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Research on the analysis of college students' job-seeking and employment behavior pattern and career planning based on cloud computing environment

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Abstract With the rapid development of cloud computing technology and big data analysis, job search and employment services for college students are gradually evolving in the direction of intelligence and precision. This paper proposes a personalized job recommendation model that integrates dynamic behavior modeling and improved collaborative filtering algorithm. An elastic resource scheduling framework based on cloud computing is constructed, and the response efficiency of the system is improved through inertia weight optimization and task allocation strategy. A behavioral-interest model is established to solve the problem of dynamic updating of user preferences. Introduce time decay factor to improve collaborative filtering algorithm and enhance the timeliness and accuracy of recommendation system. Based on the data of finance and economics graduates from University B, the average accuracy of the improved algorithm and the original algorithm are 0.47 and 0.67 respectively, and the average recall is 0.51 and 0.65 respectively, which proves that the improved algorithm in this paper is able to effectively match the interests of job seekers with the characteristics of the jobs, and it has the value of application in the college students' career planning.

Index Terms personalized recommendation, career planning, behavior-interest model, collaborative filtering algorithm, behavior analysis

I. Introduction

From the national perspective, employment is an activity to promote the economic and social development of the country, and a way for college students to serve the society after they have achieved success, and from the individual perspective, on the one hand, it is to obtain income to ensure the stability of the family, and on the other hand, it is also a need to hope to realize their own ideals and values [1]-[3]. Under the situation of increasingly fierce competition in the job market, college students are facing greater employment pressure, and it is especially important to help college students to recognize themselves scientifically and conduct employment guidance reasonably [4], [5].

The employment behavior of college graduates is the purposeful processing of collected job information to promote employment, and this purposefulness is the source of power to guide the results of employment behavior [6]. The employment behavior of college students affects the final outcome of college students' employment, and by analyzing the job-seeking and employment behavior of college students from the personal level and the external level, it can provide guidance for the effective employment of college students [7]-[9]. In order to better promote the effective employment of college students, schools should provide correct and comprehensive employment guidance for college students' employment behavior [10]. For example, schools should guide college students to formulate career planning as early as possible that meets their own abilities and personal wishes [11]. Employment career planning courses can help students set career goals, so that they can form a clear career awareness and self-positioning during the school period, thus reducing the cost of adaptation to enter the society after graduation, and reaching the goals of learning and career development in different stages in stages [12]-[15]. In addition, career planning can also provide students with a theoretical and practical framework for understanding and adapting to the needs of society, help students find their career direction in the ever-changing market environment, and lay a solid foundation for them to realize the transition from “campus people” to “professionals” [16]-[19]. The early formulation of career planning will enable college students to be fully prepared for employment, enhance their self-confidence and sense of competence in the process of employment, and improve the employment efficiency of college students [20]-[22].

This paper designs inertia weighting scheme based on cloud computing to realize efficient allocation of employment information resources. The job seeking process of job seekers is analyzed and a behavioral-interest model is established. Based on the user-employment information attribute vector matching algorithm, an improved collaborative filtering recommendation algorithm based on time decay is proposed. Descriptive statistics of the data related to graduates of finance and economics majors are used to portray the distribution of graduates' occupational interests and the distribution of characteristics of employment positions in different time periods. Based on the match between students' career interests and employment positions, the algorithm in this paper is used to realize personalized job recommendation for job seekers. The effectiveness of this paper's algorithm is examined through the performance comparison test with the original algorithm.

II. Personalized job recommendation model design for job seekers based on cloud computing

In the era of digital economy, cloud computing technology provides a new technical path for processing and analyzing massive employment information. The traditional job search platform relies on static user profiles and simple matching rules, which are characterized by information overload, recommendation lag and other defects, making it difficult to adapt to the dynamically changing career demands of job seekers. At the same time, the elastic resource scheduling and distributed computing capability of cloud computing provide technical support for the construction of intelligent employment service system. This study focuses on the analysis of job-seeking behavior patterns and optimization of career planning in the cloud computing environment, aiming to realize the efficient distribution of employment resources.

II. A.Balancing employment information resources based on cloud computing

The increasing scale of job search system software is prone to imbalance in the utilization of network resources, when additional overhead is added to improve system compatibility. Cloud computing can provide elastic expansion resources for the system and improve development efficiency. By monitoring database access operations, the response of employment information resources can be balanced. The resource layer of cloud computing is responsible for providing physical and virtual resources. The platform layer is responsible for software deployment and function realization. The application layer is responsible for connecting users and cloud computing carriers and exchanging resources of storage facilities and servers. Cloud computing can assign multiple tasks to different virtual machines for scheduling in order to select the option with the shortest overall time to accomplish the employment information resource allocation.

Inertia weights can be added to cloud computing to improve the retrieval efficiency of the allocation scheme, which is calculated as

$$\vartheta = (\vartheta_1 - \vartheta_2)\frac{M-N}{M} + \vartheta_2 \tag{1}$$

where: ϑ is the inertia weight; ϑ_1 and ϑ_2 are the two fixed weights in the retrieval, respectively; M is the maximum number of iterations; and N is the current number of iterations.

The parameters of the cloud computing task list can be adjusted by control coefficients, including task length, output file size and data type. The mapping relationship of resource nodes is established, and the scheduling path of employment information resources can be obtained. During highly concurrent access, cloud computing disperses user requests and data transactions to multiple servers to achieve task request scheduling and improve system performance. All employment information resources are stored in the cloud without time and space constraints, and the system resources are highly scalable. Cloud computing provides space for real-time communication between both enterprises and colleges and universities, effectively solving the employment problem of students. Using cloud computing to store recruitment and job application information according to different classification labels, using unified standards and formats to manage data, avoiding retrieval difficulties caused by different formats of multi-dimensional information.

II. B.Behavioral-Interest Model of Job Seekers

II. B. 1) Structure of job seeker behavior

The traditional job recommendation system takes the personal information and job expectations registered by job seekers as their user profile, and directly uses this document information to generate recommendation results through recommendation algorithms. However, in practical applications, this traditional job recommendation method, which only considers the original information of job seekers, has some defects:

(1) Because job seekers may have a biased understanding of the position, the user's personal information and job expectations (including the position, workplace, salary, etc.) may not reflect the true will.

(2) job seekers in the job search recruitment website for the first time after registering to fill in personal information, generally do not go to update the information, however, with the passage of time, job seekers' job expectations may change, that is, the user's job search status may change, the original job seeker information will be out of date and so on.

(3) The traditional job recommendation does not take into account the job seeker's online job search browsing behavior, so as to discover the user's current job search interest.

In short, the inability to accurately grasp job seekers' job search preferences may result in recommendation results that do not meet job search requirements.

To address the above problems, this study proposes a user dynamic job search interest model based on user behavior. The job search process of job seekers is shown in Figure 1. When a job seeker logs in to a job board, if it is the first time he or she logs in, he or she needs to register and fill in personal information, and then he or she can search and browse for positions of interest. When interested in the browse to the job, job seekers may apply for the job, and then continue to browse other jobs; or not interested in the browse to the job directly exit the site.

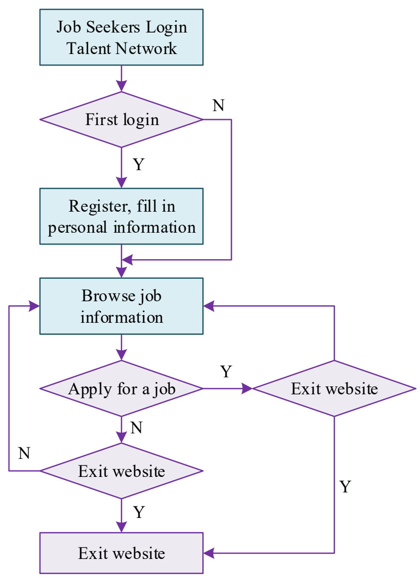

Figure 1: Job search process

II. B. 2) Behavioral-Interest Model

Job seeker behavior is divided into three categories: registration behavior, historical application behavior, and job browsing behavior. The result of registration behavior is recorded as $User-Profile$, which includes information on the user profile characteristics of job seekers such as gender, age, graduation institution, education, major, place of origin, political outlook, English proficiency, computer proficiency, and years of work experience. Recorded information of historical application behavior includes job search preference information of job seeker's desired job category, job nature, monthly salary of the job, and work location, which responds to the job seeker's job search interest and is recorded as $User-Intention$.

Definition (1):

$$F_{profile} = \{User-Profile\} \tag{2}$$

Among them:

$$\begin{aligned} User-profile &= \{x_1, x_2, x_3, \cdots, x_n\} \\ &= (\text{Gender, age, education, ..., profession}) \end{aligned} \tag{3}$$

Definition (2):

$$F_{intention} = \{User-Intention\} \tag{4}$$

Among them:

$$\begin{aligned} User-Intention &= \{y_1, y_2, \cdots, y_m\} \\ &= (\text{Nature of position, salary, ..., place of work}) \end{aligned} \tag{5}$$

In this paper, the model for $F_{intention}$, which is also known as the job seeker expectation or job seeker interest model, is built based on the model structure obtained by combining the registration behavior, historical application behavior and job browsing behavior as shown in Fig. 2.

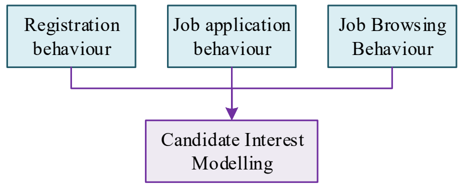

Figure 2: Structure of the job seeker interest model

Definition (3) The job seeker interest model based on the registration behavior information is:

$$F_{reg} = \{Y_1, Y_2, \cdots, Y_m\} \tag{6}$$

Definition (4) Historical application behavior information builds a job seeker interest model as:

$$F_{hist} = \{Y_1, Y_2, \cdots, Y_m\} \tag{7}$$

Definition (5) Job browsing behavior information to build a job seeker interest model as:

$$F_{brow} = \{Y_1, Y_2, \cdots, Y_m\} \tag{8}$$

where Y_i is a vector containing multiple objects, i.e:

$$Y_i = \{y_{i1}, y_{i2}, \cdots, y_{in}\} \tag{9}$$

Example:

$$\text{Location} = \{\text{Shijiaqingxin, Handan, ..., Beijing}\} \tag{10}$$

Suppose, the interest distribution probability of Y_i is $p\left(y_{ij}\right)$, where $j = 1, 2, \cdots, t$. Therefore, there are, $p_{reg}\left(y_{ij}\right)$, $p_{hist}\left(y_{ij}\right)$, $p_{brow}\left(y_{ij}\right)$, respectively, the registration behavior, Historical application behavior, web browsing behavior interest distribution probability, respectively. Among them, the interest distribution probability of registration behavior and historical application behavior is calculated according to Equation (11):

$$\begin{aligned} p_{reg}(y_{ij}) &= \frac{count(y_{ij})}{\sum_t count(y_{it})} \\ p_{hist}(y_{ij}) &= \frac{count(y_{ij})}{\sum_t count(y_{it})} \end{aligned} \tag{11}$$

where $count\left(y_{ij}\right)$ denotes the number of times y_{ij} occurs. For example, a job seeker has applied for 10 positions historically. Among them, Shijiazhuang 5 times, Handan 2 times, and Beijing 3 times. Then the probability of the interest distribution of the workplace is 0.5, 0.2, and 0.3.

The three behaviors are passed through Equation (12) to arrive at the overall interest distribution of the job seeker:

$$p(y_{ij}) = w_1 p_{reg}(y_{ij}) + w_2 p_{hist}(y_{ij}) + w_3 p_{brow}(y_{ij}) \tag{12}$$

where $\sum_{i=1}^{3} w_i = 1$.

This in turn leads to a model of the job seeker's interest $F_{Intention}$:

$$F_{Intention} = \{y_1, y_2, \cdots, y_m\} \tag{13}$$

Among them:

$$y_i = \arg\max p(y_{ij}) \tag{14}$$

That is, y_i is the y_{ij} that maximizes $p\left(y_{ij}\right)$.

II. C. Collaborative Filtering Recommendation Algorithm Based on Job Seekers

II. C. 1) User-Employment Information Attribute Vector Matching Calculation

Each job posting and each user can generate a vector (including subjective interests and objective characteristics), and all job postings will form a vector set. When a user registers in the system, he/she has already provided a list of corresponding attributes, including numerical attributes (age, salary), category attributes (workplace, company nature, profession, personal skills). In this paper, the extracted attribute vectors of the user include five attributes of the job requirements filled in when registering: profession, workplace, company nature, professional skills, salary range, and the similarity of these five attributes is calculated to perform preliminary coarse-grained personalization.

Suppose $User(I_1, I_2, I_3 \cdots I_n)(I\_m \backslash)$ is a n-dimensional job-seeking user attribute vector, then the strength of the user's attributes is represented as $user(i_1, i_2, i_3 \cdots i_n)$, where $i_m (1 \le m \le n)$ is a specific attribute value of the job-seeking user's attribute I_m.

Meanwhile, for job postings, the same method can be used. The user's education corresponds to the education requirement of the position, the user's specialty corresponds to the specialty requirement of the position, the user's workplace corresponds to the workplace of the position, the nature of the company posting the position corresponds to the user's requirement of the company, and the user's professional skill corresponds to the job description of the position (if one of the user's skills happens to meet the job requirement of the position), that is to say, the five attributes selected above, the jobseeker and the employment information all That is to say, the five attributes selected above, the job seeker and the employment information all have one-to-one corresponding attribute values.

The next step is to calculate whether the two attribute vectors match. If an attribute I_m is a binary attribute or a category attribute, take the job location for example, if the job seeker's target job location is Beijing, and the location attribute of the employment information is in Hefei, then the job location does not meet the requirements, and the job information needs to be discarded; and for one of the special occupational skills attributes, the system requires the user to submit 3-5 personal skills, and then compare this skill with the job description attribute of the job information, and the job description attribute of the job information is compared with that of the job information. If this skill appears in the job description, then the system considers that both parties are matched in this attribute.

Vector matching is performed on all the jobs according to the above rules. Once an attribute value does not match, the system immediately discards the job and continues to compare the next one. Then all the matching job messages are taken out of the database and recommended to the job seekers in chronological order.

II. C. 2) Improved time-decay based collaborative filtering recommendation algorithm

Once the number of registered users within the system gradually increases, the job search goals of job seekers are not static, for example, a job seeker may want to find a job in Beijing at the beginning, but recently he is more interested in jobs in Changsha. In order to be able to track and adjust the user's job-seeking intention in real time, this paper chooses the collaborative filtering recommendation algorithm to do personalized employment information recommendation for job-seeking users based on the user's historical job-seeking behavior. Because the frequency of updating employment information is much higher than the number of job seekers added to the system, this paper chooses the collaborative filtering recommendation algorithm based on users. Therefore, the core idea of recommendation in this paper is to obtain the historical behavior of job-seeking users in this system (such as clicking, bookmarking, applying for employment information, etc.), to find out other job-seeking users who are similar to me, and to make use of the historical behavior of similar job-seekers to make predictions and recommendations.

The above collaborative filtering recommendation algorithm has a small drawback, that is, the results recommended to the user every day are not too different, there is not much change. In the field of employment information service, this is a problem that needs to be solved. If the same job listings are recommended to job seekers every day, it not only reduces the accuracy of the recommender system, but also greatly affects the job seeking experience of job seekers. At the same time, user interest is constantly changing, perhaps a certain period of time users are interested in state-owned enterprises, may be after a period of time, the user is more interested in the private sector, then the recent user behavior will be more reliable than the previous user behavior. The traditional similarity calculation method ignores the effect of time, treating job seekers' previous job search behavior as equal to their recent job search behavior, resulting in a lack of timeliness in the similarity calculation, which is also one of the requirements of employment-based information services. For example, job-seeking user A was interested in a position in a state-owned enterprise three months ago and now wants to find a position in a private enterprise; Job Seeking Users B Now I like state-owned companies, but three months ago I was interested in private companies; And job-seeking user C liked SOEs three months ago, but now also wants to find a private sector position. Obviously for the above three, the traditional algorithm for calculating similarity does not distinguish the difference in similarity between user A and B, C but if you add in the time factor considerations to track the user's preferences, it is clear that A and C have closer interests. Therefore, adding the time decay factor can track the user's interest well, and it also caters to the requirements of recommendation algorithms on timeliness.

Combined with the fact that in the field of employment information service, only users with the same user behavior in a certain period of time have higher similarity, therefore, in the above formula for similarity calculation, this paper adds the time decay factor to get the following improved formula for similarity calculation of users based on the time decay factor:

$$sim(u,v)=\frac{\sum_{j\in N(u)\cap N(v)} f\left(\left|t_{uj}-t_{vj}\right|\right)}{\sqrt{\left|N(u)\right|\left|N(v)\right|}} \tag{15}$$

where $f\left(\left|t_{uj}-t_{vj}\right|\right)$ is the time decay factor introduced in this paper, and then where t_{uj} is the time at which the user u acted on the item j. According to common sense can be understood in this way, two users at the same time to produce interest in an item, but if they produce interest in the time interval is far away, compared to those who produce interest in the time interval is very close to the user, their similarity is necessarily the smaller, the function of the time decay is as follows:

$$f\left(\left|t_{uj}-t_{vj}\right|\right)=\frac{1}{1+\alpha\left|t_{ui}-t_{vi}\right|} \tag{16}$$

III. Empirical research on college students' career planning

III. A. Study population and methodology

The research was based on the graduates of the finance and economics program of University B in the past five years. Using typical scenario descriptions, three code sequences were used to collect the characteristics of graduates' career interests and employment positions. First, basic demographic information, such as gender, major, and year of graduation; second, information on the distribution of graduates' career interest characteristics; and third, information on the distribution of graduates' job characteristics for first-time employment, current employment, and future desired employment. The reliability and validity of the questionnaire are improved through expert interviews and multiple probing surveys. The research was based on the number of graduates and gender ratio of each major, quota stratified random sampling, and data were collected through the combination of field and network research.

Among the 947 questionnaires collected, after questionnaire review and data cleaning, 269 invalid questionnaires such as filling out irregularities and logical contradictions were excluded, and 678 valid questionnaires were collected. The basic situation of their samples is shown in Table 1. The ratio of men and women among the survey respondents is close to 1:1.2. 39.38% of the graduates have been working for more than 2 years; the proportion of graduates majoring in financial accounting, marketing and economics and trade is 30.38%, 23.16% and 17.40% respectively. Nowadays, private enterprises account for the largest proportion of jobs, as high as 71.68%, followed by institutions and state-owned enterprises, and self-employment category accounts for a minority.

Table 1: Basic Information of the survey Sample

Project	Classification	Frequency	Specific gravity
Gender	Male	315	46.46%
	Female	363	53.54%
Graduation years	Within one year	146	21.53%
	1~2 years	265	39.09%
	2~3 years	152	22.42%
	3~4 years	48	7.08%
	4~5 years	67	9.88%
Major Studied	Financial accounting	206	30.38%
	Finance and insurance	68	10.03%
	Business Administration	75	11.06%
	Human Resources and Management	54	7.96%
	Economic Trade	118	17.40%
	Marketing	157	23.16%
The nature of the current workplace	State-owned enterprises	66	9.73%
	Private enterprise	486	71.68%
	Government agencies and public institutions	71	10.47%
	Self-employment	55	8.11%

III. B. Analysis of college students' job-seeking and employment behavior patterns

III. B. 1) Analysis of the distribution and differences in occupational interests

The distribution of career interests of graduates of different genders is shown in Figure 3, and social, corporate and transactional career interests are the three most widely distributed types among finance and economics students. The proportion of students with social-type career interests is as high as more than 35%, followed by enterprise-type and transactional-type. The distribution of career interests of male and female students is distinctive and differs significantly. Both male and female students have maximum share of social type career interest which is 30.29% and 42.39% respectively. The proportion of girls' preference for the social type is much higher than that of boys, which is related to the communication trait naturally possessed by women. The distribution of male students among the six types of vocational interests is relatively even and less varied than that of female students.

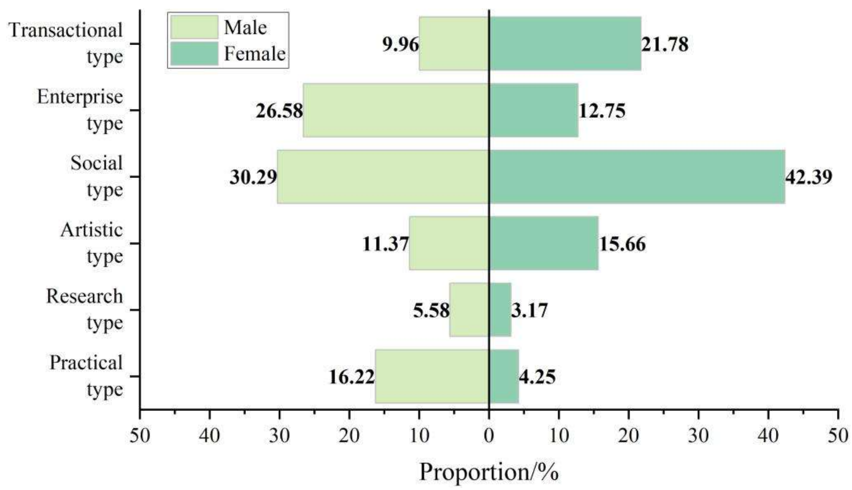

Figure 3: Distribution of career interests of graduates of different genders

III. B. 2) Analysis of the distribution of job characteristics

The distribution of the characteristics of employment jobs at different employment stages is shown in Figure 4. Practical and transactional jobs account for the highest proportion of current jobs and show a decreasing trend in future desired jobs, indicating that there is a deviation between these types of jobs and students' career expectations, which may stem from the structural adjustment of the labor market's demand for skilled personnel or students' cognitive bias. The proportion of research-type, art-type and enterprise-type positions is on the rise, reflecting the diversification of college students' career interest development. The decreasing trend in social-type positions may be related to the decline in the actual supply of this type of positions. In terms of the proportion of different types in the stages, art-based positions maintain a low proportion in all three stages (7.22% for the first job, 7.93% for the current job, and 12.57% for the expected future job), confirming the traditional conception of the career needs of business graduates.

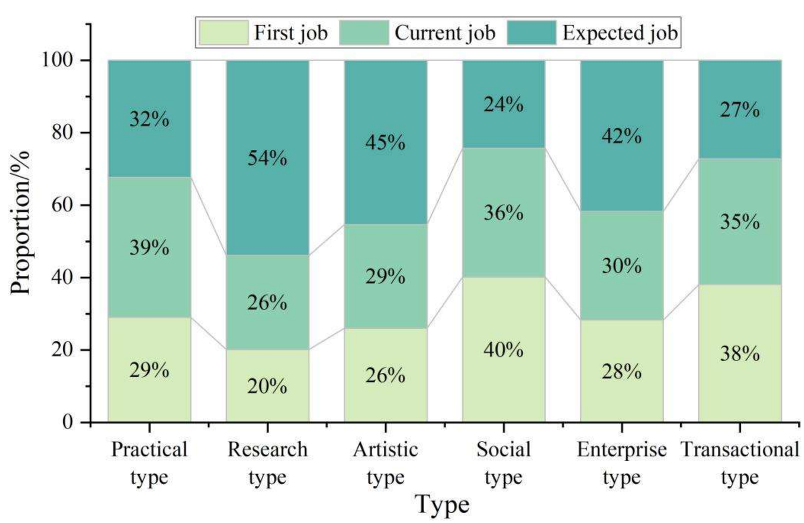

Figure 4: Distribution of job characteristics at different employment stages

III. C. Personalized job recommendation based on collaborative filtering

Based on the above behavioral model, this section implements personalized job recommendation through collaborative filtering algorithm and verifies the effectiveness of the model in career planning.

III. C. 1) Collaborative Filtering Based Job Recommendation

Based on the intention of job seekers, the improved collaborative filtering algorithm designed in this paper is used to calculate the degree of interest of job seekers, and the results of the calculation of the degree of interest of some of the research object positions are shown in Table 2.

Table 2: Interest Degree of Job Seekers(Part)

	Position interest degree														
	Major			Work location		Nature of the company			Professional skills				Salary range		
	1	2	3	1	2	1	2	3	1	2	3	4	1	2	3
1	0.34	0.23	0.43	0.62	0.38	0.35	0.28	0.37	0.18	0.26	0.14	0.42	0.48	0.22	0.30
2	0.41	0.22	0.37	0.58	0.42	0.33	0.26	0.41	0.42	0.22	0.14	0.22	0.31	0.28	0.41
3	0.33	0.23	0.44	0.55	0.45	0.24	0.53	0.23	0.25	0.31	0.15	0.29	0.31	0.32	0.37
4	0.45	0.21	0.34	0.62	0.38	0.41	0.27	0.32	0.22	0.37	0.15	0.26	0.33	0.15	0.52
5	0.44	0.27	0.29	0.23	0.77	0.25	0.33	0.42	0.31	0.25	0.16	0.28	0.35	0.17	0.48
6	0.18	0.46	0.36	0.45	0.55	0.17	0.44	0.39	0.16	0.22	0.39	0.23	0.66	0.12	0.22
7	0.27	0.45	0.28	0.61	0.39	0.28	0.33	0.39	0.42	0.11	0.08	0.39	0.25	0.33	0.42
8	0.35	0.17	0.48	0.28	0.72	0.42	0.17	0.41	0.06	0.32	0.18	0.44	0.17	0.63	0.20
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According to the job seeker model proposed in 2.2, a student is selected to start the analysis, and the user and employment information attribute model is shown in Table 3. After sorting according to the similarity from the largest to the smallest, the Top10 jobs are taken out as the recommended list data to realize the personalized job recommendation for job seekers.

Table 3: User and employment information attribute model

	Candidate Position id	User interest degree	Position freshness	Position similarity
1	425	0.2584	0.9025	0.0155
2	318	0.1985	0.8852	0.0169
3	309	0.1992	0.8326	0.0198
4	371	0.2011	0.7833	0.0266
5	405	0.2368	0.6515	0.0283
6	263	0.1962	0.6322	0.0294
7	255	0.2055	0.5811	0.0351
8	189	0.2367	0.4738	0.0389
9	256	0.1988	0.3699	0.0411
10	277	0.1953	0.3512	0.0435

III. C. 2) Performance testing and analysis

Changing the number of recommended results under the premise of fixing the number of nearest neighbors, comparing the recommendation effect before and after the algorithm improvement, repeated experiments, accuracy and recall comparison results are shown in Fig. 5 and Fig. 6, respectively. The horizontal coordinate represents the number of nearest neighbors, and the vertical coordinate represents the size of accuracy and recall, respectively.

In this paper, we test the accuracy and recall of directly adopting the original collaborative recommendation and adopting the improved collaborative recommendation when different numbers of recommendations (10 to 100) are selected. In terms of accuracy, the improved algorithm is more accurate than the original algorithm, with an average accuracy of 0.47 and 0.67, respectively, and both of them show an increasing and then decreasing trend. From the point of view of the recall rate, both of them are in an upward trend, but the recall rate of the improved algorithm is obviously higher than the original algorithm, with an average recall rate of 0.51, 0.65, respectively. It proves that the improved algorithm in this paper can enhance the quality of the calculation of the user's similarity, which in turn improves the accuracy of the collaborative recommendation.

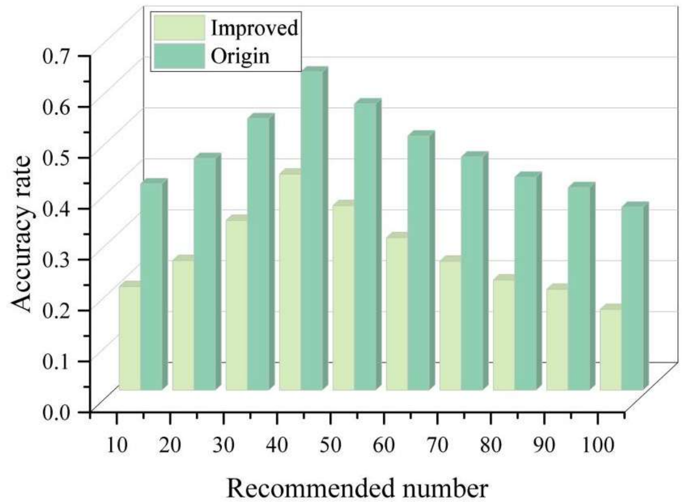

Figure 5: Accuracy comparison

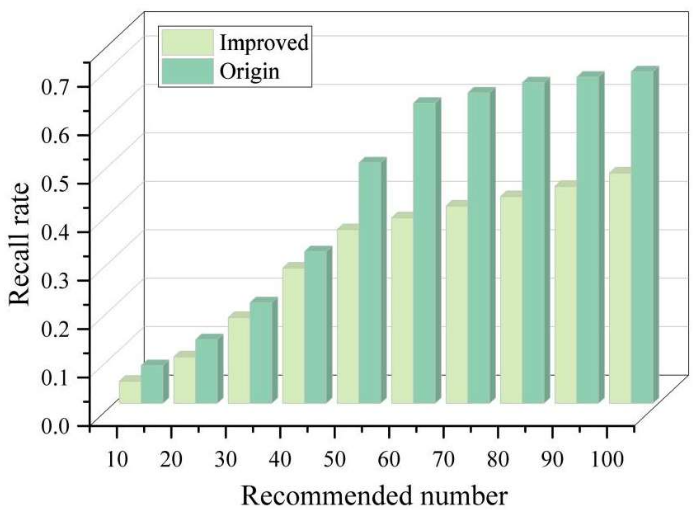

Figure 6: Recall rate comparison

IV. Conclusion

This paper designs a personalized job recommendation model for job seekers based on cloud computing to analyze the behavioral patterns of job seeking and employment of college students based on real data and make personalized job recommendations.

The proportion of students with social-type career interests is as high as more than 35%, followed by enterprise-type and transactional-type. The proportion of both male and female students in social type career interest reaches the maximum, which is 30.29% and 42.39% respectively. Practical and transactional jobs have the highest share in the current job, and show a decreasing trend in the future desired job. The proportion of research-oriented, artistic, and business-oriented jobs showed an increasing trend, and social-oriented jobs showed a decreasing trend. Artistic jobs maintain a low percentage in all three stages (7.22% in the first job, 7.93% in the current job, and 12.57% in the future desired job), confirming the traditional conception of the career needs of business graduates.

In terms of accuracy, the improved algorithm in this paper is more accurate than the original algorithm, with an average accuracy of 0.47 and 0.67 respectively, and both of them show the trend of increasing first and then decreasing. From the point of view of recall rate, the recall rate of the improved algorithm is obviously higher than the original algorithm, the average recall rate is 0.51, 0.65 respectively. it proves that the improved algorithm in this paper can improve the quality of user similarity calculation, thus improving the accuracy of collaborative recommendation.

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