An Approach To Reputation-Oriented Service Discovery

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Abstract:In recent years, service discovery has become the most widely explored domain in Service Oriented Architecture (SOA) for both industry and academia. Due to the popularity of SOA, services over the Web are growing rapidly. Therefore, service reputation measurement approach plays a vital role in selecting the most optimal service from the pool of services offering similar functionality. Feedback ratings are collected from various consumers of the service to assess the service reputation. But, it is improper to evaluate the service reputation basing directly on raw feedback ratings as because malicious consumers do exist in such online open systems who intentionally submit unfair feedback ratings to distort the service reputations. Therefore, it becomes important to assess the user credibility so that feedback ratings from high credible users can be weighted more than those of low credible users. This paper proposes a service reputation measurement approach in which the user credibility assessment methodology is devised by employing Gaussian kernel function. Experiments are performed on simulated environment to validate the effectiveness of the proposed reputation measurement approach.

Index Terms:Service Oriented Architecture, service discovery, service reputation, malicious feedback rating, feedback purity value, user credibility, Gaussian kernel function.

1 INTRODUCTION

IN SOA, with the invent of Web services, the Web has become a platform where applications, built based on services, can be automatically invoked by other Web clients [1]. W3C defines web service as: *"A Web service is a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format (specifically WSDL). Other systems interact with the Web service in a manner prescribed by its description using SOAP messages, typically conveyed using HTTP with an XML serialization in conjunction with other Web-related standards"* [2]. In SOA, three kinds of entities exist: service provider, service consumer, and service registry. In this architecture, *Service provider* provides services; *service consumer* avails these services; and *service registry* acts as a broker between the consumer entity and provider entity [2, 3]. Service providers *publish* their offered services in the service registry, so that the service consumers can *find* their desired services from the service registry and *bind* with the discovered service providers [3, 4]. Due to the popularity of SOA, services over the Web are growing rapidly. This has resulted in a number of services offering similar functionality [5]. Therefore, selecting the most optimal service from a large pool of functionally equivalent services has become a challenging task. Since the providers of the services may not perform according to what have been advertised by them [6], care must be taken while selecting a suitable service that satisfies the consumer's need. A service selection mechanism must not select any service that harms a consumer's interest. The selection mechanism must explore *'how well a service will do'* along with *'what a service can do'*.

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To take a service selection process a step forward, service reputation assessments are done. Reputation indicates the future behavior of a service based on its previous activities [7]. To achieve this, feedback ratings are collected from the potential consumers who availed the service. The feedback rating signifies a consumer's satisfaction level about the perceived service quality. These feedback ratings aid in knowing the service reputation. But, it is improper to evaluate service reputation basing directly on raw feedback ratings. This is because, in online open environment, where any consumer can join and leave the system any time, it is very hard to keep a watch on their activities. There are some consumers who often enter into the system with some malicious intention. These malicious consumers submit feedback ratings which do not conform to the delivered quality of the services. They purposely submit malicious feedback ratings in order to upgrade or downgrade the overall reputation of the service in the business market [8, 9]. Therefore, it is absolutely necessary to develop an efficient service reputation measurement approach that can deal with the presence of malicious consumers in the system. In online open system where user/consumer activities are mostly vague, the factor *'user credibility'* plays a vital role. User credibility determines how much the reputation evaluator can trust the submitted feedback ratings of the user in the process of overall service reputation evaluation. The feedback rating, if handled along with its user credibility, will help in knowing the service reputation better. This paper proposes a service reputation measurement approach in which the user credibility assessment methodology is devised by employing Gaussian kernel function. This summarizes the contribution of this paper. The remainder of this paper is organized as follows. Section 2 reviews the related works. In Section 3, we present our proposed reputation measurement approach. In Section 4, the experimental results based on simulated scenarios are discussed. Section 5 concludes the paper.

2 RELATED WORKS

In this section, we discuss some service reputation measurement approaches existing in literature. Le-Hung Vu et al. [10] developed a QoS-based semantic web service selection and ranking solution. They used the trust and reputation management application in one registry peer method to address the web service selection problem. Shanshan Song et al. [11] developed a P2P reputation system employing fuzzy logic inferences leveraging fuzzy-logic's ability to handle uncertainty, fuzziness, and incomplete information adaptively. They collected peer reputations for their system and used eBay auction-based transaction trace data to establish the effectiveness and strength of their P2P reputation system. Zaki Malik et al. [12] presented RATEWeb: a *Reputation Assessment framework for Trust Establishment among Web services* that works in the presence of malicious consumers. They developed a simple and straightforward solution which provides an automated and adaptive service reputation measurement. They evaluated reputations of services through a number of heuristics with different perspectives. They proposed decentralized techniques for service reputation assessment by aggregating feedback ratings. Hien Trang Nguyen et al. [13] developed a trust and reputation model based on *Bayesian network* that considers direct experience from the truster, consumer feedback rating and QoS monitoring information. They have used different conditions for the Bayesian network for addressing the problem of user preferences and multi QoS parameters. Shenghui Zhao et al. [14] introduced a reputation-aware model for service selection which gradually adjusts the reputation evaluation by eliminating the collusive behaviors of consumers. For reputation adjustment, three steps are used in their model: QoS similarity computation between the advertised QoS of the services by the providers and their delivered QoS as evaluated by the service consumers, arrangement of the users based on their reputations using k-means clustering, and finally used association mining rule algorithm to mine the collusive users. Mohamed Almulla et al. [15] also developed a fuzzy logic based web services selection model. For the appropriate selection of services, they used non-functional QoS requirements. They provided a proper ranking algorithm which is based on attribute dependencies for selecting the optimal service from the pool of functionally equivalent services. Shangguang Wang et al. [16] proposed a service reputation measurement methodology which consists of two steps: malicious feedback rating detection and feedback rating adjustment, to arrive at a final evaluation of reputation of services. In the first step, for detecting the malicious ratings, they used Cumulative Sum (CUSUM) control chart method. After detecting and discarding the malicious feedback ratings, in the second step, they used Pearson Correlation Coefficient (PCC) for the purpose of feedback rating adjustment. Using PCC, a set of similar users are obtained for a particular consumer and then its feedback rating is adjusted based on the feedback ratings of its similar consumers. They also used bloom filter to prevent the malicious consumers from submitting their feedback ratings in the future.Mohammed Wasid et al. [17] proposed a recommendation system using FPSO-CF strategy. Their system is based on user hybrid features which utilizes the accuracy of memory-based Collaborative Fileting and scalability of model-based Collaborative Fileting. In their work, they employed particle swarm optimization (PSO) in order to find optimal individual consumer priorities to different features of the services. And, they used fuzzy sets, to represent user features efficiently,. Miao Wang et al. [18] introduced a High-reliability Multi-faceted Reputation (HMRep) evaluation approach for online web services. In the first phase, they addressed and estimated the missing feedback ratings of various services based on rating behavior of the user and quality of the service. To efficiently assess the service reputation, their model finds and then eliminates malicious and irresponsible consumers from the system in the second step. And, then the service reputation is assessed based on its received feedback ratings and their corresponding consumers' credibility. In order to properly reflect the change in service quality, their model also makes use of historical information of the services during service reputation calculation.

3 Reputation Measurement Approach

Let, $C = \{c_1, c_2, \ldots, c_m\}$ denotes the set of m consumers and $S = \{s_1, s_2, \ldots, s_n\}$ denotes the set of n services. The feedback rating from consumer c_i to service s_j is represented as $r_{i,j}$.

3.1 User Credibility Assessment

Service reputation assessment is essential since all the consumers of a system may not be honest in reporting their feedback ratings. A service may receive incorrect or malicious feedback ratings from various consumers despite of its satisfactory performance [1, 19]. The feedback ratings which largely deviate from the deserving ratings of the services are characterized as malicious ratings and their correspondents are termed as malicious/dishonest consumers/raters. The objective of this paper is to devise a methodology to shield the reputation system from the malicious activities of such malicious consumers, so that the service providers can maintain their proper reputation in the competitive business market despite of their encounter with malicious raters. This can be achieved by assessing the user credibility efficiently. User credibility represents the quality of being trustworthy in providing feedback ratings [6]. The feedback ratings received from different consumers are then weighed based on their user credibility scores to arrive at a final evaluation of service reputation. The high credible user's feedback rating is given more weight than that of low credible user [20, 21]. In this paper, we devise an efficient user credibility assessment methodology by employing the Gaussian kernel function [22]. In the approach of user credibility assessment, each and every feedback rating reported by different consumers for different services will be assigned a weight, known as rating purity score (*RPS*). A value for *RPS* lies in the range [0, 1]; where 0 indicates low purity and 1 indicates high rating purity score. The notation $RPS_{i,j}$ is used to denote the feedback rating purity score of $r_{i,j}$. For any feedback rating $r_{i,j}$ of consumer c_i towards service s_j, its $RPS_{i,j}$ is measured by observing its deviation from the average of all feedback ratings of service s_j, $\mu(S_j)$. The more the feedback rating $r_{i,j}$ is close to $\mu(S_j)$, its $RPS_{i,j}$ will be closer to 1. The rating purity score, $RPS_{i,j}$, of consumer c_i towards service s_j for feedback rating $r_{i,j}$ is assessed by employing Gaussian kernel function and is given by: $RPS_{i,j} = \exp\left(-\frac{(r_{i,j} - \mu(s_j))^2}{2*\sigma(s_j)^2}\right)$ (1) where, $\mu(s_j)$ and $\sigma(s_j)^2$ are the mean and variance of all received feedback ratings of service s_j, respectively. They are given by: $\mu(s_j) = \frac{1}{|UA_j|}\sum_{c_i \in UA_j} r_{i,j}$ (2)and, $\sigma(s_j)^2 = \frac{1}{|UA_j|}\sum_{c_i \in UA_j}(r_{i,j} - \mu(s_j))^2$ (3) where, UA_j represents the set of consumers who have availed the service s_j and $|UA_j|$ denotes the size. The *RPS*s of each user, c_i ($i = 1$ *to* m), resulted on reporting feedback ratings for every availed service, s_j ($j = 1$ *to* n), will contribute every information in assessing its user credibility, uc_i ($i = 1$ *to* m). A value for uc_i also lies in the range [0, 1]; where 0 represents a complete dishonest user and 1 represents the most trustworthy user. For a user c_i, its user credibility, uc_i, is computed as the average of its all $RPS_{i,j}$ resulted on reporting feedback ratings $r_{i,j}$ to services $s_j \in SA_i$. Here, SA_i denotes the set of services availed by user c_i. Thus, $uc_i = \frac{1}{|SA_i|}\sum_{s_j \in SA_i} RPS_{i,j}$ (4) where, $|SA_i|$ denotes the number of services availed by user c_i.

3.2 Service Reputation Calculation

The user credibility, uc_i ($i = 1$ to m), calculated above will aid in knowing the service reputation, $repu(s_j)$ for $j = 1$ to n, better. In the calculation of service reputation, high credible user's feedback rating is to be given more importance than that of low credible user. A user's credibility will be high only when it issues feedback ratings to its availed services at par other users of the system. Also, a service's actual reputation will be disturbed, even after providing satisfactory performance, if it encounters malicious consumers. Therefore, the service reputation, $repu(s_j)$, is evaluated as the user credibility, uc_i, weighted average of its all attained feedback ratings, $r_{i,j}$ ($c_i \in UA_j$). Thus, $repu(s_j) = \frac{1}{\sum_{c_i \in UA_j} uc_i}\sum_{c_i \in UA_j} r_{i,j} * uc_i$ (5) where, UA_j represents the set of consumers who have availed the service s_j.

4 Performance Evaluations

We have conducted a series of experiments in order to evaluate the performance of the proposed service reputation measurement approach. The experiments are performed on a simulated environment consisting of 100 services and 200 consumers. The experiments are conducted in MATLAB. The results of the experiments are reported in this section. Every service maintains its own level of quality. Let, for a service, s_j ($j = 1$ to 100), it is denoted by $qL(s_j)$. A value for $qL(s_j)$ lies in the range [1, 10]. After availing a service, a consumer is also allowed to generate its feedback rating in the range [1, 10]. An honest consumer will generate a feedback rating at par the perceived service quality. While a malicious consumer will generate a random feedback rating in the range [1, 10] excluding [$max(1, qL - 2)$, $min(qL + 2, 10)$]. These feedback ratings generated by both honest and malicious consumers are the input of the proposed reputation measurement approach and the output is the estimated service reputation. Let, for a service, s_j, its estimated reputation assessed by the proposed mechanism is denoted by $eR(s_j)$. The Root Mean Square Error (*RMSE*) between qLs and eRs is used to report the performance evaluation of the proposed reputation measurement approach. $RMSE = \sqrt{\frac{\sum_{j=1}^{n}\left(qL(S_j)-eR(S_j)\right)^2}{n}}$ (3) where, $n = 100$, denotes the size of the service pool. Nine (09) experiments are conducted with varying density of malicious consumers from 10 to 90 percent, with a step of 10 percent. The *RMSE*s of all these experiments are recorded in Table 1.

TABLE 1
RMSEs recorded by varying the density of malicious consumers

Density of malicious consumers	*RMSE*
10%	0.0339
20%	0.2455
30%	0.6592
40%	1.2321
50%	1.8998
60%	2.5997
70%	3.2617
80%	3.8282
90%	4.2461

It can be seen from Table 1 that, *RMSE*s recorded for density of malicious consumers upto 40% are within acceptable range. For 50% and higher density of malicious consumers, the obtained *RMSE*s are high. This is because of existence of huge number of malicious consumers in the system. If majority of the consumers submit unfair feedback ratings, then their reports will be taken as the truth. In such situations, the honest consumers submitted fair feedback ratings will be covered up by the unfair feedback ratings of majority consumers. However, according to Whitby et al. [23], it is unfeasible to have such a huge density of malicious consumers in real-world application.

5 Conclusions & Future Works

In order to select the most optimal service from the pool of services offering similar functionality, service reputation measurement approach plays a vital role. Feedback ratings are collected from various consumers of the service to assess the service reputation. Though feedback rating is considered to be the reflector of service quality, it is often seen that the actual service reputations are distorted because of the existence of malicious consumers in the system who intentionally submits unfair feedback ratings. In such situations, the assessment of user/consumer credibility becomes very important as it conveys the quality of being trustworthy in submitting feedback ratings by the consumers. This paper adopts the Gaussian kernel function to assess the user credibility in the process of service reputation measurement. Experiments are conducted on simulated environment and results depicts that the proposed approach can fairly assess the service reputations in presence of malicious consumers in the system. Since this paper reports the results of the experiments conducted on simulated environment, in the future we aim to conduct our experiments on real world dataset. We also plan to compare the performance of the proposed model with that of another existing popular service reputation measurement approach in the future.

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