A Career Recommendation Method for College Students Based on Occupational Values

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Abstract—The numerous recruitment information and the information asymmetry between college majors and work posts make it difficult for college students to seize the job opportunities that conform to their occupational values, and the employment success rate is always at a low level. The effect of current college student career recommendation systems is usually unsatisfactory, and the existing systems haven't fully considered the role of college students' occupational values in instructing their employment. To fill in this research blank, this paper studied a career recommendation method for college students based on occupational values. At first, the paper proposed a collaborative filtering algorithm based on the features of collect students' occupational values, introduced a few features that can affect their occupational values, assigned weight values to these features, and gave the method for determining the weight. Then, based on the principle of the Kruskal's algorithm (the minimum spanning forest), this paper modified the K-Means algorithm and clustered the features of occupational values. At last, the paper elaborated in detail the principle of generating career recommendation results for college students based on occupational values, and used experimental results to verify the correctness of the proposed career recommendation algorithm.

Keywords—occupational values, employment, college students, clustering analysis, collaborative filtering algorithm

1 Introduction

For college students upon graduation, the career choice is a big choice to make. If they cannot master the effective job information or well prepare themselves for employment, then they would face a muddy choice when determining their career direction in the future [1–12]. At this time, the occupational values are playing a significant role in instructing the career decisions of college students who do not have a clear career goal, especially in aspects of career expectation, career selection, job search, job training, and job satisfaction [13–19]. The numerous recruitment information and the information asymmetry between college majors and work posts make it difficult for college students to seize the job opportunities that conform to their occupational values, and the employment success rate is always at a low level, so it's a meaningful work find an objective, effective, and personalized career recommendation method for college students based on their own occupational values.

Li and Xu [20] used an intelligent optimization algorithm to design and develop a college student employment management system. They surveyed college students' requirements for employment services provided by career instruction center, summarized the required functions of employment management system, divided the system according to user types, and designed the corresponding system function modules. To figure out the trends and status of college students' employment, Qi [21] proposed a college student employment data clustering and mining method based on feature selection, and used it to analyze the employment market of college students and gave the employment data structure; then on this basis, the employment data of college students were subjected to normalized compression, and the sparse scoring method was adopted for data feature selection based on the preprocessed data of college student employment; after that, the online clustering algorithm was adopted to conduct deep mining and clustering on the employment data of college students. To cope with the uneven distribution and poor accuracy of employment resources, Qi [22] applied social network mining to the design of the employment resource allocation algorithm for college students, the author constructed a long-term evolution system and performed interference suppression on it using inter-cell interference randomization technology, inter-cell interference cancellation technology, and inter-cell interference coordination technology, then experiment was carried out to prove that the proposed method can optimize the allocation of employment resources to a certain extent with shorter task scheduling time and higher resource allocation accuracy and efficiency. Bulankina et al. [23] reviewed existing studies and the axiological approach, in their paper, the authors considered the strategies of pluralistic concepts of socio-culture spaces in post-modernism, and discussed the axiological ideas supporting the value spheres of teachers and foreign language teachers. Chang and Lin [24] discussed the role of career development motives in the relationship between job values and job satisfaction. They sampled administrators of four private science and technology universities in northern Taiwan, the 242 effective data attained from questionnaire survey were then analyzed by a structural equation model, and the results suggest that work values have a significant impact on career development motives and job satisfaction.

Most of the existing college student career recommendation systems can hardly gain an ideal effect and they fail to fully considered the role of collect students' occupational values in instructing their employment. To fill in this research blank, this paper attempts to explore a career recommendation method for college students based on their occupational values. In the second chapter, this paper proposes a collaborative filtering algorithm based on the features of college students' occupational values, introduces a few features that can affect their occupational values, assigns weight values to these features, and gave the method for determining the weight. In the third chapter, this paper modifies the K-Means algorithm based on the principle of the Kruskal's algorithm (the minimum spanning forest), and clusters the features of occupational values. In the fourth chapter, this paper elaborates on the principle of generating career recommendation results for college students based on occupational values, and uses experimental results to verify the correctness of the proposed career recommendation algorithm.

2 Career recommendation model and feature weight of occupational values

The process of recommending suitable employer units for college students is to search for companies and job positions with the highest similarity to their career goals. Figure 1 gives the principle of conventional career recommendation for college students. Here, this paper proposes a collaborative filtering algorithm based on the feature attributes of college students' occupational values. A few features of the said occupational values and their corresponding weights of influence are introduced. The first thing is to calculate the distance between the features of college students' occupational values; then, through clustering analysis, the nearest employment set of college students that fits the features of their occupational values is found; at last, in the set, career recommendation is given according to the scores of employer units based on college students' occupational values. The proposed career recommendation algorithm generates neighbor sets with similar features of college students' occupational values, then looks for students with similar occupational values, career goals, and job post interests from the neighbor sets of similar features of occupational values, so the career recommendation quality is good.

The data form of the constructed career recommendation model is described as follows: assuming x represents the number of college students searching for jobs; y represents the number of different types of employer units; S represents the set of scores of different-type employer units given by college students based on their occupational values, wherein $S = (s_{ij})_{x \times y}$ and s_{ij} represents the score of a type of employer unit j given by college student i; in this paper, the scores are divided into six levels, that is $s_{ij} \in \{0, 1, 2, 3, 4, 5\}$, wherein the score level of employer units that do not conform to the occupational values of colleges students is rated as 0, and the score level of those that conform very much to the occupational values of colleges students is rated as 5.

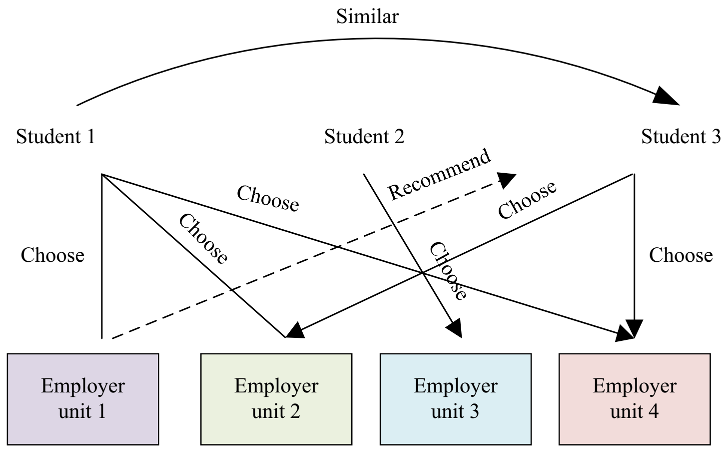

Fig. 1. Principle of conventional career recommendation for college students

After that, the scores of the employer units are clustered, according to the Pearson similarity, the college student who has the most similar score with the target student u is found out, the specific calculation formula of similarity degree is given below:

$$PVC - sim(v,u) = \sum_{i \in I_{vu}} (s_{vi} - s'_v)(s_{ui} - s'_u) / \sqrt{\sum_{i \in I_{vu}} (s_{vi} - s'_v)^2} \sqrt{\sum_{i \in I_{vu}} (s_{ui} - s'_u)^2} \quad (1)$$

Assuming: $NNES(v) = \{v_1, v_2, \ldots, v_l\}$ represents the set of nearest neighbors (namely college students hunting for jobs), and there is $v \notin NNES(v)$, $l \in [1,n)$; $PVC\text{–}sim(v, v_1)$, $I \leq l$ represents the similarity of the features of occupational values of college students v and v_1; ES_v and ES_u are the sets of scores of employer units given by college students v and u, and the intersection of the two is $ES_{vu} = ES_v \cap ES_u$; $s'_v = \sum_{i \in Iv} s_{vi} / \left| I_v \right|$ and $s'_u = \sum_{i \in Iu} s_{ui} / \left| I_u \right|$ are the average scores of employer units given by college students v and u; $|ES_v|$ and $|ES_u|$ represent the number of employer units.

Each feature of colleges students' occupational values can affect their career path after graduation to varying degrees, and the conventional college student career recommendation algorithms fail to comprehensive consider the different weights of these features. To distinguish the influence process and importance of each feature on college students' selection of employers, this paper measures the influence degrees of these features based on the rate of information gain and determines the weight coefficient of each attribute. The specific steps of the feature weights of college students' occupational values are:

Assuming: R represents the set of college students hunting for jobs; m represents the number of types of their career path after graduation, denoted as $Z = \{R_1, R_2, ..., R_m\}$; $R_j = Z_j$ represents the number of the samples of college students' career path; $|R|$ represents the total number of college students in R; $GU(R_j)$ represents the probability that a college student would take the j-th type of career path after graduation, and it meets $GU(R_j) = Z_j/|R|$, then, the information entropy of the employment system of college students can be calculated by the following formula:

$$F(R) = -\sum_{j=1}^{m} GU(R_j) log_2 GU(R_j) \quad (2)$$

Assuming: $GU(R_j)$ is the probability that R belongs to career path type j; R contains multiple feature attributes of occupational values; a feature Y has p kinds of values, namely $Y = \{y_1, y_2, ..., y_p\}$; if $Y = yl$, then it's assumed that Y_{jl} represents the number of samples belonging to the j-th type of career path, and $GU(R_j|Y = y_l) = Y_{jl}/|R_j|$ represents the corresponding probability of attribution; let A_l represent the set of record set of $Y = y_l$, then the conditional entropy of Y can be calculated by the following formula:

$$F(A_l) = -\sum_{j=1}^{m} GU(R_j \mid Y = y_l) log_2 GU(R_j \mid Y = y_l) \quad (3)$$

Assuming: $GU(R_j|Y = y_l)$ represents the probability of the j-th type of career path after graduation when $Y = y_l$, then when the feature Y is met, the information entropy of the career recommendation system can be calculated by the following formula:

$$F(R/Y) = -\sum_{l=1}^{p} GU(Y = y_l)F(A_l) \tag{4}$$

The following formula calculates the information gain:

$$Gain(Y) = F(R) - F(R \mid Y) \tag{5}$$

The information gain rate of the system increases with the decrease of its information entropy, that is, the uncertainty of the career recommendation system for college students decreases with the increase of the amount of information provided by Y. To measure the importance of the feature attributes of college students' occupational values, assuming: $SG(Y)$ represents the amount of information contributed by Y to the career recommendation system; $SL(Y)$ represents the amount of segmented information of Y, then the formula for calculating the information gain rate $GR(Y)$ is:

$$GR(Y) = SG(Y) / SL(Y) \tag{6}$$

The calculation formula of $SL(Y)$ is:

$$Split(Y) = \sum_{j=1}^{p} GU(R_j \mid Y = y_l) log_2 GU(R_j \mid Y = y_l) \tag{7}$$

The information gain of all the features of occupational values is summed, and the weight coefficient of the features of occupational values can be calculated by the following formula:

$$\omega(A) = GainRatio(A) / \sum_{a=1}^{k} GainRatio(A) \tag{8}$$

3 Clustering of the features of occupational values

The features of college students' occupational values can indicate their similarities in terms of career goal, job selection, job hunting, job training, and job satisfaction to a large extent. Introducing these features can break through the limits brought by measuring the similarity degree solely based on the scores of employer units given by students. Assuming: a_{nm} represents the m-th attribute of the n-th college student in the vector, $A = \{A_1, A_2, \ldots, A_m\}$ is the vector formed by the features of occupational values of each college student, then there is:

$$\begin{pmatrix} A_{11} & A_{12} & A_{13} & \cdots & A_{1m} \\ A_{12} & A_{22} & A_{23} & \cdots & A_{2m} \\ A_{31} & A_{32} & A_{33} & \cdots & A_{3m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_{n1} & A_{n1} & A_{n1} & \cdots & A_{nm} \end{pmatrix} \tag{9}$$

Assuming: $V = \{A_{v1}, A_{v2}, \ldots, A_{vm}\}$ and $U = \{A_{u1}, A_{u2}, \ldots, A_{um}\}$ represent the n-dimensional and m-dimensional eigenvectors of college students *v* and *u*, then the feature distance between *v* and *u* can be attained by the following formula:

$$\delta_{vu} = \sqrt{\sum_l^m \left|a_{vl} - a_{ul}\right|^2} \tag{10}$$

The similarity of the features of college students' occupational values *F-sim* can be attained based on distance and similarity coefficient:

$$F - sim_{vu} = 1/(1+\delta_{vu}) = 1/\left(1+\sqrt{\sum_l^m \left|a_{vl} - a_{ul}\right|^2}\right) \tag{11}$$

To enable the clustering analysis to get close to reality as much as possible, this paper introduces the feature weight of college students' occupational values $\omega = \{\omega_1, \omega_2, \ldots, \omega_L\}$, then, the feature distance of the occupational values of college students *v* and *u* after introducing the weight can be calculated by the following formula:

$$\delta_{vu} = \sqrt{\sum_l^m \omega_l \left|a_{vl} - a_{ul}\right|^2} \tag{12}$$

The modified similarity of college students' occupational values is:

$$F - sim^*_{vu} = 1/(1+\delta_{vu}) = 1/\left(1+\sqrt{\sum_l^m \omega_l \left|a_{vl} - a_{ul}\right|^2}\right) \tag{13}$$

To minimize the feature distance of the occupational values of college students with a same type of career path and maximize the feature distance of the occupational values of college students with different types of career path, this paper referred to the principle of the Kruskal's algorithm (the minimum spanning forest) to modify the K-Means algorithm.

Assuming: $R = \{r_1, r_2, \ldots, r_m\}$ represents the set of college students hunting for jobs; $A = \{A_1, A_2, \ldots, A_m\}$ represents the set of features of college students' occupational values; $r_1, r_2, \ldots, r_l$ represent the classes of output clusters; $x_1, x_2, \ldots, x_l$ represent the cluster center values of each class; *l* represents the number of clusters, then the execution flow of the modified K-Means clustering algorithm is:

STEP 1: College students *u* and *v* are taken as nodes that satisfy $v, u \in R$, then (v, u) represents the connecting edge between *u* and *v*, *A* represents the eigenvector of college students' occupational values, then by taking the feature distance of college students' occupational values as the weight value of each connecting edge, a weighted undirected connection graph can be created and denoted as $QM = (U, O)$, a sub-graph with *n* nodes and no edges is the time-space of the initial state, which can be expressed as $QM_0 = (u,\{\})$.

STEP 2: Select the edge with the smallest weight, if the nodes of the edge are within *QM*, then this connecting edge is put into *QM*, after that, select the edge with the smallest weight from the remaining edges, until both nodes of an edge are within *QM*, then the edge is put into *QM*, and all edges in *QM* are built into a loop. These nodes belong to the same type of career path R_i, then they are deleted from *QM*; again, from the remaining edges, the edge with the smallest weight is selected until the types of all nodes have been attained.

STEP 3: Repeat STEP 2 until all nodes form *L* types of career path R_i, $i \in [k,l]$. Assuming: $|R_i|$ represents the number of college students in R_i, $xm = \Sigma_{r\in ri} R/|R_i|$ represents the centers of *L* types of career path; at this same, the generated *L* types of career path is the initial number of clusters of college students hunting for jobs, and the corresponding center of the career path types is the initial cluster center.

STEP 4: For college students $r \in R$, calculate their distance from each career path cluster center, and divide those with the shortest distance from the career path cluster center.

STEP 5: Assign the mean value of each type of career path to the cluster center of each career path.

STEP 6: $O = \sum_i^l \sum_{r\in ri} \left| r - x_m \right|^2$ represents the squared error criterion function, repeat STEP 4 and STEP 5 until *O* is 0, then the clustering terminates.

Figure 2 shows the flow of clustering algorithm for college students' employment features.

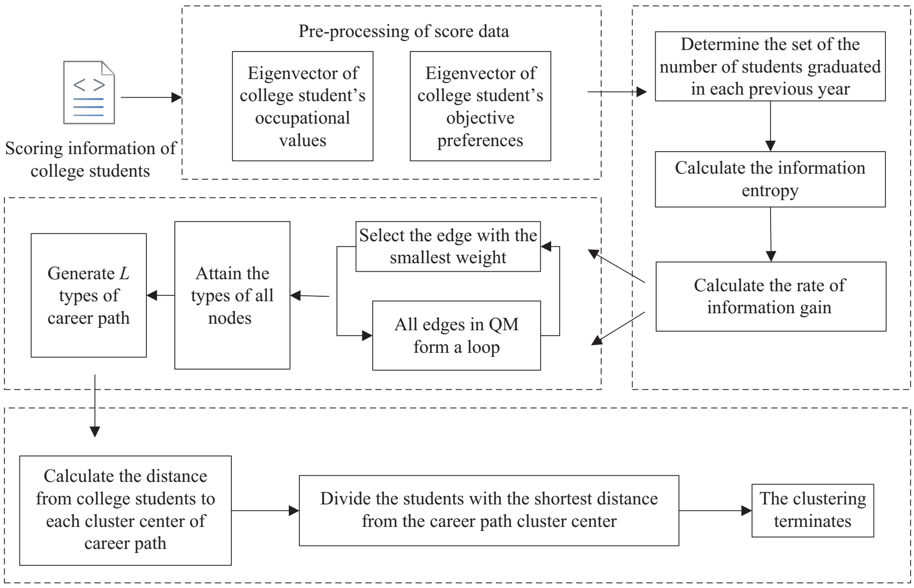

Fig. 2. Flow of clustering algorithm for college students' employment features

4 Generation principle of recommendation results

Clustering the feature matrix of college students' occupational values only classifies students with different features of occupational values into different types of career path, however, the types of the personal career path of college students can not be taken as the only criterion for judging the career recommendation results. In the decisions of the employment of college students, there're other objective factors such as the viewpoints of the students' families and friends. So, only by continuing to study the objective influencing factors of the employment of college students on the basis of the scores of employer units given by students according to their occupational values, can we find the best-matched employers for them and give the final career recommendations.

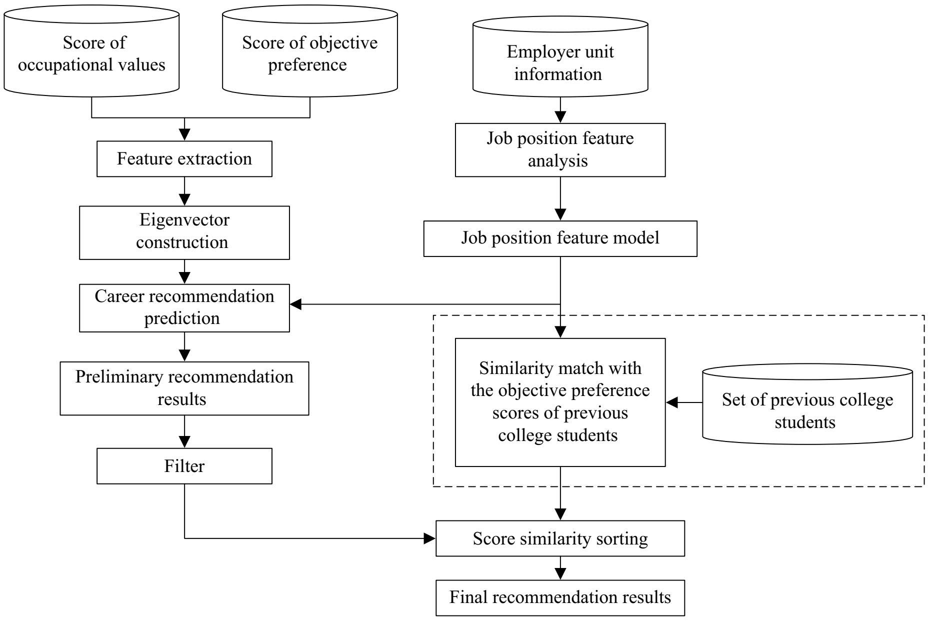

Fig. 3. Generation flow of the recommendation results

Assuming: $S = \{S_1, S_2, ..., S_m\}$ represents the vector constructed by the scores of college students' occupational values; S_m represents the scores of different-type employer units given by college students; s_{nl} represents the n-th college student's objective preference score for the l-th type of employer units, then there is:

$$\begin{pmatrix} s_{11} & s_{12} & s_{13} & \cdots & s_{1m} \\ s_{12} & s_{22} & s_{23} & \cdots & s_{2m} \\ s_{31} & s_{32} & s_{33} & \cdots & s_{3m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ s_{n1} & s_{n1} & s_{n1} & \cdots & s_{nm} \end{pmatrix} \tag{14}$$

The ideal of the career recommendation algorithm proposed in this paper is based on the sum of objective preference scores of all kinds of employer units given by target college students, the employer unit with the closest comprehensive score given by previous college students will be recommended to the target student. Details of the algorithm flow are given below:

Assuming: $S_{vu} = S_v \cap S_u$ is the intersection of the scores of all types of employer units given by college students v and u; $|S_v|$ and $|S_u|$ are respectively the number of comprehensive scores of S_v and S_u; then, the comprehensive scores of employer units s_v^* and s_u^* given by v and u can be calculated by the following formulas:

$$\overline{s}_v = \sum_{i=1}^{S_v} s_{ci} / \left|S_v\right| \tag{15}$$

$$\overline{s}_u = \sum_{i=1}^{S_u} s_{ci} / \left|S_u\right| \tag{16}$$

The definition of the similarity between college students v and u is:

$$sim(v,u) = \frac{\sum_{i \in S_{vu}} (s_{vi} - \overline{s}_v)(s_u - \overline{s}_u)}{\sqrt{\sum_{i \in S_{vu}} (s_{vi} - \overline{s}_v)^2} \sqrt{\sum_{i \in S_v} (s_{ui} - \overline{s}_u)^2}} \tag{17}$$

Through clustering, after a target college student has been classified to a type of career path with the most similar features of his/her occupational values, within this career path type, the similarity between this student and the objective preference scores of previous college students is calculated, then the scores are sorted according to similarity degree, and the employer units with the closest comprehensive score (given by previous college students) is recommended to this target student. Figure 3 gives the generation flow of the recommendation results.

5 Experimental results and analysis

The reliability values of each variable of the features of occupational values are given in Table 1. The Cronbach α coefficient of each variable (income and wealth, interest and specialty, power and status, freedom and independence, self-growth, self-realization, interpersonal relationships, physical and mental health, environmental comfort, job stability, pursuit of new ideas, and social needs) is 0.916, which means that the reliability values of these variables are all greater than 0.7, indicating that the consistency of the evaluation items is ideal.

Table 1. Reliability of feature variables of occupational values

Item	Number of the Item	*Cronbach α* Coefficient
Income and wealth	8	0.847
Interest and specialty	5	0.816
Power and status	9	0.802
Freedom and independence	23	0.936
Self-growth	9	0.825
Self-realization	5	0.819
Interpersonal relationships	8	0.937
Physical and mental health	2	0.748
Environmental comfort	7	0.853
Job stability	5	0.948
Pursuit of new ideas	6	0.884
Social needs	8	0.827
Total	12	0.916

Table 2 shows the difference analysis results of the occupational values of different-type career path. The analysis is conducted from four perspectives of occupational values: the interest type, belief type, ideal type, economy type. For college students graduated in different years between 2010 and 2020, there are significant differences in the influence of their occupational values on their career path after graduation. College students who pay more attention to ideals and performance, social relationship and sense of achievement generally choose to become employees of public institutions or work as civil servants; those who pay more attention to money tend to prefer directional employment or starting a business by themselves; and those who pay more attention to the quality of life or interests and hobbies tend to prefer flexible employment or become self-employed.

Table 2. Differences in occupational values of different career path types

Type of Career Path		Interest Type	Belief Type	Ideal Type	Economy Type
Unemployed or starting a business by oneself	2010	4.36	3.08	3.13	3.69
	2020	4.18	3.52	3.46	3.27
	Difference	–0.15**	0.02*	0.06	0.01
Directional employment	2010	4.72	3.69	3.25	3.18
	2020	4.04	3.11	3.50	3.42
	Difference	0.01	–0.03	–0.06**	–0.04**
Public institutions employee or civil servant	2010	4.25	3.41	3.62	3.19
	2020	4.06	3.12	3.27	3.84
	Difference	–0.05**	–0.16*	0.07	–0.26**
Self-employed or flexible employment	2010	4.96	3.52	3.84	3.59
	2020	4.36	3.60	3.49	3.25
	Difference	–0.02*	–0.07***	0.03**	–0.14*

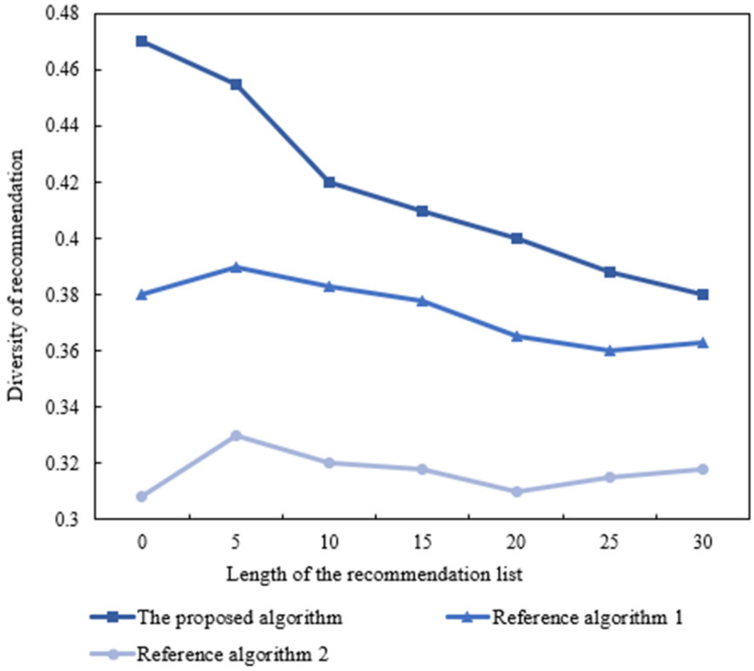

Fig. 4. Comparison of recommendation diversity of different recommendation algorithms

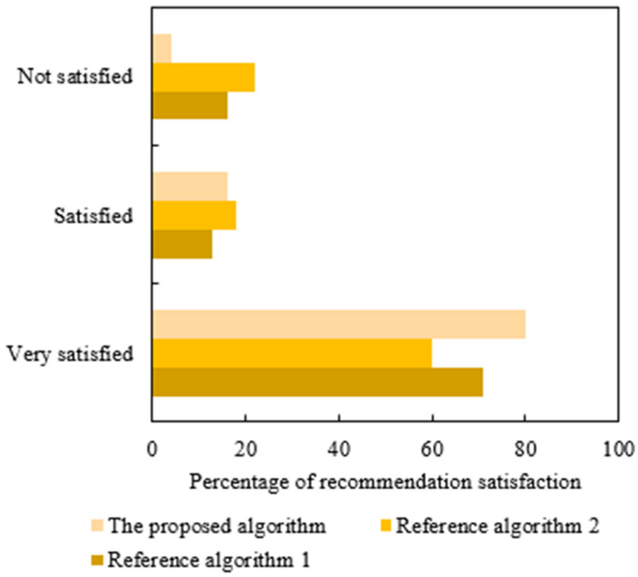

Fig. 5. Comparison of college students' employment satisfaction of different recommendation algorithms

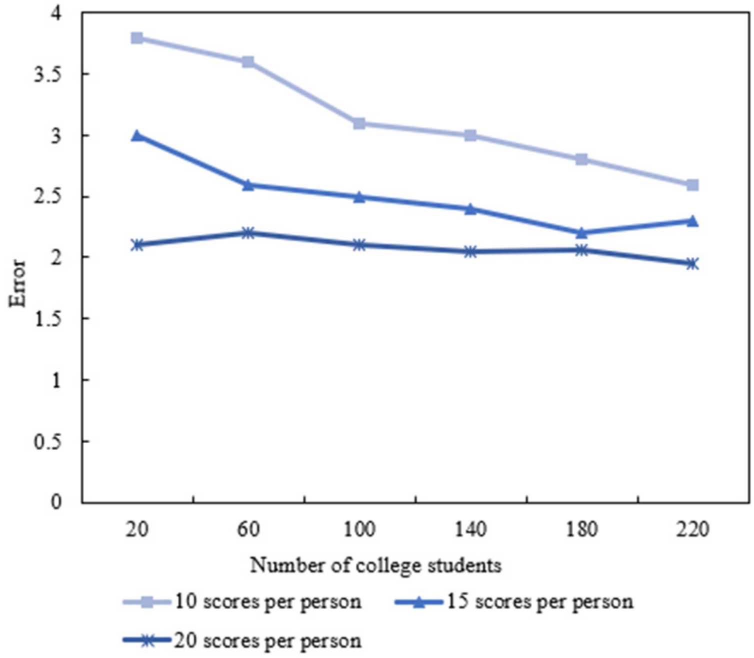

Fig. 6. Comparison of recommendation errors for different employer unit rating items

Figure 4 compares the recommendation diversity of different recommendation algorithms. The reference algorithm 1 is a career recommendation algorithm based solely on the scores of occupational values; the reference algorithm 2 is a career recommendation algorithm based solely on the scores of objective references. Results of comparative experiment show that the proposed algorithm that integrates the occupational values scores with objective preference scores has achieved a higher recommendation diversity, reaching 38% to 47%. Due to the processing the modified *K-Means* clustering algorithm, the difference between recommended employer units always stays at a high level. With the increase of the length of recommendation list, the recommendation diversity of the proposed algorithm is higher than that of reference algorithms 1 and 2, and its advantage is even more obvious in case of shorter recommendation lists.

Figure 5 compares the employment satisfaction of college students of different recommendation algorithms. Students participated in the experimental research could choose between three options of "very satisfied", "satisfied", and "not satisfied". Among all the satisfaction feedback, the proposed algorithm has gotten a higher proportion of satisfaction, indicating that comprehensively applying occupational values scores and objective preference scores to the career recommendation of college students is effective, and students' satisfaction with the career recommendation has been greatly improved.

This paper compares the recommendation errors of different employer units under the conditions of 10 scores per person, 15 scores per person, and 20 scores per person (Figure 6). Although the recommendation error is higher under the conditions of less student number and employer rating items, the advantage of the proposed algorithm is obvious still. The more the students, the more the rating items, the better the quality of the recommendation results of the proposed algorithm.

6 Conclusion

This paper studied a career recommendation method for college students based on occupational values. At first, the paper proposed a collaborative filtering algorithm based on the features of college students' occupational values, introduced a few features that can affect college students' occupational values, assigned weight values to these features, and gave the method for determining the weight. Then, based on the principle of the Kruskal's algorithm (the minimum spanning forest), this paper modified the K-Means algorithm and clustered the features of occupational values, elaborated on the principle of generating the career recommendation results based on occupational values, used experimental results to verify the correctness of the proposed career recommendation algorithm, and gave the reliability analysis results. In the experiment, difference analysis was conducted on the occupational values of college students taking different career paths after graduation and the corresponding analysis results were given. The recommendation diversity and student satisfaction of different recommendation algorithms were compared. At last, this paper compared the recommendation errors under the conditions of different employer unit rating items, and the results showed that the more the student number and rating items, the higher the quality of career recommendation results of the proposed algorithm.

7 Acknowledgment

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