Trustworthy Service Selection for Potential Users in Cloud Computing Environment

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1 Introduction

In recent years the cloud services market has grown rapidly along with the gradually matured cloud computing technology. The worldwide public cloud services market is projected to grow 17.3% in 2019 to total \$206.2 billion, up from \$175.8 billion in 2018 [1]. At present, cloud service providers (CSPs) around the world have publicized a large number of software services, computing services and storage services into the clouds. The convenience and economy of cloud services, especially, those services targeting the individual users, such as storage clouds, gaming clouds, OA cloud, video clouds and voice clouds [2, 3], are alluring to the increasing potential users to become the cloud service consumers (CSCs). However, with the rapid proliferation of cloud services and the spring up of services offering similar functionalities, CSCs are faced with the dilemma of service selection. In the dynamic and vulnerable cloud environment, the trustworthiness issue of cloud services, i.e., whether a cloud service can work reliably as expected, becomes the focus of the service selection problem.

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First of all, accurately evaluating the trustworthiness of a cloud service is a challenging task for a potential user who has not used this service. The real quality of service (QoS) of a cloud service experienced by CSCs is usually different from that declared by CSPs in the service level agreement (SLA) [2, 4]. The differences are mainly due to the following reasons [2, 5, 6]: (1) The QoS performance of a cloud service is highly related to the invocation time, since the workload status, such as the workload and the number of clients, and the network environment, such as congestion, change over time. (2) The CSCs are typically distributed in different geographical locations or network locations. The QoS performance of a cloud service observed by CSCs is greatly affected by the Internet connections between CSCs and cloud services. In addition, in reality, the long-term QoS guarantees from a CSP may not be always available [7]. For example, in Amazon EC2, only the "availability" attribute of QoS is advertised for a long-term guarantee [8].

Secondly, a user usually only invokes a small number of cloud services in the past and thus only observes the QoS values of these invoked cloud services. In order to evaluate the trustworthiness of cloud services, invoking all of the cloud services from the CSCs' perspective is quite difficult and includes the following critical drawbacks [5, 9]: (1) The invocations of services may be too expensive for a CSC because CSPs may charge for these invocations. (2) It is time-consuming to evaluate all of the services if there are a large number of candidate services.

Therefore, evaluating the real trustworthiness of cloud services and helping a potential user select the highly trustworthy cloud services among abundant candidates according to the user's requirements, have become the urgent demand at the current development stage of cloud computing. This chapter provides an overview of the related work on the trustworthy cloud service selection and a case study on user feature-aware trustworthy service selection via evidence synthesis for potential users. At the end of this chapter, a discussion is given based on the identified issues and future research prospects.

2 Trustworthiness Evaluation for Cloud Services

2.1 Definition of Trustworthy Cloud Services

In the last years, the researchers have studied the trustworthiness issues of cloud services from different angles, for example, trustworthiness evaluation [10, 11], credibility mechanism [12, 13], trust management [14, 15], reputation mechanism [16, 17], and dependability analysis [18, 19]. Essentially, they are the integration of some traditional researches, such as quality of software, quality of service, reliability of software, in a cloud computing environment.

A trustworthy cloud service is usually defined as "a cloud service is trustworthy if its behavior and results are consistent with the expectation of users" [16, 20–22]. According to this definition, the trustworthiness of cloud services is involved in three profiles. (1) User profile – The different users have different sensitivities for the trustworthiness when they use a cloud service. (2) Service behavior profile – The trustworthiness concerns are different for different types of services. (3) Trustworthiness expectation profile – different users have different trustworthiness expectations for a cloud service. Thus, whether a cloud service is trustworthy for a potential user depends on not only the QoS of the service itself, but also the quality of experience (QoE) of a specific user.

Recently, the QoE and its influence factors have been analyzed systematically. ITU defines the term QoE as: "The overall acceptability of an application or service, as perceived subjectively by an end-user" [23]. QoE is closely related to QoS and the user expectations. Lin et al. [4] discussed an evaluation model of QoE, and argued that the influence factors of QoE consist of services factors, environment factors and user factors. Casas et al. [3] presented the results of several QoE studies for different cloud-based services, and discussed the impact of network QoS features, including round-trip time, bandwidth, and so on, based on lab experiments and field trial experiments. Rojas-Mendizabal et al. [24] argued that QoE is affected by the contexts including human context, economic context and technology context. In practice, the diverse user features of CSCs further heighten the uncertainty of QoE. Even if a CSC uses the same cloud service, s/he may obtain a totally different QoE because of different client devices [25], usage time [21, 26], geographic locations [22, 27, 28], or network locations [29–32].

2.2 Evaluating Trustworthiness of Cloud Service

The traditional theories on trustworthiness evaluation, such as reliability models, security metrics, and defect predictions, are employed to evaluate the trustworthiness of a cloud service. The testing data of a cloud service is collected and the multi-attribute features and multi-source information about QoS are aggregated into the trustworthiness evaluation based on the subjective judgment or probabilistic forecasting. By analyzing behavior logics, state transitions, user data and experience evaluations, the trustworthiness of a cloud service can be measured based on the dynamic evolution and uncertainty theory.

To evaluate accurately the trustworthiness of a cloud service, the continuous QoS monitoring has been an urgent demand [21]. Currently, some organizations have carried out work on the continuous monitoring of cloud services and it becomes possible to analyze thoroughly the trustworthiness of a cloud service based on the time series QoS data. For example, Cloud Security Alliance (CSA) launched the Security, Trust, and Assurance Registry (STAR) Program [33]; Yunzhiliang.net [34] released the assessment reports for popular cloud services deployed in China. China Cloud Computing Promotion and Policy Forum (3CPP) published the trusted services authentication standards and the evaluation result for trustworthy services [35]. Besides, Zheng et al. explored the Planet-lab project to collect the real-world QoS evaluations from 142 users on 4532 services over 64 timeslots [5, 9, 36].

Additional studies [25, 37] demonstrated that the agent software deployed in the CSCs' terminal devices can easily capture the real-time monitoring data. In contrast to the discrete QoS data observed in a single timeslot, the time series QoS data produced by continuous monitoring is more likely to help a potential user investigate the real QoS of a service from a comprehensive perspective.

Considering that every CSC has only used a small number of cloud services and has the limited QoE data about them, the traditional collaborative filtering algorithms (CFA) and the recommendation system technologies integrating social network and mobile devices are often utilized in the existing researches. Aiming at the uncertainty and fuzziness of the trustworthiness evaluations from CSCs, the trustworthy service recommendation approaches are studied by improving the CFAs and introducing the data fusion methods, prediction or multi-dimensional data mining technologies [38].

2.3 Calculating Trustworthiness Value of Cloud Service

2.3.1 Direct Trustworthiness Value

A CSC can directly evaluate the trustworthiness of a cloud service in accordance with the obtained QoE after s/he used the service. Considering the differences between the cost type of QoS attributes and benefit type of QoS attributes, the calculation method of direct trustworthiness needs to be customized for every QoS attribute. Taking the response time for example, the direct trustworthiness is calculated by Eq. (1) [22]:

$$T_{ij} = \begin{cases} 1 & , E_{ij} < S_{ij} \\ 1 - \delta \times \frac{E_{ij} - S_{ij}}{S_{ij}} & , S_{ij} \le E_{ij} \le \frac{S_{ij}(1+\delta)}{\delta} \\ 0 & , \frac{S_{ij}(1+\delta)}{\delta} < E_{ij} \end{cases}, \tag{1}$$

where E_{ij} represents the real response time of the j-th cloud service experienced by the i-th CSC, namely the QoE value; S_{ij} is the expectation value of response time or the value declared by CSP of the j-th service. If $E_{ij} \le S_{ij}$, the i-th CSC thinks a service completely trustworthy. δ is the adjustment factor, which determinates the acceptable range of response time.

According to the 2–5–10 principles [22] of response time in software testing analysis, $S_{ij} = 2$ s, $\delta = 0.25$. The value of S_{ij} and δ can be adjusted for the different types of cloud services in the light of actual situations.

If the i-th CSC used the j-th service n times, the direct trustworthiness is calculated by Eq. (2):

$$\overline{T_{ij}} = \frac{1}{n} \sum_{k=1}^{n} T_{ij}^{k}. \tag{2}$$

2.3.2 Predicted Trustworthiness Value

In order to predict the trustworthiness of a cloud service for a potential user who has not used this service, it is necessary to identify the neighboring users for the potential user by calculating the user similarity based on QoS evaluation or user feature analysis. The CSCs who have high enough user similarity with a potential user can provide the valuable information about cloud services not used by this potential user. The calculation methods of user similarity can be divided into two types, namely the QoS evaluations-based methods and user features-based methods.

The former, requiring the training data about potential users, uses a vector to describe the QoS evaluations about a set of training services, and usually employs the Cosine distance or Euclidean distance to calculate the similarity between users. Recently, the service ranking method becomes a promising idea to overcome the deficiency of the existing methods based on the imprecise evaluation values [39, 40]. This method adopted the Kendall rank correlation coefficient (KRCC) to calculate the similarity between users by evaluating two ranked sequences of training services.

The latter, not requiring the training data about potential users, exploits the user features consisting of objective factors and subjective factors to measure the user similarity. Ref. [22] analyzed the objective and subjective user features systematically, and proposed the similarity measurement methods for user features in details.

Then, the CSCs who have a high enough similarity with the i-th potential user will form a set of the neighboring users, noted as N_i. On the basis of N_i, researchers have studied various methods to predict the trustworthiness value based on N_i. The traditional method to calculate the trustworthiness of the j-th service for the i-th potential user by Eq. (4):

$$T_{ij} = \sum_{k \in N_i} T_{kj} \times S_{ik} / \sum_{k \in N_i} S_{ik}, \tag{3}$$

where S_{ik} represents the similarity between the k-th CSC and the i-th potential user.

3 Typical Approaches on Trustworthy Cloud Service Selection

The typical approaches on trustworthy cloud service selection can be categorized into four groups as follows.

3.1 Recommendation-Based Approaches

These approaches exploit the user preferences based on history data and achieve the personalized service recommendation. By integrating recommendation system technologies, such as the collaborative filtering algorithm (CFA), service recommendations based on user feedbacks have become the dominant trend in service selection research.

Ma et al. [41] presented a user preferences-aware approach for trustworthy cloud services recommendation, in which the user preferences consist of usage preference, trust preference and cost preference. Rosaci et al. [25] proposed an agent-based architecture to recommend the multimedia services by integrating the content-based recommendation method and CFA. Wang et al. [42] presented a cloud service selection model, employing service brokers to perform dynamic service selection based on an adaptive learning mechanism. Ma et al. [43] put forward a trustworthy service recommendation approach based on the interval numbers of four parameters by analyzing the similarity of client-side features. In order to improve the prediction accuracy of CFA, Hu et al. [44] accounted for the time factor and proposed a time-aware CFA to predict the missing QoS values; this approach collects user data about services at different time intervals and uses it to compute the similarity between services and users. Zhong et al. [45] proposed a time-aware service recommendation approach by extracting time sequence of topic activities and service-topic correlation matrix from service usage history, and forecasting the topic evolution and service activity in the near future.

3.2 Prediction-Based Approaches

These approaches focus on how to predict the QoS of service accurately and select the trustworthy service for potential users. Techniques such as probability theory, fuzzy theory, evidence theory, social network analysis, fall into this category.

Mehdi et al. [46] presented a QoS-aware approach based on probabilistic models to assist service selection, which allows CSCs to maintain a trust model of CSP to predict the most trustworthy service. Qu et al. [47] proposed a system that evaluates the trustworthiness of cloud services according to the users' fuzzy QoS requirements and services' dynamic performances to facilitate service selection. Huo et al. [48] presented a fuzzy trustworthiness evaluation method combining Dempster-Shafer theory to solve the synthesis of evaluation information for cloud services. Mo et al. [49] put forward a cloud-based mobile multimedia recommendation system by collecting the user contexts, user relationships, and user profiles from video-sharing websites for generating the recommendation rules. Targeting the objective and subjective characteristics of trustworthiness evaluations, Ding et al. [50] presented a trustworthiness evaluation framework of cloud services to predict the QoS and customer satisfaction for selecting trustworthy services. Aiming at the diversity of user features, the uncertainty and the variation characteristics of QoS, Ma et al. [26] proposed a multi-valued collaborative approach to predict the unknown QoS values via time series analysis by exploiting the continuous monitoring data of cloud services, which can provide strong support for prediction-based trustworthy service selection.

3.3 MCDM-Based Approaches

Multiple criteria decision making (MCDM) is concerned with solving the decision problems involving multiple criteria. Typically, there is no a unique optimal solution for MCDM problems. It is necessary to use decision-maker's preferences to differentiate the candidate solutions and determine the priorities of candidates. The solution with the highest priority is viewed as the optimal one. MCDM methods can be used to solve the service selection problem, provided that the QoS attributes related to the trustworthiness and the candidate services are finite. Techniques such as analytic hierarchy process (AHP), analytic network process (ANP), fuzzy analytic hierarchy process (FAHP), elimination and choice expressing reality (ELECTRE) and techniques for order preference by similarity to an ideal solution (TOPSIS) fall into this category.

Godse et al. [51] presented an AHP-based SaaS service selection approach to score and rank candidate services objectively. Garg et al. [52] employed an AHP method to measure the QoS attributes and rank cloud services. Similarly, Menzel et al. [53] introduced an ANP method for selecting IaaS services. Ma et al. [22] proposed a trustworthy cloud service selection approach that employs FAHP method to calculate the weights of user features. Silas et al. [54] developed a cloud service selection middleware based on ELECTRE method. Sun et al. [55] presented a MCDM technique based on fuzzy TOPSIS method to rank candidate services. Liu et al. [56] put forward a multi-attribute group decision-making approach to solve cloud vendor selection by integrating an improved TOPSIS with Delphi–AHP method. Based on QoS time series analysis of cloud services, Ma et al. [21] introduced the interval neutrosophic set (INS) theory into measuring the trustworthiness of cloud services, and formulated the time-aware trustworthy service selection problem as an MCDM problem of creating a ranked services list, which is solved by developing an INS ranking method.

3.4 Reputation-Based Approaches

The trustworthiness of cloud services can affect the reputation of a CSP. In turn, a reputable CSP is more likely to provide the highly trustworthy services. Thus, evaluating accurately the reputation of a CSP facilitates to select trustworthy cloud services for potential users.

Ramaswamy et al. [57] utilized penalties, prize points and monitoring mechanism of mobile agents to ensure the trustworthiness among cloud broker, CSCs and CSPs. Mouratidis et al. [58] presented a framework incorporating a modeling language that supports the elicitation of security and privacy requirements for selecting a suitable CSPs. Ayday et al. [59] incorporated the belief propagation algorithm to evaluate reputation management systems, and employed the factor graph to describe the interactive behavior between CSCs and CSPs. Pawar et al. [60] proposed an uncertainty model that employs the subjective logic operators to calculate the reputations of CSPs. Shen et al. [61] put forward a collaborative cloud computing platform, which incorporates the multi-faceted reputation management, resource selection, and price-assisted reputation control.

4 Metrics Indicators for Trustworthy Cloud Service Selection

The metrics indicators to measure the accuracy of trustworthy cloud service selection can be classified into two types as follows.

4.1 Mean Absolute Error and Root-Mean Square Error

If an approach produces the exact QoS value for every candidate service, the mean absolute error (MAE) and root-mean square error (RMSE) are usually employed to evaluate the quality of the approach [22, 26, 43], and are defined by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|v_i^{*} - v_i^{o}\right|, \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(v_i^{*} - v_i^{o}\right)^2}, \tag{5}$$

where N denotes the total number of service selection executed; v_i^{*} represents the real QoS value experienced by a potential user; v_i^{o} represents the predicted QoS value for a potential user. The smaller the MAE is, the better the accuracy is.

4.2 Difference Degree

If an approach creates a ranked list for candidate services, the difference degree [21], defined by Eq. (7), is used to compare the ranked list and the baseline list as follows:

$$D = \sum_{i=1}^{K} \frac{|R_i - B_i|}{B_i}, \tag{6}$$

where K is the total number of Top-K candidate services in the ranked list; R_i is the predicted ranking order of the i-th candidate service; B_i is the order of the i-th candidate in baseline rankings. Obviously, the smaller values for D mean the better accuracy.

5 User Feature-Aware Trustworthy Service Selection via Evidence Synthesis for Potential Users: A Case Study

5.1 Measuring User Features Similarity Between Users

The CSCs with the similar user features may obtain the similar QoE. According to the user feature analysis [22], the diverse user features, consisting of the objective features and the subjective features, lead to the differences between users' QoEs. The objective features include the geographical location and network autonomous system (AS). The former recognizes the service level of a local ISP (Internet service provider) and the administrative controls condition of local government. The latter concerns the routing condition and communication quality of network. The subjective features include age, professional background, education background and industry background. These subjective features can influence the people's expectation and evaluation criterion deeply. In this chapter, we focus on the objective features and introduce their measurement methods of user features similarity as follows.

(1) Geographical location feature: It can be noted as a five-tuple, fl = (country, state or province, city, county or district, subdistrict). It is not necessary to use all the five levels to describe the location feature. Let fl_j^i represents the j-th location information of the i-th user. A binary location coding method as $loc = b_1 b_2 \ldots b_{n-1} b_\mathrm{n}$ is designed to measure the location similarity between users. b_1 and b_n represent the highest level and the lowest level of administrative unit, respectively. The location code of a potential user is defined as $loc^{pu} = \underbrace{11......11}_{n}$. Comparing the location feature of a CSC with loc^{pu}, the location code of the CSC is obtained as Eq. (8):

$$loc_i^{cc} = \begin{cases} 1, & if \;\; fl_i^{pu} = fl_i^{cc} \\ 0, & if \;\; fl_i^{pu} \neq fl_i^{cc} \end{cases}, \tag{7}$$

where fl_i^{pu} and fl_i^{cc} represent the feature values of the i-th location information of the potential user and CSCs, respectively. $\sum_{j=i+1}^{n} loc_j^{cc} = 0$ when $loc_i^{cc} = 0$. Thus, the similarity value of the multilevel location feature for the i-th CSC is calculated as Eq. (9):

$$s^{loc} = (b_1 b_2 \ldots b_n)_2 / \left(2^n - 1\right), \tag{8}$$

where $(b_1 b_2 \ldots b_n)_2$ and $(2^n–1)$ represent the binary-coded decimal values of location code of a CSC and the potential user, respectively.

(2) AS feature: Let as^{pu} and as^{cc} represent the AS numbers of a potential user and a CSC, respectively. The AS number is usually technically defined as a number assigned to a group of network addresses, sharing a common routing policy. $0 \leq as^{pu}$, $as^{cc} \leq 2^{32}–1$, the AS feature similarity is computed by:

$$s^{as} = \begin{cases} 1, & if \;\; as^{pu} = as^{cc} \\ 0, & if \;\; as^{pu} \neq as^{cc} \end{cases}. \tag{9}$$

5.2 Computing Weights of User Features Based on FAHP

The significance of each user feature may vary widely in different application scenarios. Thus, it is not appropriate to synthesize the similarity values of user features with the weighted mean method. Considering that the diversity of user features, the FAHP method is used to compute the weights of user features.

Suppose that $B = (b_{ij})_{n \times n}$ is a fuzzy judgment matrix with $0 \leq b_{ij} \leq 1$, n is the number of user features, and b_{ij} is the importance ratio of the i-th feature and the j-th one. If $b_{ij} + b_{ji} = 1$ and $b_{ii} = 0.5$, B is a fuzzy complementary judgment matrix. Giving an integer k, if $b_{ij} = b_{ik}$-$b_{jk} + 0.5$, B is a fuzzy consistency matrix. For transforming B into a fuzzy complementary judgment matrix, the sum of each row of this matrix is defined as b_i, and the mathematical manipulation is performed with Eq. (11):

$$c_{ij} = 0.5 + \left(b_i - b_j\right) / 2\,(n - 1)\,. \tag{10}$$

A new fuzzy matrix, namely $C = (c_{ij})_{n \times n}$, can be obtained, which is a fuzzy consistency judgment matrix. The sum of each row is computed and standardized. Finally, the weight vector is calculated by Eq. (12):

$$w_i = \frac{1}{n\,(n-1)} \sum_{j=1}^{n} c_{ij} + \frac{n}{2} - 1. \tag{11}$$

The user feature similarity is defined as matrix S by Eq. (13):

$$S = \left(S^{loc} \quad S^{as} \quad S^{a} \quad S^{e} \quad S^{p} \quad S^{i}\right)^{T} = \begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1k} \\ s_{21} & s_{22} & \cdots & s_{2k} \\ \vdots & \cdots & s_{ij} & \vdots \\ s_{61} & s_{62} & \cdots & s_{6k} \end{pmatrix}, \tag{12}$$

where S^{loc}, S^{as}, S^{a}, S^{e}, S^{p} and S^{i} are the similarity vectors of geographical location, AS, age, education background, professional background and industry background features, respectively; s_{ij} represents the similarity value of the i-th feature for the j-th user; k is the number of users. Thus, the comprehensive value of user feature similarity for the i-th user is computed by Eq. (14):

$$sim_i = \sum_{j=1}^{6} s_{ji} \times w_j. \tag{13}$$

According to sim_i, some CSCs who may provide the more valuable evaluations for a potential user than others can be identified as the neighboring users, noted as:

$$N = \left\{ u_i \middle| \quad u_i \in U, sim_i \geq s^{th} \right\},$$

where U is the set of CSCs; s^{th} is the similarity threshold.

5.3 Predicting Trustworthiness of Candidate Services for Potential User

In a dynamic cloud environment, the trustworthiness evaluations of cloud service from CSCs are uncertain and fuzzy. Evidence theory has unique advantages in the expression of the uncertainty, and has been widely applied in expert systems and MCDM fields. Thus, evidence theory can be employed to synthesize the trustworthiness evaluations from neighboring users.

The fuzzy evaluation set is defined as $VS = \{vt, vl\}$, which describes the trustworthiness evaluation. vt represents trust, and vl represents distrust. The fuzzy evaluation $v = (v^t, v^l)$ is the fuzzy subset of VS with $v^t + v^l = 1$. For example, the fuzzy evaluation of a service given by a CSC is $v^r = (0.91, 0.09)$, indicating that the CSC thinks the trustworthiness of this service is 0.91 and the distrust degree is 0.09. Denote the identification framework as $\Theta = \{T, F,\}$, where T represents this service is trusted, and F represents it is trustless. Θ is mapped to VS. The power set of Θ is $2^{\Theta} = \{\Phi, \{T\}, \{F\}, \Theta\}$. And the basic trustworthiness distribution function m is defined as a mapping from 2^{Θ} to [0, 1] with $m(\varphi) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$. m can be measured based on the trustworthiness evaluations.

Due to the possibilities of evaluation forgery and network anomaly, there might be a few false evidences in trustworthiness evaluations, which will lead to the poor evidence synthesis result. Thus, it is vital to filter the false evidences for ensuring the accuracy of data synthesis. Suppose the basic trustworthiness distribution functions of evidence E_1 and E_2 are m_1 and m_2, respectively, and the focal elements are A_i and B_j, respectively. The distance between m_1 and m_2 can be calculated by Eq. (15):

$$d(m_1, m_2) = \sqrt{\frac{1}{2}\left(\|m_1\|^2 + \|m_2\|^2 - 2\langle m_1, m_2\rangle\right)}. \tag{14}$$

The distances between evidences are small if they support each other, and the distances become large if there are false evidences. Therefore, the false evidences can be identified according to the mean distance of evidences. Suppose $\overline{d_i}$ represents the mean distance between the i-th evidence and other n-1 evidences. A dynamic function is proposed to create the mean distance threshold, and an iteration method is employed to improve the accuracy of filtering operations. The function is shown in Eq. (16):

$$\alpha = \frac{1}{n}(1+\beta) \times \sum_{i=1}^{n} \overline{d_i}, \tag{15}$$

where β represents the threshold coefficient, and its ideal value range is [0.05, 0.30]. β should be set as a greater value if the distances between evidences are quite large. β is adaptable because it is obtained based on the mean distances of all evidences.

In practice, a rational distance between evidences should be allowed. Assume ζ is the lower limit of the mean distances. The filtering operations are executed when $\alpha > \zeta$, and the i-th evidence is removed if $\overline{d_i} \geq \alpha$. The operations continue until $\alpha \leq \zeta$. The remaining evidences are viewed as reliable evidences, and their providers form a reliable user set, noted as *Ref*. These evidences cannot be synthesized directly with the D-S method due to the interrelation of them, unless the condition of idempotence is satisfied. An evidence fusion method with user feature weights is proposed in Eq. (16) [22]:

$$\begin{aligned} m(A) &= m_1(A) \oplus m_2(A) \cdots \oplus m_{|FC|}(A) = \sum_{i=1}^{|Ref|} m_i(A) \times fw_i \\ fw_i &= \frac{1}{1-sim_i} \times \frac{1}{\sum_{j=1}^{|Ref|} \frac{1}{1-sim_i}}, \end{aligned} \tag{16}$$

where fw_i is the feature weight of the i-th evidence, representing the importance of the i-th evidence. According to Eq. (16), the synthesis result of the interrelated

Table 1 User information in extended WS-DREAM Dataset

UID	IP address	Country	City	Network description/area	AS number
0	12.108.127.138	United States	Pittsburgh	AT&T Services, Inc.	AS7018
1	12.46.129.15	United States	Alameda	AT&T Services, Inc.	AS7018
2	122.1.115.91	Japan	Hamamatsu	NTT Communications Corp.	AS4713
3	128.10.19.52	United States	West Lafayette	Purdue University	AS17
...	...	...		...	...

evidences satisfies the idempotence, and can provide the reliable trustworthiness prediction value of the candidate service for a potential user. The service with the highest predicted trustworthiness will be selected as the optimal one for the potential user.

5.4 *Experiment*

We used the real-world WS-DREAM dataset [29, 36] to demonstrate the effectiveness of the proposed method. In this dataset, a total of 339 users from 31 countries or regions, a total of 5825 real-world web services from 73 countries and a total of 1,974,675 service invocation results are collected. However, this dataset has only the limited information about user features. Thus, on the basis of the original user information, some other users features, including network autonomous systems number, city and network description, are supplemented, and the detailed data are provided online [62]. The extended user information is shown in Table 1. The user features of the extended dataset are analyzed as follows. (1) 339 users come from 153 cities in 31 countries or regions, belonging to 138 AS. (2) 230 users come from education industry, 46 users from scientific and technical activities, 45 users from information and communication, and 18 users' background are unknown.

5.4.1 Experiment Setup

A three-level location coding, consisting of country-city-area, was created in the following experiments. The fuzzy complementary judgment matrix of user features based on FAHP method is defined as follows:

$$B = \begin{pmatrix} 0.5 & 0.3 & 1.0 & 1.0 & 1.0 & 0.9 \\ 0.7 & 0.5 & 1.0 & 1.0 & 1.0 & 0.9 \\ 0 & 0 & 0.5 & 0.5 & 0.5 & 0.1 \\ 0 & 0 & 0.5 & 0.5 & 0.5 & 0.1 \\ 0 & 0 & 0.5 & 0.5 & 0.5 & 0.1 \\ 0.1 & 0.1 & 0.9 & 0.9 & 0.9 & 0.5 \end{pmatrix}.$$

The weights of six user features are denoted as $W = \{w_1, w_2, \ldots, w_6\}$, which represent the weighted values of location, AS, age, education background, professional background and industry background, respectively. The computation results of weight allocation are $W = \{0.1796, 0.2048, 0.1412, 0.1412, 0.1412, 0.1739\}$.

The response time is used as the important indicator to measure the trustworthiness of services in the dataset. The trustworthiness of services is calculated for every user with Eq. (1). Suppose a potential user from Technical University of Berlin in AS680 is selected in experiments. The response time data of 5825 services is analyzed, and the standard deviation (SD) of response time is shown in Fig. 1.

These services can be divided into three service sets according to their *SD* values. The three service sets are shown in Table 2. The experiments mainly focus on these services whose *SD* is greater than or equal to 3 and smaller than 10.

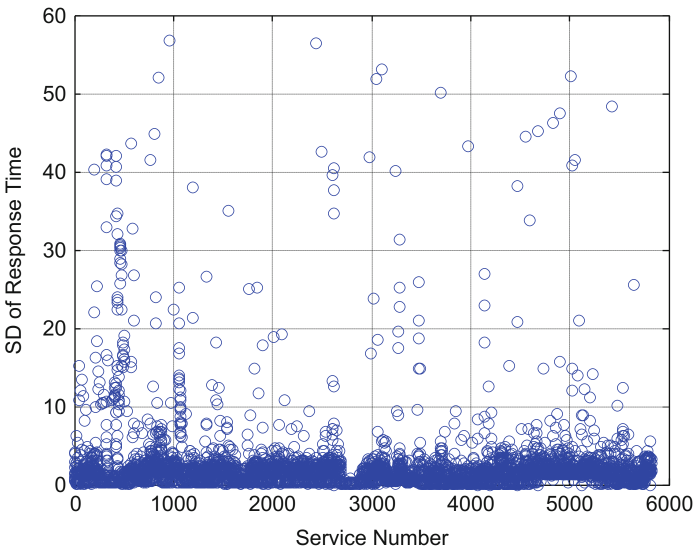

Fig. 1 SD of response time for 5825 services

Table 2 Services sets for different SD range

Service set	SD range	Service number	Mean SD	Mean response time
#1	[0,3)	5140	1.1372	1.0934
#2	[3,10)	506	4.5863	6.9452
#3	[10,∞)	179	22.967	45.2601

5.4.2 Experiment Result and Analysis

To verify the proposed method, named as UFWM, we compare it with other three methods, including Hybrid [63], distance-based weights method [64] denoted as DWM, AS distance weights method [32] denoted as ASDWM.

In the first experiment, the potential user is selected randomly from AS680 because AS680 has the most users in WS-DREAM. Twelve independent trials are performed. The first trial selects service #1 to service #500, and the second one selects service #1 to service #1000, and the remainder will continue to add another 500 services until all services have been used. MAE is employed to measure the accuracy of approaches. The result is shown in Fig. 2a. According to Fig. 2a, MAE reduces gradually along with more services used in the experiment. However, MAE has a trend of stable increase after service #3000 to #3500 are used because the number of service timeout increases sharply. All of the four methods have a poor performance of trustworthiness measurement because of the interference from false evidences in WS-DREAM. The analysis is given as follows. (1) Hybrid aggregates the history data directly with average weights due to the deficiency of training data. Affected profoundly by the false evidences, Hybrid gained the worst MAE values compared to other methods. (2) ASDWM only collects the evaluations of CSCs from AS680. Thus, the false evidences may cause the significant degradation in the accuracy easily, especially when one AS has a small number of users. According to the statistics analysis on AS information of users, 339 users are distributed in 138 ASs. AS680 is the AS with the most users in the dataset, holding 28 users. And there are 36 ASs with only one user. (3) DWM may obtain the great MAE values because the weights of evidences are proportional to the distances between evidences. Thus, if most of evidences are true, these evidences can weaken the effects of false evidences or else the situation will deteriorate further. (4) UFWM gets the highest accuracy among four methods, even if the performance of UFWM is also not good because some users provided the false evidences. As a result, it is important to filter the false evidences for improving the quality of service selection.

The second experiment is conducted after filtering the false evidences based on static mean distance threshold. The static mean distance threshold, noted as α, is employed to filter the false evidences, and the results of the experiment are shown in Fig. 2b and c, respectively when $\alpha = 0.32$ and $\alpha = 0.62$. Obviously, the MAE values obtained when $\alpha = 0.62$ are higher than the values when $\alpha = 0.32$. Most of evidences will be mistakenly identified as the false evidences when α is given a smaller value, which inevitably leads to the lower precision ratio of false evidences. Only a few false evidences can be identified if α is given a greater value, which will cause the lower recall ratio of false evidences. According to Fig. 2b, Hybrid, DWM

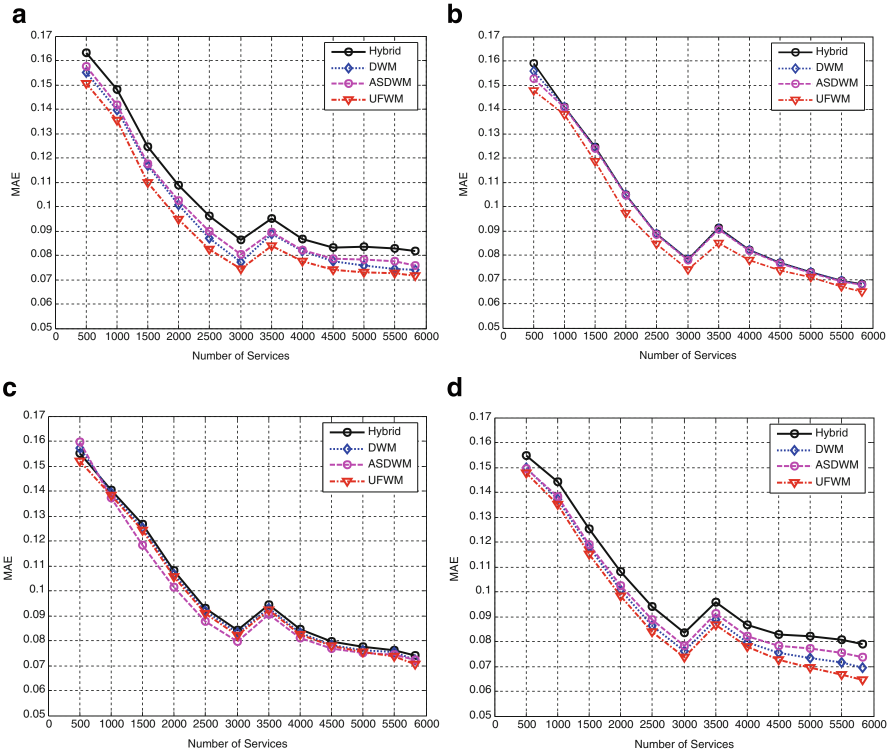

Fig. 2 Comparison analysis. (**a**) the false evidences are not filtered. (**b**) the false evidences are filtered based on static mean distance threshold when $\alpha = 0.32$. (**c**) the false evidences are filtered based on static mean distance threshold when $\alpha = 0.62$. (**d**) the false evidences are filtered based on dynamic mean distance threshold

and UFWM obtained the better MAE values in contrast to Fig. 2a. In practice, it is fairly difficult to assign an appropriate value to α. $\alpha = 0.32$ can achieve a good performance for WS-DREAM, while it maybe not suitable to other datasets.

In the third experiment, a dynamic mean distance threshold, defined in Eq. (15), is used to filter the false evidences, the neighboring users are identified with $s^{th} = 0.70$. The CSCs similar to the potential user are selected and the neighboring user set consists of 37 users. The result is shown in Fig. 2d. After the multiple iterations based on dynamic mean distance threshold, the trustworthiness measurement result based on neighboring users is closer to real value after filtering false evidences, and UFWM can provide the best results among all methods.

The above experiments do not use any training data about potential users. In the case with the cold start, all of the methods gained the good performance by identifying neighboring users and filtering false evidences out. Especially, UFWM obtained the best quality of service selection by taking into account the user feature weights.

6 Summary and Further Research

In a dynamic cloud environment, the uncertain QoS of cloud services, the fuzzy and personalized QoE of consumers, are now becoming the central challenges to trustworthy service selection problem for potential users. This chapter has introduced the related work on trustworthy cloud service selection and a case study on user feature-aware trustworthy service selection for potential users.

Based on the literature review, the further studies can be summarized as follows.

1. The abnormal data or noisy data in QoS evaluations should be paid more attentions to improve the calculation precision of the user similarity and the quality of trustworthy service selection.
2. The existing literature is lack of advanced solutions to the data sparsity and cold start problems in trustworthy service recommendation. How to design new algorithms to improve the accuracy of service recommendation and the performance of execution requires further researches.
3. The continuous monitoring of cloud service makes it possible to describe the variation feature of trustworthiness more accurately for cloud services based on the time series QoS data. Some theories, such as interval neutrosophic set and cloud model, may provide the new ideas to depict the uncertain trustworthiness of service.
4. Recently enormous cloud services have been integrated into the data-intensive applications such as cloud scientific workflow [65, 66]. Aiming at the characteristics of cloud service composition in practical applications, it is a promising research direction to delve into the trustworthy service selection problem combining the role-based collaboration in the big data environment [67].

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