An Incentive Mechanism for Game-Based QoS-Aware Service Selection

Puwei Wang* and Xiaoyong Du

Key Laboratory of Data Engineering and Knowledge Engineering of Ministry of Education, Renmin University of China
School of Information, Renmin University of China
Beijing, China, 100872
wangpuwei@ruc.edu.cn

Abstract. QoS-aware service selection deals with choosing the service providers from the candidates which are discovered to fulfill a requirement, while meeting specific QoS constraints. In fact, the requester and its candidate service providers usually are autonomous and self-interested. In the case, there is a private information game of the service selection between a requester and its candidate providers. An ideal solution of the game is that the requester selects and reaches agreement about the interest allocation with the high-QoS and low-cost service providers. This paper proposes an approach to design a novel incentive mechanism to get the ideal solution of the game. The incentive mechanism design is solved as a constrained optimization problem. Finally, the experiments are performed to show the effectiveness of the incentive mechanism.

Keywords: QoS-aware Service Selection, Game Theory, Incentive Mechanism, Contract.

1 Introduction

Service-Oriented Computing (SOC) is a computing paradigm that utilizes self-contained and platform-independent services as computational elements for developing software applications distributed within and across organizational boundaries. Currently, QoS-aware service selection is an important problem. Existing approaches of QoS-aware service selection usually focuses on the development of various QoS metrics. The work [1] proposes the QoS ontology for annotating service with QoS data, and finds optimal services by matching QoS constraints against candidate services' QoS data. In their views, the requester that offers an application requirement is considered as a controller that could choose the service providers using QoS constraints and command the selected providers to realize the requirement. In fact, the requester and the service provider usually are autonomous, rational and self-interested in nature. In the case, the requester publishes an application requirement and the service provider actively discovers the requester's requirement. The requester gets a benefit while its requirement is realized under the QoS constraints by the service providers. To motivate the service providers to realize the requirement, a part of the benefit should be regarded as a

* Corresponding author.

S. Basu et al. (Eds.): ICSOC 2013, LNCS 8274, pp. 491–498, 2013.

transfer payment to the service providers. Generally, the requester prefers to pay little transfer payment to its service providers, while each service provider prefers to get high transfer payment. Thus, in the scenario, the requester and its candidate provider have a common interest for realizing the requirement, but they have a conflicting interest over the transfer payment.

By relying on the game theory [2], this scenario could be modeled as a game. For a candidate service provider, its profit is the difference between the transfer payment and its service cost. In the game, its strategy explicitly is for maximizing its profit. For a requester, its profit is the difference between the benefit from its satisfied requirement and the transfer payment to its service providers. Considering the service providers which could gain same profit, the requester could pay less transfer payment to the service providers which have lower cost. Moreover, the higher QoS constraints, such as short response time and high availability, could bring the more benefit to the requester. The strategy of the requester thus is to find such service providers that could have high QoS and relatively low service cost (called the efficient service providers in this paper). Obviously, the QoS and service cost are the critical information in the game. Because that the QoS of a service provider is verifiable at run time, we suppose that the service provider will report its actual QoS to the requester. So, the QoS is the open information for the requester and its providers. However, the service cost of a service provider is not verifiable by the requester at any time, and the service provider definitely is not willing to expose its actual cost. Hence, there is a private information game between a requester and its candidate providers.

This paper proposes an approach to design an incentive mechanism to get an ideal solution of the private information game. We propose that the ideal solution is: 1) the requester and the efficient providers among the candidate providers could reach agreement about the QoS constraints and transfer payments; 2) in the service providers which reach agreement with the requester, the efficient provider gets more profit than that the relatively inefficient provider gets and 3) the more efficient the candidate providers are, the more profit the requester could get. The solution ensures that the efficient providers are willing to participate in the game and inefficient ones are motivated to improve their efficiency. The requester also is willing to offer their requirements in the game.

2 The Game of Service Selection

In the set up game, there involves two kinds of players: i) a requester and ii) the candidate service provider. The requester publishes a functional requirement, and the candidate service providers, which meet the functional requirement, have different QoS and different service costs. The basic model of the requester and the service provider are given as follows.

2.1 Requester and Service Provider

The functional requirement F_r is described as a finite set of desired state transitions $F_r = \{t_i | i \in [1, n]\}$. For different desired state transition, the requester could have different QoS constraints, such as response time and availability, etc. The work [3] proposes using a single QoS value to be a measurement of the QoS constraints. Based on the work, we could use a single QoS value to represent the QoS constraints of a desired state transition. The benefit that the requester r could get from a desired state transition t is described as $O_t(q)$, in which $q \in (0, +\infty)$ is the QoS of executing the desired state transition t.

The functional description of a service provider $s \in S$ also is given as a finite set of state transitions F_s. We suppose that the provider discovers the requester's functional requirement F_r while it could meet the requirement ($F_s = F_r$), and its QoS is configurable, such as the work [6], i.e., the provider is able to adjust its QoS to meet the requester's QoS constraint. According to economics, besides the QoS, the cost also depends on another factor, marginal cost. The marginal cost, an economic concept, depicts the change in cost that arises while the quality improves by one unit [4]. In other words, the smaller the marginal cost is, the service cost increases less, while the QoS improves by one unit. It could be concluded that the efficient providers, i.e., those have high QoS and low cost, have small marginal cost. Thus, it is the marginal cost of service provider that the requester wants to know in the game. In the paper, the marginal cost is called the type of service provider. Without loss of generality, we suppose that the fixed cost of a service provider is zero. The cost function of a provider for executing a state transition has two parameters: QoS and type of the provider. Formally, for a state transition $t \in F_s$, the cost function of the provider s is described as $C_t(q, \theta)$, in which q is the QoS of executing the state transition t and θ is the type of the provider s.

Generally, although the requester does not know the exact service costs of its candidate providers, the requester still could find out that the type of service provider follows a kind of probability distribution. Formally, the type of service provider follows a continuous probability distribution $\varGamma$ over the interval $(0, +\infty)$, with a probability function $f(\theta) > 0$. For an interval $[\theta_{i-1}, \theta_i] \subset (0, +\infty)$, a cumulative probability function is $P[\theta_{i-1}, \theta_i] = \int_{\theta_{i-1}}^{\theta_i} f(\theta) d\theta$.

2.2 Procedure of the Private Information Game

In the procedure of the QoS-aware service selection, as shown in Fig.1, there is a set of candidate providers whose types follows a continuous probability distribution $\varGamma$ over the interval $(0, +\infty)$. There is a requester whose functional requirement is described as a set of desired state transitions F_r. The requester could know the benefit and cost functions of the desired state transitions in F_r, but is not aware of the exact types of the candidate providers. Based on the distribution $\varGamma$ and the benefit and cost functions of F_r, the requester makes and offers a set of contracts for its desired state transitions F_r (*step 1*). The contracts are made to create the mutuality of obligation concerning the QoS constraints and the promised transfer payments about the desired state transitions. The candidate providers accept or reject the contracts by using a proposed contracting process (*step 2*). If all contracts are accepted by some of the candidate providers,

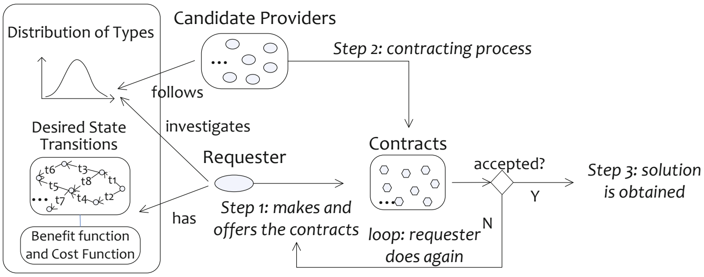


Fig. 1. Procedure of the Private Information Game

a solution of the service selection is obtained (*step 3*). A solution of the game of service selection thus is a situation where each contract offered by the requester is accepted by at least a candidate provider. If the contracts are not accepted, there exists a loop where the requester revises and offers the contracts again. The loop continues until that the revised contracts are accepted by some of the candidate providers.

3 Incentive Mechanism

In the incentive mechanism, we propose a two-phase contracting process between requester and provider. A requester r has a functional requirement F_r. Given m candidate providers $S = \{s_1, ..., s_m\}$, the requester r does not know the candidate provider's type, but it knows that the provider's type follows a probability distribution $\varGamma$.

3.1 Two-Phase Contracting

First Phase. The requester firstly makes a set of contracts for its desired sate transitions according to the benefit and cost functions of the desired state transitions and the probability distribution of the provider's type. Concretely, the requester decides a set of partition points $\varTheta = \{\theta_0, \theta_1, ..., \theta_n\}$, and gets the intervals of provider's type $\{(\theta_0, \theta_1], ..., (\theta_{n-1}, \theta_n]\}$. The requester makes a set of contracts $\{\langle t(\theta_1), q(\theta_1), \delta(\theta_1)\rangle, ..., \langle t(\theta_n), q(\theta_n), \delta(\theta_n)\rangle\}$ based on the intervals. In a contract $\langle t(\theta_i), q(\theta_i), \delta(\theta_i)\rangle$, $\delta(\theta_i)$ denotes a transfer payment to the service provider whose type is in $(\theta_{i-1}, \theta_i]$ (the provider is also called the $(\theta_{i-1}, \theta_i]$ provider in this paper) which executes the desired state transition $t(\theta_i) \in F_r$ at the QoS $q(\theta_i) \in (0, +\infty)$.

The requester does not know its candidate provider's type, but it could figure out the probability that the provider's type is in a given interval based on the probability distribution. Let $P(\cdot, \cdot)$ be the cumulative probability function of the distribution. For a contract $\langle t(\theta_i), q(\theta_i), \delta(\theta_i)\rangle$, the profit that the requester could get from the contract is $V(\theta_i) = O_{t(\theta_i)}(q(\theta_i)) - \delta(\theta_i)$. The probability that there exists at least a provider whose type is in the interval $(\theta_{i-1}, \theta_i]$ among the

m providers is denoted as $\rho(\theta_i)$. The expected profit in the phase is described as $E_{\text{first}}(V(\theta_i)) = \rho(\theta_i) \cdot V(\theta_i)$. In the phase, a service provider is permitted to choose and accept a contract. If a provider accepts a $(\theta_{i-1}, \theta_i]$ contract, the requester then knows that the provider's type is in $(\theta_{i-1}, \theta_i]$. In this way, the requester could know the scope of the most efficient candidate provider's type.

Second Phase. While there are the contracts which are not accepted in the first phase, there is a second phase. Since the requester knows the scope of the most efficient provider's type, the requester could revise the remanent unaccepted contracts to the most efficient provider. Concretely, while the $(\theta_{k-1}, \theta_k]$ provider does not exist among the candidates and the $(\theta_{i-1}, \theta_i]$ provider is the most efficient provider among the candidates in the first phase (the probability of the situation is described as $\rho(\theta_k, \theta_i)$), the requester revises the contract $\langle t(\theta_k), q(\theta_k), \delta(\theta_k)\rangle$ to be $\langle t(\theta_k), q_{\theta_k}(\theta_i), \delta_{\theta_k}(\theta_i)\rangle$ in the second phase. The revised contract $\langle t(\theta_k), q_{\theta_k}(\theta_i),\ \delta_{\theta_k}(\theta_i)\rangle$ promises that if the $(\theta_{i-1}, \theta_i]$ provider realizes the desired state transition $t(\theta_k)$ at the QoS $q_{\theta_k}(\theta_i)$, the provider will get the transfer payment $\delta_{\theta_k}(\theta_i)$. The requester could get the profit from the revised contract as $V_{\theta_k}(\theta_i) = O_{t(\theta_k)}(q_{\theta_k}(\theta_i)) - \delta_{\theta_k}(\theta_i)$. The expected profit in the phase then is described as $E_{\text{second}}(V_{\theta_k}(\theta_i)) = \rho(\theta_k, \theta_i) \cdot V_{\theta_k}(\theta_i)$.

Expected Profit Function of Requester. By adding the expected profits in the two phases, the expected profit of the requester r is described as $\digamma_{\Phi,\Gamma}$.

3.2 Constraints in the Mechanism

Participation Constraint. A service provider will quit the game, if it will get a negative profit from the contract. Thus, a contract is acceptable at least provider could get a non-negative profit. Formally, given a contract $\langle t(\theta_i), q(\theta_i),\ \delta(\theta_i)\rangle \in \Phi$, the participation constraint that ensures the $(\theta_{i-1}, \theta_i]$ provider participates in the game is described as follows: $U(\theta_i) = \delta(\theta_i) - C_{t(\theta_i)}(q(\theta_i), \theta_i) \geqslant 0$. A requester will quit the game, if it will get a negative expected profit. The participation constraint that ensures the requester to participate in the game is described as follows: $\digamma_{\Phi,\Gamma} \geqslant 0$.

Incentive Compatibility Constraint. The requester makes a contract based on an interval of provider's type. While the requester does not know the provider's type, the incentive compatibility constraint is to ensure that the provider whose type is in the interval is willing to accept the contract and the other providers whose types are out of the interval are unwilling to do so.

Constrained Optimization Problem. A set of contracts is feasible if it satisfies both participation and incentive compatibility constraints. The problem to make a feasible set of contracts that bring the requester a maximum profit becomes a constrained optimization problem. The constrained optimization problem to maximize the expected profit $\digamma_{\Phi,\Gamma}$ under the constraint (7) is given.

$$\max_{\{\langle t(\theta_i), q(\theta_i), \delta(\theta_i)\rangle | i \in [1,n]\}} \digamma_{\Phi,\Gamma} \tag{1}$$

$$\textit{subject to} \text{ the set of contracts is feasible}$$

The solution of the optimization problem is an optimal feasible set of contracts Φ. The requester offers the optimal feasible set of contracts to its candidate providers. If the contracts are accepted, a solution of the game is obtained.

4 Experimental Results

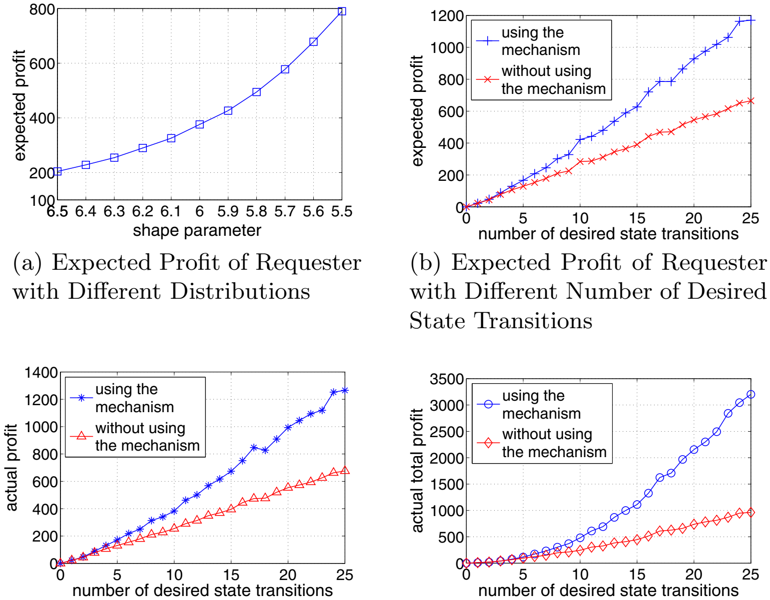
A prototype system of the QoS-aware service selection using the incentive mechanism is implemented in Java. Matlab is a numerical computing environment and the interior point algorithm [5] that is proposed for solving the constrained nonlinear optimization problem has been realized in the Matlab environment. The interior point algorithm in the Matlab is directly used for solving the optimization problem (5) to make an optimal feasible set of contracts.

A repository of 100,000 state transitions and their benefit and cost functions are generated randomly and the cost functions are sensitive to the provider's type. In real world, the most efficient and inefficient service providers usually are very few and there are many average service provider. Thus, we use the gamma distribution to imitate the probability distribution of the provider's type. As the experimental data, the requester's requirement is generated randomly as a set of desired state transitions from the repository. Each requester has 30 candidate providers whose types are generated randomly from the gamma distribution.

The gamma distribution has a shape parameter. The smaller the parameter is, the more efficient providers there exist in the candidates. The number of desired state transitions of a requester is set to be 10. Fig.2(a) plots the average expected profit of 100 requesters, while the shape parameter of the gamma distribution is set to be from 6.5 to 5.5. The result shows that the more efficient the candidate providers are, the more profit the requester could get.

We also compare our approach with a service selection without using the incentive mechanism. In this kind of service selection, the requester and its candidate providers still follow our proposed two-phase contracting process. But the expected profit function of a requester is figured out without consideration of the incentive compatibility constraint. The contracts also are made by solving the problem to maximize the expected profit. In the experiments, the shape parameter of the gamma distribution is set to be 6 and the number of desired state transitions in an requester is set to be from 1 to 25. Fig.2(b) plots the average expected profit of 100 requesters. The result shows that it is clearly better while the mechanism is employed and the expected profit increases while the number of desired transitions increases. In the game of service selection, Fig.2(c) plots the average actual profit of the 100 requesters. The result shows that the actual profit are mainly in accord with the expected profit. The selected providers of the 100 requesters also get their profits in the game. Fig.2(d) plots the average actual total profit of the selected providers. The result shows that the actual total profit of the selected providers also is better while the mechanism is employed.

The reason is that the incentive mechanism motivates the efficient providers to contract with the requester. The desired state transitions of the requester could be fulfilled at the high QoS by the efficient providers which have relatively



(a) Expected Profit of Requester with Different Distributions

(b) Expected Profit of Requester with Different Number of Desired State Transitions

(c) Actual Profit of Requester

(d) Actual Total Profit of Selected Service Providers

Fig. 2. Expected and Actual Profit of Requester and Selected Service Providers

low cost. As a result, the requester and its selected service providers both are benefited from our proposed incentive mechanism.

5 Related Work and Conclusion

The QoS in Web services is an important research issue. Various QoS models are proposed for capturing non-functional features of Web services [3]. The service selection then relys on that the services are differentiated based on the well-defined QoS attributes. Zeng [6] proposes a planning algorithm for the Web service selection with QoS constraints. But, with more and more services are deployed, the requirement begin to have the computational burden to get a solution satisfying the QoS constraints. Serhani [7] proposes the third-party broker for service registry which helps the requester conveniently knowing the services. The broker balances the burden of the requester.In the approaches, the requester takes the responsibility to choose services based on QoS constraints and command the selected services to realize its requirement. Considering the service provider's autonomy, agent-based approach is proposed. Tang [8] proposes that service providers, acting as agents, collaborate with requesters on their own initiative. The work does not focus on the incentives for requester and service provider. Recently, some incentive mechanisms are designed relying on monetary rewards. Jurca et al. [9] design the incentives for the participants according to their reputations. In the approaches, the reputation could be observable in advance and it is the open information for all players. In fact, the service cost is the critical and private information of the provider, there is a private information game of the service selection.

The requester and its candidate providers are autonomous and self-interested. There is a private information game between a requester and its candidate providers in the QoS-aware service selection. The main contribution of this paper is the novel incentive mechanism which coordinates the interests of the requester and its candidate providers in the private information game to get a ideal solution. The incentive mechanism ensures that in the ideal solution, *i*) the requester contracts with the efficient providers, *ii*) the more efficient the candidate providers are, the more profit the requester gets and *iii*) in the providers which are under contract to the requester, the efficient provider gets more profit than that the relatively inefficient provider gets. In the future work, the multilateral negotiation among the requester and its candidate providers in the private information game will be into consideration.

Acknowledgement. This work is supported by the National Fundamental Research and Development Program of China (973 Program) under Grant No.2012CB316205 and the National Natural Science Foundation of China under grant No.61003084 and No.61232007.

References

1. Wang, X., Vitvar, T., Kerrigan, M., Toma, I.: A QoS-Aware Selection Model for Semantic Web Services. In: Dan, A., Lamersdorf, W. (eds.) ICSOC 2006. LNCS, vol. 4294, pp. 390–401. Springer, Heidelberg (2006)
2. Conitzer, V.: Computing game-theoretic solutions and applications to security. In: The Conference on Artificial Intelligence (AAAI 2012), pp. 2106–2112 (2012)
3. Liu, Y., Ngu, A.H., Zeng, L.Z.: QoS Computation and Policing in Dynamic Web Service Selection. In: International World Wide Web Conference (WWW 2004), pp. 66–73 (2004)
4. Laffont, J.J., Martimort, D.: The Theory of Incentives: The Principal-Agent Model. Princeton University Press (2001)
5. Nesterov, Y., Nemirovskii, A.: Interior-Point Polynomial Algorithms in Convex Programming. Society for Industrial and Applied Mathematics (1995)
6. Zeng, L., Benatallah, B., Ngu, A.H.H., et al.: QoS-aware middleware for Web services composition. IEEE Transactions on Software Engineering 30(5), 311–327 (2004)
7. Serhani, M.A., Dssouli, R., Hafid, A., et al.: A QoS broker based architecture for efficient web services selection. In: ICWS 2005, pp. 113–120 (2005)
8. Tang, J., Jin, Z.: Assignment Problem in Requirement Driven Agent Collaboration and its Implementation. In: AAMAS 2010, pp. 839–846 (2010)
9. Zhang, Y., van der Schaar, M.: Reputation-based incentive protocols in crowdsourcing applications. In: INFOCOM 2012, pp. 2140–2148 (2012)