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Diversified Cultivation Mode of Differential Teaching in Higher Vocational Law Education

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Abstract. In order to realize the accurate analysis for the diversified training mode of differential teaching of higher vocational law education and reduce the complexity of calculation as well as maintain the precision of classification, a research method on diversified training mode of differential teaching of higher vocational law education based on fuzzy correlation cluster is put forward. Firstly, targeting at the problems of diversified training mode of differential teaching for higher vocational law education, the research thought under such mode is proposed. Secondly, the diversified training mode of differential teaching for higher vocational law teaching with low dimensional characteristic is constructed by adopting fuzzy transformation and fuzzy correlation cluster. Finally, the effectiveness of proposed method is verified through instance analysis.

Key words. Fuzzy correlation cluster, Higher vocational law, Diversification, Training mode
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1. Introduction

Data mining technology is an important application in the law field and clustering algorithm is the common one of data mining technology. What is called "birds of a feather flock together". Clustering is one of the basic cognitive activities of human beings, which can classify the samples automatically. The theoretical innovation can promote institutional innovation, scientific and technological innovation, cultural innovation and innovation in other aspects. Innovation is the soul of a nation's progress and an inexhaustible motive force for the prosperity of a country. The hope of innovation depends on the juveniles and contemporary college students undertake an unshirkable responsibility for innovation. Under such a background, it is an important task for the educators to study how to cultivate the innovative talents in the knowledge-based society.

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In recent years, law major has become one of the largest majors in China, with unparalleled development speed than other disciplines. How to cultivate the innovation capacity of high vocational law professionals becomes a problem to be solved for masses of educators. It is found from the exchange with students majoring in higher vocational law that the employers often ask some questions about the frontier knowledge and research thought in law field during interview, while most of students can not respond calmly. The main reason is that the college students majoring in high vocational law lack of the training on innovation capacity during their school days. In addition to some basic theoretical knowledge, the college students rarely contact practical research project and lack of practical experience, so that it is difficult for them to apply the theoretical knowledge learned into the practical works flexibly. Through the communication with the staffs of employment organization, it is found that the recruitment organization prefers to those applications with experience on research project or project development. Not everyone's innovation derives from scratch, innovation is to explore another channel on existing basis. Therefore, with regard to innovation, theoretical foundation is the most basic part and the practical experience is more important for innovation. Only through practice, students can broaden their minds, fully display imagination and carry forward innovative spirit. Therefore, it is necessary to cultivate the innovation capacity of higher vocational law professionals.

Targeting at the diversified training mode of differential teaching for higher vocational law education, this Paper designs a research method on diversified training mode of differential teaching for higher vocational law education based on fuzzy correlation cluster, proposing the problems and research thought of diversified training mode of differential teaching for current higher vocational education. The diversified training mode of differential teaching for higher vocational law education with low dimensional characteristic is constructed based on fuzzy transformation and fuzzy correlation cluster.

2. Problem description

2.1. Analysis of current talents cultivation problems

In recent years, higher vocational law field has invested large amount of training funds to solve the shortage problem of talents. However, the employer reflects that the input is asymmetric with the output; the employee regards the training as burden, lacking of enthusiasm. The sources resulting in such problems include the following three aspects.

(1) The lack of talents demand standard analysis and employee status analysis results in lack of pertinence and low efficiency.

(2) Lack of training effect evaluation and analysis planning. After investment of training resources aimlessly, the promotion and shortcomings of the employee are still unclear.

(3) Loss of monitoring analysis and dynamic optimal adjustment of training scheme during talents training results in waste of large amount of training resources,

manpower and time resources.

2.2. Research thought on classification training mode of higher vocational law talents

As for how to utilize training resources effectively, output talents required for business development and support the rapid and healthy development of higher vocational law, the following thoughts are put forward through deepening research.

(1) Personalized development assessment and approval standard model is formulated based on the personalized talents demand of higher vocational development to collect the status of existing employee and analyze the difference based on this.

(2) Through the construction of grey whitening weight function clustering model, the index weight and talent classification is confirmed and differential cultivation scheme is configured to excavate the potential of employee in refinement.

(3) Based on talents classification, personalized growth path and cultivation scheme is formulated through school-enterprise joint cultivation mode. Through the combination between theory and practice, internal training and external cultivation, the target rate and satisfaction rate of law talents cultivation of employer and college is greatly promoted and the person-post matching is promoted, providing talents support for the implementation of national energy policy and development planning.

3. Fuzzy correlation cluster

3.1. Method description

Two stages are covered in proposed method: training and testing. The training stage is divided into four procedures: fuzzy transformation, fuzzy correlation cluster. The purpose of training stage is to establish a disaggregated model in one set of training data, transforming the high-dimensional training mode data to the low-dimensional fuzzy correlation vector. The fuzzy cluster is calculated dynamically. During testing stage, the invisible documents can be classified according to the training model acquired from training stage. This stage can be divided into four procedures: fuzzy transformation, calculation of cluster member.

The advantages of proposed method lie in: (1) Dimensionality reduction is conducted through fuzzy transformation, the curse of dimensionality can be effectively avoided. (2) One class of such area is the combination of several sections. Therefore, complex class boundary may exist. (3) Other research method requires that the research area shall be convex, while the algorithm proposed in the Paper can break through such limit.

3.2. Fuzzy transformation

The feature number m in feature set is sizable, which may cause that the training cultivation mode data presents sparse distribution in high-dimensional space and then result in curse of dimensionality. Through fuzzy transformation, the training mode date of m dimension size is converted to the fuzzy relevance vector. Its size is p dimensionality. Where p is the class number in C. In general, p is far less than m. Therefore, it can effectively avoid curse of dimensionality while realizing the effect of dimensionality reduction.

Firstly, the correlation between feature and class can be expressed as a fuzzy relation: $R_1 : T \times C \to [0, 1]$, where the membership value of R_1 can be expressed as $\mu_{R_1}(t_i, c_j)$, which can be used to represent the correlation between feature $t_i \in T$ and $c_j \in C$. Intuitively, if there is feature of greater value in class, the correlation between such feature and class is greater. Such membership relation can be expressed as follows:

$$\mu_{R_1}(t_i, c_j) = \frac{\sum_{v=1}^{n} w_i^{(v)} y_j^{(v)}}{\sum_{v=1}^{n} w_i^{(v)}} \frac{\sum_{v=1}^{n} h_o(w_i^{(v)}) y_j^{(v)}}{\sum_{v=1}^{n} y_j^{(v)}} . \tag{1}$$

In the formula, $1 \le i \le m$, $1 \le j \le p$, and:

$$h_0(x) = \begin{cases} 1, & if\ x > 0\,, \\ 0, & if\ x = 0\,. \end{cases} \tag{2}$$

It shall be noticed that the first part of $\mu_{R_1}(t_i, c_j)$ in Formula (1) intuitively corresponds to the feature of greater correlation value in class with corresponding class. While the second part of $\mu_{R_1}(t_i, c_j)$ in Formula (1) intuitively corresponds to the feature of positive value with more training mode data in the class. The rest correlation of such class is the maximum. Meanwhile, it shall be noticed that the value range of $\mu_{R_1}(t_i, c_j)$ is among $[0, 1]$.

Given $R_2 : T \times D \to [0, 1]$ is another fuzzy relation. The correlation between the feature t_i of concept $\mu_{R_2}(t_i, \boldsymbol{d})$ and training mode data $\boldsymbol{d} =< w_1, w_2, \cdots, w_m >$ can be defined as:

$$\mu_{R_2}(t_i, \boldsymbol{d}) = \frac{w_i}{\max_{1 \le v \le m} w_v} . \tag{3}$$

In the formula, $1 \le i \le m$. Formula (3) shows that the greater the value of w_i is, the greater the correlation between t_i and training mode data $\boldsymbol{d}$. The purpose of denominator $\max_{1 \le v \le m} w_v$ in the equation is to standardize the numerator. Finally, the relevance between training mode data and class can be expressed as the fuzzy relation $S : D \times C \to [0, 1]$. Where, the membership value of S can be expressed as $\mu_S(\boldsymbol{d}, c_j)$. The correlation between the characteristic training mode data d and class c_j can be expressed as:

$$\mu_S(d, c_j) = \frac{\sum_{i=1}^{rm} \diamondsuit(\mu_{R_1}(t_i, c_j))\mu_{R_2}(t_i, \boldsymbol{d}))}{\sum_{i=1}^{rm} \perp(\mu_{R_1}(t_i, c_j), \mu_{R_2}(t_i, \boldsymbol{d}))} . \tag{4}$$

In the formula, $\diamondsuit$ and $\perp$ is indicated as fuzzy conjunction and disjunction, or probability t norm and t complementary norm respectively, which can be expressed as respectively:

$$\begin{cases} \diamondsuit(x, y) = x \times y\,, \\ \perp(x, y) = x + y - x \times y\,. \end{cases} \tag{5}$$

The numerator in Formula (4) shows that if there are more features correlating with the training mode data and class, the correlation between training mode data and class is greater.

Remarks: the value of $\mu_S(\boldsymbol{d}, c_j)$ is within the scope of $[0,1]$. For any two actual value x and y, $x, y \in [0,1]$, then $0 \leq \diamondsuit(x,y) \leq \perp(x,y)$. Therefore, the denominator is greater than or equal to numerator. As for training mode data $\boldsymbol{d} =< w_1, w_2, \cdots, w_m >$, the fuzzy correlation vector of d can be defined as $x =< x_1, x_2, \cdots, x_p >$. Where:

$$x_j = \mu_S(\boldsymbol{d}, c_j)\,. \tag{6}$$

In the formula, $1 \leq j \leq p$. Through fuzzy transformation, the training mode data of m dimensionality can be converted to fuzzy correlation vector of p dimensionality.

Principal component analysis (PCA) has been widely applied in data dimension reduction. However, principal component analysis is more suitable for unsupervised learning. Meanwhile, principal component analysis is applicable only when Gauss noise is involved. In the classification of training mode data, what we are concerned is the training mode data and the leaning training of related training mode data. By applying fuzzy transformation method, the training mode data can be used, which can effectively implement data dimension reduction. In addition, the features involved in training mode data are rarely interfered by random and Gauss noise. Therefore, the principal component analysis is not considered in the Paper.

3.3. Fuzzy correlation cluster

As for n fuzzy vectors $\boldsymbol{x}^{(1)}$, $\boldsymbol{x}^{(2)}$, $\cdots$, $\boldsymbol{x}^{(n)}$ defined, these vector can be classified by clustering algorithm. Some clustering algorithms have been proposed in related literatures. Here the clustering scheme proposed in Literature [15] is adopted and improved. The participating vector is only scanned for once. Furthermore, the user has no need to predetermine the clustering class. On the contrary, new cluster can be established automatically and incrementally. In the proposed clustering scheme, the cluster is regarded as a Gauss spot, which can be described according to the size, average, deviation and training mode data. Given G is a cluster containing q fuzzy correlation vector, $\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_q$. Each fuzzy correlation vector has p elements. Therefore, the size of G is q. Meanwhile, the average of$G$, $\boldsymbol{v} =< v_1, v_2, \cdots, v_p >$ and variance $\boldsymbol{\sigma} =< \sigma_1, \sigma_2, \cdots, \sigma_p >$ can be defined respectively as:

$$\begin{cases} v_i = \dfrac{\sum_{k=1}^{q} x_{i,k}}{q}\,, \\ \sigma_i = \sqrt{\dfrac{\sum_{k=1}^{q}(x_{i,k} - v_i)^2}{q-1}}\,, \end{cases} \tag{7}$$

the training mode data set of G, $\zeta =< \zeta_1, \zeta_2, \cdots, \zeta_p >$, where:

$$\zeta_i = \frac{\sum_{k=1}^{q} y_{i,k}}{q}\,. \tag{8}$$

In the formula, $1 \le i \le p$. What shall be noticed is that the element ζ_i in ζ expresses that the training mode data in cluster G attach to the percentage of class c_i. In addition, the cluster is characterized as membership function, which is composed of the product of p one-dimensional Gauss functions. The reason why Gauss function is adopted is that they have same features, such as smoothness, simple symbol and invariance of multiplication.

Given J is the number of current cluster, which can be expressed as $G_1, G_2, \cdots, G_J$ respectively. The size of each G_j, $1 \le j \le J$, is S_j and the average is $v_j =< v_{1,j}, v_{2,j}, \cdots, v_{p,j} >$, variance is $\sigma_j =< \sigma_{1,j}, \sigma_{2,j}, \cdots, \sigma_{p,j} >$ and the training mode data form is $\zeta_j =< \zeta_{1,j}, \zeta_{2,j}, \cdots, \zeta_{p,j} >$. In initial stage, there is no cluster, $J = 0$. The dynamic cluster is constructed. As for the first fuzzy correlation vector $x^{(1)}$, new cluster can be established through setting $J = 1$:

$$v_1 = \boldsymbol{x}^{(1)}, \zeta_1 = y^{(1)}, \boldsymbol{\sigma}_1 = \boldsymbol{\sigma}_0, S_1 = 1\,. \tag{9}$$

Where, σ_0 refers to the deviation of all the training vectors. As for every successful fuzzy correlation vector $x^{(i)} =< x_1^{(i)}, x_2^{(i)}, \cdots, x_p^{(i)} >$, $2 \le i \le n$, the similarity between $\boldsymbol{x}^{(i)}$ and every cluster G_j can be calculated:

$$\begin{aligned} I_{G_j}(\boldsymbol{x}^{(i)}) &= \ln \prod_{k=1}^{p} \exp[-(\frac{x_k^{(i)} - v_{k,j}}{\sigma_{k,j}})^2] \\ &= -\sum_{k=1}^{p}(\frac{x_k^{(i)} - v_{k,j}}{\sigma_{k,j}})^2 = \sum_{k=1}^{p} g_{k,j}^{(i)}\,. \end{aligned} \tag{10}$$

In the formula, $1 \le i \le J$. Such equation can be used to calculate the convergence of cluster G_j in p dimensional space. When p value is great, logarithm calculation can be adopted to avoid numerical overflow. The cluster similarity test is conducted for $\boldsymbol{x}^{(i)}$ in G_j. If the following condition is met:

$$I_{G_j}(\boldsymbol{x}^{(i)}) \ge \ln \rho^p\,. \tag{11}$$

Here, $\rho, 0 < \rho \le 1$ is a predefined threshold value. If the user requires for a greater cluster, a smaller ρ value can be defined. Otherwise, a greater ρ value can be defined.

Meanwhile, the similarity between $\boldsymbol{x}^{(i)}$ and the training mode data of each existing cluster G_j is defined as:

$$F_{G_j}(x^{(i)}) = \frac{\sum_{k=1}^{p} y_k^{(i)} \wedge \zeta_{k,j}}{\sum_{k=1}^{p} y_k^{(i)} \vee \zeta_{k,j}}\,. \tag{12}$$

Where, $\wedge$ and $\vee$ represents "minimax" and "maximax" operation respectively. Such formula can be used to calculate the number of similar training mode data of G_j and $x^{(i)}$.

$$F_{G_j}(\boldsymbol{x}^{(i)}) \ge \varepsilon\,. \tag{13}$$

Here, $\varepsilon, 0 < \varepsilon \leq 1$ is the predefined threshold value.

$$\boldsymbol{v}_{J+1} = \boldsymbol{x}^{(i)}, \boldsymbol{\zeta}_{J+1} = \boldsymbol{y}^{(i)}, \boldsymbol{\sigma}_{J+1} = \boldsymbol{\sigma}_0, S_{J+1} = 1\,. \tag{14}$$

However, if there is an existing cluster $\boldsymbol{x}^{(i)}$ passing related test, given G_t is the cluster of maximum cluster correlation:

$$t = \arg\max_{1 \leq j \leq J} \left(I_{G_j}(\boldsymbol{x}^{(i)}) \right)\,. \tag{15}$$

Assume that the correlation between $x^{(i)}$ and G_t is the maximum, $x^{(i)}$ is attached to class G_t and brought into σ_t through incremental mode.

$$\begin{cases} \sigma_{j,t} = \sqrt{A - B}, \\ A = \dfrac{(S_t - 1) \times \sigma_{j,t}^2 + S_t \times v_{j,t}^2 + (x_j^{(i)})^2}{S_t}, \\ B = \dfrac{S_t + 1}{S_t} (\dfrac{S_t \times v_{j,t} + x_j^{(i)}}{S_t + 1})^2, \end{cases} \tag{16}$$

$$\begin{cases} v_{j,t} = \dfrac{S_t \times v_{j,t} + x_j^{(i)}}{S_t + l}, \\ \zeta_{j,t} = \dfrac{S_t \times \zeta_{j,t} + y_j^{(i)}}{S_t + 1}. \end{cases} \tag{17}$$

In the formula, $1 \leq j \leq p$. $S_t = S_t + 1$, in such case, J does no change.

When all the fuzzy correlation vectors $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \cdots, \boldsymbol{x}^{(n)}$ are handled, the cluster process is completed. The sequence of fuzzy correlation vector can be acquired by affecting the cluster. Here the elicitation method is applied to determine the sequence. All the vectors are sorted in descending order according to the largest component. More important vector will be sent to the first and possibly core cluster.

Example: given three vectors $\boldsymbol{x}_1 =< 0.1, 0.3, 0.6 >$, $\boldsymbol{x}_2 =< 0.3, 0.3, 0.4 >$ and $\boldsymbol{x}_3 =< 0.8, 0.1, 0.1 >$, the maximum element of such three vectors is: 0.6,0.4 and 0.8. The ranking is 0.8, 0.6 and 0.4. Therefore the feed ranking is $\boldsymbol{x}_3$, $\boldsymbol{x}_2$ and $\boldsymbol{x}_1$.

4. Experimental analysis

4.1. Collection of law talent status

This paper takes the talents adaptation sequence standard as the example. The grey class is set as: Class A-cultivation preference; Class B-backup perpetual object; class C-fundamental and routine work; Class D-seeking for other cultivation direction or others.

Table 1. Talents grey class boundary matrix

	D	C	B	A
Index 1 (professional knowledge)	0∼60	60∼70	70∼85	>85
Index 2 (operational practice)	0∼60	60∼75	75∼90	>90
Index 3 (achievements and results)	0∼60	60∼70	70∼80	>80
Index 4 (performance)	0∼70	70∼80	80∼90	>90

Corresponding to the four grey classes, the whitenization weight function based on "professional knowledge"index is successively: lower limit whitenization weight function $f_1^1(x)$, moderate whitenization weight function $f_1^2(x)$, moderate whitenization weight function $f_1^3(x)$ and upper limit whitenization weight function $f_1^4(x)$, shown as Fig 1.

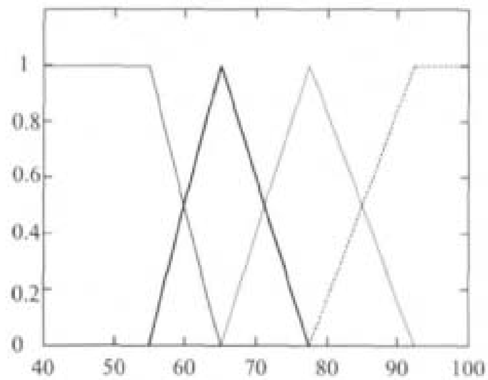

Fig. 1. Whitenization weight function diagram based on index 1.

In the similar way, whitenization weight function can be acquired. The assessment certified value of j^{th} index of i^{th} employee is identified as $x_{ij}(i = 1, 2, \cdots, 5, \cdots;$ $j = 1, 2, \cdots, 4)$ from four dimensional growth integral standard assessments. Matrix A is acquired. Through matlab programming calculation, the sample value is substituted in the function and the whitenization weight function value can be acquired.

4.2. Construction of clustering coefficient matrix

Clustering coefficient matrix vector confirms the grey variable weight cluster coefficient of object i belonging to k grey class as:

$$\sigma_i^k = \sum_{j=1}^{m} f_j^k(x_{ij}) \cdot \eta_j^k, \tag{18}$$

$$\sum = \left(\sigma_i^k\right) = \begin{bmatrix} \sigma_1^1 & \sigma_1^2 & \cdots & \sigma_1^s \\ \sigma_2^1 & \sigma_2^2 & \cdots & \sigma_2^s \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_n^1 & \sigma_n^2 & \cdots & \sigma_n^s \end{bmatrix}, \tag{19}$$

$$\sigma_i^{k*} = \max_{1 \le k \le s} \left\{\sigma_i^k\right\} . \tag{20}$$

The object i is called as grey class k. The clustering coefficient matrix and the clustering results according to it are shown as Table2.

Table 2. Clustering coefficient matrix table

Sample	D	C	B	A	Category
1	0.507	0.436	0.068	0.001	D
2	0.001	0.0014	0.223	0.773	A
3	0.097	0.608	0.298	0.002	C
4	0.472	0.331	0.182	0.003	D
5	0.002	0.353	0.553	0.092	B
6	0.003	0.001	0.417	0.587	A
7	0.208	0.160	0.573	0.052	B
8	0.001	0.201	0.613	0.192	B
9	0.325	0.398	0.271	0.001	C
10	0.001	0.586	0.421	0.002	C

Personalized talents development path and growth cultivation scheme are formulated according to the classification.

(1) Class A talents can be cultivated as core backup talents. The project results and practical activities shall be strengthened for sample 2 to improve the integral of achievement and results. The training on skill operation shall be strengthened for sample 6 to improve its integral level by adopting specific cultivation scheme, which can be admitted to backup talent pool through assessment and certification to motivate the growth of employee.

(2) As for Class B talents, sample 5, sample 7 and sample 8 can be regarded as the backup for cultivation. Sample 5 and sample 8 shall strengthen the training on practical operation and sample 7 shall strengthen the learning and training for professional knowledge. Their growth shall be notice for backup.

(3) As for Class C and Class D talents, the certification results in other sequence shall be analyzed and confirmed, which shall be optimized and adjusted to the optimal development sequence. According to this analysis, the cultivation efficiency can be improved and the cultivation direction can be confirmed so that the talent team is optimized, providing sustainable talents support for the development and planning of higher vocational law.

5. Conclusion

Through construction of grey clustering model and implementation of talent monitoring and quantitative analysis, this Paper assesses and certifies the growth status of the employee and forms talent classification in such aspects as acquisition of knowledge, operational practice, achievement and practice results as well as position performance.

(1) Assessment and certification model for talent sequence development provides reference for the formulation of vocational development planning and growth scheme of the employee, making the employee determine their development striving direction, disintegrate, and implement their goals.

(2) The employer can understand the status of talents, disintegrate the talents demand planning, formulate supporting cultivation scheme according to the industry development demand and deficiency of talent level, invest reasonable training resource and improve the utilization of training resources.

It lays the foundation for improving the school-enterprise joint cultivation efficiency, formulates talent cultivation scheme differentially, which combines the theory and practice and accelerates the cultivation of core talents in law field. The talent echelon with strong comprehensive strength and prominent professional level is formed, supporting the promotion of higher vocational law capability.

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