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Fairness Guaranteed Rating Decomposition in Service-oriented Reputation Systems*

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Service-oriented wireless sensor networks constitute the most important components in smart cities, which adopt multiple information and communication technologies (ICT) to improve our life quality. Smart devices can be cooperatively composed together to create flexible resource environments with more powerful computing capabilities. Trust relationship between devices would be an important premise to guarantee an interaction can be successfully carried on. However, some malicious services may exist in connected devices, which would behave abnormal and destroy the interaction. Recently, rating decomposition has become an emerging solution to evaluate component services in the composition. However, existing approaches are unable to solve some main challenges, such as the opaque structure, the complex invocational pattern and the subjective rating. In this paper, an efficient rating decomposition approach is proposed to fairly distribute the overall subjective ratings to each component in the opaque composite service. It first models composite services as Beta-mixture models, and learns both responsibilities and reputations through expectation-maximization (EM) algorithm. Then, it computes the contribution of each component by using the Shapley value in corporative gaming theory, and improves the efficiency of Shapley value computation by bit vector-based encoding. Moreover, the fairness can be guaranteed that no component in the composition would receive extra rewards or punishments. Finally, the approach has been validated theoretically and experimentally through simulation studies. The results demonstrate the effectiveness of the proposed approach, which can fairly decompose the consumers' rating to each component hierarchically.

Keywords: fairness, rating decomposition, trust management, reputation systems, service-oriented wireless sensor networks

1. INTRODUCTION

We are entering a smart era, in which more and more intelligent devices are contributing their computing capacities together to constitute multiple smart applications, such as E-wearable, E-home, E-community, E-traffic, *etc.* These applications will be accompanied by massive information exchanges between services on sensor nodes [1]. In service-oriented wireless sensor networks, services are modeled as self-organized, platform-independent and reusable computing entities, which are described, published, discovered and consumed via a set of uniform standards. With these standards, a cooperative environment is created to support rapid application developments across divergent

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organizations and domains. In addition, complex services can be formed by the composition of other outsourced service entities with complex logics in an automatic way [2]. However, in the open networks, every entity suffers from inherent uncertainty that forces the service consumers to take on risks before they use services. It requires a mechanism to eliminate this uncertainty. Reputation-based trust provides an effective mechanism for evaluating the quality or services (QoS) of the target entity. Typical reputation systems are widely applied into many crucial areas, such as sensor networks [3, 4], cloud computing [5], Internet of Things [6], e-commerce [7], peer-to-peer (P2P) networks [8], crowdsourcing [9], to name a few. They set up incentives for good behaviors and provide some reference information for consumers to reduce the interaction probability with malicious services. Thus, consumers can interact with the trustworthy entities without risks in every online activity [10, 11].

Recently, considerable amounts of research efforts have been undertaken on building reputation systems for service environments. Most of them focused on improving the accuracy of trust evaluation from multiple factors, such as time, cost and personal preference [12], or eliminating malicious ratings from multiple sources, such as assigning lower weights to the untrustworthy nodes [13]. Generally, reputation systems compute an evaluated result to the whole service entity, and do not specifically consider the internal structures of services, which would lead to the unfair evaluation results in the service-oriented environment. Currently, rating decomposition is a novel and effective solution to this issue. More specifically, a user is required to provide a rating based on his interaction experience. Then, a decomposition model is utilized to distribute the rating to all the component services for reputation update. Therefore, the quality of component services can be correctly observed in the upcoming transactions.

Recently, some preliminary solutions to rating decomposition have been proposed. Nepal *et al.* [14] first identified rating decomposition issue for composite services. A composite service would behave like a service consumer and distribute the evaluation score for its components, and played the role as a delegation of the corresponding consumer. They also emphasized the distribution must follow the basic rule. That is, any component service should not be awarded (or penalized) for the good (or poor) performances of other components in the composite logics. They proposed a propagation algorithm for reputation distribution according to the quality tendency and the importance degree of each component. Silva *et al.* [15] followed Nepal's idea, and designed a compensation function for decomposing evaluation scores based on past reputation record and current service performance. Additionally, Sadeghi *et al.* [16] combined trust trend and current reputation review to propagate rating in both sequential and hierarchical structures. These efforts are useful to decompose ratings with different composite structures. However, in their work, the composite structures are assumed as observable from the reviewers, and they lacked of theoretical fairness proofs. Moreover, based on the mathematical characteristic of Shapley value, Liu *et al.* [17, 18] proposed a fairness-guaranteed rating propagation for composite services. Though their work guaranteed fairness theoretically [17], unfortunately they also suffered from the observable issue, and required the mathematical expectation of the best and the worst QoS of each component service, which is a tough issue for unskilled consumers. Therefore, there are still some apparent issues, which can be summarized as follows.

- *Opaque Service Structure*. Most services are opaque to their consumers. Consumers cannot evaluate the overall services as they do not know whether the service they interacted is an atomic or not in most cases. This opaque issue poses great challenge to service selection where some malicious components may be hidden in a trustworthy blackbox-like service.
- *Intricate Composite Pattern*. A composite service may be composed of multi-level services with different invocational dependencies. The intricate dependencies among component services result in the different QoS patterns. It is necessary to establish an effective computation rules for all these structures in the composition, even with quite multiple levels in the vertical composite structures.
- *Subjective Rating*. Different users may have different evaluation criterions, including conservative (tend to give low ratings), progressive (tend to give high ratings) and neutral. The rating decomposition model should inherit the user's criterion, and play as a delegation to update all the components.

To solve the above issues, a novel rating decomposition approach is designed for the composite service. By analyzing the composite structures and the reputation aggregation rules, the proposed approach first models the composite services as Beta-mixture model, and learns the responsibility and reputation of each component in the composite services through expectation-maximization (EM) algorithm. Then, it integrates the Shapley value in cooperative game theory to compute the contribution of each component, and decomposes the reputation review to its components based on the computed contribution score. Next, the Shapley value are further optimized for more efficient computation via bit-vector encoding. Moreover, the fairness of the proposed approach is proved theoretically. Finally, a series of experiments are conducted to evaluate the features, and the comparison results to other efforts validate the effectiveness of the proposed approach.

The remainder of the paper is organized as follows. Section 2 introduces the related models for rating decomposition. Section 3 presents the detailed steps of the proposed approach. Next, section 4 shows the features and proves the fairness. Experiments and comparisons are further conducted in section 5 to illustrate the effectiveness. Finally, Section 6 concludes this work.

2. SERVICE AND REPUTATION MODELS

2.1 Service Composition Model

In wireless sensor networks, a service consists of a set of operation logics to consume its input data from its predecessors and generate output data to its successors. Additionally, as Fig. 1 shows, services deployed on sensor nodes can be composed together to form a data-flow composition structure. In Fig. 1, there are three types of service compositions: horizontal, vertical and hybrid. Horizontal composition happens when a service s_i interacts with its predecessors and successors to construct a "supply-chain" like structure. Vertical composition is formed when service s_i invokes its internal component services in its computation function $s_i.F$, and hybrid composition consists of both horizontal and vertical compositions.

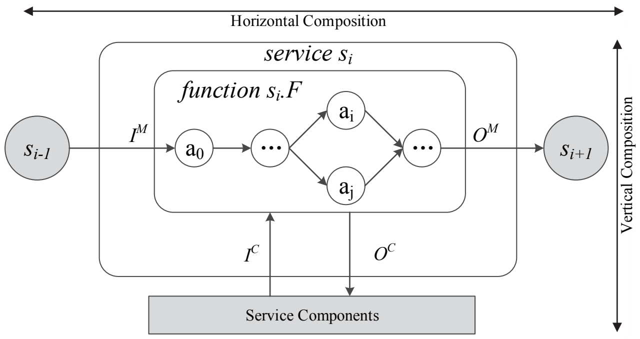

Fig. 1. Service composition model.

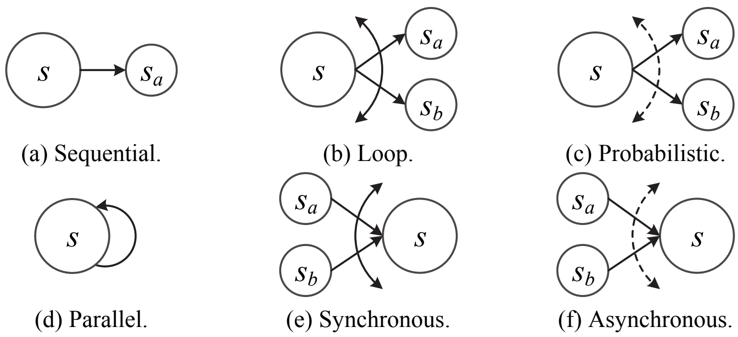

Fig. 2. Atomic service composition structures.

These composite structures are opaque to service consumers. In order to decompose consumers' rating to components, it is necessary to evaluate every invocational structure. More specifically, there are six atomic composite structures [19, 20], which are illustrated in Fig. 2. In the service runtime situation, the loop invocational pattern (see Fig. 2 (b)) is unfolded to be multiple sequential structures (see Fig. 2 (a)) as many as the loop times executed by that service component. And there is exact one determined path to be executed in the probabilistic pattern (see Fig. 2 (c)). Moreover, the synchronous (see Fig. 2 (e)) and asynchronous (see Fig. 2 (f)) patterns must start with the parallel pattern (see Fig. 2 (d)). Therefore, a composite service can be represented as an end-to-end directed acyclic graph (DAG) with a set of execution sequences. All the executed sequences can be formed as a service execution graph (SEG). Clearly, a composite service in SEG can be summarized as only two kinds of invocational patterns: deterministic and probabilistic.

2.2 Beta Reputation Model

Reputation of a service is the aggregation of opinions that consumers provided about the QoS based on its past behavior. Reputation score represents a global outcome, which means that all the members in the community can observe the same reputation information for a particular service. In order to evaluate the contribution of each service component, we apply Beta distribution-based reputation model to aggregate the rating records.

Beta probability model represents reputation as an evidence tuple $\theta=\langle\alpha, \beta\rangle$, where α and β denote the number of satisfactory and unsatisfactory interactions, respectively. The beta probability density function is expressed as:

$$f(\theta)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1} \tag{1}$$

where $\Gamma(x)=\int_0^{\infty}u^{x-1}e^{-u}du$, $0\leq\theta\leq 1$, $\alpha>0$ and $\beta>0$.

The reputation $R(s_i)$ of service s_i can be computed as the mathematical expectation of its corresponding Beta reputation model. For service s_i, $R(s_i)$ is expressed as:

$$R(s_i)=E(\theta_i)=\frac{\alpha_i}{\alpha_i+\beta_i} \tag{2}$$

where $E(\theta_i)$ represents the mathematical expectation of evidence $\theta_i=\langle\alpha_i, \beta_i\rangle$.

3. FAIRNESS GUARANTEED RATING DECOMPOSITION APPROACH

3.1 Statistical Learning of Responsibility and Evidence

Since the service is opaque to the end consumer, the consumer cannot distinguish whether the service is an atomic or a composite one. The consumer usually gave a rating after he/she interacted with the services. The rating of a composite service has to be fairly distributed to each service component. After perceiving the reputation aggregation of the composite services, the proposed approach leverages finite mixture model to statistically learn the responsibility and reputation of each component. Therefore, the opaque reputation evidence in the composite service can be observed.

Finite mixture model aggregates data objects as mixture branches, and learns about the parameters of each branch from the super-positions of multiple probability density distributions. In this paper, composite reputation data are modeled as the Beta-mixture. For a composite service with n component services s_i ($1\leq i\leq n$), the component branch for s_i is modeled as Beta probability model with parameter $\theta_i=\langle\alpha_i, \beta_i\rangle$, then the beta mixture of the composite service can be represented as:

$$p(X)=\sum_{i=1}^{n}\pi_i Beta(X\mid\theta_i) \tag{3}$$

where $X=\{x_1, x_2,\ldots, x_M\}$ is the series of observations from the composite probability distribution, n is the number of component services, and π_i ($\sum_i\pi_i=1$, $1\leq i\leq n$, $\pi_i\in[0,1]$) is the mixed coefficient for the component service, representing the proportion of every branch appearing in the beta mixture model.

Expectation-Maximization algorithm, or EM algorithm, is used to learn the maximum likelihood estimation for each component distribution with latent random variables. In this paper, a set of latent variables $Z=\{z_1, z_2, \ldots, z_n\}$ is introduced. Each z_i ($1\leq i\leq n$) controls the portion of an observation x_j ($1\leq j\leq M$) to the component s_i. In the set Z, there is exact one variable is equal to 1, that is $z_i \in \{0, 1\} \wedge \sum_i z_i = 1$, $1 \le i \le n$. Moreover, the probability of latent variable z_i represents the responsibility of component service s_i, that is $p(z_i) = \pi_i$, $p(Z) = \prod_i \pi_i^{z_i}$, and $p(X|Z) = \prod_i Beta(X|\theta_i)$. Therefore, the Beta mixture model for composite service c can be represented as:

$$p(X) = \sum_Z p(Z)p(X \mid Z) = \sum_{i=1}^{n} \pi_i Beta(X \mid \theta_i). \tag{4}$$

EM algorithm iterates E-step (Expectation Step) and M-step (Maximization Step) computations until the parameters converge. The EM algorithm in our approach is executed as follows:

E-step: it holds the current evidence tuple $\theta^{old} = \langle \alpha^{old}, \beta^{old} \rangle$ fixed, and computes the maximum likelihood estimation of $q(z) = p(Z \mid X, \theta^{old})$, where $p(Z|X, \theta^{old}) = \pi_i Beta(X|\theta_i^{old}) / \sum_k \pi_k Beta(X|\theta_k^{old})$.

M-step: it maximizes the evidence tuple $\theta^{new} = \arg\max_{\theta} \sum_{Z} q(Z)(\ln p(X, Z \mid \theta^{old}) - \ln q(Z))$ from the computed value of $q(z)$ in E-Step.

Repeating E-step and M-step until parameter θ^{new} converges with respect to its log likelihood, and current π_i^{new} and θ_i^{new} are the final statistical value of responsibility and evidence of component service s_i in the composite service.

3.2 Shapley Value-based Contribution Computation

The proposed approach introduces w_i to denote the execution probability of s_i to the whole composition. As mentioned before, the composition structures can be divided into two types: deterministic structure and probabilistic structure. In the deterministic structure (including sequential, loop, synchronous), each component is executed stepwise according to the composite structure, therefore $w_i = 1$; while in the probabilistic structure, the execution probability is the normalized ratio of its responsibility value, which can be computed from EM algorithm. For component service $s_{i,j} \in \{s_{i,1}, s_{i,2}, \ldots, s_{i,m}\}$, its execution probability can be computed as $w_{i,j} \in \{w_{i,1}, w_{i,2}, \ldots, w_{i,m}\} = \pi_{i,j}/(\pi_{i,1}+\pi_{i,2}+\ldots+\pi_{i,m})$. After obtaining the execution probability and reputation evidence the reputation can be computed with the aggregation rule [21].

Then, the user's rating is distributed based on its contribution of s_i to c, denoted as $\Delta i(c)$. To guarantee fairness, the proposed approach computes the contribution $\Delta i(c)$ with the Shapley value in cooperative game theory, which can be represented by the following equation:

$$\Delta_i(c) = \sum_{T \in c \setminus \{s_i\}} \frac{|T|!(n-|T|-1)!}{n!} (R(c \mid T \cup \{s_i\}) - R(c \mid T) - L) \tag{5}$$

where n is the number of components in the composite service c, $R(c|T)$ is the aggregated trust value of the set of components T in the composite service c, and L is a constant value in the Shapley value computation.

In Eq. (5), the constant value L is used to control the positive and negative border in the Shapley value computation. For specified set of services T, the marginal contribution of component s_i to the composite service c conditional on T can be represented as $R(c|T \cup s_i) - R(c|T) - L$, and its weight $(|T|!(n-|T|-1)!)/n!$ represents the probability of permutation that T is in the composite subset in front of component s_i in the sequence $\langle s_1, s_2, ..., s_k\rangle$. In this case, there are $|T|!$ ways to put the components in T before s_i, and $(n-|T|-1)!$ ways to put the remaining components in T behind s_i. Moreover, suppose the permutations be with equal probability, the probability of each composition is $(|T|!(n-|T|-1)!)/n!$. Therefore, $\Delta i(c)$ computed by the formula (5) can represent the marginal contribution of component s_i to the composite service c under all the possible combinations of subset T of c, which is the reputation contribution of component service s_i to composite service c.

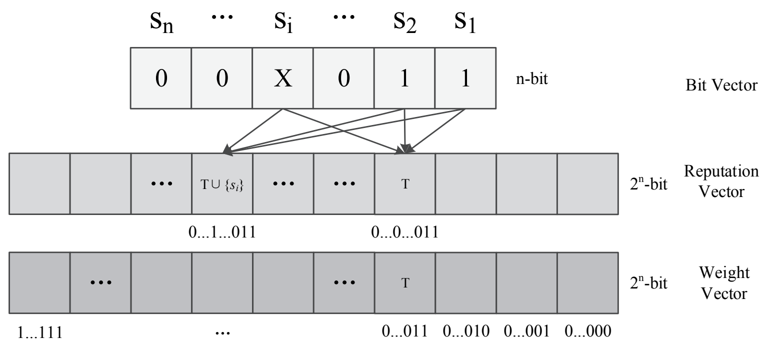

Fig. 3. Bit vector-based optimization.

3.3 Bit Vector-based Optimization for Composite Service

Evidentially, in the process of contribution computation, it needs to compute all the subsets of composite service c. For n components in c, the Shapley value computation would reach exponential time complexity $O(2^n)$ for each component service s_i. And the overall time complexity can reach $O(n\times 2^n)$ for computing the composite contributions composed of n components. The time complexity increases sharply with the size of composite services, which is the major weakness of directly applying Shapley value. To reduce the complexity, the computation procedures are optimized in this section.

In the contribution computation, all the subsets of composite service c are computed in Eq. (5), which causes totally replicate computations. To reduce the time complexity, a bit vector-based optimization is used to encode the contribution computation steps in previous section. We use one bit to encode one component service in c, and all the bits are stored in an n-length vector (see Fig. 3), where n is equal to the number of component services in c. In the vector, each bit can be 0 or 1 at a time.

The computation can be optimized based on the following three steps: (1) subset reputation computation; (2) weight computation; and (3) fast Shapley value computation, which are illustrated in Fig. 3. In the first step, the reputations of all the subsets in vector are computed and stored in the Reputation Vector. If the ith bit ($1 \le i \le n$) in the Bit Vector equals 1, the evidence $\theta_i = \langle\alpha_i, \beta_i\rangle$ is added to compute the reputation of subset T. Then, it stores the results into a 2^n-length Reputation Vector. Next, in the second step, the weights of all the subsets are computed. For each bit, the number of bits (except the ith bit) whose value is 1 is counted as the value of $|T|$ in the computation, and the number of bits (except the ith bit) of value 0 is counted as the value of $(n-|T|-1)$. Then, the weight for the contribution of service s_i can computed, the results can be stored in the corresponding bit. Finally, in the third step, the parameters for Eq. (5) can be looked up from the corresponding bit in the bit-vector tables.

After the bit vector-based optimization, the Shapley value computation requires only $O(1)$ to obtain reputation and weight scores for each subset T. Therefore, the time complexity of first two steps is $O(2^n)$, where 2^n is the length of reputation and weight bits. To compute the contributions of all the component services, the time complexity is $O(n)$. Therefore, the time complexity after optimization is $O(n)+O(2^n)$. Moreover, as the first two steps can be computed offline, it only requires a constant time complexity to obtain computation results.

3.4 Reputation Decomposition

In [14], the authors pointed out that the reputation of services has the characteristic of consistency, which indicates that if a service had performed well or badly in the past, it is expected to have the same performance tendency in the future. Thus, consumers can query reputation history for service evaluation. Based on this characteristic, the proposed approach decomposes the subjective ratings using a consistency parameter μ. Then, the decomposition equation is given as:

$$v(s_i) = R_u+\mu\cdot\Delta_i(c) \tag{1}$$

where R_u represents the user's rating to the composite service c, $\Delta i(c)$ represents the contribution of component service s_i to the composite service c, and μ_i represents the consistency degree of service s_i, $\mu_i = |R(s_i) - R(c)| / R(c)$.

Step 1: it learns the responsibility and reputation of each component from the observable finite mixture models, see Section 3.1. This step can solve the opaque service structure issue.
Step 2: it computes the contribution of each component service to the composite service with various invocational dependencies, see Sections 3.2 and 3.3. This step can solve the intricate dependency pattern issue.
Step 3: it decomposes the reputation ratings from service consumers for the composite service to its component services, see Section 3.4. If the current service is still a composite one, then our approach goes to the step 1 for vertical decomposition. This step can solve the subjective rating issue.

4. FEATURE AND FAIRNESS ANALYSIS

4.1 Feature Analysis

Based on the Beta reputation and Shapley value, a composite service can decompose the user's rating to its component services hierarchically with fairness guarantee. Accordingly, the proposed approach inherits the features of Shapley value, which can be summarized as follows.

Efficiency: $\sum\Delta i(c)=0$, $s_i \in c$. Efficiency indicates that the sum of all the contributions $\sum\Delta i(c)=0$ for s_i ($1 \leq i \leq n$) is zero. Therefore, there is no extra reputation quota during the process of rating decomposition.

Symmetry: For $\forall T \in c\backslash\{s_i, s_j\}$, if $R(c|T\cup\{s_i\})=R(c|T\cup\{s_j\})$, then $\Delta i(c)=\Delta j(c)$. Symmetry indicates that if some services have the same reputation when they work together, they will have equivalent contribution.

Balanced Contribution: For $\forall s_i, s_j \in c$, $\Delta i(c)-\Delta i(c|c\backslash\{s_j\})=\Delta i(c)-\Delta i(c|c\backslash\{s_i\})$, where $\Delta i(c|T)$ represents the contribution of service subset T to its composite service c that in the corresponding composite structure of c. Balanced contribution indicates that the reputation fluctuation caused by the composition, defined as $\Delta i(c)-\Delta i(c|c\backslash\{s_j\})$, can be balanced divided among services. Balanced contribution ensures fairness in the process of rating decomposition for each component.

4.2 Fairness Analysis

In this section, the fairness of the proposed approach will be proved. In the proof, some factors, which would change the reputation scores, are considered. $R^t(s)$, $R^{t'}(s)$, $e^t(s)$ and $e^{t'}(s)$ are used to represent the reputation scores and the number of evidences in the consecutive and equal-length time interval t and t'. Then, the difference between reputation and evidence can be represented as $\Delta R(s) = R^t(s) - R^{t'}(s)$ and $\Delta e^t(s) = e^t(s) - e^{t'}(s)$, respectively. Without loss of generality, only the positive variations the considered in our proof. We first consider the case of reputation variations when $\Delta e(s) = 0$ and $\Delta R(s) > 0$. For any invocational dependency, when the reputation of one individual component service improves, the following proposition always holds.

Proposition 1: The reputation improvement of component service s_i cannot lead to the reputation deterioration of composite service c, that is

$$\Delta R(s_i) > 0,\ \Delta R(s_j) = 0,\ \forall s_j \in c,\ s_j \neq s_i \Rightarrow \Delta R(c) \geq 0. \tag{7}$$

Similarly, for $\forall s_j \in c$, $s_j \neq s_i$ and $\Delta R(s_j)=0$, from Eq. (7), it can be obtained that

$$\Delta R(s_i) > 0,\ \Delta R(s_j) = 0,\ \forall s_j \in c,\ s_j \neq s_i \Rightarrow \Delta R(c|\{s_i\}) \geq 0. \tag{8}$$

The intuition underlying the proposition is straightforward. Note that, $R(c|s_i)=0$ represents that the reputation improvement of component service s_i cannot result in the reputation improvement of composite service c. For example, suppose two services s_A and s_B are composed together to form a probabilistic composition c. If the component s_A is executed with quite low probability, it may occur that the reputation improvement of s_A may not improve the reputation of c in the time interval t, thus $\Delta R(c|s_A)=0$. When reputation of s_A deteriorates, we can have the similar observation results. Motivated by this phenomenon, the definition of effective reputation improvement is given as follows.

Definition 1 (Effective Reputation Improvement): A component service s_i has effective reputation improvement if its reputation improvement leads to the reputation improvement of composite service c, that is

$$\Delta R(s_i) > 0,\ \Delta R(s_j) = 0,\ \forall s_j \in c,\ s_j \neq s_i \Rightarrow \Delta R(c|\{s_i\}) \geq 0. \tag{9}$$

Based on the Definition 1, we have the following proposition.

Proposition 2: For a given composite service $c = \{s_1, s_2, ..., s_k\}$ and its subset $T \in c \backslash \{s_i\}$, if $R(s_i) > R(c)$, then

$$\Delta R(c|T \cup \{s_i\}) - \Delta R(c|T) \geq 0. \tag{10}$$

Next, some lemmas are presented regarding the reputation variations of service component to the overall reputation.

Lemma 1: If component services s_i has effective reputation improvement, then

$$v(s_i) > R_u. \tag{11}$$

Proof: For $\forall T \in c \backslash \{s_i\}$, there are following two cases:

Case 1: if $T = \emptyset$, then $\Delta R(c|T \cup \{s_i\}) - \Delta R(c|T) = \Delta R(c|\{s_i\}) - \Delta R(c|\phi) = \Delta R(c|\{s_i\}) > 0$;
Case 2: if $T \neq \emptyset$, then based on Proposition 2, it can be obtained that $\Delta R(c|T \cup \{s_i\}) - \Delta R(c|T) \geq 0$.

And from Eq. (5), there is $\Delta i(c) > 0$. Thus, based on Eq. (6), it is concluded that $v(s_i) > R_u$.

Lemma 2: For $\forall T \in c$, $s_i \neq s_j$, if $R^t(s_i) < R^{t'}(s_i)$ and $R^t(s_j) < R^{t'}(s_j)$, then $v^t(s_i) < v^{t'}(s_i)$.

Proof: For $\forall T \in c \backslash \{s_i\}$, given $\forall s_k \in c$, $\Delta e(s_k) = 0$, then $\Delta R(c|s_i) < 0$, $\Delta R(c|s_j) = 0$, there are following two cases:

Case 1: if $T = \emptyset$, then $R^t(c|T \cup \{s_i\}) - R^{t'}(c|T \cup \{s_i\}) = R^t(c|s_i) - R^{t'}(c|s_i) < 0$;
Case 2: if $T \neq \emptyset$, then based on Proposition 1, it can be obtained that $R^t(c|T \cup \{s_i\}) - R^{t'}(c|T \cup \{s_i\}) \leq 0$.

Moreover, for $\forall s_j \in c$, $s_i \neq s_j$, given $R^t(s_j) = R^{t'}(s_j)$, then for $\forall T \in c$, it can be obtained that $R^t(c|T) = R^{t'}(c|T)$. Therefore, from the following equation that

$$\begin{aligned}&(R^t(c|T \cup \{s_i\}) - R^t(c|T)) - R^{t'}(c|T \cup \{s_i\}) - R^{t'}(c|T))\\&= (R^t(c|T \cup \{s_i\}) - R^{t'}(c|T \cup \{s_i\})) - (R^t(c|T)) - R^{t'}(c|T))\\&= (R^t(c|T \cup \{s_i\}) - R^{t'}(c|T \cup \{s_i\})) < 0\end{aligned}$$

then it can be obtained that

$$\begin{aligned}&v^t(s_i) - v^{t'}(s_i)\\&= W \cdot \sum\nolimits_{T \in c \backslash \{s_i\}} \frac{|T|!(n-|T|-1)!}{n!} (R^t(c\,|\,T \cup \{s_i\}) - R^{t'}(c\,|\,T \cup \{s_i\}) < 0\end{aligned}$$

where $W(W \neq 0)$ is a constant value that represents the difference between the contributions at different time intervals t and t'.

Lemma 3: For $\forall s_j \in c$, $s_j \neq s_i$, if $R^t(s_j) > R^{t'}(s_j)$ and $R^t(s_j) = R^{t'}(s_j)$, then $v^t(s_i) > v^{t'}(s_i)$.

Lemma 4: For $\forall s_j \in c$, $s_j \neq s_i$, if $R^t(s_j) = R^{t'}(s_j)$ and $R^t(s_j) = R^{t'}(s_j)$, then $v^t(s_i) > v^{t'}(s_i)$.

The proofs of Lemmas 3 and 4 are similar to the proof of Lemma 2.

The above lemmas can guarantee the fairness when the evidence scores keep constant, or $\Delta e(s) = 0$. When the number of evidences varies, or $\Delta e(s) \neq 0$, it is necessary to prove the fairness when reputation evidence of a single service changes, then consider reputation changes for service sets using some mathematical inductions. The complete inductions are similar to the proof of Lemma 2.

Theorem 1: The proposed approach can decompose the rating of composite services to its components with fairness guarantee.

Proof: Based on the above lemmas, the theorem holds.

5. EXPERIMENTS AND EVALUATIONS

5.1 Experimental Settings

In this section, we will conduct a series of experiments to show the advantages of the proposed rating decomposition approach under different service composition structures. The experiments take a composite data collection services in Fig. 4 as an example. Suppose a consumer is expected to gather data from some place, which includes the procedures of locating, data aggregation and data storage. The service provider is composed of locating (s_1), data aggregation (s_2) and data storage (s_3) components with a sequential structure to provide composite data collection service. Specifically, there are three different components in the sensors (s_4, s_5, s_6) providing data aggregation service. The invocation probabilities in the probabilistic structure are 60%, 20% and 20%, respectively.

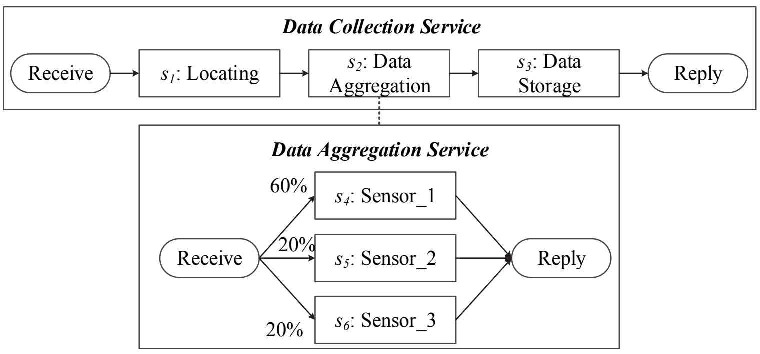

Fig. 4. Bit vector-based optimization.

Table 1. Rating decomposition for deterministic composition pattern.

Initial Parameters for s_1, s_2, s_3	The proposed approach	
	Decomposed Trust	Contributions
$\langle 18, 2\rangle, \langle 10, 10\rangle, \langle 2, 18\rangle$	0.96, 0.67, 0.50	+0.30, 0, –0.30
$\langle 18, 2\rangle, \langle 30, 30\rangle, \langle 2, 18\rangle$	0.88, 0.68, 0.54	+0.25, 0, –0.25
$\langle 24, 8\rangle, \langle 4, 4\rangle, \langle 2, 18\rangle$	0.90, 0.69, 0.47	+0.28, 0.01, –0.29

Table 2. Rating decomposition for probabilistic composition pattern.

Initial Parameters for s_4, s_5, s_6	The proposed approach	
	Decomposed Trust	Contributions
$\langle 18, 2\rangle, \langle 10, 10\rangle, \langle 2, 18\rangle$	0.85, 0.71, 0.45	+0.35, -0.05, –0.30
$\langle 18, 2\rangle, \langle 30, 30\rangle, \langle 2, 18\rangle$	0.84, 0.71, 0.50	+0.30, -0.05, –0.25
$\langle 24, 8\rangle, \langle 4, 4\rangle, \langle 2, 18\rangle$	0.76, 0.71, 0.47	+0.31, -0.03, –0.28

In the experiments, two sets of experiments are conducted to study the rating decomposition results. The results are given in the Tables 1 and 2, where the decomposed trust value are averaged based on 100 independent observations. The learning step is initialized with the method in [22]. The user's rating is given as 0.75, and the constant for Shapley value computation is given as $L = R(c)$. Some necessary parameters, such as the initial reputation evidence, can be found in Tables 1 and 2.

5.2 Evaluation Results

Table 1 gives the results of sequential composition of s_1, s_2, s_3. The experiment contains a trustworthy service s_1, an untrustworthy service s_2 and a neutral service s_3. It can be observed from Table 1 that s_1 always contributes positive while s_3 negative. Moreover, when the positive and negative evidence of s_2 equally increases (see Line 2 in Table 1), its trust value would not change. The contributions of other services would get lower. Our approach can correctly reflect the results when the evidence scores change. Furthermore, when the evidence of certain services changes but the total number of evidence remain constant, the contribution of each service will change correspondingly. However, in [14], the weight for each service is designated aforehand, which is unable to reflect how each service contributes to the total composite service.

For deterministic composition structures, the maximum statistical error is 21% in the experiments. This is because that the overlays of finite Beta mixture are represented as unimodal distributions, which lead to the inaccurate observations. In this paper, a consistent factor μ, $\mu\in(0,1)$ is introduced to reduce the errors to some extent. Furthermore, Table 1 also proves the fairness that the positive contributions are always equal to the negative ones.

Table 2 shows the results of probabilistic composition of s_4, s_5, s_6 in Fig. 4. The maximum statistical error is 4.3% in this structure. The errors are much fewer than deterministic composition since the finite mixture models for probabilistic composition appears the similar features as the multiply learning from EM algorithm. The results in Table 2 are similar to those in Table 1. As most existing approach in [14-16] cannot support the probabilistic composition, their solutions cannot fairly produce the rating results.

5.3 Computation Cost

The computation costs between traditional Shapley value-based (SV-based) computation and the proposed optimization are compared in Fig. 5. From the figure, it can be observed that the computation cost of traditional approach increases rapidly with the number of component services. For only 20 component services, the approach requires more than 7 seconds for the computation. This can reflect the exponential time complexity for computing each component. While with the bit-vector encoding, it only requires less time for online computation. And the computation is independent of the invocation structures in composite service. Moreover, if the tables are computed offline, the time complexity will be further reduced to a constant value.

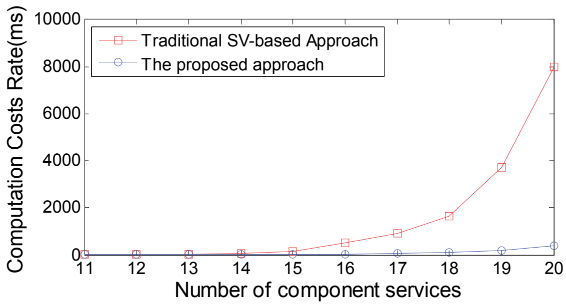

Fig. 5. Bit vector-based optimization.

5.4 Feature Comparison

The comparisons of features among different rating decomposition approaches are given in Table 3. Firstly, the proposed approach statically learns the responsibility and reputation using EM algorithm. It does not rely on the hypothesis of observable QoS or Reputation values. Therefore, it can solve the opaque structure issue for composite services. Secondly, the approach can support deterministic decomposition in the traditional structures. And it also supports the probabilistic rating decomposition, which are not specifically considered in most existing work. Therefore, the approach can comprehensively solve the intricate dependency issue. Thirdly, the approach can decompose the user's rating from the composite service to each component. There is no necessary for users to have professional knowledge about QoS judgment in trust evaluation procedures. Therefore, it can solve the subjective rating issue. Finally, the approach is proved based on the features of the Shapley value, which guarantees the fairness theoretically.

Table 3. Rating decomposition features comparison.

Features	The proposed approach	[14]	[15]	[16]	[18]
Opaque service structure	√	×	×	×	×
Intricacy dependency	√	×	×	×	√
Subjective rating	√	√	√	√	×
Fairness Proof	Yes	No	No	No	Yes

6. CONCLUSIONS

In service reputation systems, a key challenge is to design an effective rating decomposition approach by which each component service can be evaluated fairly. In this paper, an effective trust management approach has been proposed for decomposing feedback ratings from a composite service to component services. The proposed approach has three main contributions: 1) to solve the opaque service structure issue, it statistically learns the reputation history of each component in all structures based on EM algorithm; 2) to solve the intricate dependency issue, the Shapley value is employed to compute the contribution of each component to the whole composition. The computation rules are further optimized to obtain the computation results more effectively; and 3) to solve the fairness issue, a consistency factor is integrated in the evaluation process, then user's ratings can be fairly decomposed to each component in both horizontal and vertical ways. Theoretical analysis and experimental results demonstrate that the approach can effectively decompose user's rating on composite services to its components with fairness guarantee.

REFERENCES

1. J. Guo, J. Ma, X. Li, J. Zhang, and T. Zhang, "An attribute-based trust negotiation protocol for d2d communication in smart city balancing trust and privacy," *Journal of Information Science and Engineering*, Vol. 33, 2017, pp. 1007-1023.
2. O. A. Wahab, J. Bentahar, H. Otrok, and A. Mourad, "A survey on trust and reputation models for web services: Single, composite, and communities," *Decision Support Systems*, Vol. 74, 2015, pp. 121-134.
3. J. Jiang, G. Han, F. Wang, L. Shu, and M. Guizani, "An efficient distributed trust model for wireless sensor networks," *IEEE Transactions on Parallel and Distributed Systems*, Vol. 26, 2015, pp. 1228-1237.
4. D. Wu, S. Si, S. Wu, and R. Wang, "Dynamic trust relationships aware data privacy protection in mobile crowd-sensing," *IEEE Internet of Things Journal*, 2017, DOI: 10.1109/JIOT.2017.2768073.
5. J. Xiong, Y. Zhang, X. Li, M. Lin, Z. Yao, and G. Liu, "Rse-pow: a role symmetric encryption pow scheme with authorized deduplication for multimedia data," *Mobile Networks and Applications*, 2017. DOI: 10.1007/s11036-017-0975-x.
6. S. Sicari, A. Rizzardi, L. Grieco, and A. Coen-Porisini, "Security, privacy and trust in internet of things: The road ahead," *Computer Networks*, Vol. 76, 2015, pp. 146-164.
7. Y. Li, C. Wu, and C. Lai, "A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship," *Decision Support Systems*, Vol. 55, 2013, pp. 740-752.
8. X. Li, F. Zhou, and X. Yang, "Scalable feedback aggregating (sfa) overlay for large-scale p2p trust management," *IEEE Transactions on Parallel and Distributed Systems*, Vol. 23, 2012, pp. 1944-1957.

9. B. Ye, Y. Wang, and L. Liu, "Crowddefense: A trust vector-based threat defense model in crowdsourcing environments," in *Proceedings of IEEE International Conference on Web Services*, 2017, pp. 245-252.
10. A. Jøsang, R. Ismail, and C. Boyd, "A survey of trust and reputation systems for online service provision," *Decision Support Systems*, Vol. 43, 2007, pp. 618-644.
11. T. Zhang, J. Ma, N. Xi, X. Liu, Z. Liu, and J. Xiong, "Trustworthy service composition in service-oriented mobile social networks," in *Proceedings of IEEE International Conference on Web Services*, 2014, pp. 684-687.
12. Y. Wang, I. R. Chen, J. H. Cho, A. Swami, Y. C. Lu, C. T. Lu, and J. Tsai, "Catrust: Context-aware trust management for service-oriented ad hoc networks," *IEEE Transactions on Services Computing*, 2017, DOI: 10.1109/TSC.2016.2587259
13. N. Bismeyer, S. Mauthofer, K. M. Bayarou, and F. Kargl, "Assessment of node trustworthiness in vanets using data plausibility checks with particle filters," in *Proceedings of IEEE Vehicular Networking Conference*, 2012, pp. 78-85.
14. S. Nepal, Z. Malik, and A. Bouguettaya, "Reputation propagation in composite services," in *Proceedings of IEEE International Conference on Web Services*, 2009, pp. 295-302.
15. I. da Silva and A. Zisman, "Decomposing ratings in service compositions," in *Proceedings of the 11th International Conference on Service-Oriented Computing*, 2013, pp. 474-482.
16. R. Sadeghi and M. A. Azgomi, "A method for fair propagation of user perceptions for trust management in composite services," *Service Oriented Computing and Applications*, Vol. 9, 2015, pp. 157-176.
17. A. Liu, Q. Li, L. Huang, and S. Wen, "Shapley value based impression propagation for reputation management in web service composition," in *Proceedings of IEEE International Conference on Web Services*, 2012, pp. 58-65.
18. A. Liu, Q. Li, X. Zhou, L. Li, G. Liu, and Y. Gao, "Rating propagation in web services reputation systems: A fast shapley value approach," in *Proceedings of International Conference on Database Systems for Advanced Applications*, 2014, pp. 466-480.
19. L. Li and Y. Wang, "Trust evaluation in composite services selection and discovery," in *Proceedings of IEEE International Conference on Services Computing*, 2009, pp. 482-485.
20. T. Zhang, L. Zheng, Y. Wang, Y. Shen, N. Xi, J. Ma, and J. Yong, "Trustworthy service composition with secure data transmission in sensor networks," *World Wide Web*, Vol. 21, 2018, pp. 185-200.
21. T. Zhang, J. Ma, Q. Li, N. Xi, and C. Sun, "Trust-based service composition in multi-domain environments under time constraint," *Science China Information Sciences*, Vol. 57, 2014, pp. 1-16.
22. N. Bouguila, D. Ziou, and E. Monga, "Practical bayesian estimation of a finite beta mixture through gibbs sampling and its applications," *Statistics and Computing*, Vol. 16, 2006, pp. 215-225.

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