



A Multi Criteria Group Decision-making Model for Teacher Evaluation in Higher Education Based on Cloud Model and Decision Tree

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This paper proposes a cloud multi-criteria group decision-making model for teacher evaluation in higher education which is involving subjectivity, imprecision and fuzziness. First, selecting the appropriate evaluation index depending on the evaluation objectives, indicating a clear structural relationship between the evaluation index and objectives and establishing a proper evaluation system are all critical and fundamental tasks. Then, collect expert evaluation data, process data, establish training set to build the decision trees, extract evaluation rules, simplify evaluation process, while reducing the cost of evaluation in real applications. Third, establish the interval cloud evaluation matrix through the decision cloud, transforming the evaluation value through the cloud model, determining the order of importance of the decision program, and make the decision. Finally, an addressing linguistic decision-making problem for college teacher evaluation is provided to illustrate the effectiveness of the proposed model.

Keywords: college teacher evaluation, decision tree, multi-criteria group decision-making, integrated cloud, uncertainty

INTRODUCTION

Higher education broadens a person's job opportunities and makes him more valuable to potential employers. The U.S. Bureau of Labor Statistics indicated that the difference in income between the typical high school graduate and four-year college graduate was \$457 per week as of 2013. The unemployment rate also dropped from 7.5 percent for high school graduates to 4 percent for those with a bachelor's degree. More well-educated and literate people recognize the importance of health maintenance and treatment. From a global perspective, countries with high literacy rates, such as the United States and Japan, also have relatively high gross domestic

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products. These countries also have fewer people living in poverty and greater overall economic development. Personal pride, societal respect and better overall life stability are key intangible benefits of education. A person feels more confident with education, and this confidence contributes to stronger and more stable personal relationships.

Many factors contribute to a student's academic performance, including individual characteristics and family and friend experiences. Research suggests that, among school-related factors, teachers matter most.

The core of education is learning and teaching, and the teaching-learning connection works best when we have effective teachers working with every student. While effectiveness can be defined in myriad ways (Cruickshank & Haefele, 2001), the essential issue is that we have the most effective teachers possible guiding the learning of students (Stronge & Tucker, 2003).

How effective evaluation of teachers, to establish a more reasonable and effective evaluation in the actual decision-making process, due to the complexity of the external environment, uncertainty and limitations on human understandings, it is difficult for the decision makers to provide accurate information. During the decision-making case, people tend to evaluate a particular index or thing using natural language such as "excellent", "good", "medium" and "poor"...etc. (Bellman & Zadeh, 1970; Xu, 2006). Therefore, a decision-making method with qualitative and quantitative conversion becomes the key element to solve the problem of evaluation. How we quantify natural language and the processing of quantifying is the core of the research. In recent years, scholars have raised a number of multi-criteria decision-making methods such as triangular fuzzy type, linear weighting method, tuple linguistic to solve the problem of quantifying natural language information (Jiang, Wang, & Lin, 2013; Tang & Zhang, 2008) however, due to the existence of fuzziness from the subjective nature in humans and the randomness from things and events, these methods may not be applicable, and there are some differences in the results obtained.

Cloud model is a quality, quantity transformation model (Jyh, 2012) It represents language values in natural language with three numerical characteristics, expectation E_x , entropy E_n , hyper entropy H_e , allowing the randomness, fuzziness and the correlation in between to be unified under "the cloud model" (Li, Liu, & Gan, 2009). Application of the cloud model not only made it possible to obtain quantitative data range and distribution from linguistic expressions, but also the appropriate linguistic expression from exact qualitative values.

In recent years, the cloud model has been in application throughout the area of group decision-making (Liu & Jin, 2012), a decision-making cloud model is made for when the weight for multi-criteria decision-making aimed at language randomness is known, but the expert weights are unknown, when the assessment information is in uncertain languages, and when there is a problem in the case satisfaction order. Xia

State of the literature

- This description is more of intuitive, rather than subjective, way of showing such aspects of a role.
- This research clarifies the nature and purpose of decision-making, carefully analyzes the specific factors that influence teacher evaluations, establishes a hierarchical modular-based teaching job evaluation system, and determines the weights for evaluation criteria relative to evaluation objectives.
- A multi criteria group decision-making model based on the combination of the decision tree model and the cloud model is presented to provide a reliable basis for the qualitative and quantitative conversion for college teacher evaluation.

Contribution of this paper to the literature

- The proposed method assists the completion of the multi-criteria college teacher evaluation with uncertain language.
- It is hoped that the results of this research can replace expert evaluation completely while increase the confidence of the teacher evaluation results.
- 3. This paper can provide a reliable basis for addressing linguistic decision-making problems for college teacher evaluation.

Chen etc., established a description cloud and an evaluation cloud with the concept of cloud model for multi-criteria group decision-making, designed a cloud set aggregation algorithm and achieve a case make up of multi criteria values (Wang & Liu, 2012). Some scholars have presented many cloud model solution to the problems of group decision making, embodying the advantages of the cloud model, but as for problems like settling the experts weight, whether the experts' evaluation level of each attribute is scientific, whether the experts evaluations are subjective, and experts' evaluation costs...etc. still need to be further addressed (Chen & Fan, 2009; Wei, & Yi, 2009).

Building upon previous research experiences and aimed towards a decision making system, this research proposes a multi criteria group decision-making model based on the combination of the decision tree model and the cloud model which can provide a reliable basis for the qualitative and quantitative conversion for college teacher evaluation.

The rest of this paper is organized as follows. In Section 2, the definition of the cloud model and Decision Tree algorithm (DT) are briefly reviewed. Section 3 describes the steps of decision tree model and cloud model-based multi-criteria group decision making in detail. The experiment results and discussions are presented in Section 4. Finally, Section 5 concludes the paper.

BASIC METHODOLOGIES REVIEW

Uncertain linguistic variables related concepts

Definition 1 (Xu, 2006): When making a qualitative measure, decision-makers need to set an appropriate language assessment scale, assuming $H = \{H_i | i = -g, \dots, 0, \dots, g, g \in N^*\}$, in which N^* belongs to the set of positive integers, H_i represent the value of the natural language variable decision-makers may actually use, H_{-g} and H_g denote the upper and lower limit of the language variable set. Defined $H = \{H_i | i = -g, \dots, 0, \dots, g, g \in N^*\}$ herein, and satisfies:

$$(1) \text{ If } i > j, \text{ then } H_i > H_j.$$

$$(2) \text{ There is a negative operator: } \text{neg}(H_i) = H_{-i}$$

Definition 2 (Wang & Liu, 2012): in a certain natural language evaluation set $H = \{H_i | i = -g, \dots, 0, \dots, g, g \in N^*\}$, assuming uncertain linguistic value $Y' = [Y_\alpha, Y_\beta]$ ($-g \leq \alpha \leq \beta \leq g$), so $\text{len}(Y') = \beta - \alpha$, then the uncertainty of uncertain linguistic value Y' can be defined as $\psi(Y') = \text{len}(Y') / (2g + 1)$.

Definition 3 (Wang & Liu, 2012; Xu, 2006; Xu & Da, 2004): A multi-criteria group decision-making problem states, for some decision-makers d_k , the uncertain linguistic values in case A_i under criteria C_j is $a_{ij}^k = [\underline{a}_{ij}^k, \bar{a}_{ij}^k]$, so that $R_i^k = (a_{i1}^k, a_{i2}^k, a_{i3}^k, \dots, a_{im}^k)$ is the evaluation vector for case A_i with the decision-maker d_k , $R^k = (a_{ij}^k)_{m \times n}$ is decision-maker d_k 's evaluation matrix for all cases. When evaluating the uncertainty for all programs

$$\psi(R^k) = \sum_{i=1}^m \sum_{j=1}^n \text{len}(a_{ij}^k) / (2g + 1) \quad (1)$$

Definition 4 (Wei, Huang, & Wei, 2007): In group decision making, assuming the matrix the decision-maker d_k evaluated is $R^k = (a_{ij}^k)_{m \times n}$, the degree of deviation

between decision-maker d_k 's evaluation and other decision makers' evaluation is called the decision-maker degree of deviation, referred to the degree of deviation, thus $DS(a_{ij}^k, a_{ij}^t) = \sqrt{(\underline{a}_{ij}^k - \underline{a}_{ij}^t)^2 + (\bar{a}_{ij}^k - \bar{a}_{ij}^t)^2}$. Deviation of the two uncertain linguistic variables can be expressed as

$$f_k = \sum_{t \neq k} \sum_{i=1}^m \sum_{j=1}^n DS(a_{ij}^k, a_{ij}^t) \tag{2}$$

The cloud model and relevant knowledge

Definition 5 (Wu, Zeng, & Tu, 2010; Wang & Liu, 2012): Provided that U is an accurate quantitative value domain, C is the qualitative concept on U , if the quantitative value $x \in U$, and x is a random realization of qualitative concept C , x 's degree of certainty to C $y_T(x) \in [0,1]$ is a random number with a tendency of stability. $y_T(x): U \rightarrow [0,1], \forall x \in C (C \subseteq U), x \rightarrow y_T(x)$, then the x distributed over U are called the cloud, denoted $C(x)$. Each x is called a cloud droplet. If the concept's corresponding domain-dimensional space is n , then you can extend to the n cloud dimension. If x satisfies $x \sim N(Ex, En'^2)$, $y \in [0,1]$ where, $En' \sim N(En, He^2)$ and x to C certainty satisfies equation (3), then x is located the normal cloud on U . (Wu, Zeng, & Tu, 2010; Wang & Liu, 2012) conducted an in-depth research on the universality of the normal cloud used to represent uncertain knowledge.

$$y = e^{-\frac{(x-Ex)^2}{2(En')^2}} \tag{3}$$

Definition 6 (Wu, Zeng, & Tu, 2010; Wang & Liu, 2012): Assuming that decision-makers use natural language sets $H = \{H_i | i = -g, \dots, 0, \dots, g, g \in N^*\}$ (where the value g is determined by actual needs), at the same time, experts have determined the domain as $[X_{\min}, X_{\max}]$. When representing the language variable value with the cloud model, the cloud between $2g+1$ clouds is $Y_0(Ex_0, En_0, He_0)$, the corresponding natural language focuses H_0 . Adjacent clouds to $Y_0(Ex_0, En_0, He_0)$ can be expressed as:

$$Y_{-1}(Ex_{-1}, En_{-1}, He_{-1}), Y_1(Ex_1, En_1, He_1), \dots, Y_{-g}(Ex_{-g}, En_{-g}, He_{-g}), Y_g(Ex_g, En_g, He_g)$$

If natural language set H_i is mapped to the membership $\theta_i (i = -g, \dots, 0, \dots, g)$, can be expressed as:

$$f: H_i \rightarrow \theta_i (i = -g, \dots, 0, \dots, g)$$

$$\theta_i = \begin{cases} \frac{a^g - a^{-i}}{2a^g - 2} & (-g \leq i \leq 0) \\ \frac{a^g + a^i - 2}{2a^g - 2} & (0 < i \leq g) \end{cases} \tag{4}$$

We can also obtain the five clouds ($g=2$) needed for this paper, calculations are all follows (Wu, Zeng, & Tu, 2010; Wang & Liu, 2012 ; Xu, 2006):

(1) Calculating Ex_i :

$$Ex_i = X_{\min} + \theta_i (X_{\max} - X_{\min}) \tag{5}$$

(2) Calculating En_i : The cloud model generator algorithm shows that the cloud droplets x with Ex as expectation, En_i' as the variance to meet a normal random number that $x \sim N(Ex_i, En_i')$, thus En_i' satisfied with En as

expectation value; a normal random number with He as the variance, obtained through reference (Wang & Liu, 2012):

$$En'_i = \begin{cases} (1-\theta_i)(X_{\max}-X_{\min})/3 & -g \leq i \leq 0 \\ \theta_i(X_{\max}-X_{\min})/3 & 0 < i \leq g \end{cases} \quad (6)$$

$$En_{-i} = En_i = \begin{cases} (\theta_{|i-1} + \theta_{|i|} + \theta_{|g|})(X_{\max}-X_{\min})/9 & 0 < |i| \leq g-1 \\ (\theta_{|i-1} + \theta_{|i|})(X_{\max}-X_{\min})/6 & |i| = g \\ (\theta_i + 2\theta_{i+1})(X_{\max}-X_{\min})/6 & i = 0 \end{cases} \quad (7)$$

(3) Calculating the expectation: $He_{-i} = He_i = (En'^+ - En_i)/3$, where $En'^+ = \max_k \{En'_k\}$.

For example, given domain by expert $[X_{\min}, X_{\max}] = [0, 10]$, the uncertainty of natural language sets $H = \{H_{-2} = \text{very bad}, H_{-1} = \text{bad}, H_0 = \text{normal}, H_1 = \text{good}, H_2 = \text{excellent}\}$, natural language evaluation level converting to integrated cloud process:

(1) According to the results of the literature (Wang & Liu, 2012; Lu & Zhang, 2003), this research determined the rating scale $g=2$ and selected $a=1.36$. Then, the membership values θ_i :

$$\theta_{-2} = 0, \theta_{-1} = 0.2881, \theta_0 = 0.5000, \theta_1 = 0.7119, \theta_2 = 1.0000$$

(2) The expectation Ex_i :

$$Ex_{-2} = 0, Ex_{-1} = 2.8814, Ex_0 = 5.0000, Ex_1 = 7.1186, Ex_2 = 10.0000$$

(3) The estimating entropy En'_i :

$$En_{-2}' = 3.3333, En_{-1}' = 2.3729, En_0' = 1.6667, En_1' = 2.3729, En_2' = 3.3333$$

(4) The entropy En_i :

$$En_{-2} = 2.8531, En_{-1} = 2.4576, En_0 = 2.1375, En_1 = 2.4576, En_2 = 2.8531$$

(5) The High entropy He_i :

$$He_{-2} = 0.1601, He_{-1} = 0.2919, He_0 = 0.3986, He_1 = 0.2919, He_2 = 0.1601$$

The Distribution of clouds with 5 rating scales is shown in the following Figure 1.

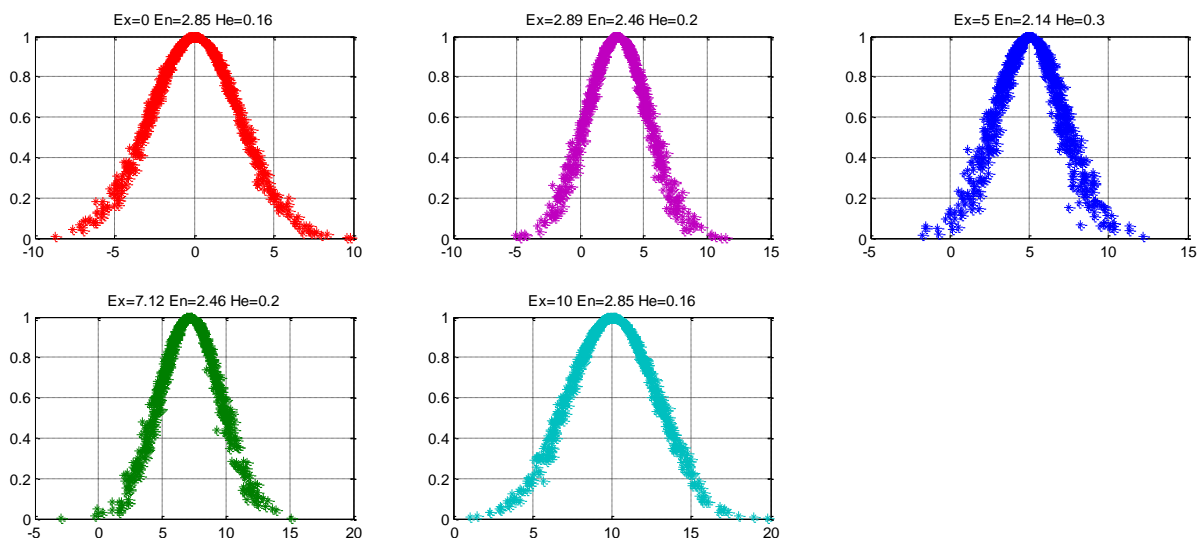


Figure 1. The Distribution of clouds with 5 rating scales

Definition 7 (Wang & Liu,2012): Set uncertain language as $[s_i, s_j]$, which were converted into two clouds, so $s_i \rightarrow Y_i = (Ex_i, En_i, He_i)$ as left cloud, $s_j \rightarrow Y_j = (Ex_j, En_j, He_j)$ for the right cloud, the two get $Y' = (Ex, En, He)$ referred to as a comprehensive cloud. When expectations between two clouds is large enough to disjoint two clouds $(Y_i \cap Y_j = \emptyset), |Ex_j - Ex_i| > 3|En_j - En_i|$, then each digital characteristics that generates the integrated cloud model $Y' = (Ex, En, He)$ is calculated as follows:

$$\begin{aligned}
 Ex &= [(Ex_i + 3En_i) + (Ex_j - 3En_j)] / 2 \\
 En &= \max\{(Ex - Ex_i) / 3, (Ex_j - Ex) / 3\} \\
 He &= \sqrt{He_i^2 + He_j^2}
 \end{aligned}
 \tag{8}$$

The principle of expectation is the midpoint of the right cloud curve and the left cloud curve. Because two clouds are way off, to overlap the domain of the two cloud expectation curves before the merge with a cloud on the domain after the merge, the uncertainty of the cloud would be too large. Therefore, this paper extracts domains till the expectation value.

Definition 8 (Wang & Liu, 2012): When an intersection exists between the left and right clouds, $(Y_i \cap Y_j \neq \emptyset)$ there is $|Ex_j - Ex_i| < 3|En_j - En_i|$, then the digital characteristics of the cloud model generated are calculated as follows:

$$\begin{aligned}
 Ex &= \frac{Ex_i En_j + Ex_j En_i}{En_i + En_j} \\
 En &= \max(En_i + (Ex - Ex_i) / 3, En_j + (Ex_j - Ex) / 3) \\
 He &= \sqrt{He_i^2 + He_j^2}
 \end{aligned}
 \tag{9}$$

The principle of expectation is the intersection of the two cloud model expectation curve, the entropy principle is that the cloud model domain post-merger must cover the two cloud expectation curve domain pre-merger.

Definition 9 (Wang & Liu, 2012): In domain U there are n cloud drops, $Y_1(Ex_1, En_1, He_1) Y_2(Ex_2, En_2, He_2) \dots, Y_n(Ex_n, En_n, He_n)$ that can generate a floating cloud, which represents a blank linguistic value expressed by two clouds between qualitative concepts. When the floating clouds move from the first to the second cloud, effects from the first cloud gradually reduces and the influence of the second cloud gradually increases. If you generate a floating cloud the digital characteristics are $Y(Ex, En, He)$, if $\omega_1, \omega_2, \dots, \omega_n$ is the attribute weights

$$\begin{aligned}
 Ex &= \omega_1 Ex_1 + \omega_2 Ex_2 + \dots + \omega_n Ex_n \\
 En &= \frac{\omega_1 Ex_1 En_1 + \omega_2 Ex_2 En_2 + \dots + \omega_n Ex_n En_n}{\omega_1 Ex_1 + \omega_2 Ex_2 + \dots + \omega_n Ex_n} \\
 He &= \sqrt{He_1^2 + He_2^2 + \dots + He_n^2}
 \end{aligned}
 \tag{10}$$

Definition 10 (Wang & Liu, 2012): Cloud droplets (x, y) allow the concept T to use $s = xy$ to represent the score function. Any cloud, as long as it is constituted by cloud droplets (assumed it is cloud A), then the estimated value s' can be understood as the sum of cloud A and the concept T .

According to definition 10, in theory, clouds can be compared. However, in most cases, the distribution of s is unknown, and s' might not be obtainable. If it is possible to get enough cloud droplets as an example, the s data in these examples can be used as the cloud's s' . Based on the various features of the cloud and its subsequent

application of cloud generator, n clouds can produce cloud droplets $\langle (x_1, y_1), (x_2, y_2), \dots, (x_n, y_n) \rangle$, cloud A 's s' forecast data can be represented as follows

$$s' = \frac{1}{n} \sum_{i=1}^n x_i y_i \tag{11}$$

There are two clouds A and B , if $s'(A) \geq s'(B)$ then $A \geq B$.

Decision tree

Although decision trees have been in development and use for over 50 years, many new forms of decision trees are evolving that promise to provide exciting new capabilities in the areas of data mining and machine learning in the years to come.

Decision tree algorithm builds the tree top-down in the following way: At the root node r , the database is examined and the best splitting criterion $crit(r)$ is computed. Recursively, at a non-root node n , $F(n)$ is examined and from it $crit(n)$ is computed. (Rokach & Maimon, 2008). This structure is shown in Figure 2 and the schema is expressed as follows:

Input: node n , partition D , classification algorithm CL
 Output: decision tree for D rooted at n

Top-down decision tree induction schema

- BuildTree(Node n , data partition D , algorithm CL)
- (1) Apply CL to D to find $crit(n)$
 - (2) let k be the number of children of n
 - (3) if ($k > 0$)
 - (4) Create k children c_1, \dots, c_k of n
 - (5) Use best split to partition D into D_1, \dots, D_k
 - (6) for ($i=1; i \leq k; i++$)
 - (7) BuildTree (c_i, D_i)
 - (8) endfor
 - (9) endif

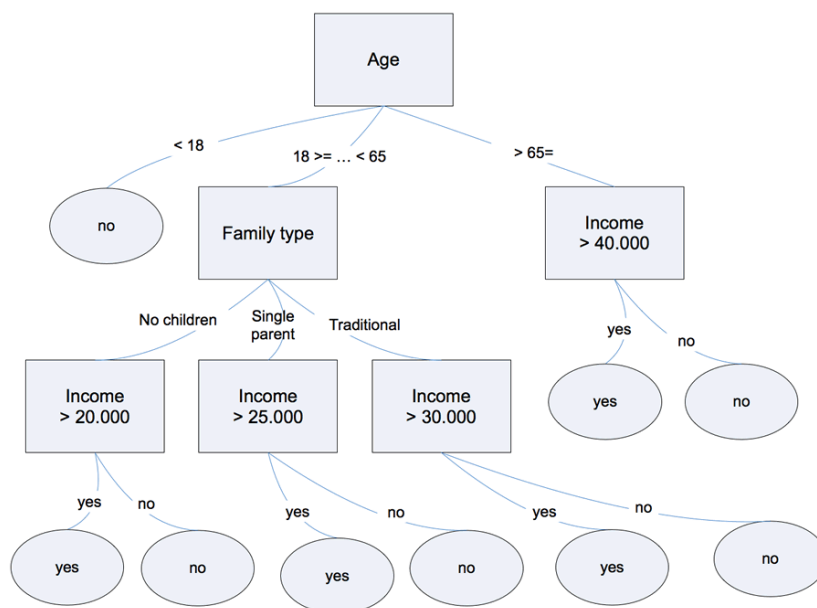


Figure 2. Decision tree structure

UNCERTAIN LANGUAGE GROUP DECISION MAKING MODEL BASED ON DECISION TREE AND CLOUD MODEL

Teachers' evaluation is a very complex process. The three key points that impact the results of the assessment are: establishment of the teachers' job evaluation system, reflection of the various evaluation criteria in respect to the weights and whether or not the evaluator of the teachers' work is objective. To achieve this, selecting the appropriate evaluation index depending on the evaluation objectives, indicating a clear structural relationship between the evaluation index and objectives, and establishing a proper evaluation system are all critical and fundamental tasks. Furthermore, ensure the data collected during the evaluation process are true and accurate so that the evaluation results can justly reflect the evaluated. Finally, in order to avoid the influence of subjective factors within the evaluators, assemble a group of experts and combine their judgments to improve the accuracy of the evaluation results. This research uses data mining techniques combined with the cloud model for a teachers' job evaluation, as shown in Figure 3, the corresponding evaluation process, specific evaluation procedures are as follows:

First, clarify the nature and purpose of decision-making, carefully analyze the specific factors that influence teacher evaluations, establish a hierarchical modular-based teaching job evaluation system, and determine the weights for evaluation criteria relative to evaluation objectives.

Second, collect expert evaluation data, process data, establish training set to build the decision trees, extract evaluation rules, simplify evaluation process, while reducing the cost of evaluation in real applications.

Finally, establish the interval cloud evaluation matrix through the decision cloud, transforming the evaluation value through the cloud model, determining the order of importance of the decision program, and make the decision.

Establishment of the Evaluation Model of College Teachers

Any evaluation activity includes two aspects: first, determine the evaluation index, and second, select an evaluation method. In the case of evaluation of teachers, a clear evaluation of the content and structure of the relationship, establishment of an appropriate evaluation system is the key foundational task. Evaluators collect

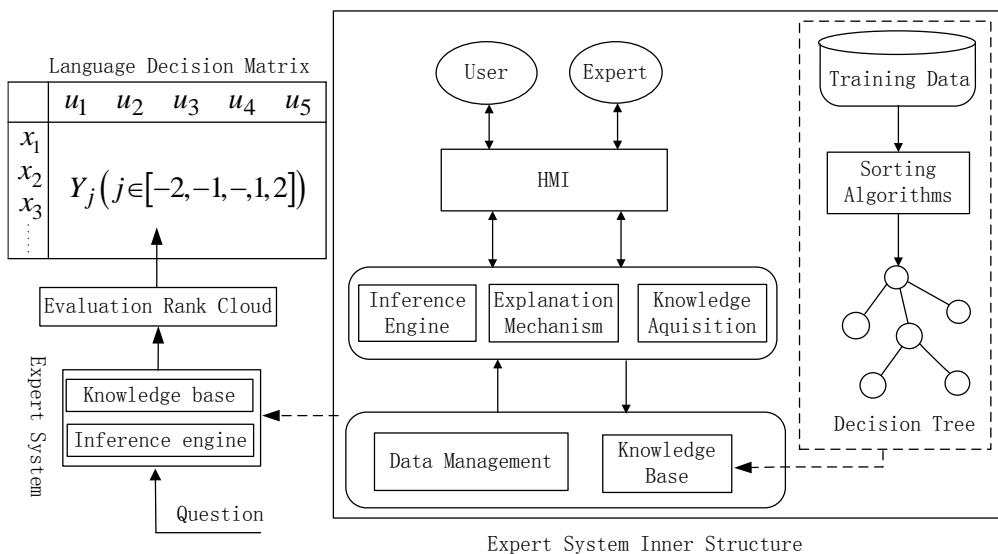


Figure 3. Evaluation process through data mining techniques

extensively for facts and information about the behavior and related activities of the evaluated teacher on the basis of this information. At the same time, select the appropriate evaluation method to determine the relative weight of the target of evaluation, reflecting the importance of the evaluation criteria relative to the evaluation objectives. Therefore, determination of a scientific and reasonable evaluation index is a vital link that directly impacts the orientation and effect of the evaluation because the index system affects the validity and value of the whole evaluation. The following are details on the two aspects of teachers' evaluation: the index system and the determination of weights.

(1) Teachers' Evaluation Index System

According to the characteristics of teaching and work regulations, the index system is adopted in accordance to four major aspects: code of ethics, teaching standards, academic standards and practical results. The specific method is to subdivide the four indicators which are further into a number of evaluation factors and are divided into different levels, constructing a multi-level model. The specific structure is shown in the following Figure 4.

- | | | |
|--------------------------|-----------------------------|----------------------------|
| B1: Professional ethic | C15: After-school tutoring | C32: Monograph publication |
| B2: Teaching level | C21: Teaching attitude | C33: Research project |
| B3: Academic level | C22: Teaching content | C34: Industrial project |
| B4: Practical ability | C23: Teaching method | C41: Student intern |
| C11: Morality | C24: Teaching effectiveness | C42: Patent implementation |
| C12: Student attitude | C31: Paper publication | C43: others |
| C13: Teaching enthusiasm | | |
| C14: Tardiness | | |

(2) Determine the index weight

Through setting the index weight, it indicates the importance of this index throughout the evaluation system. The greater weight value, the greater the impact on the result of the teachers' evaluation index, which also reflects the difference between the indexes. Therefore, when analyzing the indexes, consider the impact and importance of the index on the entire system and reduce and avoid the impact of subjective factors. Therefore, establish the index weight through scientific methods, such as the Control allocation method, AHP, Delphi and expert-opinions average method. In this paper, AHP and Delphi methods combined determine the index weight. Invite educational experts to prioritize the indexes and calculate the weighted average of the judgment matrix to determine the corresponding maximum eigenvalue and eigenvectors using the Delphi method. Finally, apply the consistency test.

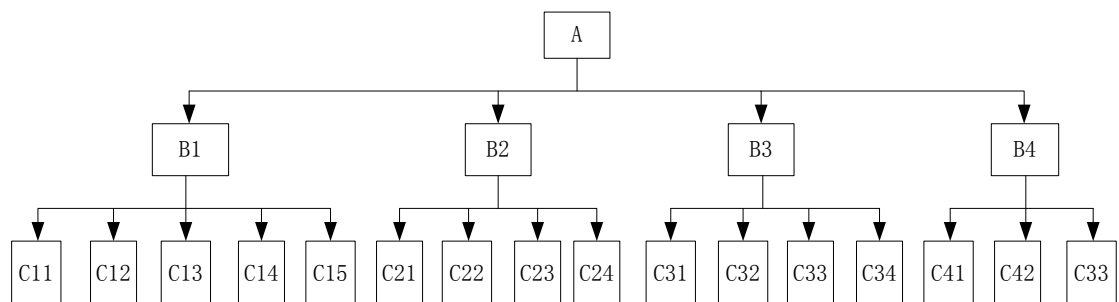


Figure 4. Teachers evaluation index system diagram

Table 1. B_4-C_{4i} Judgment matrix

$A-B_i$	B1	B2	B3	Weight (W)
B1	1	1/5	1/3	0.105
B2	5	1	3	0.637
B3	3	1/3	1	0.258

Calculate the relative weight of the first, second, and third level indexes according to the aforementioned steps. Table 1 is adopted as an example using B_4-C_{4i} .

First, calculate the product matrix of the elements of each row

$$M_i = \prod_{j=1}^4 b_{ij}, \quad j=1,2,\dots,n \quad (b_{ij} \text{ represents the elements of the } i \text{ row and the } j \text{ column})$$

Second, calculate the n th root of M_i

$$\bar{W}_{b1} = \sqrt[3]{1 \times \frac{1}{5} \times \frac{1}{3}} = 0.405, \quad \bar{W}_{b2} = \sqrt[3]{5 \times 1 \times 3} = 2.46, \quad \bar{W}_{b3} = \sqrt[3]{3 \times \frac{1}{3} \times 1} = 1$$

Then from normalizing $\bar{W}_i = (\bar{W}_{b1}, \bar{W}_{b2}, \bar{W}_{b3})^T = (0.405, 2.466, 1)^T$, we get eigenvector :

$$\sum_{i=1}^3 \bar{W}_i = 3.871, \quad W_1 = 0.105 \quad W_2 = 0.637 \quad W_3 = 0.258.$$

We get eigenvector: $W = (0.105, 0.637, 0.258)$ from normalizing, indicating the first level indexes are very important. It is obvious that the maximum vector for teachers' teaching standards is 0.637, indicating that teaching standards are quite important in the teachers' evaluation along with academic standards at 0.258 right behind. The lowest is 0.105, for code of ethics. It is important to note that weight vectors are not absolute indicators of their importance, for example, the vector for code of ethics is low, albeit it is very important during the process of teachers' evaluation.

Third, calculate the eigenvalue of the judgment matrix

$$\text{Since } \begin{bmatrix} 1 & 1/5 & 1/3 \\ 5 & 1 & 3 \\ 3 & 1/3 & 1 \end{bmatrix} \times \begin{bmatrix} 0.105 \\ 0.637 \\ 0.258 \end{bmatrix} = \begin{bmatrix} 0.318 \\ 1.196 \\ 0.785 \end{bmatrix}, \text{ then}$$

$$\lambda_{\max} = \sum_{i=1}^n \frac{(AW)_i}{nW_i} = \frac{0.318}{3 \times 0.105} + \frac{1.196}{3 \times 0.637} + \frac{0.785}{3 \times 0.258} = 3.037$$

The maximum eigenvalue λ_{\max} is 3.307, and judgment in pairwise matrix consisting of level indicators, the n value is 3. In order to ensure the accuracy and rigor, they must assess the consistency test.

$$C.I. = \frac{\lambda_{\max} - n}{n-1} = \frac{3.037-3}{2} = 0.019, \quad C.R. = \frac{C.I.}{R.I.} = \frac{0.019}{0.52} = 0.033 < 0.1, \text{ satisfactory consistency.}$$

CI and CR mean values less than 0.1, therefore B_4-C_{4i} has satisfactory consistency. The calculated result obtained proved to be acceptable and can be applied to the evaluation work. By the same token we can get the weights of the judgment matrix $B_i (i=1,2,3)$ and check its consistency. The results are shown in the following Table 2, Table 3 and Table 4.

From this, we can get each of the index value relative to the total index weight at the bottom of the teachers' evaluation system.

$$W_A = [0.035, 0.3593, 0.0752, 0.1688]^T$$

$$W_{B1} = [0.0516, 0.0244, 0.0097, 0.0145, 0.0048]^T$$

Table 2. B_1-C_{1j} Judgment matrix

B_1-C_{1j}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_{11}	1	2	3	4	7
C_{12}	1/2	1	3	2	5
C_{13}	1/3	1/3	1	1/2	1
C_{14}	1/4	1/2	2	1	3
C_{15}	1/7	1/5	1	1/3	1

$W=(0.491,0.232,0.092,0.138,0.046)$, $\lambda_{\max}=5.126$, $C.I.=0.032$, $C.R.=0.028<0.1$ *satisfactory consistency.*

Table 3. B_2-C_{2j} Judgment matrix

B_2-C_{2j}	C_{21}	C_{22}	C_{23}	C_{24}
C_{21}	1	1/7	1/3	1/5
C_{22}	7	1	5	2
C_{23}	3	1/5	1	1/3
C_{24}	5	1/2	3	1

$W=(0.055,0.564,0.118,0.265)$, $\lambda_{\max}=4.117$, $C.I.=0.039$, $C.R.=0.042<0.1$, *satisfactory consistency.*

Table 4. B_3-C_{3j} Judgment matrix

B_3-C_{3j}	C_{31}	C_{32}	C_{33}	C_{34}
C_{31}	1	1	3	3
C_{32}	1	1	3	3
C_{33}	1/3	1/3	1	1
C_{34}	1/3	1/3	1	1

$W=(0.406,0.406,0.094,0.094)$, $\lambda_{\max}=4$, $C.I.=0$, $C.R.=0<0.1$, *satisfactory matrix*

$$W_{B2}=[0.035,0.3593,0.0752,0.1688]^T$$

$$W_{B3}=[0.1047,0.1047,0.0243,0.0243]^T$$

Generation of the decision tree

In group decisions, many variable values are continuous and gradual. The goal is not to arrive at a precise output value, but to be able to make decisions while keeping the output control desirable within a certain optimization range. The decision or classification conditions or target values are expressed with cloud discrete expression; decision tree and cloud theory not only increase the intelligibility of knowledge, they also ensure the continuity of decisions or classification results. A decision tree is a top-down recursive partition type of structure, each decision or event (i.e. natural state) are likely to lead to two or more events and to different results. The generation "tree" can be divided into five steps: data preparation, decision tree construction, tree pruning, rule derivation and validation rules;

Step1: Data preparation

Data preparation includes two stages: data selection and data preprocessing. During the data mining process, complex data structures, large amounts of data, data discrepancies and data duplicates can cause negative impacts on data mining.

(1) Data determine the project objectives, develop mining plans.

(2) Data collection and acquisition. After the development of the mining project, according to the defined business object, ensuring that mining is at the data sources needed, extracting and collecting from various types of data sources.

(3) Data gathering. Data aggregation refers to the integration of data from multiple data sources, examination of the legality of data collection and data values, description under a unified standard, elimination of inconsistent or redundant including other cleaning and finishing and resolution of semantic ambiguity in order to offer a good foundation for data mining.

Step2: Decision tree construction

During the data mining process, the basis of decision tree is built upon the classical algorithm ID3 and knowledge analysis on sample data through C4.5 algorithm. All the characteristic properties of the calculated data sample are desired information and gained information values, but the information values are more suitable for small amount of output data than information ratios, and the information ratios are more suitable with a large number of data or output data than information value. Therefore, by calculating the information gain ratios of the characteristic properties, test ratio of information gain and select the corresponding property to the maximum as the split indicator of the decision tree so that the smallest tree node will obtain the maximum information.

Step3: Tree Pruning

If, during the decision tree generation process, data and categories grew excessively, then an oversized tree or oversized nodes would form and this is not conducive to making decisions (or deriving rules). Therefore, during the generation process of the decision tree, utilize the pruning strategy before and after generation to terminate construction. This paper applies the first pruning threshold law. Set an information gain value as the split threshold. Once the information gain is less than the split threshold, the tree will stop splitting at the node. Otherwise, the decision tree that stopped dividing in advance or the final sample forms a unified property.

Step4: Deriving Rules

According to the decision tree after pruning, knowledge can be found, namely obtaining the factors that impact the quality of university teachers by the "if-then" method.

In short, after the target and condition variables goes through training, you can generate a cloud tree based on the weight of each target variable through fuzzy inference layer with the analytical layer. But in order to ensure optimum generation of cloud tree, reducing and consolidating branches are necessary to make a simple configuration. This can enhance the simplicity and comprehensibility of the cloud tree, ensuring the efficiency of the cloud decision tree.

Interval cloud decision algorithm

Upon the basic theories in 3.1 and 3.2, assume that there are m decision criterions in an evaluation system $C=\{C_1, C_2, \dots, C_m\}$, corresponding criteria weights vectors are $\omega=\{\omega_1, \omega_2, \dots, \omega_m\}$ and $\omega_j \in [0,1], \omega_1 + \omega_2 + \dots + \omega_m = 1$. There are n cases, set \tilde{S} as the evaluation value in case A under the criteria C , $\tilde{S}=[s_i, s_j]$. Say there are k decision makers $D=\{d_1, d_2, \dots, d_k\}$ with unknown corresponding weight vectors. Decision maker d_k expressed the uncertain language matrix $R^k=(a_{ij}^k)_{n \times m}$. The decision maker is neutral; he or she determines the order of the cases.

Decision steps for the question above are as follows:

Step1: Transform the expert system into decision-making information

By classifying and training the sample set, a decision tree form. In the case of absence of evaluation experts, directly input valid data to obtain the corresponding level of comprehensive evaluation. The method of generating evaluation levels from experts' decisions during decision-making process is shown in the following figure.

Step2: Transform evaluation levels into evaluation integrated clouds

Apply the golden section method to generate 5 clouds ($Y_{-2}, Y_{-1}, Y_0, Y_1, Y_2$). Once domain $[X_{max}, X_{min}]$ is set, you can transform the evaluation levels in Step1 to evaluation clouds (Ex, En, He).

For example: The expert evaluation system in the decision tree transforms information from each case into ratings such as "excellent", "good", "average" and "poor", "very poor". Apply the golden section method and convert each evaluation levels into the form of evaluation clouds (Ex, En, He).

If the given domain $[X_{max}, X_{min}]$ is $[0,10]$, then we get the following from definition 6:

The five level clouds are: $Y_{-2}(0,2.85,0.16)$, $Y_{-1}(2.88,2.46,0.29)$, $Y_0(5,2.14,0.40)$, $Y_1(7.12,2.46,0.29)$, $Y_2(10,2.85,0.16)$ respectively.

Step3: Comprehensive cloud evaluation

Build your preference through the floating cloud method in the cloud theory, using formula (8) or formula (9) to generate a comprehensive evaluation value for each criteria value of a case.

For example: Suppose there are six evaluation criteria in a case, the evaluation clouds are $e_1=(4,0.437,0.073)$, $e_2=(3,0.707,0.118)$, $e_3=(2,0.437,0.073)$, $e_4=(2,0.437,0.073)$, $e_5=(1,0,0)$ and $e_6=(1,0,0)$ respectively. In accordance with formula (), integrated cloud method, the specific process can be expressed as (assume that each evaluation criteria are equally weighted $\omega_1=\dots=\omega_6=\frac{1}{6}$):

$$Ex = \frac{1}{6}(1+2+4+3+2+1) = 2.17$$

$$En = \frac{1 \times 0 + 2 \times 0.437 + 4 \times 0.437 + 3 \times 0.707 + 2 \times 0.437 + 1 \times 0}{1+2+4+3+2+1} = 0.432$$

$$He = \sqrt{0^2 + 0.073^2 + 0.073^2 + 0.118^2 + 0.073^2 + 0^2} = 0.173$$

Obtain a comprehensive evaluation of the case: $(2.17, 0.432, 0.173)$.

Step4: Compare rankings of the candidates' comprehensive evaluation

Compare the rankings according to the comprehensive cloud obtained through the theory of definition 10 and utilizing equation (11).

For example: Assume there are three alternative cases; ultimately resulting in three comprehensive evaluation clouds $A(8,2,0.2)$, $B(5,1,0.1)$, $C(10,0,0.1)$. Using the forward generator in the cloud theory which generates 1000 cloud droplets, it can be calculated, according to the definition, $\hat{s}(A)=5.677$, $\hat{s}(B)=3.549$, $\hat{s}(C)=7.042$. By comparing the three Comprehensive evaluation cloud, we obtain their rankings: $\hat{s}(C) > \hat{s}(A) > \hat{s}(B)$.

ILLUSTRATING EXAMPLE

Teachers' job evaluation system for college teachers is a teaching management assessment platform. Its main function is to organize the evaluation of teachers based on their code of ethics, teaching standards, academic standards and other indicators by collecting evaluation data from subjects such as students, colleagues, and experts...etc., providing the basis for decision making for the next step of development and management plans. The following is the practical application of this theory; using the evaluation method of data mining technologies and cloud model combined to form a comprehensive evaluate the teachers in our university.

Information mining on decision tree technology

Data sources used in this paper are data from the original evaluation of university teachers in eastern Fujian Province over the years. The existing data includes loss of data, inconsistencies, noises and other phenomena, resulting in a lower data quality. In order to ensure simplify the data process and the accuracy of the data results, thereby omitting specific data preprocessing. Here, using teaching standards as an example in following steps.

Step1: Data preparation

Teachers' evaluation standards in eastern Fujian Province University are uniform. Therefore, in specific application, evaluate the teachers, colleges in eastern Fujian Province data over the years based on data mining while the evaluation subject is the work table of teachers in our university in hopes to find the factors that affect the results of the evaluation according to the working conditions of the teachers. We also hope to use the analysis from the results to guide future evaluation of teachers and to improve the quality of teaching. Those preprocessed data are shown in the following Table 5.

The results of the evaluation value (ranging from 0 to 100) are divided into five intervals. Now set results ranging [100, 90] to "excellent", [89,80] is set to "good", [79,70] is set to "average", [69,60] is set to "poor", a score below 60 is set to "very poor". Then for each performance data, the corresponding discrete values obtained are shown in Table 6.

Table 5. Preprocessed data

Teacher's code	Evaluation Index of Teaching Quality			
	teaching attitude	teaching content	teaching method	teaching effectiveness
02001	94	76	92	86
02002	73	82	95	95
02003	92	71	77	96
02004	93	97	96	96
02005	87	83	79	77
02006	96	93	89	83
02007	82	87	91	85
02008	84	86	73	88
02009	92	80	84	93
02010	88	82	93	80

Table 6. Training set

Teacher's code	Evaluation Index of Teaching Quality				Results
	teaching attitude	teaching contents	teaching method	effectiveness	
02001	excellent	poor	excellent	good	good
02002	poor	good	excellent	excellent	good
02003	excellent	poor	poor	excellent	poor
02004	excellent	excellent	excellent	excellent	excellent
02005	good	good	poor	poor	poor
02006	excellent	excellent	good	good	excellent
02007	good	good	excellent	good	good
02008	good	good	poor	good	poor
02009	excellent	good	good	excellent	good
02010	good	good	excellent	good	good

Step2: Decision tree construction

The first decision tree can be split into four factors: teaching attitude, teaching content, teaching methods and teaching effectiveness. This research uses the C4.5 algorithm to calculate the information gain ratio of each property. With 56 teachers as samples for evaluation data, 11 were rated as excellent, 29 were rated as good, 11 averages and 1 poor. In order to make writing the formula easier, the evaluation level is defined as: Y = excellent, L = good, Z = average, J = poor, C = very poor.

First, obtain the information entropy (desired information) needed for classification based on sample data M

$$Info(M) = -\frac{15}{56} \log_2 \frac{15}{56} - \frac{29}{56} \log_2 \frac{29}{56} - \frac{11}{56} \log_2 \frac{11}{56} - \frac{1}{56} \log_2 \frac{1}{56} = 1.566$$

Second, calculate the information gain for all properties of sample M

(1) Calculate the corresponding information gain to the five levels of teaching effectiveness ($C21$) indexes:

For teaching attitude ($C21$) = Excellent (Y), there are classes $C21_Y=21$, $C21_{LY}=5$, $DY_{YZ}=5$, $DY_{YL}=11$. Calculation of information gain for teaching attitude in the "excellent" category of the sample data:

$$Info(C21_Y) = -\frac{5}{21} \log_2 \frac{5}{21} - \frac{11}{21} \log_2 \frac{11}{21} - \frac{5}{21} \log_2 \frac{5}{21} = 1.475$$

For teaching attitude ($C21$) = good (L), there are classes $C21_L=25$, $C21_{LY}=10$, $C21_{LL}=14$, $C21_{LZ}=1$. Calculation of information gain for teaching attitude in the "good" category of the sample data:

$$Info(C21_L) = -\frac{10}{25} \log_2 \frac{10}{25} - \frac{14}{25} \log_2 \frac{14}{25} - \frac{1}{25} \log_2 \frac{1}{25} = 1.183$$

For teaching attitude ($C21$) = average (Z), there are classes $C21_Z=10$, $C21_{LZ}=4$, $C21_{LL}=5$, $C21_{LZ}=1$. Calculation of information gain for teaching attitude in the "average" category of the sample data:

$$Info(C21_Z) = -\frac{4}{10} \log_2 \frac{4}{10} - \frac{5}{10} \log_2 \frac{5}{10} - \frac{1}{10} \log_2 \frac{1}{10} = 1.361$$

(2) By dividing Sample M with teaching effectiveness (D), you get the required desired information:

$$Info_D(M) = \frac{21}{56} \times 1.475 + \frac{25}{56} \times 1.183 + \frac{10}{56} \times 1.361 = 1.324$$

Table 7. The property information

	<i>Info</i>	<i>Gain</i>	<i>SplitInfo</i>	<i>GainRatio</i>
C21	1.367	0.199	1.449	0.137
C22	1.289	0.277	1.541	0.18
C23	1.301	0.265	1.504	0.176
C24	1.324	0.241	1.493	0.143

(3) can be obtained by (1) and (2), teaching effectiveness (C21) information gain is:

$$Gain(C21)=Info(M)-Info_D(M)=1.566-1.324=0.241$$

(4) can be obtained by (1), (2) and (3), teaching effectiveness (D) split information:

$$SplitInfo_D(M)=-\frac{21}{56} \times \log_2 \frac{21}{56} - \frac{25}{56} \times \log_2 \frac{25}{56} - \frac{10}{56} \times \log_2 \frac{10}{56} = 1.493$$

(5) can be obtained by (3) and (4), teaching effectiveness (C21) information gain ratio is as follows:

$$GainRatio(C21)=\frac{Gain(D)}{SplitInfo_D(M)}=\frac{0.214}{1.493}=0.143$$

Similarly, repeat steps (1) - (5), calculate the rest of the property information in the Table 7.

Finally, we get that the teaching content (C22) property information gain ratio was the highest value of several properties; so, the first node of the decision tree should be teaching content (C22) as a split index. Similarly, further divide the tree branch nodes so that all the samples belong to the same class, and no remaining properties can be further divided into new branches tree branches. Stop splitting and the ends become leaf nodes.

Step 3: Tree pruning

Set an information gain value as the split threshold, *Info*=0.79, when a node splits, but its information gain value is less than the threshold, then the tree stops splitting. Otherwise, the decision tree that stopped splitting in advance or the final sample forms a unified property.

Step4: Deriving rules

The final decision tree forms based on the C4.5 algorithm; it can be directly described by the "if-then" approach, the main evaluation factors that influence the work of teachers.

Evaluation Cloud Model

The following is joined with practical application, the use of global assessment method based on data mining technology and cloud model combined to evaluate the works of teachers in colleges. The descriptions above introduce the following conditions: according to 3.1, the university teachers' evaluation system is based on the evaluation indexes and the weight of each index. Second, in accordance with 3.2, cloud evaluation rules act as "experts" and score the candidates. Finally, according to section 3.4, use the golden section method to obtain a language scale for cloud evaluation and decision thinking, that is $s=\{s_{-2}=very\ poor, s_{-1}= poor, s_0= normal, s_1=good, s_2=excellent\}$.

Here we have three candidates up for evaluation and statistical processing to determine the rankings $x_i(i=1\cdots n)$ of the candidates. Evaluation procedures are as follows:

Table 8. Evaluation information sheet

Candidates	Evaluation principle			
	u_1	u_2	u_3	u_4
A_1	$[Y_0, Y_2]$	$[Y_{-1}, Y_1]$	$[Y_1, Y_2]$	$[Y_2, Y_2]$
A_2	$[Y_{-1}, Y_0]$	$[Y_2, Y_2]$	$[Y_{-1}, Y_0]$	$[Y_0, Y_1]$
A_3	$[Y_1, Y_2]$	$[Y_{-2}, Y_0]$	$[Y_2, Y_2]$	$[Y_0, Y_2]$

Table 9. Cloud level differentiating parameters

	S_{-2}	S_{-1}	S_0	S_1	S_2
Affiliation θ_i	0	0.2881	0.5000	0.7119	1.0000
Expectation Ex_i	0	2.8814	5.0000	7.1186	10.0000
Entropy En_i	2.8531	2.4576	2.1375	2.4576	2.8531
High Entropy He_i	0.1601	0.2919	0.3986	0.2919	0.1601

Table 10. Assessment of comprehensive cloud

Candidates	Evaluation principle			
	u_1	u_2	u_3	u_4
A_1	(7.144,3.802,0.4308)	(5,3.167,0.29)	(8.454,3.365,0.3312)	(10,2.85,0.16)
A_2	(4.014,2.838,0.4941)	(10,2.85,0.16)	(4.014,2.838,0.4941)	(5.986,2.838,0.4941)
A_3	(8.454,3.365,0.3312)	(2.856,2.855,0.4308)	(10,2.85,0.16)	(7.144,3.802,0.4308)

Step1: Conversion of information

Through the training set for training, we get a decision tree. Input the information of the candidates and get the following information in Table 8.

Step2: Conversion of decision information

The previously calculated cloud level properties are expressed in the following Table 9: Affiliation θ_i , Expectations Ex_i , Entropy En_i , high Entropy He_i .

Get 5 levels of clouds, which are $Y_{-2}(0,2.85,0.16)$, $Y_{-1}(2.88,2.46,0.29)$, $Y_0(5,2.14,0.40)$, $Y_1(7.12,2.46,0.29)$, $Y_2(10,2.85,0.16)$ respectively. The arrangement of the right and left clouds utilizing definitions and uncertainty languages to a comprehensive cloud, as shown in the following Table 10.

Step3: Comprehensive cloud evaluation

Table 10 shows the clouds generated for each candidate under evaluation criteria, calculate the comprehensive cloud integrating each property based on formula (7).

$$A_1:Y_1(7.523,3.395,0.6364) \quad A_2:Y_2(5.408,2.8424,0.8706) \quad A_3:Y_3(7.822,3.1027,0.7117)$$

Table 11. Comprehensive evaluation score

	Trial 1	Trial 2	Trial 3	Trial 4	Average
s_1'	5.4328	5.4128	5.3380	5.3805	5.391
s_2'	3.9118	3.7883	3.8199	3.7742	3.824
s_3'	5.4476	5.4985	5.5625	5.6084	5.530

$A_3 > A_1 > A_2$ The third candidate is chosen as the best.

Step4: Comparison and ranking

The key technology of the cloud droplet cloud generator uses a normal random number method. Calculate randomly selected values of cloud droplets with formula (9). To ensure the stability of data, four trials are administered and the average of those trials are compared and ranked, as shown in the Table 11.

CONCLUSION

In this paper, teachers in colleges and universities are evaluated by using data mining techniques and combination of cloud models. On the basis of comprehensive analysis technologies, apply the decision tree algorithm. Identify the inherent pattern of the data, analyze the results of data mining to identify the key factors affecting the quality of teaching, so that the results of the evaluation form a series of decision-making rules. Based on this concept, introduce the cloud model, using natural language to describe qualitative values and establish an uncertain transformation model to ensure the accuracy of the evaluation results.

The theory and practice above proved that, as summarized below:

1. Hiring experts to evaluate teachers is not only very costly throughout the evaluation, but would also affect the overall fairness of the evaluation for subjective reasons such as knowledge structure, environmental factors, mood status, etc. Data mining techniques can discover the potential patterns from a large amount of historical data, the potential pattern and potential knowledge can achieve the functions described and even forecasting capabilities. These functions can replace expert evaluation completely while increase the confidence of the evaluation results. This paper first determine project goals, develop mining plans, construct decisions through collecting, acquisition and integration of data, forming a series of decision rules, providing a basis for decision-making with cloud model.
2. The cloud model can fully express the fuzziness and randomness in natural language. Through the three number characteristics, you can retrieve a range and distribution of qualitative and quantitative data from natural language expressed in value. At the same time, it also enables exact value into the appropriate qualitative linguistic expression. Knowledge representation and preference methods of the cloud theory assist the completion of the multi-criteria university teachers' evaluation with uncertain language.
3. The distortion of information caused by the non-uniform cognitions of decision-makers to linguistic terms can be neutralized in the cloud model. However, applying cloud model to linguistic MCDM problems is definitely a new idea. The foundation of this idea involves using the linguistic assessment scale to convert linguistic variables to clouds and using cloud aggregation operators to integrate evaluation information. At this point, the method proposed in this paper can provide a reliable basis for addressing linguistic decision-making problems for college teacher evaluation.

4. The proposed model is only suitable for qualitative and quantitative analysis of multi attribute group decision making with hierarchical structure like problem of teacher evaluation with multi-layer level.

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