Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 1168796, 9 pages
https://doi.org/10.1155/2022/1168796

Research Article

Research on University Innovation and Entrepreneurship Resource Database System Based on SSH2

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Received 28 February 2022; Revised 14 March 2022; Accepted 25 March 2022; Published 22 April 2022

Academic Editor: Wei Liu

With the wide application of the Internet, the entrepreneurial resources of colleges and universities have grown at an exponential rate. With the rapid accumulation of this information, it is difficult for students to find what they are interested in from a large amount of information. To accurately recommend innovation and entrepreneurship resources, this paper proposes a recommendation algorithm based on user trust and a probability matrix. After obtaining the user trust data, the PMD (probability matrix decomposition) algorithm is used to complete the trust matrix and normalize it to get the similarity matrix. At the same time, the trust factor between users is added to the calculation process of the posterior probability, and the prediction score is obtained by maximizing the posterior probability. On this basis, the weights of users in the group are normalized, and the weighting strategy based on user interaction is used to integrate the preferences of group members to obtain the final recommendation results. When designing the recommendation system, the web system of the mainstream SSH2 framework is used to design, and the B/S structure of the entrepreneurial resource recommendation system platform is realized. Experimental results show that the proposed system has a higher recommendation quality compared with other recommended algorithms.

1. Introduction

At the end of 2014, the concept of mass entrepreneurship and mass innovation was proposed for the first time [1]. Under the background of the era of "Internet +", the innovation and entrepreneurship space, as the carrier of innovation and entrepreneurship services, conforms to the development needs of the times [2]. Taking the Internet as an important tool, the Internet platform and Internet technology provide technical support and environmental guarantee for the innovation and entrepreneurship space. Form a new ecological chain in the field of innovation and entrepreneurship [3]. The innovation and entrepreneurship space based on "Internet +" has a strategic impact on the education ecosystem of universities and even the national economic development system [4].

As the development goal of the innovation and entrepreneurship space changes from quantitative growth to quality improvement, innovation and entrepreneurship space resources based on "Internet +" have become the current hot spots in this field [5]. A large number of studies have been conducted on the development strategy and development model of innovation and entrepreneurship space resources based on "Internet +", but there is still a lack of a unified recommendation system for the recommendation of innovation and entrepreneurship space resources based on "Internet +" [6]. Based on this, we will build an operable and enforceable innovation and entrepreneurship space resource recommendation system based on "Internet +." It is of great significance for guiding its development direction, improving its management quality, and promoting regional economic development.

To make the fusion results more charted, improve the reliability and interpretability of the recommended results [7]. In this paper, a group recommendation algorithm that integrates user trust is proposed, and group fusion is carried out considering the interaction relationship between users in the group [8]. After obtaining the user trust data, the trust vector and trusted vector of group members are trained, and the mean of the trusted vector is used as the benchmark vector [9]. The trust vector of each member is given the corresponding weight by doing the dot product operation with it [10]. A list of recommendations is generated by summing the normalized weight scores to obtain a group score [11].

This paper consists of six main parts: the first part is the introduction, the second part is related work, the third part is the proposed resource recommendation algorithm, the fourth part is the university entrepreneurship resource recommendation system based on SSH2, the fifth part is the experiment and analysis, and the sixth part is the conclusion.

2. Related Work

2.1. The Necessity of Innovation and Entrepreneurship Resources in Colleges and Universities. With the spread of information technology, college students are increasingly inclined to use online learning [12]. Universities and colleges also use online tools to expand the learning resource library of innovation and entrepreneurship to provide more learning convenience for students. The innovation and entrepreneurship resource recommendation system in the new era offers students with richer learning resources, and different resources are updated in real-time, consistent with the characteristics of the innovation and entrepreneurship environment in the process of dynamic change [13].

The construction of the recommendation system for innovation and entrepreneurship resources in colleges and universities should be based on the rules of unified planning, and the software and hardware equipment in colleges and universities should be configured according to the actual educational needs [14]. In advocating the rational allocation of educational resources and enhancing the effectiveness of innovation and entrepreneurship education. The construction of the resource recommendation system needs to follow the development law of the times and cater to the learning needs of college students. Innovation and entrepreneurship are becoming important driving forces for national economic development, and it is imperative to build a resource recommendation system.

2.2. The Current Situation of Innovation and Entrepreneurship Resources in Colleges and Universities. Learning resources refer to the human and material resources that serve the main body of learning in education and teaching activities, and educational resources are rich in connotation [15]. It includes both nonlife information and physical objects and various human resources with vitality [16]. The resource recommendation system is an indispensable part of innovation and entrepreneurship education. This resource pool involves large-scale human and material resources [17]. The construction of the resource recommendation system is an essential systematic project, but there are still many problems in promoting this project.

In the context of increasingly abundant educational resources, high-quality educational resources related to innovation and entrepreneurship are still scarce. On the one hand, many colleges and universities are trying to establish a recommendation system for innovative and entrepreneurial resources, and the types of resources required for innovation and entrepreneurship education are not clear. The scale of the innovation and entrepreneurship resource recommendation system continues to expand, but the quality of improvement has fallen into a bottleneck period. On the other hand, high-quality innovation and entrepreneurship learning resources have not fully flowed between higher schools. Under the premise that there are barriers to interuniversity cooperation between universities, many universities are not really involved in the process of developing innovative and entrepreneurial resources. Since their establishment, some innovation and entrepreneurship curriculum development projects have rarely been asked about. This causes the waste of project resources and leads to the construction of resource recommendation systems becoming more inefficient.

All kinds of networked means have not been rationally applied in building a resource recommendation system. The main body of education lacks the concept of lifelong education [18]. For example, some colleges and universities try to use microcourse and MOOC resources to enrich the innovation and entrepreneurship resource recommendation system. However, to avoid learning, students directly pulled the video progress bar to the end without carefully watching the video content. However, the video terminal still shows that the student has learned relevant content due to the existing technical conditions. The existing learning resource system design is also lacking in forward looking elements [19]. Colleges and universities follow traditional educational thinking to build a learning resource library. Lack of guidance in the design and research of online courses. The content involved in various online courses is highly repetitive and cannot meet students' differentiated innovation and entrepreneurship learning needs.

Under the concept of lifelong education, the construction of the recommendation system for innovation and entrepreneurship resources in colleges and universities should be sufficient to meet the learning needs of students at different stages of innovation and entrepreneurship. It is also necessary to study the differences between different students in innovation and entrepreneurship, and provide them with differentiated learning resources. Under the existing system, the learning resources provided by universities for students at different levels are not differentiated. The cookie-cutter innovation and entrepreneurship education resources are not highly targeted. It cannot play a role in guiding students and enhancing the orientation of education [20].

3. The Proposed Resource Recommendation Algorithm

3.1. Group Recommendation Framework. The framework of the group recommendation model proposed in this paper is shown in Figure 1. The specific process is as follows:

(1) Obtain the user trust data, use the classical probability matrix decomposition algorithm to complete the trust matrix N, and obtain the user trust characteristic vectors L and R.

(2) Normalize each row of the trust matrix using softmax to obtain the similarity matrix F.

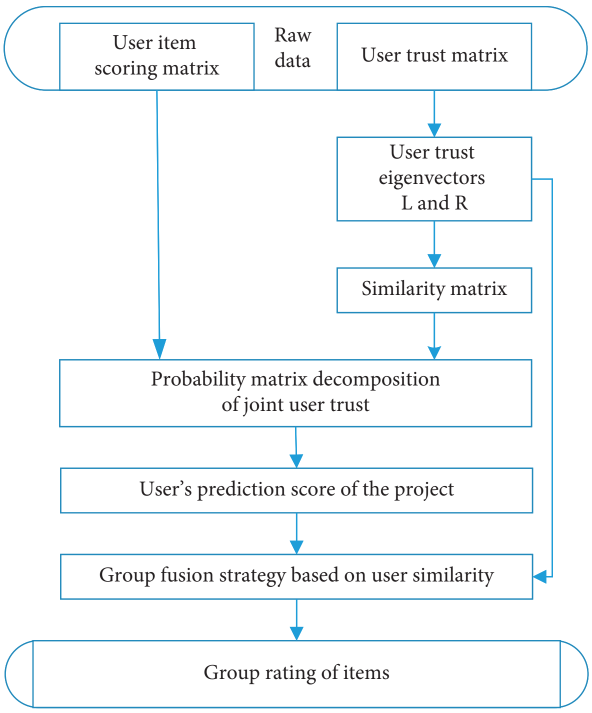

Figure 1: Group recommendation model framework.

(3) Get user-item scoring data. The probability matrix decomposition algorithm of the joint similarity is used to complete the prediction score of the unrated items.

(4) Use the confluence trust weighting strategy to combine the scores of all members of the group. It gets the ratings of items by the entire group and generates a list of recommendations based on the ratings.

3.2. User Similarity Matrix Construction. This article uses a real dataset that contains several trust relationships between users and user ratings of items. Building a user similarity matrix requires a trust relationship between two users. Therefore, the probability matrix decomposition algorithm is first used to complete the user trust matrix.

Suppose there are W users, $N_{l,r}$ represents the trust of user l to user r, forming a trust matrix of $W \times W$. The target trust matrix is decomposed into the product $L^N_{Z\times W} R_{Z\times W}$ of two matrices with lower dimensions, where Z is the potential vector dimension. L and R represent the implicit eigenvector of user trust.

Suppose that the user trust $N_{l,r}$ is determined by the inner product of the potential vector of user l and the potential vector of user r, and the trust follows a Gaussian distribution, that is, formula (1).

$$N_{l,r} \sim T\left(L_l^N R_r, \sigma^2\right). \tag{1}$$

Then, the conditional probability of the observed trust matrix is formula (2).

$$u\left(N|L, R, \sigma^2\right) \sim \prod_{l=1}^{W}\prod_{r=1}^{W} T\left(L_l^N R_r, \sigma^2\right)^{X_{l,r}}, \tag{2}$$

where $X_{l,r}$ is the indicator function. If user l has trust data for user r, it is 1. Otherwise, it is 0.

Then, assume that the potential feature vectors of users obey the Gaussian prior distribution with a mean value of 0, that is, formula (3) and formula (4).

$$u\left(L|\sigma_L^2\right) \sim \prod_{l=1}^{W} T\left(L_l \mid 0, \sigma_L^2 X\right), \tag{3}$$

$$u\left(R|\sigma_R^2\right) \sim \prod_{r=1}^{W} T\left(R_r|0, \sigma_R^2 X\right), \tag{4}$$

where X represents a diagonal matrix. Then, the posterior probabilities of L and R is formula (5).

$$u\left(L, R|N, \sigma_L^2, \sigma_R^2, \sigma^2\right) \propto u\left(N|L, R, \sigma^2\right) u\left(L|\sigma_L^2\right) u\left(R|\sigma_R^2\right). \tag{5}$$

Logarithms are taken from both sides to obtain formula (6).

$$\begin{aligned}\ln p\left(L, R|N, \sigma_L^2, \sigma_R^2, \sigma^2\right) = &-\frac{1}{2\sigma^2}\sum_{l=1}^{W}\sum_{r=1}^{W} X_{l,r}\left(N_{l,r} - L_l^N R_r\right)^2 \\ &-\frac{1}{2\sigma_L^2}\sum_{l=1}^{W} L_l^N L_l - \frac{1}{2\sigma_R^2}\sum_{l=1}^{W} R_r^N R_r \\ &-\frac{1}{2}\left(\sum_{l=1}^{W}\sum_{r=1}^{W} X_{l,r}\right)\ln \sigma^2 \\ &-\frac{1}{2} WZ \ln \sigma_L^2 - \frac{1}{2} WZ \ln \sigma_R^2 + C,\end{aligned} \tag{6}$$

where C is an independent constant.

The posterior probability is maximized by minimizing the following objective function:

$$L = \frac{1}{2}\sum_{l}^{W}\sum_{r}^{W} X_{l,r}\left(N_{l,r} - L_l^N R_r\right)^2 + \frac{\lambda_L}{2}\sum_{l=1}^{W} L_{lFro}^2 + \frac{\lambda_R}{2}\sum_{l=1}^{W} R_{rFro}^2. \tag{7}$$

where $\lambda_L = \sigma^2/\sigma_L^2$, $\lambda_R = \sigma^2/\sigma_R^2$.

Equation L obtains formula (8) and formula (9) by deriving partial derivatives of L_l and R_r, respectively.

$$\frac{\partial E}{\partial L_l} = \left(N_{l,r} - L_l^N R_r\right) R_r - \lambda_L L_l, \tag{8}$$

$$\frac{\partial E}{\partial R_r} = \left(N_{l,r} - L_l^N R_r\right) L_l - \lambda_R R_r. \tag{9}$$

Then, the random gradient descent is used to update L_l and R_r until they converge or reach the maximum number of iterations.

After training, two eigenvectors L and R of each user can be obtained. The left vector L_l of any user l is multiplied by the right vector R_r of another user r to obtain L's trust in R, that is, formula [10].

$$N_{l,r} = L_l \cdot R_r. \tag{10}$$

Firstly, the trust matrix N between each pair of users is calculated, and $N_{l,r}$ represents the trust of user l to user r. The L-to row of the matrix indicates the trust of the L-to user to other users. At this time, the softmax operation is performed on each row of data, and the sum of the trust degree of each row is normalized to obtain the similarity matrix F, that is, formula (11).

$$F_{l,r} = \frac{e^{N_{l,r}}}{\sum_{r=1}^{W} e^{N_{l,r}}}, \tag{11}$$

where $F_{l,r}$ represents the similarity between user l and user r.

3.3. FPMF Algorithm Combined with User Trust. Assuming that there are w users and t items, the score of each user and item is taken as a $W \times T$ matrix, and $R_{W\times T}, R_{x,y}$ represents the score of user x on item y. Then, assume that R obeys the Gaussian distribution with mean $P_x^N Q_y$ and variance σ_R^2, and its probability distribution is formula (12).

$$u\left(R \mid P, Q, \sigma_R^2\right) = \prod_{x=1}^{W}\prod_{y=1}^{T} T\left(P_x^N Q_y, \sigma^2\right)^{X_{x,y}^R}. \tag{12}$$

From the similarity matrix, it can be seen that the user's feature vector and other user feature vectors in the similarity matrix F should be equal after multiplying by the weight, that is, formula [13].

$$P_x = \sum_{n=1}^{W} F_{x,n} P_n, \tag{13}$$

where $F_{x,n}$ represents the similarity between user x and user n. Then, the Gaussian prior distribution of the user characteristic matrix P is as shown in formula (14).

$$\begin{aligned} &u\left(P|F, \sigma_P^2, \sigma_F^2\right) \propto u\left(P|\sigma_P^2\right) u\left(P|F, \sigma_F^2\right) \\ &= \prod_{x=1}^{W} T\left(P_x|0, \sigma_P^2 X\right) \times \prod_{x=1}^{W} T\left(P_x \Big| \sum_{n=1}^{W} F_{x,n} P_n, \sigma_F^2 X\right). \end{aligned} \tag{14}$$

Suppose again that the item eigenvector Q also obeys the Gaussian distribution, that is, formula (15).

$$u\left(Q|\sigma_Q^2\right) = \prod_{y=1}^{T} T\left(Q_y|0, \sigma_Q^2 X\right). \tag{15}$$

Then, the posterior probability distribution of P and Q can be obtained as follows:

$$\begin{gathered} u\left(P, Q|R, F, \sigma_R^2, \sigma_F^2, \sigma_P^2, \sigma_Q^2\right) \propto \\ u\left(R|P, Q, \sigma_R^2\right) u\left(P|F, \sigma_P^2, \sigma_F^2\right) u\left(Q\sigma_Q^2\right). \end{gathered} \tag{16}$$

Logarithm is taken on both sides to get formula (17).

$$\begin{aligned} \ln\, p\left(P, Q|R, F, \sigma_R^2, \sigma_F^2, \sigma_P^2, \sigma_Q^2\right) &= -\frac{1}{2\sigma_R^2} \sum_{x=1}^{W}\sum_{y=1}^{T} X_{x,y}^R \left(R_{x,y} - P_x^N Q_y\right)^2 \\ &- \frac{1}{2\sigma_F^2} \sum_{x=1}^{W} \left(\left(P_x - \sum_{n=1}^{W} F_{x,n} P_n\right)^N \left(P_x - \sum_{n=1}^{W} F_{x,n} P_n\right)\right) \\ &- \frac{1}{2\sigma_P^2} \sum_{x=1}^{W} P_x^N P_n - \frac{1}{2\sigma_Q^2} \sum_{y=1}^{T} Q_y^N Q_y - \frac{1}{2}\left(\sum_{x=1}^{W}\sum_{y=1}^{T} X_{x,y}^R\right) \ln\, \sigma_R^2 \\ &- \frac{1}{2} WZ \ln\, \sigma_P^2 - \frac{1}{2} TZ \ln\, \sigma_Q^2 + C. \end{aligned} \tag{17}$$

The posterior probability is maximized by minimizing the following objective function:

$$\begin{aligned} L = &\frac{1}{2}\sum_{x=1}^{W}\sum_{y=1}^{T} X_{x,y}^R \left(R_{x,y} - P_x^N Q_y\right)^2 + \frac{\lambda_P}{2}\sum_{x=1}^{W} \left\|P_x\right\|_{Fro}^2 \\ &+ \frac{\lambda_Q}{2}\sum_{y=1}^{T} \left\|Q_y\right\|_{Fro}^2 + \frac{\lambda_F}{2}\sum_{x=1}^{W} \left\|P_x - \sum_{n=1}^{W} F_{x,n} P_n\right\|_{Fro}^2, \end{aligned} \tag{18}$$

where $\lambda_P = \sigma_R^2/\sigma_P^2 . \lambda_Q = \sigma_R^2/\sigma_Q^2 . \lambda_F = \sigma_R^2/\sigma_F^2$.

Then, the gradient descent method is used to update P_x and Q_y until they converge or reach the maximum number of iterations.

3.4. Convergence Strategies. This paper proposes a new fusion strategy based on user interaction in terms of group fusion. This will again leverage the previously acquired network of user trust. The specific process is further discussed.

The implicit eigenvector R of the trust degree of all users is obtained, and the average value R_{mean} of R is also obtained, that is, formula (19).

$$R_{\text{mean}} = \frac{1}{W}\sum_{l=1}^{W} R_l. \tag{19}$$

The left vector L of each user is multiplied by point R_{mean} to obtain the weight of the user, that is, formula (20).

$$m_x = \langle L_x \cdot R_{\text{mean}} \rangle. \quad (20)$$

When recommending a group, normalize the weight of users in the group using the softmax function, that is, formula (21).

$$m_x = \frac{e^{m_x}}{\sum_{y=1}^{W} e^{m_y}}. \quad (21)$$

The weight strategy is used to combine the scores of users in the group with the scores of groups, that is, formula (22).

$$R(A, y) = \sum_{x \in A} m_x R_{x,y}, \quad (22)$$

where $R(A, y)$ represents the score of group A on item y.

4. Design of University Entrepreneurship Resource Recommendation System Based on SSH2

The traditional information network resource management system adopts the C/S architecture. Each client needs to install the appropriate software for the relevant configuration. The system adopts the B/S architecture, and the user does not need to install software. Only the browser needs to be installed to access the system, and the technical requirements for the user are not high. In addition, the system uses SSH2 as the framework, uses the Java language and MySQL database, and introduces JavaScript, CSS, and other web technologies. It realizes the five functions of login verification, permission management, data retrieval, data management, and version management.

4.1. Overall Framework Design of the Resource Recommendation System. The resource recommendation system adopts a B/S architecture, and the framework diagram of the entire system is shown in Figure 2.

It is divided into 4 floors, from bottom to bottom, entity layer, DAO layer, service layer, and WEB layer. There is an interaction between the DAO layer, the service layer, and the WEB layer (3 layers). The upper layer can call the services of the lower layer, and the lower layer can return data to the upper layer.

The entity layer is mainly used to encapsulate the data of the entire repository system, including form data transmitted from the foreground page to the webserver and the web service to the database mapping data. Data transfer from the client to the webserver requires the corresponding POJO (plain ordinary Java object) variable to be defined in the controller. The corresponding get and set methods are provided for this variable. This allows Struts2 to pass data from the client form to the controller's corresponding properties in the POJO object. Data is passed from the web server to the database, mainly by defining a corresponding POJO object for each table in the database, and then configuring a mapping between the POJO and the database table in Hibernate's configuration file. This allows it possible to pass data between the web server and the database via POJO. This layer is the basis for the data exchange of the entire system, and the data exchange of all layers is the data encapsulated using the entity layer.

The service layer is the business processing layer of the entire system, which is mainly responsible for handling the business logic. Each time the controller receives a request, it calls the corresponding processing method of the service layer. After the service receives the processing task, it calls the methods of the DAO layer, completes the logical operations required by the request, and finally passes the returned data to the controller of the WEB layer. The service layer is the brain of the entire repository system, and all the complex logic is written in this layer.

The DAO layer is the bridge between the server and the database. The data processed by the WEB server is persisted to the database by the DAO layer, and the data in the database is transmitted to the WEB server through the DAO layer. To optimize the operation of the repository on the database, the DAO layer of the repository system adopts the Hibernate framework. The framework provides a pool of database connections placed in a connection pool each time the system starts with a certain number of database connections based on Hibernate's configuration file. Each time a database connection needs to be established, it is not necessary to establish another database connection, but instead takes a database connection from the connection pool, use it up, and then put it back into the connection pool. This connection pooling pattern avoids consuming too many resources every time due to the establishment and release of connections.

4.2. Graphic Design of Entrepreneurial Resource Recommendation System. The functional module design of the startup resource recommendation system is shown in Figure 3.

5. Experiments and Analysis

This section uses real data sets and implements the algorithm in Python. The experiment is carried out on a computer configured with Windows 7, 2.5 GHz CPU, and 8 GB memory.

5.1. Datasets. The experiment uses real data sets, all from the college student innovation and entrepreneurship resource library system, based on personalized recommendations, composed of two parts: rating data ratings.txt and user trust data trust.txt. The ratings.txt contained 35497 data, with a scoring range of 0.5 to 4.0, a step size of 0.5, and an intensity of 1.044%. The trust.txt contains 1853 data with an intensity of 0.069%.

5.2. Evaluation Indicators. To test the effectiveness of the proposed algorithm, the mean absolute error (MAE), coverage rate (COV), and comprehensive evaluation index (F1) are used to evaluate the performance of the recommended system. The average absolute error refers to the average value of the difference between the resource score recommended by the recommendation system for the user and the score of

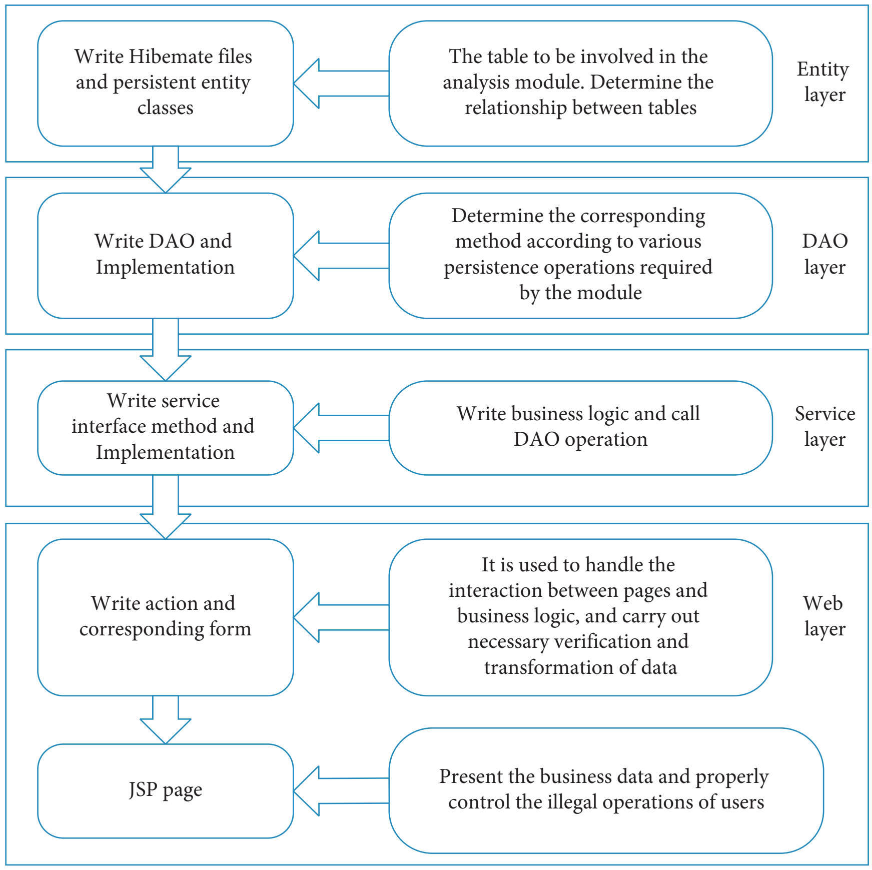

Figure 2: Resource recommendation system framework.

the real user resource in the test set, and the smaller the value, the more accurate the prediction score, as shown in equation (23). Coverage refers to the ratio of the number of scoring resources that the recommendation system can predict for the user to the total number of resources in the test set, the higher the value, the stronger the ability of the algorithm to mine long-tail resources, as shown in equation (24). The F1 value refers to the comprehensive evaluation index of the recommendation system, and the higher the value, the better the performance, and the calculation formula is shown in equation (25).

$$W_{\mathrm{MAE}} = \frac{\sum_{x=1}^{T} \left| r_x - r_u \right|}{T}, \tag{23}$$

$$C_{\mathrm{COV}} = \frac{\left| L_p \right|}{t}, \tag{24}$$

$$F1 = \frac{2 \times U_{\mathrm{Precision}} \times C_{\mathrm{COV}}}{U_{\mathrm{Precision}} + C_{\mathrm{COV}}}, \tag{25}$$

$$U_{\mathrm{Precision}} = 1 - \frac{W_{\mathrm{MAE}}}{r_{\max} - r_{\min}}, \tag{26}$$

where r_x is the true score of item x in the test set. r_u is the resource prediction score of the recommendation system for the target user. $|L_p|$ represents the number of scoring resources predicted by the push system for the target user. T represents the total number of resources in the test set. $r_{\max}$ and $r_{\min}$ represent the highest score and the lowest score in the push system, respectively.

5.3. The Results and Analysis. The experiment selects 80% of the real data set as the training set and 20% as the test set, uses the recommendation system to compare the resource score recommended by the user with the resource score in the known test set, and uses the given evaluation index to measure the performance of the recommendation algorithm. Comparing the proposed algorithm with the traditional user-based recommendation algorithm literature [21], the fuzzy C-means clustering-based collaborative filtering algorithm literature [22], and the implicit trust-based recommendation algorithm literature [22], with the same parameters set, evaluate the performance of the recommendation algorithm by scoring and top-N predictions.

The algorithm of this article involves parameters α and β. Among them, the α is the proportion of the comprehensive trust value between users in the comprehensive direct trust value, and the β is the proportion of the global trust value between users in the comprehensive trust value. As shown in Figure 4, different α values have a larger impact on the

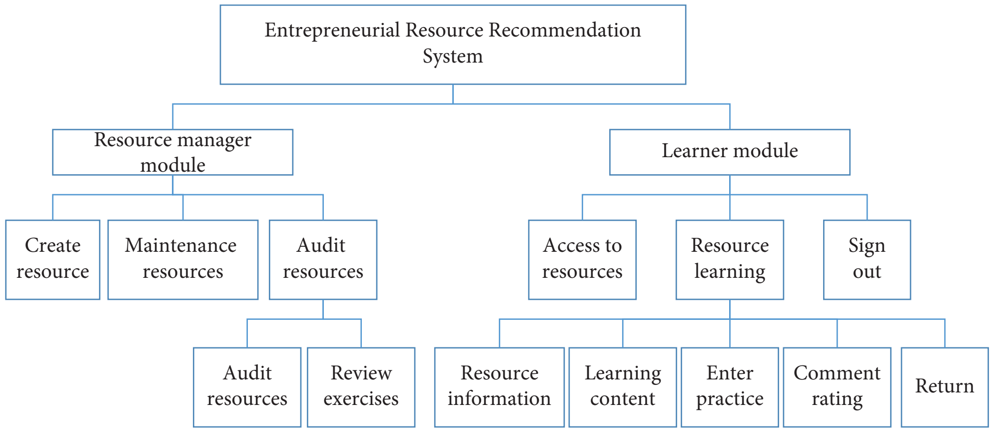

Figure 3: System function module.

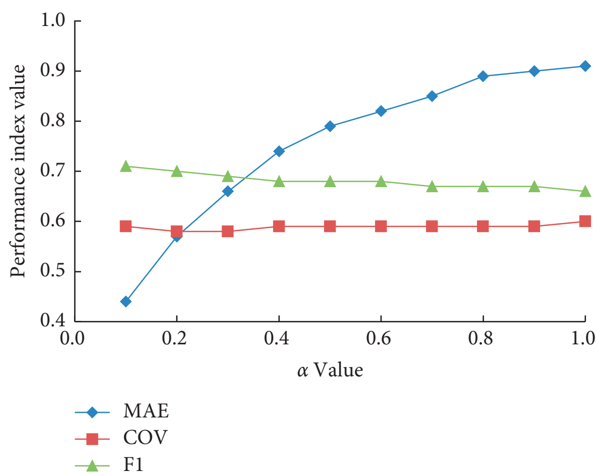

Figure 4: Influence of α value on recommended quality.

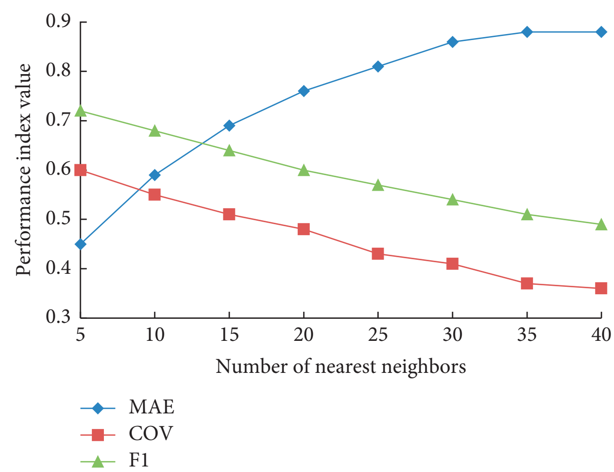

Figure 5: Influence of number of neighbours on recommendation quality.

average absolute error of the prediction score. The average absolute error value is minimal at $\alpha = 0.1$ and $\beta = 0.9$. Coverage and $F1$ values are the largest, at 0.45, 0.593, and 0.715, respectively. Note that when there are many sparse data and cold-start users, the proposed algorithm relies more on obtaining the best trust neighbours through trust passing between users to achieve scoring prediction.

Figure 5 shows the recommended quality comparison of the proposed algorithm at different neighbours. As can be seen, as the number of near neighbours increases, the quality of recommendations continues to decrease and eventually flattens out. Where MAE increases with the number of neighbours, the reason is that the comprehensive trust value between users continues to decrease as the number of neighbours increases, resulting in a continuous decrease in the quality of recommendations. Eventually, the values of COV and F1 decrease with the increase of the number of neighbours, which proves that the recommended quality of the proposed algorithm is better when the number of neighbours is 5.

Figure 6 shows the variation of the proposed algorithm and the comparison algorithm under different neighbour numbers. It can be seen that when there are different numbers of neighbours, the MAE of the literature [21] and literature [22] algorithms first declines, then rises, and finally tends to be stable. Moreover, the MAE value is above 1.0, and the proposed algorithm and the literature [22] algorithm are both stable as the number of neighbours increases as the MAE value increases. And the MAE is significantly smaller than the literature [21] and literature [22] algorithms.

Figures 7 and 8 show the changes of COV and F1 values of the algorithm and the comparison algorithm under different numbers of nearest neighbours. It can be seen that with the increase of the number of nearest neighbours, the long tail resources and personalized resources recommended for the target users are reduced, resulting in the continuous reduction of COV. When the number of COV is 40~35, it is not very different from the algorithm in this paper. However, when the number of nearest neighbours is 5~20, this algorithm has a better mining effect for long-tail resources and a better recommendation effect than the comparison algorithm.

Combined with the abovementioned experimental results, the results show that compared with the traditional user-based recommendation algorithm, the collaborative filtering algorithm based on fuzzy c-means clustering, and

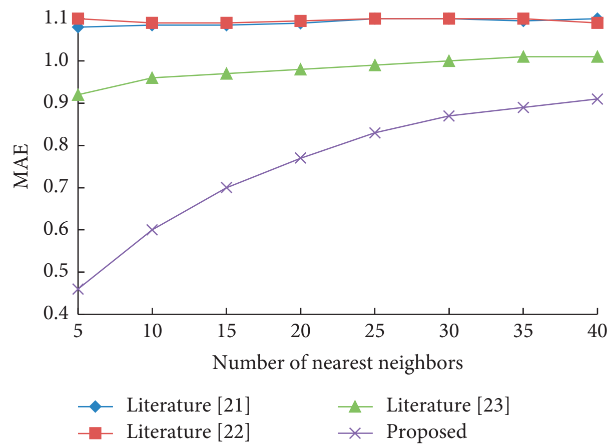

Figure 6: MAE comparison of four recommended algorithms.

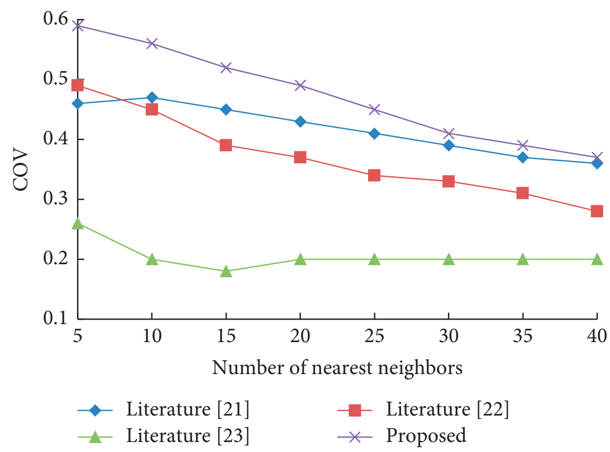

Figure 7: COV comparison of four recommended algorithms.

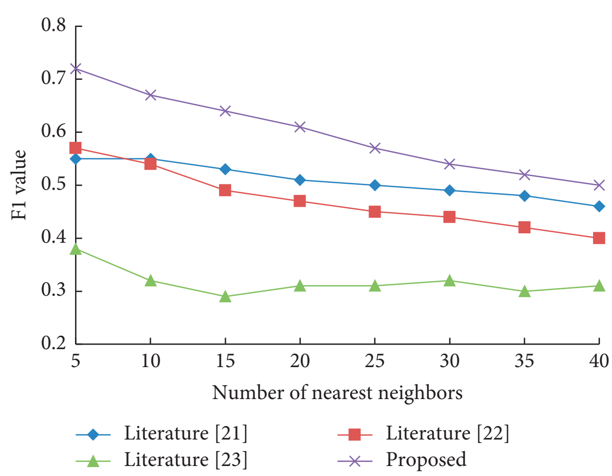

Figure 8: F1 comparison of four recommended algorithms.

the recommendation algorithm based on implicit trust, the proposed algorithm has better performance in terms of average absolute error, mining ability of long-tail resources, and comprehensive evaluation index. Especially in the case of a few neighbours, the proposed algorithm can still make accurate recommendations for target users under the problems of sparse data and cold start.

6. Conclusion

An accurate and effective recommendation system for efficient entrepreneurial resources is an inevitable requirement for developing the innovation and entrepreneurship space based on "Internet +". To accurately recommend entrepreneurial resources, this paper proposes a recommendation algorithm based on user trust and a probability matrix. To test the effectiveness of the proposed algorithm, the average absolute error (MAE), coverage rate (COV), and comprehensive evaluation index (F1) are used to evaluate the performance of the recommended system. When designing the recommendation system, the web system of the mainstream SSH2 framework is used to create, and the B/S structure of the entrepreneurial resource recommendation system platform is realized. Experimental results show that the proposed system has a higher recommendation quality compared with other recommended algorithms. In the future, the impact of trust propagation among users on the performance of the recommendation system will be studied to further improve the recommendation quality and user experience.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This work is supported by the Hebei Federation of Social Sciences: Research on the cultivation of students' volunteering practice based on the perspective of social governance modernization (No. 20200602034).

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