Smart Campus Microservice Recommendation Algorithm Based on Neighborhood Clustering and Time Collaboration

Jin Lian1,2, Ming Gao2*

1School of Artificial Intelligence, Jianghan University, Wuhan, Hubei, 430056, China
2Network Information and Teaching Equipment Management Center, Jianghan University, Wuhan, Hubei, 430056, China
*Corresponding author’s e-mail: gaoming@jhun.edu.cn

Abstract: The basic algorithm research of smart campus construction is the basic path for education to benefit from the development of science and technology. Based on the application environment of higher education teaching and management, according to the teaching periodicity and the closed-loop characteristics of the business system in universities, a neighborhood-based user attribute clustering algorithm is used in this paper to form user clusters, which are coupled micro-application clustering with periodic time. Finally, through normalized conversion and Pearson correlation coefficient analysis, the Top-N recommendation list is obtained, and a recommendation algorithm suitable for smart campus microservice system is constructed. In this paper, matrix sparsity and cold start are discussed, and data compensation is carried out by analyzing the general behavior patterns of teachers and students, which effectively solves the problem of insufficient recommendation list caused by matrix sparsity and cold start. Upon data analysis before and after the algorithm deployment, the algorithm effectively reduces the number of times that users use the search function.

1. Introduction
With the development of the smart campus, its software architecture changes from management type to service type, its data structure extends from centralized processing to divergent collection, and its business management shifts from an integrated system to a scattered microservice platform. At present, information systems such as a unified online service hall and a network office are introduced in the construction of the smart campus to solve data collection, remote approval, data processing and feedback. The microservice framework is adopted, and the agile development mode adapts to the development and change of technology and business [1]. The scattered microservices have been transformed from a few or a dozen systems into hundreds of microservice applications, resulting in the problem of microservice overload. Each system is organized according to different departments and businesses. Generally, the top ten or so microservices of each department or subject business system are displayed, while others are hidden. Even so, a lengthy page will be generated.

With the continuous innovation of data mining and recommendation algorithms, it is a good idea to form a personalized recommendation list to solve the problem of microservice overload. The smart campus application system forms a recommendation list based on user classification and clustering and microservice usage frequency, which can achieve a certain effect, but the workload of clustering segmentation and manual management is heavy and cannot adapt to changes. According to the application characteristics of university information systems, this paper proposes a microservice recommendation algorithm based on neighborhood clustering and time collaboration, which can better...
realize personalized recommendation of microservices and improve user efficiency.

2. Related Works
In the context of information overload, recommendation algorithms can be seen everywhere. E-commerce product recommendation, news content recommendation, and Moments advertisement recommendation are all non-personalized or personalized recommendations achieved through algorithms under certain data collection, which brings us convenience and saves time. The recommendation algorithm has attracted worldwide technical attention, such as professional journals AI Communications (2008), ACM Transactions on Interactive Intelligent Systems (2013), ACM Transactions on Intelligent Systems and Technology (2015)[2]. A large number of professional researches are based on collaborative filtering recommendation algorithm, content-based recommendation algorithm, and hybrid recommendation algorithm, which are also the main classification methods of recommendation algorithms [3]. Efficient and iterative e-commerce companies such as JD.COM, Amazon, Taobao, and more professional conference organizations, such as ACM recommendation system conference, SIGMOD, constantly innovate recommendation accuracy on the basis of big data [4].

At present, the collaborative filtering recommendation algorithm is widely used in recommendation system based on e-commerce, and the basic method of collaborative filtering algorithm is based on neighborhood and implicit semantic model technology [5, 6]. Supported by big data, this algorithm has many advantages, such as rich semantics, high reliability, high accuracy of user recommendation, fast iteration speed and so on. Of course, there are also many problems. For example, when studying the recommendation algorithm in the field of e-commerce, there are many problems, such as a large number of users, sparse data, cold start, inaccurate similarity calculation, which affect the recommendation results. Although the above problems also exist in the smart campus microservice recommendation algorithm, they are very different in terms of order of magnitude and periodicity, and their own attributes. The smart campus is closed to users, the teaching and scientific research work presents periodic rules, the users’ start is fast, the selection range is small, popular applications are used frequently, and semantic rules can be easily found by personnel clusters. A good recommendation algorithm can significantly improve the efficiency of microservice. At present, only a few researches are conducted on intelligent algorithms based on smart campus application scenarios, and recommendation algorithms are pertinent and narrowly adaptable, so the research on recommendation algorithms for smart campus micro-applications has practical application value.

3. Analysis on Characteristics of Smart Campus Microservice System
With the deepening of the construction of smart campus and the strategic promotion of educational informationization by the state, the field of artificial intelligence for the education industry is still in its infancy [7], but it is bound to become the main front for the construction of the next smart campus. After several years of construction, the smart campus has changed from a centralized integrated management system to a distributed and fast-delivery microservice architecture [1].

Smart campus microservice system is a loosely coupled service cluster developed with service-oriented architecture. Its essence is to establish a fine-grained, lightweight service process with SOA architecture based on the original MIS system according to the business flow [8]. Therefore, the microservice system projects are all derived from the fragmentation and miniaturization of the original traditional business system, and follow the business classification and definition of the original business system, resulting in a closed management mode which is based on the defined business process in quantity and inherits the original business system in attributes.

In terms of users, compared with the e-commerce system, user types are simplified, and application demands are strong and irreplaceable. The smart campus microservice system is developed and designed for teachers and students in universities. The users are only faculty, staff and students. The business demands are regulated in teaching, scientific research, management and daily life in universities. Due to limited roles and scope of activities, user clusters based on attributes and business clusters based on
functions are easy to be formed, so the number is relatively small and the analysis is more accurate.

The use of microservice applications is characterized by enhancement, and the possibility of re-use is greatly increased after users use it once. This is very different from the situation that the purchased goods need to be consumed in a certain period or the users no longer purchase the same goods. For certain positions, it is a very common phenomenon to use fixed N services within a certain period.

4. Microservice Recommendation Algorithm Based on Neighborhood Clustering and Time Collaboration

Symbol description of algorithm: In order to establish the correlation data model of User, Microservice and Time, the algorithm defines user set $U$, microservice set $M$ and user-microservice matrix $R$, where $U_i$ is the $i$th user, $M_j$ is the $j$th micro-application, and matrix $R_{ij}$ records the number of times that the user $I$ uses the microservice $j$. A time set $T$ and a microservice-time matrix $S$ are defined, where $T_m$ is the $m$th time point in a year, $M_n$ is the $n$th microservice, and $S_{mn}$ records the number of times that the microservice $n$ is called at time $m$. The matrix $R$ is used to form neighborhood-based user clusters, and the matrix $S$ is used to form time-based microservice usage characteristics, and forms a Top-N recommendation list through collaborative analysis with user clusters.

4.1. Assumptions of recommendation algorithm

In order to further simplify the difficulty of the algorithm and improve the feasibility and pertinence of the algorithm while ensuring accuracy, the following assumptions based on experience are proposed:

1. Smart campus microservice application is closed and its attributes are determined.
2. University business has a stable frequency and takes the academic year (period) as the cycle.
3. The user's attribute is clear and has a good portrait foundation.

The above assumptions determine the applicable scope of the algorithm, reduce the calculation dimension, improve the robustness in specific scenarios, and provide basic constraint reference for the effectiveness of the algorithm practice.

4.2. Normalize $R_{ij}$ and $S_{mn}$

Due to the large difference in the number of times that microservices are used, they cannot be used directly in the correlation analysis, so it is necessary to normalize the matrices $R$ and $S$. In this paper, Z-Score normalized matrices $R$ and $S$ are adopted, and attribute vectors are formed by using the characteristics of their average values at a given data distance, so as to normalize the frequency values and calculate the required relationship vectors.

Obtain the standard deviation:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2}$$ (1)

Substitute formula (1) into

$$z = \frac{(x - \mu)}{\sigma}$$ (2)

Where $\sigma$ is the standard deviation of the overall sample space, $x$ is the original sample, $z$ is the normalized value, and $\mu$ is the average value of the overall sample space. After normalization, the values of $R_{ij}$ and $S_{mn}$ all fall between $[0,1]$.

4.3. Use Pearson correlation coefficient calculation formula for user clustering calculation

$$d = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}}$$ (3)

d represents the correlation between two users, and $\bar{X}$, $\bar{Y}$ are the average values of samples. By formula (3), the similarity of two users in the matrix $R$ can be calculated, and similar user clusters can be formed according to the recommendation Top-N demands.

4.4. Time collaboration

Clustering is carried out by using the relation of $p$ users of the nearest neighbor relation, and a recommendation list $E$ is formed on $R$. At the same time, a microservice List $F$ in time is formed by
clustering the adjacency of microservices.

\[ I_{\text{Top-N}} = (i \in E) \cup (i \in F) \quad (4) \]

Through step (4), the two sets are formed into a coupled set, so as to obtain a recommendation set with dual characteristics of user attribute and time period, which supplements the recommendation error caused by the periodicity of university management work, and obtains the personalized recommendation list \( I_{\text{Top-N}} \).

4.5. Cold start problem

The recommendation algorithm has a cold start problem when it encounters new faculty and freshmen entering the university. However, in the university microservice system, the attributes of service objects are relatively fixed. After clustering analysis by using Pearson coefficient, a number of related user groups are obtained. After analyzing the characteristics of faculty user groups, a user cluster with similar multi-dimensional attributes such as majors, departments, positions, academic qualifications, and professional titles are obtained. And the cold start problem is also very concentrated in the time dimension, that is, the time period for freshmen and new employees entering the university in August and September each year. According to this feature, the system optimizes the microservice recommendation for regular new faculty members, recommends the applications such as system registration and new entry in August and September, and then recommends commonly-used function of the corresponding departments (schools). After the transition period from September to December, relevant microservice application data are accumulated, so the cold start problem is solved.

5. Algorithm Results and Effect Analysis

A group of users A, B, C and D is selected to perform cluster analysis and output similarity coefficients. At the same time, the top5 recommendation coefficient table calculation results of this group of users are output as follows:

| Table 1 User Similarity Coefficients | Table 2 Top5 Recommendation Coefficients |
|--------------------------------------|------------------------------------------|
|                                      | top1     | top2     | top3     | top4     | top5     |
| A                                    | 1        | 0.973    | 0.822    | 0.587    |          |
| B                                    | 0.973    | 1        | 0.879    | 0.544    |          |
| C                                    | 0.822    | 0.879    | 1        | 0.436    |          |
| D                                    | 0.587    | 0.544    | 0.436    | 1        |          |
| A                                    | 0.314    | 0.251    | 0.186    | 0.167    | 0.154    |
| B                                    | 0.299    | 0.226    | 0.171    | 0.159    | 0.144    |
| C                                    | 0.173    | 0.142    | 0.113    | 0.113    | 0.106    |
| D                                    | 0.410    | 0.266    | 0.104    | 0.092    | 0.087    |

It can be seen from the results in Table 1 that users A and B have high similarity and strong relevance, while user D has poor similarity with the others. It can be seen from the results in Table 2 that the recommendations for micro-applications can form a sequential sequence.

Due to the lack of research on recommendation algorithm of smart campus microservice platform, it is impossible to form test data and comparison results. Therefore, this paper selects the relatively stable school year from March to June, extracts the number of times the search microservice tool is used, and analyzes the impact of the algorithm before and after use to verify the effect of the algorithm. Data collection is shown in Figures 1 to 4.
By September 2020, the system has provided 172 microservices. The number has not changed much in the past three years, with annual visits exceeding 1.4 million times. Before using the recommendation algorithm, the system search tool microservice is used for about 11,000 times. Among them, from March to June in 2018 and 2019, the tool was used for about 4,000 times. After using the recommendation algorithm, the number of times in each month has fallen every month, and the total number in four months is about 2,200 times. Through data analysis of faculties, freshmen and juniors, the usage frequency of the three groups of people is quite different, but after using the recommendation algorithm, the use of search tools is effectively reduced. Due to the problem of data sparsity, the effect of the freshmen is significantly lower than that of the juniors, so the algorithm needs to be improved in this point. In general, the effect of the algorithm is obvious, and the recommendation list is used to a large extent to meet user demand and reduce the time cost of searching microservices.

6. Conclusions
Artificial intelligence serving campus teaching, scientific research and management is another development stage of intelligent campus construction. In this paper, the general recommendation algorithm is introduced into the smart campus microservice system, and the Top-N list recommended by microservice application is designed and implemented based on the periodic rule of university teaching management and the analysis of teachers and students' behavior patterns, which significantly reduces the use of search tools and achieves good results. Aiming at the intelligent algorithm and its application in education information system, the depth and breadth of the current research are obviously insufficient, and only a few reference cases are available. The algorithm proposed in this paper has many shortcomings, such as the attribute and clustering of microservices, the clustering analysis of teachers and students, and the correlation analysis of time attributes. Few researches are conducted by in-depth application of big data and recommendation algorithms. All the above-mentioned directions are of great benefit to the improvement of the accuracy of the algorithm, and will also be the main directions of the research.
algorithm research.

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