Cloud Service Selection Based on Contextual Subjective Assessment and Objective Assessment

(Extended Abstract)

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ABSTRACT

This paper proposes a novel cloud service selection model based on the comparison and aggregation of contextual subjective assessment and objective assessment of cloud services. In this model, objective assessment provided by some professional testing parties is used as a benchmark to dynamically filter out biased subjective assessment extracted from cloud user feedback according to assessment context similarity. Through this model, the overall quality of cloud services can be effectively reflected with less subjective bias for potential cloud consumers.

Categories and Subject Descriptors

H.3.5 [**Online Information Services**]: Web-based services

General Terms

Performance

Keywords

Cloud Computing, Service Selection, Context Similarity

1. INTRODUCTION

Due to the diversity of cloud services, a challenging problem for potential cloud consumers is how to select the most suitable cloud service. In the literature, there are two types of approaches which can be used to conduct such a selection. The first type is based on objective performance assessment from predesigned benchmark monitoring and testing [5]. The second type is based on user subjective assessment extracted from cloud user feedback [2]. Nevertheless, these two types of approaches have their own limitations, because some performance aspects of cloud services can be hardly evaluated by objective assessment (e.g., data privacy and after-sales services), and subjective assessment may involve cloud users' subjective bias. In addition, as cloud users are usually spread throughout the world, for any cloud service, the subjective assessment from a cloud user in a context (e.g., morning in Sydney) may be much different from that of another user in a different context (e.g., afternoon in Paris). Hence, the effectiveness of cloud service selection approaches can be significantly affected by all these factors.

This paper proposes a novel cloud service selection model based on the comparison and aggregation of contextual subjective assessment and objective assessment. In this model, an objective assessment of a cloud service is applied as a benchmark to filter out biased subjective assessments since objective assessment through scientific and statistical analysis is usually more accurate than users' subjective feelings. In order to guarantee the accuracy of such filtering, our model considers the contexts of assessments. The process of such filtering is based on the context similarity between objective assessment and subjective assessment. The more similar the context, the more reliable subjective assessments, so that the benchmark level is dynamically adjusted. After such filtering, the final aggregated results based on the remaining assessments can reflect the overall performance of cloud services according to potential users' personalized requirements.

2. CONTEXTUAL ASSESSMENT

In our prior work [3], we proposed an agent-based framework for cloud service selection. In this framework, a cloud user gives his/her subjective assessment for a cloud service according to his/her perception. Each aspect that users can assess can be considered as a *subjective attribute* of the cloud service. These subjective attributes are expressed by linguistic variables (e.g., "good", "fair" and "poor"). On the other hand, objective assessment of cloud services is provided by professional cloud performance testing parties. Each performance aspect tested by these parties can be considered as an *objective attribute* of a cloud service. All these objective attributes are expressed in quantitative forms (e.g., $2.15s$ for *service response time*). Furthermore, some subjective attribute and some objective attribute can represent the same performance aspect of a cloud service. Such attributes are called *associated attributes* in our model. Figure 1 illustrates an example, where there are s subjective attributes, o objective attributes and u pairs of associated attributes for a cloud service ($u \leqslant s, u \leqslant o$).

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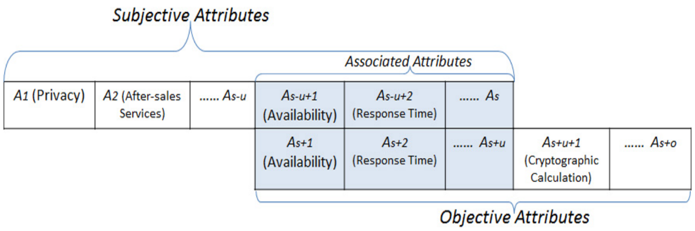

Figure 1: The Relationship of Subjective Attributes and Objective Attributes [3]

2.1 Context Similarity

The definition of a context varies in different application environments [4]. The context of an assessment for a cloud service in our model refers to a group of values of the features of the assessment, which can affect the result of the assessment. At the current stage, we consider two assessment features (i.e., *location* and *time*). Through a modified bipartite SimRank algorithm [1], the context similarity between objective assessment and subjective assessment is computed to determine the benchmark level of the filtration of biased subjective assessments. Such a similarity computation consists of two steps. The ***first step*** is to compute the similarity between two values from the same feature; The ***second step*** is to model all contexts and their relevant assessment features as a graph and compute the overall similarity between contexts. Figure 2 illustrates an example of two contexts A (*Sydney, morning*) and B (*Singapore, afternoon*).

Let A and B denote two contexts, and $s(A,B) \in [0,1]$ denote the similarity between A and B. If $A = B$, then $s(A,B) = 1$. Let c and d denote assessment features for both A and B, and $s(c,d) \in [0,1]$ denote the similarity between c and d. Let $V_c(A)/V_d(A)$ and $V_c(B)/V_d(B)$ denote the values of the feature c/d in A and B respectively. If $c = d$, then $s(c,d) = Cmp_c(V_c(A), V_c(B)) = Cmp_d(V_d(A), V_d(B)) \in [0,1]$, where Cmp_c or Cmp_d is the comparator for c or d. Now, A, B and c, d can be formed to a directed graph pointing from contexts to features. Let $I(v)$ and $O(v)$ denote the set of in-neighbors and out-neighbors of v respectively, where v is a node in the graph. $I_i(v)/O_i(v)$ denotes an individual in-neighbor/out-neighbor of v for $1 \leq i \leq |I(v)|/1 \leq i \leq |O(v)|$. The similarity between A and B is computed using the following recursive equations: for $A \neq B$,

$$s(A,B) = \frac{C}{|O(A)||O(B)|} \sum_{i=1}^{|O(A)|} \sum_{j=1}^{|O(B)|} s(O_i(A), O_j(B)), \quad (1)$$

and for $c \neq d$,

$$s(c,d) = \frac{C}{|I(c)||I(d)|} \sum_{i=1}^{|I(c)|} \sum_{j=1}^{|I(d)|} s(I_i(c), I_j(d)), \quad (2)$$

where $C \in (0,1)$ is a constant which can be considered as a confidence level or a decay factor. And the similarity among the values of the assessment feature c or d should be computed through a specific designed comparator.

3. THE PROPOSED MODEL

Our cloud service selection approach consists of six steps:

Step 1 (Normalizing the values of subjective attributes): The values of subjective attributes are converted into fuzzy ratings through a mapping from linguistic variables to trapezoidal fuzzy numbers [3].

Step 2 (Normalizing the values of objective attributes): The values of objective attributes are first represented by trapezoidal fuzzy numbers, and then converted into fuzzy ratings by comparing the values of the same objective attribute in all alternative cloud services.

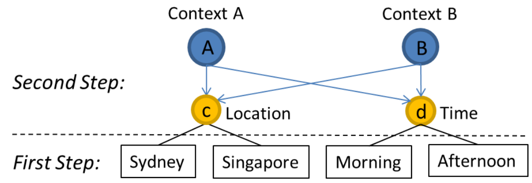

Figure 2: An Example of Two Contexts

Step 3 (Computing the importance weight for each attribute): An importance weight expressed in the form of linguistic variables is given to each attribute by the potential cloud consumer who asks for cloud service selection, and then converted into a normalized weight.

Step 4 (Determining the dynamic benchmark levels): According to the context similarity between objective assessment and subjective assessment, a group of filtration thresholds are computed for each alternative cloud service based on the given importance weights and the theoretical maximum Euclidean distance between the normalized fuzzy ratings of the corresponding associated attribute pairs.

Step 5 (Filtering biased subjective assessments): The Euclidean distance between the normalized fuzzy ratings of the corresponding associated attribute pairs is computed for each alternative cloud service. If such a distance exceeds a threshold determined in the last step, we take the objective assessment as a benchmark to filter out the biased subjective assessments having the exceeded distances. The less similar the context, the less reliable the subjective assessments, and therefore, the lower the threshold.

Step 6 (Aggregating all attributes): The remaining fuzzy ratings of all the attributes are aggregated according to the given importance weights. Then the aggregated results of all alternative cloud services are ranked for selection.

4. CONCLUSION

This paper has proposed a novel model of cloud service selection based on the comparison and aggregation of contextual subjective assessment and objective assessment of cloud services. Through dynamic filtration of biased subjective assessments, the final aggregated results can effectively reflect the overall performance of cloud services.

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