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A Multilevel Data Analysis and Decision Support System for Ideological Dynamics of Party Members in Higher Education Management

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Abstract The use of big data to build a "smart party building" model, and do a good job of related security, is conducive to more quickly control the overall situation of party building work. In this paper, we propose a method for determining party members' rank by combining principal component analysis and K-means clustering, and combine the improved decision tree algorithm with big data for party building to realize the design of a decision support system for intelligent party building. The research results show that the proposed joint analysis method of dimensionality reduction and clustering can classify party members into different grades, and its k-s test significance is 0.214>0.05, obeys normal distribution, and the observed values are more in line with the expected values, so it can effectively assess the ideological dynamics of party members. The precision and accuracy of the designed decision support system are more stable, maintaining at about 87% and 94% respectively, which is significantly better than the traditional system, and is of great significance to improve the efficiency of management of party members' ideological dynamics in colleges and universities.

Index Terms principal component analysis, K-means, improved decision tree algorithm, party members' ideological dynamics, decision support system

I. Introduction

Ideological and political work has always played the role of "lifeline" to lead thought, cohesion, and stabilization of the team [1]. In the process of high-quality development of colleges and universities, the challenges and difficulties faced by the party members of the impact, corresponding to the characteristics of ideological and political work changes [2]. In order to effectively respond to the challenges of party members' ideological dynamics management, colleges and universities need to establish a set of scientific and reasonable, standardized and efficient, synergistic and powerful linkage management mechanism for party members' ideological dynamics [3], [4]. Taking big data analysis as the core means, it realizes the comprehensive mastery and accurate identification of party members' ideological dynamics by collecting, integrating, analyzing and utilizing all kinds of relevant data of party members [5]. At the same time, the mechanism takes the branch secretary as the main body, and through the establishment of a grid-based linkage pattern, it forms a regularized process of information collection, analysis and processing to achieve timely guidance and effective solutions to the ideological dynamics of party members [6], [7].

For a long time, decision-making has been regarded as a kind of art and skill relying on the personal experience and intuition of decision-makers [8]. With the continuous development of the informationization process, the links between the various departments of universities are becoming closer and closer, and the influence of each other is becoming more and more complex [9], [10]. Under such conditions, simply relying on the insight, reason and experience of decision makers can no longer meet the decision-making needs of the ideological dynamics of university party members [11]. The concept of decision support system was proposed in the 1970s by two people, Scott Morton and Keen, who analyzed the functions, principles, structures and uses of decision support systems, emphasized the positive auxiliary role of such systems for the decision-making process, and since then opened up a new field of applied science [12]-[14]. The application of decision support systems to the analysis of party member ideological dynamics in university management is a path of innovation and development for the analysis of party member ideological dynamics.

In this paper, we use principal component analysis to reduce the dimension of party thought dynamics data and combine it with K-means clustering method to propose a multilevel analysis method of party thought dynamics, which realizes a reasonable determination of party thought dynamics level. Then, an intelligent party building decision support system based on big data was constructed by utilizing the improved decision tree algorithm. Then, the comprehensive evaluation model of party members' ideological dynamics based on principal component analysis-clustering is simulated and examined, and the accuracy and precision of the system are assessed by comparing the constructed system with the traditional system.

II. A Model for Determining Party Members' Ranks and Measuring Ideological Dynamics in Higher Education Management

In this chapter, for the problem of management of party members' ideological dynamics in colleges and universities, a party member grade determination method combining PCA and K-means clustering is proposed, as well as an intelligent assessment method of party members' ideological dynamics based on the improved decision tree algorithm.

II. A.Party Rank Determination Based on PCA and K-means

Both PCA and K-means alone have certain limitations when dealing with complex large-scale data. Therefore, this paper combines the advantages of PCA and K-means to carry out the research on the method of determining the rank of party members in colleges and universities for big data.

II. A. 1) Principal Component Analysis

Principal Component Analysis (PCA) [15] realizes the mapping of high-dimensional data to low-dimensional space by extracting the main features of the data, specifically, the method re-projects the original data into a new coordinate system through linear transformation, so that the projected data retains as much as possible the variance information of the original data. The core idea is to project the data into a set of mutually orthogonal principal components in the direction of the variance, and these principal components are ordered according to the size of the variance, so that the first few principal components can effectively represent the main information of the original data, so as to achieve the effect of dimensionality reduction.

Let the original data matrix be $X=[x_1,x_2,\cdots,x_n]\in\mathbb{R}^{d\times n}$, where d is the dimensionality of the data and n is the number of samples. Firstly, center the X, i.e., compute the mean vector $\mu\in\mathbb{R}^{d\times 1}$ for each dimension, and then subtract the mean vector μ for each data sample x_i to obtain the centered data matrix X_c.

Compute the covariance matrix M of the centered data matrix X_c as:

$$M=\frac{1}{n}X_cX_c^T \tag{1}$$

where $M\in\mathbb{R}^{d}\times d$ is the d-dimensional covariance matrix. By eigenvalue decomposition of the covariance matrix M, a set of eigenvalues $\lambda_1\geq\lambda_2\geq\lambda_2\geq\cdots\geq\lambda_d$ and their corresponding eigenvectors $v_1,v_2,\cdots,v_d$. The eigenvectors corresponding to the first k larger eigenvalues are selected to form a matrix $V_k=[v_1,v_2,\cdots,v_k]\in\mathbb{R}^{d\times k}$, and then the data can be projected to the low-dimensional space by equation (2):

$$Y=V_k^TX_c \tag{2}$$

where: $Y\in\mathbb{R}^{k\times n}$ is the data matrix after dimensionality reduction, and V_k is the eigenvector matrix of the first k principal component directions.

After the above process, PCA realizes the mapping of high-dimensional data into k-dimensional space, so that the projected data retains the variance information of the original data as much as possible, which effectively reduces the dimensionality of the data and improves the efficiency of data processing.

II. A. 2) K-means based clustering methods

K-means clustering is a classical unsupervised clustering algorithm, whose basic idea is to make data samples within the same cluster closer in the feature space by dividing them into k different clusters and minimizing the sum of the distances between each sample and its cluster center [16].

The algorithm obtains the cluster partitioning results that satisfy the minimization distance criterion through a continuous iterative process of updating the cluster centers and reallocating the samples. Let the dataset be $X=\{x_1,x_2,\cdots,x_n\}$, where $x_i\in\mathbb{R}^d$ denotes the i th data sample, d is the dimensions of the samples, and n is the total number of samples. Let k be the number of clustering clusters and define the center of each cluster as $\{c_1,c_2,\cdots,c_k\}$ where $c_j\in\mathbb{R}^d$ denotes the center of the j th cluster. The objective of the method is to minimize the sum of the distances of the sample points to the centers of the clusters to which they belong, i.e., the objective function:

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} | x_i - c_j |^2 \tag{3}$$

where: J is the total objective function value, C_j is the set of samples in the j th cluster, and $| x_i - c_j |$ is the Euclidean distance between the samples x_i and the cluster center c_j.

The K-means algorithm iteratively updates the cluster centers and sample assignments through the following two steps until the objective function converges.

(1) Cluster assignment step. For each sample x_i, calculate the distance between it and each cluster center c_j, and assign the sample x_i to the nearest cluster, i.e:

$$C_j = \{x_i : | x_i - c_j |^2 \leq | x_i - c_l |^2, \forall l = 1, 2, \cdots, k\} \tag{4}$$

(2) Center update step. After completing the sample assignment, recalculate the center c_j of each cluster by updating it to the mean of all the samples in that cluster, i.e:

$$c_j = \frac{1}{| C_j |} \sum_{x_i \in C_j} x_i \tag{5}$$

where: $| C_j |$ is the number of samples in the j th cluster, and $\sum_{x_i \in C_j} x_i$ is the sum of all samples in the j th cluster.

By repeating the above steps, the K-means algorithm makes the objective function value J decrease gradually, and finally realizes the optimal cluster division of the dataset.

II. A. 3) Joint analysis methods for dimensionality reduction and clustering

The core idea of joint analysis lies in the iterative feedback mechanism of PCA dimensionality reduction and K-means clustering, which enables the direction of dimensionality reduction to be adaptively adjusted so as to obtain a low-dimensional representation that is more in line with the clustering structure.PCA can map high-dimensional data to a low-dimensional space, but since PCA only focuses on the global variance structure of the data, which may not be completely in line with the needs of the clustering, it is necessary to introduce K-means clustering through the introduction of clustering feedback.

The working principle and process of the joint analysis method of dimensionality reduction and clustering are shown in Fig. 1, and the working mechanism of the method realizes the joint analysis of data by combining PCA dimensionality reduction with K-means clustering, and by providing feedback through multiple iterations in order to optimize the adaptability of the dimensionality reduction space. First, the high-dimensional data are initially downscaled using the PCA algorithm to map them into a low-dimensional space that retains the main variance information. Next, K-means clustering is performed within this dimensionality reduction space, and the clustering results are used to assess whether the current direction of dimensionality reduction can effectively reflect the cluster structure of the data. Then, the dimensionality reduction direction is adjusted by feedback according to the distribution characteristics of the clustering results, and the selection of principal components and the dimensionality reduction strategy are dynamically optimized, so that the PCA is gradually adjusted in each round to compress the data dimensionality in a way that is more suitable for the clustering effect. Through this iterative process, the clustering separation of the data in the low-dimensional space is continuously enhanced, and more accurate low-dimensional representation and clustering results are finally obtained.

Specifically, let the input data matrix be $X \in \mathbb{R}^{n \times d}$, where n denotes the number of samples and d denotes the dimension of the original data. The initial PCA dimensionality reduction obtains the eigenvector matrix W by constructing the covariance matrix to decompose its eigenvalues, thus constructing the low-dimensional mapping $Y = XW$, where $Y \in \mathbb{R}^{n} \times k$ is the representation of the data after reduced to the k dimension.

In the initial reduced dimension space, K-means clustering is performed to analyze the clustering of Y by minimizing the sum of the squared distances of the sample points within the cluster to their respective cluster centers in order to obtain the optimal clustering assignments under the current direction of the reduced dimension.

Thereafter, a feedback update is performed on the downscaling matrix W by analyzing the distribution of cluster structures in the clustering results to enhance the separation of cluster structures in the low-dimensional space. The feedback mechanism is adjusted based on the contribution of each principal component in distinguishing different clusters, so as to determine which principal components are more important for improving the clustering effect, and appropriately increase the weights or selections of these principal components to adjust the direction of dimensionality reduction. In a new round of dimensionality reduction after feedback, the covariance matrix is recomputed and eigen-decomposed to make the newly obtained W matrix more consistent with the current clustering structure, thus optimizing the low-dimensional representation.

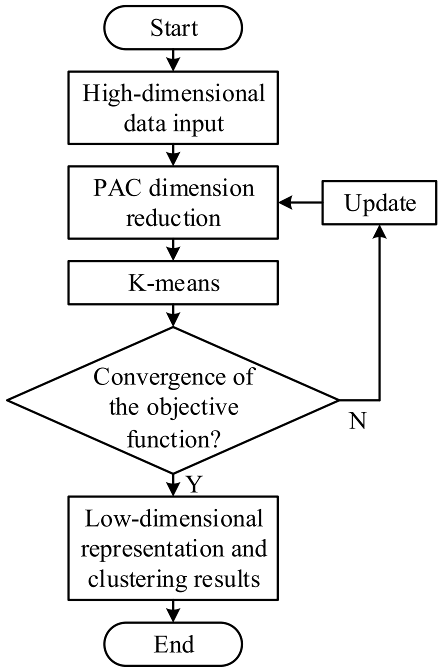

Figure 1: The working principle and process of the joint analysis method

This feedback process is iterated repeatedly, and in the low-dimensional mapping Y after each update, the intra-cluster tightness and inter-cluster separation of the data are gradually enhanced, and ultimately a low-dimensional data representation Y^* that meets the characteristics of clustering is obtained, i.e., a dimensionality reduction result that satisfies the requirements of a specific clustering structure:

$$Y^* = XW^* \tag{6}$$

II. B.Measurement of party members' ideological dynamics based on improved decision tree algorithm

In the process of assessing the ideological dynamics of party members with the constructed assessment framework, assessment indicators are needed to visualize the assessment results. In the process of manifestation, due to the repetitive nature of the selected assessment indicators, the assessment results are not uniform, therefore, in order to ensure the reliability of the assessment results, it is necessary to fit the calculation of the characteristic factors of the assessment indicators to improve the accuracy of the assessment results. In this paper, the improved decision tree algorithm [17] is utilized to fit the measurement factors. In this case, the construction and improvement process of the decision tree algorithm is as follows:

$$\begin{cases} T = I(X) = \sum_{j=1}^{m} \frac{X_j}{X} \times I(X_j) \\ N = -P\sum_{j=1}^{m} I(X_j)\log_2 I(X_j) \times T \end{cases} \tag{7}$$

where T denotes the constructed decision tree, $I(x)$ denotes the parent node of the decision tree, $I(X_j)$ denotes the child node of the decision tree, X_j denotes the expected value of the child node, X denotes the expected value of the parent node, m denotes the number of nodes of the decision tree, and N denotes the improved decision tree.

The improved decision tree algorithm is applied by first scanning the output thought dynamic dataset and counting the number of times a single thought dynamic data occurs to define the support of individual data. Using the above data as a basis, the data set is scanned twice. Based on the scanning results, the support degree of the scanned data is set twice, and as a result, a new candidate dataset is generated. The generated candidate data set is used as the base data, traversed, and according to the traversal results, the support degree of the data in the candidate data set is calculated. If the calculated support degree of the data is less than the defined support degree, the data in the candidate data set is deleted to ensure that all the data in the candidate data set satisfy the set conditions. Cycle the above steps until no new candidate data set can be generated. The application of the improved decision tree algorithm in the above process can delete duplicate assessment factors and optimize the application of the assessment factors, screening out assessment factors with higher quality or stronger characteristics. At the same time, after processing through the above multiple cycles, the specific description of the assessment factors is as follows:

$$\alpha = \frac{\sum_{i>1}^{n} NG_{in} \times T}{\sum_{i>1}^{n} dG_{in}} - r \tag{8}$$

In the formula, α denotes the measurement factor of loop processing, G_{in} denotes the computational parameters of the dataset, n denotes the structure of the application of the improved decision tree algorithm, i denotes the number of loops, and r denotes the amount of computational load of the measurement factor in the improved decision tree algorithm. Through the above formula, the data set of measurement factors is obtained. In order to realize the fitting of the assessment factors, it is necessary to assign the assessment factors first, and then fit the processing to get the intelligent assessment method of party members' ideological dynamics, and its specific calculation process is as follows:

$$\begin{cases} y(\alpha) = 1 - \varepsilon \times 2 f_s^{'} \alpha \\ h_j(\alpha) = \dfrac{N}{1 + \exp \dfrac{v}{4}} \end{cases} \tag{9}$$

where $y(\alpha)$ denotes the result of assignment to the assessment factor, ε denotes the weight parameter of the assessment factor in the assessment, $f^{'}$ denotes the degree of overlap of the features of different assessment factors, s denotes the degree of feature fuzzy of the assessment factor, $h_j(\alpha)$ denotes the result of feature fitting of the assessment factor's feature fitting result, i.e., the result of intelligent assessment of party members' ideological dynamics, j denotes the process of fitting, and v denotes the fitting speed of the assessment factor. Through the above formula, the fitting of feature factors is completed to improve the measurement box degree of the assessment, and to prepare for the subsequent realization of the intelligent assessment of party members' ideological dynamics. So far, the design of fitting intelligent assessment factors based on the improved decision tree algorithm is completed.

III. Design of a decision support system for intelligent party building with improved decision trees

In order to solve the problem of party member ideological dynamics management in college management, and to promote the informatization and wisdom of party building in colleges and universities, this paper measures the ideological dynamics of party members based on the improved decision tree algorithm, and combines the big data technology to realize the design of a decision support system for intelligent party building in colleges and universities.

III. A. Business architecture design

A large amount of objective, real, effective and real-time data generated in the process of party building operation and informationization construction in colleges and universities is a true reflection of the history and current situation of party building business operation in colleges and universities, and is also an effective support for business decision-making. The establishment of an effective data platform, on the basis of which the data are properly processed, appropriate data are provided for different analysis scenarios, and at the same time, the data are presented in a more comprehensible visual graphical way, which is an effective way to apply the data to the support of business decision-making. The business architecture is shown in Figure 2.

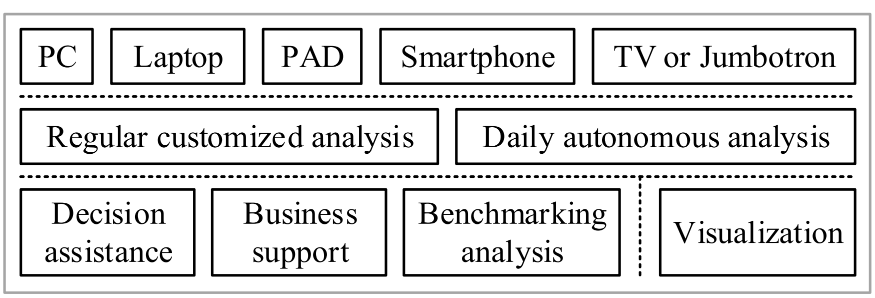

Figure 2: Business Architecture

III. B. Technical architecture

The system architecture of the Smart Party Building Information Technology Project adopts a distributed service architecture, and the Odin (LEAF6) cloud computing technology framework is used for the development of this project. The related technologies it uses are as follows.

III. B. 1) Server-side technologies

Server-side technology core framework using Spring Boot2, view framework SpringMVC, Apache Shiro for the permissions framework, MyBatis for the persistence layer framework, with Alibaba Druid as a database connection pool , the database using the most popular Redis distributed caching database technology , Quartz as a job scheduling Quartz as a job scheduling framework , storage with QcloudCOS, using Maven to do project build management , Swagger2 as a document generation tool , Fastjson as a parsing library .

III. B. 2) Front-end technology

Front-end technologies include JQuery, front-end page engine using JSP technology, standard tag library using JSTL, calendar management, date and time controls using Fullcalendar and Laydate technology, data tables using Jqgrid, data charts using Echarts.

III. C. Data flow design

Data flow refers to a set of sequential, starting and ending set of bytes, the program receives data from the keyboard or writes data in, as well as read and write operations of data on the network connection, can be done using data flow, it is a data distribution technology, data generator writes data records into the ordered data flow, the user of the data can read the data from the data flow in the same order. Data flow in a system is like the blood of the system, which determines the smoothness of the system and is a very important yardstick to test the goodness of the system. According to the analysis of the system, the system data flow design has been debugged and tested, and the system is lag-free and smooth, achieving the expected design effect. The data flow of grassroots party building in colleges and universities is shown in Figure 3.

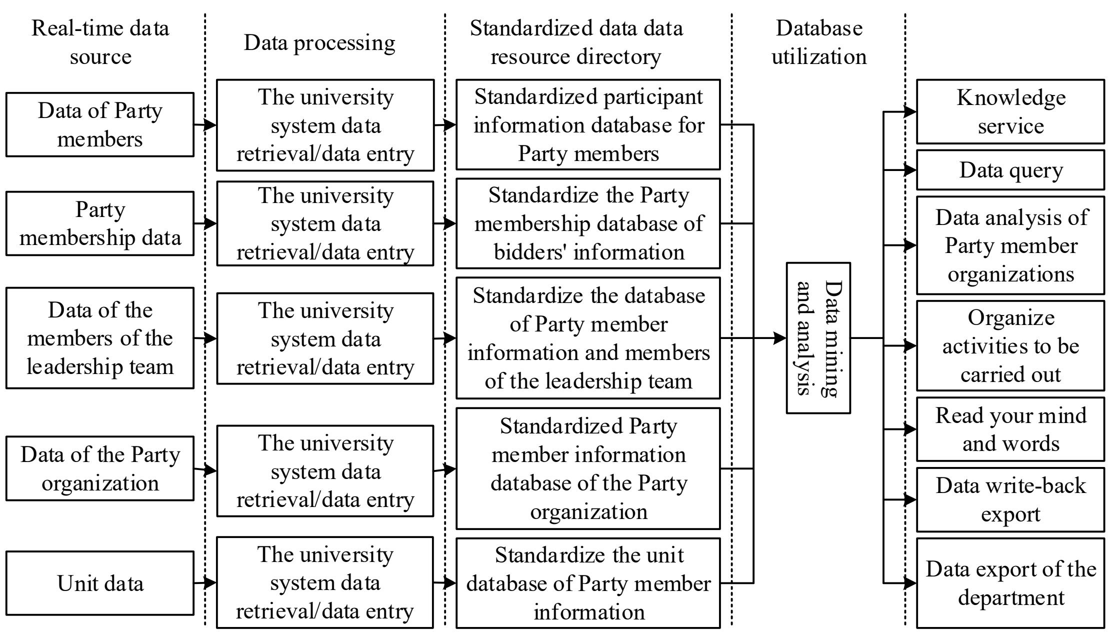

Figure 3: Data flow of grassroots party building in universities

III. D. System module design

According to the demand analysis, the system is designed with the following modules: grass-roots party building, comprehensive business analysis, cadre management, comprehensive assessment and analysis, comprehensive management of civil servants, and data center for organizers.

III. D. 1) Cadre management module

(1) Cadre policies and regulations library: Combined with the characteristics of cadre management business and the use of demand-oriented, it supports the query and retrieval of different dimensions.

(2) Cadre inspector team management: realizes the management of cadre inspector team in universities, including basic information of personnel, entry and exit management, evaluation of previous cadre inspections and team analysis.

(3) Management of college management cadres' ranks: building management system of college organs' cadres' ranks, mastering the use of college organs' ranks, providing analysis of the basic operation of the leadership team, and recording the whole process of deploying basic information, motion information, democratic recommendation information, inspection information, discussion and decision information, and posting information.

(4) On-site teaching point management: including on-site teaching point basic information maintenance management, on-site teaching point reservation management, on-site teaching point evaluation and display.

(5) Cadre Supervision Collaborative Management: Relying on the cadre supervision work joint conference system, led by the Organization Department of the University Committee, with the participation of all member units, it builds a collaborative and efficient supervision collaborative working mechanism with collaboration and interoperability, each in its own way.

(6) Cadre information portable query system: building cadre information portable query system, based on cadre management system collected cadre data analysis.

III. D. 2) Module on grass-roots party building

(1) Party Care Management: This function is used for the maintenance of party care information in the background, mainly including the title, publisher, release time and other information.

(2) Management of Party Organization Leaders: Establishing the information database of party organization leaders in colleges and classes, and forming “one person, one table” files.

(3) Management of grass-roots party building guidance stations: information feedback on supervision of organizational activities, evaluation of opinions, information entry and maintenance of information for the instructors of grass-roots party building guidance stations, direct selection of personnel for information extraction and binding, instructor guidance visit records and collection, maintenance of information on grass-roots party building guidance stations, questions from party members to guidance stations, administrator management background to answer questions, and recommendation, review and display of outstanding activity cases. The administrator manages the background to answer questions, and the excellent activity cases are recommended for review and display.

(4) Organizational life: management statistics for organizations that have not completed the requirements for organizational activities, and new types of organizational life meetings.

(5) Boutique “microclassroom”: recommending, auditing and managing excellent microclasses, and displaying excellent microclasses on PC and mobile.

(6) Fixed roster: add corresponding data segments in the basic information of party members and provide roster generation tools.

III. D. 3) Comprehensive assessment and analysis module

(1) Annual comprehensive appraisal: docking with the provincial comprehensive appraisal system, obtaining annual comprehensive appraisal result data through the data interface.

(2) Leadership appraisal management: leadership appraisal includes annual appraisal, special appraisal, usual appraisal, term appraisal and other contents. Utilizing the relevant assessment result data, analysis and research.

(3) Comprehensive appraisal analysis mobile terminal: the basic situation of the appraisal of the appraisal unit in previous years as well as the appraisal materials are imported into the mobile terminal in accordance with the appraisal subgroups for use by the appraisal team during the appraisal period.

III. D. 4) Integrated business analysis module

(1) Online research system: through the online design of questionnaires, relevant questionnaires are dynamically generated for users, which helps to understand the ideological dynamics of party members in a timely and rapid manner and make timely intervention decisions.

(2) Publicity and Information Submission Management System: In order to integrate the publicity and information resources of the organization and work of universities, open up the channel of information submission, and create an information management support platform for the information and publicity work of the organization and work, the publicity and information submission management sub-system is constructed.

III. D. 5) Organization data center

The data center has realized the function of statistical analysis and display of data, so that colleges and universities can have a more intuitive understanding of the current situation of their party members and organizations. In the later stage of planning, it will also display relative statistical analysis on civil servants, talents and cadres.

IV. Model simulation and testing

This chapter simulates the comprehensive evaluation model of party members' ideological dynamics based on principal component analysis-clustering algorithm to test the effectiveness of the model.

IV. A. Quantification of data

The research object is 140 party members in a university, and their relevant information is collected, including basic personal information such as name, gender, age, education, degree, title, honorary awards and so on. In order to transform the qualitative indicators into quantitative data, the criteria for honorary bonus points, party activities awards and punishments, as well as the scoring criteria for cultural level were formulated as shown in Tables 1 to 3, respectively.

Table 1: Standards for bonus points of honor

Standard	Score
Have won the special, first, second and third prizes at or below the municipal level	+4, 3, 2 and 1 points respectively
Have won the special, first, second and third prizes at the municipal level	+8, 7, 6 and 5 points respectively
Have won the provincial special, first, second and third prizes	+12, 11, 10 and 9 points respectively
Have won the national special, first, second and third prizes	+20, 18, 16 and 14 points respectively

Table 2: Standards for rewards and punishments in Party affairs activities

Standard	Score
The average number of meetings per month	+3 points per time
Participate in the activities of the Party organization	+3 points per time
Participate in voluntary activities	+3 points per time
Absent from the Party members' meeting	-6 points per time

Table 3: Educational attainment scoring criteria

Educational background	Score
Junior high school	+60 points
High school	+65 points per time
Junior college	+70 points per time
Undergraduate	+80 points per time
Master's degree student	+85 points per time
Doctoral student	+90 points per time

The quantification of qualitative data according to developed criteria can facilitate the processing of data to uncover useful information.

IV. B. Data pre-processing

Raw data is processed to make it suitable for analysis. Data preprocessing in data mining technology can not only effectively improve the quality of data, but also make the data more suitable for specific data mining techniques and tools to facilitate data analysis. First, through data sampling, select the representative data among them as sample data. Here, data related to research work such as honorary awards and attendance can be extracted. Then, the data are cleaned to remove some incomplete information and contradictory data. The data obtained after these two steps is the data sample set for the next experiment. The schematic information of party members after data preprocessing is shown in Table 4.

IV. C. Factor analysis

This paper uses SPSS28.0 software to factor analyze the data after preprocessing.

(1) The KMO test value is 0.814, which is greater than 0.5, indicating a strong correlation between the data.The Bartlett's spherical test chi-square P is close to 0, which is less than 0.05, indicating that the sample set is suitable to be used for factor analysis.

(2) Extraction of common factors

The results of factor analysis are shown in Table 5, the eigenvalues of the first three factors are greater than 1, and the contribution rate of the three factors accounts for 85.9% of the total factors, so these three factors are selected as the common factor to represent the overall data for analysis.

Table 4: Information illustration of 140 Party members in a certain university

Party member number	Democratic scoring	Honor and award scoring	Participate in the meeting scoring	Voluntary activity scoring	Participate in the organizational activities scoring	Cultural level score
1	80	88	79	69	84	80
2	85	75	80	84	79	85
3	90	80	76	76	78	70
…	…	…	…	…	…	…
139	78	75	83	75	79	85
140	69	72	79	85	71	90

Table 5: Factor analysis eigenvalue illustration

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	6.456	4.451	0.447	0.447
2	2.247	0.804	0.285	0.732
3	1.652	0.548	0.127	0.859
4	0.945	0.072	0.075	0.934
5	0.864	0.385	0.034	0.968
6	0.743	0.173	0.032	1

The first common factor F1 can be abstracted as “democratic assessment” since it affects the main indicators of democracy and voluntary activities. The second common factor F2 can be abstracted as “work performance”, and its main influencing variables are honor and award scores, culture level scores. The third common factor F3 can be abstracted as “self-construction”, and its main influence indicators are the rating of participation in meetings and the rating of participation in party organization activities. The attributes of the specific indicators are categorized as shown in Table 6.

Table 6: The attribute classification of specific indicators

Indicator attribute	Indicator name	Variable m
Democratic assessment	Democratic scoring	m1
	Voluntary activity scoring	m4
Work performance	Honors and awards scoring	m2
	Cultural level score	m6
Self-construction	Participate in the meeting scoring	m3
	Participate in the Party organization activities scoring	m5

(3) Factor scores

The factor score matrix was calculated by regression algorithm as shown in Table 7.

From the results of Table 7, the individual factor scores can be obtained as follows:

$$F1 = 0.082m1 + 0.065m2 - 0.046m3 - 0.064m4 + 0.032m5 - 0.041m6 \tag{10}$$

$$F2 = -0.280m1 + 0.072m2 + 0.016m3 - 0.393m4 + 0.039m5 + 0.003m6 \tag{11}$$

$$F1 = 0.480m1 - 0.351m2 + 0.065m3 + 0.331m4 - 0.379m5 + 0.155m6 \tag{12}$$

IV. D. Analysis of the ideological dynamics of party members based on the comprehensive evaluation model

As can be seen from the previous section, this paper obtains three principal components of “democratic evaluation”, “work performance” and “self-construction” after a series of processing of sample data.

On this basis, the K-means clustering algorithm is further used for classification, and the clustering results based on the principal component analysis - clustering evaluation model are shown in Figure 4 and Table 8, which are divided into five party members' ideological dynamics evaluation grades of excellent, good, general, qualified and unqualified, and the classification results are:

$$\begin{cases} \text{Excellent} & z_i^2 \in [85.62, 100] \\ \text{Good} & z_i^2 \in [77.85, 85.62) \\ \text{General} & z_i^2 \in [71.54, 77.85) \\ \text{Qualified} & z_i^2 \in [64.25, 71.54) \\ \text{Unqualified} & z_i^2 \in [0, 64.25) \end{cases} \tag{13}$$

Table 7: Common factor score matrix

Indicator	Factor F1	Factor F2	Factor F3
Democratic scoring m1	0.082	-0.280	0.480
Honors and awards scoring m2	0.065	0.072	-0.351
Participate in the meeting scoring m3	-0.046	0.016	0.065
Voluntary activity scoring m4	-0.064	-0.393	0.331
Participate in the Party organization activities scoring m5	0.032	0.039	-0.379
Cultural level score m6	-0.041	0.003	0.155

Table 8: The clustering results based on the PCA-clustering evaluation model

Indicator	The first category	The second category	The third category	The fourth category	The fifth category
Upper boundary	71.07	84.74	78.26	98.05	63.42
Lower boundary	65.08	78.21	71.16	88.47	55.46
Clustering center	69.26	80.95	74.68	92.84	59.21

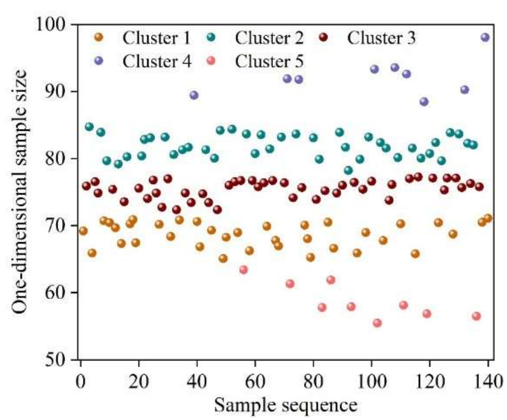

Figure 4: The clustering results of the evaluation model based on PCA-clustering

As shown in Table 8 and Figure 4, the first is qualified, the second category is good, the third category is average, the fourth category is excellent, and the fifth category is unqualified, in which the percentage of excellent, good, average, qualified, and unqualified are: 6.43%, 29.29%, 32.14%, 25.71%, and 6.43%, respectively.

IV. E. Model testing

This paper uses two methods to test the effectiveness of the comprehensive evaluation model.

Method 1: Randomly select the party members of the university to conduct a non-anonymous questionnaire survey, the comparison of the actual situation and the model calculation results to judge the accuracy of the valence model, based on the principal component analysis - clustering algorithm clustering of the comprehensive evaluation model and the actual situation with a difference level of 0.2.

Method 2: k-s test of the comprehensive evaluation model based on principal component analysis - clustering algorithm [18], k-s test results are shown in Table 9, and draw the normal probability distribution of the observed value and the expected value as shown in Figure 5. In the k-s test based on principal component analysis-clustering algorithm, the significance is 0.214>0.05, which obeys normal distribution, and the normal probability distribution graph shows that the data points are basically near a straight line, so it can be further determined that the data obeys normal distribution.

Table 9: The k-s test results of the PCA-clustering evaluation model

Kolmogorov-Smirnov (K)a			Shapairo-Wilk		
Statistics	df	Significance	Statistical	df	Significance
0.43	139	0.214	0.975	139	0.505

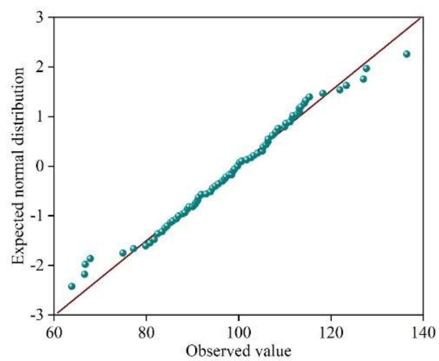

Figure 5: Normal probability distribution

Combining the results of the two methods, it can be seen that the constructed model is effective, i.e., the analysis method of joint PCA and K-means clustering algorithm is able to effectively assess the ideological dynamics of party members.

V. System performance testing

In order to verify the effectiveness of the design of the intelligent party building decision support system, this paper carries out the test work on Fastone, the test data from the party information center of a university, and compares the precision and accuracy of this system with the traditional system.

V. A. Accuracy tests

The accuracy can reflect the overall performance of the system, the higher the accuracy, the better the monitoring, and vice versa. The comparison of the accuracy of the system in this paper and the traditional system is shown in Fig. 6. From the test, it can be seen that with the increase of time, the accuracy of this system is basically stable, maintained at about 87%, while the accuracy of the traditional system is rapidly decreasing after stabilization, the highest is only about 68%. It can be seen that the use of improved decision tree algorithm can significantly improve the accuracy of the system, which is of positive significance for improving the efficiency of monitoring the ideological dynamics of party members.

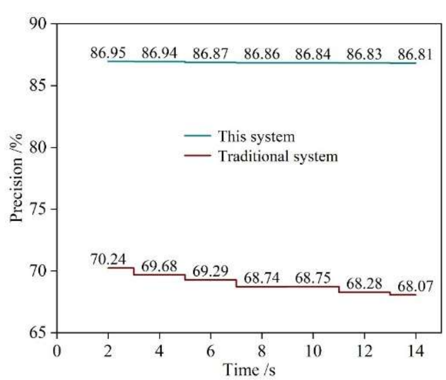

Figure 6: Precision comparison

V. B. Accuracy testing

The comparison of the accuracy rate between this paper's system and the traditional system is shown in Fig. 7. It can be seen that when the number of samples increases from 10 to 400, the accuracy rate of this paper's system basically stays at about 94%, with more stable ups and downs. With the increase of the number of samples, the accuracy rate of the traditional system continues to decline, indicating that it is greatly influenced by the number of samples, and the more the number of samples, the lower the accuracy rate of the system.

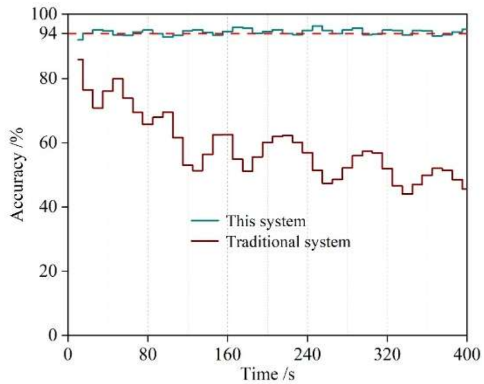

Figure 7: Accuracy comparison

In order to further verify the accuracy of the system, the noise interference parameter is increased, and the accuracy comparison results are shown in Table 10. As can be seen from the test, with the increase of noise interference, the accuracy rate of the system in this paper changes less, when the number of samples is 400 people, the noise interference is 30dB, the accuracy rate of the system in this paper is 87.06%, while the accuracy rate of the traditional system is 32.64%, which shows that the system is more resistant to interference, even if it is subjected to strong noise interference, it can also be a better monitoring of party members' ideological dynamics, and the stability is stronger.

Table 10: Accuracy depth comparison

Sample size/person	Noise interference /dB	This system	Traditional system
		Accuracy /%	
20	15	91.35	89.24
	30	90.89	84.45
50	15	91.04	79.31
	30	90.42	75.26
100	15	90.37	70.42
	30	89.43	63.44
200	15	88.45	56.18
	30	88.06	48.36
300	15	87.95	45.27
	30	87.42	40.41
400	15	87.39	38.58
	30	87.06	32.64

VI. Conclusion

This paper proposes a party member ideological dynamic grade determination model with joint principal component analysis and K-means clustering method, builds a smart party building decision support system based on improved decision tree algorithm, and evaluates its performance.

In this paper, three principal components are extracted from the sample data of party members, which are democratic assessment, work performance and self-construction, and are clustered into five classes, which are divided into five ideological dynamics grades of excellent, good, average, qualified, and unqualified, accounting for 6.43%, 29.29%, 32.14%, 25.71%, and 6.43%, respectively. For the k-s test based on principal component analysis-clustering algorithm, its significance is 0.214>0.05, obeying the normal distribution, while in the normal probability distribution graph, the data points are basically near the straight line, which further determines that the data obeys the normal distribution, and verifies the validity of the model in the assessment of party members' ideological dynamics.

With the increase of time, the accuracy of this system is basically stable and stays around 87%, while the accuracy of the traditional system decreases rapidly after stabilization, with a maximum of only around 68%. At the same time, the accuracy of this paper's system basically stays around 94%, with more stable ups and downs, while the accuracy of the traditional system continues to decline as the number of samples increases. In addition, with the increase of noise interference, the accuracy rate of this paper's system changes less, when the number of samples is 400 people and the noise interference is 30dB, the accuracy rates of this paper's system and the traditional system are 87.06% and 32.64%, respectively. It shows that this system is significantly better than the traditional system, which can better monitor the party members' ideological dynamics and is more stable.

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