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Subjective Trust Inference in Composite Services

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Abstract

In Service-Oriented Computing (SOC) environments, the trustworthiness of each service is critical for a service client when selecting one from a large pool of services. The trust value of a service is usually in the range of [0,1] and is evaluated from the ratings given by service clients, which represent the subjective belief of these service clients on the satisfaction of delivered services. So a trust value can be taken as the *subjective probability*, with which one party believes that another party can perform an action in a certain situation. Hence, subjective probability theory should be adopted in trust evaluation. In addition, in SOC environments, a service usually invokes other services offered by different service providers forming a composite service. Thus, the global trust of a composite service should be evaluated based on complex invocation structures.

In this paper, firstly, based on Bayesian inference, we propose a novel method to evaluate the subjective trustworthiness of a service component from a series of ratings given by service clients. Secondly, we interpret the trust dependency caused by service invocations as conditional probability, which is evaluated based on the subjective trust values of service components. Furthermore, we propose a joint subjective probability method to evaluate the subjective global trust of a composite service on the basis of trust dependency. Finally, we introduce the results of our conducted experiments to illustrate the properties of our proposed subjective global trust inference method.

1 Introduction

In recent years, with the development of Internet technologies and distributed systems, Service-Oriented Computing (SOC) has become more and more important. SOC is a computing paradigm that utilizes services as basic constructs to support the development of rapid and low-cost composition of distributed applications even in heterogeneous environments (Papazoglou et al. 2008). In SOC, a service is an autonomous, platform-independent computational entity, which can be described, published, discovered and dynamically assembled for developing massively distributed systems (Papazoglou et al. 2008). In fact, any piece of code or application component deployed on a system can be taken as a service (Papazoglou et al. 2008).

By varying the requirements of different applications, it is usually necessary to effectively compose different kinds of services across domains forming a composite service, which requires that the involved service can be trusted by service clients and other collaborating services (Jøsang, Ismail, and Boyd 2007). Also, it is necessary for a trust management authority to be responsible of maintaining the list of trustworthy services and service providers, and bringing them to service clients (Vu, Hauswirth, and Aberer 2005).

Conceptually, trust is the measure taken by one party on the willingness and ability of another party to act in the interest of the former party in a certain situation (Knight and Chervany 1996). If the trust value is in the range of [0,1], it can be taken as the subjective probability with which, one party expects that another party performs a given action (Jøsang, Ismail, and Boyd 2007).

A binary rating system is adopted in eBay reputation management system and peer-to-peer (P2P) information-sharing networks (Jøsang, Ismail, and Boyd 2007; Xiong and Liu 2004). However, in SOC, a rating given by a service client is usually in the range of [0,1] (Jøsang, Ismail, and Boyd 2007; Vu, Hauswirth, and Aberer 2005), representing the subjective belief of the service client on the satisfaction of a delivered service. Based on the collected trust ratings representing the reputation of a service, the trust value of the service can be evaluated by the trust management authority.

In SOC environments, trust management is a very complex issue. To satisfy the specified requirement, a service may have to invoke other services forming composite services leading to complex invocation structures and trust dependency among services (Menascé 2004). Given a set of various services, different compositions may lead to different service invocation structures. Although these compositions certainly enrich service provision, they greatly increase the complexity of subjective trust evaluation and thus make a proper subjective global trust evaluation very challenging.

In the literature, though there are a number of studies on the global trust inference of composite services (Li and Wang 2009; Li, Wang, and Lim 2009), some problems remain open.

- According to the definitions introduced in (Jøsang, Ismail, and Boyd 2007; Knight and Chervany 1996), trust can be taken as the *subjective probability*, i.e. *the degree of belief that an individual has in the truth of a proposition* (Hamada et al. 2008; Jeffrey 2004), rather than the *classical probability* that we are familiar with, which is *the occurrence frequency of an event* (Hines et al. 2003; Jeffrey 2004). Hence, *subjective probability theory* should be adopted in trust evaluation.

- In our previous work (Li, Wang, and Lim 2009), a Bayesian inference based subjective trust evaluation approach has been proposed for aggregating the trust ratings of service components. It assumes that the trust ratings of each service component conform to a normal distribution, which is a continuous distribution. However, in most existing rating systems[1][2][3], trust ratings are discrete numbers, making them nearly impossible to conform to a continuous distribution. Therefore, the trust ratings of each service component should conform to a discrete distribution, based on which subjective probability theory can be adopted properly in trust evaluation.
- In composite services, all the dependency between service components results from direct invocations. When subjective probability theory is adopted in trust evaluation, the trust dependency should be interpreted properly with subjective probability theory.
- Although there are a variety of trust evaluation methods existing in different areas (Knight and Chervany 1996; Vu, Hauswirth, and Aberer 2005; Xiong and Liu 2004; Zacharia and Maes 2000), they either ignore the subjective probability property of trust ratings, or neglect the complex invocation structures. As a result, no proper mechanism exists yet for the subjective global trust inference of composite services.

In this paper, we first propose a Bayesian inference based subjective trust estimation method for service components. In addition, we interpret the trust dependency caused by service invocations as conditional probability, which can be evaluated based on the trust values of service components. Furthermore, we propose a joint subjective probability method to evaluate the subjective global trust of a composite service on the basis of trust dependency.

This paper is organized as follows. Section 2 reviews existing studies in trust management, service selection and service composition. Section 3 briefly introduces composite services with six atomic invocations. Section 4 presents our novel joint subjective probability method in composite services. Experiments are presented in Section 5 for further illustrating the properties of our proposed method. Finally Section 6 concludes our work.

2 Related Work

The trust issue has been widely studied in many applications. In e-commence environments, the trust management system can provide valuable information to buyers and prevent some typical attacks (Wang and Lim 2008; Zacharia and Maes 2000). In P2P information-sharing networks, binary ratings work pretty well as a file in P2P networks is either the definitively correct version or not (Yu, Singh, and Sycara 2004). In SOC environments, an effective trust management system is critical to identify potential risks, provide objective trust results to service clients and prevent malicious service providers from easily deceiving clients and leading to their huge monetary loss (Vu, Hauswirth, and Aberer 2005).

As we have pointed out in Section 1, trust is the *subjective belief* and it is better to adopt *subjective probability theory* to deal with trust evaluation. In the literature, there are some works to deal with subjective ratings. Jøsang (2002) proposes a framework for combining and assessing subjective ratings from different sources based on Dempster-Shafer belief theory. Wang and Singh (2007) set up a bijection from subjective ratings to trust values with a mathematical understanding of trust in multiagent systems. However, both models use either a binary rating (positive or negative) system or a triple rating (positive, negative or uncertain) system that is more suitable for security-oriented or P2P file-sharing trust management systems. In SOC, a rating as a numerical value in $[0, 1]$ is more suitable (Yu, Singh, and Sycara 2004).

In real SOC applications, the criteria of service selection should take into account not only functionalities but also other properties, such as QoS (quality of service) and trust. In the literature, a number of QoS-aware Web service selection mechanisms have been developed, aiming at QoS improvement in composite services. Zeng et al (2003) present a general and extensible model to evaluate the QoS of composite services, and a service selection approach using linear programming techniques to compute the optimal execution plan for composite services. The work by Haddad et al (2008) addresses the selection and composition of Web services based on functional requirements, transactional properties and QoS characteristics. In this model, services are selected in a way that satisfies user's preferences, expressed as weights over QoS and transactional requirements. Xiao and Boutaba (2005) present an autonomic service provision framework for establishing QoS-assured end-to-end communication paths across domains. Although the above works have their merits in different aspects, none of them has taken parallel invocation into account, which is atomic and one of the most common invocations in composite services (Menascé 2004; Yu, Zhang, and Lin 2007).

Xu et al. (2007) propose a reputation-enhanced QoS-based Web service discovery algorithm for service matching, ranking and selection based on existing Web service technologies. Malik and Bouguettaya (2009) propose a set of decentralized techniques aiming at evaluating trust with ratings to facilitate trust-based selection and composition of Web services. These works adopt non-binary discrete ratings. However, in these works, neither the subjective probability property of trust nor service invocation structure has been taken into account.

Considering service invocation structures in composite services, Li and Wang (2009) propose a global trust evaluation method. However, this method has not taken the sub-

[1]http://www.eBay.com/
[2]http://www.epinions.com/
[3]http://www.youtube.com/

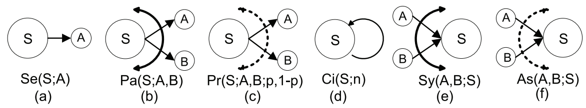

Figure 1: Atomic invocations

jective probability property of trust into account. Li, Wang, and Lim (2009) propose a Bayesian inference based subjective trust evaluation approach which aggregates the subjective ratings from other clients. Nevertheless, this approach still has some drawbacks. Firstly, it assumes that trust ratings conform to a normal distribution, which is a continuous distribution. However, trust ratings adopted in most existing rating systems[1,2,3] are discrete numbers. Thus, they cannot conform to a continuous distribution. Secondly, the subjective probability method (Bayesian inference) in (Li, Wang, and Lim 2009) is to evaluate the trust values of service components, rather than the global trust value of composite services. Finally, although it has considered service invocation structures, the global trust evaluation of composite services has not taken the subjective probability property of trust into account.

Considering the complex invocations of composite services, a proper subjective global trust inference method is necessary and important for trust-oriented composite service selection and discovery. This is the focus of our work in this paper.

3 Service Invocation Model

A *composite service* is a conglomeration of services with invocations between them. Six atomic invocations (Li and Wang 2009; Li, Wang, and Lim 2009) in composite services are introduced below and depicted in Fig. 1.

- *Sequential Invocation*: A service S invokes its unique succeeding service A. It is denoted as $\mathsf{Se}(S:A)$ (see Fig. 1(a)).
- *Parallel Invocation*: A service S invokes its succeeding services in parallel. E.g., if S has successors A and B, it is denoted as $\mathsf{Pa}(S:A,B)$ (see Fig. 1(b)).
- *Probabilistic Invocation*: A service S invokes its succeeding service with a certain probability. E.g., if S invokes successors A with the probability p and B with the probability $1-p$, it is denoted as $\mathsf{Pr}(S:A|p,B|1-p)$ (see Fig. 1(c)).
- *Circular Invocation*: A service S invokes itself for n times. It is denoted as $\mathsf{Ci}(S|n)$ (see Fig. 1(d)).
- *Synchronous Activation*: A service S is activated only when all its preceding services have been completed. E.g., if S has synchronous predecessors A and B, it is denoted as $\mathsf{Sy}(A,B:S)$ (see Fig. 1(e)).
- *Asynchronous Activation*: A service S is activated as the result of the completion of one of its preceding services. E.g., if S has asynchronous predecessors A and B, it is denoted as $\mathsf{As}(A,B:S)$ (see Fig. 1(f)).

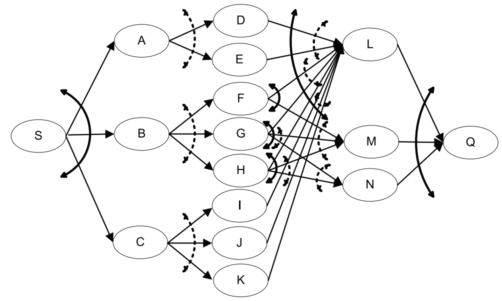

Figure 2: The *SIG* for the travel plan

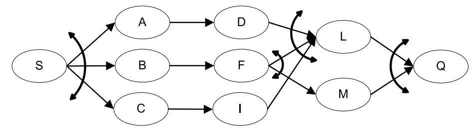

Figure 3: A service execution flow (*SEF*) in *SIG*

Here we introduce an example of composite services.

Example 1 Smith in Sydney, Australia is making a travel plan to attend an international conference in Atlanta, Georgia, USA. His plan includes conference registration, airline from Sydney to Atlanta, accommodation and local transportation. Regarding conference registration *A*, Smith could pay online *D* or by fax *E* with a credit card *L*. Regarding accommodation reservation *B*, Smith could make a reservation at hotel *F*, *G* or *H* with credit card *L*. According to the hotel choice, Smith could arrange the local transportation, e.g. take a taxi *M* to *F*, take a taxi *M* or a bus *N* to either *G* or *H*. Regarding airplane booking *C*, Smith could choose from airlines *I*, *J* and *K* with the credit card *L* for the payment.

In Example 1, starting with a *service invocation root S* and ending with a *service invocation terminal Q*, the composite service consisting of all combinations of travel plans can be depicted by a *service invocation graph* (*SIG*) in Fig. 2. Each feasible travel plan is termed as a *service execution flow* (*SEF*), which is the subgraph of *SIG*. An *SEF* example of the *SIG* in Fig. 2 is plotted in Fig. 3.

When a client searches the optimal *SEF* with the maximal global trust value from multiple *SEF*s in an *SIG*, a proper mechanism is necessary for the subjective global trust inference of an *SEF* from the trust ratings of service components and invocations between service components. This trust inference mechanism will be introduced in the next section.

4 Subjective Trust Inference

If a trust rating of a service is scaled to the range of $[0,1]$, it can represent the subjective probability with which the service provider is believed to be able to perform the service satisfactorily (Jøsang, Ismail, and Boyd 2007). Therefore, *subjective probability theory* (Hines et al. 2003; Jeffrey 2004) is the right tool for dealing with trust ratings (Li, Wang, and Lim 2009).

In Section 4.1, based on *Bayesian inference* (Hamada et al. 2008; Hines et al. 2003), which is an important component in subjective probability theory, we propose a novel method that evaluates the subjective trust of service components from a series of ratings given by service clients. In Section 4.2, we interpret the trust dependency caused by service invocations as conditional probability, which is evaluated based on the subjective trust values of service components. In Section 4.3, we propose a joint subjective probability method that evaluates the subjective global trust value of an *SEF* from the trust values and trust dependency of all service components.

4.1 Trust Estimation of Service Components

In most existing rating systems[123], trust ratings are discrete numbers, making the number of occurrences of ratings of each service component conform to a multinomial distribution (Hines et al. 2003). That is because in statistics if each trial results in exactly one of k (k is a fixed positive integer) kinds of possible outcomes with certain probabilities, the number of occurrences of outcome i ($1 \leq i \leq k$) must follow a multinomial distribution (Hines et al. 2003).

Rating Space and Trust Space In real systems, the trust ratings of a service given by service clients are represented by a series of fixed numbers. For example, the ratings at eBay[1] are in the set of $\{-1, 0, 1\}$. At Epinions[2], each rating is an integer in $\{1, 2, 3, 4, 5\}$. At YouTube[3], each rating is in $\{-10, -9, \ldots, 10\}$. In order to analyze these ratings, they should be normalized to the range of $[0, 1]$ in advance. Hence, the interval $[0, 1]$ is partitioned into k mutually exclusive ratings, say $r_1, r_2, \ldots$, and r_k ($0 \leq r_{i-1} < r_i \leq 1$). For example, at Epinions[2], after normalization, the ratings are in $\{0, 0.25, 0.5, 0.75, 1\}$. Hence, $r_1 = 0$, $r_2 = 0.25$, $r_3 = 0.5$, $r_4 = 0.75$, and $r_5 = 1$. Let $p_i = P(r_i)$ be the probability for a service to obtain the rating r_i ($i = 1, 2, \ldots, k$), and $\sum_{i=1}^{k} p_i = 1$. Let x_i be the number of occurrences of rating r_i in the rating sample, and $n = \sum_{i=1}^{k} x_i$.

Traditionally, some principles (Jøsang, Ismail, and Boyd 2007; Wang and Lim 2008) have been considered in trust evaluation. One of them is to assign higher weights to trust values of later services (Li and Wang 2008; Zacharia and Maes 2000), which can be interpreted as discounting former x_i over time. Because of such discount, x_i is taken as a real number. Accordingly, the rating space is modeled as $R = \mathbb{R}^k$, a k-dimensional space of reals.

Definition 1 The *rating space* for each service component is

$$R = \{X = (x_1, x_2, \ldots, x_k) | x_i \geq 0, x_i \in \mathbb{R}, i = 1, 2, \ldots, k\}.$$

Following the definition in (Jøsang 2001), the trust space for each service component can be partitioned into *trust* (a good outcome), *distrust* (a bad outcome) and *uncertainty*.

Definition 2 The *trust space* for each service component is

$$T = \{(t, d, u) | t \geq 0, d \geq 0, u \geq 0, t + d + u = 1\}.$$

Hence, if C is a service component in composite services, then let t_C, d_C and u_C denote the trust, distrust and uncertainty of C, respectively.

Bayesian Inference The primary goal of adopting Bayesian inference (Hamada et al. 2008; Hines et al. 2003) is to summarize the available information that defines the distribution of trust ratings through the specification of probability density functions, such as prior distribution and posterior distribution. The *prior distribution* summarizes the subjective information about the trust prior to obtaining the rating sample $X = (x_1, x_2, \ldots, x_k)$. Once X is obtained, the prior distribution can be updated to have the *posterior distribution*.

Let $V = (p_1, p_2, \ldots, p_{k-1})$ and $p_k = 1 - \sum_{i=1}^{k-1} p_i$. Because of lacking additional information, we can first assume that the prior distribution $f(V)$ is a uniform distribution. Since the rating sample X conforms to a multinomial distribution (Hines et al. 2003), i.e.

$$f(X|V) = \frac{n!}{\prod_{i=1}^{k}(x_i!)} \prod_{i=1}^{k} p_i^{x_i}, \qquad (1)$$

the posterior distribution can be estimated (Hines et al. 2003)

$$f(V|X) = \frac{f(X|V)f(V)}{\int_0^1 \int_0^1 \cdots \int_0^1 f(X|V)f(V)\mathrm{d}p_1 \mathrm{d}p_2 \cdots \mathrm{d}p_{k-1}} \qquad (2)$$

$$= \frac{(1 - \sum_{i=1}^{k-1} p_i)^{x_k} \prod_{i=1}^{k-1} p_i^{x_i}}{\int_0^1 \int_0^1 \cdots \int_0^1 ((1 - \sum_{i=1}^{k-1} p_i)^{x_k} \prod_{i=1}^{k-1} p_i^{x_i}) \mathrm{d}p_1 \mathrm{d}p_2 \cdots \mathrm{d}p_{k-1}}$$

Certainty, Expected Positiveness and Expected Negativeness The certainty of trust captures the confirmation of trust from ratings, i.e. for services with the same trust value, a service client prefers the service with the trust value determined by more ratings (Jøsang 2001).

In this section, the certainty of trust is defined based on statistical measure (Wang and Singh 2007). Since the cumulative probability of the probability distribution of V within Ω must be 1, let the distribution of V follow the function given below $g : \Omega = [0, 1] \times [0, 1] \times \cdots \times [0, 1] \to [0, \infty)$ such that $\int_\Omega g(V)\mathrm{d}V = 1$. Hence, the mean value of $g(V)$ within Ω is $\frac{\int_\Omega g(V)\mathrm{d}V}{(1-0)^{k-1}} = 1$. Following the common principle in statistics (Hines et al. 2003), without additional information, we can take the prior distribution $g(V)$ as a uniform distribution. The certainty can be evaluated based on the mean absolute deviation from the prior distribution (Wang and Singh 2007). Since $g(V)$ has a mean value of 1, both increment and reduction from 1 are counted by $|g(V) - 1|$. So $\frac{1}{2}$ is needed to remove the double counting. Therefore, the certainty is defined as follows:

Definition 3 The *certainty* based on rating sample X is

$$c(X) = \frac{1}{2} \int_\Omega \left| \frac{(1 - \sum_{i=1}^{k-1} p_i)^{x_k} \prod_{i=1}^{k-1} p_i^{x_i}}{\int_\Omega ((1 - \sum_{i=1}^{k-1} p_i)^{x_k} \prod_{i=1}^{k-1} p_i^{x_i}) \mathrm{d}V} - 1 \right| \mathrm{d}V$$

Since $\frac{1}{2}$ is the middle point of the range of ratings $[0, 1]$, which represents the neutral belief between distrust and trust, the ratings in $(\frac{1}{2}, 1]$ can be taken as positive ratings and the ratings in $[0, \frac{1}{2})$ can be taken as negative ratings.

Table 1: Ratings for service components in the *SEF*

	S	A	B	C	D	F	I	L	M	Q
t_1	1	0.5	1	0.75	1	0.75	1	1	0.75	1
t_2	1	0.75	1	0.75	1	1	1	0.75	1	1
t_3	1	0.75	0.75	0.75	0.25	1	1	1	1	1
t_4	1	1	1	0.75	1	1	1	1	0.75	1
t_5	1	1	1	1	1	0.75	1	1	1	1
t_6	1	1	0.75	0.75	0.25	0.75	1	1	1	1
t_7	1	0.5	1	0.75	0	0.5	1	1	0.75	1
t_8	1	1	0.75	0.75	1	0.75	0.75	1	1	1
t_9	1	1	0.75	0.75	0.75	1	0.5	1	1	1
t_{10}	1	0.75	0.75	0.75	0.75	0.75	1	0.75	1	1
t_{11}	1	0.75	0.75	0.5	1	1	0.75	1	1	1
t_{12}	1	0.75	1	1	0.75	1	0.5	0.75	0.5	1
t_{13}	1	0.75	0.75	0.75	1	1	0	1	0.5	1
t_{14}	1	1	0.5	0.75	0.75	1	1	1	1	1
t_{15}	1	1	1	0.75	1	0.75	1	1	0.75	1
t_{16}	1	1	1	0.75	1	1	1	1	0.75	1
t_{17}	1	1	1	0.25	0.25	1	0.5	0.75	1	1
t_{18}	0.75	1	0.75	0.5	1	1	1	1	1	1
t_{19}	1	0.75	0.75	1	1	1	0.75	0.75	1	1
t_{20}	1	1	1	0.5	1	0.75	1	1	0.75	1

Definition 4 The *expected positiveness* is defined to be the expected degree for ratings to be positive

$$\alpha(X) = \frac{\sum_{r_i > \frac{1}{2}} (2r_i - 1)x_i}{\sum_{i=1}^{k} x_i}, \tag{3}$$

and the *expected negativeness* is defined by

$$\beta(X) = \frac{\sum_{r_i < \frac{1}{2}} (1 - 2r_i)x_i}{\sum_{i=1}^{k} x_i}. \tag{4}$$

From Rating Space to Trust Space

Definition 5 Let $Z(X) = (t, d, u)$ be a transformation function from rating space R to trust space T such that $Z(X) = (t, d, u)$, where $t = \alpha(X)c(X)$, $d = \beta(X)c(X)$, and $u = 1 - (\alpha(X) + \beta(X))c(X)$.

According to Definition 5, we have $t + d + u = 1$ and the following property.

Property 1 For each trust rating $r_i \in [0, 1]$, we have

$$r_i \text{ is} \begin{cases} \text{distrust}, & \text{if } r_i \leq d; \\ \text{uncertainty}, & \text{if } d < r_i < d + u; \\ \text{trust}, & \text{if } r_i \geq d + u; \end{cases} \tag{5}$$

Example 2 We take the service execution flow (*SEF*) in Fig. 3 as an example to illustrate the trust estimation of a service component. All ratings of the service components in Fig. 3 are taken from Epinions[2] and are listed in Table 1.

For service component C, according to Definitions 3, 4 and 5, based on the ratings listed in Table 1, we can obtain $c = 0.88$, $\alpha = 0.48$, $\beta = 0.03$, $t = 0.42$, $u = 0.56$ and $d = 0.02$. According to Property 1, for a rating r_{Ci} of C, we have

$$r_{Ci} \text{ is} \begin{cases} \text{distrust}, & \text{if } r_{Ci} \leq 0.02; \\ \text{uncertainty}, & \text{if } 0.02 < r_{Ci} < 0.58; \\ \text{trust}, & \text{if } r_{Ci} \geq 0.58. \end{cases} \tag{6}$$

4.2 Probability Interpretation of Trust Dependency

In composite services, all the dependency, i.e. a state in which one object uses a functionality of another object, between service components results from direct invocations (e.g. atomic invocations in Fig. 1), i.e. if there is a direct invocation from A to B, then service component B is dependent on service component A. Therefore, the *service dependency principle* is introduced below.

Principle 1 In composite services, a service component is only dependent on its direct predecessor(s), and independent of any other service components.

According to Principle 1, the following *trust dependency principle* in composite services is derived.

Principle 2 In composite services, the trust of a service component is only dependent on its trust propensity and the trust of its direct predecessor(s), and independent of the trust of any other service components.

In an attempt to formalize the probability interpretation of trust dependency proposed in Principle 2, we identify the probability of the trust dependency of $Pd \succeq Sc$ with $P(Sc|Pd)$, where Pd is the direct predecessor of Sc and P is the subjective probability function. In the endeavor to furnish a logical analysis of trust dependency in composite services, according to the theorems about probabilities of conditionals and conditional probabilities (Hójek 2001), the following principle is introduced.

Principle 3 There is a certain invocation $\succeq$ in a composite service such that for the rational subjective probability function P, if the direct predecessors of a service component Sc are $Pd_1, Pd_2, \ldots, Pd_k$ in the composite service, we have

$$P(Pd_1 \wedge Pd_2 \wedge \ldots \wedge Pd_k \succeq Sc) = P(Sc|Pd_1 \wedge Pd_2 \wedge \ldots \wedge Pd_k)$$

Following Principle 3, the important link between probability theory and invocations in composite services has been well established. Then probability theory will be a source of insight into the invocation structure of composite services.

The graphical representation of composite services, service invocation graph (*SIG*), pictorially represents the service dependency properties in composite services (Li, Wang, and Lim 2009). In addition, Principle 3 enables an *SIG* to prove arbitrary service dependency conjectures concerning any service component in composite services. For example, in the *SEF* of Fig. 3, which is one of feasible service compositions of the *SIG* in Fig. 2, we can immediately read off the graph that

$$Q \perp\!\!\!\perp (S \wedge A \wedge B \wedge C \wedge D \wedge F \wedge I) \text{ and } (L \wedge M) \succeq Q, \tag{7}$$

where $\perp\!\!\!\perp$ denotes "is independent of".

Now we try to evaluate the conditional probability for the trust dependency in composite services. In subjective probability theory (Jeffrey 2004), the following principle has been proposed for building a bridge from objective probability, i.e. the occurrence frequency of an event (Hines et al. 2003), to subjective probability, i.e. the degree of belief that an individual has in the truth of a proposition (Hamada et al. 2008; Hines et al. 2003).

Principle 4 In subjective probability theory, without any additional knowledge, our knowledge that the chance of hypothesis H has probability p guarantees that our subjective probability for H is p. I.e. if P(the chance of H has p)=1, then $P(H) = p$.

Therefore, according to the definition of conditional probability and Property 1, in an *SIG*, the trust dependency, which is the conditional probability of the trust of a service component given the trust of its predecessors, can be evaluated based on Principle 4. In addition, since the service invocation root in an *SIG* has no predecessor, its trust dependency can be evaluated according to Property 1 and Principle 4 directly.

Here we assume that when a rating of a delivered service is stored by the trust management authority, the invocation relationship (i.e. its predecessor(s)) is also recorded.

Example 3 Let us continue the computation in Example 2 to illustrate the evaluation of the conditional probability for the trust dependency in composite services. In Example 2, every rating of a service component can be judged as distrust, uncertainty or trust. Here we take trust dependency $P(t_I|t_C)$ as an example to illustrate the computation details.

Following Principle 2, $P(t_I|t_C)$ has no relation to the trust of any other service component, making it possible to adopt Principle 4. Hence, following the definition of conditional probability, $P(t_I|t_C)$ is the chance of the trust of service component I given the trust of service component C. According to the ratings in Table 1, we have $P(t_I|t_C) = 13/20 = 0.65$.

4.3 Joint Subjective Probability Method

In this section, the *joint subjective probability method* is proposed to take the subjective global trust value of an *SEF*, $P(t_{SEF})$, as a joint probability distribution.

Definition 6 The subjective global trust value of an *SEF* can be factorized into a series of trust dependency in the *SEF*, i.e.

$$P(t_{\text{SEF}}) = \prod_{v \in \text{SEF}} P(t_v | \bigwedge_{u^{(i)} \in \text{SEF}, u^{(i)} \succeq v} t_{u^{(i)}}). \tag{8}$$

Let's take the *SEF* in Fig. 3 as an example to illustrate our proposed joint subjective probability method. Following Definition 6, we can obtain

$$\begin{aligned} P(t_{SEF}) = P(t_S)P(t_A|t_S)P(t_B|t_S)P(t_C|t_S)P(t_D|t_A) \\ P(t_F|t_B)P(t_I|t_C)P(t_L|t_D \wedge t_F \wedge t_I) \\ P(t_M|t_F)P(t_Q|t_L \wedge t_M) \end{aligned} \tag{9}$$

By applying the breadth-first search algorithm, since each trust dependency (e.g. $P(t_I|t_C)$ or $P(t_Q|t_L \wedge t_M)$) in an *SEF* (e.g. those in Eq. (9)) can be evaluated (as illustrated in Example 3), the subjective global trust value of the *SEF* in Fig. 3, $P(t_{SEF})$, can be computed. Due to space constraints, the details of this algorithm are omitted.

5 Experiments and Analysis

In this section, we will study the properties of our trust estimation method for service components, after which we will present the results of our conducted experiments for studying our subjective global trust inference method.

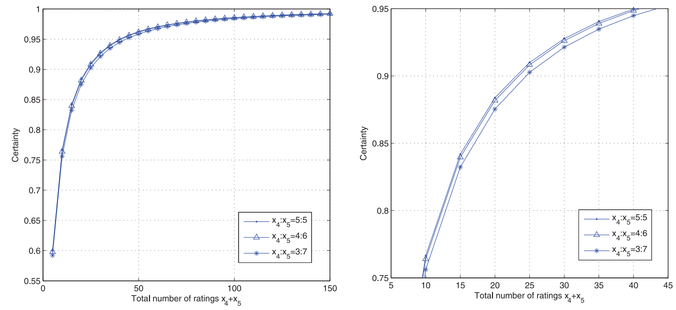

Figure 4: Certainty with fixed ratio of x_4 and x_5

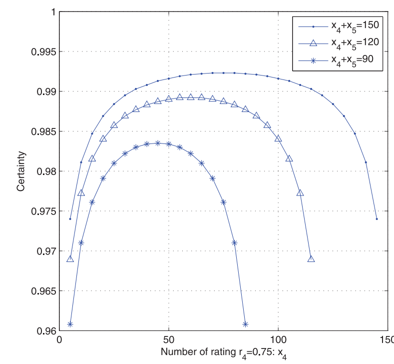

Figure 5: Certainty with fixed $x_4 + x_5$

In these experiments, ratings are taken from Epinions[2], which is a popular online reputation system, and each rating is an integer in $\{1, 2, 3, 4, 5\}$. After normalization, a rating is in $\{0, 0.25, 0.5, 0.75, 1\}$. The rating dataset adopted in this paper has 664824 ratings in total, out of which 6.50% are 0, 7.62% are 0.25, 11.36% are 0.5, 29.23% are 0.75 and 45.28% are 1. In general, the ratings at Epinions are observed to be surprisingly positive.

5.1 Important Properties in Trust Estimation

Since certainty is important for trust estimation of service components, which is the foundation of our proposed subjective global trust inference method, we will illustrate its important properties in this section.

Let x_i be the number of occurrences of rating r_i in the rating sample ($0 \leq i \leq k$). In this section, we will mostly focus on the cases when $x_1 = x_2 = x_3 = 0$, which corresponds to the scenario that our adopted Epinions rating dataset is observed to be surprisingly positive. This scenario also universally exists in the other rating datasets, such as eBay, as reported in (Jøsang, Ismail, and Boyd 2007).

Firstly, let us consider a scenario where the total number of ratings is increasing when $x_1 = x_2 = x_3 = 0$ and the ratios of x_4 and x_5 is fixed. Let $x_4 : x_5$ be $3 : 7$, $4 : 6$

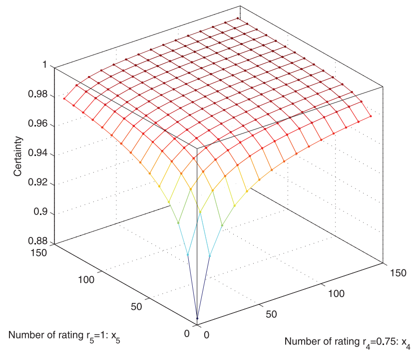

Figure 6: Certainty with x_4 and x_5 when $x_1 = x_2 = x_3 = 0$

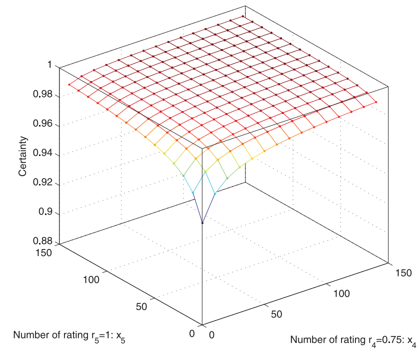

Figure 7: Certainty with x_4 and x_5 when $x_1 = x_2 = 0$ and $x_3 = 10$

Table 2: Trust estimation of service components

	S	A	B	C	D	F	I	L	M	Q
c	0.83	0.89	0.89	0.88	0.62	0.88	0.62	0.87	0.89	0.82
α	0.98	0.73	0.73	0.48	0.7	0.78	0.73	0.88	0.75	1
β	0	0	0	0.03	0.13	0	0.05	0	0	0
t	0.80	0.65	0.64	0.42	0.43	0.69	0.45	0.76	0.67	0.82
u	0.20	0.35	0.36	0.56	0.49	0.32	0.52	0.24	0.33	0.18
d	0	0	0	0.02	0.08	0	0.03	0	0	0

Table 3: Trust dependency in *SEF*

$P(t_A\|t_S)$	1	$P(t_D\|t_A)$	1	$P(t_L\|t_D \wedge t_F \wedge t_I)$	0.65
$P(t_B\|t_S)$	0.8	$P(t_F\|t_B)$	0.8	$P(t_M\|t_F)$	1
$P(t_C\|t_S)$	1	$P(t_I\|t_C)$	0.65	$P(t_Q\|t_L \wedge t_M)$	1

and $5:5$ respectively, and we can observe how the function curve of certainty changes in Fig. 4, where Fig. 4 (right) is a part enlarged from Fig. 4 (left). Below we introduce a theorem that generalizes the case illustrated in Fig. 4.

Theorem 1 If $x_i : x_j$ $(i \neq j)$ is fixed, given the fixed x_h $(h \neq i, h \neq j)$, the certainty of ratings increases with the total number of ratings.

Proof idea: Show that $c'(x_j, x_k, x_l, x_m, x_i) > 0$ for $x_i : x_j = k$ and fixed x_k, x_l and x_m. □

Due to space constraints, the full proofs of all theorems in this paper are included in our technical report available at http://www.comp.mq.edu.au/∼yanwang/TR201001.pdf.

Secondly, let us consider a scenario where x_4 is increasing when $x_1 = x_2 = x_3 = 0$ and $x_4 + x_5$ is fixed. We set $x_4 + x_5 = 150$, 120 or 90 respectively, and observe how the function curve of certainty changes in Fig. 5. Hence, we can have the following theorem generalizing the observations.

Theorem 2 If $sum = x_i + x_j$ $(i \neq j)$ is fixed, given the fixed x_h $(h \neq i, h \neq j)$, the certainty of ratings is increasing when $x_i < sum/2$; otherwise, the certainty of ratings is decreasing when $x_i > sum/2$.

Proof idea: Show that the deviation from the prior distribution increases with the increment of x_i when $x_i < sum/2$, and the deviation from the prior distribution decreases with the increment of x_i when $x_i > sum/2$. □

In addition, let us consider a scenario where x_4 and x_5 are increasing when $x_1 = x_2 = x_3 = 0$.

In Fig. 6, when x_4 is fixed and $x_1 = x_2 = x_3 = 0$, the certainty of ratings increases with the increment of x_5. Meanwhile, when x_5 is fixed and $x_1 = x_2 = x_3 = 0$, the certainty of ratings increases with x_4. Furthermore, we can observe that the plane of certainty function is symmetric with the plane of $x_4 = x_5$. Hence, we can have the following theorem.

Theorem 3 $c(x_i, x_j, x_k, x_l, x_m) = c(x_j, x_k, x_l, x_i, x_m)$ for fixed x_k, x_l and x_m.

Proof: According to Definition 3, $c(x_i, x_j, x_k, x_l, x_m) = c(x_j, x_k, x_l, x_i, x_m)$ for fixed x_k, x_l and x_m. □

Finally, let us consider a scenario where x_4 and x_5 are increasing when $x_1 = x_2 = 0$ and $x_3 = 10$. The properties illustrated in Fig. 7 are similar to those in Fig. 6. Hence, we can have the following theorem.

Theorem 4 The certainty of ratings increases with x_i, the number of occurrences of rating r_i, given the fixed x_h $(h \neq i)$.

Proof idea: Show that given the fixed x_h, the deviation from the prior distribution increases with the increment of x_i. □

The above theorems show how certainty, which is important to determine the trust according to Definition 5, evolves with respect to the increment of the number of a rating's occurrences under different conditions. Following these theorems, a service provider, who wishes his/her service to achieve a specific level of certainty, can ask the trust management authority to find out how many trust ratings would be needed under a certain condition, or a service client can ask the trust management authority to compute certainty to see if a service has reached an acceptable level.

5.2 Experiment on Subjective Trust Inference

In this section, we take the service execution flow (*SEF*) in Fig. 3 as an example to illustrate the computational details of our subjective global trust inference method.

Experiment on Trust Estimation of Service Components In this experiment, all the ratings of service components are taken from Epinions[2] and are listed in Table 1.

Following Definitions 3, 4 and 5, with the ratings listed in Table 1, the certainty c, expected positiveness α, expected negativeness β, trust t, uncertainty u and distrust d can be calculated respectively and listed in Table 2. According to Table 2 and Property 1, each rating of a service component can be judged as distrust, uncertainty or trust. Please refer to Example 2 for details.

Experiment on Joint Subjective Probability Method Every trust dependency in Fig. 3 can be evaluated (as illustrated in Example 3), and the computed results are listed in Table 3. The trust of service invocation root S can be computed based on the ratings directly (as illustrated in Example 2), and $P(t_S) = 1$.

Following the joint subjective probability method proposed in Section 4.3, the subjective global trust value of the *SEF* in Fig. 3, $P(t_{SEF})$, can be evaluated by Eq. (9) and $P(t_{SEF}) = 1\times1\times0.8\times1\times1\times0.8\times0.65\times0.65\times1\times1 = 0.3328$.

6 Conclusions

In this paper, firstly, our proposed subjective trust estimation method for service components is based on Bayesian inference, which is a component of subjective probability theory. This novel method can aggregate the non-binary discrete subjective ratings given by service clients and keep the subjective probability property of trust. In addition, the trust dependency caused by service invocations is interpreted as conditional probability, which is evaluated based on the subjective trust estimation of service components. This novel interpretation makes it feasible to deal with invocation structures with subjective probability theory. Furthermore, on the basis of the above fundamental subjective trust estimation and probability interpretation of trust dependency, a joint subjective probability method has been proposed to evaluate the subjective global trust value of a composite service.

To our best knowledge, this is the first work in the literature on subjective trust estimation for service components based on non-binary discrete ratings. This is also the first work in the literature on subjective global trust inference of composite services with complex invocation structures.

In our future work, with our subjective global trust inference model, efficient algorithms will be studied for trust-oriented composite service selection and discovery.

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