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RESEARCH ARTICLE

Bayesian Approach with Maximum Entropy Principle for Trusted Quality of Web Service Metric in E-commerce Applications †

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ABSTRACT

Trust Quality of Web Service (QoWS) issue is critical for E-commerce applications. However, many existing studies have little work in situations which is insufficient or has no historical information regarding QoWS data. In this study, we propose a trusted QoWS metric approach, i.e., Bayesian Approach with Maximum Entropy Principle. The key of our proposed approach is to extract QoWS prior distribution of Web service using Maximum Entropy Principle and then to infer QoWS posterior distribution of Web service using Bayesian Approach. Based on the obtained QoWS posterior distribution, trusted quality of Web service can be measured. We conduct extensive simulations to evaluate our proposed approach. The simulation results demonstrate that our proposed approach can obtain trusted quality of Web service effectively. Copyright © 2010 John Wiley & Sons, Ltd.

KEYWORDS

Quality of Web service; Bayesian Approach; Maximum Entropy Principle; Fuzzy decision making

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1. INTRODUCTION

Web service technology is designed to support the rapid creation of new, value-added applications in E-commerce, which makes business processes span diverse organizations and computing platforms [1-3]. Concretely, eBay Developer Program and Amazon Web Services are illustrative examples of Web services being used in mission critical and truly large-scale applications in E-commerce environment. However, there exists a large number of services which provide similarly function. Multiple services with similarly functional characteristics give rise to the problem of service selection. Consumers not only expect the service to meet functional aspects but they also demand good quality of Web service (QoWS) such as service reliability, security and trust. Hence, verifying whether a service implementation is conforming to its service-level agreements, is important to inspire confidence in services in E-commerce environment [4].

However, because some services may not perform what they promise, it implies that service users need to trust the ability of the provider to deliver the required function before starting the interaction. So a service customer faces a difficult task of choosing the best service that meets his requirement. Hence, it is imperative to devise techniques to assist service consumers in finding trust QoWS attributes according to the desired level of QoS. Hence, trusted QoS metric is crucial for service customers in open E-commerce environment. In order to get trusted QoSW for service customers, various QoWS metric approaches have been proposed in the lectures [5-9].

Although some efforts and results above have been made, existing technologies are still not mature in open E-commerce environment because of the following two factors. First, service providers may publish dishonest QoWS, i.e., the QoWS published is higher than the actual service level. For example, in finance, online transaction or e-commerce applications, in order to attract a large

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number of customers in a short time and obtain lots of illegal profits, some service providers publish some false or exaggerated QoWS to deceive service customers. Second, when the historical statistical information of a service is little, it is difficult to evaluate the QoWS published by service providers. For example, when a service initially registers for business, no other service consumers has interacted with it, and no record exists of its past behavior [6].

To overcome the two weakness mentioned above, in this paper, we propose a trusted QoWS metric approach (i.e., Bayesian Approach with Maximum Entropy Principle) for service customers in open E-commerce environment. The main contributions of this paper can be summarized as follows.

(i) In order to obtain trusted subjective data from service providers and QoWS experts, we propose a trustworthy expert algorithm based on fuzzy decision making.
(ii) Based on trusted subjective data, we use Maximum Entropy Principle to extract QoWS prior distribution from objective data (QoWS historical statistics).
(iii) We employ Bayesian Approach to infer the posterior distribution of QoWS according to observation information and prior distribution, and based on the obtained QoWS posterior distribution, trusted QoWS can be measured.
(iv) We conduct extensive simulation based on a real dataset and a simulation data. The simulation results demonstrate our proposed approach is effective for trusted QoWS metric in open E-commerce environment.

The remainder of this paper is organized as follows. We discuss the related work about QoWS metric in Section 2. Section 3 describe our proposed approach, i.e., Bayesian Approach with Maximum Entropy Principle. Section 4 gives the simulations to evaluate our proposed approach. Finally, conclusions are drawn in Section 5.

2. RELATED WORK

Trust QoS research has gained much attention in recent years due to the growth of online transactions and e-business activities in service-oriented environments.

In our pervious work [5], we proposed a web service selection approach based on QoS estimation. The aim of the approach to perform accurate QoS estimation (i.e., every service should be assigned an actual QoS) and provide reliable composition services for customers. In the approach, we firstly adopt fuzzy synthetic evaluation method to calculate evaluation values of service providers and the context of customers. Then a proposed slight non-uniform mutation operator is used to obtain the weights of the QoS from service providers, historical statistics and the context of customers. Based on the weights above, QoS can be calculated by means of a weight sum model. Finally, the best composition service can be found using mixed integer program based on estimated QoS.

Z. Malik and A. Bouguettaya [6] presented two approaches that can aid each other in assessing a newcomer's initial reputation. The first relies on cooperation among services to compute a newcomer's reputation in a peer-to-peer manner. The second functions under a "super peer" topology in which the community provider is responsible for assigning the new customer's reputation. However, a single bootstrapping approach can't be universally adopted in different domains and conditions(such as different QoS of WSs,), the effectiveness of the bootstrapping approach will be limited.

D. Ardagna and B. Pernici [7] proposed multiple QoS measure models (aggregation functions) to five QoS attributes such as availability, execution time, data quality, price and reputation. These models are simple and effective to service composition application, but they are lacking in considering existing malicious QoS data from service providers, which makes the services obtained fail to satisfy customers' requests. When customers' QoS requests cannot be met (no solution), the authors adopted QoS negotiating between customers and service providers to perform the second optimization (reoptimization) for satisfying their requests. However, due to existing malicious service providers, the QoS negotiating may be difficult to achieve success. Moreover, the models do not support the context of customers, which makes selected services usually deviate from customers' requests (customers' expectation and actual solution obtained is inconsistent).

S. Hwang et. al [8] analyzed the QoS metrics for Web services and proposed a probability-based QoS model. A QoS measure of an atomic or composite web service is quantified as a probability mass function. The authors described algorithms to compute the QoS measures of a web service workflow from those of its constituent Web services, introduced the problem of computing the least error QoS probability mass function during composing a web service workflow, and provided a dynamic programming formulation for the optimal solution and an efficient approximation heuristic. Although the authors developed an effective framework to derive a QoS measure of a web service workflow from those of its constituent Web services, there is little work that adequately addresses the context sensitivity, and considers malicious QoS data sources.

Base on the fact that users and providers can express their QoS in very flexible ways, L. Pei et. al [9] made the management of QoS a very complex task and proposed a computing-oriented description of QoS and an approach to QoS-based service evaluation based on hierarchical constraint logic programming (HCLP). This approach allows web service designer to describe the real values that non-functional properties (NFPs) will expose at run time

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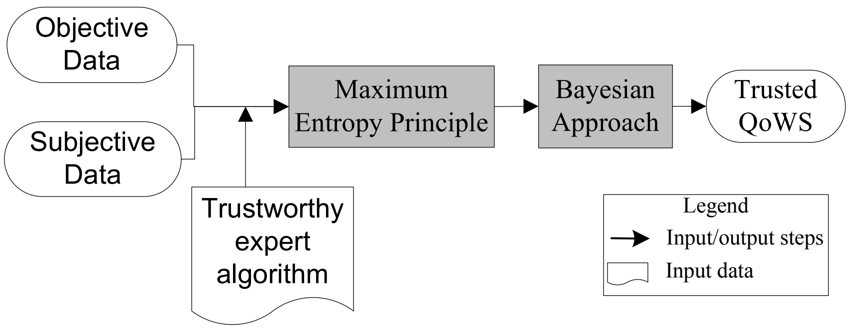

Figure 1. Procedures of our proposed approach

by means of proper mathematical functions, and allows users to specify their preferences on NFPs by exploiting HCLP and introducing tendency functions. Unfortunately, the work is based on the assumption that QoS data of all service is accurate and trustworthy. However, the assumption is invalid in practical business application.

3. OUR PROPOSED APPROACH

As shown in Fig. 1, our proposed approach contains three phases. In Phase 1 (Section 2.1), we propose a trustworthy expert algorithm to obtain trusted subjective data from service providers and QoWS experts. In Phase 2 (Section 2.2), we employ Maximum Entropy Principle to extract QoWS prior distribution from objective data (QoWS historical statistics) and trusted subjective data. Finally, we infer the posterior distribution of QoWS and calculate trusted QoWS according to observation information and prior distribution using Bayesian Approach in Phase 3 (Section 2.3).

3.1. Trustworthy Expert Algorithm

As it is well known that objective data (without any subjective influence) are more credible than some subjective data (such as the experts' opinions). Hence, objective data can be directly used. However, subjective data might be wrong or deviate too much from the reality, and wrong data can be worse than no information. So, they should be checked out. In this section, we propose a trustworthy expert algorithm (TEA) to obtain trust data for using Maximum Entropy Principle in next phase (Section 2.2).

As shown in Fig. 2, TEA contains three Steps, i.e., (expert suggestion) Filtering; (expert suggestion) Extraction and (expert suggestion) Validation. In Step 1, QoWS expert suggestions are filtered, and the remaining suggestions are extracted by means of fuzzy decision making [10] in Step 2 , and finally, the posterior distribution of QoWS are validated if necessary in Step 3.

3.1.1. Filtering

QoWS expert suggestions' filtering means that the collected suggestions need to be checked before it is used for formulating the constraints as the basis of Maximum Entropy Principle. We propose preparing a survey form for the experts to fill out when their suggestions are collected. This form contains not only the suggestions information but also confidence levels associated with the corresponding suggestions. However, because some experts may be conservative, whereas some others may be aggressive or neutral, we cannot simply use the ranking of confidence levels to filter different experts' opinions

The survey form for each expert can be defined as four tuples: $<$ *Expert, Suggestion, Credible Level, Correct Ratio* $>$ where *Correct Ratio* is defined as the probability of a certain expert's suggestion being correct. Thus, we should set up a threshold of credible degree, denoted by $ratio'$. Then, each expert has previous records of their suggestions in the previous projects with the ranking of confidence levels.

Suppose there are K ranks. Then, at each rank, the correct ratio of the i-th expert $(i = 1, \cdots, N)$ for the QoWS can be calculated as

$$ratio_i^k = \frac{RNC_i^k}{\sum\limits_{i=1}^{N} NC_i^k} \tag{1}$$

where NC_i^k is the suggestion for the k-th credible degree from i-th expert in previous records, RNC_i^k is the number of correct NC_i^k.

If $ratio_i^k < ratio'$ ($ratio'$ is the threshold of credible degree that we set up, which could be initialized according to users' requirement), the suggestions should be filtered. So the different experts' opinions (whether conservative or aggressive) can be filtered according to this criterion of credible degree, which is fairer and more reasonable than the way which simply uses an absolute rank to filter the suggestions.

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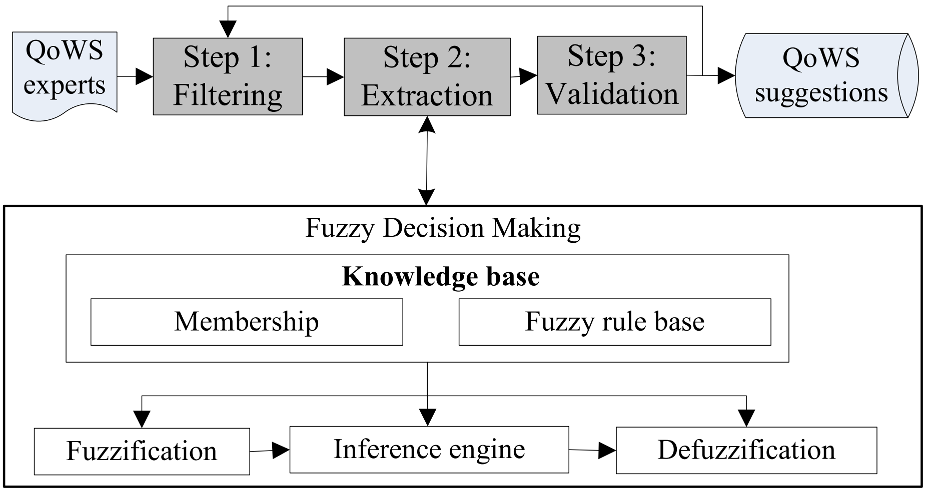

Figure 2. Procedures of trustworthy expert algorithm

3.1.2. Extract

After filtering we need to extract the unfiltered suggestions. In the suggestions, some data can be directly applied to our proposed approach. However, many fuzzy data cannot be directly applied. For example, a value is slightly larger than 3. Therefore, we use Fuzzy Decision Making (FDM) to extract these indistinct experts' suggestions as follows.

(i) Fuzzification. By using the membership functions defined (such as Gaussian membership function, Triangle membership function), we translate the input values of Expert suggestions and credible degree into a set of linguistic values and assign a membership degree for each linguistic value.
(ii) Inference. The inference engine makes decisions based on fuzzy logic inference rules. Each rule is an IF-THEN [11] clause in nature, which determines the linguistic value of each suggestion according to the linguistic values of expert suggestions and credible degrees.
(iii) Defuzzification. We adopt the most common defuzzifcation method, called center of gravity [12], to get the appropriate suggestion's crisp value. With the crisp value, we map it into its fuzzy membership and choose the linguistic value whose membership degree is the largest as the final suggestion.

3.1.3. Validate

After the posterior distribution is derived, we need to validate the posterior distribution by applying it to measure and predict QoWS during the observation. Comparing the predicted QoWS value with the real observed QoWS value, if the mean square error is too large over a certain preset threshold, it means that the model does not fit the observed data. Then, Step 1 is repeated with new $ratio'$, otherwise, TEA is effective and can be applied to extract QoWS suggestion data.

3.2. Maximum Entropy Principle

Although some services lack sufficient QoWS data for service selection, still historical data, experts' suggestions, and other information are useful. For example, QoWS experts participated in a large number of QoWS assessment, have rich experience about QoWS. Therefore, the related information can be transformed into a prior distribution of Bayesian Approach by means of Maximum Entropy Principle (MEP) [13-14].

MEP is a technique that applies the physical principle of Entropy, which states that, without external interference, the Entropy that measures the disorder always tends to the maximum. Entropy has a direct relationship to information theory and, in a sense, measures the amount of uncertainty in the probability distribution. This measure provides a probability distribution that is consistent with known constraints expressed in terms of one or more quantities [14]. MEP is based on the premise, i.e., when estimating the probability distribution, one should select the distribution model which gives the largest remaining uncertainty(i.e., the maximum entropy).

Let Y be a random variable of QoWS with probability distribution function f, which is defined on $D_y \in R$. Then considering prior knowledge about Y, the most likely distribution of Y is a distribution that maximizes $H(f)$ subject to (3) and (4) as follows.

Maximize:

$$H(f) = \int_{Dy} f(y) \cdot \ln f(y) dy \tag{2}$$

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Subject to:

$$\int_{Dy} f(y) \cdot y_r(y) dy = \tilde{y}_r \tag{3}$$

$$\int_{Dy} f(y) dy = 1 \tag{4}$$

where $y_r(r = 1, 2 \cdots m)$ from (3) are a group of known functions, (4) denotes the probability of Y must sum to one.

The solution to this MEP problem is a constrained optimization problem. We use the method of Lagrange multipliers [15] to solve the problem and can obtain the optimal solution.

3.3. Bayesian Approach

We apply Bayesian Approach (BA) [16-17] here to measure QoWS. This approach combines the prior information of the unknown parameters with current data (QoWS observations) to deduce the posterior probability distribution of the parameters. Moreover, this approach can also handle the correlation among those parameters by using the joint distributions. The approach to infer QoWS as follows:

1. The parameters modeling the QoWS of a service are denoted by $\theta = \{\theta_1, \theta_2, \cdots, \theta_m\} \sim f(\theta)$. $f(\theta)$ is the prior joint distribution of the parameters, which is unknown. It can be comprehensively derived from experts' QoWS suggestions and historical QoWS data.
2. The service is used and some QoWS data have been observed. We assume that X is random variable of QoWS data. Let $f(x|\theta)$ denote QoWS data observed which are conditionally independent.
3. Finally, given the prior distribution and observations, the posterior distribution can be obtained by

$$f(\theta|X) \propto f(\theta) \cdot f(x|\theta) \tag{5}$$

The above standard BA is well known and straight forward. However, applying this to measure QoWS poses several challenges that are specific to Web services. It is an important characteristic that QoWS data are usually scarce in a new or rarely used service. The lack of QoWS data in E-commerce environment has challenged the creditability of service composition, which makes estimating proper posterior distributions more difficult. Fortunately, prior information such as expert knowledge and historical data from similar services is typically available. Therefore, we propose to theoretically incorporate the experts' suggestions (objective data) and historical data (subjective data) from previous services into the prior distribution in (5), i.e., $f(\theta)$. The following shows how we can transform expert knowledge and historical data by integrating MEP into the BA.

After deriving the priori distribution from MEP and observing data (such as $f(x|\theta)$), the posterior distribution can be obtained by (5). Then, the marginal density function with respect to each parameter can be obtained as $f_i(\theta_i|X), i = 1, 2, \cdots m$. Then, the mean value of the corresponding parameter can be obtained by

$$\hat{\theta}_i = E(\theta_i) = \int_{-\infty}^{+\infty} \theta_i \cdot f_i(\theta_i|X) d(\theta_i) \tag{6}$$

The mean value can serve as a point estimate for the unknown parameter of QoWS Distribution and then based on the distribution, we can measure the actual data of QoWS in open E-commerce environment.

4. SIMULATIONS

4.1. Simulation Setup

We conducted all our simulations on Dell Power Edge R710 machine with 4 Intel Xeon E5504 2.6GHz processors and 24GB RAM. The machine is running under Linux (ubuntu 8.105) and Java 1.4.

To expert suggestions, we simulate 100 expert survey forms as shown in Table 1. In addition, we take the reputation of QoWS as an example to evaluate our proposed approach. Table 1 gives the expert survey form to provide appropriate QoWS suggestions to our approach. For example, the first expert gives some suggestions (e.g., $\mu_a > 5.1$), in which the Confidence Level is 5 and the Correct Ratio is 53.2%)

In this simulation, we need all the experts to early select or define membership function corresponds to their preferences. Then, we set the fuzzy sets such as $\{L, ML, M, MB, B\}$ and the related linguistic variable are L="little", ML="little middle", M="middle", MB="middle big", B="big". Furthermore, we select the triangle membership function as all input and output variables membership functions as shown in Fig. 3, and we simultaneously set 10 fuzzy levels. The fuzzy rules model that we use is IF-THEN as shown in Fig. 4. For example, if the expert suggestion is "MB" and the confidence level is "LM", then the corresponding QoWS distribution function parameter is "MB". Here, QoWS distribution function parameter represents the relative values inferred by expert suggestion and confidence level. The function surface plot of QoWS distribution function is shown in Fig. 5.

In order to further evaluate our proposed approach, we also conduct another simulation using a publicly available collection of services with QoWS information, i.e., QWS dataset as shown in Fig. 6. For QWS dataset, it comprises measurements of 9 QoWS attributes as shown in Fig. 6 for 2500 real-world Web services. These services were collected from public sources on the Web, including UDDI registries, search engines and service portals, and their QoWS values were measured using commercial benchmark tools. More details about this dataset can be found in [18-20].

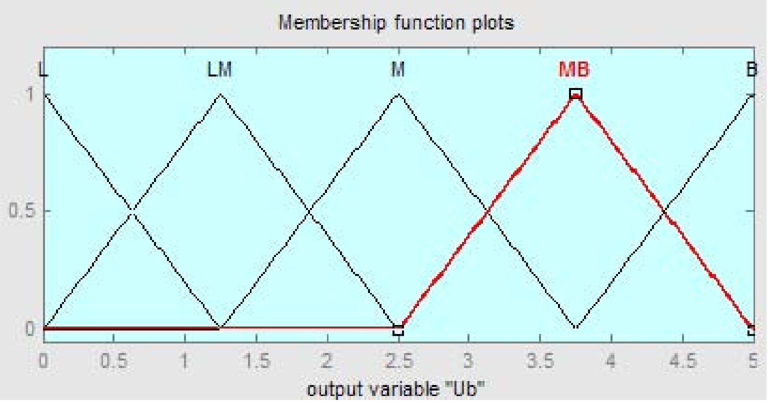

Figure 3. Membership function

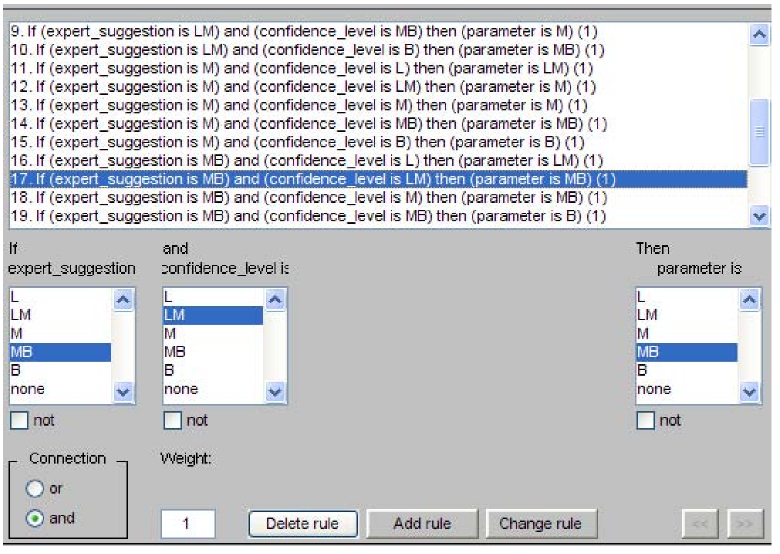

Figure 4. Fuzzy rules

Table I. Expert survey form

ID	Expert Suggestion	Confidence Level (5 levels)	Ratio
1	$\mu_a > 5.1, \cdots, \sigma_b < 1$	5	53.2%
...	...	...	...
100	$\mu_a \in [4, 5.2], \cdots, \sigma_b = 1 \pm 20\%$	5	67.3%

4.2. Simulation Results on Accuracy

As shown in Table 2, we take reputation attribute as an example to simulate 30 QoWS data with $a = 5$ and $b = 2$.

Suppose we can obtain the mean a and variance b of reputation form QoS expert suggestions. Then, suppose the probability distribution of the reputation X can be denoted $f(x), x \in [0, 10]$. The probability distribution with the maximum entropy is given as:

Maximize:

$$H_x = -\int {}_0^{10} f(x) \ln f(x) dx \tag{7}$$

Subject to:

$$\int_0^{10} f(x)dx = 1 \; and \; \int_0^{10} (x - a)^2 f(x)dx = b^2 \tag{8}$$

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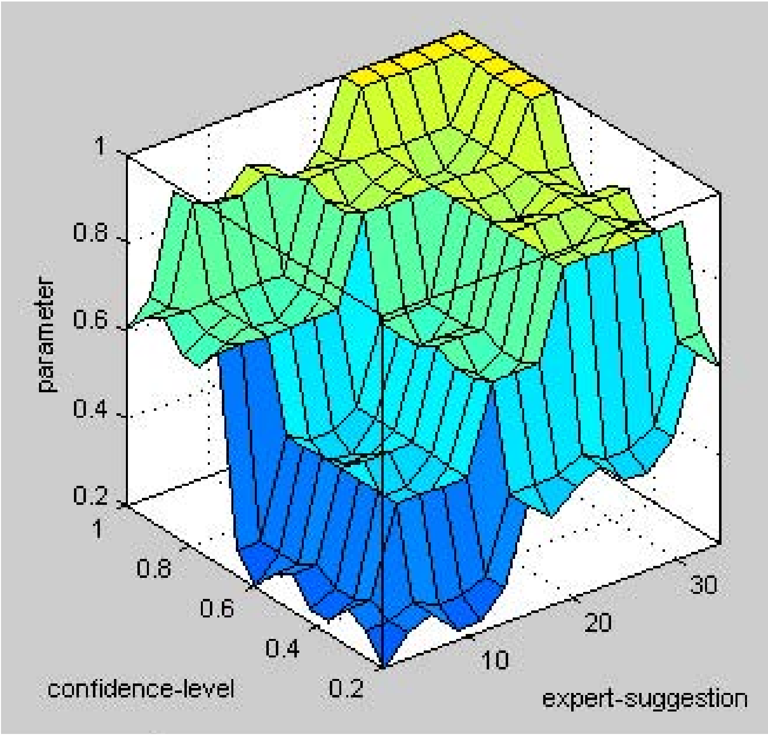


Figure 5. Surface plot of QoWS distribution function

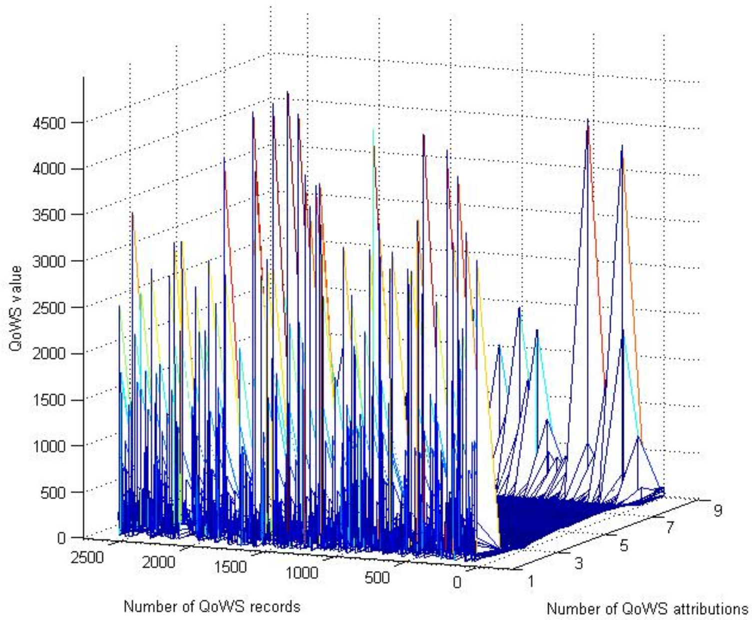


Figure 6. QWS dataset

The solution is given as follows:

$$f(x) = \frac{1}{\sqrt{2\pi}b}\exp(-\frac{(x-a)^2}{2b^2}) \qquad (9)$$

(9) The above formulate mean service reputation can be denoted by the Gaussian distribution, which is similar to the assumption of [21]. Hence, (9) indicates that MEP is effective for prior distribution information.

Table II. Simulation QoWS data

Number	QoWS data				
1-5	3.2916	2.5974	4.7603	4.8694	5.9706
6-10	3.8090	4.7007	4.1305	4.8413	8.0703
11-15	3.7870	2.3053	5.9388	3.1929	5.0718
16-20	3.7449	6.0708	6.1058	4.5926	0.8914
21-25	5.2651	8.1859	7.0368	1.8392	4.8427
26-30	3.6367	2.9509	2.5313	5.5776	4.1414

By using the Maximum Likelihood Estimate (MLE) in Table 2, a and b are estimated as $\hat{a} = 4.49$, $\hat{b} = 1.68$, which have 10.2% and 16% of errors from the preset real values. Then, we implement our proposed approach to analyze the same data.

We suppose that there is knowledge of some statistics archived from TEA. The mean of a is $\mu_a = 5$ and the standard deviation is $\sigma_a = 1$, whereas the mean of b is $\mu_b = 2$, and the standard deviation is $\sigma_b = 1$.

By using MEP in (9), we can get the priori distribution, $a \sim N(5, 1)$ and $b \sim N(2, 1)$, respectively. Thus, the prior joint distribution satisfies:

$$f(a, b) \propto \frac{1}{2\pi\sigma_a\sigma_b} \exp(-\frac{(a-\mu_a)^2}{2\sigma_a^2} - \frac{(b-\mu_b)^2}{2\sigma_b^2}) \tag{10}$$

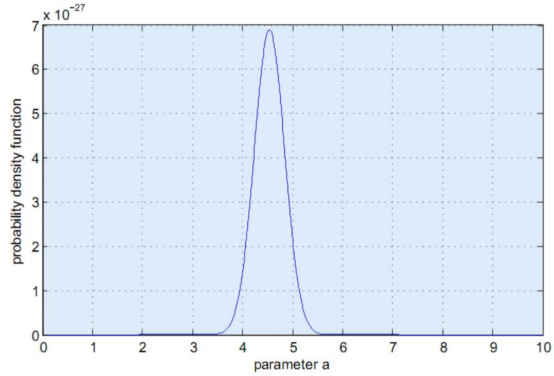
By using (5), we can obtain the posterior distribution:

$$f(\theta|X) \propto \frac{1}{2\pi\sigma_a\sigma_b} \exp(-\frac{(a-\mu_a)^2}{2\sigma_a^2} - \frac{(b-\mu_b)^2}{2\sigma_b^2}) \cdot h(x) \tag{11}$$

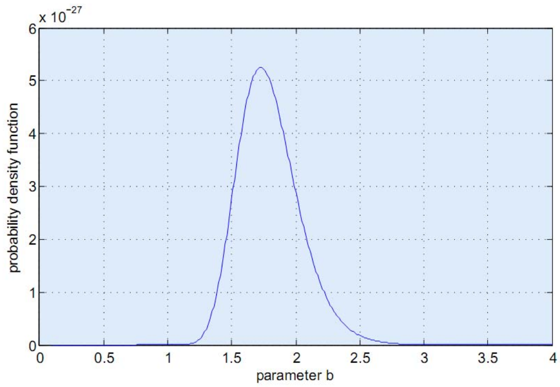
where $h(x) = \prod_{i=1}^{30} \frac{1}{\sqrt{2\pi}b} \exp(-\frac{(x_i-a)^2}{2b^2})$.

According to (5), (6) and (9), the marginal density functions with respect to a and b can also be obtained as shown in Fig. 7, respectively.

By using our approach in Table 2, a and b are estimated as $\hat{a} = 4.55$, $\hat{b} = 1.74$ which have 9% and 13% of errors from the preset parameters. It is obvious that our approach is more accurate than MLE (10.2% and 16%) on the service reputation model. Due to the paper space limitation, the experiments of other QoWS attributes are similar to current simulations. These additional simulation results show our approach is still better than MLE.



(a) Probability density function of parameter a



(b) Probability density function of parameter b

Figure 7. Marginal posterior density function with a and b

4.3. Simulation Results on Success Ratio

An important goal of QoWS metric is to select reliable Web services for service customers. However, due to several factors, the selected service often deviate from the result of service execution in business application of E-commerce.

Hence, the aim of the simulation is to evaluate the success ratio of proposed approach in service selection. According to the definition (success ratio) of our previous work [22], in Fig. 8, we also compare the success ratio with the approach (called NotM in this paper) of [7] that did not design a QoWS metric approach in a 90 percent confidence intervals.

From Fig. 8, regardless of the number of services, the success ratio of our approach is significantly higher than that of NotM. For example, in Fig. 8(a), our approach performs better on success ratio. Its success ratio on average is up to 86.1%, while that of NotM is only 48.5%. In Fig. 8(b), the success ratio of our approach is significantly better than that of NotM. The success ratio of our approach is 78.1%, on average, while that of NotM is only 47.1%. Hence, the above results show that the

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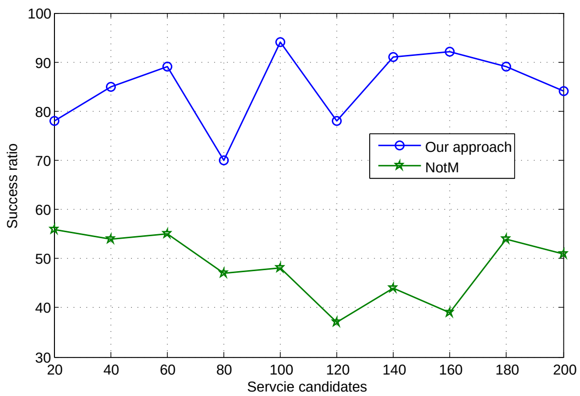
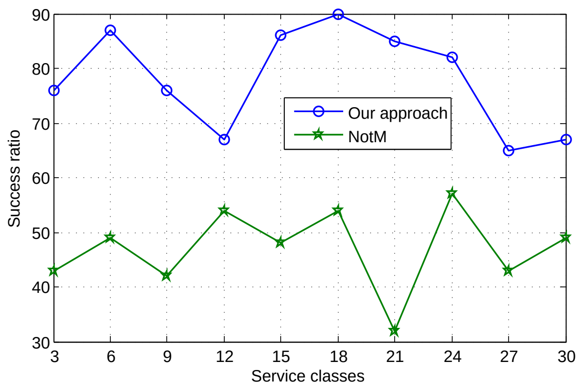


(a) Comparisons results with respect to the number of service candidates



(b) Comparisons results with respect to the number of service classes

Figure 8. Comparison results

performance of our approach is much better than that of NotM.

The reason why our approach has a better performance than NotM is that our approach can effectively reduce the difference between selected services and actual execution results by means of QoWS metric. Hence, our approach can help service consumers obtain trusted services in open E-commerce environment,

5. CONCLUSION

In this study, we propose a quality of Web service metric approach. The approach uses Maximum Entropy Principle to extract the QoS prior distribution from the objective data and subjective data. Then the prior distribution extracted and observation data are used to infer the posterior distribution by Bayesian Approach. Once obtaining the posterior distribution, the QoWS distribution can be got with estimated parameters from the posterior distribution. By means of QoWS distribution, we can obtain trusted QoWS data.

In order to accurately estimate the parameters with appropriate expert suggestions, we propose a trustworthy expert algorithm. The algorithm can obtain the effective QoWS suggestions that are applied to our proposed approach by suggestions' filtering, extraction and validation. The simulation results show that our approach can effectively measure quality of Web service and obtain trusted QoWS in open E-commerce environment.

One of the future work is to extend the QoWS distribution from signal parameter to multi parameters, and enable it to handle more complicated QoWS distributions. The others focus on the application of wireless network environment [23-26] and ubiquitous network environment [27-28].

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REFERENCES

1. S. Wang, Q. Sun, and F. Yang, "Towards Web Service selection based on QoS estimation," *International Journal of Web and Grid Services*, vol. 6, pp. 424-443, 2010.
2. S. Wang, Q. Sun, and F. Yang, "An approach for QoS measure of web service with multifactor support," *In Proceedings of IEEE GLOBECOM Workshops on Web and Pervasive Security*, pp. 1586-1590, 2010.
3. F. Yang, S. Su, and Z. Li, "Hybrid QoS-aware semantic web service composition strategies," *Science in China Series F-Information Sciences*, vol. 51, pp. 1822-1840, 2008.
4. H. Rajan and M. Hosamani, "Tisa: Toward trustworthy services in a service-oriented architecture," *IEEE Transactions on Services Computing*, vol. 1, pp. 201-213, 2008.
5. S. Wang, Q. Sun, and F. Yang, "Towards web service selection based on QoS estimation," *International Journal of Web and Grid Services*, vol. 6, pp. 424-443, 2010.
6. Z. Malik and A. Bouguettaya, "Reputation Bootstrapping for Trust Establishment among Web Services," *IEEE Internet Computing*, vol. 13, pp. 40-47,2009.
7. D. Ardagna and B. Pernici, "Adaptive service composition in flexible processes," *IEEE Transactions on Software Engineering*, vol. 33, pp. 369-384, 2007.

8. S. Hwang, H. Wang, J. Tang, and J. Srivastava, "A probabilistic approach to modeling and estimating the QoS of web-services-based workflows," *Information Sciences*, vol. 177, pp. 5484-5503, 2007.
9. L. Pei, M. Comerio, A. Maurino, and F. De Paoli, "An Approach to Non-functional Property Evaluation of Web Services," *In Proceedings IEEE International Conference on Web Services (ICWS 2009)*, pp. 1004-1005, 2009.
10. G. Klir and B. Yuan, Fuzzy Sets and Fuzzy Logic Theory and Applications. *Prentice-Hall PTR*, 1995.
11. Zadeh and L. A., "Fuzzy sets," *Information and Control*, vol. 8, pp. 338-353, 1965.
12. E. Van Broekhoven and B. De Baets, "Fast and accurate center of gravity defuzzification of fuzzy system outputs defined on trapezoidal fuzzy partitions," *Fuzzy Sets and Systems*, vol. 157, pp. 904-918, 2006.
13. C. Robert, The Bayesian Choice: A Decision Theoretic Motivation. Heidelberg. *Springer-Verlag*, 1994.
14. Y. Dai, M. Xie, Q. Long, and S.-H. Ng, "Uncertainty analysis in software reliability modeling by Bayesian approach with maximum-entropy principle," *IEEE Transactions on Software Engineering*, vol. 33, pp. 781-795, 2007.
15. R. T. Rockafellar and R. J.-B. Wets, Variational Analysis. *Springer-Verlag*, 2004.
16. Berger and J. O, Eds., Statistical Decision Theory and Bayesian Analysis. *Springer-Verlag*, 1985.
17. J. M. Bernardo and A. F. M. Smith, Eds., Bayesian Theory. Wiley, 1994, Pages.
18. E. Al-Masri and Q. H. Mahmoud, "Discovering the best web service," *In Proceedings of the 16th International Conference on World Wide Web (WWW 2007)*, pp. 1257-1258, 2007.
19. E. Al-Masri and Q. H. Mahmoud, "QoS-based Discovery and Ranking of Web Services," *In Porceedings of the 16th International Conference on Computer Communications and Networks(ICCCN 2007)*, pp. 529-534, 2007.
20. E. Al-Masri and Q. H. Mahmoud, "Investigating Web Services on the World Wide Web," *In Proceedings of the 17th International Conference on World Wide Web(WWW 2008)*, pp.795-804, 2008.
21. X. Li and L. Ling, "PeerTrust: supporting reputation-based trust for peer-to-peer electronic communities," *IEEE Transactions on Knowledge and Data Engineering*, vol. 16, pp. 843-857, 2004.
22. S. Wang, Z. Zheng, Q. Sun, H. Zou, and F. Yang, "Cloud model for service selection," *In Proceedings of the 30th IEEE Conference on in Computer Communications Workshops on Cloud Computing (INFOCOM WKSHPS 2011)*, pp. 666-671, 2011.
23. P. Sarkar and A. Saha, "Security Enhanced Communication in Wireless Sensor Networks Using Reed-Muller Codes and Partially Balanced Incomplete Block Designs", *Journal of Convergence*, Vol.2, pp.23-30, 2011.
24. Y. Ponomarchuk and D.W. Seo, "Intrusion Detection based on Traffic Analysis and Fuzzy Inference System in Wireless Sensor Networks", *Journal of Convergence*, Vol.1, pp.35-42, 2010.
25. B. Xie, A. Kumar, D. Zhao, R. Reddy, and B. He, "On secure communication in integrated heterogeneous wireless networks", *International Journal of Information Technology, Communications and Convergence*, Vol.1, pp.4-23, 2010.
26. D. Kumar, T.rilok, C. Aseri, and R.B. Patel, "Multi-hop communication routing (MCR) protocol for heterogeneous wireless sensor networks", *International Journal of Information Technology, Communications and Convergence*, Vol.1, pp.130-145, 2010.
27. M. Lee, J. Lee, K. Kim and S. S. Park, "Evaluating Service Description to Guarantee Quality of U-service Ontology", *Journal of information Processing Systems*, Vol.7, pp.287-298, 2011.
28. H. Lim, K. Jang and B. Kim, "A Study on Design and Implementation of the Ubiquitous Computing Environment-based Dynamic Smart On/Off-line Learner Tracking System", *Journal of Information Processing Systems*, Vol.6, pp.609-620, 2010.

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