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Intelligent Recommendation Method for Talent Resources Based on Big Data

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Abstract. In order to provide an efficient and reliable way to address recruitment challenges in talent resource management and improve the efficiency and quality of the entire recruitment process, a big data-based intelligent recommendation method for talent resources is proposed. Firstly, using the principles of big data mining, construct an adjacency matrix to complete the mining of talent resource data. Secondly, based on the excavated talent resource data, describe the characteristics of the talent resource data and calculate the similarity of talent resource scores and labels. Finally, based on the predicted results of talent resource ratings, complete the recommendation of talent resources. The test results show that the method proposed in this paper can reduce the root mean square error between the actual and predicted scores of talent resources, and improve the accuracy of talent resource recommendation.

Keywords. Big data; Talent resources; Intelligent recommendation; Label similarity

1. Introduction

With the rapid development of information technology and the popularization of the Internet, the acquisition and allocation of human resources have become an important issue in the management of various industries and organizations [1]. In the current Internet era, the traditional talent recruitment and recommendation methods are no longer efficient, and intelligent technology is needed to improve the matching efficiency and quality of talents. The traditional talent recruitment process usually consumes a lot of time and human resources. In the era of information explosion, how to quickly and accurately select the most suitable talents from the numerous job seekers has become a challenge [2]. By analyzing and mining information in big data, intelligent recommendation method can quickly match job seekers, improve recruitment efficiency, and help enterprises find the right talents more quickly and accurately. Intelligent recommendation method can improve the quality of talent matching. The allocation of human resources is crucial to the development of enterprises. Suitable talents can better adapt to the working environment, complete work tasks more efficiently, and have greater potential and development space [3]. Through deep learning, natural language processing and other technical means, intelligent recommendation method can more comprehensively and accurately understand the skills, experience and ability of job seekers, so as to improve the quality of talent matching, and provide support for enterprises to attract and retain outstanding talents. Intelligent recommendation method can promote the globalization of talent flow and talent allocation.

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Reference [4] proposes a recommendation method based on imbalanced language extension TOPSI, which uses imbalanced language to depict decision information and analyze the psychological and behavioral characteristics of decision-makers. Using ordinal preference ranking method to improve the decision matrix, and using TOPSIS multi-attribute decision-making method to complete recommendations. However, there is a significant deviation in the recommendation results of this method. Reference [5] proposes a recommendation method based on graph convolutional neural networks, which constructs a user target bipartite graph and obtains user neighborhood preference information through continuous convolutional layers in the graph convolutional neural network to complete resource recommendation. However, this method has the problem of significant loss.

In order to address multiple issues with existing recommendation methods, a talent resource intelligent recommendation method based on big data is proposed in this study.

2. Talent resource mining based on big data

Big data technology can collect, organize, and store a large amount of talent information data, including educational background, work experience, skills, etc. By analyzing these data, more comprehensive and detailed talent information can be obtained, helping enterprises to more accurately understand the abilities and potential of candidates. Through big data analysis, it is possible to identify and discover some overlooked or hidden talents. Big data technology can utilize various data sources, such as social media and professional websites, to find talents with potential talents and suitable for specific positions, thus providing more choices. Big data technology can improve efficiency in the talent recruitment process [6-8]. By automating the processing and analysis of candidates' resumes and resumes, it is possible to quickly screen candidates that meet the requirements, reducing the workload and time costs of the human resources department. The principle of talent resource mining based on big data is shown in Figure 1.

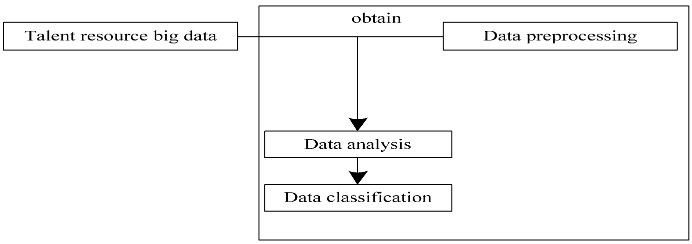


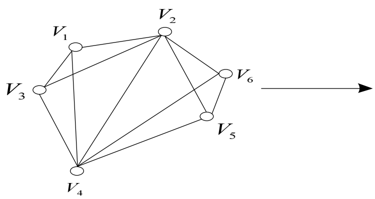
Figure 1. Principles of talent resource mining

Based on the weighted network graph, construct an adjacency matrix for talent resources and analyze the correlation between different talent resource data. The expression of the adjacency matrix is:

$$A_{ij} = \begin{cases} w_{ij}, if(v_i, v_j) or < v_i, v_j > \in E(G) \\ 0 if(v_i, v_j) or < v_i, v_j > \notin E(G) \end{cases} \tag{1}$$

In the formula, G represents the weighted network graph, w_{ij} represents the edge weights of the network graph, and v_i and v_j represent the vertices of the i-th row and j-th column elements in the weighted graph.

Schematic diagram of generating adjacency matrix from weighted full graph is shown in Figure 2.



$$A_6 = \begin{bmatrix} 0 & 2 & 1 & 4 & 3 & 3 \\ 2 & 0 & 3 & 5 & 2 & 1 \\ 1 & 3 & 0 & 2 & 3 & 4 \\ 4 & 5 & 2 & 0 & 2 & 4 \\ 3 & 2 & 3 & 2 & 0 & 1 \\ 3 & 1 & 4 & 4 & 1 & 0 \end{bmatrix}$$

Figure 2. Schematic diagram of adjacency matrix generation

The construction of adjacency matrix can improve the relevance of talent resource data mining, help improve the diversity of talent resource data, and improve recommendation accuracy [9].

The correlation between talent resource data is used as a weight to weight the correlation between two points, and a adjacency matrix of talent resources is constructed. The method of generating a minimum tree is used to segment the minimum tree edge in an MST in this weight graph according to the size of the MST edge assignment, and obtain the subtree, which is the optimal cluster.

Standardize the types and units of talent resource data with significant dimensional or order of magnitude differences. Based on the attribute values of talent resources, Euclidean distance is used to analyze their distance correlation:

$$d(x_i, x_j) = \left[\sum_{i,j} (x_{ik} - x_{jk})^2 \right] \tag{2}$$

In the formula, x_{ik} and x_{jk} respectively represent talent resource data points.

Using each talent resource data as a vertex and the distance between the data as a weight, a two-dimensional adjacency matrix is constructed and a complete graph $G(V, E, W)$ is generated, where $V = \{v_i, v_j, ..., v_n\}$ represents the set of n talent resource data, which is the node of the entire graph; $E = \{e_{ij} \left| 1 \le i, j \le n \right.\}$ represents the edge set of the entire graph, and e_{ij} is the connecting edge between v_i and D v_j.

The MST is the one with the minimum weight of all obtained spanning trees compared to W, which satisfies the following conditions:

$$W = \min \left\{ \sum_{i,j} W(v_i, v_j) \right\} = \min \left\{ \sum_{i,j} d(x_i, x_j) \right\} \tag{3}$$

The schematic diagram of the weighted full graph MST is shown in Figure 3.

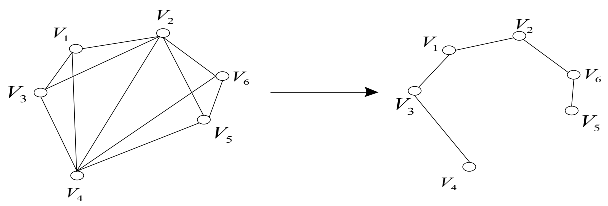


Figure 3. Weighted full graph MST schematic diagram

Cut the MST assignment edge from large to small, obtain the subtree of MST, and assign the largest weighted edge e_m in MST. The process of obtaining subtrees is shown in Figure 4.

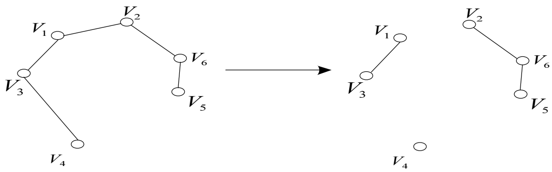


Figure 4. Acquisition process of subtrees

The constraint conditions for the maximum weighted edge e_m are:

$$e_m = \max\left\{W(v_p, v_q)\right\} = \max\left\{d(v_p, v_q)\right\} \tag{4}$$

After cutting, the edges of the subtree are the global optimal clustering clusters. If k maximum edges are obtained through cutting, the number of optimal clustering clusters is $k+1$, resulting in more accurate talent resource mining results.

3. Intelligent recommendation of talent resources

After completing the mining of talent resource data, a detailed description of talent resources is provided from four aspects: learning ability, major, education, and interest. When users enter the system, they cannot directly calculate talent resources with similar interest through similarity. However, if talent resources are labeled, similarity can be calculated based on talent resource labels [10]. The expression for the talent resource label is:

$$T_u = \left[t_{ua}, t_{um}, t_{ur}, t_{ui}\right] \tag{5}$$

In the formula, t_{ua}, t_{um}, t_{ur}, and t_{ui} respectively represent the abilities, majors, learning, and interest characteristics of talent resources.

(1) The learning ability of talents can be described in four levels: poor, medium, good, and excellent. The calculation formula for the similarity of talent resource learning ability is:

$$sim(t_{ua}, t_{va}) = 1 - \frac{\left|t_{ua} - t_{va}\right|}{3} \tag{6}$$

(2) The formula for calculating the similarity of talents' learning majors is as follows:

$$sim(t_{um}, t_{vm}) = \begin{cases} 0, if\ \ different\ \ disciplines \\ 0.5, if\ \ same\ \ discipline,\ different\ \ majors \\ 1, if\ \ same\ \ major \end{cases} \tag{7}$$

(3) The educational qualifications of talents can be divided into secondary education and higher education. Secondary education includes technical secondary schools and high schools, while higher education includes vocational, undergraduate, master's, and doctoral students. The calculation formula for talent education similarity is:

$$sim(t_{ur}, t_{vi}) = \frac{1}{m * n} \sum_{a \in I_u} \sum_{b \in I_v} sim(t_{ua}, t_{vb}) \tag{8}$$

(4) The calculation formula for talent interest similarity is:

$$sim(t_{ui}, t_{vi}) = \frac{1}{m * n} \sum_{a \in I_u} \sum_{b \in I_v} sim(t_{ua}, t_{vb}) \tag{9}$$

In the formula, I_u and I_v respectively represent the interest set of talent resources, while m and n respectively represent the size of the interest set.

Integrate the above four features to calculate the overall similarity of talent resource labels:

$$sim_{t(u,v)} = \alpha sim(t_{ua}, t_{va}) + \beta sim(t_{um}, t_{vm}) + \gamma sim(t_{ur}, t_{vr}) + \delta sim(t_{ui}, t_{vi}) \tag{10}$$

In the formula, $\alpha + \beta + \gamma + \delta = 1$ represents the weights of feature similarity.

Calculate the similarity between talent resource ratings and labels using a linear weighting method:

$$sim(u, v) = \varphi sim_{i(u,v)} + (1 - \varphi) sim\_t(u, v) \tag{11}$$

In the formula, φ represents the fusion weight, $sim_{i(u,v)}$ represents the similarity of talent resource scores, and $sim\_t(u,v)$ represents the similarity of talent resource initialization labels.

After calculating the similarity of talent resources, select the top N adjacent talent resources as the target to generate a set of similar talent resources $S_u = \{s_{u1}, s_{u2}, s_{u3}, \ldots, s_{uN}\}$. Find talent resources in set S_u that have not been evaluated by the user, and predict the user's rating of the resource:

$$\hat{r}_{ui} = \hat{r}_u + \frac{\sum_{v \in S_u} sim(u, v)(r_{vi} - \hat{r}_v)}{\sum_{v \in S_u} sim(u, v)} \tag{12}$$

In the formula, $sim(u,v)$ represents the similarity between two users, r_{vi} represents the user's rating of talent resources, and $\hat{r}_v$ represents the average historical rating of the user.

According to the calculation of formula (12), Top-N human resources with the highest score are recommended to relevant enterprise users.

4. Experimentation

To validate the effectiveness of the proposed big data-based intelligent recommendation method for talent resources, comparative testing experiments were conducted.

The talent resource samples used in this experiment are from a talent recruitment website, as shown in Table 1.

Table 1. Talent resource data

Education classification	Number of people	Illustrate
primary school	10	Domestic services, basic labor skills
junior high school	50	Sales, customer service, production and manufacturing, etc
high school	80	Administrative assistant, technical support, finance, etc
Vocational and technical schools	100	Electricians, mechanical operators, beauticians, etc
junior college	120	Marketing, human resources, software development, etc
undergraduate course	100	Management, professional field research, etc
master	30	Scientific research, education, etc
doctor	10	Academic, technological innovation, high-end research positions, etc

Based on the talent resource data shown in Table 1, and using the root mean square error between predicted and actual scores, as well as the recommendation accuracy of talent resources, this method was compared and validated with the methods in reference [4] and [5].

The formula for calculating the root mean square error between the predicted score and the actual score is:

$$RMSE = \sqrt{\frac{\sum_{(u,i)\in T} (r_{ui} - \hat{r}_{ui})^2}{|T|}} \tag{13}$$

In the formula, T represents the test data of talent resources, and r_{ui} represents the actual score.

The accuracy of talent resource recommendation refers to the accuracy and effectiveness of the talent recommendation system in matching and recommending candidates. The higher the accuracy of talent resource recommendation, the stronger the recommendation performance of the method.

The root mean square error is used to analyze the accuracy of resource ratings for recommendation methods. The smaller the root mean square error between actual and predicted values, the more accurate the rating of talent resources. The root mean square error results of talent resource scoring for this method and reference [4] and reference [5] methods are shown in Figure 5.

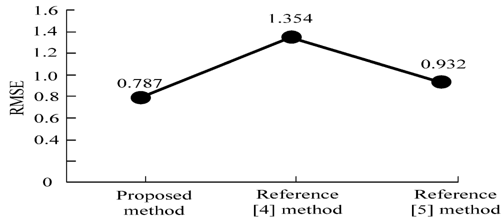


Figure 5. Root mean square error results of talent resource rating prediction

From Figure 5, it can be intuitively seen that among the three methods, the root mean square error of talent resource scoring prediction in this paper is the smallest, with a value of 0.787, while the root mean square error decibels of scoring prediction in reference [4] method and reference [5] method are 1.354 and 0.932. Therefore, it indicates that the method proposed in this article can provide a more accurate rating of talent resources, which helps to improve the effectiveness of talent resource recommendation results.

The accuracy verification of talent resource recommendation can evaluate and confirm the accuracy and effectiveness of the talent recommendation system to determine whether it can provide high-quality candidates that meet specific job requirements. By verifying the accuracy of the recommendation system, it can be ensured that the system can accurately match candidates with job requirements, thereby reducing manpower and time consumption in the recruitment process. This helps to improve recruitment efficiency and accelerate the matching speed between candidates and positions. The accuracy results of talent resource recommendation using three recommendation methods are shown in Figure 6.

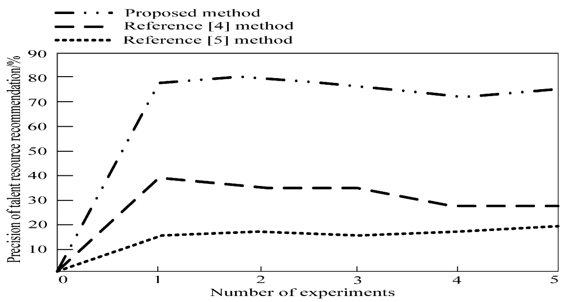


Figure 6. Precision results of talent resource recommendation

From Figure 6, it can be seen that under multiple testing experiments, the accuracy of talent resource recommendation in this method is consistently higher than that of the methods in reference [4] and [5]. As the experiment progressed, there were different fluctuations in the recommendation accuracy of the three methods, but the recommendation accuracy of this method remained above 70%. The recommended accuracy of the methods in reference [4] and reference [5] does not exceed 40%.

Therefore, it indicates that this method can improve the accuracy of talent resource recommendation.

5. Conclusion

The intelligent recommendation method for talent resources based on big data has significant significance and potential, which can greatly improve the efficiency and quality of the recruitment process. By analyzing and mining massive candidate and job data, these methods can accurately evaluate candidates' skills, experience, and adaptability, thereby more accurately matching candidates with job requirements. The intelligent recommendation method for talent resources based on big data can also discover some hidden patterns and trends. By utilizing data mining and predictive analysis techniques, changes in talent demand in different industries and positions can be revealed, helping organizations and recruiters make more forward-looking decisions. The intelligent recommendation method for talent resources based on big data is a promising research field. It combines big data analysis with human resource management to provide more efficient, accurate, and intelligent talent recommendation services for recruiters. In the future, with the continuous evolution of data volume and algorithms, these methods are expected to achieve more accurate matching and deeper talent insights, bringing greater competitive advantages to organizations.

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