cultivation of students' humanistic qualities, improve cross-cultural communication skills, gain insight into cultural differences, and enhance international vision, but also to enable students to master the knowledge of English language and skills through English language learning while improving their character cultivation and industry literacy, so as to lay a good foundation for the future smooth entry into the workplace [10-13]. Under the background of the Ministry of Education vigorously advocating the construction of the Golden Class, intelligent teaching, with its distinctive advantages and information platform, provides a new carrier and a new method for the construction of the Golden Class of higher vocational English [14-15]. For a long time, higher vocational English classroom teaching is mainly dominated by theoretical professors, with low students' enthusiasm for learning and insufficient classroom communication and interaction, which makes it difficult to obtain idealized teaching results [16-17]. The teaching mode based on intelligent algorithms guides a new direction for the high-quality development of higher vocational English teaching, and promoting the innovation of traditional classroom teaching with the construction of the Golden Class is the inevitable way for higher vocational English teaching in the context of the integration of industry and education [18-20].

In this paper, the index system of English classroom teaching quality assessment is formulated from three aspects of classroom teaching: information transmission, process control and teaching strategy, and a recursive Bayesian network structure model is proposed for the actual situation and needs of classroom teaching quality assessment. In order to avoid the problem of overfitting to examples that may result from using Gaussian kernel function to estimate the conditional density of attributes, shape parameters are introduced into the Gaussian kernel function and Bayesian optimization is used to improve the classification recognition accuracy of the classifier. On the basis of the study, a quantitative model is used to identify possible influencing factors with a view to further analyzing the key factors affecting the teaching evaluation, and finally, the analysis is conducted based on the empirical results and corresponding comments and suggestions are provided.

2. Research methodology

2.1. Bayesian networks

2.1.1. Bayesian network concepts. For ease of presentation, before introducing the basic concepts associated with Bayesian networks, a brief description of the representation of some common variables is given.

Set of random variables: $U=\{X_1,\ldots,X_n\}$.

Data set D: $D=\{C_1,\ldots,C_m\}$.

Structure of a directed acyclic graph: $G(V,E)$, where V denotes the set of vertices, E denotes the set of directed edges, and directed edges $\langle u,v\rangle$.

Definition 1 (Conditional Independence) In a probability space (Ω,P), the conditional probability of any subset A,B,C on a set Ω of variables is satisfied if:

$$P(A\mid B,C)=P(A\mid C) \tag{1}$$

Then it means that set A is conditionally independent from set B in the probability distribution P given set C, i.e. $Ind(A;B|C)$.

Definition 2($d-$ separation) For edge set l, if any subset Z of node set V satisfies any of the following, then edge set l is said to be separated by node subset $Zd-$:

For a subchain $l1\, v_i \to v_j \to v_k$, $l1 \in l$ or a subchain $l2$: $v_i \leftarrow v_j \to v_k, l2 \in l$, where $v_j \in Z$;

For a child chain $l3$: $v_i \to v_j \leftarrow v_k, l3 \in l$, where $v_j \notin Z$ and the descendant nodes $de(v_j)$ of v_j satisfy $de(v_j) \notin Z$.

In a directed graph $G(V,E)$, a set X and a set Y are separated by a set $Zd-$ if and only if every path l from node $x_i \in X$ to node $y_i \in Y$ is separated by a set $Zd-$, i.e., $Dsep(X;Y|Z)$.

Definition 3 ($V-$ Structure) A node v_1, v_3 has a $V-$ structure at node v_2 if in a directed graph $G(V,E)$ there exists a node $v_1, v_2, v_3 \in V$ such that there are edges $v_1 \to v_2$ and edges $v_3 \to v_2$ in the set of directed edges and there is no edge between node v_1 and node v_3.

Definition 4 (Dirichlet distribution) If the conditional probability of a variable θ with respect to prior information I_0 is:

$$P(\theta | I_0) = Dir(\alpha_1, \alpha_2, ..., \alpha_r) = \frac{\Gamma(\sum_{i=1}^{r} \alpha_i)}{\prod_{i=1}^{r} \Gamma(\alpha_i)} \prod_{k=1}^{r} \theta_k^{\alpha_k - 1} \tag{2}$$

where parameter $\theta_k = P(Y = Y_k | \theta, I_0)(K = 1, 2, ..., r)$, then θ satisfies the Dirichlet distribution with respect to prior I_0, where $(\alpha_1, \alpha_2, ..., \alpha_r)$ is the Dirichlet index.

2.1.2. Bayesian mathematical modeling. The Bayesian network (BN) structure is a directed acyclic graph (DAG), so its mathematical model generally adopts the representation of a directed graph in graph theory, i.e., $G(V,E)$, where V denotes the set of all vertices, which corresponds to the random variables, and E denotes the set of all directed edges in the network, which corresponds to the relationships among the random variables [21].A DAG is a kind of directed graph that starts from any node and follows the directed edges, and none of them can go back to the starting node, so Bayesian network is a special kind of directed graph. In the Bayesian network, the directed edge $X \to Y$ indicates that node X is the parent node of node Y, and node Y is the child node of node X. $Pa(X)$ denotes the set of parent nodes of node X and $de(X)$ denotes the set of child nodes of node X. Also Bayesian networks graphically represent the joint probability distribution of variables, which can reduce the complexity in the description and computational inference process. Bayesian network $B = (G, \theta)$, where G denotes the BN structure, which is used to describe the conditional independence between the variables, and θ denotes the conditional probability table of the network, which quantitatively represents the relationship between the variables in the network. The joint probability of the BN is:

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_1, ..., X_{i-1}) \tag{3}$$

The conditional independence of nodes has been described in the Bayesian network structure, giving the set of parent nodes $Pa(X)$ for each node, so that the conditional probability of node X_i is only related to its parent node, independently of the other non-parent nodes, then:

$$P(X_i | X_1, ..., X_{i-1}) = P(X_i | Pa(X_i)) \tag{4}$$

Combining Eq. (3) and Eq. (4) yields:

$$P(X_1,\ldots,X_n)=\prod_{i=1}^{n}P(X_i\mid Pa(X_i)) \tag{5}$$

To better understand the joint probability distribution of a BN, an example of a BN is given as shown in Figure 1. The meaning of this network is that when a person smokes (H), it may cause bronchitis (B) and lung cancer (L), and both of them may make the person feel uncomfortable (F) or cause a problem with chest CT (C), which is a graph-theoretic representation of an uncertain problem. According to the structure of the network, it is known that the conditional probability of node L is independent of the non-parent nodes B, F, and C when its parent node H is known, and according to the conditional probability table of the network it can be derived as $P(F=y\mid B=y,L=y)=0.75$, which indicates that the probability of being uncomfortable when one has bronchitis and lung cancer is 0.75, describing the degree of dependence of the node F on the node B and the node L.

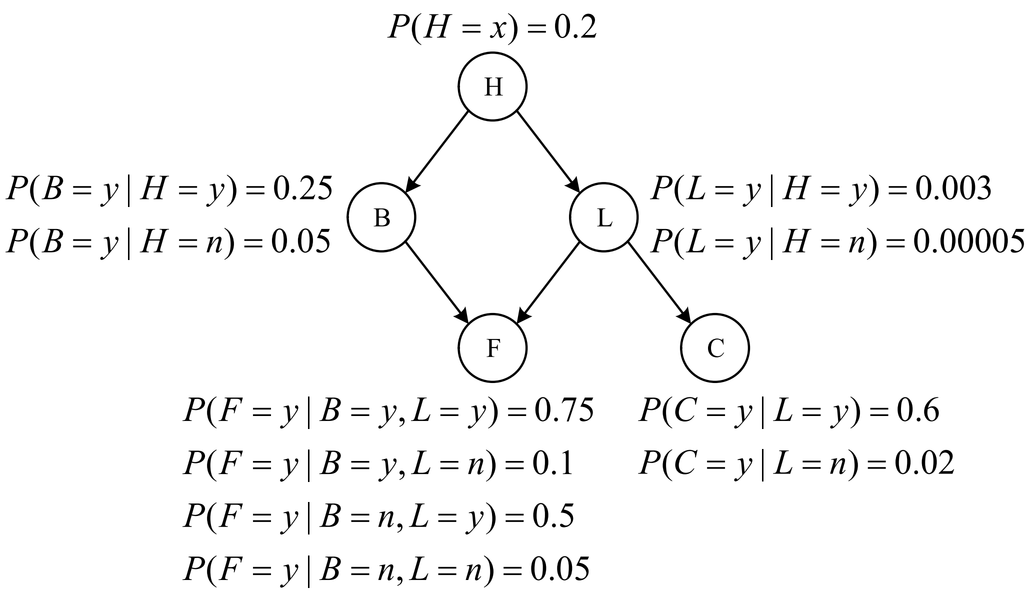


Fig. 1. Bayesian network example

2.1.3. Bayesian structure learning. The main research hotspot on Bayesian network structure learning is the data-driven learning method, so this chapter focuses on the method of learning BN structure based on sample data. Bayesian network structure learning analyzes the given sample data with a view to obtaining a structural model that accurately describes the relationships between nodes ($G(V,E)$). After research and exploration by scholars, many structure learning methods have been proposed and improved, and these algorithms can be mainly categorized into three main groups, namely: learning methods based on conditional independent testing, network structure learning methods based on search scoring, and hybrid learning methods that combine the two.

2.2. Bayesian network structure learning based on recursive methods

2.2.1. Related concepts. Recursive Autonomous Identification Algorithm (RAI) is a constraint-based structure learning algorithm, which makes full use of conditional independence test and Bayesian network directionality rule, and learns the whole structure by decomposing the big picture into smaller subgraphs and then learning them recursively. The advantage is that it reduces the complexity of the algorithm and enhances the reliability of the conditional independence test.

Definition 1: d-Segmentation degree

Let $G=(V,E)$ be a directed acyclic graph, $X,Y\in V$ and X,Y are not adjacent to each other, then the size of the minimum d-partition set of the pair of nodes that d-partition X,Y is called the d-partition degree of node X,Y.

Definition 2: Graph d-partitioning degree

The d-partitioning degree of a graph is the value of the highest d-partitioning degree of all non-adjacent nodes X, Y in the graph

Definition 3: Deriving subgraphs

Let $G=(V,E)$ be a directed acyclic graph with node set $U\subset V$. The subgraph consisting of U as the node set and all the edges in G whose both endpoints belong to U as the set of edges is called the subgraph of G derived from node set U.

Definition 4: External causes

Let $G=(V,E)$ be a directed acyclic graph DAG and let $G^{'}=(V^{'},E^{'})$ be its derived subgraph, i.e., satisfying $V^{'}\subset V,E^{'}\subset E$. A node Y is said to be an external cause of a graph $G^{'}=(V^{'},E^{'})$ if node Y satisfies $Y\notin V^{'}$ and either $Y\in Pa(X,G)$ or $Y\notin Adj(X,G)$ for any $X\in V^{'}$.

where $Pa(X,G)$ denotes the set of parent nodes of X in G and $Adj(X,G)$ denotes the set of neighbor nodes of X.

Definition 5: Autonomous substructure

Let $G=(V,E)$ be a DAG and $G^{A}=(V^{A},E^{A})$ a derived subgraph of G. $G^{A}=(V^{A},E^{A})$ is said to be autonomous if there exists a G^{A} set of external cause nodes $V_{ex}\subset V$ such that for any $X\in V^{A}$, there is $Pa(X,G)\subset\{V^{A}cupV_{ex}\}$.

The advantage of the definition of an autonomous substructure is that in some sense its nodes retain the Markov property. That is, given a structure G of a directed acyclic graph, the nodes of any set of two non-adjacent node partitions in an autonomous substructure G^{A} are contained in G^{A} or in an external cause of G^{A}. $G^{A}=(V^{A},E^{A})$ is an autonomous substructure of G. Since nodes X_1 and X_2 are external causes of G^{A} (i.e., they are either parents of G^{A} or nonadjacent to G^{A}), G^{A} is said to be an autonomous substructure of G, given nodes X_1 and X_2.

2.2.2. Algorithmic RAI Foundations. The RAI algorithm proposes a new method for constraint-based learning of Bayesian network structures [22]. Compared to other constraint-based learning methods, the RAI algorithm not only gets a reduction in conditional independent testing but also in the order of conditional independent testing. Along with the reduction, the accuracy of the learned Bayesian network structure is also improved as compared to other algorithms.

As with other constraint-based structure learning algorithms, the RAI algorithm proceeds under the fidelity assumption while assuming that the data is large enough to allow for reliable conditional independence (CI) testing, the

Lemma 1: In a directed acyclic graph DAG, if X and Y are not adjacent and X is not a descendant node of Y, then X and Y are d-partitioned given $Pa(Y)$.

Lemma 2: If $G^{A}=(V^{A},E^{A})$ is an autonomous substructure of $G=(V,E)$ and $V_{ex}\subset V$ is the set of external cause nodes of G^{A}, if $X\perp Y\mid S$, where $X,Y\in V^{A},S\subset V$, then $\exists S^{'}$ makes $S^{'}\subset\{V^{A}\cup V_{e\alpha}\}$ and $X\perp Y\mid S^{'}$.

2.2.3. Recursive Autonomous Recognition Algorithm. The n st iteration of the RAI algorithm is performed on top of the $n-1$nd iteration, and after the $n-1$rd iteration contains the structure G_{start} with d-partitioning degree $n-1$, the set of structures G_{ex} containing G_{start} external causes, and the structure G_{all} containing G_{start} and G_{ex} connected together. At the first iteration, $n=0,G_{ex}=\varnothing$, G_{start} is a completely undirected graph, $G_{all}=G_{start}$

The RAI algorithm consists of four phases; phase A aims to cut the connections G_{start} and G_{ex} and orient G_{start} them; phase B aims to cut and orient G_{start}, and after orienting it, decompose the cut G_{start} into descendant substructures and ancestor substructures; phase C is a recursive call to the ancestor substructures in phases A, B, and C; and phase D is a recursive call to the descendant substructures in phases A, B, C and D phases.

The RAI algorithm utilizes CI tests to approximately reduce the graph and decompose it into smaller subgraphs by directional information, on which CI tests are then performed. This reduces the total number of CI tests and the number of higher-order tests, but it does not fully utilize the directed information and does not address some avoidable CI tests.

2.3. *Teaching quality evaluation model based on recursive Bayesian network*

2.3.1. Bayesian network modeling. Using Bayesian network to evaluate the effect of information technology application, first of all, it is necessary to model Bayesian network for the evaluation index system of information technology application effect. Constructing Bayesian network from the index system usually has the following two links.

1) Determine the node variables. According to the established evaluation index system, the indicators at all levels are identified as the corresponding network nodes of the Bayesian network. Bayesian networks were initially proposed in the 1980s to solve the problem of representation and inference of uncertain knowledge mainly through probabilistic analysis and graph theory. A Bayesian network is a directed acyclic graph with a probabilistic interpretation, including both the network structure and the probability distribution of the variables. A Bayesian network with N nodes can be represented by $\langle\langle V,E\rangle P\rangle$, where: $\langle V,E\rangle$ denotes a directed acyclic graph with N nodes, node $V=\{V_1,V_2,\cdots,V_n\}$ represents the variables, and directed edges E represent the relationships between the variables; P denotes a conditional probability distribution associated with each node. For directed edges (V_i,V_j), V_i is called the parent node of V_j and V_j is called the child node of V_i. In addition to parent and child nodes, a Bayesian network includes root and leaf nodes; a node without a parent is called a root node and a node without a child is called a leaf node. Let $P_d(V_i)$ be the set of parent nodes of V_i and $A(V_i)$ be the set of non-descendant nodes, then there exists a conditional independence assumption in the directed graph that satisfies the following relationship:

$$P(V_i \mid P_a(V_i), A(V_i)) = P(V_i \mid p_a(V_i)) \tag{6}$$

Given the conditional probability distribution of the root node, the joint probability distribution containing all nodes can further be obtained based on the conditional independence assumption relation:

$$P(V_i) = P(V_1,V_2,\cdots,V_n) = \prod_{i=1}^{n} P(V_i \mid V_1,V_2,\cdots,V_{i-1}) \tag{7}$$

The indicators of the bottom layer are used as the root nodes of the Bayesian network, and the evaluation targets are used as the leaf nodes of the Bayesian network.

2) Determine the network structure. Analyze the influence relationship between the indicators in the evaluation index system, combine the determined node variables, determine the connection relationship of the Bayesian network nodes according to the causal relationship between the nodes, and construct the Bayesian network.

2.3.2. Determination of key model parameters. After constructing a Bayesian network model for evaluating the effectiveness of information technology applications, the model needs to be solved. For Bayesian networks, the prior probability of the root node and the conditional probability of the child nodes are the key parameters for solving the Bayesian network model. For this reason, the root node prior probability and child node conditional probabilities need to be determined first.

2.3.3. Evaluation implementation steps. After completing the Bayesian network modeling and identifying the key parameters of the model, the evaluation of the effectiveness of IT application can be implemented. For ease of operation, the implementation steps for the evaluation of the effectiveness of IT application are shown in Figure 2.

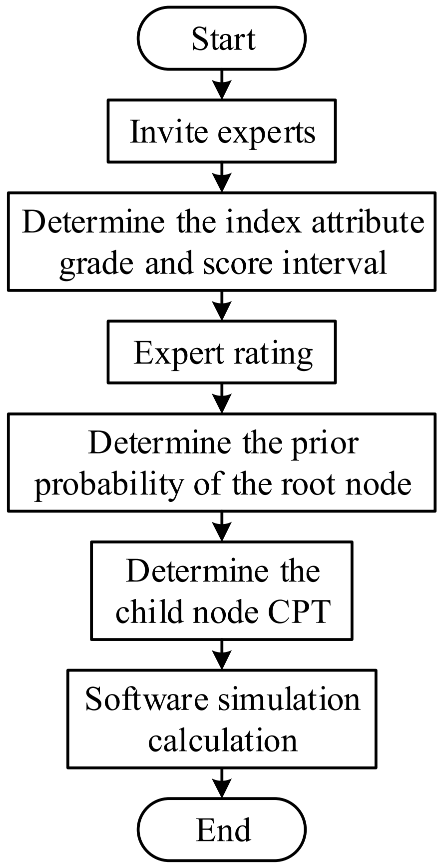


Fig. 2. Evaluation implementation steps

In the implementation steps of the entire evaluation of the effectiveness of information technology application, the software simulation calculation is also an important part of the entire evaluation work. The Bayesian network model established by the analysis has many nodes and variables and a large amount of calculation, so it is necessary to use a professional Bayesian network toolbox to realize the simulation calculation of the model.

3. Empirical evidence and analysis

3.1. Assessment of the Quality of Teaching and Learning in the English Gold Class Building

3.1.1. Classroom Teaching Assessment Indicator System. Indicator system is a prerequisite for classroom teaching assessment. A three-level indicator system for classroom teaching assessment is established based on educational cybernetics, principles of system science and classroom teaching mechanism, and the indicator system can also be expanded at different levels according to actual needs. 1) Level 1 Indicators. Classroom teaching grade (C) is divided into 4 levels, namely: Grade A (excellent), Grade B (good), Grade C (average), Grade D (poor).

2) Secondary Indicators. The secondary indicators to which classroom teaching belongs are: classroom information transfer (X1), classroom teaching control (X2), classroom teaching strategy (X3). They are all divided into three grades, which are Grade A (good), Grade B (moderate) and Grade C (poor).
3) Three-level indicators. Classroom information transfer belongs to the three-level indicators: teacher's information transfer to students (grammatical information transfer (X11), semantic information transfer (X12, pragmatic information transfer (X13)), and student's information transfer to the teacher (feedback information (X14), feed-forward information (X15), feed-back information (X16)).

Classroom instructional control belongs to the three levels of indicators: knowledge structure control (concepts (X21), rules (X22), problem solving (X23)), cognitive structure control (cognitive operations (X24), motivation supply (X25), cognitive strategies (X26)), and modality control (procedural control (X27), stochastic control (X28)).

Three levels of indicators belonging to classroom teaching strategies: didactic teaching (X31), heuristic teaching (X32), deductive teaching (X33), generalization (X34), retrospective teaching (X35).

3.1.2. Classifier models for classroom assessment. According to the above classroom teaching assessment index system can be obtained two-level recursive Bayesian classifier structure, as shown in Figure 3.

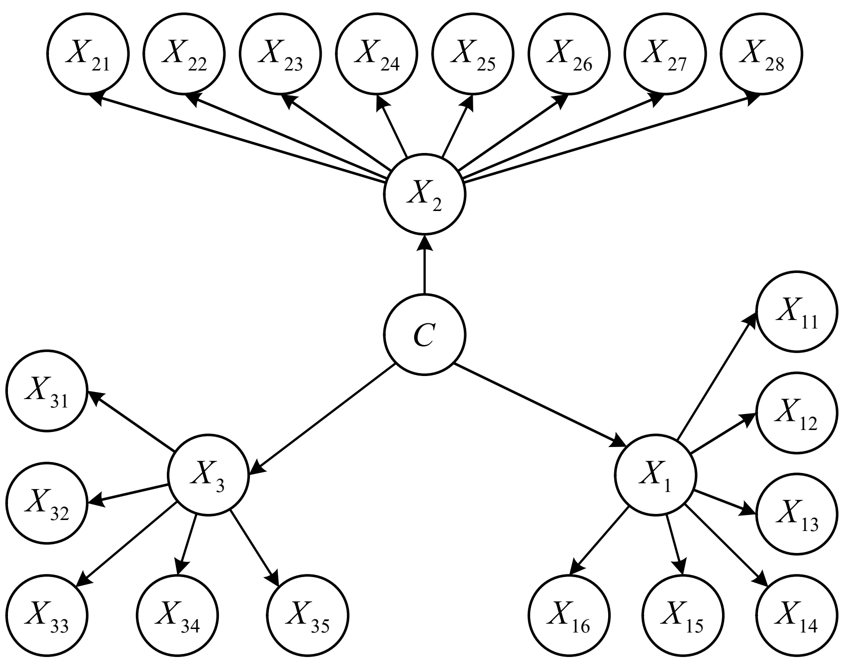


Fig. 3. The structure of the subbereses classifier for classroom teaching evaluation

Based on the classifier structure and example data for parameter estimation, thus obtaining a recursive Bayesian classifier for classroom teaching evaluation, inputting the latest classroom teaching information, the classroom teaching grade can be obtained through classification operations.

3.1.3. Recursive Bayesian Classifier Reliability Experiments and Analysis. Twelve categorical datasets with continuous attributes were selected from the UCI Machine Learning Data Warehouse for classification prediction using the NBN classifiers obtained by pairwise Recursive Identification (RAI), Gaussian Density Estimation (GNBN), Gaussian Kernel Density Estimation (GKNBN), and Bayesian Networks Model (BN), respectively, and the classification accuracy of the classifiers was estimated using a 10-fold cross validation method. As shown in Table 1. From the table, it can be seen that the

RAI classifier has good classification accuracy, while the GKNBN classifier is better than the RAI and GNBN classifiers, and the BN classifier is also better than the GKNBN classifier. This suggests that using the recursive Bayesian classifier obtained by combining the RAI and BN classifiers hierarchically will be more reliable for classroom assessment level judgments.

Table 1. Comparison of classification prediction accuracy

Example set	Sample quantity	Class number	Discrete attribute	Continuous property	RAI %	GNBN%	GKNBN%	BN%
iris	155	4	0	5	96.31±211	97.00±2.13	97.00±2.13	97.71±1.89
wine	179	4	0	14	93.42±2.75	98.74±1.74	97.57±2.41	99.01±1.63
glass	215	4	0	10	67.55±2.59	47.58±4.42	66.31±3.74	70.61±2.55
wpbc	201	7	0	35	66.00±2.71	67.41±3.12	72.00±3.23	77.00±3.47
wdbc	571	3	0	32	95.12±1.92	94.17±1.53	95.31±1.64	95.31±1.64
New_thyroid	217	3	0	6	79.11±2.83	96.00±2.13	95.04±2.41	97.55±2.22
Heart_disease	270	4	0	14	83.91±2.34	86.91±2.17	83.11±2.31	87.22±2.18
Liver_disease	346	3	0	7	62.44±2.41	56.31±2.91	69.31±2.79	74.85±2.71
Pima_indians	771	3	0	9	74.41±2.81	76.01±2.89	77.12±2.41	81.41±1.91
Sick_euthyriod	1357	3	12	7	91.55±1.31	88.65±2.09	93.41±1.21	96.57±1.69
Sick_euthyriod	1347	3	14	6	93.41±1.41	97.45±1.41	98.11±1.34	98.11±1.34
Hypothyroid	695	3	10	7	85.61±2.15	77.85±1.87	86.27±1.83	89.51±1.97
Average					82.23	82.78	85.29	88.71

3.2. *Example analysis*

Taking a university in Hefei City, Anhui Province as an example, in order to avoid evaluation interference caused by different courses, different teachers and different grades, the evaluation of classroom teaching quality of a teacher teaching English courses in different classes (Class A and Class B) was selected for analysis. 115 students in Class A and 85 students in Class B participated in the evaluation. A total of 10 students were selected by school leaders and experts from the teaching supervision team, and 10 students were selected by their colleagues. According to the classroom teaching quality evaluation system constructed on the basis of recursive Bayesian network and the size of the weights of each index, the teaching quality evaluation score table of a teacher is obtained through calculation, as shown in Table 2.

Table 2. The quality evaluation score of a teacher's teaching

	The number of students who are reviewed	Effective evaluation	Weighted evaluation scores
Class A	115	95	91.786
Class B	85	70	91.773

As can be seen from the table, although the subjects involved in the evaluation are different, the evaluation scores based on the evaluation system for the same course taught by the same teacher are basically similar, and there is no situation where there is a large gap. Therefore, the evaluation results are basically reasonable. According to the above method, the evaluation scores of the teaching quality of a teacher by the teaching supervisory group and colleagues are calculated as follows: A_2 =87.485; A_3 =89.023 Since the influence of students, experts of the supervisory group and colleagues on the evaluation of the quality of classroom teaching is different, the final evaluation result of a teacher is calculated according to the weighting used by the Academic Affairs Office of the university. Firstly, by averaging the evaluation scores obtained from Class A and Class B, i.e., A_1 =91.784, and the weighting adopted by the Senate is $u=(u_1, \ u_2, u_3)=(0.4, 0.3, 0.3)$, the final evaluation results of a teacher in a particular semester are as follows:

$G = u \bullet A = (u_1, u_2, u_3) \bullet (A_1, A_2, A_3) = (0.4, 0.3, 0.3) \bullet (91.784, 87.485, 89.023) = 91.7155$ Thus, the final evaluation score for a teacher for that semester was 91.7155, which means that the overall evaluation result was at the excellent level.

3.3. Analysis of Factors Influencing the Teaching Quality of English Gold Classes

3.3.1. Classical linear regression models. The general form of the classical linear regression model is $y_i = \alpha + \beta x_i + \varepsilon_i$.

where i=1,2... ,94. ε_i are independent and identically distributed from each other, E(ε_i) = 0 and $Var(\varepsilon_i) = \sigma^2$, then there is εi $\sim N(0, \sigma^2)$. The above assumptions ensure that the observations come from the same population, i.e., there is no random error in the independent variable and its effect on the dependent variable is fixed. The simple linear model was fitted and estimated by least squares to obtain the estimates of the coefficients of Model I as shown in Table 3.

Table 3. The simple linear model is estimated by parameters

	Estimate	Std.Erro	t value	Pr(>|t|)	
Intercept	4.16861	0.15735	26.6144	<2.18E-15	***
Beauty	0.27774	0.03598	7.8597	2.87E-13	***
Genderfemale	-0.23077	0.05894	-3.9676	8.18E-04	***
Minorityyes	-0.247	0.08995	-2.7685	0.00643	**
Nativeno	-0.25109	0.09799	-2.5809	0.009862	**
Tenureyes	-0.1328	0.0616	-2.1852	0.027765	*
Divisionlowe	-0.04134	0.06204	-0.6784	0.483345	
Creditssingle	0.68778	0.11561	5.9864	4.52E-07	***
Age	0.00171	0.00333	0.3903	0.691609	

Signif.codes: 0‘***’0.001‘**’0.01‘*’0.05‘.’0.1‘

Analyzing the above table, it can be concluded that: ① the statistical relationship between teaching ratings and teachers' appearance ratings is the most significant and positively correlated, i.e., teachers with higher appearance ratings are more likely to receive higher teaching ratings; ② the lower the number of credits in a course, the higher the ratings received by the teachers; ③ the teaching ratings of female teachers, black teachers, teachers whose native language is not English, and teachers who have received tenure, are comparatively lower; ④ Age differences, while student grade differences had no significant effect on teaching ratings.

Figure 4 shows the relationship between beauty and eval, the straight line is the regression fit curve, it can be visualized that as the teacher appearance rating increases, the teaching rating also increases accordingly.

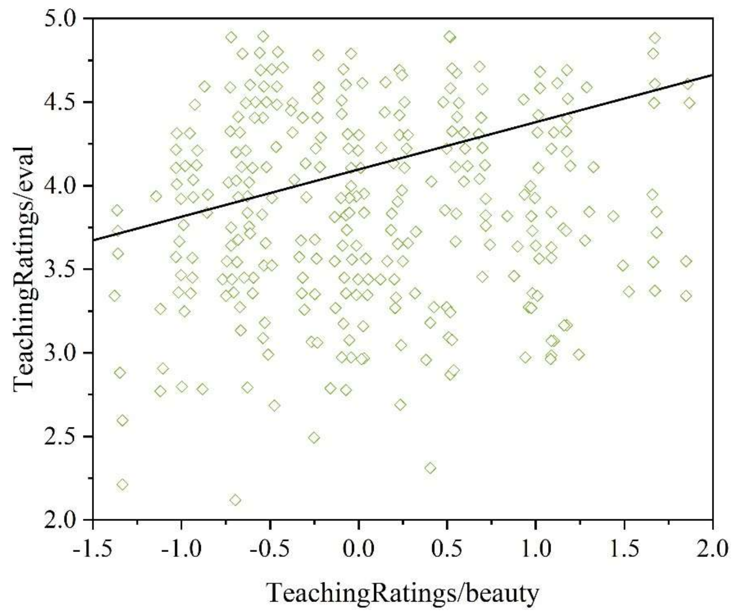


Fig. 4. Linear regression curve

The regression model obtained by keeping the coefficients to two decimal places is as follows:

$$\begin{aligned} y_i &= 4.19 + 0.31 beauty_i - 0.25 gender_i - 0.27 \min ority_i \\ &-0.27 native_i - 0.15 tenure_i - 0.05 division_j + 0.71 credits_j + 0.002 age_i \end{aligned}$$

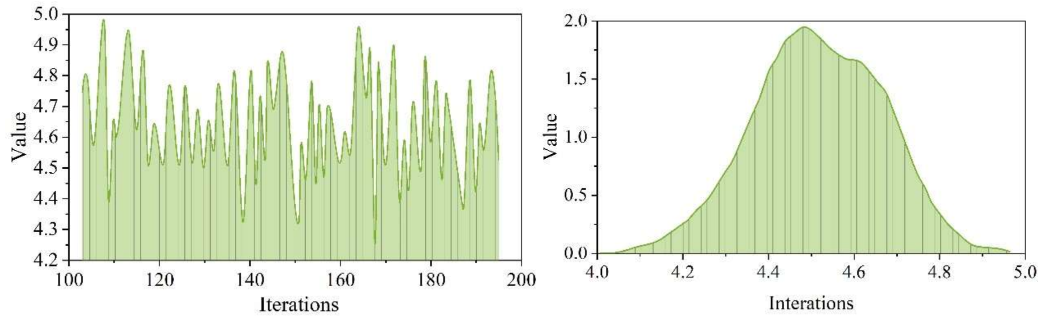
where i = 1,2...94.

3.3.2. Bayesian mixed effects modeling. Unlike the linear mixed effects model, the recursive Bayesian model assumes that the teacher's appearance rating variable B_1 follows a normal distribution and assumes that its parameters follow a certain prior distribution. The form of the prior distribution has been stated previously, and the parameters of the prior distribution use an uninformative prior that can be computed from the functions dwish and rwish in the R language installation package MCMCpack. Using B_1 as a random effect, $X_1, X_2, X_3, X_4, X_5, X_6, X_7$ as a fixed effect, and the teaching score Y as the dependent variable, the expression for the recursive Bayesian network is obtained as follows:

$$y_{ij} = \beta_0 + \sum_{m=1}^{7} \beta_m x_{ij} + b_{1i} B_{1j} + b_{0i} + \varepsilon_{ij} \tag{8}$$

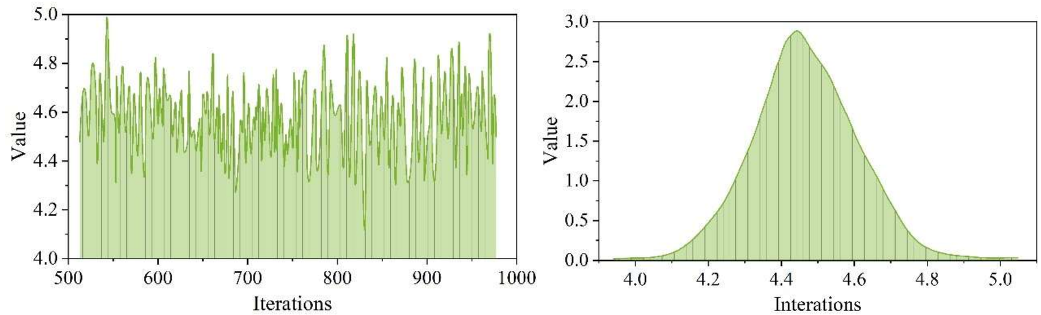
where i =1,2... , 94 correspond to 94 teachers, j =1,2... nj , correspond to the j nd observation of the i st teacher, respectively, β_0 is the fixed-effects intercept, b_{1i} is the coefficient of the random effect, b_{0i} is the random intercept, and ε_{ij} is the error term.

It is important to note that in the estimation of any MCMC-based Bayesian model, tests about the convergence of the model are essential. The convergence of an MCMC model is achieved when the simulation results are derived from the smooth or target distribution of the constructed Markov chain.The smoothness of the intercept term and the state of the density function for an increasing number of 200 iterations are shown in Fig. 5, and the smoothness of the intercept term and the state of the density function for an increasing number of 1000 iterations are shown in Fig. 6. From the figure, it can be directly seen that after 200 sampling iterations, the martensian chain is still not converged, while after 1000 sampling iterations, it can be considered that the martensian chain reaches a smooth convergence state and the density function of the intercept term approximately obeys a normal distribution.



(a)Trace of beta (b)Density of beta

Fig. 5. The markov chain iterates 200 times convergence stability



(a)Trace of beta (b)Density of beta

Fig. 6. The markov chain iterates 1000 times convergence stability

The expression for the recursive Bayesian model can be obtained as follows:

$$y_i = 4.52 + b_{li} beauty_{ij} - 0.3 gender_{ij} - 0.22 \min ority_{ij} - 0.37 native_{ij}$$
$$-0.24 tenure_{ij} - 0.2 division_{ij} + 0.44 credits_{ij} - 0.008 age_{ij} - b_i$$

Since there are too many estimates obtained from the recursive Bayesian model to list them here, the average of the 94 estimates for the random intercept and variable B1 were calculated separately to compare with the linear regression model. Where: $\overline{b_1}$ =0.01634, $\overline{b_0}$ =0.21316.

The fit of the predicted scores to the original scores from the recursive Bayesian model is shown in Figure 7, which shows that the predicted scores fit the original scores better.

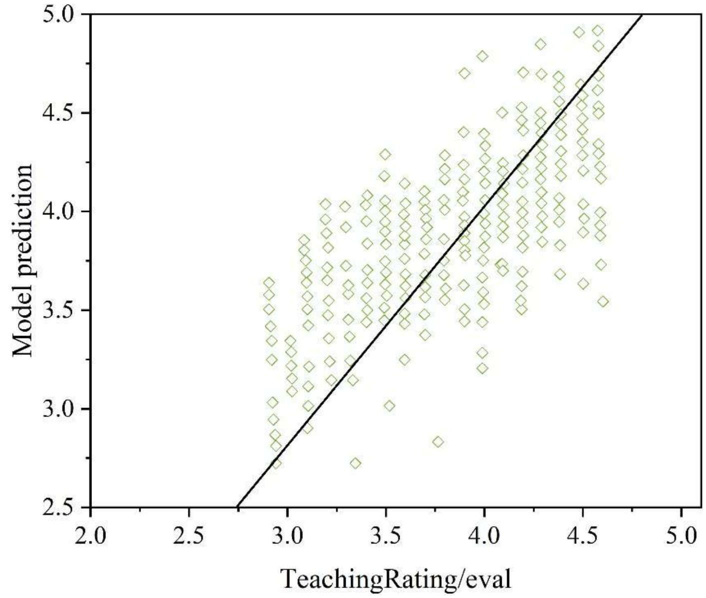


Fig. 7. Model prediction teaching score

3.3.3. Analysis of results. The comparison of each parameter of linear regression model, recursive Bayesian model is shown in Table 4. As can be seen from the table: the BEAUTY coefficient in the recursive Bayesian model is much smaller than the linear regression model. This is due to the fact that the recursive Bayesian model considers all teachers as 94 levels respectively, and for each level is modeled. That is, the observations under the same level are considered to be interrelated, so for each teacher, the BEAUTY coefficient is the same. While the observations between different levels are independent of each other, the variability between them is neutralized by the random intercept, and the reduction of the BEAUTY coefficient reduces the error caused by the teachers' appearance ratings.

Overall, it can be seen from the comparison results that the recursive Bayesian model obtained by applying the recursive Bayesian model to estimate the variable B_1 and its random intercept separately is superior. It can be concluded that the Bayesian approach synthesizes the a priori data and the actual teacher appearance ratings, which serves to reduce the error.

Table 4. Comparison of different model parameters

Model parameter	Classical linear model	Recursive bayesian model
Intercept	4.16851	4.50629
Beauty	0.27764	0.01682
Random intercept		0.20438
Genderfemale	-0.23087	-0.19951
Minorityyes	-0.2471	-0.20801
Nativeno	-0.25119	-0.34866
Tenureyes	-0.1329	-0.22431
Divisionlower	-0.04144	-0.10094
Creditssingle	0.68768	0.41758
Age	0.00161	-0.0057

4. Conclusions and recommendations

4.1. Conclusion

In this paper, an improved algorithm - Recursive Bayesian Learning Algorithm - is proposed on the basis of the original algorithm RAI, and then an evaluation model of the application effect based on the Recursive Bayesian Learning Algorithm is constructed. A three-level index system for English classroom teaching evaluation is given based on educational cybernetics, system science principles and classroom teaching mechanism, etc. Experimental results show that the optimization of Bayesian network model can significantly improve the classification accuracy of the classifier, which indicates that the evaluation identification results obtained by using it for classroom teaching quality evaluation will be more reliable. Finally, the linear regression model is compared with the recursive Bayesian model, which proves that the Bayesian hierarchical linear regression method is more suitable for hierarchical data than the classical linear regression. The study is of great significance for the construction of English courses and the analysis of factors affecting the evaluation of teaching quality.

4.2. Recommendations

1) Innovate the teaching concept of English course. Colleges and universities should start from the characteristics of the English course, closely focus on the student-centered status, and update the teaching concept of the course. First of all, establish a student-centered teaching concept. Influenced by the traditional teaching concept, in the past teaching process is often the role of the teacher occupies a dominant position, the teacher according to their own teaching tasks and teaching content for the students to explain the knowledge. However, with the development of the times, the traditional teaching concept has obviously not adapted to the development of modern teaching. Modern teaching methods require teachers to firmly establish a student-centered teaching philosophy, fully mobilize students' learning initiative, and constantly improve students' innovative thinking ability.

2) Optimize the teaching resources of English courses. The development of English course teaching requires rich teaching resources to guarantee, and to improve the level of teaching resources construction, we need to pay attention to the following three aspects: first, the integration of digital teaching resources. The resource management platform can effectively realize the integration of English teaching resources including teaching materials, courseware, audio, video, online courses, etc. The digitally integrated teaching resources can be used by teachers and students to conveniently retrieve, store and use these English resources on the resource management platform. Second, develop personalized learning resources. Big data analysis technology can analyze and obtain information on reading materials, listening exercises, learning videos and other contents needed by students according to the different needs of students at different levels, and then develop personalized learning methods and learning contents for students according to these different needs, so as to better satisfy the learning needs of learners and help students better develop personalized learning resources.

3) Innovative Teaching Modes of English Courses. Through the innovative teaching mode of English courses in colleges and universities, students' interests can be fully mobilized, and students can be promoted to realize intelligent learning, deep learning, and comprehensively master the knowledge and skills of English courses, laying a good foundation for their future participation in related fields. Teachers should design the teaching mode scientifically from the characteristics of English courses, closely focusing on students' learning rules and learning needs. First, blended mode. Blended mode refers to a kind of English intelligent learning mode that integrates online and offline learning modes and organically combines online learning with classroom teaching. Second, interactive mode. In order to better realize the internalization of language in multi-party communication and interaction, the interactive mode of teaching requires that students, teachers and students, and learning groups can realize language communication and interaction anytime and anywhere.

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