A Dynamic Trust Network Based Simulation Framework for Reputation-based Service Selection

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ABSTRACT
Service-oriented computing is a promising approach to software system construction by selecting and composing autonomous services under the open, dynamic and non-deterministic Internet environment. Appropriate selection of high quality services used in from numerous candidates declaring similar functionalities is crucial to the overall quality of the composed system. As authority centers are not generally available in open environments, reputation-based mechanisms must be adopted to evaluate services. With more and more reputation systems proposed in the literature, there is an increasing need to evaluate and compare them objectively and systematically with a common controlled experiment of trust network environment. In this paper we propose a general simulation framework based on dynamic trust network for this purpose. Especially, the framework is capable to simulate the dynamic evolutions of the trust network, in addition to the static snapshots of the trust relationships. With this framework, some case studies are made to evaluate the effectiveness of several representative reputation mechanisms, and some interesting characters are revealed.

Categories and Subject Descriptors
D.2.8 [**Metrics**]: Performance measures – *simulation scenario.*

General Terms
Measurement, Performance

Keywords
Internetware, service selection, reputation, trust network

1. INTRODUCTION
Service-oriented computing is a popular paradigm which utilizes services as fundamental elements to develop software systems on the web[1]. It enables users to build online applications, e.g. Internetware[29] by interacting with services[19]. In order to construct a high confidence software system, selecting reliable services is an important step. Reputation system[2][16] is designed as an evaluation mechanism to find whether services could supply desired resources. Since services are developed, published and used in an open environment where no central authority exists, the reputation of service is usually established on feedback gathered from past consumers. The service with high reputation is most likely to satisfy users' demands[15].

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In reality, people are more likely to accept recommendations from friends in social networks than those from strangers[28]. The friends are trusted recommenders of the user. Trust connections can be generated in multiple ways, e.g. similar tastes, honest behaviors in past interactions and professional competence in the domain. They are always used as the filtering factors to weigh opinions on services which are stored in a centralized depositary[3][4][12]~[14] or maintained by past consumers distributed in the network[5]~[8]. Therefore, the reputation which is employed to predict performance of services can be regarded as accumulated based on trust networks. Until now, a variety of such kind of reputation-based service selection approaches have been suggested to choose the right service from a pool of candidates with similar functions.

Along with the multitude of approaches have come a similarly large number of methods to evaluate the proposals. These testing methods are often developed under the designers' own devising, and proposed approaches are demonstrated to be efficient by simulations conducted in a particular scenario. However, there have been several limitations in the evaluations typically used by authors: 1) in the absence of established testing methods, different experimental simulations are designed in accordance with contexts of proposed approaches. The observations are not surprising that some approaches work well in specified scenarios. Nevertheless, to investigate efficiency of competitive approaches, it is necessary to construct a framework with customizable parameters where meaningful comparisons can be performed among diverse approaches. 2) Rational behaviors of individuals are always ignored. Since trust networks are basis of reputation-based approaches, its characteristics should be further discussed to simulate the real world issues. Trust network is a kind of social network which has the common feature that people are clustering to pursue maximum interest. So in practice, users are probably not willing to offer personal experiences, but depend on defined social strategies. 3) Trust networks remain static once being created. Aside from cooperation among users is usually temporal due to rational behaviors, satisfaction on selected services also lead to connection mutations in trust networks. Many trust networks in simulations are constructed according to social network snapshot extracted from interaction records in real world applications. The network conforms to real world situations, but it lacks of adjustability to modify properties, such as network topology, to observe the effectiveness of approaches in various settings. Additionally, connections extracted from specific sites have personalized features which lacks of capability to modify parameters flexibly. All these lead to separation of trust network formation and service selection results. But in fact, service selection results benefit from collaborative social relations and satisfaction on selected services guides users to reconsidering social relations as well.

In this paper, we design a generic simulation framework to support reputation-based service selection analysis on dynamic trust networks. We 1) present a formal model for describing common modules of reputation aggregation, computation and update phrases in most approaches, 2) design an artificial trust network which takes into account individuals' rational behaviors inherent in a traditional social network as well as other application-specific characteristics in service selection scenario, 3) implement the simulation framework where trust networks do not remain static but evolves with users' satisfaction on service selection results. In the case study, we demonstrate utilities of proposed framework by comparing and analyzing representative approaches in each phrase during the formation and evolution of trust networks. The rest of this paper is organized as follows: we discuss the motivation and related work in Section 2. Section 3 describes the design of simulation framework. We give a concrete case study and some discussions in Section 4 and finally conclude the paper and look into the future work in Section 5.

2. MOTIVATION AND RELATED WORK

The majority of reputation-based service selections approaches have been evaluated using methods of their authors' own devising. They are proven to be efficient in a well-designed scenario. As evaluations are different from each other, results presented by different experiments are not comparable. To establish a general simulation framework, a fundamentally reasonable trust network is the essential consideration.

Open websites like eBay[12], Epinion[13] are typical sources for extracting authentic data of simulation scenario. The data involves user's feedback on many different types of services, e.g. software, books, and trust relationships created through historical interactions such as exchanging recommendations, bargaining transactions. Experimental datasets used in [5] is crawled from an online scientific literature digital library. They feed co-authorship relations to form trust networks. The possibility one will refer a paper (regarded as a specific kind of service) is predicted based on the number it is listed as references in friends' papers. [6] mines the real-world data from the self-devised film review webpage. Opinions on movies and trust relations among individuals are come from historical reviews. Users choose potentially favorite films with highest ratings given by their friends. However, real relations accumulated in daily life are convincing to test efficiency of approaches, but their flexibility is limited as the scale and topology of networks are fixed. And the accuracy of evaluations also relies on data extraction methods employed as missing data may distort the statistics severely. On the other hand, previous research shows that different networks exhibit various characteristics[15]. It is unknown whether the trust network formed in daily activities is identical with those in service selection contexts. If a link in the network is different from a specific friend relationship in the application, the simulation may be biased. Moreover, trust networks established on real-world snapshots remain static rather than evolving upon satisfaction on service chosen. It may lead one to question whether the simulation results can reveal the performance of the approaches in any phrase. In fact, the highly dynamic characteristic of service-oriented computing environment indicates that individuals and services attempt to enter and leave the running system at random. Another setting of service and individual behaviors in the simulation scenario will probably influence the performance of proposed approaches.

An alternative way to address the issues noted above is to construct an artificial simulation scenario. Both services and clients are synthetic data created by programs according to specific requirements. For example, connections among users in [7] are created based on similar expectations. Likewise, [8] provides each user a friend list to share opinions on services' performance. Such simulated scenario allows modifying properties of trust networks including quantity and behaviors of nodes. However, most existing experimental scenarios have shortcomings that several assumptions are suggested to simplify problems, e.g. users are absolutely willing to share information instead of acting with incentives to acquire maximum interest, and links in networks are generated by rewiring edges with probability which has no relation with applications.

Tag system[10][17] use computational sociology techniques to enable combination between trust network evolution and applications. It works on the basis of three values: 1) Tag: defined as a mark attached to individuals and can be observed by others. It is social cue which indicates that people with similar tag tends to gather together. 2) Strategy: describing behaviors that individuals will perform in social activities, e.g. Prisoner Dilemma (PD)[18] reflects selfish instincts of each person. 3) Utility: computed by payoff assigned in the strategy. It is a measure of individual's performance. By comparing utilities with each other, people move to the social group which will help them attain high utility. SLACER is a self-organizing protocol implemented on PeerSim[20] Platform. It uses tag system technique to simulate coordination in peer-to-peer networks[9] with no central authority. An artificial social network fulfilled with basic topological features is generated through playing PD game among people. Inspired by SLACER, we suggest employing tag system to realize interactions between trust network evolution and service selection results, and using PD game to simulate rational behaviors of individuals in artificial trust networks. Pertinent aspects of this proposal are discussed later in the paper.

3. THE SIMULATION FRAMEWORK

As illustrated in Fig.1, a typical service selection scenario comprises three basic elements: services, individuals and selection mechanism. Users build applications by interacting with a variety of services. When the user has not enough experience to make decisions, he turns to friends for recommendations. Trust networks are used to gather relevant information for evaluating candidate services. Reputation-based service selection approaches are responsible to discovery feedback from trust networks, compute reputation of services and update personal experiences on using services. For convenience of understanding, we first present a formal model for reputation-based service selection approaches on trust networks and specify notations used throughout this paper.

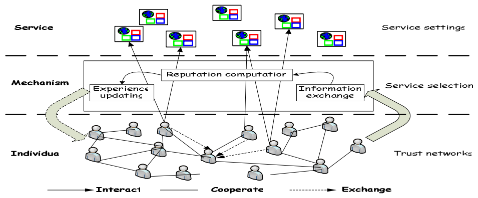


Fig.1 The overview of the service selection scenario

3.1 The Formal Model

Experiences are transactions between users and services. They represent ratings given by users on services. The rating is described by a tri-tuple:

$$Rating =< Service, Value, Confidence >$$

Where $Service$ is service identity, $Value \in [0,1]$ is satisfaction given by the client on the service with confidence $Confidence$. The function ρ aggregates ratings into reputation:

$$\rho : Rating -> Reputation$$

Many strategies are proposed to compute the reputation, e.g. threshold-based[21][8], recommendations are considered only when the user's experience is inadequate; weight-based[22][26][7], personal opinions and other's feedback are assigned hierarchical importance based on honesty, similarity, capability of recommenders.

After interacting with the service, users update opinions on selected services:

$$\theta : Rating -> Rating'$$

Here, two elements in the rating are updated: $Value$ and $Confidence$. The function θ indicates the update method, e.g. recent priority[23][7] drops old records periodically or reduces their importance; cache windows[24][27] reserves a fix number of records in the repository to be referred; confidence interval[25][8] adjusts the confidence on the value given on the performance of the service based on the quantity of interaction. These fresh experiences will then have effects in the next round of information exchange.

3.2 Trust Network Protocol

We reset several parameters in SLACER and make some adjustments to simulate trust network used in the reputation-based service selection application:

1) Add an active degree α to simulate people's social behaviors in the real world. It means individuals are not of the same kind. Whether one will use a service depends on the frequency he takes take part in the social event. The more interactions are performing, the more possible the user can give an accurate judgment on the performance of the service. So this factor can distinguish the quality and quantity of information one holds. In the simulation, active degree of each individual is assigned by the normal probability distribution function.

2) Reset the utility value in the Prisoner Dilemma game. The concept of the game shows each node has an individual incentive to defect so as to gain more profits. Here, we suggest that if both players decide to collaborate, they share services using experience with each other. The utility value in the following payoff matrix is set to compare who can get more information.

Player2 \ Player1	C	D
C	R_1/R_2	T/S
D	S/T	P/P

```
For each cycle
        Each node periodically do
            Compare utility with a randomly chosen node
            The node with lower utility do
                Drop current links with high probability
                Link to the node With high utility
                Copy its tag and Strategy
                Mutate tag and strategy With low probability
                Reset utility
            End
        End
        If this node is active
            Exchange information with all neighbors
            Aggregate the gathered ratings
            Select the service with high reputation to interact with
            Update personal experience
        End
End
```

Here, C means cooperate and D is defect. R1 refers to reward to who acquire information with higher confidence, and R2 is given to the relatively lower one. Other symbols: temptation (T), sucker (S) and punishment (P) are identical to those in SLACER. The payoff values meet the constrains: $T > R_1 > R_2 > P > S$, $2R_2 > T + S$ ($2R_1 > T + S$). Notice that if two cooperative players have the same number of interactions experience, they are rewarded by the same utility value R.

3) Add a service selection action. In each cycle of protocol, the user not only compares utility with a random user periodically, asks for previous experience to identify a service, but also chooses a service according to the calculated reputation and updates personal opinions on services. The step in each cycle is described in the above pseudo-code.

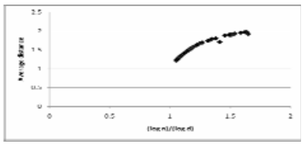
After every cycle, the trust network is evolved with satisfaction on selected services.

3.3 Trust Network Metrics

As summarized in [11], realistic social networks are characterized by three main traits: a low average network distance, a moderate clustering coefficient and an approximately power-law distribution of node degrees. We use these criterions to test trust networks generated in our simulation. The trust network is composed of 200 nodes. The service selection runs 100 cycles and each user initiates a service evaluation in each cycle according to the active degree set.

3.3.1 Average network distance

This character is explained as "small world" effect which requires average network distances between people to be low and approximately $\frac{\log n}{\log d}$, here n denotes the number of people and d is the average degree in the network. Fig.2 shows 100 average distances of different trust networks in all cycles. The result shows that the generated trust network satisfies this character.



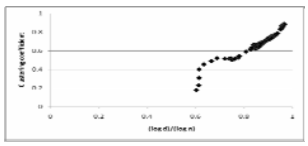


Fig.2 Average network distance **Fig.3 Clustering coefficient**

3.3.2 Clustering coefficient

Clustering coefficient is the probability that node A connects to node B under the condition that both node A and node B connect to node C. It is called the formation of triangles and should be close to $\frac{\log d}{\log n}$. The data of 100 trust networks in Fig.3 roughly meets this factor except few statuses in the initial states.

3.3.3 *Power-law distribution*

The degree of nodes in the trust network is supposed to follow the power-law distribution, namely, if we designate the node of the highest degree with rank (r) 1, analogously, the lowest degree with the last rank, then the relationship between $\log d$ and $\log r$ should follows a rough linear. The 100 trust networks generated in the simulation framework fulfill this requirement. Here, we extract four figures from the experiment in Fig.4 as an illustration.

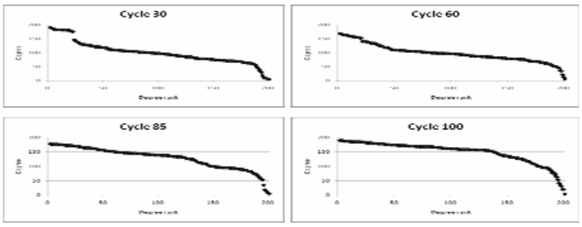


Fig.4 The distribution of nodes in trust networks

4. CASE STUDY

In this section, we demonstrate the effect of a representative trust-based service provider selection approach[8]. From the result, we get some interesting findings.

4.1 Trust Service Provider Selection (TS)

TS is one reputation-based service selection approach which helps users achieve a better satisfaction by selecting the best service, especially when the user lacks sufficient personal experience to judge a service. Its basic idea is when the user has adequate experience about a provider/service pair, he uses it to evaluate the provider. If insufficient previous experience is available, the client asks for opinions of friends to reason the best service.

We implement TS into our simulation framework with some minor adjustments: 1) to give a simple view of trust networks, we suggest that a service provider offers one kind of service, so the service provider selection can be simply regarded as service selection. 2) The reliability measure of the confidence in TS is normalized in the interval [0, 1]. It is the value reflects how certain a client is about its own confidence on a particular provider performing a service. To be simplified and without losing the generality, we use the interaction numbers to predict the reliability. 3) Compared with the given friend list in TS, in our simulation, every node's neighbors are their friends and they are dynamically changed with the evolvement of the trust network. At the beginning of the simulation, as no previous experience and social connections exist, the service is selected at random.

The important parameters in the simulation are listed in Table 1, most factors in SLACER are inherited and we assign the remnant factors in Prisoner Dilemma and TS.

Table 1. Selective parameters in the simulation framework

SLACER		Prisoner Dilemma		TS	
Parameter	Value	Parameter	Value	Parameter	Value
cycle	100	penalty	0.1	threshold	5
node	100	sucker	0	alpha	0.5
service	20	temptation	1	update	0.5
mutation	0.005	$reward_{1,2}$	0.8,0.	active	0.9
tag mutation	0.01	reward	0.7	performance	0~1

The average performance of services is assigned hierarchically in the interval [0, 1]. In each round, the satisfaction value of the service is generated from a normal probability distribution with $\mu = performance$ and $\sigma^2 = 0.01$. Moreover, the node chooses whether to interact with the service in terms of the active degree. If the client picks a service, we record the satisfactory value given on the performance of the service. The average satisfaction of all nodes in the simulation scenario is plotted as follows.

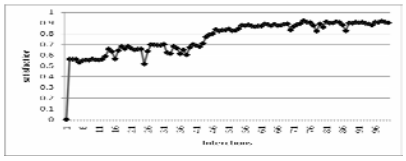


Fig.5 Satisfaction of the service selection

4.2 Discussion

Compared with the simulation result in TS, our result shows that the performance of the reputation-based service selection approach is not only related to the suggested computation method, but also to the dynamic trust network. The convergence in our simulation takes more time than that in TS, especially when the activity degree is low. The reason is that the more the previous experience are, the more precise the reputation is computed. Due to the rational behavior of individuals, information is not available every time. It depends on the interest between users. On the other hand, the satisfaction of selected service is more stable than that in TS. It is because with the evolvement of the trust network, the user appears to cluster around the recommender with rich and precise information. It is useful for the user to indentify the right service. However, the feedback value is not always goes to the satisfying direction especially when the information source refuses to cooperation. Without enough knowledge, it is indeed difficult to make a right decision. This result is more close to the real event taking place in the life. So as to improve the reputation-based service selection approach, we should pay attention to the specific settings in the application scenario and design efficient strategies to deal with potential unmatched factors. Otherwise, it will be probably resulted in a confused situation that even a method seems to be efficient but is not suitable to the real world application. For example, the reputation system without considering effects of group fraudulence in the dynamic trust network will not work as well as that in honest conditions.

Additionally, to investigate an efficient reputation-based service selection approach which completely adapts to the real world, we are going to do more case studies by means of implementing more dimensions into generating the dynamic trust network such as similarity between user's expectations, capability of recommenders. These topics will be discussed in our future work.

5. CONCLUSION

In conclusion, our approach has two main contributions: 1) we propose a general simulation framework which has common modules in evaluating reputation-based service selection approaches. In the simulated environment, proposed approaches can be compared in different customized scenario to analyze in what situation the approach is efficient. 2) We combine service selection results with trust network evolution based on tag system. The trust network does not remain static but dynamically changes with the rational behavior of people who are actually perform activities. However, more case studies on the basis of the dynamic social network involved taking account of recommenders' similarity, honesty and capability will be discussed to devise a simulation framework of complete functions in future work.

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