Research on Enterprise Management Training Based on Cluster Computing

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Objectives: Based on the cluster calculation, in this paper, the implementation of the training of enterprise personnel recruitment management was studied, starting with the employment recommendation form as the starting point.Methods: First of all, making rational use of previous employment data of college graduates and concludes with a Sensitive-Personal Rank algorithm to calculate the sensitivity of graduates interested in the historical recruitment data of each enterprise.Results:Furthermore, sensitivity to the current graduates and the graduates of the existing correlation between the calculation methods was optimized; finally, it was similar to the previous graduates to the recent graduates to recommend, so as bringing effective employment reference and guidance.Conclusion: The experimental results showed that, RBSI had a relatively high recommendation accuracy and satisfaction.

Keywords: cluster computing; personnel training; sensitive-personal rank algorithm
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Under the background of continued expansion of enrollment and continuous increase in the number of graduates in universities, the employment of college graduates has been valued by all sectors of society [1]. Recruitment preferences based on the method by virtue of historical information on the enterprise to conduct an analysis of the gradual differences in the characteristics of enterprises to pay attention to the characteristics of the implementation of this recommendation, this approach is widely used in graduate employment recommendation, to recommend the performance of the system to be Effective optimization [2.] However, there are still some problems that need to be improved: In view of the fact that the acquisition of historical information of undergraduates in school may encounter constraints from many aspects such as schools, the relevant research focuses on the implementation of recommendations based on the job descriptions of graduates and does not possess the historical information of graduates' Many researches emphasize students' preference in the process of recommending, but they are not concerned about the dominant position of the enterprises in the process of actual recruitment. In many researches, the general choice of position information released by the enterprises to explore the preference of enterprises recruits, the lack of orientation Hiring Preferences of Graduate Historical Employment Data. In view of the above problems, this paper presents an employment recommendation algorithm based on the sensitivity of business interests.

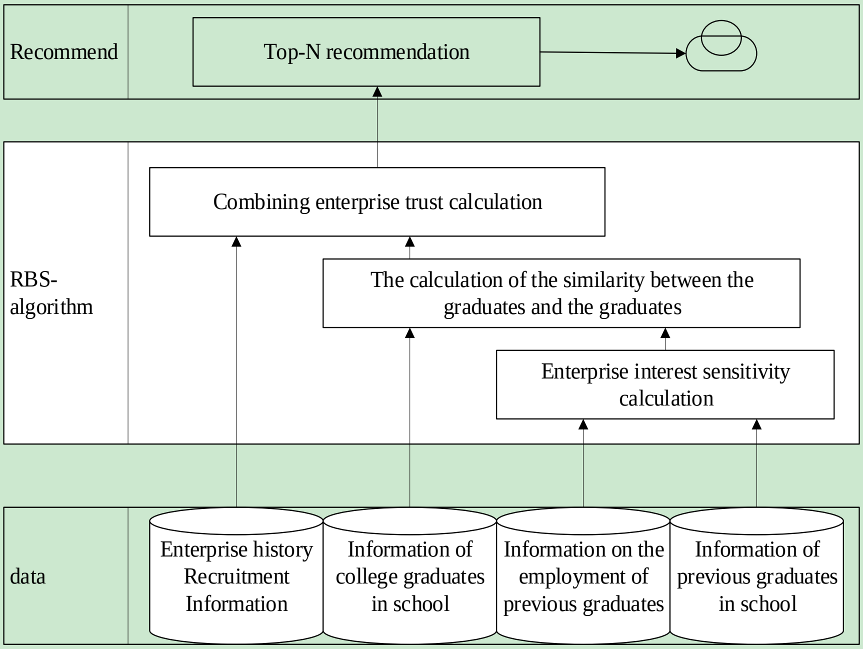
In the context of the rapid development of multimedia and other technologies, the amount of information brought by users shows a trend of explosive growth [3]. For the accumulation of many information, if users want to get valuable information about themselves, they must spend a lot of time and energy, "information overload (Information Overload)" phenomenon [4]. The recommendation system is a reasonable tool to deal with the information overload, which obtains the user's behavior data by implicit or explicit methods, and takes a reasonable approach to explore the user's interest to recommend to the user to match their interests [5]. The application of the recommendation system is reasonable and reduces the impact of information overload, not only reduces the user participation, but also saves the user's time, making the user access to information more efficient. In view of the recommendation system has the information filtering level The various advantages of this technology have been widely applied both at the video push of product recommendation and on demand of music [6]. The recommendation system consists of three parts, the recommendation strategy module in Guangzhou and the background object modeling module, in which the recommendation strategy module is the main body of the recommendation system design. The recommendation system generally includes two kinds of methods to obtain the user's requirement information [7]. One is to take the initiative to submit personal preference information by the user's use of the system; the second is the system by virtue of implicit or explicit way to obtain user behavior data. For the recommendation strategy module, the recommendation system designs a scientific recommendation algorithm to implement the recommendation according to the obtained user preference information and the data and the actual needs of the user, or directly uses the more perfect recommendation algorithm in the system .

METHODS

Sensitive-Personal Rank algorithm Main Ideas and Steps

This paper presents a job-based recommendation algorithm (RBSI), basing on interest sensitivity. It aims at the degree of preference of school-training enterprises in the process of recruiting for the difference of graduation characteristics. It constructs a business-attribute bipartite graph Model, and then take a class of optimized Personal Rank algorithm to calculate the sensitivity of the enterprise to graduates' characteristics by using the random walk in the business attribute bipartite graph model, and to associate the similarity calculation method with the enterprise sensitivity To optimize the calculation method of the previous cosine similarity, and finally contact Top-N recommendation for the enterprise employment index. The above recommendation process is shown in FIG. 1. This method can be divided into four basic steps: one is to build a business-attribute bipartite graph model; the other is to calculate the sensitivity of business interest; the other is to calculate the correlation between fresh graduates and previous graduates; N recommended.

Figure1
Flow Chart Based on the Interest Sensitivity Recommendation Algorithm

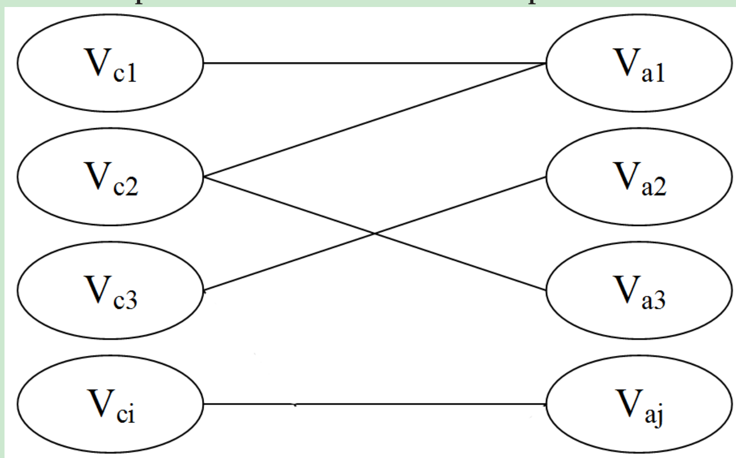


After that we build a business - attribute dichotomy. With the employment of historical data analysis, gender, whether there is internship experience and other related attributes and characteristics of college graduates in the employment of the impact of meticulous elaboration goes to its characteristics and the quantification process, as shown in Table 1:

Table1
Attribute Quantizing

Attribute	Explain	Quantitative standard
Gender	Graduate sex	Male: 1, female: 0
Practice experience	Participation in social practice	Times of social practice
Party member	Whether or not a party member is a party member	Party members: 1, not party members: 0
Achievement point	Transformation of University achievements into achievement points	Calculating method of calculating average point of achievement by using Peking University
competition	The number of awards in the competition during the University	Actual number of awards
Scholarship	The number of scholarships received during the University	Number of scholarships
Class dry	Have you served as a class	It's Ben: 1, not class: 0

Figure2
Enterprise Attributes Two Partite Graph Models



In this process, the attributes of all businesses and past graduates must be organized as a business-attribute bipartite graph, $G(V,B)$, as shown in Figure 2, which applies to the modeling and calculation of the potential linkages between business and graduate traits. In the bipartite graph, $V = V_{company} \cup V_{attribute}$, V is the set of enterprise vertices $V_{company}$ and attribute vertex $V_{attribute}$, where the enterprise vertex set $V_{company} = \{V_{c1}, V_{c2}, V_{ci}, \ldots, V_{cm}\}$, where V_{ci} represents the i-th business vertex, m represents the number of enterprises, $i \in [1,m]$, attribute vertex set $V_{attribute} = \{V_{a1}, V_{a2}, V_{aj}, \ldots, V_{an}\}$, Where V_{aj} represents the j-th business vertex, n represents the number of attributes, $j \in [1,n]$. If any firm vertex V_{ci} and any attribute vertex V_{aj} have a relationship, then the two vertices connected to a line. The set of edges $E = \{e_{11}, e_{22}, e_{1j} \ldots e_{21}, e_{2j} \ldots e_{31}, e_{32} \ldots e_{ij}\}$, where e_{ij} said that there is an edge between the enterprise vertex V_{ci} and the attribute vertex V_{aj}, V_{ci} and V_{aj} have an edge or not need to use formula (1) to make it clear.

$$e = \begin{cases} 1, \text{If the enterprise } V_{ci} \text{ recruitment is } V_{aj} \\ 0, \text{If the enterprise } V_{ci} \text{ recruitment does not exist } V_{aj} \end{cases} \quad (1)$$

As far as the calculation of enterprise's sensitivity of interest is concerned, the specific is the sensitivity of recruiting enterprises to the various characteristics of graduates. In view of the difference in the importance attached to different characteristics by enterprises, in the recruitment process, if graduates meet the characteristics of enterprise's needs, Enterprises will be able to maintain a greater sensitivity to this feature, and the chances of graduates applying for success will increase significantly. Therefore, accurately obtaining the interest sensitivity of enterprises is an important step toward improving the success rate. With the optimization of PersonnalRank, A Senstive-Personal Rank algorithm, used in the calculation of the enterprise's interest sensitivity. The weight of the bipartite graph and the number of times of choosing the same attribute are in positive proportion, and the number of times of choosing the attribute of interest is inverse proportion. Combined with the above-mentioned Sensitive-Personal Rank algorithm to update the node formula as (2):

$$PR(v)=\begin{cases}\alpha\sum_{v'\in in(v)}\frac{PR(v')c_{vv'}}{c_{v'}}(v=v_u)\\(1\text{-}\alpha)+\alpha\sum_{v'\in in(v)}\frac{PR(v')c_{vv'}}{c_{v'}}(v\neq v_u)\end{cases}\quad(2)$$

Among them, α belongs to the random walk depth factor. With the comparative analysis of the experimental results, the value of α is 0.70, the value of $PR(v')$ is the value of the adjoining point, and the $c_{vv'}$ is the number of times of connecting edges that the node must walk from nowadays. $c_{v'}$ belongs to this node The sum of all node selection times. The process of Sensitive-Personal Rank algorithm specifically includes: inputting the attributes of enterprises and enterprises to recruit students to construct the bipartite graph $G(V,E)$, the initial node v_u and the set number of iterations p. Export business recruitment interest sensitivity spr. Select the enterprise vertex v_u as the starting node of random walk, and initialize the PR value of this point to 1; select the random walk probability α, v_u belongs to the starting node composed of the business attribute bipartite graph for random walk, and The formula (2) is used to update the PR (v) values of each fixed point, and the convergence of the PR (v) values of each vertex is judged.

In terms of similarity calculation, when calculating the similarity between fresh graduates and previous graduates, the effective sensitivity of combining different business-oriented attributes should be effectively combined to ensure that the similarity calculation results meet the actual needs of enterprises and the accuracy of recommendation results Enhance. In order to solve the sensitivity of enterprises to various characteristics of students, a weighted cosine similarity calculation method based on the sensitivity of interest is designed. Taking the attribute-oriented sensitivity of enterprises as the weight of matching attributes, the sensitivity Large on behalf of this business in the recruitment process, the greater the focus on this property, combined with the above analysis of the students for the previous st st students' similarity calculation formula as follows (3):

$$sim(st,st')=\frac{\sum_{j=1}^{n}st_j\times st_j{}'\times spr_{i,j}^2}{\sqrt{\sum_{j=1}^{n}(st_j\times spr_{i,j})^2}\times\sqrt{\sum_{j=1}^{n}(st_j{}'\times spr_{i,j})}}\quad(3)$$

st_j belongs to the jth attribute value in the current student vector, st_j' belongs to the jth attribute value in the previous generation vector, and spr_{ij} belongs to the enterprise i's interest sensitivity to this attribute j. Based on the purpose of improving the accuracy of recommendation, the article adds the enterprise trust $Trust(com_i)$, that is, the activity level of a company's enrollment. $Trust(com_i)$ and the number of enterprises in the college enrollment in a short period of time there is an association, the larger the number on behalf of this enterprise in this school enrollment activities more frequently. The degree of company activity needs to be directly proportional to the number of students enrolled, and inversely proportional to the enrollment interval. The actual formula can be expressed as:

$$Trust(com_i)=\sum_{t}^{T}\frac{c_{it}}{c_{it}+\beta(T-t)}\quad(4)$$

In formula (4), in formula (4), c_{it} represents the enrollment number of enterprise com_i at time t, β belongs to the time influence factor, the value of β is 0.5, and T represents the date of the recent enrollment. In view of the fact that some enterprises conducted campus recruitment in this school a long time ago, they did not recruit in the near future, and they can be regarded as less accredited by this enterprise. It is necessary to reduce the probability that the enterprise is recommended to the graduates. Therefore, based on the consideration of the sensitivity of the interest in implementing the Top-N recommendation, the formula (5) is obtained according to the enterprise trust $Trust(com_i)$, and by this formula, N One of the most similar past college salaries recommended to fresh graduates as a basis for employment reference. Freshmen and business fitness com_i, take the formula (5) said:

$$\Pr e(st, com_i) = sim(st, st') \times Trust(com_i) \quad (5)$$

The similarity calculation result of $sim(st, st')$ in the formula (5) can be obtained according to the formula (3), and the com_i enterprise trust belonging to the enterprise i can be obtained through formula (4).

Algorithm Evaluation Index

Set the number of enterprises is m, the number of attributes is n, the maximum number of iterations is p, the number of fresh graduates is q, the number of previous students is z, and the number of recommended lists is N. In the four steps of the algorithm, the first step is to build the user - the complexity of the project bipartite model is $O(m*n)$; the second step is to calculate the sensitivity of the enterprise, the complexity is $O(p*m*n)$; the third is the corresponding students and past students of the correlation calculation, the time complexity is $O(q*z)$; The fourth step Top-N recommended complexity is $O(q*z*N)$. Combined with the above discussion, the overall time complexity of the algorithm is $O(m*n)+O(p*m*n)+O(q*z)+O(q*z*N)<O(2n^3+2n^2)$, ie $O(n^3)$. The evaluation index selected in this paper specifically covers three evaluation indexes: recommendation accuracy rate (P), average order countdown (MRR), and user satisfaction (S). For the recommended accuracy (P), this index is commonly used in the recommended system to define the accuracy of the recommended algorithm is one of the key evaluation indicators, the merits of this indicator can show the advantages of the recommended algorithm. The definition of the accuracy of the article is: the exact number of positions recommended in the total number of jobs to occupy the proportion of. Test graduates, if the list of candidates with the graduates have signed the business, you can determine the recommendation is successful. Let the current graduates collection is C, any graduates $stu \in C, N(stu)$ belongs to the algorithm to stu recommended list of jobs, so that the real sign contractor studios W (stu) said. Combined with the above analysis, the calculation method of the recommended accuracy P selected in this paper is as follows (6).

$$p = \frac{\sum_{stu \in C} 1}{|C|}, N(stu) \in W(stu) \quad (6)$$

In terms of MRR, this indicator is generally used in the recommendation system to recommend the quality of the recommendation list, which is one of the more common evaluation indicators in the recommendation system. The relevant result of the indicator and the user is that The higher the recommended list, the better the recommended quality on behalf of the algorithm. The paper defines MRR as the average of the reciprocal position of graduates in the recommended list in the list of recommended graduates. The larger the value, the higher the value is, indicating that businesses that are associated with graduates are among the best in the recommended results. Remember that the fresh graduates are C and any graduates, so that the corresponding list of stu is N (stu) and the stu contracting company is written as W (stu). If W (stu) is in the recommended result, let W (Stu) The position of the recommended result is L (stu). Based on the above discussion, the MRR measurement formula selected in this paper is as follows (7).

$$MRR = \frac{\sum_{stu \in C} \frac{1}{L(stu)}}{|C|}, \frac{1}{L(stu)} = \begin{cases} \frac{1}{L(stu)}, W(stu) \in N(stu) \\ 0, N(stu) \notin W(stu) \end{cases} \quad (7)$$

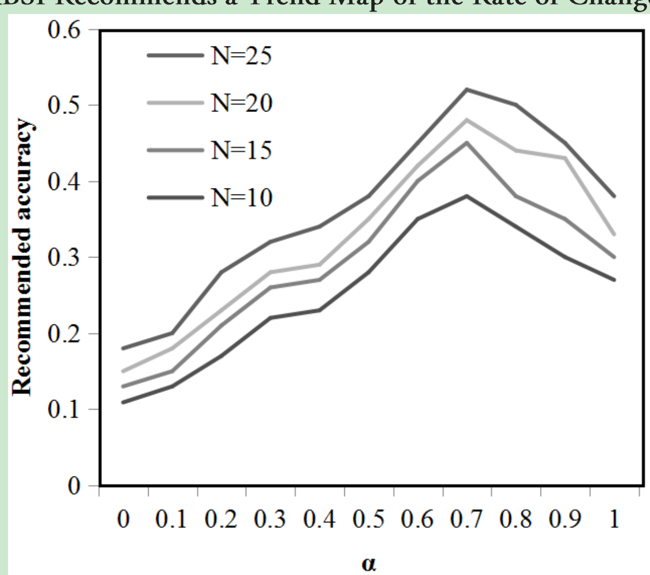
In terms of recommendation satisfaction (S), this indicator is used in the recommendation system to assess user acceptance of the system recommendation results. After using the system, graduates make "Satisfaction", "Satisfaction" and "Dissatisfaction" as the result of the three choices, and implement the statistical analysis by means of the above three types of evaluation results to represent the validity of the algorithm.

RESULTS

This section chooses W1 as a test set for algorithmic profiling. Taking the above mentioned recommended evaluation indexes; the performance of RBSI algorithm is tested. Based on the analysis of P indicator and MRR index, initial values of optimal recommended list degree N and a are determined. A value represents the initial weight of the algorithm in formula (2). After that, the validity of this algorithm was tested by comparison with the recommended performance of other algorithms. Finally, with the use of user systems, the results of user evaluation to be statistically analyzed the user satisfaction test.

Firstly, we evaluate the P indicator so that RBSI recommendation list length is N, and test N belongs to different values, the recommended accuracy P, P is under different N values to follow the change trend of the initial weight a in formula (2) image 3.

Figure3
RBSI Recommends a Trend Map of the Rate of Change

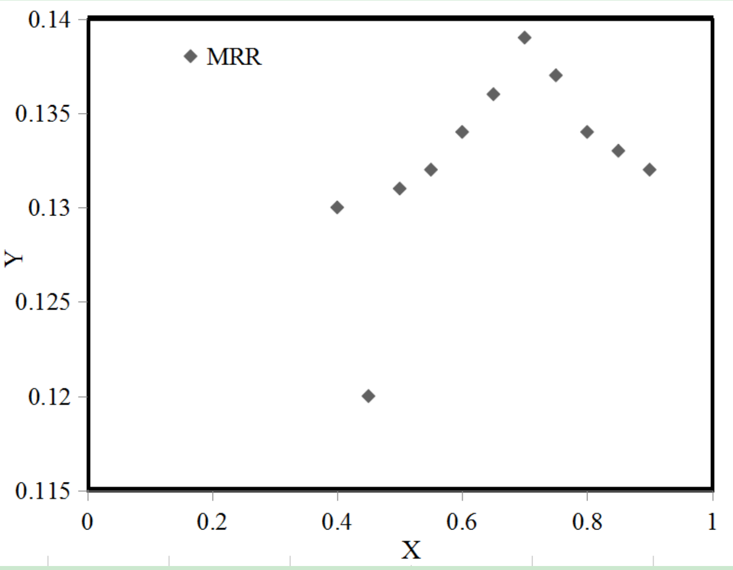


It is clear from Figure 3 that in the case of a = 0.05, the P indicator in RBSI is lower than other values. With a increasing value, the P indicator first rose, and the trend of increasing at a between 0.65 and 0.75 continued to slow down, with the highest accuracy P between 0.7 and 0.75. Combined with the above analysis shows that the recommended list of different a value of the time are more similar. In the case of a = 0.75, the recommended accuracy is the highest when the recommended list length is N = 25, but the recommended accuracy is basically the same when

N = 25 and N = 20. In the case of N = 20 and N = 25, The rising trend continued to slow down, representing more irrelevant results added to the list of recommendations in the case of continued growth of the list of recommendations. Under normal circumstances, P similar to the premise, you need to choose a smaller value of N. Therefore, RBSI recommendation list length N = 20, with the highest accuracy rate up to 49%, get better recommendation results, which can provide scientific and effective guidance to the employment of graduates.

For the MRR index evaluation, using the accuracy analysis of the above N values, it is clear that the recommended list length of the RBSI algorithm is N = 20. To the performance of the recommended algorithm and a value of the implementation of in-depth analysis and evaluation, the paper adopts the average sort countdown to implement the evaluation.

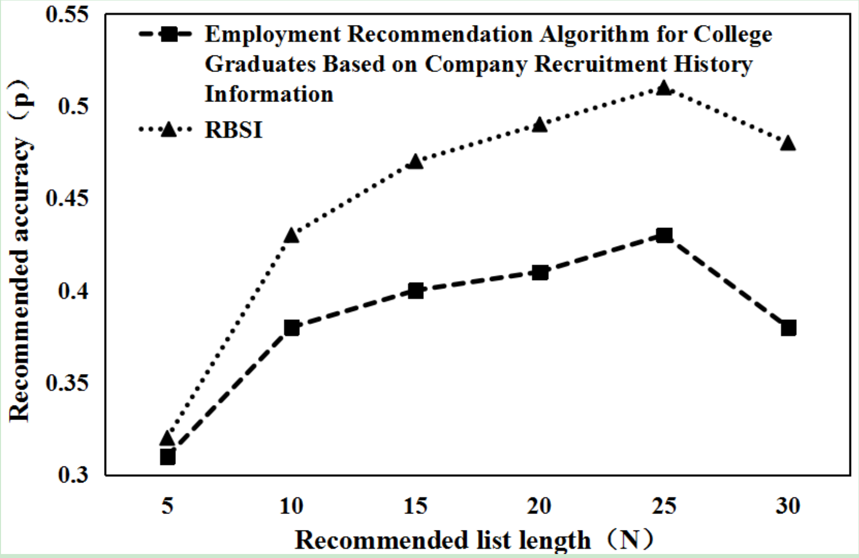
Figure4
MRR Trend Map



It can be seen from Fig. 4 that under the condition of N = 20, the trend of the MRR curve is irregular during the initial stage, and then the trend of increasing and then decreasing first appears. When the value of a is between 0.5 and 0.9 And the accuracy of the change in the trend of P basically consistent, can be understood from the figure a = 0.70, MRR continued to decline, but the recommended accuracy showed a slow rise in the situation. With the analysis of the two performance indexes a = 0.70 and a = 0.75, the recommended accuracy and the MRR are two cases. When a = 0.70, the RBSI can choose to get a better candidate list length performance. Therefore, this algorithm sets the initial random walk weight a to be 0.70 and the recommended length to be N = 20.

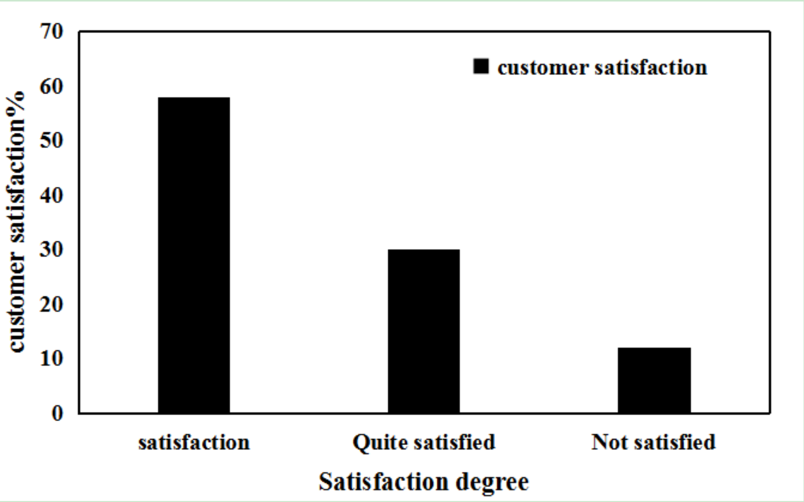
After that, we compare the algorithm in this paper with other algorithms. By comparing the performance of this algorithm with the existing algorithms, the paper proposes a new employment recommendation algorithm for college graduates based on the company's employment history information. And the article based on the sensitivity of the job-based employment recommendation algorithm for comparison. As can be seen from the recommended results in Figure 5, the performance of the RBSI algorithm and the college graduates' employment recommendation algorithm based on the company's hiring history information are basically the same when the initial recommendation list N = 5. Under the condition of increasing, the P indicators of the two kinds of algorithms all showed a rising trend, showing the trend of first increasing and then decreasing, and the highest accuracy could be achieved under N = 20 and N = 25, As can be seen from the figure, RBSI has a clear advantage over the college graduates' employment recommendation algorithm based on the company's employment history information.

Figure5
Algorithm Comparison Result Diagram



In terms of user satisfaction, 50 2016 fresh graduates at Shandong Normal University were randomly selected to evaluate the recommended results. Graduates use the login system to select the 20 recommended records of accreditation. According to the evaluation results, there are 581 satisfaction evaluations, accounting for 58.1% of the total number of recommendations. There are 306 relatively satisfactory evaluations, accounting for 3.3% of the total number of recommendations, as shown in the figure 3-6. Judging from the evaluation, most users agree with the recommendation result of this algorithm, and only 11.3% of the user recommendation results hold a negative trend. This represents the relatively high practicability of the recommended results caused by the RBSI, which can give the graduates more satisfactory recommendation services.

Figure6
The Use of Evaluation Statistics for Graduates



DISCUSSION

Combining the training process of graduates for graduates and the difference of emphasis on graduates' characteristics, this paper proposed an employment recommendation algorithm based on the sensitivity of enterprises' interests, which was especially applied in dealing with school training and enterprise recruitment preference acquisition and graduates' historical information using problem .This algorithm initially explored the hiring of graduates in the historical employment information of the enterprise. In the premise of effectively contacting the information of university graduates and previous employment data, this algorithm optimized the Personal Rank algorithm and displays the performance of enterprises in the historical employment data out of the sensitivity of the characteristics of the graduates; then, in the light of the sensitivity of interest to design the correlation between the graduates and the previous graduates calculation; finally, contacted the trust of enterprises, similar to the previous graduates employment to the new graduates recommend to bring effective employment reference. The experimental results and the evaluation of the corresponding graduates came out, this area could provide clear help to graduates seeking job objectives, promote employment, and provide graduates with scientific and effective employment guidance.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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