Computer Fraud and Security
ISSN (online): 1873-7056

The Application and Exploration of Cloud Computing in the Collaborative Cultivation of Embedded Network Security Talents between Schools and Enterprises

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Abstract:

With the rapid development and popularization of network technology, network security issues have become increasingly complex and diverse, and their importance has become more prominent. The demand for high-quality and specialized cybersecurity talents has sharply increased. Through embedded network technology, more intelligent and integrated network defense systems can be built, which can be tightly integrated into network devices to achieve real-time monitoring and automatic response, significantly enhancing the security defense capabilities of network systems. This article proposes an innovative cloud based collaborative training model between schools and enterprises, which integrates the characteristics of embedded network technology. This model utilizes the flexibility and scalability of cloud computing to build a comprehensive talent development platform that covers theoretical teaching, embedded system practice, and network security assessment. On this platform, we utilize cloud computing resources to build a highly simulated network environment. And integrate embedded network devices to simulate real attack and defense scenarios, providing students with a realistic learning experience.

Keywords: cloud computing, network security, personnel training, school-enterprise collaboration, embedded network

1. INTRODUCTION

With the continuous optimization and improvement of China's education system, the cultivation of cybersecurity talents has gradually received unprecedented attention. As a bridge connecting theory and practice, school enterprise cooperation has emerged with new models, significantly promoting the deep integration of educational resources and enterprise needs, and further expanding the scale and efficiency of cybersecurity talent cultivation. However, in the context of the rapid rise of industrial Internet platforms, the traditional network security knowledge query and problem processing mode has been difficult to keep up with the pace of technology iteration, resulting in the existing network security talent pool is difficult to fully meet the growing security protection and emergency response needs of enterprises [2]. Under the new model of school enterprise cooperation, although both parties are committed to jointly cultivating versatile talents, they still face many challenges in the face of the complexity and variability of network security [3]. On the one hand, the diversity of talent structure requires the education system to be more flexible and forward-looking to adapt to the skill requirements of different positions [4]; On the other hand, the rapid development of the field of cybersecurity has led to a continuous widening of the talent gap, especially for high-end and professional security talents, which are in short supply. This has to some extent hindered the in-depth development of school enterprise cooperation and the effective transformation of cooperation results [5]. In response to this challenge, in recent years, the application of data mining algorithms in new models of school enterprise cooperation has been increasingly valued. Through in-depth analysis of the massive data on the school enterprise cooperation platform, it is possible to accurately identify weak links in talent cultivation, optimize curriculum settings, and improve teaching targeting and effectiveness [6]. Embedded network technology, as an important branch of information technology, has great potential in enhancing network system security due to its highly integrated and intelligent characteristics. This article aims to explore how to apply embedded network technology to the cultivation of network security talents, in order to strengthen school enterprise cooperation and jointly cultivate high-quality network security talents who can cope with future challenges. Firstly, we will introduce the basic theory and key technologies of embedded networks, including their application examples in different fields [10]. Subsequently, this article will elaborate on the broad application prospects of embedded networks in the field of network security, particularly in areas such as network architecture reinforcement, development of embedded security devices, and security monitoring and response systems. Furthermore, this article will delve into the core position and value of the school enterprise cooperation model in the cultivation of cybersecurity talents. By comprehensively analyzing the gap between the current network security education system and the actual needs of enterprises, we will propose a series of targeted solutions and strategies [11]. We recognize that school enterprise cooperation is not only a deep integration of theoretical knowledge and practical experience, but also a key force in promoting technological innovation and industrial upgrading. By deepening school enterprise cooperation, the distance between education and industry can be significantly shortened, ensuring that the trained cybersecurity talents can quickly adapt to and lead the latest trends in industrial development [12]. In the process of analyzing the gap in depth, we will focus on the following aspects: firstly, the timeliness and foresight of the curriculum design, ensuring that the teaching content can keep up with the latest developments in network security technology; The second is the adequacy and effectiveness of practical teaching, which enhances students' practical skills and problem-solving abilities through simulating real scenarios and participating in actual projects; The third is the optimization and integration of teaching staff, inviting industry experts and technical backbone of enterprises to participate in teaching, enriching teaching content, and improving teaching quality [13].

2. STATE OF THE ART

In the process of talent recruitment and training, many new platforms for school enterprise cooperation currently rely too much on superficial demand matching, while neglecting the depth and breadth of talent selection [14]. This simplified demand-oriented model is difficult to fully and accurately reflect the real needs of enterprises for network security talents, and it is also difficult to effectively explore and cultivate outstanding talents with innovative potential and comprehensive qualities [15]. In addition, the communication and cooperation between the two parties in terms of talent cultivation goals, curriculum design, and practical teaching are not deep enough, resulting in a certain disconnect between the students trained and the actual job positions. [16]. The new model of foreign school-enterprise cooperation has been combined with a more advanced intelligent model, so this model has an early warning effect on the cultivation and loss of talents [17]. After the brain drain occurs, enterprises can find ways to make up for the shortage of talent in time, which greatly promotes the common development of enterprises and campuses [18]. Since the 21st century, the new model of school-enterprise cooperation in China has been improved rapidly, but it has also fallen into the dilemma of mismatch between enterprise development and talent training. Based on China's huge talent base, due to the lack of a professional cloud platform system, many platforms are difficult to operate in a targeted and systematic way [19]. The rise of embedded network technology has significantly improved the existing difficulties. The combination of new algorithms and embedded network technology will play a crucial role in this process. By utilizing advanced machine learning algorithms and the unique advantages of embedded network technology, we are able to predict industry development trends more accurately, analyze subtle changes in talent demand in detail, and provide a solid and scientific decision-making foundation for school enterprise cooperation [20]. The application of these technologies can not only help us optimize the talent training plan, ensure the progressiveness and practicality of education content, but also promote the in-depth cooperation between schools and enterprises in knowledge sharing, technological innovation and other aspects to a new height. The importance of school enterprise cooperation as a key path for cultivating applied and skilled undergraduate talents is irreplaceable. It not only builds a bridge for students to transform theoretical knowledge into practical abilities, but also promotes the effective integration and complementarity of educational resources and enterprise resources. In the connotative development and innovative exploration of applied undergraduate education, school enterprise cooperation is not only a key strategy to achieve educational goals, but also a powerful engine to drive educational reform and industrial upgrading [21]. As a cutting-edge application-oriented undergraduate education model, embedded network technology closely meets the practical needs of economic and social development. It has promoted the transition of education from closed to open, achieving socialization, marketization, and commercialization, which is crucial for cultivating high-quality skilled talents that meet market demands. In this mode, enterprises provide students with real internships and work scenarios, while schools provide enterprises with talents with professional skills, jointly building a mutually beneficial and win-win cooperation ecosystem [22]. Especially since the 21st century, with the joint efforts of governments at all levels, higher vocational colleges and industrial enterprises. The enthusiasm of industrial enterprises to participate in application-oriented undergraduate education is also increasing [23]. All these make application-oriented undergraduate education increasingly attractive. School-enterprise cooperation has brought about many new developments and new changes: the employment rate of higher vocational colleges, the rate of professional matching, the salary of graduates, and the satisfaction of employers have steadily increased. To a certain extent, it alleviates the problem of "difficult employment of college students" [24].

3. METHODOLOGY

3.1 Branch-bound algorithm for cloud platform operation

The application of new technology requires a certain degree of the performance of algorithm intention. The filter value is automatically set to the node in the input process of an algorithm. After strict examination, it was found that, generally, at the beginning, the number of nodes should be greater than 8, so the number of nodes was set to more than 8. By automatically connecting each node, all points were connected in a preliminary order, and they were given different codes. In this way, the code can be directly input into the next algorithm, which saves the data transmission space. Then, a node was selected as the start node, and the whole graph topology was checked again, with the purpose of replacing the topological module code. The node allocation of the algorithm is shown in the table 1 below:

Table 1 Node assignment algorithm

Project Name	Node position	Node action
business side	Network security	data classification
Campus aspect	Talents	data selecting
School enterprise cooperation path	intermediate node	information transmission

3.2 Embedded network managed by cloud platform

Service management is the medium of communication between developers and enterprises of the third-party application platform. Here, the third-party platform can clearly manage the enterprise's various information and enterprise's mission requirements. The intelligent development model based on the Internet of Things and cloud computing can clearly deal with the problems between enterprises, third-party software, and enterprise talents, and can also meet the needs of different people for different information. Moreover, this development model can choose different cloud processing modes according to different enterprise conditions. Small businesses can use the public cloud; medium enterprises can use the hybrid cloud; large enterprises can choose the private cloud. The simple operation process of cloud computing is shown in the **Figure** 1 picture:

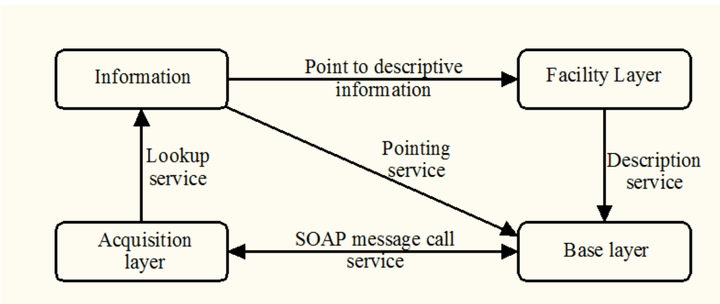

Figure 1. Operation mechanism of cloud services

In the exploration stage of the new model of school enterprise cooperation, we can draw on the logical framework of algorithms to conduct reasonable reasoning that adapts to the characteristics of embedded networks. The overall process design is as follows: using a recursive strategy to search for potential frequent itemsets in the collaborative transaction database in an embedded network application environment. Firstly, consider each embedded network related technology or application in the data table of school enterprise cooperation partners as a candidate itemset. Subsequently, conduct a comprehensive scan of the database; Determine the support level of each candidate itemset through calculation. Next, the sets of items with support greater than or equal to the preset minimum support are used as frequent itemsets, and new candidate itemsets are further generated based on these frequent itemsets to expand the search scope through connection operations. This process iterates until no new frequent itemsets can be generated, and the algorithm terminates. In the data preprocessing stage, we carried out more refined processing, abandoning the traditional general resource classification method and adopting a fine-grained classification strategy to clearly distinguish the requirements of each level from the specific applications of embedded network technology. After data separation, we have focused more on the actual situation of talent reserves, technology platforms, and embedded network application practices among various enterprises, reducing the analysis based on overall general conditions and improving the accuracy and pertinence of the analysis.

$$\lambda = \frac{n\sum xy - \sum x \sum y}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}} \tag{1}$$

The specific implementation of data encoding involves in-depth analysis of the characteristics, ability levels, and job requirements of each type of talent, in order to design a scientifically reasonable encoding system. This system needs to accurately reflect the comprehensive quality, professional skills, and degree of matching with enterprise needs of talents, so that computers can automatically identify and classify them. Through such encoding processing, the originally chaotic data can become orderly and traceable, providing great convenience for subsequent data integration and analysis. In terms of data alignment, we utilize the above coding system to uniformly format and standardize data scattered across different channels and formats, ensuring that all data is logically consistent and comparable. This step is crucial for data integration, as it directly affects the accuracy and reliability of subsequent analysis results.

$$\begin{aligned} y &= a + bx \\ b &= \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - \left(\sum y\right)^2} \\ a &= y - bx \end{aligned} \tag{2}$$

3.3 Algorithm optimization in path selection

After the application of the algorithm, the whole module was not represented by other forms, and they evolved into corresponding parameters, forming a new basic sequence. The combination of parameters was used to establish a new path of school-enterprise cooperation. After the completion of the sequence collocation, the correspondences between the sequences were detected. In the parameterization process, first of all, $\left\{V_{1,1}^i \cdots V_{1,10}^i \cdots V_{n,1}^i \cdots V_{n,10}^i\right\}$ needs to be converted to $V_j^{i'}$:

$$V_j^{i'} = \sum_{k=1}^{10}\left(V_{j,k}^i \times 2^{10-k}\right), i = 1, \cdots 100, j = 1, \cdots n \tag{3}$$

Then, $V_j^{i'}$ needs to be mapped to the real number $\{0,1\}$.

$$V_j^i = 0 + V_j^{i'} \times \frac{1-0}{2^{10}-1}, i = 1, \cdots, 100, j = 1, \cdots, n \tag{4}$$

In this way, the maximum value $max\left(X_j\right)$ and minimum value $min\left(X_j\right)$ of each module index can be obtained.

For the calculation of fitness, the following formula was adopted to carry out simple calculation and integration:

$$fitness\ (i) = \frac{Y_{1(i)}}{N_1} \times \frac{Y_{2(i)}}{N_2} i = 1, \cdots 100 \quad (5)$$

The screening method was used to select individuals with strong adaptability as incidental inheritance. The probability of choosing the I generation is as follows:

$$P^{(i)} = \frac{fitness(i)}{\sum_{j=1}^{100} fitness(j)}, i = 1, \cdots 100 \quad (6)$$

The corresponding technical supports were provided for the sorting between each sequence to avoid the clutter between the sequences. After the completion of the basic algorithm data collocation, the design idea was tested by the output of the data. The mechanism of the algorithm modelling model can not only make us far away from the complexity of the cloud platform between campus and enterprise but can also bring different model constructions.

4. RESULT ANALYSIS AND DISCUSSION

4.1 Collaboration of Embedded Neural Networks

In the research field of recommendation systems, the application of embedded networks and the complexity they bring constitute a key issue. Especially in the in-depth exploration of collaborative filtering recommendation systems, the integration and application of embedded networks have become a new challenge to improve algorithm performance and recommendation quality. Collaborative filtering, a recommendation technique based on user or project similarity, aims to construct and effectively utilize a complex network of relationships between users and projects to predict their potential interests. With the rapid development of the Internet, despite the unprecedented wealth of information and services, users' attention, interest and time resources are still limited. This limitation often results in users only having in-depth interactions or evaluations with a few projects (such as specific types of embedded devices, services, or applications), creating a large number of "blank" or unexplored areas in the "network" of user project interactions. This phenomenon is similar to traditional "data sparsity", but in this context, we focus more on information loss and incompleteness in embedded network environments. Due to the concentration of user interests and differences in preferences, popular projects receive a large number of ratings, while most long tail projects are rarely visited, which further exacerbates the sparsity of the rating matrix. The sparsity of the user-item scoring matrix is shown in Table 2.

Table 2 the sparse case of the user-item rating matrix

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	3			5	
User 2			4		1
User 3		1			
User 4	2				
User 5				4	

In such a sparse scoring matrix, when calculating user similarity, there is very little common score data among users. The accuracy of the calculated similarity is very poor. To solve the effect of data sparsity on similarity accuracy, the user-item scoring matrix needs to be filled. If the total score of 22 between users increases, the accuracy of similarity can be increased.

Then the classical clustering algorithm is adopted -- the K-means algorithm. Cluster calculation is done for graduates and recruitment positions respectively. As a kind of clustering algorithm, the K-means algorithm is convenient and efficient. It is widely used in data mining. K-means algorithm first chooses the centre of initial clustering of K objects from data randomly. Then calculate the distance of all the data in each cluster center to each cluster center. If the object is clustered into the K class, all data need to be calculated K times. Then the objects nearest to each cluster centre into one class were divided, and the centre values of objects in each class, respectively. It is used as the central value of a new cluster. By constantly calculating new cluster sets and cluster centres, the clustering calculation is stopped if the centre values of each class are constant or change within the specified threshold. The K-mean clustering process is shown in Figure 2.

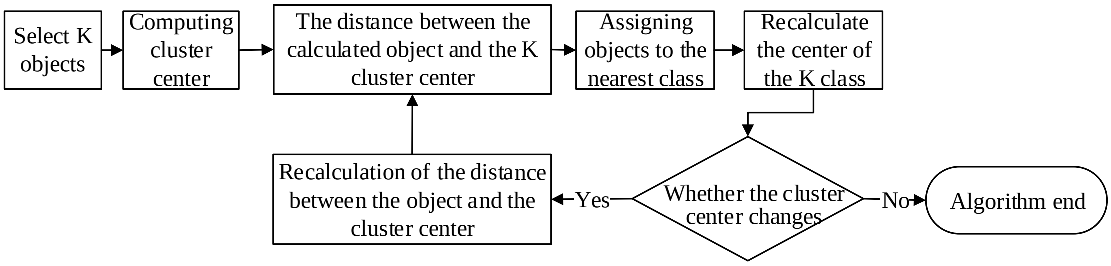

Figure.2 The clustering process of K-means algorithm

In the clustering calculation of job seekers and jobs, the preference vector model of users can be established by analyzing the graduates' job search information and recruitment information. In the distance calculation process of the K-means algorithm, the cosine value of the user preference vector is used to represent the distance between the object and the cluster centre.

$$D=\cos\theta=\frac{\sum_{i=1}^{n} w_i\left(d_1\right)^{*} w\left(d_2\right)}{\sqrt{\left(\sum_{i=1}^{n} w_i^2\left(d_1\right)\right)\left(\sum_{i=1}^{n} w_i^2\left(d_2\right)\right)}} \tag{7}$$

The predicted score will be used to fill in missing items in the original scoring matrix, forming a denser scoring matrix. When filling, it is necessary to consider the confidence level of the predicted score, that is, the reliability of the predicted score. For prediction scores with low confidence, weighting or filtering can be used to reduce their impact on the recommendation results. After obtaining the filled rating matrix, project-based embedded algorithms can be further applied to generate recommendations.

$$sim\left(a,i\right)=\frac{\sum_{k\in CSI_j\left(a,i\right)}\left(R_{a,k}-\bar{R}_a\right)\left(R_{i,k}-\bar{R}_i\right)}{\sqrt{\sum_{k\in CSI_j\left(a,i\right)}\left(R_{a,k}-\bar{R}_a\right)^2 \sum_{k\in CSI_j\left(a,i\right)}\left(R_{i,k}-\bar{R}_i\right)}} \tag{8}$$

Among them, $\bar{R}_a$ and $\bar{R}_i$ represent all the user ratings matrix after clustering of project a and I score average respectively. $CSI_j\left(a,i\right)$ is a subset of users that has been evaluated for the project a and project I in project set SI_j. $r_{i,j}$ represents the score of user i to item j in the user-item matrix $R_{m\times n}$. Then, according to the scoring information of the target project and the evaluation information of the neighbour items, the score of the evaluation items is scored. And take the largest N items in the prediction value as the recommended evaluation set. The calculation formula of the predicted value is as follows:

$$P_{a,k}=\bar{R}_a+\frac{\sum_{v\in SNI_j} sim\left(a,v\right)\times\left(R_{v,k}-\bar{R}_V\right)}{\sum_{v\in SNI_j} sim\left(a,v\right)} \tag{9}$$

In order to make the user item rating matrix more dense and effective, we first need to use a series of predictive models to estimate the potential ratings of users for unrated items. These predicted ratings are then added to the original user item rating matrix to generate a more complete matrix. This process not only significantly reduces the sparsity of the matrix, but also provides a richer data foundation for subsequent recommendation algorithms, which is expected to improve the accuracy and user satisfaction of the recommendation system. When filling in prediction scores, we can use various advanced prediction methods, including but not limited to matrix factorization, deep learning models (such as neural networks), and content-based prediction. These methods can capture user behavior, project characteristics, and the interaction between users and projects, thereby generating relatively accurate predictive ratings. After filling in the scoring matrix, we further conducted cluster analysis on the projects. Clustering aims to group similar items in order to more effectively utilize this similarity information in the subsequent recommendation process. Through clustering, we can reduce computational complexity while improving the specificity of recommendations. The NU users with the highest similarity will be the neighbours of the user. Then, according to the user's scoring value and its NU nearest neighbour's evaluation information, the user's rating prediction value was calculated for its non-scoring items. The largest N value in the prediction value is used as a recommendation evaluation set. Then, the collection of recommended evaluations is merged. Finally, the first N prediction value was selected from the combined recommendation evaluation set to make the final recommendation set. Finally, the items were extracted in the recommended score set and generated the recommended item set of user i.

4.2 Establishing user preference model

In the field of network job search, users don't have significant scoring behaviour. The preference information is expressed by feedback behaviour and implicit feedback behaviour. The system establishes a user preference scoring model by collecting these behaviours, so as to provide score data support for the recommendation system. The user mainly has the following kinds of feedback behaviour. One is to show the score. When users are interested in the posts or resume information, they can take some affirmative action to confirm the information. The two is the browsing behavior. When users spend much time browsing jobs or resume information, they also represent users' interest in the information they are browsing. The three is sharing behaviour. When users are interested in posts or resume information and hope to share information of interest with others, they can click share. Publish the information to the social network. The fourth is the application of the position. When a user clearly indicates that he wants to sign a contract with a job seeker or recruiter, he can click on his job application. The five is search. Users can search for their interested applicants or positions through the recruitment function of websites. The sixth is to download the attachment. When users encounter information that they are interested in, and want to see detailed information, they will download the accessories provided by the other party for further understanding.

In embedded network recommendation systems, in order to improve the accuracy and personalization of recommendations, we can also introduce a time weighted strategy. Here, it is no longer limited to traditional collaborative filtering frameworks, but extends its concept to embedded network environments. Time weighting methods, including linear weighting and nonlinear weighting, can be applied to optimize embedded network recommendation algorithms. Specifically, the linear time weighting method assumes that users' interests exhibit a certain linear trend over time when dealing with embedded network user preferences. Under this assumption, recent user interaction behaviors (such as using specific embedded devices, accessing specific services or applications) will contribute more to interest prediction than early behaviors.

$$f(t) = e^{\lambda t} \quad (10)$$

Introduce a time weighting mechanism in the model to distinguish the importance of user behavior at different time points. Recent user interactions often better reflect their current state of interest, therefore higher weights should be given when calculating preference ratings. This consideration of time sensitivity helps to improve the timeliness and accuracy of recommendations. Analyze and utilize the inherent connections and interaction patterns between embedded devices, services, and applications, such as device compatibility, service associations, etc., to enrich the dimensions of user preferences. These features may be overlooked in traditional recommendation systems, but they have significant value in embedded network environments. In the process of comparing the effectiveness, we not only focus on the accuracy of the recommendation results (such as MAE, RMSE and other error indicators), but also examine multidimensional evaluation indicators such as diversity, novelty, and user satisfaction of the recommendation list. These indicators can more comprehensively reflect the performance and user experience of recommendation algorithms. To verify the performance of the two recommendation methods under different data sparsity conditions, we carefully divided the available operational information (such as user ratings, browsing history, purchase history, etc.) into two independent sets: the training set and the testing set. The training set is used to construct recommendation models, including user clustering, item clustering, and recommendation rule generation based on clustering results; The test set is used to evaluate the actual recommendation performance of the model, ensuring the objectivity and accuracy of the evaluation results. Among them, the proportion of the training set is x. By adjusting the different ratios of x, the recommendation effect of the two recommendation algorithms was calculated respectively. By adjusting the sparsity of data, the F values and MAE values of the two recommendation algorithms are calculated respectively. Below is the F value of two recommended ways in the process of recommending jobs to graduates.

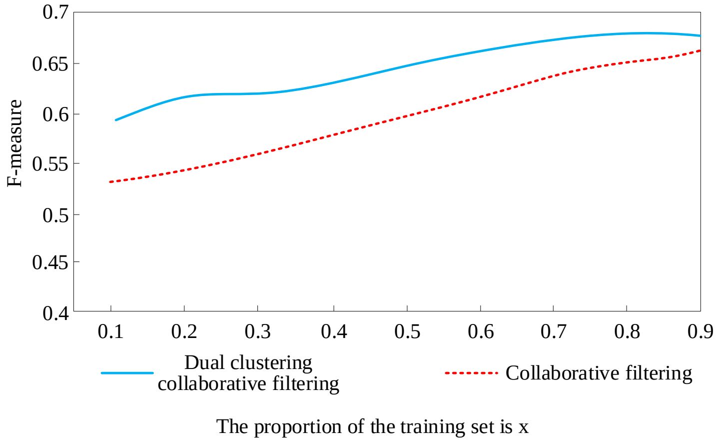

Figure 3 The F value of two kinds of recommendation algorithms

From Figure 3, it can be seen that with the increase in the proportion of the training set, the recommendation effect of the two recommendation algorithms is obviously improved. The two algorithms are more dependent on the density of user behaviour information. The average F value of the traditional collaborative filtering recommendation algorithm is about 0.6. The average F value of the dual clustering collaborative filtering algorithm is about 0.65, which is significantly higher than that of the former. This is because the recommendation method fills the scoring matrix by predicting the non-scoring items, alleviating the impact of data sparsity. Below is the MAE value of two recommended ways to recommend resumes to recruiters.

The dual clustering algorithm, in embedded network environments, achieves more detailed segmentation of user groups and project categories by synchronously analyzing the clustering results of users and projects. This fine-grained partitioning strategy helps to reveal local similarity features that may not have been fully valued in traditional embedded network recommendations, thereby promoting the generation of recommendation content that is more closely aligned with users' personalized needs. Therefore, the embedded network recommendation system using dual clustering method generally has lower mean absolute error (MAE) values than traditional recommendation strategies, indicating higher accuracy and reliability of its recommendation results. When faced with the common challenge of sparsity in user item rating matrices in embedded network recommendation systems, traditional methods may struggle to accurately calculate the similarity between users and items due to insufficient data. However, the dual clustering algorithm effectively alleviates the problems caused by data sparsity to some extent through its unique clustering process, and improves the performance and stability of recommendation systems when dealing with sparse data. As shown in Figure 4, the comparison of MAE values derived from recommendations based on content filtering, collaborative filtering recommendation, and mixed recommendation respectively in the process of recommending job information for graduates. The abscissa is the recommended number.

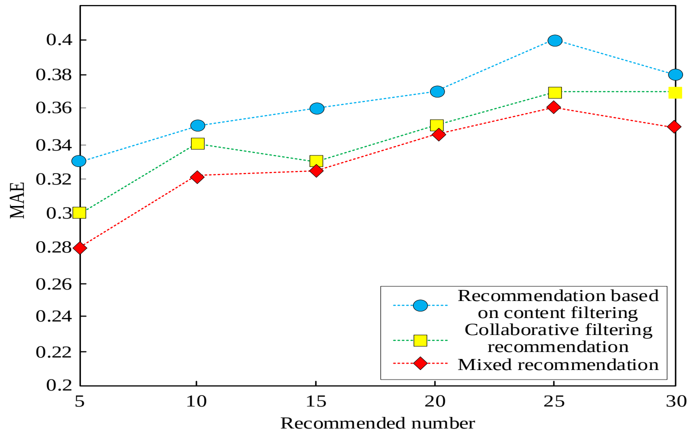

Figure.4 The comparison of MAE values of several algorithms

As shown in Figure 4, the hybrid recommendation method performs well in calculating MAE values, lower than the other two single recommendation algorithms (collaborative filtering and content filtering). This directly proves the effectiveness of hybrid recommendation in improving recommendation accuracy. By combining the advantages of different algorithms, hybrid recommendation can more comprehensively capture user preferences and item features, thereby generating more accurate recommendations. In hybrid recommendation algorithms, content-based filtering is particularly helpful in solving the cold start problem caused by the lack of interaction data for new users or projects. As shown in the figure, the F-means of the hybrid recommendation algorithm for new user recommendations exceeds 0.68, significantly higher than other algorithms, demonstrating its advantage in cold start scenarios. The F-value of collaborative filtering recommendation algorithm gradually increases, which reflects that the increase of user behavior data helps to improve the recommendation effect. However, the F-value of recommendation algorithms based on content filtering has decreased, possibly because their content similarity calculation does not depend on changes in user behavior. The hybrid recommendation algorithm maintains a relatively stable F-value, which is higher than the previous two, demonstrating its adaptability under different user activity levels. Flexibility of recommendation quantity: When exploring the response time of hybrid recommendation systems under different recommendation quantities, we found that hybrid recommendation can achieve faster response speed through optimization algorithms while maintaining high accuracy. This is particularly important for recommendation systems that require high real-time performance, such as recruitment platforms during candidate screening and recommendation processes.

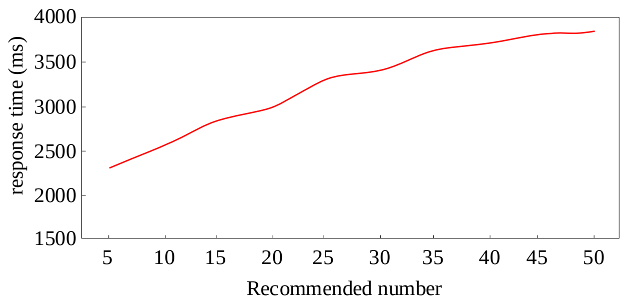

Figure.5 The response time for the hybrid recommender system

The data trend shown in Figure 5 clearly reveals an important trade-off point in recommendation systems: as the number of recommendations increases, the system's response time also increases accordingly, gradually increasing from the initial 2 seconds to about 4 seconds. This phenomenon reflects the increased amount of data and computational complexity that recommendation systems need to handle when facing higher loads. However, it is important to recognize that this increase in response time is still within the acceptable range for most users, especially in scenarios that require detailed screening and personalized recommendations, such as recruitment platforms recommending positions for graduates. In solving the problems of system cold start and data sparsity, hybrid recommendation methods have also demonstrated strong practicality. The cold start problem is particularly tricky in recommendation systems, as new users or projects lack sufficient interaction data to build accurate recommendation models. Hybrid recommendation, by introducing content-based filtering, can rely on the content characteristics of items for initial recommendations when user behavior data is insufficient, effectively alleviating the problem of cold start. At the same time, with the increase of user activity and the accumulation of data, the collaborative filtering part gradually plays a role, further improving the accuracy and diversity of recommendations.

5. CONCLUSIONS

The traditional education model has exposed significant shortcomings in cultivating such composite talents, which has made innovation in school enterprise cooperation models a necessary path. In this context, integrating branch and bound algorithms with embedded network technology into the construction of cloud platforms has become a new attempt to improve platform efficiency and security. In the algorithm testing phase, the experimental group used embedded network technology for data inference, demonstrating an accuracy rate of up to 90%, while the control group did not use embedded network technology, with a data inference accuracy rate of only 30%. This contrast vividly demonstrates the significant advantages of embedded network technology in enhancing data processing and analysis capabilities. On this basis, enterprises can more effectively implement data management strategies to ensure the security and effective utilization of data. Regarding the performance evaluation of the branch and bound algorithm, the test results show that the algorithm exhibits excellent distributed search capabilities and can smoothly process user requests, making it more efficient compared to other algorithms as the number of data access requests increases. This feature ensures that the cloud platform can maintain stable operation in high concurrency scenarios, improving user experience and system reliability.

ACKNOWLEDGMENTS

This work was supported by the Education Department of Hainan Province “Teaching reform，Master guidance, school-enterprise collaboration, Service Hainan -- Research and practice of network security talent training “, project number:Hnjg2023ZD-67

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