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Trust-based Service Recommendation in Social Network

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Abstract: With the number of Web services increasing constantly on the Internet, how to recommend personalized Web services for users has become more and more important. At present, there emerged some service recommendation systems utilizing influence ranking and collaborative filtering algorithms in service recommendation. However, they neither considered trust relationships among users, nor deal with the cold start problem very well. Fortunately, the popularity of social network in nowadays brings a good alternative for service recommendation to avoid those. In this study, we propose a social network-based service-recommendation method, which considers users' history service invocation behaviors, users preferences as well as trust relationships among users implied in social network and users comments/reviews on services. We have applied this method in a data set extracted from www.epinions.com. A series of experiments on 86,719 users, 604,190 user trust-relationships and 963,591 reviews on 292,713 services/produces show that this recommendation method get better recall rate, precision, f-measure and rank score.

Keywords: Web service, Service recommendation, Social network

1 Introduction

Web service has played an important role in the fields of Enterprise Application Integration, E-commerce and Business Process Management [1]. It has achieved a great success both in academia and industry and its number is growing rapidly especially in the age of Cloud Computing and Big Data [2,3]. This incurs the difficulty for users to find appropriate services from a large number of candidate services to meet their functional and non-functional requirements.

Although service discovery method can help users to retrieve target services in some cases, it is a passive process requiring users to know their requirements clearly in advance. However, in many cases, users are neither able to know what they need clearly, nor know the existence of potential services on the Internet. As a result, service recommendation plays a more and more important role to help users out of the service overload predicament, and automatically recommend proper services for users.

Currently, recommendation system has been widely used in various fields and its performance is mainly influenced by recommendation algorithms. The classical recommendation algorithms can be divided into two types: Influence ranking [4,5] and collaborative filtering [6,7]. Influence ranking recommendation is designed to find the most influential people in a social network. A service recommendation system based on influential ranking aims at recommending the most popular services to active users. Influential ranking mainly includes algorithms such as Reputation, Hits, and PageRank [8]. Collaborative filtering algorithm is more widely used in service recommendation, which is based on users service-invoking history and rating records. It first finds the similar users to the active user; then recommend the services with high evaluation value by the similar users. The algorithms can be subdivided into user-based and item-based collaborative filtering algorithm [9]. Although the current recommendation systems work well, they still have two main defects: (1) they do not consider the trust issue among users while recommending services; (2) they do not deal with the cold start problem very well.

In this study, we propose a social-network based service recommendation method based on users trust-relationship and mainly consider: 1) Users preferences. We capture users preferences based on history records which contain the invocation of services, the reviews on services and feedbacks from other users as well; and 2) Trust relationship among users. In general, active user mainly prefers to invoke the services recommended by the person he trusts. The whole

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recommendation procedure runs according to the following 4 steps: 1) Building user characteristic vector; 2) Calculating similarity value between active user and other users; 3) Selecting Top-M similar users to the active user and calculating rank score of candidate services; 4) recommending Top-K services to the active user. We have applied this recommendation method in a data set extracted from www.epinions.com. The experiments on 86,719 users, 604,190 user trust-relationships and 963,591 reviews on 292,713 services/produces show that our recommendation method outperforms others.

The rest of this paper is structured as follows: Section 2 introduces the background of service recommendation and reviews some related work. Section 3 presents a motivating scenario. Section 4 gives the social-network based service recommendation method in details. Section 5 illustrates the experiments and comparison results. Section 6 concludes this study and discusses the future work.

2 Related Work

With more and more Web services emerged on the Internet, it becomes difficult to find a suitable Web service meeting users requirements from massive services. Traditional service discovery approaches are somewhat passive in discovering Web services for users since they highly depend on the clear users request description as well as services functional and non-functional description. Thus, as an important alternative to service discovery, service recommendation attracts more and more attention nowadays.

Numerous research works have been done on Web service recommendation [9,10,11,12,13,14,15,16]. Since our method is based on collaborative filtering, here we only concentrate on introducing related work on collaborative filtering based approaches for Web service recommendation.

Collaborative filtering (CF) proposed by Rich has been proved to be a kind of successful approaches for recommendation systems [10]. Shao proposed a user-based CF algorithm using PCC (Pearson Correlation Coefficient) to compute similarity between users [13]. Users who have similar historical QoS experiences on Web services are deemed to be similar. For any active user, the missing QoS values of a Web service can be predicted by considering the corresponding QoS values of services used by his/her similar users. Finally, Web services with high-predicted QoS values are recommended. Zheng proposed a novel hybrid collaborative filtering algorithm for Web service QoS prediction by systematically combining both item-based PCC (IPCC) and user-based PCC (UPCC) [14]. However, they failed to solve the cold start problem. If a user never has QoS experiences on any service, the method cannot recommend any service to him.

In order to improve the accuracy of recommendation for Web services, several new enhanced methods are proposed [18,19,20] Hao Ma, Haixuan Yang, et al, recognized data sparsity, scalability and prediction quality as the three most crucial challenges that every recommender system based on collaborative filtering algorithm confronts, and proposed a probabilistic matrix factorization method for social recommendation [17]. Chen Xi, Liu Xudong, et al. recognized the influence of user location in Web services QoS prediction and proposed a novel method [18]. The method groups users into a hierarchy of regions according to users locations and their QoS records, so that the users in a region are similar. When identifying similar users for a target user, instead of searching the entire set of users, the method only searches the regions that the target user belongs to. However, it does not consider service location in recommending Web services. Jiang proposed that the influence of personalization of Web service items should be taken into account when computing degree of similarity between users [19]. That is, more popular services or services with more stable QoS from user to user should contribute less to user similarity measurement. Zhang suggested that it was better to combine users QoS experiences, environment factor and user input factor to predict Web services QoS values [20]. But the environment factor and user-input factor can hardly represent users subjective opinions.

In general, most of the current Web service recommendation approaches aim to predict the values of QoS attributes of Web services and use historic invocations to extract users interests or preferences, but consider little about the trust issue [21,22]. As a consequence, they cannot be directly employed in a real Web service recommendation system to recommend services actively without users interference. Compared with prior related works, this paper makes the following major contributions. First, we consider not only QoS of services but also users trust relationships, and present a novel service-rating model. We show that both QoS of services and users trust relationships can be used in improving performance and accuracy of service recommendation significantly. Second, we carry out a series of experiments on a large-scale real dataset extracted from a social-network website www.epinions.com to show that considering users trust can improve the accuracy of recommending personalized services to target user. Furthermore, since the trust relationships between users are considered, the proposed method can partly solve the cold start problem. If a user do not invoked any services before, traditional approaches can hardly recommend services to him/her. But our approach can recommend services by utilizing the trust network of users according to his/her trusted users.

3 Motivation Scenario

In order to show the importance of the trust factor in service recommendation, consider a recommendation scenario based on Table 1, which shows the records of service invocation by users. The numbers indicate the times of invocation of a service by a user. For example, it shows that Tom has invoked s_1 4 times and s_2 2 times, yet has not invoked the other three services before.

Table 1: Service Invoking History

	s_1	s_2	s_3	s_4	s_5
Tom	4	2			
Merry	3	3		2	
Bob		2	1		
Jack			1	1	1

To recommend top-2 services for Tom, most of the current recommendation methods based on collaborative filtering will firstly calculate the similarity between Tom and other 3 users according to their service-invoking behaviors and then rank Merry, Bob and Jack based on the similarity values. Thus, Merry is ranked high among the three users because Merry have invoked the same services with Tom more than Bob and Jack; contrarily, Jack is ranked last because they do not invoke any same services with Tom. That means the preference of Tom is more similar with that of Merry than others. Thus, the services invoked by Merry tend to be the ones Tom will invoke. Accordingly, s_4 and s_3 are recommended to Tom as the top-2 services. The result is indeed good when we do not consider the relationship among users. However, supposing Jack is Toms friend and they have the same interests, in this case, Tom tend to use the services recommended by Jack more likely than the services recommended by Merry and Bob.

Moreover, only considering the trust relationship among users is not enough; the reviews on services given by users will affect the recommendation result as well. Continue to consider the above scenario. In order to recommend Tom top-2 services invoked by Jack, the review or comment on s_3 s_4 and s_5 given by Jack will determine the result. In general, the services with better comment are more likely recommended.

With social-network websites attract more and more attention nowadays, people like to share their shopping experiences and their comments. It gives us a good platform to carry out products/services recommendation. In this paper, we propose a social-network based service recommendation method. It not only mines the trust relationships from social networks among users to help recommendation, but also considering users history service-invoking behaviors and users comments/reviews on products/services.

4 Social-network-based Service Recommendation

4.1 Social-network-based Recommendation Framework

The framework for the social-network-based service recommendation is illustrated in Fig. 1. Firstly, the active users preference is built according to his service invocation history and trust relationships with other users. Then the similarity value between the active user and each user is calculated. The users with higher similarity value are picked out as the similar users of the active user. Then the rank scores of candidate services are calculated based on the similar users ratings. Finally, services with higher rank scores are recommended to the active user.

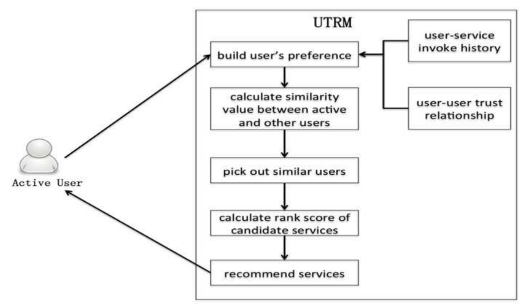


Fig. 1: Social-network based Recommendation Framework.

4.2 Basic Definitions

In order to make the service recommendation method understood easily, we give some notations and definitions.

Definition 1 (Historic Service Invocation Records): A service recommendation system is made up of m users and n Web services, represented as $U = u_1, u_2, \ldots, u_m$ and $S = s_1, s_2, \ldots, s_n$, respectively. After invoking a service, the user will rate the service based on the invocation experience. The historic service invocation records of the $u_i (u_i \in U)$ is represented as :

$IH_i = (s_{i1}, category_j, rate_{i1}), \ldots, (s_{in}, category_j, rate_{in})$
where:

(1) s_{i1} means user u_i invoked service s_1,

(2) $category_j$ represents the category that the service belongs to;

(3) $rate_{i1}$ represents the rating value given by the user u_i to the service s_1.

(4) the 3-tuple $(s_{i1}, category_j, rate_{i1})$ represents a service-invoking record which means user u_i invoked service s_1 and rated s_1 as $rate_{i1}$.

Definition 2 (Trust Relationship): The trust relationship between users can be divided into two types: 1) explicit trust relationship, which means users specify whom to trust definitely, the form goes like 'u_1 trusts u_2'; 2) implicit trust relationship, which means we can obtain the implicit trust relation between users through mining the association activities among users. Given two users u_1 and u_2, u_1 trusts u_2 if u_1 has paid attention to u_2s reviews on services and thinks they are helpful.

For example, user posts a review targeted on the service which he/she invokes, then, other users publish feedbacks which express the idea of whether the review is helpful to them or not, at last, we can mine the implicit trust relation between feedback users and the user who posts the review. The explicit and implicit trust relationship constitutes complete trust relationships between users.

Definition 3 (User Characteristics Vector): The tuple $CV_i =< category_1,...,category_p >$ constituted by each service category forms the prototype of user preference where p is the number of categories.

4.3 Key Steps

4.3.1 Building Users Preference

According to Definition 3, for the initialization of a user characteristic vector, each service category is initialized as 0. Given a user u_i, the building of u_i's user characteristic vector mainly includes the following steps: Firstly, traverse all the services from u_is historic service invocation records IH_i and extract the service categories which the services belong to, then plus 1 on the corresponding service category of the user characteristic vector. Besides, the user characteristic vectors of the users who u_i trusts are merged into u_is own user characteristic vector. The merging rule is:

$$CV_i = CV_i + \mu \sum_{j \in T_{u_i}} CV_j, \qquad (1)$$

where μ is a balancing factor $(0 < \mu \leq 1)$, which used to adjust the impact on users characteristic vector and determined by experiment later. T_{u_i} represents the user set which user u_i trusts.

4.3.2 Calculating Similarity Between Users

The step of calculating similarity value between active and other users is the core step for the proposed recommendation framework. The Euclid Distance is adopted to calculate the similarity value, the formula is as follows.

$$sim(u_i,u_j) = \sqrt{\sum_{k=1}^{p} (CV_{ik} - CV_{jk})^2}, \qquad (2)$$

(1) the Euclidean Distance also known as a Euclidean metric, is a commonly used distance definition. It is the true distance between the points in the m-dimensional space.

(2) u_i represents the active user and u_j represents the trust user $(u_j \in T_{u_i}, T_{u_i}$ represents the user set which user u_i trusts).

(3) the smaller the value of $sim(u_i,u_j)$ is, the more similar of user u_i and u_j are.

For example, given two users u_1 and u_2 whose user characteristic vectors are $< 5,1,2 >$ and $< 1,0,1 >$ respectively, then the similarity value between u_1 and u_2 is 4.242.

4.3.3 Calculate Rank Score of Candidate Services

After calculating the similarity values of the active user and other users. We choose a number of similar users to calculate the rank score of the candidate services. The number of similar users is an adjusted parameter for our framework and in our experiment it is set as 100. The rank score of service is a comprehensive evaluation of the active user's personal preference and the relationship of trust between active and other users. Calculation of the rank score mainly consists the following steps: Firstly, traversing each service of each similar user's history service-invoking record and picking out the service which active user didn't have invoked. Secondly, calculating the rank score of the service according to the following formula.

$$rs_{s_k} = \sum_{j \in set_{s_k}} (sim(u_i,\ u_j) \times rate_{js_k}), \qquad (3)$$

Where $s_k \in (\bigcup_{j \in T_{u_i}} IH_j - IH_i)$, T_{u_i} represents the user set which active user u_i trusts, set_{s_k} is consisted of the user who has invoked service s_k, $rate_{js_k}$ is a rating given by user u_j to the service s_k.

Finally, these candidate services are classified according to the service category. After calculating the rank scores of the candidate services, it is intuitive to recommend the top-k services with higher scores in each category to the active user.

5 Experiment and Evaluation

In order to verify the effectiveness of the proposed social-network-based service recommendation method, we carry out a series of experiments to measure 3 different metrics, i.e., recall rate, precision ,f-measure and rank score; and compare with other 5 popular recommendation methods, i.e., UserCF, ItemCF, Hits, Reputation and Pagerank.

5.1 Datasets Description

In this paper, we select www.epinions.com as data source, which is operated by Shopping.com, Inc., a leading provider of comparison shopping services. Epinions is a premier consumer reviews platform on the Internet and provides a reliable source for valuable consumer insight, unbiased advice, in-depth product evaluations and personalized recommendations.

We crawled two sets of data from this website, including user trust relationship and user reviews and feedback on reviews.

a) User Trust Relationship: A user is allowed to build his personal trust network on the basis of specifying whom he trusts. Web of trust is a network of reviewers whose reviews and ratings a user has consistently found to be valuable. According to web of trust, the system predicts how helpful a review to a user and promotes the reviews of trusted members. So, a user can find what he/she is looking for more easily and gets the most out of his/her time on the website. We acquire 86,719 nodes and 604,190 edges from Epinions using a crawler. The nodes and the edges represent users and trust relationships between users, respectively.

b) User Reviews and Feedback: Users are allowed to post reviews on a service/product he bought or used before. In addition, Epinions allows users to post feedback on these comments, indicating how valuable the reviews to them. The rating on a comment is divided into four levels shown in Table 2.

Table 2: Feedback grade and value

No	Feedback Grade	Grade Value
1	Very Helpful	3
2	Helpful	2
3	Somewhat Helpful	1
4	Not Helpful	0

Table 3 shows an example of user reviews. Userid represents different users and each line records one review posted by a user. We grabs 963,591 reviews which target on 292,713 different products by 57,301 users from this platform, about 17 reviews per each user. An example of feedback is illustrated in Table 4. Each line represents one feedback on a specific review (identified by the review title). At present, we crawl 23,142,103 feedbacks from Epinions and find that there are about 24 feedbacks for each review.

5.2 Measure Metrics

A recommendation system is launched to generate a ranked list of recommendations of Top-K products. In general, the recommendation quality is measured based on the number of hits (recommendations that match the products actually purchased by the consumer as recorded in the testing set) and their positions in the ranked list, as shown in Table 5. The following recommendation-quality metrics regarding relevance, coverage, the combination of relevance and coverage as well as the ranking quality of the ranked list recommendation [20] are used in our experiments.

Table 5: User feedback example

	Recommended	Not Recommended
Purchased	True-Hits(TH)	False-UnHits(FUH)
Not Purchased	False-Hits(FH)	True-UnHits(TUH)

5.2.1 Recall Rate

Recall rate refers to the ratio of correctly predicted (True-Hits) products to the number of all products purchased (True-Hits and False-UnHits) by the consumer in the testing set [23].

$$RR = \frac{\#TH}{\#TH + \#FUH}, \tag{4}$$

5.2.2 Precision

Recommendation precision refers to a ratio of correctly predicted (True-Hits) products to the number of all products predicted (True-Hits and False-Hits) [23].

$$RP = \frac{\#TH}{\#TH + \#FH}, \tag{5}$$

5.2.3 F-Measure

The F-Measure is a measure of a statistic experiment's accuracy. It considers both recall and precision measures of the experiment to compute the score. We could interpret it as a weighted average of the recall and precision, where the best f-measure score has its value at 1 and worst score at the value 0 [23].

$$F - Measure = \frac{2 \times RR \times RP}{RR + RP}, \tag{6}$$

5.2.4 Rank Score

The recall, precision and f-measure are standard performance measures to argue the relevance and coverage of the recommended items relative to the consumers' potential purchases. The f-measure is the harmonic mean of recall rate and precision. Because

Table 3: User review example

Userid	Title	Product	Category	Rating	Review Date
007girl	Blue my mind!	Here on earth	Movies	1	2000-05-07
007girl	Chicks dig maxim too	Maxim Magazine Subscription	Magazines & Newspapers	5	2000-10-22
00focus	Ford Focus ZX3	2000 Ford Focus	Cars & Motorsports	4	2000-07-09
00Shoe	All's Well but the hearing	Sony Personal CD Player	Electronics	3	2003-04-16

Table 4: User feedback example

Userid	Title	Rating	Feedback Date
oofocus	One of the most watched networks at my house	3	2001-01-25
01400ex	Don't let power rating deceive you	3	2001-12-25
092566	Chin-Chin is Yum-Yum	3	2001-07-28
1-2many	A fun little Lefty treat	3	2006-02-22

recall and precision are potentially competing measures, the f-measure provides a single-index performance measure to balance them. The rank score measure [20] has adopted in many studies [24,25] to evaluate the ranking quality of the recommendation list. Suppose the two recommendation lists with the same set of correct recommendations (matched with future purchases) for a target consumer. If the index of each of the correct recommendations in the first list is smaller than (closer to the top of the list by one position) that of correct recommendation in the second list, although the two lists would achieve the same recall, precision and f-measure, the first list is better than the second as the recommended items in the first list are ranked higher than those in the second list. In this case, the rank score of the first list is larger than that of the second and its value can be calculated according to the following formula.

$$RS = 100 \times \frac{\sum_c RS_c}{\int_c RS_c^{max}} (RS_c = \sum_j \frac{q_{cj}}{2^{(j-1)/(h-1)}}), \quad (7)$$

Where j is the index for the ranked list; h is the viewing half-life and

$$q_{cj} = \begin{cases} 1\ if\ \ j\ is\ in\ c's\ testing\ set \\ 0\ otherwise \end{cases} \quad (8)$$

Where $RS_c{}^m ax$ is the maximum achievable rank score for consumer c if all future purchases had been at the top of a ranked list [26].

5.3 Comparison with other algorithms

We divide user review and feedback datasets into training set and validation set according to a time-stamp. The choice of time-stamp based on the principle that the size of training set equals to the size of validation set.

5.3.1 Impact of Parameter μ

In our experiement, the balancing factor μ is ranged from 0 to 1 with the interval 0.2. We set Top-K to be 20 and the number of most similar users to be 100. Fig. 2 illustrates the values of rank score, recall, priecision and f-measure. It shows that the value of recall, precision and f-measure increases as μ increases, and the value of rank score is the smallest when μ is 1. All of the four measure metrics increase as balancing factor becomes larger and arrives at the biggest value at the same time when μ goes up to 1. It indicates user's own history service-invoking records and trust users' history service-invoking records are equally important when building user characteristic vector. So, we assign $\mu = 1$ in the following experiments.

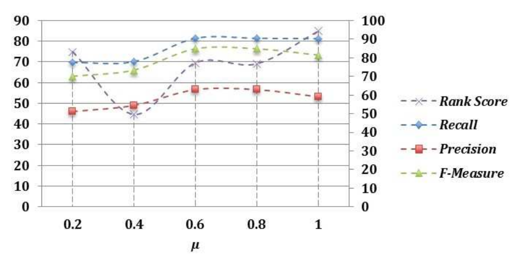
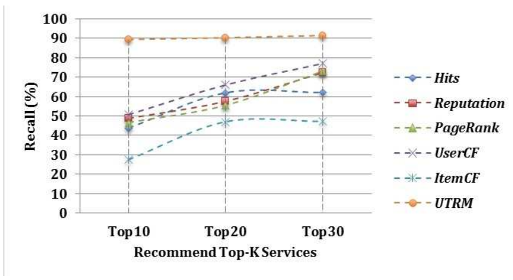


Fig. 2: Impact of parameter μ.

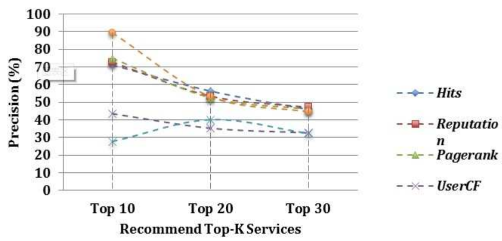
5.3.2 Comparisons with other algorithms

In order to show the advantages of the social-network-based recommendation method, we compare it to the other five popular methods such as UserCF, ItemCF, Hits, Reputation and PageRank. We set top-K to be 10, 20 and 30.

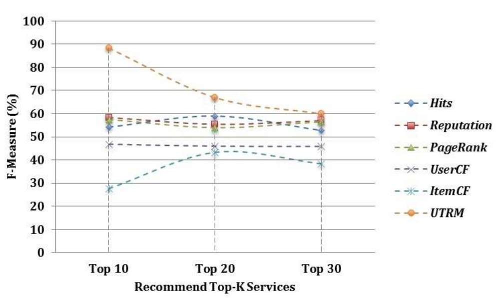
Fig. 3(a)-4(c) illustrates the results of the experiments. It indicates that the proposed social-network-based recommendation method outperforms other in all the first four metrics. Fig. 3(d) shows the services recommended by the proposed model tends to be firstly invoked by the active user after time-stamp than others.



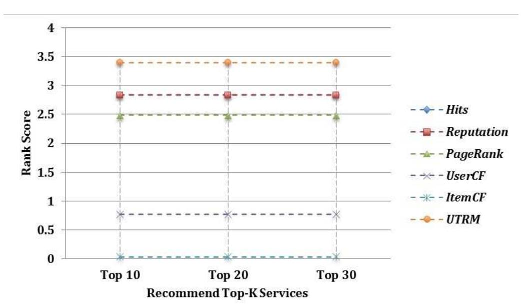
(a) Recommendation recall rate



(b) Recommendation precision



(c) Recommendation f-measure



(d) Recommendation rank score

Fig. 3: Comparisons with different algorithms.

6 Conclusion and Future Work

In this paper, we propose a social-network-based service recommendation method, which both considers users' history service invocation behaviors, users preferences as well as trust relationships among users implied in social network and users comments/reviews on services. We apply this method in a real large-scale data set extracted from a popular social network www.epinions.com. A series of experiments show that this recommendation method gets better recall rate, precision, f-measure and rank score. Our future work focuses on the following two points: 1) distinguishing explicit and implicit trust relationship between active user and other users; 2) considering the dynamic update of user's characteristic vector.

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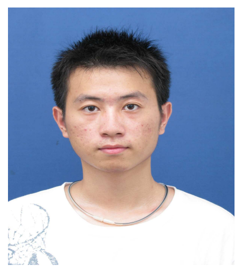

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