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Architecture and Computational Optimization of Community Employment Support System for Digitally Intelligent Students Led by Digital Party Building Based on Field Theory

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ABSTRACT

In this paper, K-prototype algorithm is chosen to cluster and analyze the data of students' behavior in the educational field. Further, a model of students' employment interest is constructed based on the job rating data of different classes of students. The timeliness is introduced in the model to improve the recommendation accuracy. Synthesize the algorithm and model to build an employment support system. Apply the system to the clustering study of college students' behavioral data to verify its career recommendation value. Set up comparison experiments to find the optimal similarity fitting parameters and number of neighbors to improve the system recommendation accuracy and judge the system recommendation effect. Preliminarily divide students into 3 categories by analyzing students' online behavior and book borrowing behavior. Preliminarily categorize students into 4 categories based on their grades. Combined with the performance labels and grade categories of professional courses, the employment direction of students was finally clustered into four categories, namely "postgraduate entrance examination", "civil servant application", "company work" and "others". The highest accuracy of the system job recommendation is achieved when the similarity fitting parameter $\lambda = 0.5$ and the number of neighbors $N = 50$.The RMSE value of the K-prototype algorithm ranges from 0.6011 to 0.731, and the recommendation effect is better than the comparison algorithm.

Keywords: educational field, K-prototype algorithm, employment interest model, timeliness, employment support system

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1. Introduction

With the rapid development of information technology and digitalization, party building work is also gradually transformed to digitalization and intelligence. Digital party building refers to a new mode of using modern information technology means to promote the construction of party organizations and the education and management of party members [1-4]. In the context of the new era, the construction of digital party building has become an important means to promote the innovation and development of party building work, and the digital party building platform can not only provide convenient and efficient information management and services for party organizations, but also provide support for student employment in the context of the times when it is difficult for college students to find employment [5-8].

In recent years, with the popularization of higher education, the employment situation of college students has gradually become severe. Problems such as difficult employment, low salary, unstable work and so on have been intensified, which bring many troubles to graduates as well as job seekers, and how to respond to the plight of college students' employment must be formulated with corresponding supportive policies [9-12]. And in the context of digitalized party building, with the development of a new round of technological revolution led by cutting-edge technologies such as artificial intelligence, big data, cloud computing, etc., the digital community has become a fast-developing and widely-radiating platform for students to gather [13-15]. It plays an important role in promoting employment and driving new economic development, and the transformation of digital intelligence has become a priority for higher education to carry out reforms in the digital era [16-18]. For this reason, the realization of student employment support through the construction of a community employment support system for digitally intelligent students is of strategic importance for national economic development, social harmony and stability [19-21].

Literature [22] developed a systematic introduction to the student employment portal project, indicating that the student employment portal facilitates personalized job recommendations for students with the help of artificial intelligence, improves the job matching process, and presents the impact of technology on the job search process of students. Literature [23] introduced a big data and AI based employment analysis program for college students that can effectively process and analyze large textual datasets and exhibit good data classification performance. Literature [24] proposed an AI-based student employment system designed to meet the employment needs of most students, which can respond quickly to user needs, provide users with a good experience, and is featured with rich functionality, security and stability. Literature [25] pointed out the opportunities and challenges brought by AI for college students' employment, and emphasized the importance of employment guidance services in colleges and universities as well as the strategies to be adopted, including the construction of the employment guidance course system and the establishment of an up-to-date employment guidance teacher team, etc., in order to promote the high-quality employment of college students. Literature [26] analyzes the current situation of college students' employment difficulties based on the development of college students' employment information service system, and builds an employment information service system with big data to solve the employment problems of college students. Literature [27] combines AI with ideological and political education to propose a career counseling system for college students, which is able to fully integrate the functions of students' employability and employment guidance system based on the preferences and needs of students and employers, and has good interpretability. Literature [28] designed an intelligent recommendation system for graduate employment based on AI, which collects students' job-seeking information and provides them with multi-dimensional and personalized employment information recommendation services, realizing accurate and intelligent employment recommendation and improving the success rate of graduates' job-seeking.

The study of students' behavioral data in school helps to understand their academic performance and employment directions of interest in the educational field, accurately recommend positions for students, and reduce the cost of students' job search. In this paper, the K-prototype algorithm is used to calculate the weight values of various types of student behaviors and label them with appropriate classification labels. The students are clustered by combining the various labels. Analyze the corresponding career direction of each type of students to provide accurate job recommendations. Further, based on the students' job operation behavior, calculate the students' job scoring data and build the employment interest model. Add the time factor to rank the recommended positions. Set up computational optimization experiments to study the values of similarity fitting parameters and the values of the number of neighbors when the system has the highest recommendation accuracy. Compare the size of RMSE values of similar recommendation algorithms, and analyze the advantages and disadvantages of the recommendation effect.

2. Analysis of the structure of the employment support system based on field theory

Based on the correlation between the implicit education field and the real education field on the Internet, the study of various types of behavioral relationships of students in the education field, the establishment of the employment support system, which provides accurate job recommendations for different categories of students, can effectively help college students better connect their school life with the workplace, and help to improve the quality of employment. This chapter mainly analyzes the specific operation process from the perspective of technical realization of the employment support system.

2.1. Research on the relationship between the Internet and the educational field

A field can be defined as a network or configuration of objective relationships that exist between various locations. There are various fields in society, such as the physical field, the economic field, and the social field. Each of these fields has its own internal logic and constitutes a network of relationships with some kind of objective relationship and behavioral structure of necessity. Educational field is one of them. The so-called educational field, as an objective social existence, refers to an objective relationship network formed between educators, educated people and other educational participants, based on the production, transmission, dissemination and consumption of knowledge and information, and aiming at the development and improvement of human beings. This relationship network is the integration of multiple relationships and the reorganization of various forces, the sum of the tension formed by the interaction between educators and educated people to realize the effect of interaction and group dynamics and the interaction between their internal needs and the external environment, and the educational synergy formed by the integration of various factors and forces of education from various levels. As for the Internet as an emerging social field, some scholars have found, after comparing it with the educational field, that the network society, as a new space for social survival, has the characteristics of immateriality, randomness, hiddenness, interactivity and other characteristics closely related to the characteristics of the educational field. From this, it can be seen that the rapidly developing Internet has educational significance and value, and has become a hidden educational field that compares and complements the real educational field.

2.2. Analysis and modeling of technical methods

2.2.1. Research framework. Combining the Internet as a hidden educational field with the real educational field, through the study of multiple relationships related to student behavior in the overall educational field, students are clustered and grouped according to certain classification rules, thus providing targeted employment support for different types of students. Figure 1 shows the research framework of this paper. This paper focuses on the study of student clustering and grouping, and based on the analysis results, it provides educational decision-making support for managers related to party building in colleges and universities. For students, it can understand the academic characteristics and academic needs of different student groups and improve the learning experience. For educators, through the data mining technology, they can understand student behavioral characteristics more deeply so as to improve educational management methods and scientific decision-making. The research in this paper focuses on the following aspects: first, how to apply the clustering model to the academic analysis of students in the context of educational Internet big data, and how to obtain implicit educational laws through the intellectual discovery of the attributes of the past educational data in order to improve the academic performance of students? Second, how to better mine multi-source educational data? Third, how can this study help to support decision-making on employment support for college parties?

In order to make the study more scientific, this paper constructs a mixed-attribute educational dataset with rich data sources and complete time span. Driven by the mixed-attribute multi-source educational data, traditional clustering methods such as K-means can no longer solve the clustering problem of this dataset, while supervised learning methods such as decision trees and neural networks are not applicable to this scenario, therefore, this paper uses a novel unsupervised learning algorithm of K-prototype to group students and quantitatively analyze the identified clusters for a better understanding of students' academic performance. The study also compares traditional clustering models to verify the suitability of this paper's model for the educational data research field.

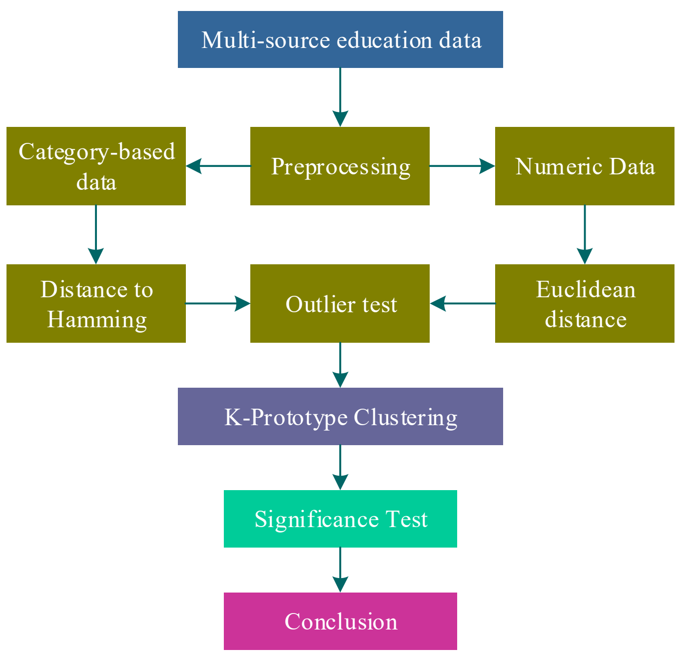

Fig. 1. Research framework

The education dataset constructed in this paper includes two categories of categorical features (e.g., information such as gender, school number, graduation year, etc.) and numerical features (e.g., data such as the length of time spent on the Internet, the number of times a book is checked out, the total number of GPAs, the number of failed classes, etc.). Since the commonly used clustering methods cannot handle categorical data, different data preprocessing methods are used to complete the data preparation. First, the data were fed into the K-prototype algorithm to discover the optimal number of clusters. Based on this clustering result, the Kruskal-Wallis test was used to identify differences in features between groups and to discover significant features that affect student categorization. Finally, the experimental results and practical experience are combined to suggest appropriate educational decisions.

2.2.2. Definition of the problem. Let $X=\{X_1,X_2,\ldots,X_n\}$ be an educational dataset, $X_i=(X_{i1},X_{i2},\ldots,X_{im})$, $i=1,\ldots,n$ be a piece of educational data, and m be a dimension of data attributes. In this paper two different categories of attributes are considered which are numeric attributes and categorical attributes. Numerical attributes include grades, number of times a book is borrowed, etc. while categorical attributes include gender, student number, year of graduation, etc. Let u be the number of numerical attributes, then X_{ij}, $j=1,\ldots,u$ are the data attributes of X_i and X_{ij}, $j=u+1,\ldots,m$ are the categorical attributes of X_i, where m is the dimension of the data.

Let the dataset X be divided into k clusters after clustering, then $C_i(i=1,\ldots k)$ denotes the set of data objects contained in the cluster i. Then the clustering result must satisfy the following constraints:

$$\begin{cases} C_1\cup C_2\cup\cdots\cup C_k=X \\ C_i\cup C_j\neq\varnothing, i\neq j \end{cases} \tag{1}$$

2.2.3. K-prototype algorithm. In this paper, a new unsupervised learning algorithm K-Prototype clustering algorithm is used for analyzing mixed educational data.The detailed procedure of K-Prototype algorithm is given below:

In K-Prototype algorithm, the numerical attribute terms of dataset X are first normalized. Then k samples from X are randomly selected as clustering center vectors. The algorithm enters into an iterative clustering process. In each iteration, each cluster set is first initialized to an empty set. Then, the distance d_{ij} between each sample and each cluster center is computed, which reflects the variability between the samples and the centers.

The distance between samples X_i and μ_j can be defined as:

$$d_{ij}=\sum_{j=1}^{v}\left(X_{ij}-\mu_{ij}\right)^2+\gamma\sum_{j=w+1}^{m}\delta\left(X_{ij},\mu_j\right) \tag{2}$$

where Euclidean distance is used to measure the distance of numerical attributes, $\delta\left(X_i,\mu_g\right)$ is the Hamming distance used to measure the categorical data, and if $X_{ij}=\mu_{ij}$ then $\delta\left(X_{ij},\mu_{ij}\right)=0$; otherwise $\delta\left(X_{ij},\mu_{ij}\right)=1$. The algorithm divides the samples into the closest clusters based on the distance between the samples and the centers. Update μ for the newly generated clustering centers, where

$$\mu_{ik}=\frac{1}{|C_i|}\sum_{X_j e_i}^{u}X_{jk}, k=1,\ldots,u \tag{3}$$

Assume the j st categorical attribute of the data $v_1,v_2,\ldots,v_q$, $\mu_i=v_r$, $j=u+1,\ldots,m$, where $r=\arg\max_{j=1,\cdots,q}P\left(v_j\right)$, $P\left(v_j\right)$ represent the probability of taking v_j in cluster C_i. Finally, the algorithm checks if the clustering center has been updated. If there is an update or the number of iterations is less than a threshold, the algorithm continues with the clustering iterations, otherwise the algorithm ends.

2.2.4. Model of students' interest in employment. After obtaining the student behavior information feature matrix, the next step is to determine the weight of each behavior. In the system, we need to determine the corresponding weights of student behaviors by entropy method.

Through the above data standardization, a new matrix data is obtained, according to the new matrix we need to calculate the proportion of the j nd behavioral attribute under the i st user to the proportion of that user p_{ij}, the corresponding formula is shown in Equation (4), after obtaining the corresponding proportion of information, the information entropy of the corresponding behavior can be calculated based on the above obtained proportion, the calculation formula is shown in Equation (5).

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{4}$$

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right) \tag{5}$$

where e_j represents the information entropy corresponding to the j nd behavior, and $e_j > 0$. For the above formula, the case of $p_{ij} = 0$ may occur in the process of calculation, in order to avoid the information entropy can not be calculated, so when $p_{ij} = 0$, defined $\lim_{p_{ij}=0} p_{ij} \ln\left(p_{ij}\right) = 0$. Finally, according to the calculated information entropy to calculate the corresponding weight of each behavior. The weight calculation formula is shown in formula (6).

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}\left(1-e_j\right)} \tag{6}$$

where w_j is the weight corresponding to the j nd behavior. Through the above calculation process, the corresponding weights of each behavior of students can be obtained in the system, and using the above weights, students can be labeled according to their behavioral information for final classification. We recommend jobs that may be of interest to students of different behavioral categories, and calculate the students' ratings of these jobs through their actions on these recommended jobs (e.g., clicking on the options of “Favorite” or “Not Interested, Reduce Recommendations”). Data. The formula is shown in equation (7).

$$o_{up} = \sum_{j=1}^{n} w_j \times a_{uj} \tag{7}$$

The o_{up} in the above formula represents the rating information of student u for position p, and the a_{uj} represents the number of times student u operates on the j th behavior of position p.

After the above analysis of user behavior, the students' rating data for positions are derived, and the student position interest set is constructed using the rating data as a measure of student interest. The positions rated by student i are constructed as student candidate career interest set G_u, and G_{uj} is the rating data of student u for position j. A threshold value k is set to treat positions with position ratings greater than k in the student candidate interest set as positions of interest to the user. Where the value of threshold k is taken as the average of the ratings of all the positions in the student candidate interest set G, and the formula is calculated as in Equation (8).

$$k_u = \frac{\sum_{j \in G_u} G_{uj}}{\left|G_{uj}\right|} \tag{8}$$

The k_u in the above equation represents the position rating threshold for student u. In G, positions with scoring data greater than k are used as the student's positions of interest. Find all the positions of interest of the student and construct the student's career interest model. The student's career interest model is represented using the VSM vector space model, and each vector that constitutes the vector space model is composed of two parts, eigenvalues and weights, in this paper, the student's position of interest position as the eigenterm, and the student's rating data for the position d as the weights, and this is used to construct vectors, which give the following student's career interest model. Where $position_i (i \in [1,n])$ represents the position of interest to the student, and $o_i (i \in [1,n])$ represents the student's rating of $position_i$.

$$\left\{ \left(position_1, o_1 \right), \left(position_2, o_2 \right), \cdots, \left(position_n, o_n \right) \right\} \tag{9}$$

2.2.5. Recommendations for timeliness. Finally, after obtaining the final populated job scoring matrix, the scoring data is calculated and sorted according to the timeliness of the job recruitment demand. Considering that the chances of students being successfully hired by the enterprise with the recruitment position in the number of people in the demand and time is a negative correlation between the relationship between the number of people in demand, that is to say, with the prolongation of the recruitment time of the position, the number of people in demand for the position is also declining, and the chances of students applying for the job are also reduced, so in the end, taking into account the effect of the timeliness of the recruitment demand on the success of applying for a job, the time factor is added, and according to the formula (11), the calculation of the the time factor of job recruitment T. Then, according to formula (10), the above scoring matrix is calculated, and the jobs are sorted in descending order according to the calculated values, and finally the TOP-N is selected to be recommended to students.

$$\mu_{ui} = O_{ui} \times T_i \tag{10}$$

$$T_i = \frac{1}{1 + \left(t_n - t_{i_b} \right)} \tag{11}$$

where μ_{ui} denotes the final timeliness rating value of student u for position i, and for uniform representation, O_{ui} is used to denote the rating value of the populated rating matrix, T_i denotes the time factor for position i, t_n denotes the current time, and t_{i_b} denotes the time when recruitment for position i began.

3. Employment support system applications and computational optimization

Using K-prototype algorithm and the student employment interest model with the addition of timeliness factor together to establish an employment support system, which is applied to the behavioral data clustering of students in colleges and universities and the recommendation of jobs of interest to explore the practical use value of the system. Experiments are set up to optimally solve the fitting parameters and the number of neighbors of the algorithm, and RMSE values are introduced to compare the recommendation effect of K-prototype algorithm and other algorithms.

3.1. Behavioral Features Extraction and Analysis in Schools

3.1.1. Analysis of Internet behavior. With the popularization and development of the Internet, college students' online behaviors are becoming more and more frequent, and the campus network, as one of the main tools for students to access the Internet, its comprehensive coverage and intelligent popularization make students realize the sharing of learning resources through the network at any time, and make use of the network to enrich their entertainment life. Using K-prototype algorithm to cluster analysis of students' online behavior, students can be classified into different categories based on the characteristics of online behavior, and determine how online behavior affects students' studies and then affects students' job selection behavior.

In order to better analyze students' online behavior, the time period of students' online behavior is refined, and students' online behavior is divided into two categories: online behavior during class time and online behavior during sleep time for the situation that students' class time is relatively fixed. Specifically, the statistics of a college student's online time from Monday to Friday 8:00-11:30am, 13:00-16:30pm and after 23:00pm were used to analyze whether the students' online behavior is regular. In the following, we take the average daily Internet time of students in the electrical college as an example to visualize the students' Internet behavior data.

Figure 2 shows the average daily time spent on the Internet by students in the School of Electrical Engineering of a university. Observing the data of students' online hours in Figure 2, students can be roughly categorized into 3 groups. Nearly 1/3 of the students in this college spend 0-60 minutes online during class hours, which is reasonable and regular, and the online health is good. A very small number of students spent 180 minutes or more on the Internet and were connected for too long. This small group of students may need some reasonable guidance and help from the relevant education administrators to shift their attention to studying and finding employment opportunities. The majority of students spend 60-180 minutes, i.e., 1-3 hours, on the Internet. This group of students may also be given appropriate guidance on Internet access and be guided to utilize the Internet more scientifically to assist their life and employment.

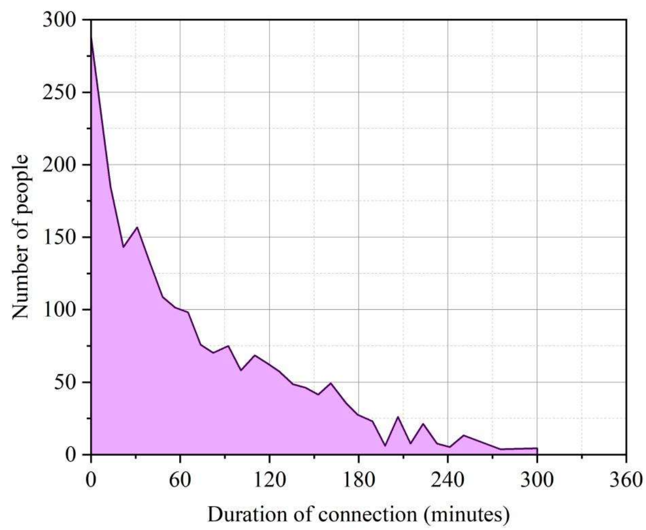

Fig. 2. Duration of Internet connections during class

3.1.2. Analysis of Book Borrowing Behavior. As an important departmental unit of higher education institutions that keeps and collects books, library can provide students of various majors with study reference materials, which plays an important role in improving students' independent learning ability, enhancing the scientific research ability of colleges and universities as well as their comprehensive strength. With the construction of employment support system, the mining of library information management has also become a hotspot for scholars of various universities to compete for research, through the analysis of students' book borrowing situation, can also understand the students' extracurricular learning and employment behavior initiative. Therefore, this paper collects a total of 9000 student book borrowing data from three colleges of electrical, economic management and civil engineering of the university through the library management system to analyze the student book borrowing.

Figure 3 shows the book borrowing situation of students in the three colleges in one semester. The overall number of books borrowed by students in the three colleges is relatively consistent, concentrated in the range of 1-11 books, and there is little difference in the initiative of students' learning and employment behavior. Among them, the average number of books borrowed by students in the College of Electricity was 4.5 per person in a semester, with a maximum of 70; the average number of books borrowed by students in the College of Economics and Management was 5.3 per person in a semester, with a maximum of 74; and the average number of books borrowed by students in the College of Civil Engineering was 3.5 per person in a semester, with a maximum of 68. Comparatively speaking, students in the College of Economics and Management borrowed more books per capita than the other two colleges, which may be related to the fact that the other two majors emphasize more on practice rather than theory.

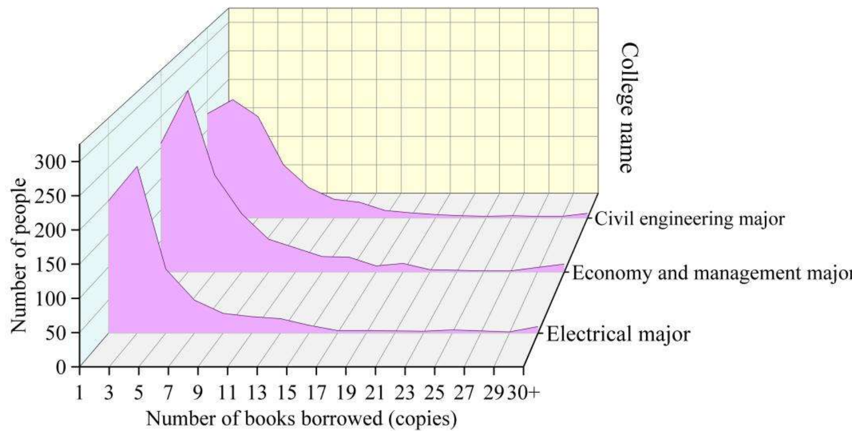

Fig. 3. The number of books borrowed by different colleges

3.1.3. Analysis of achievement behavior. As one of the important indexes to measure whether students' performance in school is excellent or not, students' graduation and employment have far-reaching influence. The K-prototype algorithm through the calculation of distance will be close to the data classified as a class of student performance behavior clustering classification, you can visualize the student performance situation, to better help the party building managers to fully understand the students, accurately grasp the specific situation of the students, timely and appropriate guidance.

This section uses the four-year college performance data of students graduating in 2020, 2021 and 2022 in the dataset to conduct mining analysis, and divides the student performance behavior data contained therein into the following five categories: total student performance, the number of failed subjects, graduation internship results, English proficiency, computer proficiency. Comprehensive students' performance in the 5 categories of achievement behavior, the school's graduates in these 3 years were divided into 4 categories, and the proportion of the 4 categories of students in the total number of students was calculated to provide a descriptive analysis of the excellence of the performance of current students.

Table 1 shows the results of clustering student achievement. Figure 4 shows the proportion of students in the 4 categories. Combining Table 1 and Figure 4 for clustering analysis. Students in category 1, total GPA>130, internship GPA>3.5, number of failed courses is 0, English level of grade 6 and above, computer level of grade 2 and above, the overall performance of students in this category is higher, and they are very self-motivated and proactive in study and employment. Students in category 2, total GPA > 120 but, internship GPA > 3, the number of failures $\leqslant$ 3, English level 6 and above or computer level 2 and above, to meet one can be, this category of students can basically ensure that the daily study and employment direction to look for, the English or computer scores still need to be improved. Students in category 3, total GPA > 110, internship GPA = 3, number of failed courses $\leqslant$ 4, English and computer proficiency is not required, this category of students still have high room for improvement in their daily performance, and their study and employment autonomy needs to be improved. Students who do not meet the above three categories are categorized as Category 4, which has poor self-discipline, and the school should pay attention to this category of students, provide timely guidance on study and employment, and tailor the education to the needs of the students. The proportion of students in category 1 is 9.6%, in category 2 is 24.3%, in category 3 is 38.7%, and in category 4 is 27.4%. Overall, the percentage of students with a high degree of autonomy in learning and employment is not as high as the percentage of students who need guidance.

Table 1. Clustering results of student achievement

Category	Total GPA	Internship GPA	Flunks	English proficiency	Computer level
1	130.5	3.6	0	3	3
2	128.5	3.1	1	2	2
3	118.5	3	3	0	2
4	107.5	2.7	6	0	1

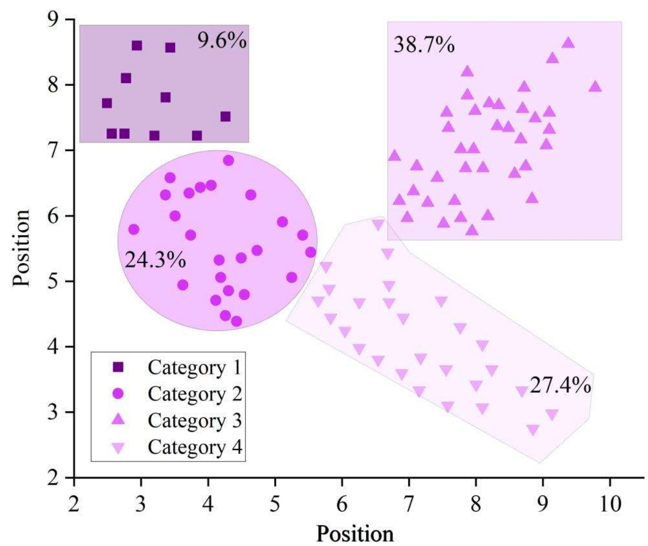

Fig. 4. The proportion of 4 types of students

3.2. Student Behavior Analysis System Implementation

3.2.1. Label Attenuation. The student user's base tag and behavioral tag can highlight the user's behavioral characteristics and show the student's potential behavioral motivation and employment interest direction in a concise and clear manner. The basic label is static and will exist for a certain period of time after it is generated, i.e., there is a labeling period. However, student behavior labels are dynamic, because student behavior data changes over time, and the generated behavior labels also change over time, which requires adding weights to the labels, according to the label weights to show the importance of the labels in the analysis of student behavior data. After feature extraction and preliminary classification of various student behavioral data using the K-prototype algorithm, the weight value of each behavior is further calculated, and appropriate clustering labels are affixed to various types of student behaviors for the convenience of subsequent employment interest analysis and systematic job recommendation.

For example, Student A got a good score of 90 points in comprehensive English in the recent semester, and his performance in comprehensive English is very active in class, with the classroom activity degree recorded as 1, and his homework is completed on time, with the homework completion degree recorded as 1. We formulate the performance label of "English master" for Student A, and calculate the weight of the label by writing the rules first, as follows. The basic weight = [0.75*(score/total score)+0.10*(classroom performance)+0.05*(homework completion)], get W=0.90. Assuming that the time decay factor is recorded as R, with the extension of time D (days), the decay factor R will be linearly reduced, R=1-0.005*D. Labeling weight=basic weight *decay factor.

From this, it can be calculated that the weight of the label of English Master, which Student A possesses, was 0.90 when it was first generated, then a label can be given to Student A: English Master. After 20 days the decay factor decays to 0.90, and the label weight is 0.81, then the label of Student A still exists in the label of the English-speaking person, and the label weight is still ahead of the other labels of this type, so this label has the priority to be displayed relative to the other labels. When the label weight continues to decay, its weight is less than the weight of the other labels of this type of label, the label's priority is less than the other labels, it will not be prioritized for display. When the tag weight keeps decreasing over time to less than a certain value of 0.35, Student A will no longer have the tag Englishista, i.e. the tag Englishista that Student A has is no longer valid. When Student A receives an English achievement such as an English competition award during this period, the attenuation factor of the label English Master will be reset to 1 and D will restart from 0. In response to the change in Student A's label, the system can categorize students who also have the label English Achiever in this category and analyze the change in the academic situation and employment position interest of this category of students during this 20-day period to provide different job recommendations.

Table 2 shows some of the labels of a student at a certain time period (no special things happened). The initial weights of different labels are not necessarily the same, the label decay factor decreases according to the number of days, and each label has a minimum threshold; when the weight of a label is less than the minimum threshold of that label, the label becomes invalid. By combining the four label changes of this student in this time period, the overall cluster analysis of this student's behavior can be done to improve the accuracy of the analysis of the changes in the academic situation and employment interests of this class of students, which in turn improves the accuracy of the system's job recommendation and increases the success rate of employment.

Table 2. Some tags of a classmate

Label name	Initial weight	Attenuation factor	Tag weight	Minimum threshold	Whether it is valid or not
English master	0.90	R=1-0.005*D	0.90*R	0.35	Yes
Breakfast clock	0.89	R=1-0.03*D	0.89*R	0.45	Yes
Main consumer	0.85	R=1-0.02*D	0.85*R	0.15	No
Book company	0.70	R=1-0.001*D	0.70*R	0.20	Yes

3.2.2. Label-based academic analysis. Selected students' professional course performance data, using the K-prototype algorithm to calculate the weight value of each behavioral performance of the students in the professional course, affixing different labels for the students, and analyzing the academic situation and behavioral characteristics of the students based on the labels to provide a reference basis for the subsequent clustering analysis of student employment. Table 3 shows some of the selected data. Taking the student with the school number 2020**04 in Table 3 as an example, the student often arrives late or leaves early, has an average homework completion, has a stealthy classroom performance, has a high level of consumption, never goes to the library to study, has a long time on the Internet, and has a failing grade. Calculating the weights of the student's seven behavioral characteristics, the student can be labeled as "in need of academic warning". After labeling "Academic Warning", the student can no longer be assigned to the "College and Graduate School" related employment cluster, and combined with other behavioral labels, analyze the student's employment interests, complete the final clustering and then provide job recommendations.

Table 3. Select student data

Number	2020**01	2020**02	2020**03	2020**04	2020**05	2020**06
Sex	Boy	Girl	Girl	Boy	Boy	Girl
Being late or skipping class	Now and then	Never	Now and then	Frequently	Seldom	Seldom
Job completion	Preferably	Preferably	Good	Normal	Good	Good
Classroom performance	Vigorous	Bubbling	Invisible	Invisible	Invisible	Bubbling
Degree of consumption	Moderate	Underdegree	Altitude	Altitude	Moderate	Moderate
Library learning	Frequently	Now and then	Frequently	Never	Never	Now and then
Internet access	Normal	Longer	Normal	Longer	Less	Less
Grade	Outstanding	Outstanding	Good	Flunk	Good	Flunk

3.2.3. Cluster-based employment analysis. In this section, the behaviors of numerical categories such as students' GPA, library hours, competition awards, foreign language proficiency, scholarships, etc. are used as clustering variables for K-Prototype algorithm clustering analysis, and combined with the performance behavior labels of professional courses in 3.2.1 for comprehensive classification, resulting in different clusters. The proportions of further education, civil service, company, and other in each cluster are counted, and the result with the largest proportion in each cluster is determined to be the most interesting employment direction for the students in that category, and the most suitable job recommendation is given.

The number of clusters was set to 4. The number of iterations was chosen to be 60 in order to converge the data and make the clustering more effective. The different graduation destinations of students in each cluster were counted based on the clustering results. Figure 5 shows the proportion of each graduation destination in the clustered clusters. As shown in Figure 5, the proportions of students' destinations vary in different clusters, and there are four types of students' graduation destinations in each clustered cluster: higher education, civil service, company and other, and this study chooses the largest proportion as the experimental result, i.e., the largest proportion in each clustered cluster as the result of the cluster.

In Cluster I, the students' graduation direction is to go to graduate school, which accounts for 70% of the whole cluster, while civil servants, companies, and other directions account for 6%, 14%, and 10%, respectively, which indicates that students classified into the first cluster have a high probability of choosing to go to graduate school when they graduate. In cluster II, the largest proportion of students classified into this cluster is civil servants, which reaches 70%, and similarly, students inside this cluster are very likely to enroll in the civil service after graduation. Similarly, the results of the analysis of cluster III and cluster IV are entry into the company and other, respectively.

It can be said that a student who has a high GPA during his undergraduate period, who has studied more days in the library, who has participated in the Party Building Knowledge Contest and won awards, and who has passed the fourth or sixth level of foreign language proficiency, and who has won scholarships for many times during his time at the school, then it is very likely that this student will be categorized into the category of the clustering cluster Ⅱ applying to the civil service, i.e., it is very likely that this student's likely destination after graduation is applying to the civil service, and then the system can appropriately Then, the system can appropriately recommend some job information related to the national examination and provincial examination to improve the possibility of success of the civil service examination for this category of students.

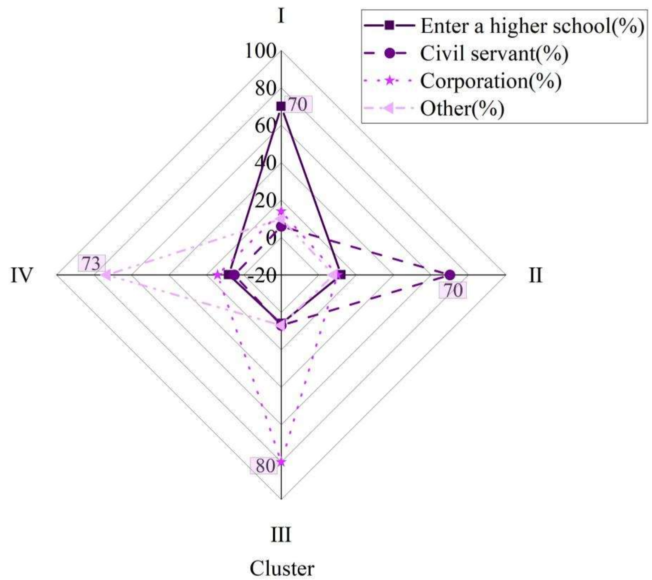

Fig. 5. The proportion of each graduation destination in the cluster

3.3. System computational optimization experiments

3.3.1. Effect of similarity fitting parameter λ on recommendation accuracy. In order to improve the job recommendation accuracy of the system, two criteria, RMSE and P-value, are selected in this chapter, and the comparison experiments between the K-prototype algorithm and the currently commonly used User-based Collaborative Filtering algorithm (UCF) and Clustering-based Collaborative Filtering algorithm (CCF) on the employment data of the students in our university are designed, and experiments on the influence of the fitting parameter λ on the accuracy are designed at the same time.

The two similarity calculations are fused in the K-prototype algorithm, and in order to find the optimal solution of the fusion several sets of comparative experiments are designed to test the effect of different λ values on the recommendation accuracy, and at the same time, to find the optimal combination value of the number of neighbors N and the fitting parameter λ.

Figure 6 shows the effect of similarity fitting parameter λ on the accuracy of recommendation algorithm, and also shows the change of the accuracy of K-prototype algorithm under the joint effect of different number of neighbors N and similarity fitting parameter λ. From Fig. 6, it can be seen that the accuracy of recommendation increases with the increase of fitting parameter λ, and the accuracy reaches the maximum when λ=0.5, and thereafter the change of accuracy tends to level off with the increase of fitting parameter. And the accuracy basically reaches the maximum at λ=0.5 when comparing different N values. Through the above two sets of experiments, this paper concludes that the optimal parameters of the K-prototype algorithm are λ=0.5 and N=50.

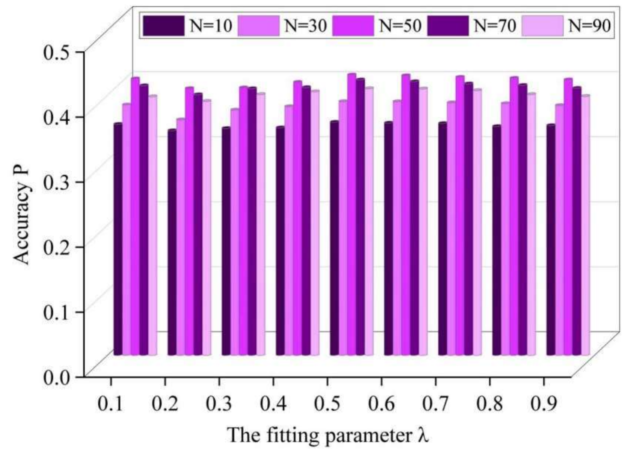

Fig. 6. Influence of fitting parameter λ on accuracy p

3.3.2. Effect of the number of neighbors N on recommendation accuracy. The number of neighbors N is an important factor affecting the recommendation results in collaborative filtering algorithms, in order to test the advantage of K-prototype algorithm over other algorithms in terms of accuracy, therefore, a separate experiment is designed to compare the change in accuracy of different recommendation algorithms as the number of neighbors N changes.

Fig. 7 demonstrates the effect of the number of recommended neighbors N on the accuracy of the recommendation algorithm, and also compares the accuracy variation of UCF, CCF and K-prototype with the same number of neighbors. From the trend of Fig. 7, it can be seen that the accuracy of all three recommendation algorithms increases with the growth of the number of recommended neighbors N. The accuracy of recommendation reaches the highest when the number of neighbors N=50, which is 0.2502, 0.2696, and 0.4302, respectively. It is demonstrated that increasing the number of neighbors of the target user in a small range is effective in enhancing the recommendation accuracy. Comparison experiments also show that the accuracy of the improved K-prototype algorithm is greater than 0.35 at any number of neighbors, much higher than the other two algorithms. It is verified that the number of neighbors N=50 can be combined with the fitting parameter λ=0.5 to jointly optimize the recommendation accuracy of the K-prototype algorithm.

Fig. 7. Influence of neighbor number N on accuracy p

3.3.3. Comparison of RMSE values of different recommendation algorithms. Since the algorithms will have predicted the ratings of the positions that students may be interested in, in order to more accurately represent the difference between the predicted ratings and the real ratings, the RMSE evaluation criteria are introduced to test the three algorithms, K-prototype, UCF, and CCF, in the experiments on the data of student employment in our university. Figure 8 shows the comparison results of RMSE values of different recommendation algorithms. This set of experiments demonstrates the comparison of the recommendation quality of this paper's algorithm K-prototype with UCF and CCF under the same conditions, and it can be clearly seen from the figure that, due to the addition of a strong timeliness recommendation and the optimization of parameter λ, the RMSE value of the K-prototype algorithm ranges from 0.6011-0.731, which is smaller than that of the other two algorithms, and it can therefore be concluded that The recommendation quality at any value of N is higher than the traditional UCF algorithm and CCF algorithm, which can well recommend interested and suitable positions for students.

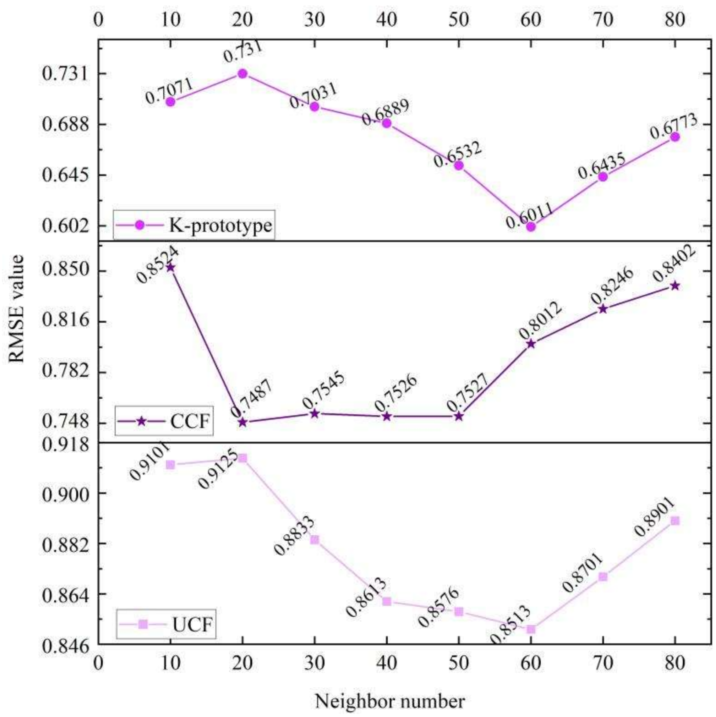

Fig. 8. Comparison of RMSE values of three recommendation algorithms

4. Conclusion

Based on the field theory, this paper establishes and applies the employment support system to study the in-school behavioral data of college students, conducts cluster analysis of students according to different behavioral labels, realizes the precise recommendation of employment positions, and improves the employment rate and quality of employment in colleges and universities under the leadership of digital party building. Extract students' online behavioral characteristics, and initially classify students' online characteristics into 3 categories according to the online duration of 0-60 minutes, 60-180 minutes, and more than 180 minutes. Extracting students' book borrowing behavior, according to the number of books borrowed 0-11 books, 12-21 books, and more than 21 books, initially classifying students' book borrowing characteristics into 3 categories. Extract students' achievement behavior characteristics, according to the differences in the total grade point, the number of failed subjects, graduation internship results, English proficiency, computer proficiency performance, initially divided into 4 categories.

Using the label weight formula, the weight values of various types of behavioral characteristics of students are calculated, and dynamic clustering labels are affixed to students to provide support for the clustering of final employment direction. According to the employment direction, the students were clustered into four categories, and the most likely employment directions of the students in the cluster were determined according to the maximum proportion in different clusters, which were "postgraduate entrance examination", "civil servant examination", "company work" and "others". The system will make accurate job recommendations for students according to the maximum percentage of employment directions. Meanwhile, through comparison experiments, it is found that when the similarity fitting parameter is set to 0.5 and the number of neighbors is set to 50, the recommendation accuracy of the system can be further optimized and improved. In the comparison of RMSE values, the RMSE value of the K-prototype algorithm of the system in this paper is in the interval of [0.6011,0.731], and the recommendation effect is better.

Under the leadership of digital party building, researching student behavioral data in the educational field and providing personalized employment job recommendations for students with different characteristics can not only change the limitations of the current university's insufficient investment in student employment services, but also promote the pace of intelligent digital development of employment support and alleviate the employment problems of college students.

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