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A PRACTICAL APPROACH FOR FINANCIAL SERVICES DISCOVERY BASED ON USER CLUSTERING

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Abstract. *Service discovery is a research hotspot in service computing. Although most of the existing methods have a better performance in theory, their practicability is not strong, so they cannot meet the needs of modern financial activities. To address the problem, we proposed a practical service discovery towards financial application. Firstly, we established a new service discovery architecture applicable to financial activities. Secondly, we studied the characteristics of financial activities, on this basis, designed a user clustering relationship model and then provided a service discovery algorithm based on the relationship. Finally, we conducted experiments to verify the performance of the method. The experimental results show that our proposed approach leads to a substantial increase in the precision and efficiency of financial services discovery.*

Keywords: Financial services, Discovery, User clustering, Precision, Efficiency

1. **Introduction.** With the further application of Web technology, more and more financial Web services appear in the online financial information market, and many famous financial data solutions providers such as Xignite are putting a lot of effort to provide high-quality specialized commercial finance Web services for users [1]. According to a Mckinsey Quarterly survey conducted on more than 2800 companies worldwide, 80% of them are using or planning to use Web service to achieve transactions with their partners and/or offer on-line services [2]. It can be said, Web service is one of the most important technologies in modern finance. However, for ordinary financial users, due to the lack of professional network knowledge, they often find it is difficult to locate specific services in an increasingly wide range of potential services that offer similar functionality. Therefore, service discovery has become an urgent problem in modern Internet financial activities. However, there are few methods specifically for the financial field in the study of Web service discovery. The performance of the existing methods in financial field is not satisfactory yet.

In this paper, we propose a new service discovery towards financial application based on user clustering, which gives full consideration to the characteristics of financial activities, and adopts an efficient service discovery algorithm based on user clustering relationship. In particular, the method differs from the existing ones mainly in its effective and flexible matching analysis, and more specifically it employs a useful user personalization model based on ontology technology to gradually narrow matching range to reduce the computational cost and meet users' requests rapidly. Experimental results show that compared with similar methods, the proposed method has higher efficiency and accuracy, and can better adapt to the characteristics of financial activities.

This paper is organized as follows. In Section 2 we will review the related approaches in financial service discovery as well as analyze their strength and weakness. Corresponding models and algorithm are introduced in Section 3, followed by the experiments in Section 4. The conclusion is given in Section 5.

2. **Related Work.** Web service discovery is a highly intelligent information processing technology. In order to get more accurate results and better process automation, traditional methods often consume a lot of resources to describe services and build rules. Generally, these methods usually only focus on the parsing of service requests, while ignoring making effective use of the extra auxiliary information from users, so they are often troubled with low efficiency, high computational cost and large communication overhead. Moreover, to improve the recall and precision, these methods always increase the complexity of algorithms, and add extra computation; thus, their efficiency tends to be low [3].

From the recent research, mining and using connotative user information to improve the performance of service discovery is a feasible and effective way [4]. A trusted service discovery based on trust and recommendation relationships was proposed in [5], which can reduce the searching path and search trusted service in a short time. Data mining techniques were applied to SOAP-based service descriptions in order to infer patterns providing a summarized and integrated representation of service functionalities, which can be directly queried or used to drive exploratory searches [6]. In [7], a provenance-based approach to semantic Web service description and discovery was presented, in which a critical component of the implementation was the ability to discover a service's implementation details regardless of their acceptance within a broader user community. A trust model supporting service discovery and composition based on trustworthiness was presented in [8]. The method can use direct and indirect user experience to discover the trustworthiness of the services and service providers. A new service discovery method based on referral network and ant-colony algorithm was proposed in [9]. The approach can make use of recommendation and ant colony algorithm to improve the success and recall rate of service discovery. In [10], an approach including two main sub processes: query expansion and service ranking was proposed. It enables the retrieval of relevant Web services during the discovery process by considering lexical similarity and semantic similarity.

Although the above methods introduced connotative social information into service discovery in different extents, the improvement of their performance is not satisfactory. Furthermore, their applicability in financial activities has not been verified effectively; thus, it is necessary to put forward a new service discovery method that adapts to the characteristics of actual financial activities well.

3. **Financial Services Discovery.** In this section, we propose a new approach for financial services discovery. Specially, we will explain the architecture of the method, as well as elaborate the discovery algorithm.

3.1. **Architecture of services discovery.** The architecture of our method is shown as Figure 1. It contains four main components: the client, the user personalization model, the discovery execution module and a service pretreatment module.

The client has three main functions: to provide users a friendly operation interface and display the discovery results, collect the user's evaluation of Web services while recording the user's operation behavior, and at the same time, realize the communication between the client and the discovery execution module. Additionally, in order to formalize evaluation values about services, we normalize the ratings with integers in the range from 1 to 5.

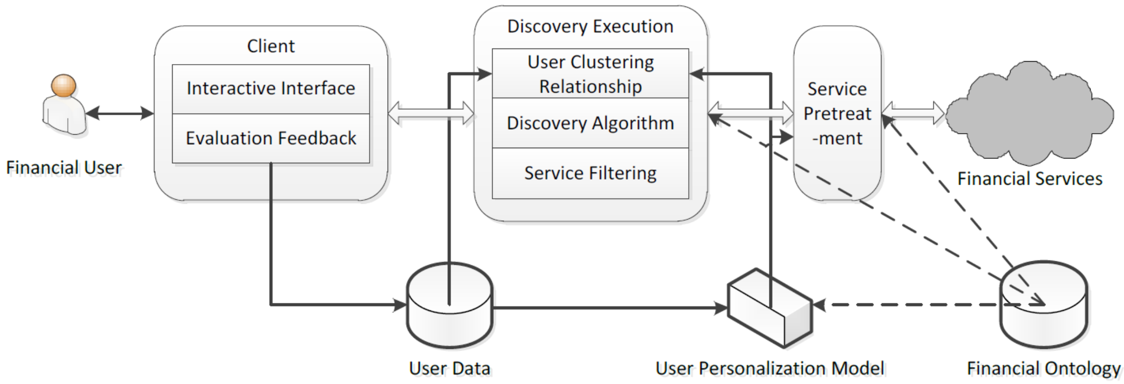

FIGURE 1. Architecture of financial services discovery

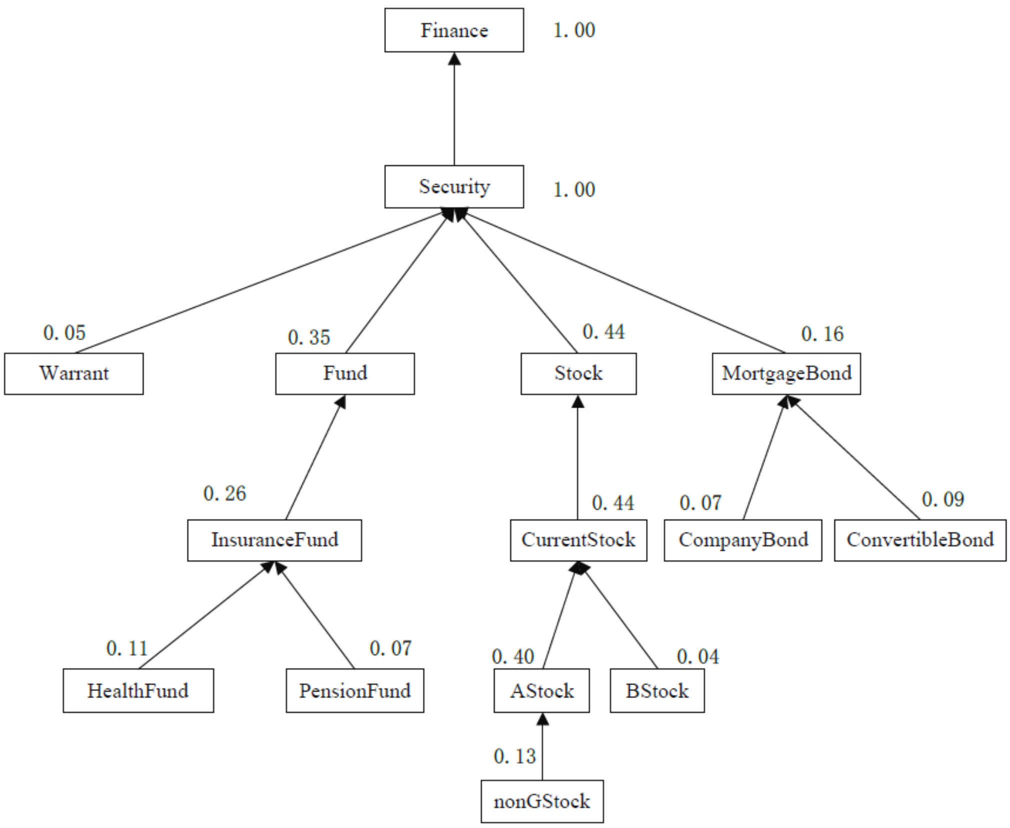

FIGURE 2. A sample of financial user personalization model

In our approach, the user personalization model is a prerequisite of the algorithm, which is based on users' operation history, and has an important influence on the establishment of a user clustering relationship. In a previous study [11], we have designed a new user personalization model for Web service discovery based on pruning strategy, which is essentially a subtree of single domain ontology, and is suitable for a special application field so we adopt the model in this paper. Likewise, we use the Financial Ontology constructed in [1]. Thus, a sample of financial user personalization model can be shown as Figure 2.

The discovery execution module is the core component of the architecture. Its main functions are: to utilize user information to establish user clustering relationships, respond to service requests from the client and return the final results, perform a specific service discovery algorithm, and filter findings according to the needs of users.

Service pretreatment module is used to monitor, register and manage available financial services under the current network environment, while recording their functional attributes and QoS parameters, and classify available services according to user preference models. Furthermore, it can also implement invoking of specific services.

3.2. **Discovery algorithm based on user clustering.** A Web service discovery based on user community relations has been proposed in [4]. On the basis of it, combining with the characteristics of financial activities, here we present a service discovery algorithm based on user clustering.

For $\forall u_a$, $u_b \in U$, S_a and S_b are the sets of services called and evaluated by u_a and by u_b, respectively. S_{ab} is the intersection set between S_a and S_b. Q is the set of service QoS parameters. Therefore, the user clustering relationship of u_a can be described as Equation (1):

$$C_a = \{(u_n, d_{an}) | u_n \in U_a, d_{an} > d_0\} \tag{1}$$

where C_a means the user clustering relationship of u_a, and U_a is the set of users in C_a. d_{an} is the clustering degree between u_a and u_n, and d_0 is the threshold of d_{an}. Here, d_{an} can be calculated by Equation (2):

$$d_{an} = Psim_{an} \times \frac{\sum_{s_i \in S_{an}} \prod_{q_j \in Q} \left(1 - \frac{\left|v_{ij}^a - v_{ij}^n\right|}{V_0}\right)}{|S_{an}|} \tag{2}$$

where $Psim_{an}$ is the similarity degree between the user personalization model of u_a and the user personalization model of u_n, which can be defined and quantitated in [11]. v_{ij}^n is the rating value of service s_i on QoS parameter q_j by user u_n and V_0 is maximum value of the rating on QoS parameter. $|S_{an}|$ is the number of services in S_{an}.

Based on the above work, we propose a service discovery algorithm based on user clustering (DUC), which is shown as follows.

Input: u_a and request r

Output: result list L

1) establish C_a
2) initialize $L = \emptyset$, $L_0 = \emptyset$
3) for each service $s_i \in S_a$, if $p_{ai} < p_0$, add s_i into L_0; else calculate Sim_i
4) if $Sim_i > \tau_m$, then add s_i into L; else add s_i into L_0
5) for each user $u_n \in U_a$, and for each service $s_j \in S_n$, if $p_{nj} < p_0$, add s_j into L_0; else calculate Sim_j
6) if $Sim_j > \tau_m$, then add s_j into L; else add s_j into L_0
7) for each service $s_k \in S \wedge s_k \notin L_0 \wedge s_k \notin L$, calculate Sim_k
8) if $Sim_k > \tau_m$, then add s_k into L
9) return L

In the above algorithm, Sim_i is the similarity between s_i and r, p_{ai} is the user experience of u_a on s_i, and they are defined as follows:

$$Sim_i = Rsim_i \times \prod_{q_j \in Q} \frac{e_{ij}}{V_0} \tag{3}$$

$$p_{ai} = \frac{\sum_{q_j \in Q} v_{ij}^a}{|Q| V_0} \tag{4}$$

where $Rsim_i$ is the matching degree between s_i and r, and it can be calculated according to [4]. e_{ij} is the real value of QoS parameter q_j of service s_i, and it can be detected by the service pretreatment module. $|Q|$ is the number of QoS parameters in Q.

4. **Experiment.** To verify the performance of the method proposed in this paper, we constructed a prototype system and conducted the following experiments. In order to give an objective evaluation, we considered two comparison partners that have been reviewed in the former context: Ant-Algorithm-Based Service Discovery Algorithm (ABSDA) [9] which also adopts recommendation mechanism, and Lexical Semantic Service Search (LS3) [10] which is essentially based on semantic technology like DUC. These two approaches are partly similar to our proposed method on the principles of algorithms.

To obtain sufficient user data, this paper simulated 60 financial users to perform specific operations, these users were independent of using this system at different times, and they produced a total of more than 1,200 pieces of operation records. We used the way of actual annotation and random generation to generate 1,000 financial Web services, which cover almost all the concepts of the Financial Ontology. In the experiments, we set the QoS parameters as Price and Response Time, $\tau_m = 0.2$, $d = 0.3$, $p_0 = 0.3$, $V_0 = 5$.

Firstly, we created 10 different financial requests, set the initial number of candidate Web services to 300. Secondly, we gradually added services with an increasement of 100 until the number reached 1,000, while recording the completion time and computing the precision of the three methods in each test. Finally, we compared the average completion time and the average precision of these methods. In the experiments, we adopted the definition of precision introduced in [4].

Seen from Figure 3, LS3 needs the longest completion time from beginning to end; when the number of services is not more than 600, the discovery completion times of DUC and ABSDA are roughly equal; after the number is over 600, the discovery efficiency of DUC is significantly better than that of ABSDA. And with the growth of the quantity of services, the difference is more and more obvious. Moreover, with the growing of the quantity of services, the difference is more and more obvious. The reason is that, with the increasing of user operation, the user clustering relationships are clear and abundant step by step; thus, the services with lower evaluation or little affinity can be filtered in advance. So the following matching range will be gradually narrowed down.

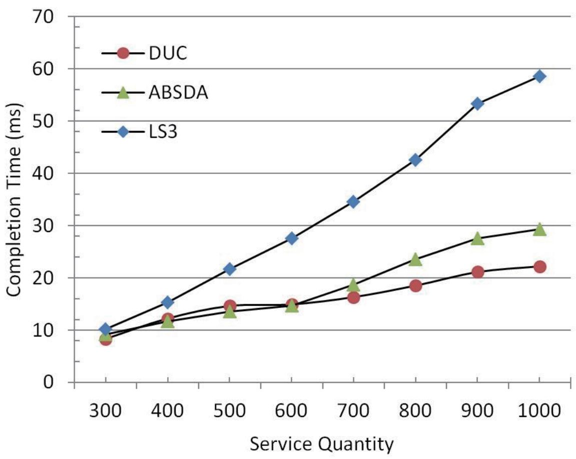

FIGURE 3. Comparison of efficiency

Figure 4 shows the comparison result of discovery precision. It is clear that, compared with ABSDA and LS3, DUC has a highest discovery success rate throughout. This is because DUC can match preferentially and definitely the related services with the help of user clustering relationships; therefore, its discovery results can meet the target users' request most accurately.

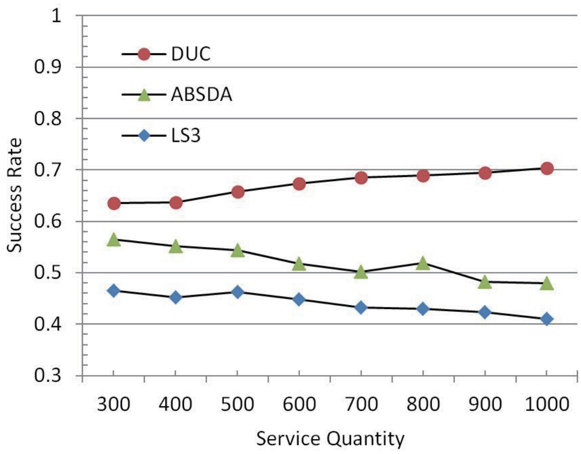

Figure 4. Comparison of precision

5. **Conclusions.** In this paper we proposed a practical approach for financial services discovery based on user clustering. Firstly, we presented a new architecture of financial services discovery as well as elaborated its main components. Then, based on the formalization of user clustering relationship, we presented a service discovery algorithm based on user clustering. Through comparing completion time and success rate with two typical algorithms, the performance of our proposed model is verified. The experimental results show that the proposed model can effectively improve the precision and efficiency of service discovery, and has a satisfactory performance in financial activities. As future work, we plan to enrich the clustering factors in relationship formalization and deal with real time preferences in user personalization model, to further improve the performance of our method.

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