Correlated Contribution Analysis for Service Composition in Dynamic Environments

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***Abstract*—Service Oriented Computing Systems can be considered as a type of complex systems consisting of a number of loosely coupled autonomous and adaptive components (i.e., service components). Service quality depends on the performance of the "service group", and many dynamic factors including the expectation of service consumers, the availability of resources, etc. Trust is an important factor for determining the interrelationships among service components. In this paper, we consider the dynamic factors in service composition, and propose a trust management approach, which adopts related methods in information theory, to enable more reliable service composition in dynamic environments. From the experimental results, we claim that the proposed approach can effectively handle dynamic factors in open environments, and obtain better service composition results.**

I. Introduction

In Service Oriented Computing (SOC) Systems, services are regarded as resources to support the development of low-cost, inter-operable, evolvable and massively distributed application [2]. In a SOC system, different individual services may belong to different providers, and provide overlapping (or even identical) but limited functions. To handle some complex tasks, composite services are required to provide higher level solutions. Service composition is the process of discovering, selecting and grouping available service components. The flexibility of SOA is helpful for providing value-added services easily and quickly by composing existing services [2], but meanwhile, also brings difficulties for trust management and the control of the quality of service (QoS).

The inter-component dependency and correlation among service components of a composite service are loose and multivariate. After each execution, the quality of service (QoS) can be measured by using some standard criteria, e.g., response time, availability, etc, or based on the feedbacks from the service consumer(s). However, as the measurement can only reflect the overall performance of the whole "group" (i.e., the composite service), it is impossible to have accurate trust evaluation without analyzing the inter-relationships among different service components. Therefore, how to select the individual service from large number of candidates, to compose a group service for the particular request from service consumers and also guarantee high QoS to some extent, is a challenging task in SOC systems.

In this research, we intend to propose a more robust service composition approach for dynamic environments. Different with traditional approaches, our approach adopts some methods in information theory to reveal "trust relationships" among different service components. The correlations and dependencies among both service types and individual services are considered in trust analysis and prediction. Service compositions are generated based on the prediction of composite services' trust values.

The rest of this paper is organized as follows. First, we briefly mention the related work in Section 2. The description of the problems we want to handle, and some assumptions in this research are presented in Section 3. The details of the Correlated Contribution Model is described in Section 4. Finally, the paper is concluded and future work is outlined in Section 5.

II. Background and Related Work

Services are self-contained, self-describing and modular applications that can be published located, and invoked across the Web [1]. According to the request from a service consumer, multiple services are aggregated into a composite service to accomplish task. There are two types of service composition, i.e., static composition and dynamic composition. Firstly, if concrete services for the service composition are chosen at design time, it is called static composition. On the other hand, in terms of dynamic composition, all concrete services are chosen at runtime. When referring to the approaches of service composition, it contains three steps: (1) planning, (2) definition, and (3) implementation [1]. At the beginning, the structure of service composition about the abstract service components and workflow will be defined in the request module. Then, the concrete services for each service component are defined by the trust calculation module and the evaluation module. Finally, the reply module will return the most trustable service composition and obtain the feedback from consumer once completing the service composition implementation [11].

With various objectives, several popular algorithms and models for service composition have already been proposed. A cost-based workflow scheduling algorithm is proposed in [12]. The algorithm minimizes execution cost while meeting time constraint for delivering solutions. Garg et al. introduced the

LPGA algorithm to reduce the combined user spending and resource utilization [5]. Taking running time and reliability as scheduling objectives, Dongarra et al. proposed a bi-objective scheduling algorithm in [4]. All these models target at the balancing between the cost and running time for service composition, but there also exit other attributes may reflect composite services' QoS. In terms of priority distributions on attributes of the service, Su et al. proposed a GTrust model applying different merits to evaluate the trust value of services [11]. However, the GTrust model only considers the historical records for each group members, but ignores many other factors such as the uncertainty of the environment and the correlation among different individual services and service types.

To cover some limitation in the existing service composition methods, in this paper, we propose a novel service composition approach, which takes dynamic factors (e.g., the expectation of service consumers, the availability of resources, etc) into account. In our service composition approach, the qualities of composite services are considered as random "behaviors" of "service groups". In addition, some methods in information theory are adopted in our approach to manage randomness and enable better service composition in SOC systems.

In information theory, information is a method to measure the amount of information required to describe both regular, rule-governed behavior and irregular, random behavior [3]. Probability p is used as a tool for dealing with uncertainty, which represents the likelihood of an event based on knowledge of physical law and on the historical events. Actually, probability is the ratio of the favorable cases to the whole number of cases possible, so it is a theoretical expectation of a frequency of occurrence [6].

Three concepts in information theory, i.e., Entropy $H(X)$, Mutual Information $I(X;Y)$ and Conditional Mutual Information $I(X;Y|Z)$, are adopted in our approach. Firstly, entropy is used to calculate the uncertainty level of composite services' QoS. Secondly, mutual information is used to measure the reduction of a particular service type or individual service to the uncertainty level. Finally, the conditional mutual information measures the reduction of QoS's uncertainty due to the knowledge of one service type ST_i (or individual service s_i^k) when another service type (or individual service) is given [3].

III. Problem Definition

In our approach, we suppose that there is a universe of n service types ST=$\{ST_1, ST_2, ST_3,..., ST_n\}$ which have already been predefined in a SOC system. All individual services, owned by diverse service providers, are loosely coupled. When an individual service s is registered with the system, it is classified into a particular service type. An *individual services* is represented as s_i^l, where i is the ID of the service type s_i^l belongs to, and l is the unique ID of s_i^l in its service type, i.e., ST_i.

Definition 1: A *service request* R is defined as a 3-tuple, i.e., $R = (RequestID, ReqTypeSet = \{ST_i, ST_j, ST_k, ...\})$. *RequestID* is the unique identifier for each service request, and *ReqTypeSet* is a finite set of service types, which are required to achieve the functional requirement of the request.

When a service consumer submits his/her functional requirements to system, the system will generate a request *R* containing a subset of service types to meet the functional requirement. For example, in the Ecommerce domain, a request can be R=(0001, $\{ST_1, ST_5, ST_7\}$), where ST_1 stands for "Manufacturer", ST_5 stands for "Seller", and ST_7 stands for "Delivery". For each selected service types ST_i in the subset, the system will choose a particular individual service s_i^l to actually complete the task. Therefore, the system will generate a group of individual services (or composite service) for the request. After the completion of the composite service, the system will generate service feedback RF which both contains the information about group member and QoS.

Definition 2: The *service feedback* Rf is defined as a 3-tuple, $RF =< TranID, GS, Q >$. $TranID$ is the ID of the composite service that the *Rf* corresponding to. *Q* is the QoS value of the composite service. GS represents which individual services are selected from each service type:

$$GS = \begin{pmatrix} ST_i & ST_j & ST_k \\ s_i^l & s_j^m & s_k^n \end{pmatrix}$$

Definition 3: The *correlated contribution* CR is defined as the correlations among different service types or individual services in contributing to the deduction of uncertainty levels of QoS value.

We believe correlated contributions to QoS are existing in two levels, i.e., the service type level and the individual service level. In this research, two undirected weighted graphs [8], i.e., the Service Type Graph and the Individual Service Graph (refer to Definitions 4 and 5), are used to represent the correlations in the two levels, respectively.

Definition 4: The *service type graph* is an undirected weighted graph $G_{ST}(ST, STCE)$. Every node of G_{ST} corresponds to a particular service type, i.e., ST_i. $STCE_{ij}$ represents correlated contribution edge between two service types, i.e., ST_i and ST_j, and $STCR_{ij}$ ($0 \leq STCR_{ij} \leq 1$) is defined as the weight of edge between ST_i and ST_j (see Fig. 1).

Once received a request R, the system will generate a finite set of service types (required types) to meet the functional requirement. As the same service type may play different roles in different types of service requests, trust contribution of service types (i.e., nodes) will be calculated based on the value of $STCR_{ij}$ and required types in *R*.

After the required types have been fixed, all possible compositions of individual services can be known. In order to calculate the trust value for the possible compositions, we should find out the correlated edge between individual services as well.

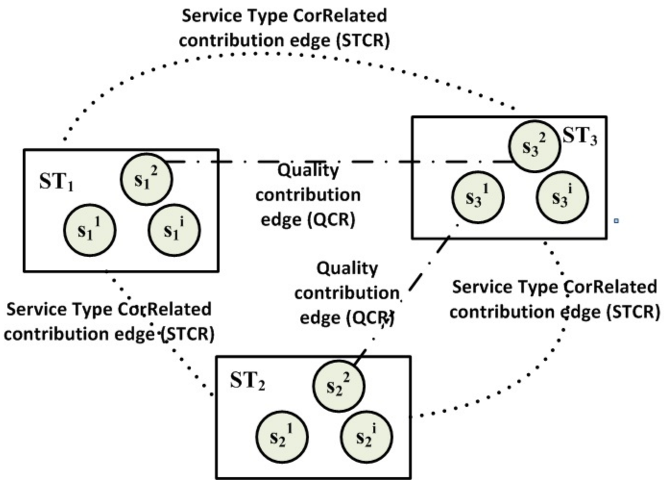


Fig. 1: Correlated Contribution among Service Types and Quality Contribution among Individual Services

Definition 5: The *individual service graph* is an undirected weighted graph $G_{IS}(IS, ISCE)$. Every node of G_{IS} corresponds to a particular individual service, i.e., s_i^l. $ISCE_{il,jm}$ represents quality contribution edge between two individual services, i.e., s_i^l, s_j^m, and QCR_{ij} $(-1 \leq QCR_{il,jm} \leq 1)$ is defined as the weight of edge between s_i^l, s_j^m.

Different with $STCR_{ij}$, the value of $QCR_{il,jm}$ is determined by not only the correlation degree between two individual services, but also historical performance of composite services, which contain both of the two individual services. Therefore, $QCR_{il,jm}$ can have a negative value, which means the coexistence of s_i^l and s_j^m will cause poor performance in composite services. The equations for calculating $STCR_{ij}$ and $QCR_{il,jm}$ will be introduced in Section IV.

IV. Analysis of Correlated Contribution

As mentioned in the previous section, there are dependencies and correlations between service types in a SOC system. For example, in the food industry, the main service types are manufacture, delivery and retailing. Service qualities of manufacture and delivery will directly influence the quality of the food. Obviously, these two service types have very strong correlation with food quality. On the other aspect, the collaboration relationship between a manufacturer and a delivery company will also impact on the quality of the food. Therefore, correlated contributions exist in both the service type level and the individual service level. In our approach, we intend to analyze such correlations, and predict the most "trustable" compositions according to the analysis results.

In this approach, the QoS of a composite service is assumed as a random behavior. The uncertainty of such a random behavior is related with the required types in the service request, and can be reduced with the existence of a particular individual service. Therefore, we firstly calculate the Quality Entropy ($H(Q)$) by using Equation 1 to measure average uncertainty of the QoS value of composite services [3]. Then, mutual information (i.e., $I(Q;X)$) [10] is used to measure how much reduction can a particular service type ST_i or individual service s_i^k make to the uncertainty of the QoS value. Finally, the conditional mutual information (i.e., $I(Q;X|Y)$) [3] is calculated by using Equation 2 to measure the uncertainty reduction due to a service type or individual service (X in Equation 2) when another service type or individual service (Y in Equation 2) is given [9].

$$H(Q) = -\sum p(Q) \log_2 p(Q) \tag{1}$$

$$\begin{aligned} I(Q;X,Y) &= I(Q;X) + I(Q;Y|X) \\ &= I(Q;Y) + I(Q;X|Y) \end{aligned} \tag{2}$$

If service types (or individual services) X and Y are strongly correlated, $I(Q;X)$ should be smaller than $I(Q;X|Y)$. Furthermore, when a service type ST_j or individual service s_j^l is given, the reduction of QoS uncertainty due to another service type ST_i or individual service s_i^k is larger than the reduction caused by ST_i or s_i^k. If a service type or individual service (i.e., X) is totally independent with the QoS value, $I(Q;X) = 0$. If a service type ST_j or individual service s_j^l (i.e., X) is independent with the QoS value and another service type or individual service (i.e., Y), then $I(Q;X|Y) = 0$.

A. Calculation of Service Type Correlated Contribution

Mutual information and conditional mutual information are used to calculate correlated contribution edges in the service type graph $G_{ST}(ST, STCR)$ for different request R. The "decision" Q is set to the selection of individual services for achieving expected QoS. The correlation measurement is to quantify the information redundancy between ST_i and ST_j with respect to Q in all request records by using Equations 3 and 4.

$$STCR_{ij} = \frac{I(Q;ST_i,ST_j)}{H(Q)} \tag{3}$$

$$WST_{ij} = \frac{STCR_{ij}}{STCR_{ij} + STCR_{ik} + STCR_{jk}} \tag{4}$$

where WST_{ij} is correlated contribution of ST_i and ST_j for the required types in request R. The larger $STCR_i j$ is, the closer between service types ST_i and ST_j are, and the less uncertainty the QoS value is. When service types ST_i and ST_j are completely correlated, they contribute 100 percents in determining Q, i.e., $STCR_{ij}$=1.

B. Calculation of Joint Individual Service Quality Contribution

The correlation between two individual services is also impacted by the service types they belong to. Hence, we also use service quality contribution edge to decide the optimum route for the final service composition. However, the correlation values may have two different meaning, i.e., complementariness or exclusion. Complementariness means that two individual services, e.g., s_i^l and s_j^m, are positively correlated with respect to the QoS value of the composite services they participate to. Namely, a high QoS is more likely to be achieve. Exclusion means that two individual services, e.g., s_i^m and s_j^n, are negatively correlated with respect to the QoS value of the composite services they participate to. Namely, a low QoS value is more likely to be obtained. Therefore, in our approache, the QoS value of previous composite services participated by these two individual services are also been taken into account by using the following Equation 5.

$$p(Q^{threshold}) = \frac{count(Q_i \geq threshold)}{\sum_{q=1}^{n} count(Q_i)} \tag{5}$$

In Equation 5 $p(Q^{threshold})$ represents the proportion of previous composition where both s_i^l and s_j^m have involved, and with QoS value greater than the required quality threshold. In addition, users can also define their quality weight assignment functions $W_{Q_q} = f(Q_q)$ $(-1 \leq W_{Qq} \leq 1)$, where Q_q is a QoS value and W_{Q_i} represents the assigned weight value for the QoS value. For example, if "level 1" and "level 4" represent the highest and lowest quality levels, respectively. A user can have the following quality weight assignment function: $W_{level1} = 1$ and $W_{level4} = -1$.

The weight of the quality contribution edge (QCR) between two joint individual services s_i^l and s_j^m can be calculated by using the following two equations.

$$CR(s_i^m, s_j^n) = \frac{I(Q; s_i^m) - I(Q; s_i^m | s_j^n)}{H(Q)} \tag{6}$$

$$QCR(s_i^m, s_j^n) = CR(s_i^m, s_j^n) * \sum_{q=1}^{n} p(Q_q) * W_{Q_q} \tag{7}$$

When individual services s_i^m and s_j^n are positively correlated with respect to the QoS value of composite services, the quality contribution edge will range from 0 to 1, which means there exists complementariness correlation between these two individual services. One the other hand, if there exists exclusion correlation between two individual services s_i^m and s_j^n, the quality contribution edge will range from 0 to -1. Moreover, if they contribute 100 percent information in determine decision Q, the absolute value of $QCR(ST_i, ST_j)$ equals to 1, which means that these two individual services s_i^m and s_j^n are completely correlated and all previous group service records including these two individual services reaching to same quality level. According to the $STCR_{ij}$ calculated from the service type level and the weighted service type correlated contribution edge WST_{ij} with respect to particular request, we can get different relevant correlation between different service type required by request by using Equation 8:

$$rST_{i,j} = WST_{ij} * STCR_{ij} \tag{8}$$

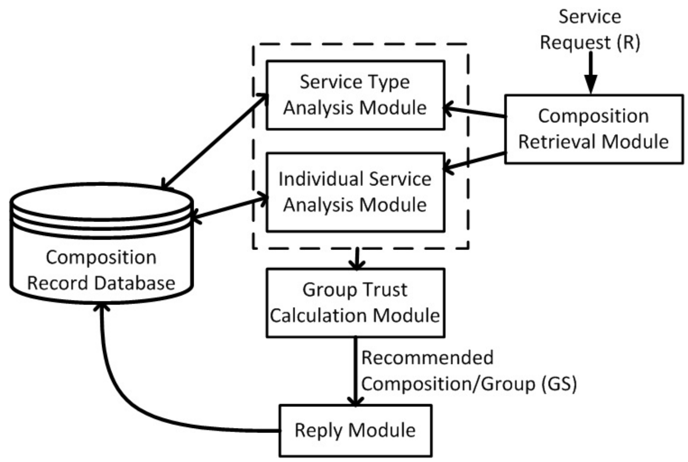


Fig. 2: Composition protocol

Therefore, the trust value for possible group composition can be calculated by summing all edge value within the path. Then, the best composition is the nodes (individual services) in the path with highest sum value (refer to Equation 10).

$$\begin{aligned} Trust \quad = \quad & rST_{i,j} * QCR(s_i^l, s_j^m) \\ & + rST_{i,k} * QCR(s_i^l, s_k^n) \\ & + rST_{j,k} * QCR(s_j^m, s_k^n) \end{aligned} \tag{9}$$

C. Composition protocol

In our approach, a service composition is generated from the protocol in Fig. 2. There are six major components in the protocol. Firstly, after the system receives a request, a service request R based on the functional requirements from the service consumer will be generated. Then the service request will be sent to the Composition Retrieval Module. The Composition Retrieval Module will search for all possible service groups which can satisfy *R*, and the number of possible groups is based on how many service types required in R and how many individual services are available in different service types. Then, based on the records in the Composition Record Database, the Service Type Analysis Module and the Individual Service Analysis Module will update the correlated contribution edge between service types, and the quality contribution edge between individual services. According the service request R, the Service Type Analysis Module will weigh the $STCR_{ij}$ and return rST_{ij} to the Group Trust Calculation Module. The default value for each $STCR_{ij}$ is 1.0. The default value will be not be updated until all $STCR_{ij}$ can be calculated. Therefore, at the beginning, all service types are given the same weight within the request. According to each possible potential group composition, the Individual Service Analysis Module will return $QCR(s_i^m, s_j^n)$ to the Group Trust Calculation Module. The default value for each $QCR(s_i^m, s_j^n)$ is 0.0, because we intend to give each individual service the same chance for being selected. Then, the Group

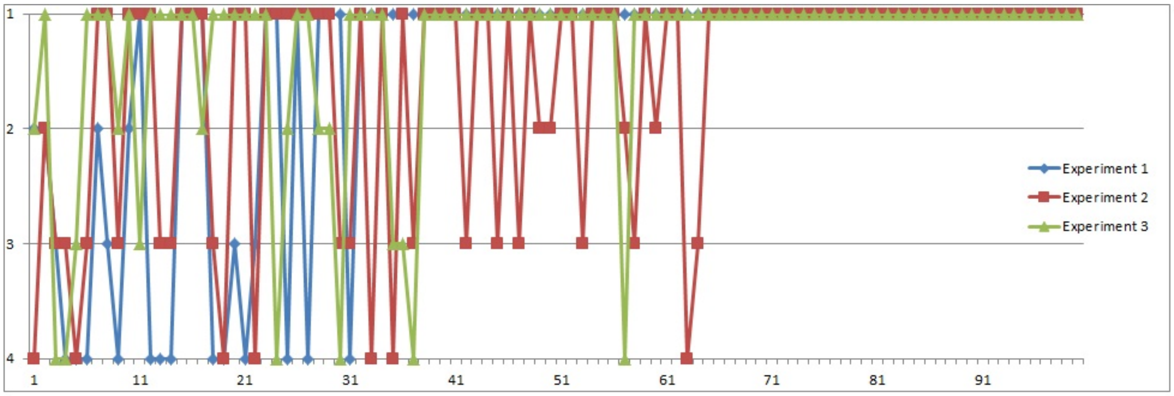


Fig. 3: Changing Trend of Quality of Composite Service by using Correlated Contribution Model

Trust Calculation Module will estimate a $Trust$ value for each potential group, and select the group (GS) with highest trust value. Then GS is returned to the Reply Module. If there are more than one groups obtain the highest trust value, the Group Trust Calculation Module will randomly pick a service group within these alternatives. Finally, the Reply Module generate a feedback RF for the recommended group (composite service) GS after the execution, and store the information into the Composition Record Database.

V. Experiment

A. Experiment setup

In the experiments, we included four service types, i.e., $\{ST_0, ST_1, ST_2, ST_3, ST_4\}$, in the system. Each service type contains five registered individual services, i.e., $ST_0 = \{s_0^0, s_0^1, s_0^2, s_0^3, s_0^4\}$, $ST_1 = \{s_1^0, s_1^1, s_1^2, s_1^3, s_1^4\}$, $ST_2 = \{s_2^0, s_2^1, s_2^2, s_2^3, s_2^4\}$, $ST_3 = \{s_3^0, s_3^1, s_3^2, s_3^3, s_3^4\}$. Each request R need three different service types to meet the functional requirements. Therefore, there exists four different kinds of requests: $\{ST_0, ST_1, ST_2\}$, $\{ST_0, ST_1, ST_3\}$, $\{ST_0, ST_2, ST_3\}$ and $\{ST_1, ST_2, ST_3\}$. There are six service type correlated contribution edges among the four service types, which are $STCR_{01}$, $STCR_{02}$, $STCR_{03}$, $STCR_{12}$, $STCR_{13}$ and $STCR_{23}$, respectively. Four quality levels are adopted for representing QoS (i.e., Level 1, 2, 3 and 4). Level 1 stands for the highest quality and Level 4 stands for the lowest. In the real word, it can be based on quality metrics for various QoS attributes, such as response time, reliability and availability, to measure QoS. In order to find the highest quality group service, we set four different quality weights for these four class: $W_1 = 1$, $W_2 = -0.1$,$W_3 = -0.5$ and $W_4 = -1$.

Firstly, we predefined six pairs of individual services with highly correlated relationships. Four of them have exclusion correlation, i.e., they have high possibility (over 90%) to generate low QoS values (e.g., Level=4). We also include two pairs of individual services with complementariness correlation, which means they have high possibility (over 90%) to generate high QoS values (e.g., Level=1). Secondly, we predefined all classification level for each possible group composition for each kind of request and saved them as true value table. There are 500 possible group composition in the true value table, 78 for Level 1 (high quality), 111 for Level 2, 140 for Level 3 and 171 for Level 4 (low quality). Thirdly, based on our algorithms we random generated 100 request and calculate the trust value for each alternative group composition. Then, choose the most trustable group composition. If the highest trust value equal to 0.0 (initial value), all the recommended group service will be randomly pick from those composition whose trust value equal to the highest trust value, because we want to get same chace for these group composition. Fourthly, in terms of each recommended group service, we get the predefined quality level GP for the true value table and then put it with group service member information GS into the feedback RF, and saved them as historic records for further calculation. All feedback will be stored in the Historic Group Service Record Database for further calculation.

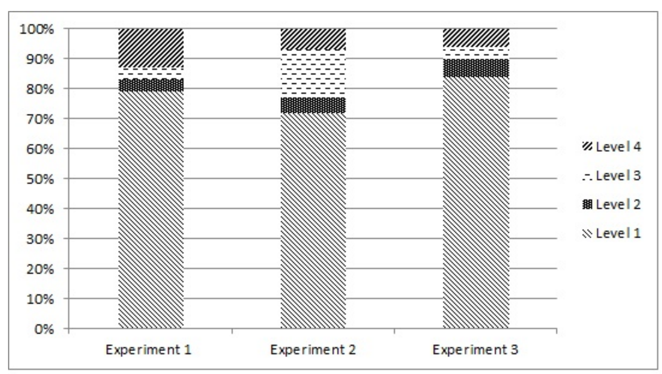


Fig. 4: QoS distribution of Composite Service by using the Correlated Contribution Model

B. Experimental Results

Fig. 3 shows the results of three experiments by using the proposed service composition approach. Each line represents the changing trend of 100 group service records for a particular experiment. The first line for Experiment 1 shows all records maintain at high quality since the 32th request. Though the

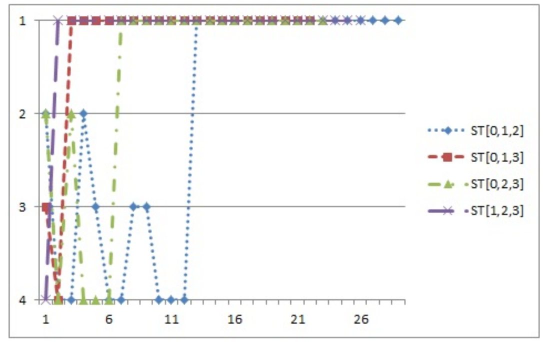
Experiment 2 performs most poorly, it also can find the best group composition for all request since 65th request. According to the Fig. 5a, in terms of one kind of particular request, at the beginning, the model randomly pick potential service group due to without enough knowledge until the highest quality service group appears. Once the high quality service group has been selected, the following quality of service group for such request will stand at highest level and maintain. In Fig. 4, the proportion of high quality service group picked for the request occupied at more than 70%, and even it reaches 84% in Experiment 3.

In order to compare the performance of Correlated Contribution model, we put the same dataset on Reputation Model and Random model and then get the result as following. Usually, the Reputation-Based models are implemented as a centralized rating system so that clients can report about the quality of composite service in previous transaction via rating [7]. The reputation of the individual service is based on the average quality of previous service group which the individual service used to join. We also conduct three times experiments for each model. Neither performance of Reputation-Based model or Random model is stable. In terms of Reputation-Based model, the general performance of group services increases compared with the beginning, but the quality is not stable. In Fig. 5b, the Reputation-Based model only figures out the highest quality (Level =1) service group for one kind of service request (i.e., $ST[0,2,3]$. It terms of the other three kinds of request, once the model pick a potential service group whose performance is better than previous, the quality may maintain at certain level without increasing any more, even it has not reached at the highest level. At the end, we compare the quality of group service distribution of the winner within each model in Fig. 6. From this figure, it can be seen that the Correlated Contribution model performs significantly better than the other two, as it generate more than 80% highest group service and the low quality records are less than 10%. In terms of the average quality of group service (see Fig. 7), our algorithm performs better than the Reputation-Based Model and Random Model and are increasingly closed to the highest quality level(Level=1).

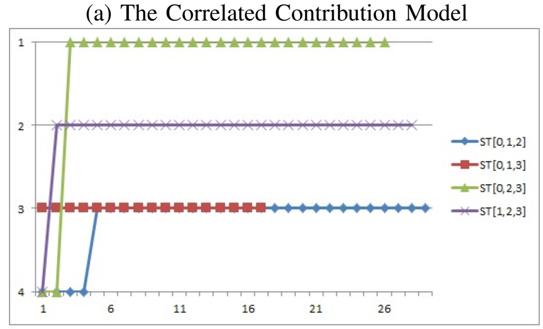
VI. Conclusion

In this paper, an efficient approach for service composition is proposed. The proposed approach can evaluate the correlation between both service types and individual services, which have directly contributions to the QoS value of composite services. Experimental results showed that the performance of the proposed approach is better than the Reputation-Based service composition, which is widely applied in QoS systems. Especially, our approach has demonstrated a significant improvement in the quality QoS value of composite services when receiving dynamic requests.

In the current stage, we only use the single dimension values to represent QoS. In the future, we are going consider multi-dimensional QoS values in the approach. Furthermore, trust information in the proposed approach is still managed in a centralized manner. Another future direction of this research is to develop a trust management approach for distributed environments.



(a) The Correlated Contribution Model



(b) The Reputation-Based Model

Fig. 5: Comparison of QoS changing trends by using the Correlated Contribution Model and the Reputation-Based Model

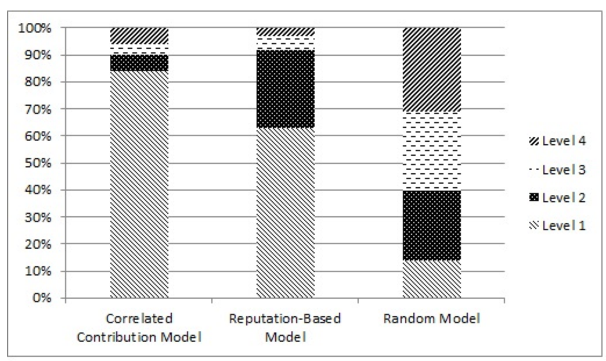


Fig. 6: Comparison of QoS Distribution by using the Correlated Contribution Model, the Reputation-Based Model and the Random Model

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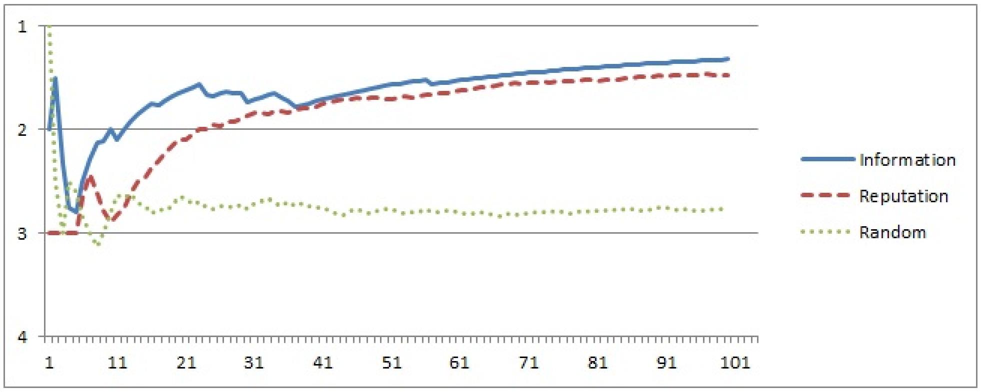

Fig. 7: Average QoS Level for Correlated Contribution Model vs Reputation-Based Model vs Random Model

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