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Abstract—Some Web Service Discovery and Composition (WSDC) approaches have been used to distinguish similar Web services by combining a collection of services using functionality of the service. Existing approaches for solving the WSDC problem focus mainly on the functional QoS properties of the service rather than the consumer satisfaction and trust aspects. However, different consumers regularly hold differing views of the service contents. Accordingly, the present study proposed a trust-based selection model for QoS-aware service selection referring to Shaikh et al.'s WSDC model considering both the direct rating and the collaborative rating in social trust networks. It appropriately reveals the customer satisfaction of a group on service compositions. The trust score aggregating both QoE (Quality of Experience) and QoC (Quality of Compliance) is introduced to discriminate the priority of service composition based on D-S evidence theory. Finally, an example of QOS-aware web services selection is illustrated to demonstrate the proposed approach. The proposed model effectively solves the trust transition problem in the collaborative rating of the service selection and also enables deception detection in terms of existing evidences that excludes the fraud reports of unreliable agents.

Index Terms—Web service, service selection, trust, QoS-aware.

I. INTRODUCTION

A single online Web service is constantly not sufficient to fulfill all the user's requirements such that Web Service Discovery and Composition (WSDC) approaches [3,7-8] are proposed to achieve business agility thru aggregating the associated network services. For example, travelers often used online services such as Expedia, Priceline, Paypal and Google maps to arrange and pay for their trips. Generally, WSDC process regularly complies with the following four sub-steps: planning, discovery, selection and binding.

While many web services have overlapping or even identical, the composition should be discriminated according to the level of QoS (Quality of Service) provided. Therefore, in attempting to meet consumers’ service requirements by composing web services, service providers are faced with a QoS-Aware Service Selection (QASS) problem [4-5]. Importantly, consumer often has satisfied by excellent QoS, it will bring trust to consumer. Many consumers experienced a service with excellent QoS will generate the reputation on the corresponding service, i.e., network services with a greater number of positive recommendations gain a higher reputation score and are perceived to be more trustworthy. Thus, in solving the QAAS problem typically is supposed to include collecting consumer feedbacks and other’s recommendations via referrals in social networks. For example, blog recommendation for service selection which belongs to another form of Collaborative Rating (CR) [12] which aggregates opinions of a group of public users to decide which services to promote.

Some enterprises have developed reputation management system [5-6] to assess the degree of trust in their services by analyzing the feedback records received from consumers. eBay is an important practical example of reputation management system using 'central authority' which stresses its consumers to assess and submit their comments and then uses the average rating rule to gain the overall reputation over the last six months.

The aforementioned approach belongs to a 'Direct Rating (DR)' which asks consumers to explicitly reveal their rating to others. Thus, the consumers may lose control to the central authority. Therefore a mixed model combining collaborative rating and direct rating is proposed for central authority to service selection in social networks.

Particularly, our scheme treats the selection of QoS-driven web service with matchmaking composition as a constraint satisfaction problem to locate the service compositions (SCs) which satisfied request specifications. Then, selecting right service with global trust score based on consumer satisfaction degree and network user referrals in an attempt to assist potential consumers in making better decisions. Then, a deception detection index adopting the support degree of the evidence is introduced to enhance the discrimination the quality of existing evidence for avoiding malicious reports of unreliable agent. Finally, consumer makes the reasonable selection by outranking the reputation of service alternatives.

The remainder of the paper is organized as follows. Section 2 reviews previous work in the field. The proposed model is introduced in Section 3. Section 4 takes an example to illustrate the method. Section 5 draws the conclusions.
II. TRUSTNET AND NETWORK REFERRAL

This section reviews the use of two schemes, namely network referral methods and D-S evidence theory for forming the model in Sec. 3.

A. Network referral in TrustNet

A TrustNet [1-2] is a representation constructed from the referral chains generated from agent A’s query. It is used to systematically incorporate the testimonies of the various witnesses regarding a particular party for service referral. Service referral activities represent an indirect type of trust transition process in the social network. In constructing the TrustNet for CR in the social networks, the first step is to map the social service connections among a set of agents to establish the corresponding social trust network. Network referral links (chains) are then built to indicate the consumers who jointing into this assessment.

Let agent B be agent A’s neighbor, agent A is asking agent B regarding service composition SCi’s reputation because B is the most dependable neighbor. Similarly, B is well-ordered asking agent D,E,F. After a series of l referrals, a testimony about SCi’s reputation is returned from agent D,E,F, respectively. One of referral chains in this case is a referral chain <A→B→D→E> (see Fig.1) from A to E with length 3.

Let \( \theta \) be a frame of discernment. A basic probability assignment (bpa) is a function, \( m:2^\theta \rightarrow [0,1] \) where \( m(\emptyset) = 0 \), and \( \sum_{E_k \subset \Theta} m(E_k) = 1 \). A bpa is analogous as a probability assignment. \( E_k \) denotes an evidence \( k \) on satisfaction degree of service \( s \).

\[
\sum_{E_k \subset \Theta} m(E_k) + \sum_{E_k \subset \Theta - \{s\}} m(E_k) + \sum_{E_k \subset \Theta - \{\neg s\}} m(E_k) = 1
\]

For a subset \( A \) of \( \Theta \), the belief function \( Bel(A) \) is defined as the sum of the beliefs committed to the possibilities in \( A \), that is,

\[
Bel(A, \neg A) = m(A) + m(\neg A) + m(A, \neg A) = 1
\]

For individual members of \( \Theta \), i.e., in the case, A and \( \neg A \), \( Bel \) and \( m \) became equal, \( Bel(A) = m(A) \), and \( Bel(\neg A) = m(\neg A) \). Broadly, \( Bel(A) \) accounts for satisfaction degree of supporting ‘satisfied (A)’ based on all evidences belonging to A,

\[
Bel(A) = \sum_{E_k \subset \Theta} m(E_k), Bel(\neg A) = \sum_{E_k \subset \Theta - \{s\}} m(E_k)
\]

III. TRUST-AWARE SERVICES SELECTION MODEL

A. Basic Idea

Inspired by [8], a trust-aware service selection model is described as shown in Fig.2. Fig.2 shows how service discovery module accepts the consumer’s request and returns a set of matched services using Semantics Web Service (SWS) techniques. Followed by two assessment phases, Phase I: Matchmaking process - match the service requirements of consumer with the service descriptions in the service repository with WSDL [10]. Phase II: Trust-aware service selection - outranked the QoS priority based on service trust score from the matched services using consumer’s trust policy. (Note that three items with asterisk notation are extended by authors considering the supplementary of original work).

B. Dempster-Shafer Evidence Theory

Let \( S \) mean that the service considers a given correspondent to be satisfied. In contrast, unsatisfied is denoted by \( \neg S \) and uncertain represented by \( \{S, \neg S\} \). A frame of discernment \( \Theta = \{S, \neg S\} \) is the set of propositions under consideration. Let

\[
\theta_k \rightarrow B \rightarrow D \rightarrow E
\]

\[
\sum_{E_k \subset \Theta} m(E_k)
\]

\[
Bel(A) = \sum_{E_k \subset \Theta} m(E_k), Bel(\neg A) = \sum_{E_k \subset \Theta - \{s\}} m(E_k)
\]

\[
Bel(A) = \sum_{E_k \subset \Theta} m(E_k), Bel(\neg A) = \sum_{E_k \subset \Theta - \{s\}} m(E_k)
\]

\[
Bel(A) = \sum_{E_k \subset \Theta} m(E_k), Bel(\neg A) = \sum_{E_k \subset \Theta - \{s\}} m(E_k)
\]
and Service Level Agreement (SLA) are used as a means of specifying the parameters of service level and criterion between consumer and service provider based on WSLA language. The SLA parameters are designed to quantify the functional QoS criterion of service for service matching as shown in Table 1.

**Table 1. Metrics of Functional QoS**

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Notation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Response Time</td>
<td>ART</td>
<td>ms</td>
</tr>
<tr>
<td>Transactions Rate</td>
<td>TR</td>
<td></td>
</tr>
<tr>
<td>Real Transactions Rate</td>
<td>RTR</td>
<td></td>
</tr>
</tbody>
</table>

For each node (i.e., SLO) in request SLO tree, if the condition of \( \text{resource SLO spec} > \text{request spec} \) is satisfied, then transaction performs. The Service Level Matchmaking algorithm is described by PDL as follows and illustrated by Fig.3.

Input: Service level objects (SLOs) and Service Level Agreement (SLA) of user and resource provider

Output: Suggested service composition

**Algorithm SLMA: Service Level Matchmaking Algorithm**

- Initial phase;
  1. tree_construct(request_SLA); create SLOs for request spec
  2. tree_construct(resource_SLA); create SLOs for offer spec
  3. output_list_construct()
  4. Read consumer’s request table into SLOs
  5. Read provider’s service offer table from repository into SLOs

- Comparison phase; compare (request_SLA, resource_SLA)
  6. loop
  7. for each node (SLO) in request_SLA do
  8. if (request_spec < resource_spec) or (request_spec located with resource_spec_interval)
  9. output_list ← resource_spec_id
  10. end if
  11. return (output_list)
  12. end for
  13. end loop

In practice, the perceived trustworthiness of a service is determined both by the individual’s own experience of the service, i.e., \( \text{QoE} \) (Quality of Experience) belonging to subjective evidence and by the recommendations of others, while, \( \text{QoC} \) (Quality of Compliance) belonging to objective evidence, respectively. As a result, both aspects should be taken into account when evaluating the reputation of different services with a seemingly identical functionality. In discovering the trust-aware computation context, ‘influence diagram’ is incorporated into analyzing cause-effect relationships to specify the evaluation criteria as shown in Table 2 and Fig.4.

**Table 2. Metrics of Non-Functional QoS**

<table>
<thead>
<tr>
<th>Basic Criterion</th>
<th>Notation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company scale</td>
<td>( CS_i )</td>
<td>VS(0.1), S(0.3), M(0.5), L(0.7), VL(1.0)</td>
</tr>
<tr>
<td>Reliability</td>
<td>( RE_i )</td>
<td>interval [0~1]</td>
</tr>
<tr>
<td>Availability</td>
<td>( AV_i )</td>
<td>interval [0~1]</td>
</tr>
<tr>
<td>Cost</td>
<td>( CO_i )</td>
<td>$0~$10000 USD</td>
</tr>
</tbody>
</table>

**C. Trust-Aware Algorithm for Service Selection**

**C.1 Trust-aware services selection process**

The trust-aware service selection model proposed in this study quantifies the reputation of a service utilizing the modified scheme of reputation management with agent techniques [3,8,11-12], developed by Yu and Singh [1-2].
where $x_j$ represents the actual resource/price offer of web service $s_j$ with respect to criterion $c_j$, $x_j \in [-q, q]$, $q$ denotes the ratio of over/under specification which reasonably is proportional to credit score. Assume that there are two basic types of QoS criteria: utility-oriented and cost-oriented criteria. Reputation credit is decided by the ratio of over specification as

$$cr_j(s_c) = \frac{x_j(s_c) - r_j(s_c)}{r_j(s_c)},$$

where $j \in \text{utility criteria}$

$$cr_j(s_c) = \frac{p_x(s_c) - x_j(s_c)}{p_x(s_c)},$$

where $j \in \text{cost criteria}$

where $r_j(s_c)$ represents the request utility specification to $SC_i$ and $p_j$ stands for the request price. The total reputation credit of a service composition is derived by

$$CR_i(s_c) = \sum_{j=1}^{n} w_j \cdot cr_j(s_c), \quad \sum_{j=1}^{n} w_j = 1,$$

where $w_j$ represent the weight of each criterion given by the consensus of a group according to the importance of service provision. The criteria for service reputation (company scale, promptness, reliability, availability and cost) shown in Table 2 are determined by a rule set by the following formula Eqs.(8)~(17) and determination of trust score based on QoS ranking of a set of matched service related to a specified request.

C.2.1 QoE metrics assessment

In researching satisfaction, resource provider generally ask customers whether their service has met or exceeded expectations, based on service level agreement. Thus, the brief degree of evidences can be decided by satisfaction degree of request to response in order to make a decision whether matched services are satisfactory or not,

$$E_s(cr_{sc}) = \begin{cases} S & \text{if } offer_{spec} \geq req_{spec} \\ -S & \text{if } req_{spec} < offer_{spec} \end{cases},$$

where evidence $E_s(cr_{sc})$ might be classified as either satisfaction ($S$) or dissatisfaction ($-S$) on service. The belief function on satisfaction degree of service composition $SC_i$ is denoted as $Bel(S_{sc})$. Thus reputation credit on a service composition based on individual’s own experience is given by

$$\Gamma_{QoE}(x_{sc}) = Bel(S_{sc}) + Bel(S_{sc} \land \neg S_{sc}) - Bel(\neg S_{sc}),$$

where $Bel(S_{sc})$, $Bel(\neg S_{sc}) \in [0,1]$, $\Gamma_{QoE}(x_{sc}) \in [1,-1]$.

C.2.2 QoC metrics assessment

Suppose consumers get acquainted with each other in the group and accept the service credit by friend’s referrals, then the reputation credit can be computed by their witness, $w_{1, i}$, $w_{n, i}$, respectively. Notably, a TrustNet might be limited in a rational depth limit for avoiding misinterpreting. Once consumer $c_i$ has given a local reputation credit, $\tau_{sc}$, from each witness on a service composition $SC_i$, then an aggregation process summarizes all witnesses to gain a global reputation credit $\pi(S_{sc})$ with satisfaction ($S$) on $sc$ as

$$\pi(S_{sc}) = f(\tau_{sc}, \ldots, \tau_{sc}, L),$$

where aggregation function $f$ is decided by operations of network referrals; $L$ is a depth limit. The trust value between two agents is attached to link weights of social networks, as shown in Fig.5.

Figure 5. The Referral Link with trust value

Suppose agent A is asking agent B thru a referral chain to compute the reputation credit regarding $SC_i$, agent B is not very familiar $SC_i$, agent B refers to agents D, E who are the most reliable friends in social networks. If referral evidences are collected by a finite set of positive comments from agent A to agent E with referral length 3, then Eq. (10) became

$$\pi(S_{sc}) = f(\tau_{sc}, \ldots, \tau_{sc}, L) = \frac{1}{3} [S_{AB} \otimes S_{BE}] + 
\tau_{AB} \otimes S_{BC} + \tau_{BE} \otimes S_{DC}]$$

where $\otimes$, $\oplus$ is the multiplication and additive operator of referral activity, respectively. Similarly, a reputation of dissatisfaction $\neg S_{sc}$ can be derived by giving negative credit from agents thru witness. Thus, the reputation credit of collaborative rating is decided by all witnesses based on the times of comments in cooperation period (positive or negative) as depicted in Table 3.

<table>
<thead>
<tr>
<th>Table 3. Collaborative rating in social networks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Referral links</td>
</tr>
<tr>
<td>Times of Positive Comment</td>
</tr>
<tr>
<td>Times of Negative Comment</td>
</tr>
<tr>
<td>Link Weights $\tau_{AB} = 0.90$</td>
</tr>
</tbody>
</table>

In summary, the trust score derived from reputation credit of witnesses thru network referrals on service $sc_i$ is given by

$$\Gamma_{QoC}(x_{sc}) = \pi(S_{sc}) - \pi(\neg S_{sc}),$$
where $\pi(S_{sc}) \cdot \pi(-S_{sc}) \in [0,1]$, $\Gamma_{QoC} (sc_{c}) \in [-1,1]$.

### C.3 Trust score computing

The overall service trust score from all evidences on service $sc_{c}$ can be decided by summing up two major quality metrics $QoE$ and $QoC$ as

$$
\Gamma_{r} (sc_{c}) = \alpha \Gamma_{QoE} (sc_{c}) + (1 - \alpha) \Gamma_{QoC} (sc_{c}),
$$

where $\Gamma_{QoE}(s_{i})$ represents a reputation credit obtained by individual’s own experience feedbacks, while $\Gamma_{QoC} (sc_{c})$ denotes a reputation credit drawn from other’s referrals; $\alpha$ is an adjustable parameter which is decided by the quality of evidence. Two specific cases may be happened, that is, $\alpha = 1$ indicates a sufficient historical own experience records being provided, $\alpha = 0$ show no previous experience records existed. Finally, decide to trust a service can be determined by the rule

$$
\Gamma_{r} (sc_{c}) > \Gamma_{r} \text{ (threshold)}
$$

Obviously, a rational trust threshold can be decided by the net difference value of a group consensus on service credit, i.e.,

$$
\Gamma_{r} \text{ (threshold)} = \frac{1}{n} \sum_{j=1}^{n} \text{Bell}(T_{sc_{c}}) - \text{Bell}(\text{Neg}_{sc_{c}})],
$$

where $n$ represents a group of service consumer $j = 1, \ldots, n$.

### C.4 Detecting deception in reputation management

The network reputation mechanism often need identify the associated allies like unreliable agents or not. Detecting deception algorithms defined to compute belief interval attached to those designed for malicious reports. Particularly, an agent with honest report (reliable agent) need be rewarded by society whereas an agent with extra extreme comments ruins his credit that will be categorized as unreliable agent.

Importantly, the upper and lower boundary of reputation credit (trustiness) on service $s_{i}$ need be specified in advance for illustrating the evidence belonging to the trustworthy ($T$) or untrustworthy ($\text{Neg}$). Let $u$ represents the average reputation credit of a service in a fixed observation period and $\sigma$ represents the standard deviation of service credit.

$$
\mu = \frac{1}{n} \sum_{j=1}^{n} \text{Bell}(T_{sc_{c}}), \quad \sigma = \sqrt{\frac{\sum_{j=1}^{n} (\text{Bell}(T_{sc_{c}}) - \mu)^{2}}{n-1}},
$$

To effectively maintain the reputation of a specific service, provider constantly delivers a stable service level for the consumers. Thus, detection of reputation management is decided by the belief interval $[\Omega_{r} - w_{r}]$ which is given by

$$
[\Omega_{r} - w_{r}] = [\mu + \Delta, \mu - \Delta],
$$

where $\Delta = \gamma \sigma$. $\gamma$ is a parameter decided by statistical reports within an observation period by the public third-party. When a credit score is greater than $\Omega_{r}$ or less than $w_{r}$, reported from an agent, it may be regarded as an invalid feedback, otherwise valid report. After collected enough amount of reports, all agents can be identified as either a reliable agent to cooperate or an unreliable agent not to cooperate in the future based on its belief interval in an assessment time period.

### IV. CASE STUDIES

Assume that the evaluation is performed by the public third-party based on the feedbacks or referrals received by a representative group of service consumers, $c_{i} (k = 1, \ldots, 40)$ to twenty-six competing service alternatives. $s_{j} (i = 1, \ldots, 26)$ Table 4 illustrates the social context considered in solving the resulting service selection problem. The details of each step in the proposed reputation-based service selection method are described in the following.

Step 1. Web service screening with matchmaking algorithm

There are total 26 travel-related WS which are categorized into five categories to provide the complete travel-related service solution, as depicted in Table 4.

### Table 4. WEB SERVICE CATEGORY

<table>
<thead>
<tr>
<th>Service category</th>
<th>Web services</th>
<th>Provider</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel touring consulting</td>
<td>$W_{11a}, W_{12a}, W_{13b}, W_{14b}, W_{15b}$</td>
<td>A, B, C</td>
</tr>
<tr>
<td>Ticket booking</td>
<td>$W_{21h}, W_{22e}, W_{23e}, W_{24f}, W_{25e}$</td>
<td>D.E.F,G</td>
</tr>
<tr>
<td>Online payment</td>
<td>$W_{31h}, W_{32e}, W_{33e}, W_{34m}, W_{35e}$</td>
<td>H.L.J</td>
</tr>
<tr>
<td>Accommodation</td>
<td>$W_{41k}, W_{42k}, W_{43h}, W_{44m}, W_{45n}$</td>
<td>K.L,M, N.O</td>
</tr>
<tr>
<td>Network access &amp; data store</td>
<td>$W_{51h}, W_{52i}$</td>
<td>P.Q</td>
</tr>
</tbody>
</table>

Followed by matchmaking algorithm described in Sec 3.1, screen out un-suitable service compositions which are unsatisfied with request specifications, then only four service composition alternatives left, i.e., \{W_{11a}, W_{21h}, W_{31h}, W_{41k}\}, \{W_{11a}, W_{21h}, W_{31h}, W_{42k}\}, \{W_{12a}, W_{21h}, W_{32e}, W_{41k}\}, \{W_{13b}, W_{22e}, W_{33e}, W_{42k}\}, \{W_{12a}, W_{22e}, W_{33e}, W_{44m}, W_{52i}\} are selected as assessment targets of next phase, respectively.

Step 2. Service reputation computing

Step 2.1 $QoE$ metrics assessment

Assume that the service composition 1–4 have been assessed, reputation credit based on satisfaction degree of each service alternative with weights (%) are listed as shown in Table 5.

### Table 5. REPUTATION CREDITS OF $sc_{c}$

<table>
<thead>
<tr>
<th>Service</th>
<th>Functional QoS</th>
<th>Non-functional QoS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Sc_{1}$</td>
<td>ART 40/400/800</td>
<td>TR 40/400/800</td>
</tr>
<tr>
<td>$Sc_{2}$</td>
<td>50/70/100</td>
<td>6.5/10/60/30</td>
</tr>
<tr>
<td>$Sc_{3}$</td>
<td>50/70/100</td>
<td>6.5/10/60/30</td>
</tr>
<tr>
<td>$Sc_{4}$</td>
<td>50/70/100</td>
<td>6.5/10/60/30</td>
</tr>
</tbody>
</table>
(Data format in Table 4 is the 'requirement specification/provide specification'). By applying Eqs. (4)~(9), the reputation credit on services $SC_1$~$SC_4$ are shown in Table 6.

<table>
<thead>
<tr>
<th>$SC_1$</th>
<th>$SC_2$</th>
<th>$SC_3$</th>
<th>$SC_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Bel(Bel(S))$</td>
<td>$Bel(Bel(S))$</td>
<td>$Bel(Bel(S))$</td>
<td>$Bel(Bel(S))$</td>
</tr>
<tr>
<td>0.117</td>
<td>0.05</td>
<td>0.35</td>
<td>0.1175</td>
</tr>
<tr>
<td>$\Gamma_{QoC}(SC_1)$</td>
<td>$\Gamma_{QoC}(SC_2)$</td>
<td>$\Gamma_{QoC}(SC_3)$</td>
<td>$\Gamma_{QoC}(SC_4)$</td>
</tr>
<tr>
<td>0.067</td>
<td>0.288</td>
<td>-0.077</td>
<td>0.0117</td>
</tr>
</tbody>
</table>

Step 2.2 QoC metrics assessment (see Fig 6)

The reputation credit on service $SC_1$ on refer chains $(A \rightarrow B \rightarrow D)$, $(A \rightarrow B \rightarrow E)$, $(A \rightarrow B \rightarrow F)$ is computed by

$$\tau_i(SC_i) = \frac{1}{3}(r_i^A \otimes r_i^B \otimes w_i^D) + (r_i^A \otimes r_i^B \otimes w_i^E) + (r_i^A \otimes r_i^B \otimes w_i^F)$$

Let $r_i^A = (0.7)$; $r_i^B = (0.65)$; $r_i^B = (0.8)$; $r_i^B = (0.8)$; $w_i^D = (0.5)$; $w_i^E = (0.3)$; $w_i^F = (0.45)$. By applying Eqs. (10)~(12), then we have a reputation credit on $SC_1$ as 0.216. On the contrary, agent $A$ is asking negative witness on $SC_4$, then $w_i^{SC_4} = (-0.2)$; $w_i^{SC_4} = (-0.1)$; $w_i^{SC_4} = (-0.25)$; $w_i^{SC_4} + w_i^{SC_4} < 1$, where $w_i^{SC_4}$ represent negative comment on $SC_i$ from the agent $D$. Similarly, $\Gamma_{QoC}(SC_i)$ of the rest three services are listed in Table 7.

<table>
<thead>
<tr>
<th>$SC_1$</th>
<th>$SC_2$</th>
<th>$SC_3$</th>
<th>$SC_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau_{SC_1}$</td>
<td>$\tau_{SC_2}$</td>
<td>$\tau_{SC_3}$</td>
<td>$\tau_{SC_4}$</td>
</tr>
<tr>
<td>0.216</td>
<td>0.099</td>
<td>0.24</td>
<td>0.06</td>
</tr>
<tr>
<td>$\Gamma_{QoC}(SC_1)$</td>
<td>$\Gamma_{QoC}(SC_2)$</td>
<td>$\Gamma_{QoC}(SC_3)$</td>
<td>$\Gamma_{QoC}(SC_4)$</td>
</tr>
<tr>
<td>0.115</td>
<td>0.18</td>
<td>-0.05</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Step 3: Trust score computing

By setting $\alpha=0.0, 0.5, 1.0$, this step generates synthetic values to form Table 8 using Eq. (13).

<table>
<thead>
<tr>
<th>$SC_1$</th>
<th>$SC_2$</th>
<th>$SC_3$</th>
<th>$SC_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Gamma_i(s)$</td>
<td>$\Gamma_i(s)$</td>
<td>$\Gamma_i(s)$</td>
<td>$\Gamma_i(s)$</td>
</tr>
<tr>
<td>$\alpha=0.0$</td>
<td>0.115</td>
<td>0.18</td>
<td>-0.05</td>
</tr>
<tr>
<td>$\alpha=0.5$</td>
<td>0.091</td>
<td>0.431</td>
<td>-0.064</td>
</tr>
<tr>
<td>$\alpha=1.0$</td>
<td>0.067</td>
<td>0.234</td>
<td>-0.077</td>
</tr>
</tbody>
</table>

From Table 8, the ranking order of four web services can be stated as $SC_2 > SC_1 > SC_4 > SC_3$ . In summary, a decision of selecting $SC_2$ is suggested.

Step 4. Detecting fraud measures in reputation management

Trust and reputation often identify other related entities like fraud and information application. Importantly, algorithm defined in Eq. (16)~(17) is ready to compute the belief interval of reputation credit for detecting fraud measures or deception testing. Lack of trust leads means higher possibility of fraud or fraud agents try and take over reputed member’s trust to commit fraud. Mechanisms that restrict such takeover are of importance to build low fraud applications.

V. CONCLUSION

In this work we present a QoS-aware trust-based service selection scheme, effectively detecting malicious assessments, objectivity analyzing the witnesses via network referrals and compatibly outrank service compositions. Moreover, the model presented in this study is an application extension of approach presented by Ali et al. [8] to that the reputation and trust management problem in the context of service discovery and selection applications.

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